5G Private Network Deployment Optimization Based on RWSSA in Open-Pit Mine

Zhaozhao Chang, Qinghua Gu, Caiwu Lu, Yanhong Zhang, Shunling Ruan, and Song Jiang

***Abstract*—5G communication network is vital to the intelligent and unmanned technology of open-pit mine, but the high cost of 5G base station deployment will bring huge cost increases to mining enterprises. Thus, this article proposes an improved sparrow search algorithm (SSA) using random walk strategy (RWSSA) to optimization the distribution and signal coverage of 5G base stations in open-pit mine. In order to verify the performance of the algorithm, the SSA, the modified ant lion optimizer, the particle swarm optimization, and the RWSSA were used to compare and analyze the accuracy and speed of the algorithm in solving high dimensionality benchmark functions, respectively. The dimensions used in the test are 30, 100, and 500 dimensions. After that, four algorithms were applied to a real example to optimize the deployment of 5G base stations, including macrobase stations and microbase stations. RWSSA has very good performance in terms of performance and practical application. Therefore, RWSSA is more suitable for the application of 5G base station distribution optimization in open-pit mines.**

***Index Terms*—5G base station deployment, open-pit mine, random walk strategy, signal coverage, sparrow search algorithm (SSA).**

I. Introduction

As THE latest wireless communication technology in the commercial field, 5G communication network has become the foundation of this industrial revolution [1]. With the application of 5G communication network, open-pit mines can put unmanned remotely controlled equipment for production, thereby greatly improving mine safety. Thus, an efficient 5G wireless communication network can cover the entire open-pit mining area with a minimum of routing nodes, which can save the number of network base station deployed, and maximize the entire mining area with network signals [2]. As the deployment of 5G base stations requires a huge amount of money, the most optimized 5G base station deployment is a necessary condition for early investment in mine intelligence. With the realm of open-pit mines, optimizing the deployment of infrastructure nodes to maximize the coverage area of each 5G base station is one of the most effective ways to save communication costs [3]–[5].

In the mining area, the 5G network coverage problem is similar to the wireless sensor network (WSN) problem, which is a self-organizing network composed of 5G equipment capable of signal transmission [6]. Network area coverage is a key issue in WSN. Optimizing the coverage distribution of transmission nodes can improve network service treatment and energy consumption balance [7]–[9]. Due to its high construction cost, the location of the 5G base station is optimized before deployment and the minimum number of base stations is used to meet the signal coverage of the entire mine. The following Fig. 1 shows the layout of 5G macrobase stations in open-pit mine.

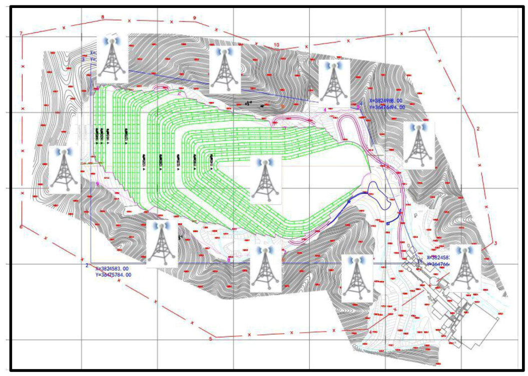

Fig. 1. Schematic diagram of 5G macrobase station layout in open-pit mine.

In recent years, swarm intelligence algorithms have been widely used in WSN sensor node coverage optimization problems [10]. The genetic algorithm is applied to the coverage control of WSN and has been optimized, but the algorithm is more complicated and the convergence speed is slow [11]. A WSN deployment optimization method based on the extrapolation artificial bee colony algorithm. Although it converges quickly, it has no obvious advantage in the coverage improvement compared

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with other algorithms [12]. Particle Swarm algorithm is widely used in WSN coverage optimization due to its features such as few control parameters, fast convergence speed, and easy implementation [13]. An improved particle swarm algorithm, which introduces a seed hybrid strategy, has achieved better results, and is easier to implement than genetic algorithms [14]. The WSN coverage optimization algorithm based on chaotic particle swarms has better global search capabilities than standard particle swarms. However, in the later stage of the search, particles with a high probability of chaotic perturbation are not conducive to refined search, and the computational complexity is greatly increased [15]. The evolution factor and aggregation factor are introduced into the inertia weight coefficient in the particle swarm optimization algorithm, and the collision and rebound strategy is adopted to ensure the diversity of the particle swarm, which has a more obvious effect on WSN coverage optimization [16]. The chaotic quantum particle swarm algorithm is applied to the coverage optimization of WSN, and the precocious judgment mechanism of elite individual fitness variance is proposed, which improves the coverage of WSN. However, this precocious judgment mechanism has limitations and cannot fully reflect the aggregation of particles [17]. The dynamic adaptive chaotic quantum particle swarm algorithm is applied to the coverage control of WSN. Compared with other improved particle swarm algorithm, the coverage rate has been improved, but its accuracy and node uniformity are not ideal [18]. Improved gray wolf optimization algorithm based on multiple strategies is used for node coverage optimization. The coverage and convergence speed are better than the basic gray wolf optimization algorithm, but its optimization results do not have advantages compared with other algorithms [19]. A network coverage optimization algorithm that combines Voronoi diagram, virtual force perturbation, and cuckoo search algorithm, effectively improves coverage [20]. Using Bayesian prediction algorithm ideas for reference to improve the artificial bee colony algorithm, a good coverage effect has been achieved, but it needs to be improved to achieve approximately complete coverage [21]. A network coverage optimization method based on a hybrid strategy to improve the ant lion algorithm, which improves the network coverage and optimizes the distribution of nodes more evenly [7]. The abovementioned research results show that a variety of different swarm intelligence algorithms are effective when applied to WSN network coverage optimization, but the optimization effect still needs to be improved. Therefore, it is necessary to propose a more novel swarm intelligence algorithm to apply to the network signal coverage problem.

