Dual-Population Co-Evolution Multi-Objective Optimization Algorithm and Its Application:

Power Allocation Optimization of Mobile Base Stations

Yu Bo, Zhijing Mining Group Co. Ltd., China
Fahui Gu, Guangdong Polytechnic, China*

ABSTRACT

In the multi-objective optimization algorithm, the parameter strategy has a huge impact on the performance of the algorithm, and it is difficult to set a set of parameters with excellent distribution and convergence performance in the actual optimization process. Based on the MOEA/D algorithm framework, this paper constructs an improved dual-population co-evolution MOEA/D algorithm by adopting the idea of dual-population co-evolution. The simulation test of the benchmark functions shows that the proposed dual-population co-evolution MOEA/D algorithm have significant improvements in IGD and HV indicators compared with three other comparison algorithms. Finally, the application of the LTE base station power allocation model also verifies the effectiveness of the proposed algorithm.

KEYWORDS

Co-Evolution Strategy, Diffusion Algorithm, Dual-Population MOEA/D Algorithm, Mobile Base Station Power Allocation, Multi-Objective Optimization

1. INTRODUCTION

1.1 Description of Multi-Objective Optimization Problem

In production activities, multi-objective optimization problems are widespread, such as: RGV dynamic scheduling problem (Li et al., 2020), adaptive parameter estimation problem in wireless networks (Dash et al., 2020). Under normal circumstances, the sub-goals of a multi-objective optimization problem are contradictory to each other, and it is impossible to make all the sub-goals reach the optimal value at the same time. It is often necessary to coordinate and weigh among the sub-goals (Tamaki et al., 1996; Tan et al., 2002). The optimization solution of the multi-objective optimization problem is not unique, but a set of optimal solutions, called the Pareto optimal solution. The decision

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*Corresponding Author

maker should select the appropriate element from the Pareto optimal solution as the final decision plan according to the needs.

1.2 Research Status of Multi-Objective Optimization Algorithms

The early multi-objective optimization uses linear programming to optimize, but it will become difficult to face complex nonlinear problems. Since the birth of evolutionary algorithm, due to its heuristic search strategy, it has been used in multi-objective problem optimization and has achieved excellent performance. Current multi-objective evolutionary algorithms can be divided into four categories: a. Multi-objective evolutionary algorithms based on Pareto dominance, represented by SPEA, PESA algorithms and their improved algorithms (Zitzler et al., 2001; Lalitesh & Prawendra, 2020); b. Multi-objective evolution based on decomposition Algorithm. In 2007, Zhang first proposed the MOEA/D (Zhang & Li, 2008) algorithm. In recent years, it has become a popular algorithm framework in the field of multi-objective optimization; c. Multi-objective evolutionary algorithm based on indicators, which knows evolution strategies through evaluation indicators, such as SMS-EMOA (Beume et al., 2007), R2-MOGA (Zhu et al., 2017), etc.; d. Hybrid algorithm, combining the advantages of the previous three algorithms to form a hybrid algorithm to solve high-latitude multi-objective complex optimization problems, for instance, a hybrid algorithm HCGA-PSO is proposed based on the global search ability of genetic algorithm and the fast convergence performance of PSO algorithm (Li et al., 2019), while Dang (Dang et al., 2016) proposed an analytical approach based on Newton's methods and nonlinear barrier method to solve this large-scale joint multi-objective optimization problem.

However, some novel multi-objective optimization algorithms for solving large-scale complex multi-objective optimization problems have been reported recently. Zhou proposed a SIR-DNA algorithm (Zhou, 2020) which was constructed based on the DNA-based SIR (susceptible-infectious) infectious disease model, and the algorithm has the advantages of strong global search ability and has a high convergence speed for solving complex optimization problems. Dang and Kinsner introduced an adaptive multi-objective mimetic optimization algorithms (AMMOA) (Dang & Kinsne, 2016), it guides the process of adaptive selection, clustering and local learning according to the information theory criterion, and adopts the robust stop criterion of AMMOA. These novel algorithms provide more useful alternatives for multi-objective optimization problems.

1.3 Research Ideas of This Article

In the study of multi-objective optimization problems, it is found that the parameter setting of the optimization algorithm has a great influence on the optimization result. It is difficult to set a set of fixed parameters with good distribution and convergence performance. Inspired by the idea of dual-population coevolution for TLBO algorithm (Gu et al., 2019), this paper proposes three co-evolution strategies to achieve co-evolution among sub-populations, so that the distribution and convergence of the algorithm achieve the best results. In addition, in view of the uneven distribution of the weight vector of multi-objective optimization algorithm based on decomposition when facing problems with three or more dimensional targets, an improved pressure diffusion algorithm is proposed to improve the distribution of the weight vector and improve the performance of the algorithm. Taking the MOEA/D algorithm as an example, this paper proposed a dual-population MOEA/D algorithm based on the above two improvement measures, and the ZDT and DTLZ benchmark functions were used to carry out simulation tests to verify the effectiveness of the improvement measures.

Finally, this paper carried out the application research of the improved dual-population MOEA/D algorithm in the power allocation optimization of mobile base stations. Take the LTE wireless network optimization problem for example, a base station power allocation optimization model was established, and then MOEA/D algorithm and the improved dual-population MOEA/D algorithm were used to optimize the model.

2. DUAL-POPULATION CO-EVOLUTION MULTI-OBJECTIVE OPTIMIZATION ALGORITHM

In the process of multi-objective optimization, the setting of optimization algorithm parameters has a great influence on the optimization results, and the setting of algorithm parameters often has to be weighed between distribution and convergence. In the multi-objective optimization of a single population, it is difficult to set a set of fixed parameters with both good distribution and convergence, and the dynamic adjustment of parameters often lacks universality for different problems. An effective solution is to adopt a dual-population evolution strategy. The two sub-populations adopt different parameter strategies. For example, one sub-population adopts a distribution-oriented strategy, the other sub-population adopts a convergence-oriented strategy, and the two sub-populations communicate with each other to achieve the best optimization effect.

2.1 Research of Co-Evolution Strategies for Dual-Population

In the dual-population multi-objective optimization algorithm, the dual-population co-evolution strategy is the key to improving the performance of the algorithm. Dual-population co-evolution strategies includes the following types: competition-based evolution strategies (Wang et al., 2015), collaboration-based evolution strategies (Han et al., 2013), greedy evolution strategies (Mu, 2016), etc. This paper proposes a cooperative-based co-evolution strategy for the dual-population MOEA/D algorithm, which including the following three aspects.

