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Multi-objective optimization-based site planning for communication networks

Haoran Liang*

School of Civil Engineering, Hebei University of Engineering, Handan, 056038, China
**Corresponding author: 915334933@qq.com*

Abstract: *In this paper, a multi-objective optimization model is established, and the objective function is to minimize the total cost of base station construction and maximize the coverage of total services at weak coverage points, and the constraints are the threshold value of the distance between new and existing sites and the coverage of macro and micro base stations, and then the particle swarm optimization algorithm based on genetic algorithm is improved to solve the problem. 523, 5932 micro-base stations, the total cost is 11162, and the ratio of new base station service to total service is 91.267%.*

Keywords: *site planning, multi-objective optimization, genetic algorithm, particle swarm algorithm*

1. Introduction

In practical work, in order to better solve the problem of weak coverage, we carry out regional clustering of weak coverage points according to the coverage range of the current live network antenna, cluster the close weak coverage points into a class, find out the weak coverage area of the current live network, select some specific points, so that these points can solve the weak coverage problem of the current live network after the establishment of new 5G base stations. At present, more than 34 countries and regions have implemented 5G commercial use, and 5G infrastructure has become a fortress for all countries to compete for. It is expected that by 2025, the cumulative investment in 5G network construction in China will reach 1.2 trillion yuan, which will drive the upstream and downstream industry chain and the application investment in various industries to exceed 3.5 trillion yuan. Large-scale 5G network construction is in urgent need of a practical and effective 5G site planning to adapt to it, to achieve the purpose of cost reduction and quality improvement [1].

In the process of mobile communication technology development, network coverage quality has always been one of the most important performance evaluation indicators of mobile communication networks. With the technological evolution and network deployment of mobile communication, especially in scenarios such as the number of large-scale access users, complex terrain and high-density base stations, the technical computation involved in coverage calculation and coverage optimization is huge and the algorithm convergence speed is slow. Therefore, the technical pain point problems such as computational complexity and algorithm efficiency of existing coverage calculation and coverage optimization are addressed [2].

2. Building the foundation of the model

2.1 Construction of the objective function

The multi-objective problem of finding the optimal solution for the coverage of the total service volume at weak coverage points with the minimum station construction cost is the main research of this paper. In general, this paper decomposes the multi-objective problem of mobile communication network site planning into two sub-objectives: the total cost of building macro base stations and micro base stations [3] and the coverage rate of total service volume at weak coverage points, and the specific sub-objective functions are given below.

Let the set of macro base stations be: $S1=(1,2,3,...,N)$; the set of micro base stations be: $S2=(1,2,3,...,M)$. The case of macro base station i is selected (new) as $Xi\in\{0,1\},i\in S1$; the case of micro base station j is selected (new) as $Xj\in\{0,1\},i\in S2$.

The total cost of mobile communication network site planning mainly includes the construction cost

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of macro base stations and micro base stations, and the cost formula is shown in equation (1).

$$F_1 = \sum_{i=1}^{N} S_{1i} X_1 + \sum_{j=1}^{M} S_{2j} X_2 \tag{1}$$

Where F1 is the total cost of building macro and micro base stations, S1i and S2j are the number of macro and micro base stations, respectively, and X1 and X2 are the individual costs of macro and micro base stations, respectively.

The coverage ratio of total services at weak coverage points is the second objective function with a coverage range of 30 for macro base stations and 10 for micro base stations, and the main formula is shown in equation (2).

$$F_2 = \sum_{i=1}^{N} S_{1i} l_1 + \sum_{j=1}^{M} S_{2j} l_2 \tag{2}$$

Among them, F2 is the coverage ratio of the total service volume of weak coverage points, and l1 and l2 are the coverage areas of macro base stations and micro base stations, respectively.

The above functions constitute the main objective function system of the multi-objective planning model for station site planning of mobile communication networks.