In 2020, a new group intelligence algorithm based on sparrow foraging is proposed, namely the sparrow search algorithm (SSA) [22]. Compared with other swarm intelligence algorithms, SSA has the characteristics of high search accuracy, fast convergence speed, good stability, and strong robustness [23]. Although SSA has just appeared, due to its superior performance, many scholar are still interested in it and make exploratory improvements on the basis of the original algorithm. Some scholars have enhanced the local search ability and improved the search accuracy of the algorithm by introducing the method of Gaussian mutation [24]. Some scholars have proposed an improved sparrow algorithm that combines Cauchy mutation and reverse learning to obtain ISSA with faster convergence speed and higher accuracy, and the global optimization capability is greatly improved [24]. Some scholars have proposed a hybrid SSA. It uses the reverse opposition learning strategy to improve the quality of the initial population, and mixes the Metropolis criterion of the simulated annealing algorithm to avoid the algorithm from falling into the local optimum, so that it has a faster convergence speed and higher solution accuracy [24]. This article uses a random walk SSA, which uses a random walk strategy to perturb the optimal sparrow to improve its global search performance.

The random walk strategy is used to improve the original SSA, namely RWSSA, which can improve the global search ability of the original SSA, and has obtained a more accurate optimal solution. First of all, the optimal solution of the benchmark function in different dimensions is solved based on the simulation experiment, and compared with the original SSA, MS-ALO, and PSO to verify the effectiveness of RWSSA. Then, the four algorithms are applied to the optimal solution of the 5G base station layout problem in open-pit mines to verify the superior performance of RWSSA.

The rest of this article is organized as follows. Section II presents the 5G network base station deployment model. Section III describes SSA and how the random walk strategy improves SSA. Section IV compares the performance of the improved algorithm with other algorithms in finding the optimal solution in different dimensions. Section V conducts and application experiment of optimized distribution of 5G base stations in mines to compare the signal coverage of the four algorithms. Section VI mainly discusses the comparative analysis of the four algorithms in the application of 5G base station deployment in open-pit mine. Finally, Section VII concludes this article.

II. Problem Model

The area of open-pit mines are all measured in square kilometers. Therefore, the area of large-scale open-pit mines is very huge, which is very necessary for the optimization of the site selection of 5G base stations in open-pit mines. Assume that N 5G base stations are randomly deployed inside the open-pit mine with an area of $S = L_1 \times L_2$. The base station point set is defined as $Z = \{z_1, z_2, \cdots, z_n\}$, z_i position coordinates are (x_i, y_i), $i = 1, 2, \cdots, N$. The coverage radius of each base station node is R_s, and the communication radius is R_c. The coverage area of a 5G base station node is a closed circular area with itself as the center and R_s as a fixed radius. For the convenience of calculation, the signal coverage area is discretized into $M \times N$ pixels to be covered, and the set is $H_j = (x_j, y_j), j \in \{1, 2, \ldots, m \times n\}$. The geometric center point of each pixel is covering the optimized target position.

If the distance between pixel H_j and any node is less than or equal to the signal coverage radius R_s, it is deemed that H_j has been covered by the communication network. The distance between node Z_i and pixel H_j is defined as

$$d(z_i, H_j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}. \tag{1}$$

The probability $p(z_i, H_j)$ that pixel H_j is perceived by base station node z_i is defined as

$$p(z_i, H_j) = \begin{cases} 0, R_s \leq d(z_i, H_j) \\ \exp\left(-\lambda \frac{d(z_i,H_j)-R_s-R_e}{R_s-d(z_i,H_j)}\right), R_s{-}R_e{<}d(z_i,H_j){<}\ R_s \\ 1, R_s - R_e > d(z_i, H_j) \end{cases} \tag{2}$$

where $R_e$is the communication error of the base station node; λ is the signal attenuation coefficient.

In an open-pit mine, any pixel can be sensed by multiple base station nodes at the same time, and its joint perception probability $p(Z, H_j)$ is defined as

$$p(Z, H_j) = 1 - \prod_{i=1}^{N} [1 - p(z_i, H_j)]. \tag{3}$$

The coverage ratio of this area R_{cov} is the ratio of the total number of pixels covered by the node set Z to the total number of pixels in the area, defined as

$$R_{\text{cov}} = \frac{\sum_{j=1}^{m\times n} p(Z, H_j)}{m \times n}. \tag{4}$$

Therefore, formula (4) is used as the objective function of the random walk improved SSA to solve the 5G signal coverage optimization problem, i.e., all position variables are within the mine boundary, and the improved algorithm is used to optimize the maximum coverage rate R_{cov}.

III. Algorithm and Improvement Strategy

A. Algorithm Principle

In the simulation experiment, virtual sparrows are used to search for food. A population of n sparrows can be expressed as follows:

$$X = \begin{bmatrix} x_1^1 x_1^2 \cdots x_1^d \\ x_2^1 x_2^2 \cdots x_2^d \\ \cdots\cdots\cdots\cdots \\ x_n^1 x_n^2 \cdots x_n^d \end{bmatrix}. \tag{5}$$

Among, d represents the dimension of the variable to be optimized, and n is the number of sparrows. Therefore, the fitness value of all sparrows can be expressed as

$$F_x = \begin{bmatrix} f\left(\left[x_1^1 x_1^2 \cdots x_1^d\right]\right) \\ f\left(\left[x_2^1 x_2^2 \cdots x_2^d\right]\right) \\ \cdots f\left(\left[x_n^1 x_n^2 \cdots x_n^d\right]\right) \end{bmatrix} \tag{6}$$

where f represents the fitness value.