2.1.1 Sharing Reference Point

In the MOEA/D algorithm, the reference point is the known optimal value of each space vector in its target space, and the reference point plays a role in guiding the evolution direction of the population. For this reason, in the dual-population MOEA/D algorithm, two sub-populations can share reference points, that is, a new optimal reference point is formed by the optimal values of the reference points from the two sub-populations, as shown in formula (1), which accelerates the optimization process:

$$Zr = \begin{bmatrix} \min(Zr_{1i}, Zr_{2i}) \\ \min(Zr_{12}, Zr_{22}) \\ \cdots \\ \min(Zr_{1M}, Zr_{2M}) \end{bmatrix} \tag{1}$$

Among them Zr are the next-generation reference points of dual populations, Zr_{1i} and Zr_{2i} ($i = 1,2,\ldots,M$) are the values of the reference points in the last iteration of subpopulation 1 and subpopulation 2 in the i th dimension, M is the target numbers of the optimization problem.

2.1.2 Differentiated Cross Mutation Strategy

The crossover mutation strategy of the classic MOEA/D algorithm uses Simulated Binary Crossover (SBX) operators (Agrawal et al., 1994) and Polynomial Mutation (PM) operators (Zeng et al., 2016). Where the propagation factor of the SBX operator is a parameter that reflects the difference between the offspring and the parent, and is defined as follows:

$$\beta = \left| \frac{C_1 - C_2}{P_1 - P_2} \right| \tag{2}$$

Among them, C_1, C_2 are two offspring individuals, P_1 and P_2 are two parent individuals. The larger the value of β, the greater the difference between the offspring and the parent, and the smaller the value of β, the smaller the difference between the offspring and the parent. The value generally fluctuates around 1. In addition, in the SBX operator, the sum of the offspring and the parent is always equal, that is:

$$P_1 + P_2 = C_1 + C_2 \tag{3}$$

From formula (2) and formula (3), we can get:

$$\begin{cases} C_1 = \frac{1}{2}(P_1 + P_2) - \frac{1}{2}\beta(P_2 - P_1) \\ C_2 = \frac{1}{2}(P_1 + P_2) + \frac{1}{2}\beta(P_2 - P_1) \end{cases} \tag{4}$$

Once the value of β is determined, two offspring individuals can be calculated based on the parent. The probability distribution of β determines the performance of the SBX operator. The probability density distribution function of β is as follows:

$$c(\beta) = \begin{cases} 0.5(n+1)\beta^n & \beta \le 1 \\ 0.5(n+1)\frac{1}{\beta^{n+2}} & \beta > 1 \end{cases} \tag{5}$$

The SBX operator controls the degree of mutation after crossover of offspring through the control the value of n. Using a fixed n is often difficult to adapt to the evolution process of the algorithm. If n is set too large, the difference between the offspring and the parent will be smaller, which will cause the initial evolution of the algorithm to slow down or even converge to the local optimal solution; While if n is set too small, the difference between the offspring and the parent will be greater, and then result in the slower convergence speed as well as the lower convergence accuracy. For this reason, in the dual-population MOEA/D algorithm in this article, the value of n in one subpopulation is set to a larger value ($n = 6$), and n 's value of another subpopulation is set to a smaller value ($n = 2$). There is also individual swap between the two subpopulations, which balances the problems caused by n settled to be too large or too small.

The definition of PM algorithm is as follows:

$$x_{t+1} = \begin{cases} x_t + \delta, & rand < \mu \\ x_t, & rand \ge \mu \end{cases} \tag{6}$$

Among them, $rand$ is a random number in the range of [0,1], μ is the mutation probability threshold, and δ is the mutation operator, defined as follows:

$$\delta = \begin{cases} (2u_i^{\frac{1}{\eta_u+1}} - 1), & u_i < 0.5 \\ 1 - [2(1-u_i)]^{\frac{1}{\eta_u+1}}, & u_i \ge 0.5 \end{cases} \tag{7}$$

where, u_i is a random number and η_u is the variation factor.

In PM operator, the mutation probability of offspring can be affected by adjusting the mutation probability threshold μ. If a fixed threshold μ is set, when the threshold μ is set too large, the algorithm's global search capability will be enhanced, but the later convergence speed will be reduced. When the threshold μ is set too small, the algorithm's convergence capability will increase, but the global convergence capability will decrease, which result in the distribution of the solution set decreases or even falls into a local optimal solution.

For this reason, in the dual-population MOEA/D algorithm in this paper, one subpopulation is set to a larger value of μ ($\mu = 4 / D$), and the other subpopulation is set to a smaller value of μ ($\mu = 1 / D$), where D is the state space dimension of the problem to be optimized. There is also individual swap between the two sub-populations, which balances the problems caused by too large or too small value of μ.

2.1.3 Greedy Exchange Strategy

The swap between the two sub-populations uses a greedy strategy to exchange members of each other: after each round of update is completed, a certain sample is drawn from sub-population 2, and then an equal number of individuals from sub-population 1 are randomly selected. The selected individuals from the two sub-populations were compared with each other one by one. If the target mean value of the sample individuals of subpopulation 2 is better than the corresponding individuals of sub-population 1, then the sample of sub-population 2 will be used to replace the corresponding individuals of sub-population 1. On the contrary, a certain sample is drawn from sub-population 1, and then the equivalent individuals of sub-population 2 are compared in a one-to-one correspondence. If the target average of the sample individuals of subpopulation 1 is better than that of individuals of sub-population 2, the sample of sub-population 1 will be used to replace the corresponding individuals of sub-population 2. Then the swap between the elite individuals of the two sub-populations completed and the co-evolution process also realized.

2.2 Research on Improvement of Weight Division Algorithm

In the decomposition-based MOEA/D algorithm, the weight vector has a direct impact on the optimization result. The ideal weight vector should be uniformly distributed in the target space, and the resulting solution set has a good distribution. The weight vector is a set of normalized solutions in the target space, which can be expressed as:

$$W = \begin{bmatrix} w_1 \\ w_2 \\ \cdots \\ w_M \end{bmatrix} \tag{8}$$

Among them, $w_1 + w_2 + ... + w_M = 1$, M is the target dimension. For a 2-dimensional target problem, it represents a straight line. For a 3-dimensional target problem, it represents a plane. For a 2-dimensional target problem or a 3-dimensional target problem, the decomposition weight planning is to find uniformly distributed points in a straight line or a plane. The space above 3 dimensions is much more complicated, so we won't discuss it here. The basic MOEA/D algorithm uses the linear decomposition method to generate the weight vector. The weight vector in the 2-dimensional target problem and the 3-dimensional target problem is shown in Figure 1.