2.2 Determination of constraint conditions

When optimizing the objective, it is also necessary to consider the constraints in the topic. The station planning scheme is an optimization of the decision variables (location, number, and type of base stations) achieved under certain constraints. The Euclidean distance between new base stations and weak coverage points is less than 30 or 10. According to the existing network base stations, the threshold between two new base stations or the threshold between new base stations and weak coverage points is not less than 10; the coverage range of macro base stations is 30 and the coverage range of micro base stations is 10. The resulting constraints are established as shown in equation (3).

$$s.t.\begin{cases} \sum_{i=1,j=1}^{n} w_j \times p_i + \sum_{i=1,j=1}^{n} w_j \times q_i \geq 6350607 \\ \sqrt{(x-x_0)^2-(y-y_0)^2} \leq 30, (x, y\ is\ \ macro\ base\ station) \\ \sqrt{(x-x_0)^2-(y-y_0)^2} \leq 10, (x, y\ is\ a\ micro\ base\ station) \end{cases} \tag{3}$$

2.3 Improved particle swarm optimization algorithm based on genetic algorithm

The particle swarm optimization algorithm is efficient in search capability, fast in computation, and beneficial in obtaining optimal solutions in a multi-objective sense[4]. The algorithm has good generality, suitable for dealing with many types of objective functions, and has superior performance in complex combinatorial optimization [5] problems. However, when the particle swarm optimization algorithm calculates the extreme value of a function, the phenomenon of premature maturity often occurs and thus leads to large deviations in solving the extreme value of the function. However, the genetic algorithm for finding the optimal solution of a function often takes the objective function as the search information directly, and uses selection, crossover and compilation operator operations in a probabilistic manner, thus enhancing the global search capability of the particle swarm optimization algorithm, improving the convergence precision, and speeds up the evolution of the algorithm.

Genetic Algorithm (GA) is a method to seek the optimal solution by simulating the natural evolution process through simulating the genetic mechanism of biological evolution and the computational model of natural selection of Darwinian biological evolution.

For example, according to the principle of survival of the fittest and survival of the fittest, after the generation of the first generation of binary coding, individuals are selected in each generation according to the fitness of individuals in the problem domain. With the help of genetic operators, selection, crossover and mutation are carried out to select the population representing the new and better approximate solution set by generation evolution. This process, like natural evolution, produces the next generation population that is more adaptable to the environment than the previous generation population. After decoding, the optimal individuals in the last generation population can be used as the approximate optimal solution to the multi-objective optimization problem.

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(1) Initial population

First a number of initial station sites are randomly generated.

(2) Fast dominance sorting

NSGA2 fast non-dominated sorting is to stratify the population based on the level of individual non-inferior solutions and let the algorithm search towards the optimal solution.

(3) Confrontation distance

In order to sort the individuals within a stratification, it is necessary to use the adversarial distance between individuals. The adversarial distance of individual i is the i-1 and i+1 distance adjacent to i.

The specific steps are

Step 1: initialize the distances of individuals in the same stratum such that $L[0]_d = 0$.

Step 2: arranging the sibling individuals in ascending order.

Step 3: ensure that edge individuals have selection power such that $L[0]_d = L[i]_d = \infty$.

Step 4: Calculate the adversarial distance.

$$L\left[i\right]_d = L\left[i\right]_d + \frac{(L\left[i+1\right]_m + L\left[i-1\right]_m)}{f_m^{\max} - f_m^{\min}} \tag{4}$$

where $L[i+1]_m$ is the m th objective function of the i+1th individual, $f^{max}{}_m$ is the maximum value of the m th objective function inside the set, and $f^{min}{}_m$ is the minimum value of the m th objective function.

Step 5: repeat the operation steps 2-4 for the objective function to obtain the crowding distance of individual i.

(4) Selection operation

In the selection, first compare the ranks of 2 individuals, and if they are different, eliminate the individual with lower rank.

(5) Crossover and variation operations Crossover and variation confer good traversal performance to the NSGA2 algorithm. (5) Crossover and variation operations give NSGA2 algorithm good traversal performance. In the variation of the scheduling scheme, the variation adopted is the variation of the bus model.

(6) Elite strategy

The elite from the parent generation is guaranteed to enter the later generation.

Genetic algorithms provide a general framework for solving optimal solution problems of complex systems, because in the computation, genetic algorithms only need the objective function that affects the search direction and the corresponding fitness function, and their overall search strategy and optimal search method are independent of other auxiliary knowledge.

2.4 Particle swarm optimization algorithm

Starting from a stochastic solution, the particle swarm optimization algorithm iterates to find the optimal solution, and the evaluation of the quality of the optimal solution is achieved by the degree of adaptation.

Particle swarm optimization algorithms are simpler to compute than genetic algorithms in terms of rules, because the "selection", "crossover", and "mutation" operations of genetic algorithms are much simpler than those of genetic algorithms. The particle swarm optimization algorithm finds the global optimal solution by following the optimal value of the current search. Particle swarm optimization algorithms have demonstrated their superiority in solving real-world problems through their fast convergence, high accuracy, and ease of implementation, and have also gained widespread attention in academia.

