PSO-GA based Optimization for Base Station Deployment in Three-dimensional CAD System

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Abstract

Good base station deployment plan help network operators save cost and increase total revenue significantly. By taking the cost, coverage and signal interference as the optimization objectives the base station deployment is conducted as multi-objectives combination optimization problem. Intelligent optimization algorithm such as genetic algorithm, particle swarm optimization algorithm can effectively solve these problems, but standard genetic algorithm has poor local search ability, PSO algorithm is easy to fall into local optimal solution. Therefore, relying on a single algorithm solely cannot effectively to solve the problem. In this paper, by transforming the PSO algorithm into PSO operator to replace mutation operator of genetic algorithm, an improved genetic algorithm (PSO-GA) is proposed, which retains the advantages of two algorithms and overcome the shortage. The simulation results show PSO-GA algorithm is superior to PSO and GA in coverage optimization and signal interference optimization. Another innovation of is using Google Earth com technology and ACIS technology to build a three-dimensional CAD system which takes the three-dimensional geographic coordinates as the input of the algorithm is different from the traditional methods which only uses two-dimensional coordinates, In addition, the simulation of real terrain reconstruction is conducted on the three-dimensional instead of traditional two-dimensional plan.

Keywords

PSO-GA, Base Station Planning, Signal Interference, ACIS, CAD System.

1. Introduction

In recent years, mobile communication technology has developed rapidly, leading to more and more competitive mobile communication market. Faced with this situation, rapid businesses, reducing operating costs, improving communication quality become the key factors to win market competition for the competitors. However the focus of these key factors is the underlying network architecture. A good network planning program can greatly increase the overall capacity of the network. The wireless network planning includes traffic estimates, the base station planning, frequency planning, channel planning, system simulation and optimization, and planning for different business. The base station planning plays an important role in the connection of network planning. The base station planning is directly related to the operator's network investment income, which accounting for nearly 2/3 of the total investment.

The base station planning has been a hot topic in wireless network planning. Therefore, the base station planning problem has a good theoretical and practical significance [3][13].The base station network planning is to establish a reasonable mathematical modeling which can ensure the quality of network service and meet the needs of users by optimizing the number and the location of Base station [2]. The number and positions of base station have direct influence on the coverage and quality of the communication network. Thus the purpose of the base station planning is to find the optimal number of base station to achieve the maximum coverage rate and optimal network quality by adjusting the position and the number of base stations. That is, the goal is to reduce cost by minimizing the number of base station as much as possible under the premise of ensuring network quality and network coverage. Coverage target is to make the signal coverage area of the base station could cover all users. Signal quality target is to reduce signal interference between different base stations. The problem of base station planning has been proven to be NP-Hard [1].

There has been some planning about base station deployment based intelligent optimization algorithm (such as genetic algorithm, immune algorithm, PSO etc.)[9]. However, base stations deployment optimizing needs to consider signal interference area, coverage and cost, however the current intelligent optimization algorithms are not very good to solve the problem of the large number of candidate solutions, the complexity of the optimization process, the distribution of the search space and so on[7-8]. Therefore, it is of great practical significance and practical value to propose the improved genetic algorithm to solve the optimal location problem of the base station. In addition, the previous two-dimensional simulation experiments do not take into account the coordinates of the terrain elevation that is very critical to the selection of link model, which directly affects the coverage radius of base station. Therefore, in order to better simulation, this paper uses ACIS, Google Earth to build three-dimensional CAD system that fully consider the terrain elevation and calculate the objective function according to the different terrain of the cover radius.

ACIS is a development platform based on C++ structure graphics system, which includes a series of C++ functions and classes (including data members and methods). Developers can use these classes and functions construct a Three-Dimensional software system for end users [2].

Google Earth provides a set of COM components that can be embedded into visual studio development platform by the COM technology. Through the secondary development of Google Earth, we can obtain the longitude latitude and height of the real terrain. This information can be transformed into three-dimensional coordinates of CAD system screen. The coordinates are as the inputs of proposed algorithm in CAD systems so as to simplify dates and facilitate calculation. The proposed algorithm is used to optimize the locations of base stations and obtain the optimization coordinates, then the coordinates are mapping to real latitude, longitude, height information of real terrain as output.

2. Problem Statement and Formulation

2.1 Problem Statement

The objectives of the base station planning problem are to optimize the cost, coverage and quality by adjusting the positions and numbers of the base stations. Therefore, the problem can be considered as a multi-objectives combinatorial optimization problem [10-11].

Cost is a very important optimization objective because the investment in the base stations planning counts for about two-thirds of the total investment in the whole network. Therefore, a lower cost of the base stations can effectively reduce the total network investment so as to enhance the competitiveness of the enterprise. The construction cost of each base station is fixed, so the number of base stations becomes the most important factor to consider. In other words, under the premise of the signal quality, the base station planning problem is to find the least number of base stations that can meet the network coverage requirements. In this paper, the number of base stations determines the length of chromosome. In the simulation process, we will continue to change the length of the chromosome to find the shortest chromosome which can meet the goal of coverage rate and coverage quality.