It can be seen from Figure 1 that the weight vector of the 2-dimensional objective optimization problem is uniformly distributed in a straight line, but the weight vector of the 3-dimensional

Figure 1a. Weight vector of 2-dimensional problems

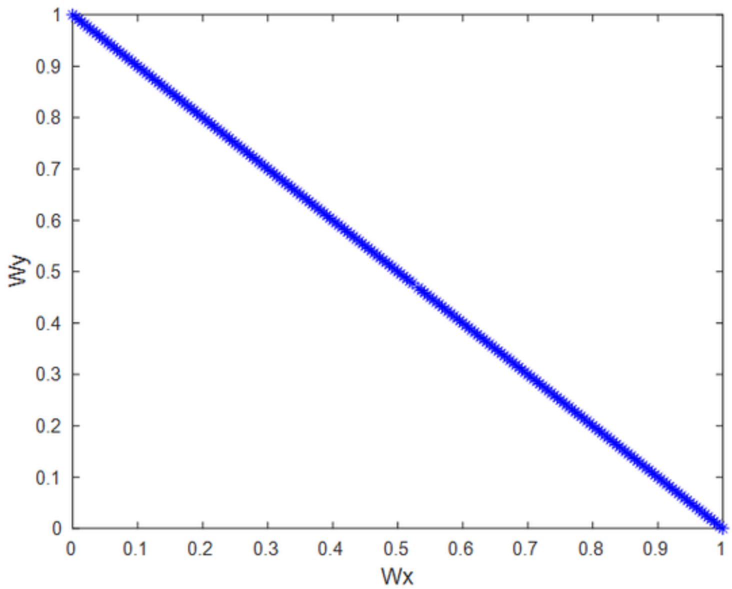
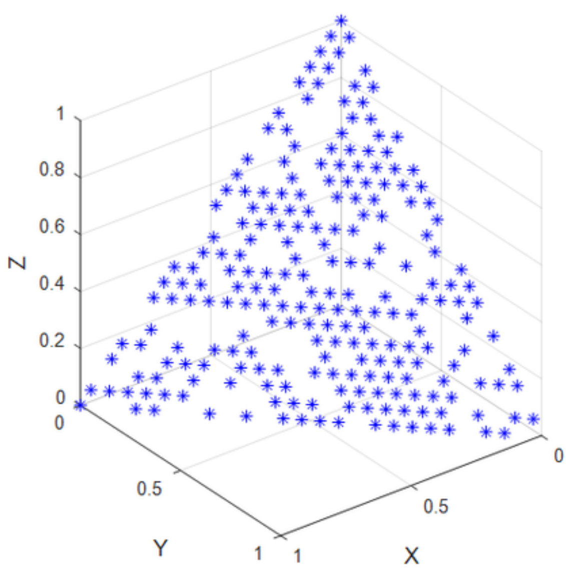


Figure 1b. Weight vector of 3- dimensional problems



objective optimization problem is unevenly distributed, which will reduce the distribution of the final optimization result. For this reason, this paper proposes an improved diffusion algorithm to produce uniformly distributed weights in the target space.

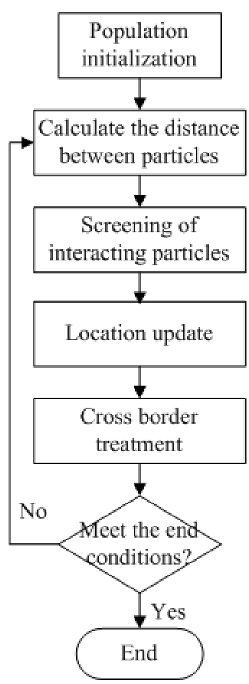
2.2.1 Diffusion Algorithm Based on Pressure

The pressure diffusion algorithm simulates the process in which microscopic particles spread out in a limited space due to the interaction force between them, and finally are uniformly distributed in the limited space. The algorithm is based on Newtonian mechanics, by calculating the interaction force between particles, and then using Newton's second law to update the velocity and position of each particle. The algorithm steps include: initialization -> calculating the distance between particles -> calculating the force between particles -> calculate the resultant external force -> speed, position update -> cross-border processing -> loop or end.

2.2.2 Improved Diffusion Algorithm Based on Pressure

The pressure diffusion algorithm can successfully simulate the diffusion process, but when the number of particles is large, the calculation amount of the algorithm increases geometrically; and there is a problem of slow convergence speed in a limited space. For this reason, three improvements are proposed to the pressure diffusion algorithm: first, because the force between particles is inversely proportional to the square of the distance, the interaction force between particles whose distance is greater than a certain threshold can be ignored; second, the distance between two points is used update the position, omit the calculation process of Newtonian mechanics, and increase the calculation speed; finally, random components were introduced in the position update process to simulate the complexity of microscopic particle motion. The flow of the improved pressure diffusion algorithm is shown in Figure 2. The position update formula of the improved pressure diffusion algorithm is as follows:

Figure 2. The flow of the improved pressure diffusion algorithm



$$X_i = X_i + (X_i - X_j) + rand * Step \quad (9)$$

where, X_i, X_j are the current positions of the i-th and j-th particles, respectively, X_i' are the updated positions of the i-th particle, and $(X_i - X_j)$ represent the reverse vector of the direction from the i-th particle to the j-th particle, that is, the particles are always far away from each other by repulsion, $rand$ is a random number between [0,1], $Step$ is the random diffusion step size.

As we can see, compared with Figure 1(b), the weight vector in Figure 3(c) is more evenly distributed in the 3D target space, which will be ready to improve the performance of MOEA/D algorithm.

2.3 Dual-Population Co-Evolution Multi-Objective Optimization Algorithm

Based on the above research, this paper proposes a dual population co-evolution multi-objective optimization algorithm based on improved diffusion weight. The proposed algorithm takes MOEA/D algorithm as the basic framework, and uses the improved pressure diffusion algorithm to generate evenly distributed weight vectors to ensure the good distribution of the optimization algorithm. At the same time, in order to balance the convergence and distribution of the multi-objective optimization algorithm, the algorithm sets up two subpopulations, and the three strategies of sharing reference points, differential cross mutation strategy and greedy communication strategy are adopted between the two subpopulations. In co-evolutionary strategy, one parameter setting of two subpopulations is conducive to convergence, the other parameter setting is conducive to distribution, and the two subpopulations interact and co-evolutes with each other. The improved multi-objective co-evolutionary algorithm is shown in Algorithm 1.