Compared with other population-based evolutionary algorithms, which have in common that they initialize a set of random solutions and then search for the optimal solution through iterations, these optimization algorithms differ in that unlike evolutionary computation, which follows the principle of

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survival of the fittest, particle swarm optimization algorithms express each possible solution as one of the swarm flying at a certain speed in the search space and has its own velocity vector and position vector and a fitness determined by the objective function, and all particles find the global optimum by following the current searched for optimum.

The particle swarm optimization algorithm requires each particle to maintain two vectors, a velocity vector and a position vector, in the process of finding the optimal dimension of the solution problem. The velocity of a particle determines the direction and speed of its motion, while the position reflects the location of the solution represented by the particle in the solution space and is the basis for assessing the quality of that solution. The algorithm also requires each particle to maintain a vector of its own historical optimal position and the population also maintains a global optimal vector, and the specific algorithm steps are as follows.

Step 1: Initialize all particles, their velocities and positions, and set the particle's historical best pBest to the current position, while the best particle in the population is used as the current global best vector.

Step 2: In each iteration, calculate the fitness function value of each particle.

Step 3: if the current fitness function value of the particle is better than the historical best, then the historical best will be replaced by the current position.

Step 4: if the particle's historical optimum is better than the global optimum, the global optimum will be replaced by the particle's historical optimum; Step4: if the particle's historical optimum is better than the global optimum, the global optimum will be replaced by the particle's historical optimum.

Step 5: The velocity and position of the dth dimension of each particle i are updated according to Eqs. (5) and (6), respectively.

$$v_i^d = \omega \times v_i^d + c_1 \times rand_1^d \times (pBest_1^d - x_i^d) + c_2 \times rand_2^d \times (gBest_2^d - x_i^d) \tag{5}$$

$$x_i^d = x_i^d + v_i^d \tag{6}$$

Where, w inertia weight, c is the acceleration constant, and regulate the maximum step of learning.

Step 6: If the end condition is not satisfied, then go to Step2, otherwise output the global optimal vector end.

The three sub-objective functions are combined using the ideal point method with weighted minimal mode, and the combined single objective function is shown in equation (7).

$$\min F = \lambda_1 \left| \frac{F_1 - F_{1\min}}{F_{1\min}} \right| + \lambda_2 \left| \frac{F_2 - F_{2man}}{F_{2\max}} \right| \tag{7}$$

$$\begin{cases} \lambda_1 + \lambda_2 = 1 \\ \lambda_1 > 0 \\ \lambda_2 > 0 \end{cases} \tag{8}$$

Where, λ_1, λ_2 are the weight values of the objective functions $F_{1\min}$ and $F_{2\max}$, respectively, and $F_{1\min}$, $F_{2\max}$ are the ideal points of the optimization subproblem $F_{1\min}$, $F_{2\max}$.

The single objective function constructed by the above equation can not only clearly express the deviation between each objective value of the solution and the ideal point objective values $F_{1\min}$ and $F_{2\max}$, and reflect the quality of the solution; the decision maker can also adjust the weight values to obtain the optimal solution in accordance with his preference. In addition, the single objective function constructed by using the ideal point with weighted minimal mode also solves the problem of inconsistency and difficulty in unifying the two sub-objectives in this problem.

3. Results

3.1 Mobile communication network site planning program

According to the established model and the solution, the mobile communication network station site

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planning scheme can be derived. The distribution range of the original network base stations according to Annex 2 is shown in Figure 1.

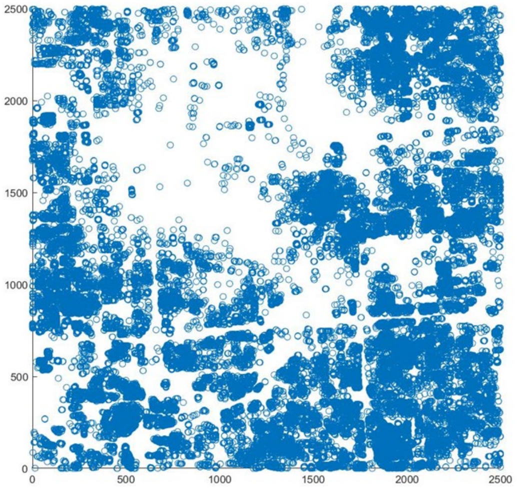

Figure 1: The distribution picture of the original network base station

According to the above method, the number and location of macro base stations and micro base stations are solved, and finally the number of macro base stations needed to be built is 523, micro base stations are 5932, the total cost is 11,162, and the proportion of new base station services to total services is 91.267%. In order to show the effect more intuitively, the distribution of macro base stations and micro base stations are shown separately, as shown in Figure 2 and Figure 3.