In SSA, discoverers with better fitness values will get food first in the search process. Because the discoverers are responsible for finding food for the entire sparrow population, meanwhile, proving foraging directions for all joiners. Therefore, the discoverers can obtain a larger foraging search range than the joiner. According to formula 5 and formula 6, in each iteration, the location update of the discoverers is described as follows:

Algorithm Improvement Random Walk Strategy

```
% Randomly walk the best sparrow to improve search ability
 RA = Get the beat random walk position of the sparrows;
 XRA = RA(i,:);
 If  use sparrow position to judge < fitness(1))
     X(1,:) = XRA;
     fitness(1) =  the optimal sparrow performs a random walk;
 end
 % Update the global optimum
 If (fitness(1) < Globally optimal sparrow)
    Globally optimal sparrow = fitness(1);
    Global optimal position = X(1,:);
 end
```

Fig. 2. RWSSA improvement strategy code.

$$X_{i,j}^{t+1} = \begin{cases} X_{i,j}.\exp\left(-\frac{i}{\alpha.iter_{\max}}\right), \text{if} R_2 < ST \\ X_{i,j} + Q.L, \text{if} R_2 \geq ST \end{cases} \tag{7}$$

where t represents the current number of iterations $j = 1, 2, 3, \ldots, d$. $iter_{\max}$is a constant, which represents the maximum number of iterations. X_{ij} represents the position information of the ith sparrow in the jth dimension. $a \in (0, 1]$ is a random number. $R_2(R_2 \in [0, 1])$ and $ST(ST \in [0.5, 1])$, respectively, represent the warning value and the safety value. Q is a random number following a normal distribution. L represents a matrix of $1 \times d$, in which each element in the matrix is all 1.

When $R_2 < ST$, there are no predators around the foraging environment, and the discoverers can perform a wide range of search operations. If $R_2 > ST$, it means that some sparrows in the population have found a predator and have issued an alarm to other sparrows in the population. Therefore, all sparrows need to fly quickly to other safe places for food.

For joiners, they need to implement formula (7) and formula (8). During the foraging process, some joiners will will always monitor the discoverers. Once they realize that the discoverers have found better food, they will immediately leave their current position to compete for food. If they win, they can immediately obtain the finder's food, otherwise they need to continue to execute formula (8). The location update description of the joiners are as follows:

$$X_{i,j}^{t+1} = \begin{cases} Q.\exp\left(\frac{X_{\text{worst}} - X_{i,j}^t}{i^2}\right), \text{if } i > n/2 \\ X_P^{t+1} + \left|X_{i,j} - X_P^{t+1}\right|.A^{+}.L, \text{otherwise} \end{cases}. \tag{8}$$

In the formula, X_p is the best position currently occupied by the discoverers, and X_{worst} is the worst position in the global. A represents a matrix of $1 \times d$, in which each element is randomly assigned a value of 1 or -1, and $A^+ = A^T(AA^T)^{-1}$. When $i > n/2$, it indicates that the Bth joiner with a lower fitness value did not get food, and it was very hungry. Therefore, it needs to fly to other places to find food to get more energy.

In the simulation experiment, it is assumed that these dangerous sparrows account for 10% to 20% of the total number. The initial positions of these sparrows are randomly generated in the population. Its mathematical expression can be expressed as the

TABLE I
BENCHMARK FUNCTION

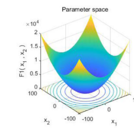
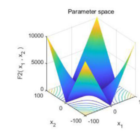
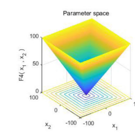
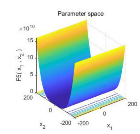
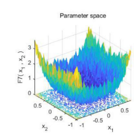
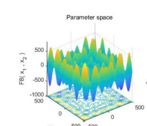
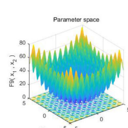
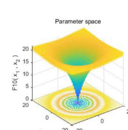
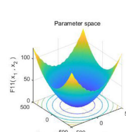
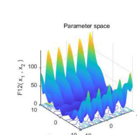
Function Name	Mathematical Expression	Range	Theoretical Optimal Value	Function Graph
Sphere	$f_1(X)=\sum_{i=1}^{D} x_i^2$	$[-100,100]$	0	
Schwefel 2.22	$f_2(X)=\sum_{i=1}^{D}\lvert x_i\rvert+\prod_{i=1}^{D}\lvert x_i\rvert$	$[-10,10]$	0	
Schwefel 2.21	$f_3(X)=\max_i\{\lvert x_i\rvert,1\le i\le D\}$	$[-100,100]$	0	
Rosenbrock	$f_4(X)=\sum_{i=1}^{D-1}\left[100\left(x_{i+1}-x_i^2\right)^2+\left(x_i-1\right)^2\right]$	$[-30,30]$	0	
Niose	$f_5(X)=\sum_{i=1}^{D} x_i^4+random[0,1)$	$[-1.28,1.28]$	0	
Schwefel 2.26	$f_6(X)=\sum_{i=1}^{D}-x_i\sin\left(\sqrt{\lvert x_i\rvert}\right)$	$[-500,500]$	-12569.5	
Rastrigin	$f_7(X)=\sum_{i=1}^{D}\left[x_i^2-10\cos(2\pi x_i)+10\right]$	$[-5.12,5.12]$	0	
Ackley	$f_8(X)=-20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{D}x_i^2}\right)-\exp\left(\frac{1}{n}\sum_{i=1}^{D}\cos(2\pi x_i)\right)+20+e$	$[-32,32]$	0	
Griewank	$f_9(X)=\frac{1}{4000}\sum_{i=1}^{D}x_i^2-\prod_{i=1}^{D}\cos\left(\frac{x_i}{\sqrt{i}}\right)+1$	$[-600,600]$	0	
Penalized	$f_{10}=\frac{\pi}{D}\left\{10\sin^2(\pi y_1)+\sum_{i=1}^{D-1}(y_i-1)^2\left[1+\sin^2(3\pi y_{i+1})\right]+(y_D-1)^2\right\}+\sum_{i=1}^{D}u(x_i,10,100,4)$	$[-50,50]$	0	