The goal of coverage rate is for the communication signal to reach all the targeted users and to meet the communication needs of the targeted user. The base stations have different coverage radius which can be taken as the radius of the coverage area (a circular area) of each base station. The radius of the base stations can be obtained by propagation model and path loss model depending on the location of base stations. In the simulation process, the users are abstracted as demand points that are randomly generated in different terrain because the actual user profiles are unavailable. The models solve the radius of the base stations in different terrain mainly according to the elevation information of the terrain. According to their elevations, the terrains are divided into three types. For different types of terrains we obtained different base station signal coverage radius by using different propagation models and using the maximum path loss model. Therefore, the coverage goal is to make the signal of the base stations cover as many demand points as possible. In other words, as many as possible demand points should be within the radius of the signal coverage area of some base stations.

The quality objective is to reduce signal interference between different base stations. Base station coverage areas overlapping and some user demand points may be located in the signal overlapping areas of different base stations. Users in an overlapping area communicate with one of the base stations that have the strongest signal. The signal strength depends on the distance between the base station and the demand point (the shorter the distance, the stronger the signal). However, demand points within overlapping areas subject to signal interferences from other stations. As shown in Figure 1, there are two types of signal interferences. On the figure, u1 and u2 are demand points, and s1-s5 are base stations. On the left of Figure 1, u1 is located in the signal overlapping area of two base stations s1 and s2. Because u1 has a shorter distance to s1 than to s2, u1 mainly communicates with s1 but subjects to signal interferences from s2. On the right of Figure 1, u2 is located in the signal overlapping area of three base stations s3, s4 and s5. Because u2 has the shortest distance to s3, u2 mainly communicates with s3 but subject to signal interference from s4 and s5. Therefore, the quality goal is to minimize signal interference between base stations.

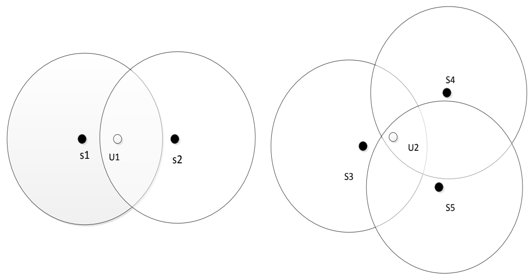

Figure 1. Two types of signal interference

2.2 Problem Formulation

After the above analysis, the goal of cost is achieved by adjusting the length of the chromosomes in the experiment. In addition to that we need to list the objective function of coverage and signal quality. There is no doubt that coverage is the primary goal, and the quality objective is closely related. So we list coverage objective function firstly, and then list the quality objective function. By setting different weights for two objective functions we get the final objective function which is the fitness function of our PSO-GA algorithm.

2.2.1 Coverage

The section headings are in boldface capital and lowercase letters. Second level headings are typed as part of the succeeding paragraph (like the subsection heading of this paragraph). All manuscripts must be in English, also the table and figure texts, otherwise we cannot publish your paper. Please keep a second copy of your manuscript in your office. When receiving the paper, we assume that the corresponding authors grant us the copyright to use the paper for the book or journal in question. When receiving the paper, we assume that the corresponding authors grant us the copyright to use the paper for the book or journal in question. When receiving the paper, we assume that the corresponding authors grant us the copyright to use.

Coverage rate is calculated by dividing the number of demand points which are covered by the total number of the demand points in the different terrains. We know that a demand point may be cover by multiple base stations, so in order to avoid repeat counting of demand point; each demand point is counted only once by the nearest base station which coverage area include this point. To formulate coverage targets we defined as follows: U is the set of all demand points; j is the demand points which $j \in U$, T is the set of all base stations; i is the base station which $i \in T$. d_{ij} is the distance between base station i and demand point j, r_i is coverage radius of base station i, the coverage area of base station i, denoted by C_i, is defined as the collection of demand points which is within the coverage area of i and has the shortest distance from i among all the base stations. Formally stated, C_i is given by:

$$C_i = \{j \in U \mid d_{ij} \le r_i \wedge (d_{ij} \le d_{i'j}, \forall i' \in T \wedge i \ne i')\} \quad (1)$$

The purpose of the coverage optimization is to achieve full coverage of all demand points by using the minimum number of base stations.