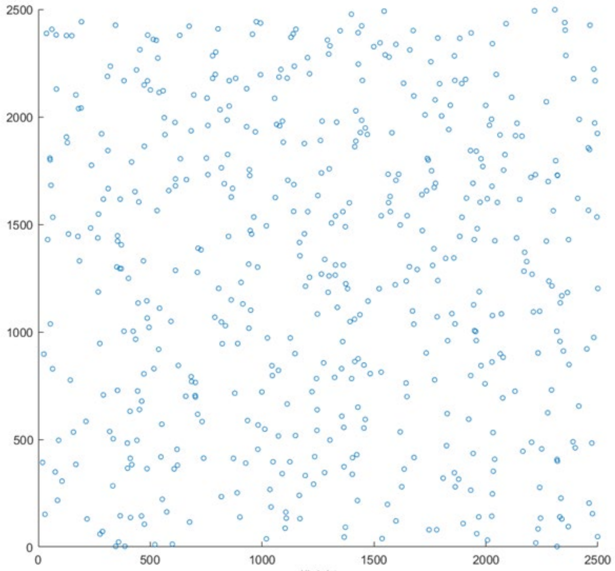

Figure 2: Macro base station distribution map

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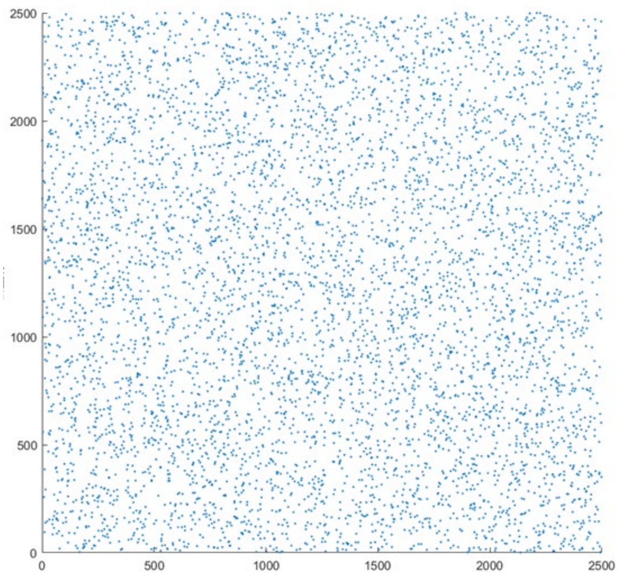

Figure 3: Micro base station distribution map

The specific locations are shown in Table 1 and Table 2 (the number is too many, 8 coordinates data are randomly selected to show), and all the coordinates locations are shown in the annex.

Table 1: Macro base station site coordinates

Number	Horizontal coordinate	Vertical coordinate
1	1473	1143
2	1714	1638
3	2352	2438
4	1978	1805
5	366	1617
6	1898	109
7	1019	1493
8	906	1230

Table 2: Micro-base station site coordinates

Number	Horizontal coordinate	Vertical coordinate
1	1616	965
2	2407	136
3	1931	1974
4	2263	465
5	62	858
6	2330	201
7	602	2047
8	404	403

4. Conclusions

With the rapid development of mobile communication technology and the increasing operation scale, the communication network is becoming more and more complex. With the development of 5G [6], the communication bandwidth is getting bigger and bigger, but the coverage range of base stations is getting smaller and smaller, which makes the number of base stations needed to cover the same area become more and more. In addition, there are more types of base stations and antennas. This makes the planning of communication network especially the site selection become more and more complicated. The problem of site selection is as follows: according to the coverage of the antenna of the live network, select a certain number of points for the weak coverage area of the network, so that the coverage problem of the weak coverage area of the live network can be solved after the new base station is built on these points. Multi-objective optimization is used to improve the coverage of base stations and reduce the total cost when designing the site planning scheme for mobile communication networks.

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