Figure 3a. Diffusion process of weight vector generation in 3D target space by improved diffusion algorithm: Initial population

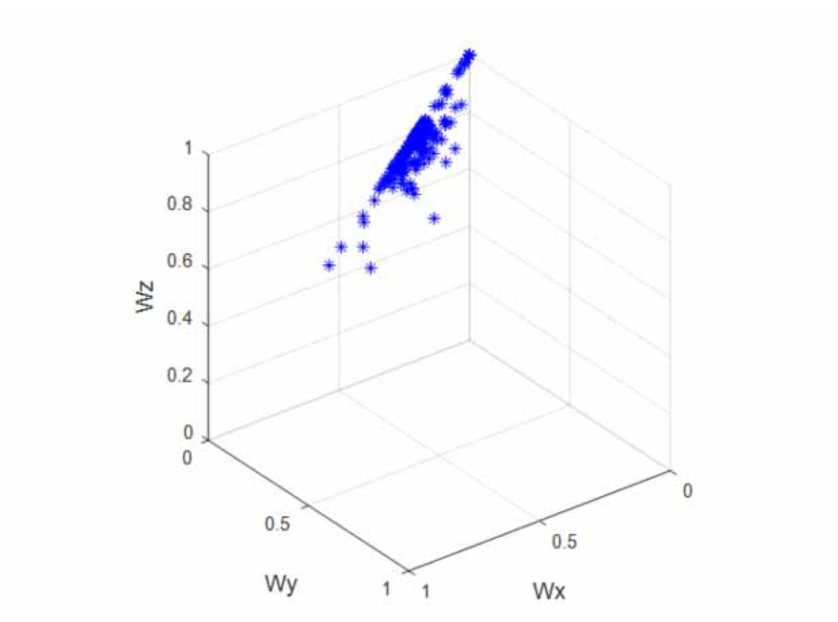


Figure 3b. Diffusion process of weight vector generation in 3D target space by improved diffusion algorithm: Population after diffusion (after 10 iterations)

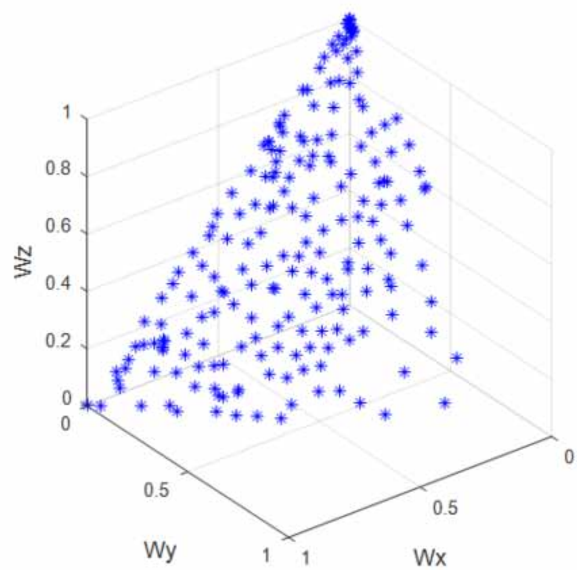
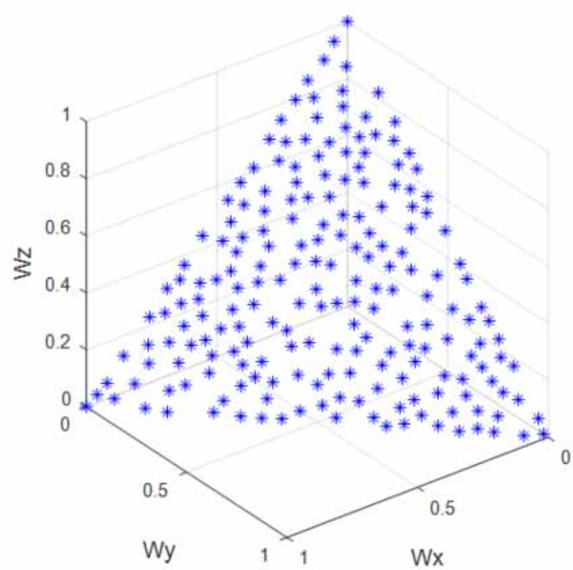


Figure 3c. Diffusion process of weight vector generation in 3D target space by improved diffusion algorithm: Population after diffusion (after 1000 iterations)



Algorithm 1: Dual-population co-evolutionary multi-objective optimization algorithm based on improved diffusion weight

```
Initialization of basic parameters;
Generate weight vector by using improved pressure diffusion algorithm;
Population initialization: initialization of individual
position, neighbor relationship and cross mutation parameters
of subpopulation 1 and subpopulation 2;
Initialize Z value;
while gen<Maxgen do
   for X1_i do
     Generate new individual y by cross mutation;
     Cross border treatment;
     The fitness of y was calculated;
     The value of Z1 was updated by Chebyshev method;
     Neighbor update;
   end for
   for X2_i do
     The new individual y was produced by cross mutation;
     Cross border treatment;
     The fitness of y was calculated;
     The Z2 value was updated by Chebyshev method;
     Neighbor update;
   end for
   Shared Z value: z = min (Z1, Z2);
   population exchange;
end while
```

3. MULTI-OBJECTIVE COOPERATIVE OPTIMIZATION OF MOBILE BASE STATION POWER

In order to verify the effectiveness of the two population co-evolution multi-objective optimization algorithm based on the improved diffusion weight, three classical algorithms NSGA-II, SPEA-II and MOEA/D are selected as the compared algorithm to carry out the performance verification test. The basic parameters of the experiment are as follows: the total number of individuals of all algorithms is 220, the number of iterations is 1000, and five ZDT test functions and five DTLZ (Deb, 2005) test functions are selected. And three statistical indexes of MS (Zitzler, 1999), IGD (David et al., 1998) and HV (Zitzler, 1999) were selected. Each function was tested five times independently, and the average value of the five experiments was taken as the test result. Through the simulation test on MATLAB platform, the test results are shown in Table 1 Table 2 and Table 3.