In the solution process, we define f_{CT} as a function of the base station coverage goals. The total number of all demand points covered by all base stations is given by $\sum_{i\in T} C_i$. The total number of all demand points deployed on the terrain is denoted by $|\mathrm{U}|$. When f_{CT}=1, all demand points in the terrain are fully covered. However, a $f_{CT} = 0.95$ is quite acceptable. Although a $f_{CT} = 1$ is too costly to achieve, f_{CT} is maximized in the model. f_{CT} is defined as follows:

$$f_{CT} = \frac{\sum_{i\in T} C_i}{|\mathrm{U}|} \quad (2)$$

The coverage objective function is then:

$$\max . f_{CT} \quad (3)$$

2.2.2 Signal Interference

Reducing the signal interference can improve the quality of service. Signal interference exists in each overlapping area. The uses who are locate in the overlapping area will suffer signal interference the quality of service will be affected, the larger the overlap, the more users subject to interference, and the closer to other base stations, the greater the interference . To measure the degree of interference signal, we introduce the variable E_i to represent the signal threshold value, which is the minimum signal strength required for a demand point to be covered by the base station i. When a demand point receives signal stronger than the threshold value from the base station i, the demand point can be covered by base station i. E_i is defined as follows:

$$E_i = \frac{50}{(10 * r_i + 1)^2} \quad (4)$$

The signal strength that demand point j receives from the base station t_i is represented by E_{ij} ,that is defined as follows:

$$E_{ij} = \frac{50}{(10 * d_{ij} + 1)^2} \quad (5)$$

When $E_{ij} \ge E_{i'j}$ and at the same time $E_{ij} \ge E_i$ and $E_{i'j} \ge E_{i'}$ for some i', the demand point j suffers signal interference from the base station i'. We use φ_j to represent the signal interference that demand point j receives from all base stations i' such that $i' \ne i$. φ_j is defined as follows:

$$\varphi_j = \sum_{E_{ij} \ge E_{i'j} \wedge E_{ij} \ge E_i \wedge E_{i'j} \ge E_{i'}} (E_{i'j} - E_{i'}) \quad (6)$$

If demand point j is served by base station i, i.e., base station i is the communication base station of demand point j, the signal strength from base station i much be higher than the signal interference from all the other base station i'. This requirement means $E_{ij} / (E_{ij} + \varphi_j)$ should be close to 1. When $E_{ij} / (E_{ij} + \varphi_j)$ is close to 1, the signal interference of demand point j can be ignored. That means the best signal quality, and then we use f_{SI} to represent the signal quality of the whole system that is defined as follows:

$$f_{SI} = \frac{\sum_{i \in T, j \in U} (E_{ij} / (E_{ij} + \varphi_j))}{|\mathrm{U}|} \tag{7}$$

Where $|\mathrm{U}|$ is the number of demand points. The signal quality objective function is then

$$\max . f_{SI} \tag{8}$$

From the formula (6) can be seen, only when the demand point is covered by two or more base stations, the demand point suffer signal interference and at this time $E_i / (E_{ij} + \varphi_j) < 1$. When the demand point j is covered by only one point base stations, $E_i / (E_{ij} + \varphi_j) = 1$. When demand point j never be covered, $E_i / (E_{ij} + \varphi_j) = 0$. We can see from formula (2), once the demand point belongs to the coverage area of a base station, the number of demand points that covered by this base stations will pluses one. So, it is obviously that, $f_{SI} < f_{CT}$. So in this paper we set f_{CT} up to 0.95 that can meet the signal coverage requirements, and f_{SI} up to 0.9 can meet signal quality requirements.

2.2.3 The Comprehensive Objective Function

Through the above section 2.2.1 and 2.2.2 we have defined two objective functions, which value range in [0, 1], In this section, we construct a comprehensive objective by them.

We know that the bigger the values are, the better the base station deployment is. Therefore, we still directly and linearly transform the two objectives into a comprehensive objective. The final objective function is weighted sum of the coverage function f_{CT} and the signal quality function f_{SI} . Because the coverage objective is as important as the signal quality objective, we give the same weights to the two objective functions, i.e., $w_1 = w_2 = 1$. The final objective function is defined as follows:

$$F = w_1 f_{CT} + w_2 f_{SI} \tag{9}$$

It can be known from the above two sections that the comprehensive objective value should up reach to 1.85 to meet the requirement of signal coverage and signal quality.

3. Design of PSO-GA algorithm

3.1 Problem Formulation

The input of the proposed algorithm is the three-dimensional screen coordinates which is adapted to the CAD system that is converted by elevation, latitude and longitude coordinates of the actual terrain that is obtained by google Earth [2]. We take use of the elevation information to divide the terrain into three types: parts-populated areas, semi-intensive areas and sparse areas. The lowest area is populated area; the highest terrain is sparse area. Different area has different signal coverage radius. The coverage radius of populated areas is defined as r1, semi-intensive areas as r2, and sparse areas as r3, where r1> r2> r3 [3]. In order to calculate the radius, firstly we use the link budget model to calculate the maximum path loss, and then the maximum path loss is used in the propagation model to calculate the coverage radius. Link budget model used in this paper is as follows:

Uplink formula:

$$PL\_\mathrm{UL} = Pout\_\mathrm{UE} + Ga\_\mathrm{BS} + Ga\_\mathrm{UE} - \mathrm{Lf\_BS} - Lp - Lb - Mf - Mp - Mi - S\_BS \tag{10}$$

Downlink formula:

$$PL\_DL = Pout\_\mathrm{BS} + Ga\_\mathrm{BS} + \mathrm{Ga\_UE} - \mathrm{Lf\_BS} - Lp - Lb - Mf - Mp - Mi - S\_UE \tag{11}$$

PL_UL is the maximum path loss of uplink and PL_DL is the maximum path loss of downlink. Final maximum path loss is the bigger between PL_DL and PL_UL. Other specific parameters obtained through literature review. Because it is not the focus of this paper, so we don’t explain more.