TABLE II
COMPARISON OF OPTIMIZATION RESULTS OF BENCHMARK FUNCTIONS

Function Name	Algorithm	Optimal Result	Time Cost	Dimension	Optimal Result	Time Cost	Dimension	Optimal Result	Time Cost	Dimension
Sphere	RWSSA	**0**	2.572s	30	**0**	5.391s	100	**0**	32.329s	500
	SSA	**0**	2.068s		**0**	3.752s		**0**	22.619s	
	MS-ALO	191.9895	63.986s		12440.0931	173.054s		23904.6462	660.110s	
	PSO	1.2222e-08	**1.804s**		0.0035187	**2.647s**		33744.3039	**6.291s**	
Schwefel 2.22	RWSSA	**0**	2.450s	30	**0**	5.575s	100	**0**	32.329s	500
	SSA	**0**	1.964s		**0**	3.727s		**0**	23.324s	
	MS-ALO	0.54091	62.591s		85.4305	170.797s		265.614	674.575s	
	PSO	0.43641	**1.686s**		11.5182	**2.548s**		327.0974	**6.757s**	
Schwefel 2.21	RWSSA	**0**	2.424s	30	**0**	5.566s	100	**0**	32.704s	500
	SSA	**0**	1.966s		**0**	3.701s		**0**	23.379s	
	MS-ALO	8.1492	62.825s		41.9167	163.629s		67.6986	665.218s	
	PSO	3.5019	**1.733s**		24.305	**2.503s**		34.2666	**6.246s**	
Rosenbrock	RWSSA	**1.102e-08**	2.561s	30	**3.3386e-13**	5.730s	100	**9.582e-13**	32.209s	500
	SSA	9.3514e-07	2.073s		4.5884e-06	3.978s		4.1262e-09	23.759s	
	MS-ALO	16434.3863	60.178s		784050.89	162.074s		3440042.5286	649.433s	
	PSO	114.7336	**1.999s**		214.5515	**2.852s**		5285384.9653	**6.626s**	
Niose	RWSSA	**3.1686e-06**	2.633s	30	**7.182e-05**	6.025s	100	0.00015559	34.976s	500
	SSA	0.00045083	2.174s		0.00019766	4.316s		**4.7369e-05**	25.130s	
	MS-ALO	0.16182	59.215s		4.277	167.237s		313.5375	640.154s	
	PSO	0.03886	**1.874s**		0.74337	**3.097s**		57.3745	**7.333s**	
Schwefel 2.26	RWSSA	-7713.2221	2.565s	30	-23819.2674	5.650s	100	**-208488.2139**	33.143s	500
	SSA	**-11609.0229**	1.994s		-41896.48	4.042s		-209338.4938	24.129s	
	MS-ALO	-4829.4246	69.868s		**-10081.5879**	167.645s		-28431.6217	664.740s	
	PSO	-5850.9233	**1.744s**		-22725.0911	**2.565s**		-86413.5523	**6.579s**	
Rastrigin	RWSSA	**0**	2.539s	30	**0**	5.530s	100	**0**	32.271s	500
	SSA	**0**	1.983s		**0**	3.762s		**0**	23.475s	
	MS-ALO	92.792	73.175s		314.5881	177.413s		3626.9147	666.311s	
	PSO	35.8185	**1.742s**		140.2995	**2.555s**		2179.0881	**6.762s**	
Ackley	RWSSA	**8.8818e-16**	2.400s	30	**8.8818e-16**	5.546s	100	**8.8818e-16**	33.003s	500
	SSA	**8.8818e-16**	2.050s		**8.8818e-16**	3.852s		**8.8818e-16**	23.421s	
	MS-ALO	6.4332	63.149s		8.598	171.118s		10.7956	670.838s	
	PSO	2.1201	**1.855s**		4.4201	**2.563s**		12.1778	**6.582s**	
Griewank	RWSSA	**0**	2.548s	30	**0**	5.530s	100	**0**	33.572s	500
	SSA	**0**	2.031s		**0**	3.816s		**0**	24.566s	
	MS-ALO	1.8466	60.434s		147.9564	172.085s		104.6437	673.174s	
	PSO	0.027052	**1.822s**		0.10713	**2.411s**		284.0004	**6.794s**	
Penalized	RWSSA	**7.6368e-15**	3.540s	30	**4.2083e-13**	7.429s	100	**2.171e-15**	39.272s	500
	SSA	1.0818e-10	3.082s		7.6872e-09	5.717s		4.1115e-10	30.957s	
	MS-ALO	2.3271	65.619s		595.681	166.142 s		136859240.6737	650.105 s	
	PSO	5.3262	**2.728s**		8.5493	**4.420s**		79.3453	**13.796s**	

TABLE III
PARAMETER SETTINGS

Parameter	Value
Area	S=1000m×1000m
Number of GPS Coordinates (Number of Pixels)	1000×1000
Number of base stations (Number of Nodes)	V=7
Communication Radius	R_c=250m

following form:

$$X_{i,j}^{t+1} = \begin{cases} X_{\text{best}}^{t} + \beta.\left|X_{i,j}^{t} - X_{\text{best}}^{t}\right|, \text{if } \mathrm{f}_i > f_g \\ X_{i,j}^{t} + K.\left(\frac{X_{i,j}^{t} - X_{worst}^{t}}{(f_i - f_w) + \varepsilon}\right), \text{if } \mathrm{f}_i = f_g \end{cases} \quad (9)$$

where X_{best} is the current global optimal position. As the step size control parameter, β is a random number that obeys a normal distribution with a mean of 0 and a variance of 1. $K \in [-1, 1]$ is a random number, and f_i is the fitness value of the current individual sparrow. f_g and f_w are the current global best and worst fitness values, respectively. ε is a constant to avoid zero in the denominator.

When $f_i > f_g$, the sparrows are at the edge of the population and are extremely vulnerable to predators. X_{best} indicates that the sparrow at this position is the best position in the population and it is very safe. When $f_i = f_g$, sparrows in the middle of the population are aware of the danger and need to be close to other sparrows to minimize their risk of predation. K represents the direction in which the sparrow moves and is also a step length control parameter.