As can be seen from Table 1, the MS index of dual population MOEA/D algorithm is generally better than that of NSGA-II and PESA-II algorithm, but is basically the same as that of MOEA/D algorithm; and from Table 2 we can see that the IGD index of dual-population MOEA/D algorithm is significantly improved compared with that of NSGA-II, PESA-II and MOEA/D algorithm, but it is inferior to that of NSGA-II and PESA-II algorithm in DTLZ1 and ZDT2; we can also get from Table 3 that the HV index of the dual-population MOEA/D algorithm is also significantly improved compared with that of NSGA-II, PESA-II and MOEA/D algorithm, but it is also inferior to that of NSGA-II and PESA-II algorithm in the DTLZ2.

Table 1. MS test index

Test functions	NSGA-II		SPEA-II		MOEA/D		Dual-population MOEA/D
DTLZ1	1.21E-02	+	4.15E-02	+	1.00E+00	=	1.00E+00
DTLZ2	9.62E-01	+	1.00E+00	=	1.00E+00	=	1.00E+00
DTLZ3	1.00E+00	=	1.00E+00	=	1.00E+00	=	1.00E+00
DTLZ5	6.30E-01	+	7.11E-01	+	9.94E-01	+	9.96E-01
DTLZ6	1.00E+00	=	1.00E+00	-	9.96E-01	=	9.96E-01
ZDT1	9.83E-01	+	9.67E-01	+	1.00E+00	=	1.00E+00
ZDT2	9.93E-01	+	9.80E-01	+	1.00E+00	=	1.00E+00
ZDT3	1.00E+00	-	9.99E-01	=	9.99E-01	=	9.99E-01
ZDT4	8.08E-01	+	9.07E-01	+	1.00E+00	=	1.00E+00
ZDT6	9.85E-01	+	1.00E+00	=	1.00E+00	=	1.00E+00

Note: "+" indicates that the MS index of the dual-population MOEA/D algorithm is better than that of the corresponding comparison algorithm; "-" indicates that the MS index of the dual-population MOEA/D algorithm is worse than that of the corresponding comparison algorithm; "=" indicates that the MS index of the dual-population MOEA/D algorithm is equal to that of the corresponding comparison algorithm.

Table 2. IGD test index

Test functions	NSGA-II		SPEA-II		MOEA/D		Dual-population MOEA/D
DTLZ1	1.46E-02	-	1.81E-02	-	5.86E-02	+	2.27E-02
DTLZ2	8.03E-02	+	7.89E-02	+	4.52E-03	-	4.69E-03
DTLZ3	9.59E+00	+	1.01E+00	+	2.50E-02	+	2.15E-02
DTLZ5	2.80E-01	+	2.91E-01	+	3.35E-03	+	3.30E-03
DTLZ6	4.29E-01	+	4.50E-01	+	3.38E-03	=	3.38E-03
ZDT1	4.60E-03	+	4.73E-03	+	1.36E-03	+	1.32E-03
ZDT2	6.49E-04	-	6.48E-04	-	9.02E-04	+	8.49E-04
ZDT3	6.34E-03	+	6.51E-03	+	4.02E-03	+	4.01E-03
ZDT4	2.08E-02	+	5.72E-02	+	2.11E-03	+	2.10E-03
ZDT6	4.79E-02	+	4.99E-02	+	7.95E-04	+	7.93E-04

Note: "+" indicates that the IGD index of the dual-population MOEA/D algorithm is better than that of the corresponding comparison algorithm; "-" indicates that the IGD index of the dual-population MOEA/D algorithm is worse than that of the corresponding comparison algorithm; "=" indicates that the IGD index of the dual-population MOEA/D algorithm is equal to that of the corresponding comparison algorithm.

It can be seen that the test indexes of the dual-population co-evolutionary MOEA/D algorithm based on the improved pressure diffusion weight algorithm are better than that of NSGA-II, PESA-II and MOEA/D algorithms, in which the MS index is stable compared with that of the MOEA/D algorithm, and the IGD and HV index are significantly improved compared with that of the three comparison algorithms. It shows that the three co-evolution strategies and the improved pressure diffusion weight algorithm have significant effect on improving the convergence of the multi-objective optimization algorithm.

Table 3. HV test index

Test functions	NSGA-II		SPEA-II		MOEA/D		Dual-population MOEA/D
DTLZ1	1.34E+07	+	2.51E+07	+	3.09E+07	=	3.09E+07
DTLZ2	8.27E+01	-	8.84E+01	-	4.55E+01	+	4.74E+01
DTLZ3	2.02E+04	+	8.76E+03	+	2.74E+05	=	2.74E+05
DTLZ5	7.79E+00	+	8.17E+00	+	2.93E+01	+	2.98E+01
DTLZ6	4.92E+04	+	5.00E+04	+	2.59E+05	=	2.59E+05
ZDT1	8.82E-02	+	9.58E-02	+	8.12E-01	+	8.33E-01
ZDT2	9.49E-01	=	8.56E-01	+	9.06E-01	+	9.49E-01
ZDT3	3.10E+02	+	4.84E+02	+	5.32E+02	=	5.32E+02
ZDT4	7.54E+03	-	2.38E+03	+	5.82E+03	+	5.84E+03
ZDT6	8.43E+01	+	8.89E+01	+	5.43E+02	-	5.40E+02

Note: "+" indicates that the HV index of the dual-population MOEA/D algorithm is better than that of the corresponding comparison algorithm; "-" indicates that the HV index of the dual-population MOEA/D algorithm is worse than that of the corresponding comparison algorithm; "=" indicates that the HV index of the dual-population MOEA/D algorithm is equal to that of the corresponding comparison algorithm.

4. MULTI-OBJECTIVE COLLABORATIVE OPTIMIZATION OF POWER ALLOCATION FOR MOBILE BASE STATIONS

4.1 Problem Description

Power allocation of mobile base station has always been the focus and difficulty in network optimization. There is a high-dimensional nonlinear complex relationship between base station power and network performance. Taking LTE network as an example, the main performance indicators of LTE wireless network are reference signal receiving power (RSRP), signal to interference plus noise ratio (SINR), and overlap coverage rate.

1. RSRP is the received signal power (dBm) of the terminal. In LTE system, its value range is generally from -40dBm to -140dBm. In the network environment, the calculation formula of RSRP power P_r is defined as follows:

$$P_r = P_t - 10n \lg r \tag{10}$$

Among them, P_r is the received signal power (dBm), P_t is the transmitted signal power (dBm), n is the path loss factor, generally in the range of [2,4], and is related to the wireless environment. r is the distance between the receiving point and the base station. It can be seen from equation (10) that the relationship between distance and distance is logarithmic.