Propagation model is used in this article is as follows:

$$L_M = 69.55 + 26.16\lg f - 13.82\lg h_t \alpha(h_r) + (44.9 - 6.55\lg h_t)\lg d \quad (12)$$

Solving the propagation model through assigning the maximum path loss to LM, d is the radius. At the same, other specific parameters obtained through Literature review. Finally, by calculating r1 is 0.3 which is actually a length of 1.5 kilometers, r2 is 0.2 which is actually a length of 1 kilometer, r3 is 0.15 which is the actual length of 0.75 kilometers.

3.2 Analysis of GA Algorithm and PSO Algorithm

Genetic algorithm (GA for short) is an intelligent optimization algorithm [12]. It has the advantages of good versatility, fast search speed and strong ability of global search. But it also has some weak point such as poor local search ability which will lead to disadvantage of “premature” that it often mistakes the local optimal solutions for the global optimal solution. In Genetic algorithm, when population update, it will go through selection, crossover and mutation three processes. As we all know, select and crossover operator makes genetic algorithm has better global convergence ability, and mutation make genetic algorithm has the ability of local search. In order to overcome the poor local search ability of genetic algorithm, we improve the mutation operator.

PSO algorithm does not require gradient information, and does not need to adjust many parameters which make it easy to implement, and has the advantages of strong local search capability, and fast convergence [4-6]. But the particles iterate rely on the two "extreme value": individual extreme PBEST and global extreme GBEST. If the PBEST and the GBEST fall into Local optima, PSO algorithm is likely to fall into local extreme, and cannot obtain the global optimal solution. When dealing with complex issues, phenomenon such as premature convergence, low convergence precision will become more apparent.

Since the single algorithm revealed a variety of problems in solving practical problems, a hybrid algorithm combined with two or more algorithms is the key to avoid weaknesses. In this section, the focus is how to make more effective combination of GA and PSO two algorithms.

GA algorithm combined with PSO algorithm has been a hot research for scholars. PSO-GA serial hybrid algorithm (PGSHE) is a typical combination of ways. In POSHE algorithm, firstly it gets a solution after the implement of PSO algorithm, and then the genetic algorithm is executed. The shortage of this algorithm is more time-consuming, and it does not take the advantages of two algorithms.

3.3 PSO-GA based Solution

From analysis of the previous section of the article, it shows that selection and crossover operator ensure the global search ability of Genetic Algorithm. Mutation operator is used to realize local search, but because the mutation operator only has a single dimension variation, and there is no direction, the local search ability of genetic algorithm is relatively weak. Although the PSO algorithm has poor global search ability, it performs well in local search ability, and fast convergence ability which can make up for the deficiencies of GA. So, by transfer the PSO algorithm into PSO operator to replace the mutation operator of genetic algorithm, an improved genetic algorithm is proposed (PSO-GA) to solve this problem, which retains the advantages of two algorithms and compensates for their disadvantages and different from PSO-GA serial hybrid algorithm.

In the classic improved PSO algorithm, Inertia coefficient w is often changed in a non-linear decreasing manner. So in the early of algorithm that can ensure greater inertia coefficient that make PSO algorithm has better global search capability. In the later stage of the algorithm, the PSO algorithm has a small inertia coefficient that ensures the algorithm has a better ability of local optimization. In the PSO-GA algorithm PSO algorithm is simplified as PSO operator, it uses the global optimal solution of the population and the optimal solution of individual in history to update the current individual to realize mutation. Which effetely improve the mutation operator in a random and blind manner in traditional genetic algorithm. The PSO-GA algorithm improve the local search ability by setting small inertia weight, small step size and constant parameter adjustment , which combine with the selection operation and crossover operation make it has a good global convergence ability and perform better than single algorithm.

In the improved PSO-GA algorithm, $X_i = \{x_{i1}, x_{i2}, x_{i3}, ..., x_{i,3m-2}, x_{i,3m-1}, x_{i,3m}\}(m = |T|)$ is the encoding of i-th chromosome of GA $(x_{i,3m-2}, x_{i,3m-1}, x_{i,3m}) \in X_i$ $(k = 1 \ldots m)$ is the three-dimensional coordinates of i-th base station. $F = W_1 f_{CT} + W_2 f_{SI}$ is the objective function of entire system, so $F(X_i)$ is the fitness value of i-th chromosome, That is a measure of the solution of deployment of m base stations in the planning region. The fitness value is closer to 2, indicating that the program closer to the optimal. Improved PSO-GA differ from PSO-GA serial hybrid algorithm (PGSHE), it design PSO mutation operator by using PSO algorithm thinking instead of the traditional mutation operator rather than series the two algorithms simply. The pseudo-code of the PSO-GA algorithm has shown in the Table 1:

Table 1. the pseudo-code of the PSO-GA algorithm

PSO-GA based optimizing base stations deployment

//**Input**: The coordinates of deployed demand points U , the number of deployed base stations $\|T\|$
//**Output:** The locations of the deployed base stations
Initialize the population X in terms of coordinates and $\|T\|$;
Initialize Maxgen, Pbest, FitThre, and so on;// Maxgen is the maximum number of //iterations, Pbest is the best position of chromosome, FitThre is the fitness threshold that //can meet the requirement.
For $ith = 1$ to Maxgen
For i=1 to |X|//|X| is the size of population
GetChromoRoulette();//According to the fitness value select | X | best individual //in a Roulette way
End for;
For i=1 to |X|, i=i+2// Step size is 2
Cross（chromosome[i],chromosome[i+1];// Perform crossover operation
End for;
For i=1 to ChromLen// ChromLen is the length of chromosome, ChromLen =3*|T|
If(random()<mutationRate){
PSOupdate(chromosome[i]);//Take use of Pbest and Gbest to update, //Wherein the inertial coefficient and speed is all //smaller that can ensure that the operator has a //strong local searching capability.
End for;
}
Calcfitness(|X|);// calculate the best fitness value of the population

Algorithm flow chart is as follows:

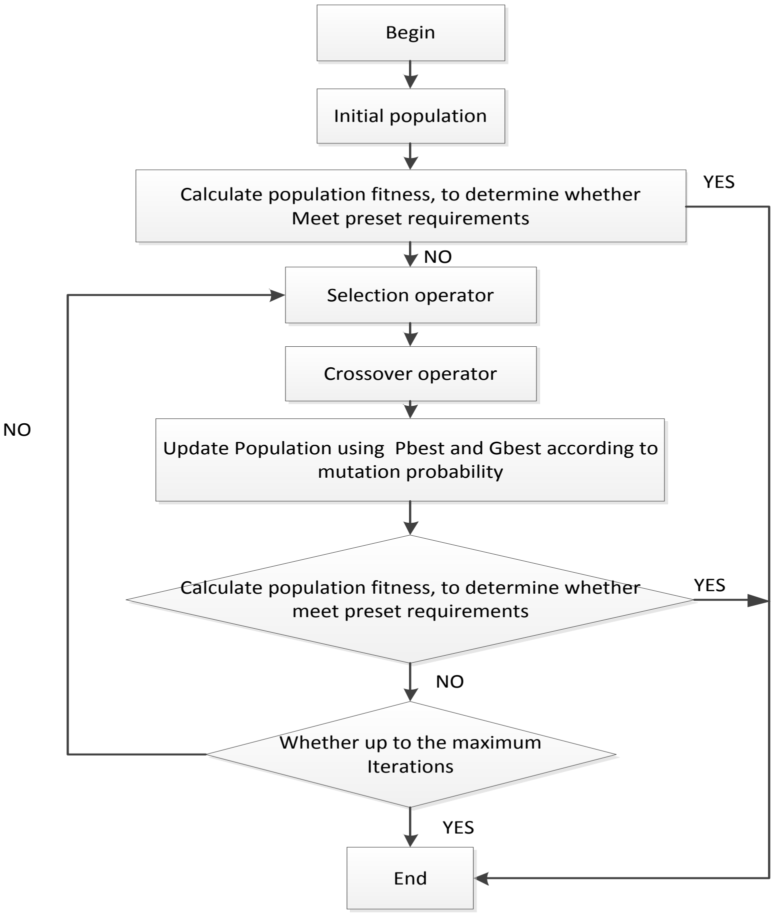

Figure 2. PSO-GA Algorithm's flowchart

4. Simulation and Analysis

The simulation experiment are conducted on visual studio which combined with ACIS widget that can build three-dimensional hoops project and the performance parameters of the executing host are Win 7, Inter (R) 3.4 GHz Core(TM) i7-4770, X86, 8GB (RAM). We uses C++ (with STL) to encode the algorithm and uses Matlab to make figure. Simulation terrain is 10 * 10 kilometers terrain of Licheng District, Jinan. The data for the algorithm is the screen coordinates which is transformed by elevation, latitude and longitude coordinates that is obtained by Google Earth of the terrain. We use ACIS technology to reconstruct the terrain in three-dimensional. Base station is abstracted to a cone. Signal coverage area is abstracted to a transparent circular. According to the actual population density, it sets 800 user points which are distributed randomly on the terrain.

4.1 Cost-based Experiments

Cost optimization is the ultimate goal, and the costs depend on the number of base stations. In the current round of experiments changes the number of base stations by continuously adjusting the length of the chromosome, to obtain a number of base stations that can achieve the objective function requirements. First, it obtains the approximate range of the base station number by a simple calculation—each base station coverage area is divided by the terrain. Because there are three different types of base stations, so the number of base stations in the interval [14, 32] inner. Experiment with different number of base stations, we remains the best fitness value after convergence at each number of base stations. The result has shown in Figure 3.