B. Random Walk Strategy

The improvement is mainly to use random walk to perturb the optimal sparrow and improve its searchability. At the beginning of the iteration, the random walk has a larger boundary, which helps to improve the global search performance. After multiple iterations, the wandering boundary becomes smaller, which improves the local searchability of the optimal position of the algorithm.

The process of random walk can be expressed mathematically as

$$X(t) = [0, \mathrm{cussum}(2r(t_1) - 1), \ldots, \mathrm{cussum}(2r(t_n) - 1)] \quad (10)$$

where $X(t)$ is the set of step of random walk; $\mathrm{cussum}$is calculated cumulative sum; t is the number of random walk steps (this article takes the maximum number of iterations); $r(t)$ is a random function, defined as

$$r(t) = \begin{cases} 1, \mathrm{rand} > 0.5 \\ 0, \mathrm{rand} \leq 0.5 \end{cases} \quad (11)$$

where $\mathrm{rand}$is a random number of $[0, 1]$.

Due to the boundary of the feasible region, (10) cannot be used directly to update the position of the sparrow. In order to ensure a random walk within the feasible range, it needs to be based on (12) normalization

$$X_i^t = \frac{(X_i^t - a_i) * (d_i^t - c_i^t)}{(b_i - a_i)} + c_i t \quad (12)$$

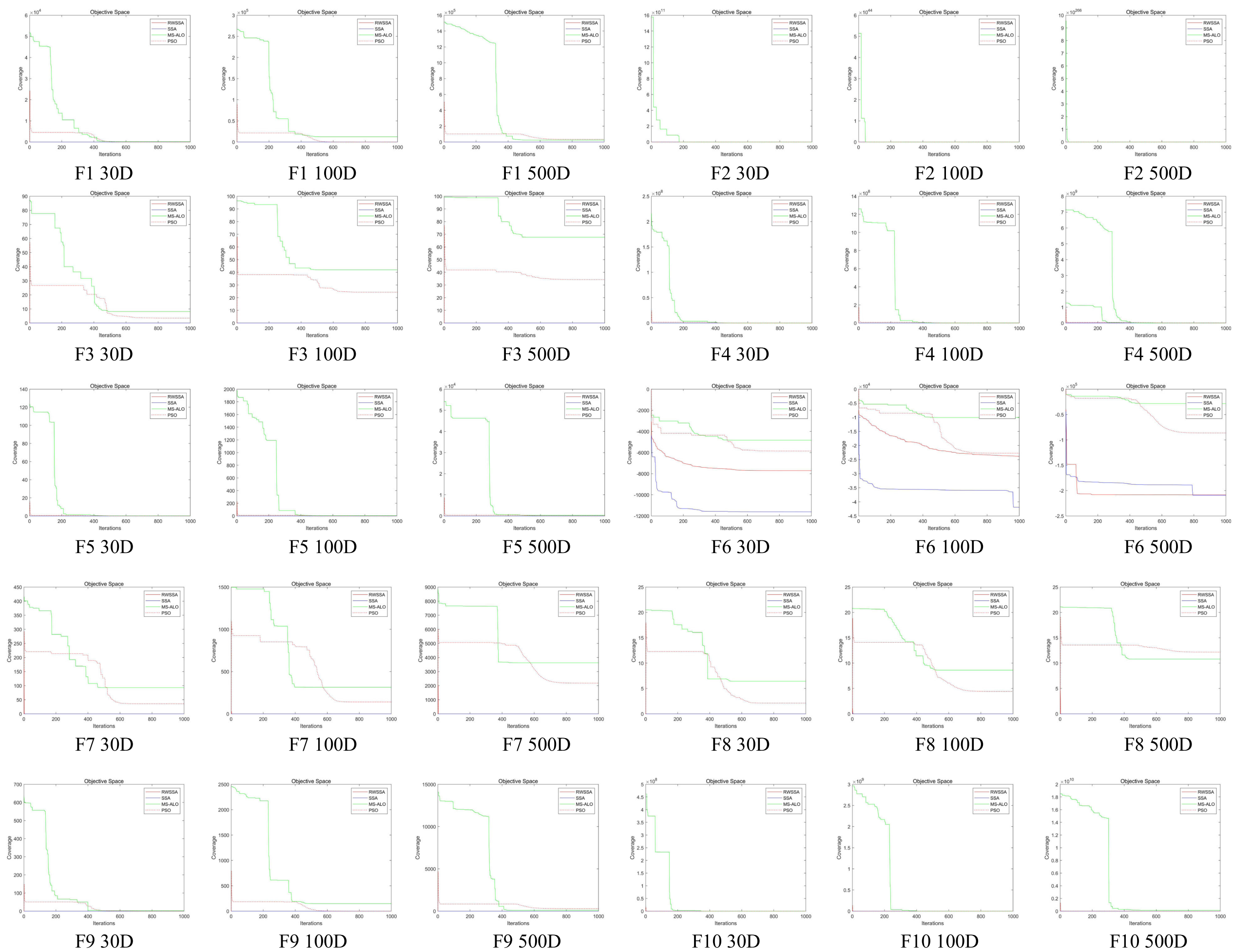


Fig. 3. Comparison chart of test function results.

where $a_i$is the minimum value of the random walk of the ith dimension variable; b_i is the maximum value of the random walk of the ith dimension variable; c_i^t is the minimum value of the ith dimension variable at the tth iteration; d_i^t is the maximum value of the ith dimension variable in the tth iteration.

C. Algorithm Code

Random walk strategy is often applied to improve the global search ability of various evolutionary algorithms and improve the local search ability of the optimal location. The main purpose of the improvement of the sparrow algorithm in this article is to improve the search performance of the optimal sparrows so that they will not fall into the local optimal solution. Its code is shown in Fig. 2. In the latter stage of the iteration, the local searchability of the algorithm in the optimal position can also be improved, which is conducive to obtaining the optimal solution. After calculating the fitness value and updating the position of the sparrow, the random walk strategy is used to update the optimal position of the sparrow, so that it can quickly jump out of the local optimal trap and improve the global search ability of the population.