2. SINR is also referred to as "signal to noise ratio", which means that the higher the signal quality, the better. If the signal power is in dB, it is defined as follows:

$$\mathrm{SINR} = P_S - P_N \tag{11}$$

where, P_S is the occupied cell signal power, and P_N is the noise power. By substituting equation (10) into equation (11), the relationship between SINR and P_t is obtained as follows:

$$\text{SINR} = P_t - 10n\log r - P_N \tag{12}$$

Because the composition of P_N is complex, mainly including the atmospheric background noise and the power of adjacent area, SINR has a complex non-linear relationship with power P_t. When P_t is too small, the bottom noise becomes the main factor of SINR, the smaller the P_t is, the lower the SINR is; when P_t is too high, the collar power also increases, which also reduces the SINR.

3. Overlap coverage rate (OLC rate) is a measure of the "clutter degree" of signals in a spatial area. Because LTE is a network with intra-frequency, the more signals in the same area, the closer the power level is, and the greater the interference between them, the higher the overlapping coverage of the area. The definition of overlapping coverage in LTE system is as follows: in TD-LTE intra-frequency network, the area with more than 3 overlapping coverage cells (including service cells) whose signal strength is less than 6dB and RSRP CRS is greater than -110dBm is called overlapping coverage area. Then the overlapping coverage rate is determined as the ratio of overlapping coverage sampling points to the total number of sampling points.

Obviously, the smaller the P_t is, the lower the overlap coverage of the same area is, and the lower the overlap coverage is; the larger the P_t is, the higher the overlap coverage of the same area is, and the higher the overlap coverage is. That is to say, there is a positive correlation between the overlapping coverage rate and P_t.

4.2 The Establishment of the Model

In order to study the optimal relationship between power allocation of mobile base station and RSRP, SINR and overlap coverage index, a network model composed of 9 base stations is constructed to carry out simulation test. The initial transmit power of the base station is set as -40dBm by default, and the LTE base station (eNodeB) is simplified as omni-directional base station. The simulation experiment is carried out on the MATLAB platform, and the RSRP, SINR and overlapping coverage of the sampling points on 9 sections of roads in the area are shown in Figure 4. The average RSRP, SINR and overlapping coverage rate of the network before optimization are -87.68dBm, 7.43dB and 9.04% respectively.

4.3 The Application of the Algorithm

MOEA/D and dual-population co-evolutionary MOEA/D algorithm are used to optimize the LTE wireless network optimization model established in the previous section. The power of nine base stations is used to construct a 9-dimensional independent variable, and RSRP, SINR and overlap coverage are used as three-dimensional target variables. The objective function is constructed according to the definition of RSRP, SINR and overlap coverage in Section 3.1:

$$fun(Samp, PT) = \begin{cases} RSRP = P_t - 10n\lg r_{\min}, & -140 \le P_t \le -20, 2 \le n \le 4, r_{\min} > 0 \\ SINR = P_t - 10n\lg r_{\min} - \sum_{i=1}^{n} P_i, & -140 \le P_t \le -20, 2 \le n \le 4, r_{\min} > 0, -140 \le P_i \le -20 \\ OLC = \dfrac{N_{overlap}}{N_{Samp}}, & N_{samp} > 0, 0 \le N_{overlap} \le N_{samp} \end{cases} \tag{13}$$

Among them, $Samp$ is the collection of network sampling points, which is composed of 3100 points covering the road in the map with an interval of 1m, PT is the base station transmit power,

Figure 4a. Coverage effect of LTE network model before optimization: RSRP overlay map

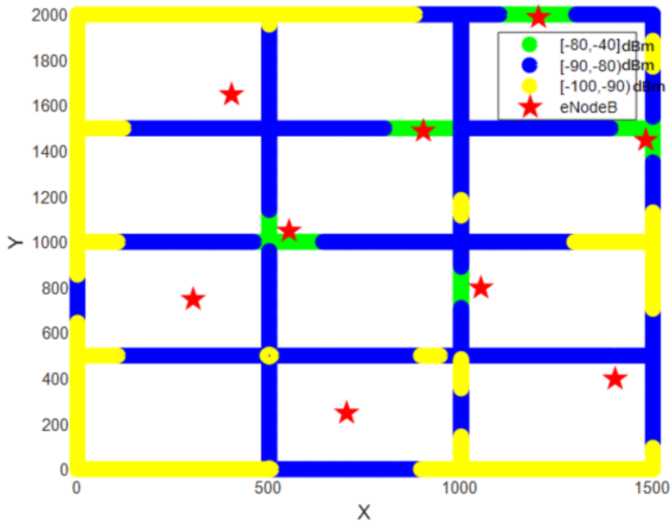
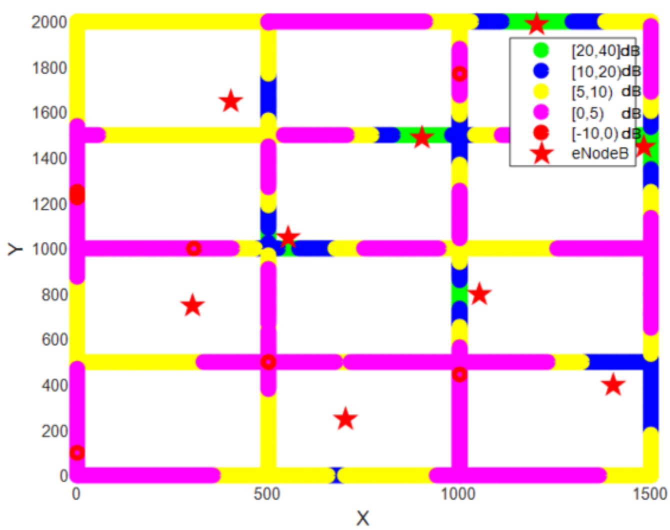
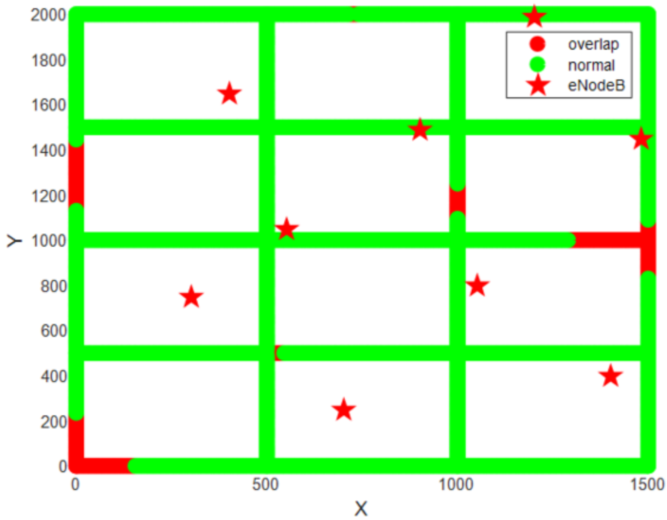