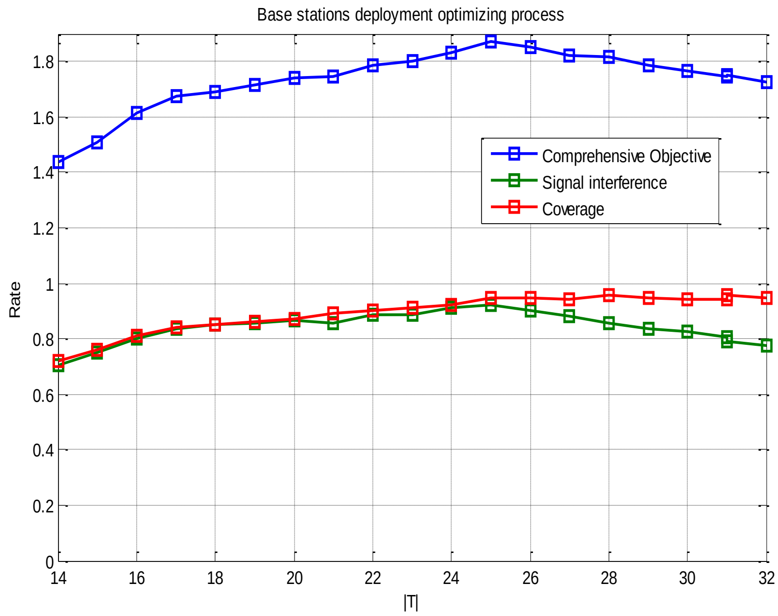

Figure 3. The Optimal Results with the PSO-GA in deferent number of base stations

In the figure 3, the blue line represents the comprehensive objective; the red line represents coverage rate, and the green line represents signal interference (signal quality). From figure3, we can see that when the number of base stations less than 25, the coverage rate increases as the number of base stations increases and the signal interference rate up to maximum when the number up to 25. So the comprehensive objective rate continues to increase as the number of base stations increases until the number up to 25. When the number of base stations more than 25, the coverage rate increases slowly and the signal interference reduces quickly. From the analysis of the second section, we know that the difference between the coverage rate and signal interference rate reflects the degree of signal interference that demand point received, the greater the difference, the greater the degree of interference. Form figure 3 we know that when the number of base stations less than 25, the degree of signal interference is small and when the number of base stations more than 25, the degree of signal interference becomes larger. From the blue line, we know that the comprehensive objective up to the maximum when the number of base stations is 25. So 25 is the optimal number that up to the optimal objective in lowest cost.

In order to understand the influence of the number of base stations on the coverage and signal interference more vividly, we simulates the deployment of the base stations when the number is 14, 20,25 and 30 in the three-dimensional CAD system. The result has shown in Figure 4. And Figure 5 shows the iterative process of base station deployment optimizing in different four numbers of base stations.

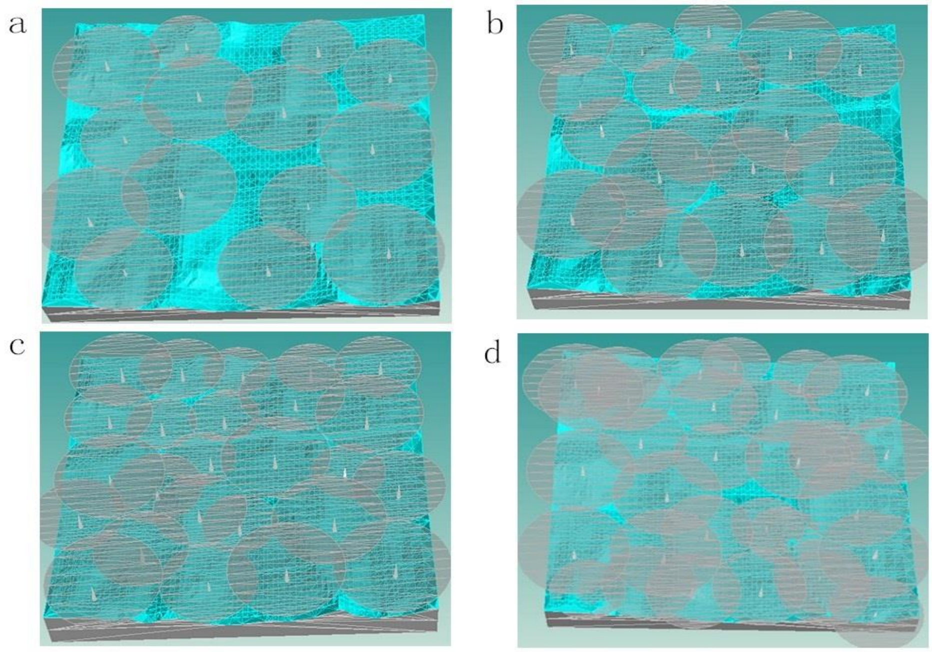

Figure 4. The simulation diagram in the three-dimensional CAD system under four different numbers of base stations (a)|T|=14(b)|T|=20(c)|T|=25(d)|T|=32