IV. Performance Evaluation in Different Metrics

In order to verify the effectiveness of RWSSA, six benchmark functions were selected for numerical simulation experiments from low to high dimensions. The dimensions were selected as 30, 100, and 500 dimensions, and compared with SSA, MS-ALO, and PSO. The names, mathematical expressions and other parameters of the 1 benchmark functions used in the experiment are shown in Table I. Among them, f_1˜f_5 are unimodal functions; f_6˜f_{10} are multimodal functions. In order to ensure the fairness of the algorithm optimization performance test, the parameter settings of all algorithms are consistent: population size N = 30, maximum number of iterations T = 1000. Meanwhile, in order to reduce the influence of random interference, different algorithms are run independently for each benchmark function 30 times, and the average value of the experimental results is used for comparison.

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Table II records the optimization results of the four algorithms for 10 benchmark functions in different dimensions under

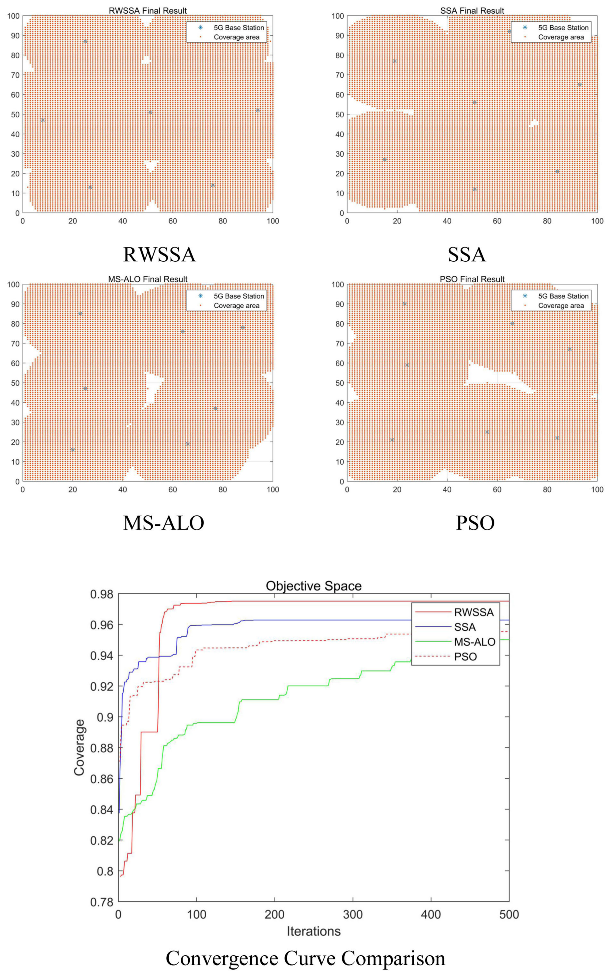

Fig. 4. Signal coverage diagram and convergence curve comparison diagram of the forth Algorithms.

the same test conditions. Fig. 3 shows the comparison of the four algorithms in the optimization convergence process of the benchmark function in different dimensions. Among them, the abscissa is the number of iterations, and the ordinate is the average fitness value of the algorithm running 30 times. From the analysis of Table II and Fig. 3, RWSSA has achieved more accurate optimization results compared to the MS-ALO and PSO algorithms, but it is basically the same as the optimization results of SSA. In the aspect of unimodal function optimization, the convergence accuracy of RWSSA for f_1~f_3 is higher than that of the other algorithms. It shows that using random walk to perturb the optimal sparrow can improve the ergodicity of the algorithm and increase the convergence speed of the algorithm. For the multimodal function optimization problem, in the 30, 100, and 500-D search space, taking the nonlinear functions Rastrigin(f_4) and Griewank(f_5) with a large number of local extreme points as examples, the average result of RWSSA's optimization is better than that of other algorithms. It shows that the improved strategy can make the algorithm effectively jump out of the local optimum, and the algorithm has good multi-peak optimization ability. Although PSO has the fastest convergence speed, it is not as accurate as RWSSA because it is very easy to fall into a local optimum.

In summary, the RWSSA algorithm is superior to other algorithms in terms of dimensional change, convergence accuracy, convergence speed, multipeak optimization ability, and robustness to benchmark function optimization, which verifies the effectiveness of the improved random walk strategy. Therefore, the algorithm can be further applied to the optimization problem of 5G base station deployment in open-pit mines.

TABLE IV
COMPARISON OF COVERAGE OPTIMIZATION RESULTS

Algorithm	Optimal Coverage (20 runs)
RWSSA	97.51%
SSA	96.28%
MS-ALO	95.01%
PSO	95.53%

TABLE V
OPEN-PIT MINE PARAMETER

Parameter	Value
Area	S=1350m×960m
Number of GPS Coordinates (Number of Pixels)	1000×1000
Number of macro base stations (Number of Nodes)	N
Communication Radius	R_c=250m
Number of macro base stations (Number of Nodes)	n
Communication Radius	r_c=80m

TABLE VI
NUMBER AND SIGNAL COVERAGE OF MACROBASE STATIONS

Algorithm	Number of Micro Base Stations	Average Coverage
RWSSA	6	**86.759%**
SSA		84.807%
MS-ALO		84.452%
PSO		80.71%
RWSSA	7	**91.042%**
SSA		88.511%
MS-ALO		88.326%
PSO		89.182%
RWSSA	8	**94.583%**
SSA		91.173%
MS-ALO		91.875%
PSO		90.494%

V. COVERAGE OPTIMIZATION PROBLEM

In order to fully verify the optimization performance of RWSSA coverage of 5G base stations in open-pit mine, the SSA, MS-ALO, PSO algorithms were selected to perform coverage optimization comparisons for different numbers of 5G base stations in the corresponding deployment areas. The experimental parameters are set as Table III.

In order to reduce the interference of randomness on the experimental results, the RWSSA, SSA, MS-ALO, PSO algorithms were used to optimize the area 20 times, and the optimal coverage ratio was compared.