Figure 4b. Coverage effect of LTE network model before optimization: SINR overlay map



P_t is the power of the nearest base station received from the sampling point, $r_{\min}$ is the minimum distance between the sampling point and the base station, P_i is the other signal power received by the sampling point except for P_t, OLC is the overlap coverage rate, $N_{overlap}$ is the number of sampling points counted as overlap coverage, and N_{Samp} is the total number of sampling points. Then the optimization problem is transformed into a 9-input, 3-output optimization problem. Comparative

Figure 4c. Coverage effect of LTE network model before optimization: Overlapping coverage rate statistical map



optimization experiments are carried out under the framework of MOEA/D algorithm. It should be noted that since RSRP and SINR are positive optimization objectives, that is, the larger the better, negation and normalization should be carried out in the optimization process, so that they can be used as minimum optimization objectives together with OLC.

Under the framework of MOEA/D algorithm and the framework of dual-population co-evolution MOEA/D algorithm, the optimization model of formula (13) is run respectively. After 100 rounds of iterative optimization, the optimization effect (select a group of optimization solutions as the representative) is shown in Figures 5a – 5f.

Figure 5a. Coverage effect of LTE network model after optimization: RSRP(MOEA/D)

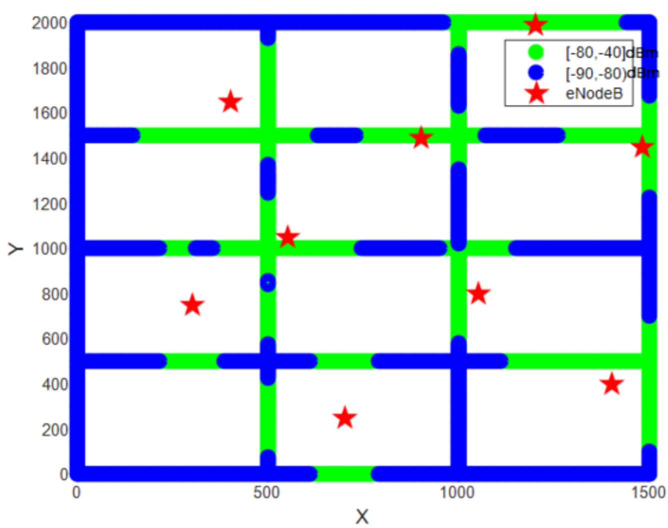


Figure 5b. Coverage effect of LTE network model after optimization: RSRP(dual-population MOEA/D)

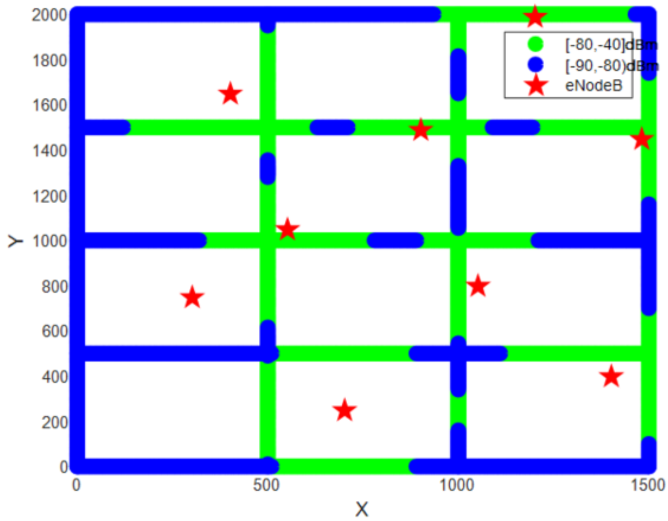
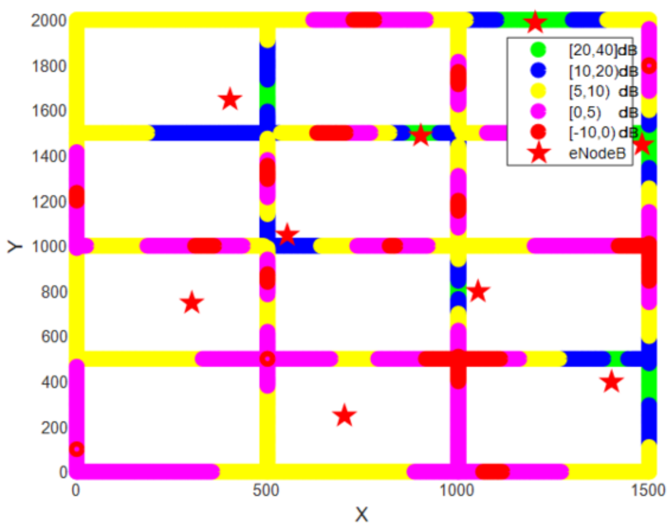


Figure 5c. Coverage effect of LTE network model after optimization: SINR(MOEA/D)



As can be seen from Figure 5, the RSRP, SINR and overlapping coverage of LTE network model are improved after the optimization of the two multi-objective optimization algorithms, and the improvement of RSRP is the most significant. This proves the applicability of the two multi-objective optimization algorithms to LTE network optimization model. Then through the index statistics, the comparative effects of RSRP, SINR and overlapping coverage before and after optimization are obtained, as shown in Table 4.