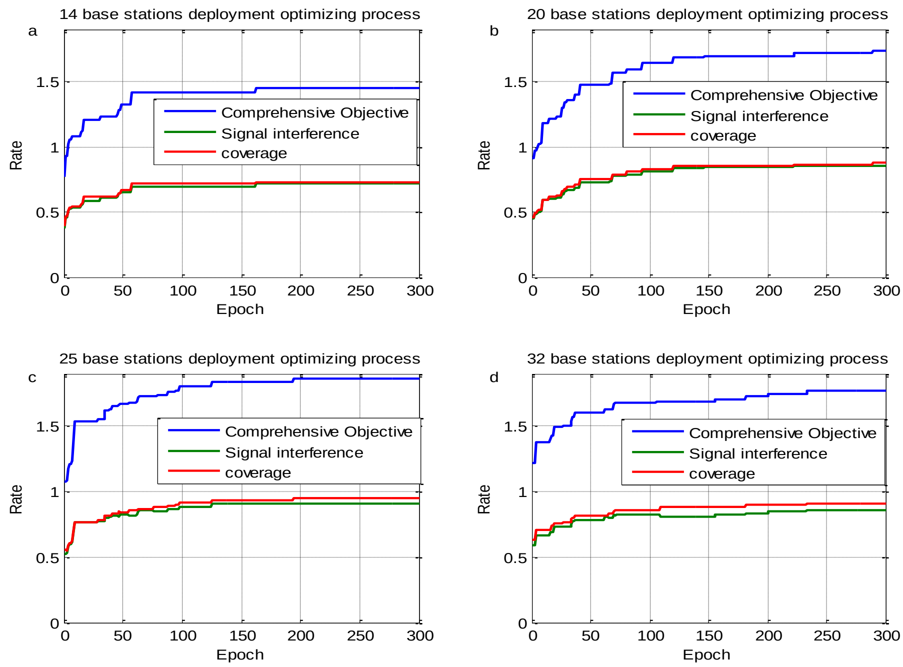

Figure 5. Base stations deployment optimizing process, under four different numbers of base stations (a)|T|=14(b)|T|=20(c)|T|=25(d)|T|=32

In the Figure 4,the cone represents base station; the circle represents the signal coverage area of base stations. Base station located in the reconstructed terrain, and the base stations located in high terrain have a lager coverage radius, the base stations located in low terrain have a smaller coverage radius.Figure4 (a) simulates when the base station number is 14, and corresponds to Figure5 (a), we can see that the signal interference between base stations is small, but the coverage of the base station is lack. From figure5 (a) we know that signal interference rate is 0.720378; Coverage rate is 0.730000. Figure4 (b) simulates when the base station number is 20, and corresponds to Figure5 (b), we can see that the signal interference between base stations increase, but the coverage of the base stations increase more. From figure5 (b), we know that signal interference rate is 0.856653; Coverage rate is

0.880000.Figure4(c) simulates when the base station number is 25, and corresponds to Figure5(c), we can see that the base station signal coverage and interference achieves a balance, and the comprehensive objective rate is highest. From figure5 (c), we know that signal interference rate is 0.910741; Coverage rate is 0.950000.Figure4(d)simulates when the base station number is 32, and corresponds to Figure5 (d), we can see that the base station can achieve a good coverage, but the interference between base stations is indeed increasing. From figure5 (d), we know that signal interference rate is 0.859534; Coverage rate is 0.950000.

4.2 PSO-GA Algorithm and GA Algorithm Comparison

This section shows comparative experiments between PSO-GA algorithm and PSO algorithm. We also set the length of chromosome is 75, and compare the two algorithms in two aspects of the convergence and the rate of comprehensive objective. The result has shown in Figure7.