Table IV shows the comparison of the optimization results of the average coverage of algorithms. Fig. 3 shows the distribution of nodes in this area after the four algorithms are optimized.

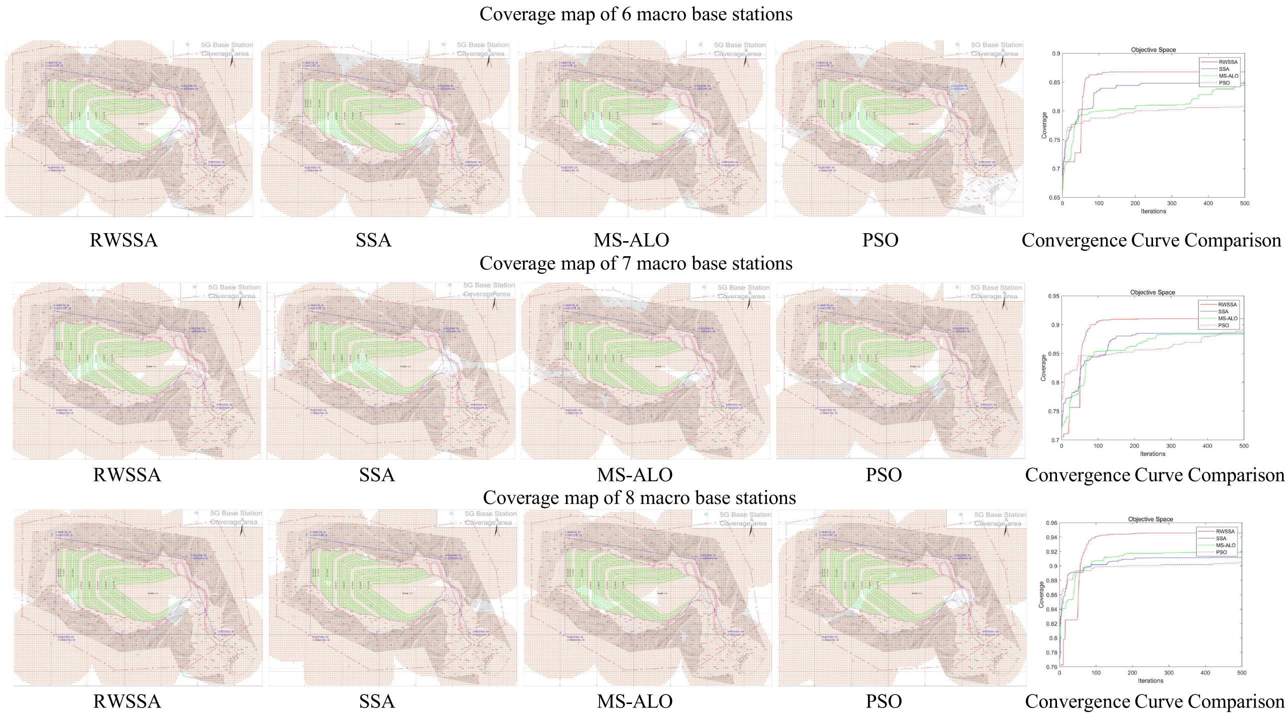

Fig. 5. 5G macrobase station signal coverage map and convergence curve comparison.

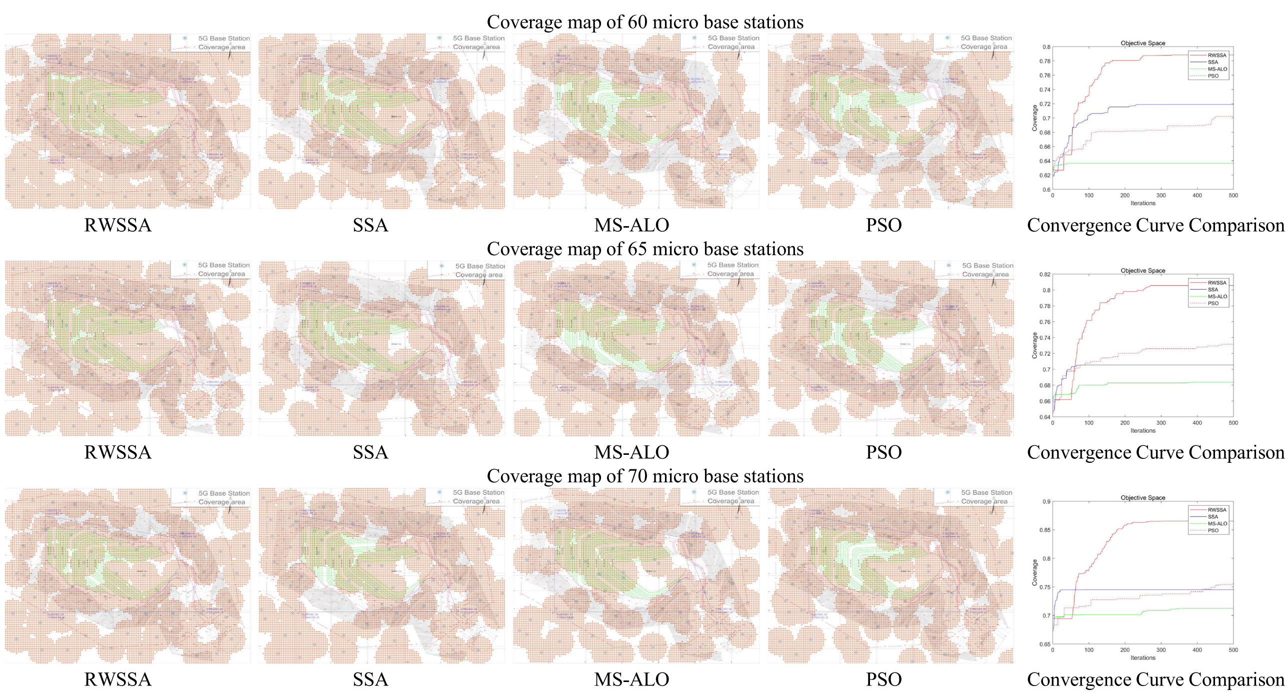

Fig. 6. 5G macrobase station signal coverage map and convergence curve comparison.