It can be seen from Table 4 that after the optimization of the two optimization algorithms, the RSRP of LTE network model has been improved by about 10dBm, which means that the

Figure 5d. Coverage effect of LTE network model after optimization: SINR(dual-population MOEA/D)

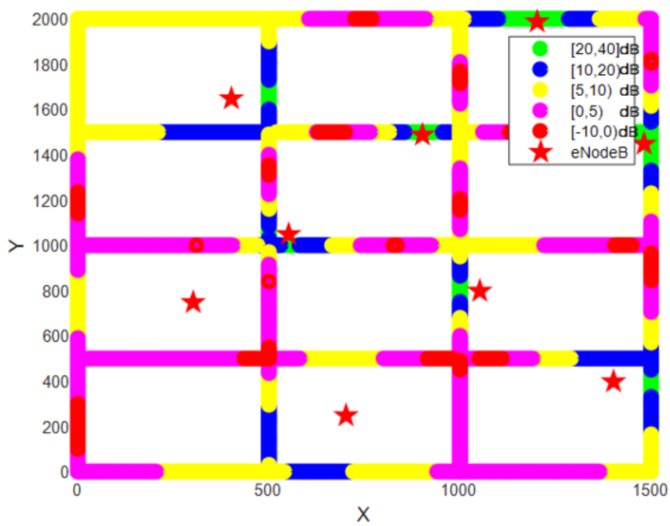
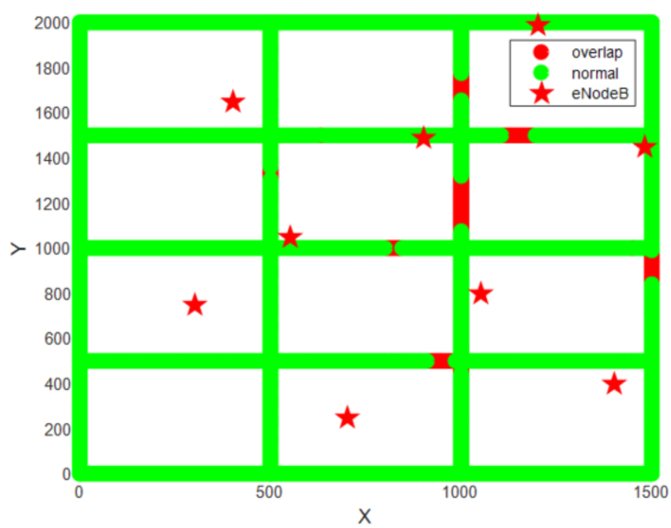


Figure 5e. Coverage effect of LTE network model after optimization: OLC(MOEA/D)



signal of LTE became stronger; SINR has been improved by about 0.7dB, which means the nose for LTE signal reduced; and the overlapping coverage has been reduced by 3.86% and 1.16% respectively, which means the LTE signal became purer; while the improvement of RSRP and SINR of the dual-population MOEA/D algorithm is greater than that of MOEA/D algorithm, but the optimization effect of overlapping coverage rate is slightly lower than that of MOEA/D algorithm. In general, in the application of LTE wireless network optimization model, both of the two algorithms can effectively enhance LTE signal strength, reduce interference, improve signal purity, and significantly improved the quality of LTE signal,

Figure 5f. Coverage effect of LTE network model after optimization: OLC(dual-population MOEA/D)

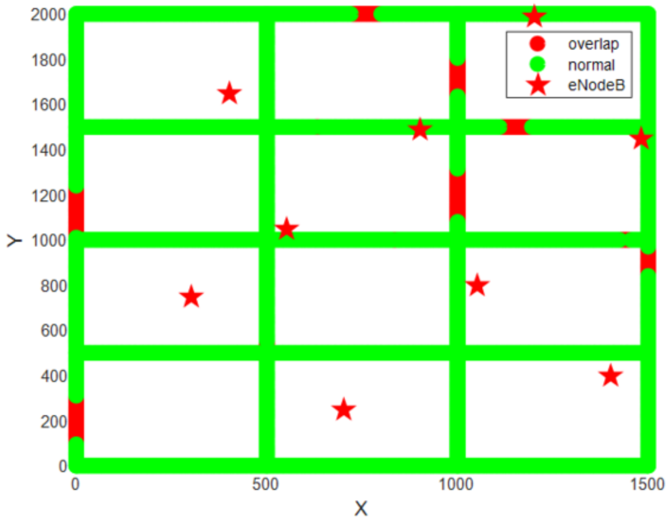


Table 4. Comparison of indexes before and after optimize of LTE network model

Index	Before optimize	Optimized by MOEA/D algorithm	Optimized by dual-population MOEA/D algorithm
RSRP/dBm	-87.68	-79.71	-78.98
SINR/dB	7.43	8.12	8.15
OLC/%	9.04%	5.18%	7.88%

but the dual-population MOEA/D algorithm performs better than the MOEA/D algorithm in two of the three optimization indexes. Its shows that the proposed dual-population MOEA/D algorithm has better comprehensive performance than MOEA/D algorithm in complex optimization problems.

5. CONCLUSION

In this paper, a dual-population co-evolutionary MOEA/D algorithm is proposed. The algorithm adopts three co-evolutionary strategies: shared reference point, differentiated cross mutation strategy and greedy communication strategy. The improved diffusion algorithm is used to divide the weights to enhance the distribution of the weights. Through the simulation test of the test function, it shows that the dual-population co-evolutionary MOEA/D algorithm is better than NSGA-II, PESA-II and MOEA/D algorithm in general, and the MS index is stable compared with MOEA/D algorithm, while the IGD and HV index are significantly improved compared with the three compared algorithms. This paper also takes LTE wireless network as an example to build a distributed multi-objective collaborative optimization model of mobile base station power, and then uses MOEA/D algorithm and dual-population co-evolutionary MOEA/D algorithm to optimize the model. The results show that the two algorithms can significantly improve the three optimization objectives of the model, but the overall performance of dual-population co-evolutionary MOEA/D algorithm is better than that of MOEA/D algorithm.

This paper not only has theoretical significance, but also has good application value in the field of multi-objective area. In the future, dual-population co-evolution with different multi-objective evolutionary algorithms is worthy of further research.

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Bo Yu received the B.E degree in from Hefei University of Technology University, Hefei City, China, in 2005 and M.E Degree in software engineering from Xiamen University, Xiamen City, China, in 2008. He has worked in the information department of Zijin Mining Group for a long time and is now the executive deputy general manager of the information R & D center. He has successively presided over the information projects of the group, such as OA, ERP, hybrid cloud, SD Wan, Financial Sharing Center, engineering project management, supply chain management platform, safety production management platform, global network optimization, group big data and so on, and have rich experiences in infrastructure construction and software project management.

Fahui Gu received the ME. E. degree in computer application technology from Jiangxi University of Science and Technology, Ganzhou city, China, in 2008 and PhD degree in agricultural electrical and automation from South China Agriculture University in 2017. He worked as a professor in the school of information technology in Jiangxi College of Applied Technology, Ganzhou city, China, from 2004 to 2019. He is the director of the dean's office of Guangdong Polytechnic, Foshan city, China. His current research interests include areas of evolutionary algorithms, co-evolution strategy, and wireless communication.