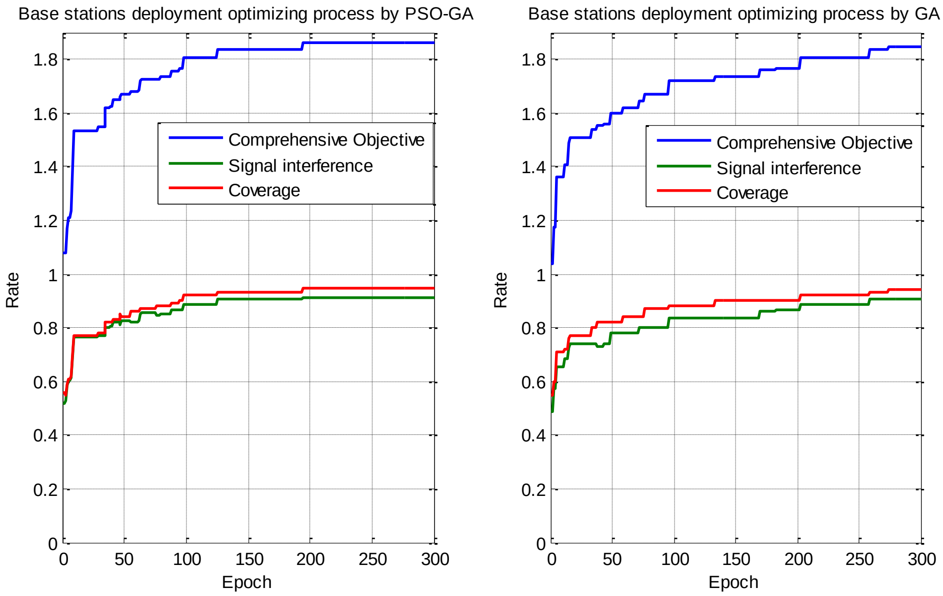

Figure 6. PSO-GA and GA comparative experiments

The left of Figure 6 shows base stations deployment optimizing process by PSO-GA, it shows that the comprehensive objective rate is 1.860741; the signal interference rate is 0.910741; the coverage rate is 0.950000. PSO-GA algorithm converges when the epoch is 194, and the result up to global optimum.The right of Figure 6 shows base stations deployment optimizing process by PSO algorithm, it shows that the comprehensive objective rate is 1.846517; the signal interference rate is 0.906517; the coverage rate is 0.940000. GA algorithm converges when the epoch is 274, and the result close to global optimum.By comparison we know that PSO-GA algorithm can converge earlier, and the result most tend to be higher than the GA algorithm.

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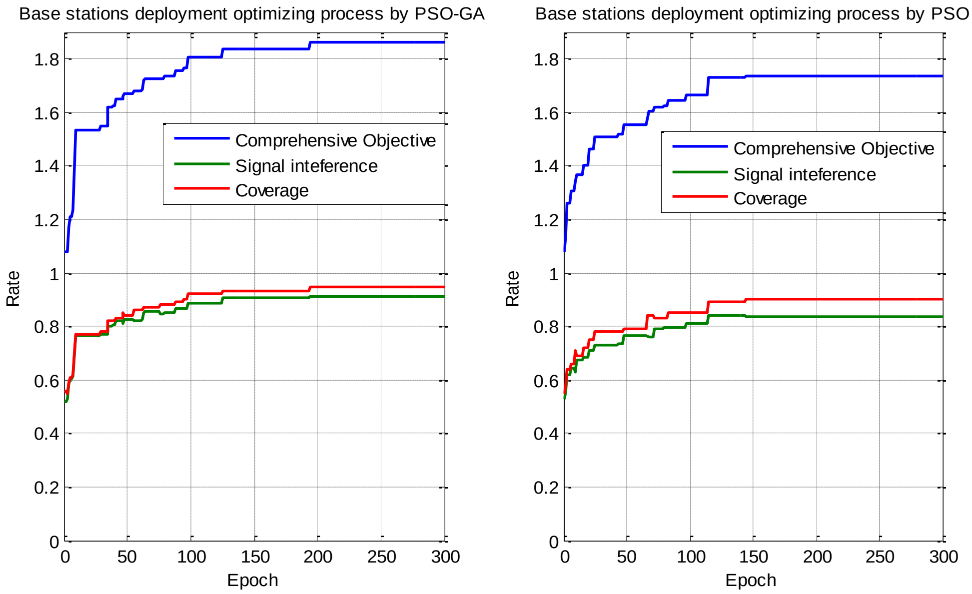

Figure 7. PSO-GA and PSO comparative experiments

The left of Figure 7 shows base stations deployment optimizing process by PSO-GA, it shows that the comprehensive objective rate is 1.860741; the signal interference rate is 0.910741; the coverage rate is 0.950000. PSO-GA algorithm converges when the epoch is 194, and the result up to global optimum.The right of Figure7 shows base stations deployment optimizing process by PSO algorithm, it shows that the comprehensive objective rate is 1.734181; the signal interference rate is 0.834181; the coverage rate is 0.900000. PSO algorithm converges when the epoch is 144, but the result fall into local optimum.By comparison we know that although PSO-GA algorithm converges no earlier than PSO algorithm, but PSO-GA can get a better optimum value.

5. Conclusion

With the development of wireless communication technology, a good base plan is the essential factors for a communication company to save costs and improve the competitiveness. In this paper, by taking the cost, coverage and signal quality (signal interference) as the optimization objectives and deducing the objective ranges, the base station deployment is considered as a multi-objectives combination optimization problem. It has also been confirmed that the problem belongs to NP-Hard. To solve this problem, we propose a PSO-GA algorithm by transfer the PSO algorithm into PSO operator instead of genetic algorithm mutation operator, which retains the global convergence of GA algorithm, and retains the ability of converges fast of PSO algorithm. From the experimental results we know PSO algorithm has good convergence, but it is often easy to fall into local optimum. So, the future work we will continue research on PSO improved algorithm to enable them to jump out of local optimum. And continue research on improving other traditional intelligent optimization algorithm like Ant Colony Algorithm and implement it on a three-dimensional CAD system.

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