Fig. 4 shows the distribution and signal coverage of 5G base station in this area after the optimization of four algorithms, as well as the convergence curve of the algorithms.

From the analysis of Table IV, under the same test conditions, the optimal coverage of the 20 optimization runs of RWSSA is increased by 1.23%, 2.5%, and 1.98% compared with other algorithms, respectively, and the algorithm optimization performance is superior. Meanwhile, it can be directly seen from Fig. 4 that the signal coverage of RWSSA is significantly better than that obtained by other algorithms. After the RWSSA optimization, the node distribution is more uniform, the 5G network coverage is wider, and the problem of large blind area

TABLE VII
NUMBER AND SIGNAL COVERAGE OF MICROBASE STATIONS

Algorithm	Number of Micro Base Stations	Average Coverage
RWSSA	60	**78.835%**
SSA		71.906%
MS-ALO		63.673%
PSO		70.255%
RWSSA	65	**80.571%**
SSA		70.548%
MS-ALO		68.364%
PSO		73.156%
RWSSA	70	**86.543%**
SSA		74.522%
MS-ALO		71.258%
PSO		75.548%

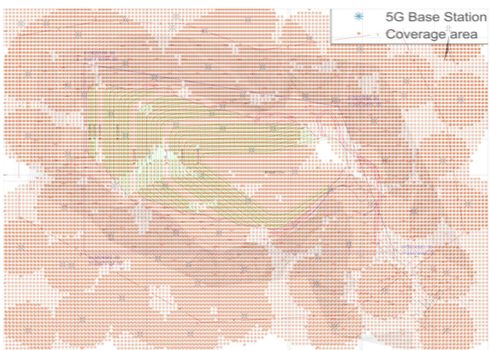

Fig. 7. Full coverage map of 5G signal in open-pit mine.

coverage at the boundary of the optimized node distribution area is improved.

In summary, by comparing with the experimental results of the forth algorithms under the corresponding test conditions, RWSSA has achieved a higher optimal coverage rate, a more uniform 5G base station distribution and fewer network coverage blind spots, which validates the algorithm it has better network coverage optimization performance.

VI. CASE STUDY

The verification fully verified the solution of the 5G base station deployment problem in open-pit mines. Four algorithms of RWSSA, SSA, MS-ALO, and PSO were used to optimize the deployment of different numbers of 5G base stations in the mine deployment area, including the deployment of macrobase stations and microbase stations optimization. The mine parameters are set as Table V.

A. Macrobase Station

Through optimization calculations, we increased the number of macrobase stations from 6 to 8 to compare and analyze the impact of changes in the number of macrobase stations on the signal coverage rate of the mining area. The coverage is shown in Table VI.

The signal coverage map is as Fig. 5.

Through analysis, among the solution results of the four algorithms, the result of RWSSA is better than the other three algorithms. And it can be determined that the greater the number of macrobase stations, the better the signal coverage, but the greater the construction cost of the 5G network. Therefore, while meeting the signal coverage requirements, the smaller the number of base stations, the lower the construction cost of 5G private networks.

B. Microbase Station

The function of the microbase station is to receive the transmission signal of the Internet of Things in the whole mining area and transmit the data to the macrobase station to achieve the purpose of remote data transmission. We started to verify the number of 60 microbase stations, increasing the number of microbase stations by 5 each time, and finally increased to 70, to compare and analyze the impact of changes in the number of macrobase stations on the data transmission of the Internet of Things in the mining area. The coverage is shown in Table VII.

The signal coverage map is as Fig. 6.

Among the four algorithms, the result of RWSSA is still the best. Therefore, by using RWSSA to optimize the deployment of 5G network microbase stations, a better solution can be obtained, which maximizes 5G signal coverage while minimizing the number of 5G microbase stations.

C. 5G Base Station Deployment and Converged Network

The coverage rate of the macrobase station reaches 90% and the coverage rate of the microbase station reaches 80%, which can meet the requirements of unmanned production in the mine, and the macrobase station and the microbase station can complement each other, so that the signal coverage rate of the entire mine network reaches 100%. Therefore, the number of macrobase stations is 7 and the number of microbase stations is 65, which can not only meet the production needs of mines, but also greatly reduce the construction cost, as Fig. 7.

VII. CONCLUSION

Aiming at the goal of maximizing the coverage of 5G networks in open-pit mines, this article proposed a RWSSA to improve the performance of SSA search and optimize the coverage of 5G base station nodes. The algorithm disturbed the optimal sparrow by random walk, which improved the algorithm's ergodicity and convergence speed in the search space; at the beginning of the iteration, the random walk has a larger boundary, which was beneficial to improve the global search performance; at the later stage of the iteration, the walk the boundary becomes smaller, which improved the local searchability of the optimal position of the algorithm, and improves the problem that the algorithm is easy to fall into the local optimum. The effectiveness of the improved strategy is verified by the optimization of different forms and dimensions of benchmark functions and the comparison with SSA, MS-ALO, and PSO.

RWSSA is further applied to wireless sensor network coverage optimization, and compared with SSA, MS-ALO, and PSO under the same test conditions. The experimental results showed that the average coverage rate obtained by running the 5G base station coverage optimization algorithm based on RWSSA for multiple runs can greatly improve SSA, MS-ALO, and PSO; meanwhile, by comparing with the 5G base station node optimization distribution map, the node distribution after RWSSA optimization It is more uniform and the coverage blind area is smaller; then, by comparing the coverage optimization convergence curve, it is verified that the improved strategy can effectively improve the convergence speed. Therefore, the algorithm in this article can better improve the performance of 5G networks. However, how to further improve the convergence speed of the algorithm while ensuring the convergence accuracy of a higher coverage rate is the next step that the RWSSA algorithm needs to improve.

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