

# Site Planning For 5G Communication Base Stations Based On The Idea Of Binary Mask

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## ABSTRACT

With the boom in 5G technology, the bandwidth of communications is increasing while the coverage area of base stations is getting smaller and smaller, making it necessary to have more base stations to cover the same area. On the other hand, the variety of base stations and antennas is also increasing. This complicates the problem of site planning for 5G communication base stations. The core of the site selection problem is to select a certain number of coordinate points for the weak coverage areas of the existing network according to the coverage of the existing network so that the coverage of the weak coverage areas of the existing network can be solved by building new base stations on these coordinate points. Therefore, this proposes a 5G base station planning model based on the idea of the binary mask, combining differential evolution algorithm and Monte Carlo simulation to fully consider the correlation and synergy between new 5G base stations and existing base stations. According to the experimental results, 186 new micro base stations and 1930 macro base stations were built, and the coverage rate of the new base stations in the region reached 91.2% of the total service volume of the weak coverage points. This shows that the method proposed in this paper can effectively solve the problem of siting 5G communication base stations and achieve the rational utilization of urban spatial site resources and the minimization of economic costs.

**Keywords:** 5G technology; 5G Base Station; Site Selection Planning; Binary Mask; Differential Evolution Algorithm; Monte Carlo

## 1. INTRODUCTION

In recent years, 5G technology has been used in an increasingly wide range of mobile communications, spawning a variety of applications such as immersive content, smart factories, driverless cars, and smart cities. However, due to the high frequency and fast fading of 5G signals, it placed high demands on the number and location of base stations to be deployed. Based on the available coverage, 5G base stations are divided into macro base stations and micro base stations. Macro base stations cover a wide area and have low cost per unit area, but they are large and more complex to deploy, while micro base stations are small and simple to deploy but cover a small area. A reasonable combination of macro base stations and micro base stations can achieve the balance of coverage area and cost of the 5G network.

The siting problem of the base station generally refers to the determination of the station location matrix based on the existing weak coverage point traffic volume matrix, so that the new base station can cover the maximum traffic volume of the point. The site selection problem of the base station is a typical NP-hard problem, just like the traditional site selection problem. The mainstream solution methods include genetic algorithm, particle swarm algorithm, immune algorithm, etc[1]. The siting problem is essentially a nonlinear 0-1 planning problem, which is similar to the pattern of nature's chromosomes. Therefore, it is suitable for solving using a genetic algorithm. However, the traditional genetic algorithm not only converges slowly but also is easily trapped in the local optimal solution[2]. The differential evolution algorithm uses improved selection, crossover, and variation operators, which both greatly improve the convergence speed and reduce the probability that the population is trapped in a local optimal solution[3]. The objective function adopts the idea of binary mask in the field of image processing. It uses logical operations instead of numerical operations, which effectively improves the operation speed, thus enabling the intelligent optimization algorithm to give a better solution in the same solution time.

This paper proposes a solution to the problem of location selection for base stations and similar facilities. Based on the known traffic matrix, the differential evolution algorithm is used to solve the problem; to further improve the solution

speed of the algorithm, the mask idea is used to optimize the speed of the objective function, which can effectively plan the location and type of base station construction.

## 2. 5G BASE STATION SITE PLANNING MODEL

### 2.1 Selection and processing of research subjects

In this paper, the existing network coverage in the Nanping area of Nan'an District, Chongqing, China (as shown in the figure below, where the red part was the weak coverage area) was selected as the object of study. For the purpose of calculation, the area was divided into small grids, and only the center point of each grid was considered. In total, the area was divided into 2500\*2500 grids, i.e., 2500\*2500 points.



Figure 1. The existing network coverage in the Nanping area of Nan'an District, Chongqing

### 2.2 The idea of binary mask

In the process of building the model in this paper, we found that the coverage of the base station and the limited area of the threshold had the same characteristics, which was that the center point of a certain area can affect the state of all the points around a certain range at the same time. Before the operation and processing, if we could integrate each such area into a whole through this characteristic, we would greatly reduce the number of operations in our solution process. Therefore, This paper proposes an idea for the operation of matrices based on a template such as the binary mask in the field of image processing, named the idea of binary mask.

The idea was essentially the construction of a matrix model that represents some specific weights in terms of differences in the values of the elements at each position, an example of which is given.

- With all elements set to zero, create a 2500\*2500 matrix, called a region matrix;
- Construct a matrix of size 21\*21, called a binary mask, where the elements are all set to 0;
- Find the centroid in the area matrix that needs to change itself and a certain range of values around it, overlap that centroid with the binary mask centroid, and perform a logical or operation on the elements at the corresponding positions.

In this case, a binary mask-sized area on the area matrix, which was all 0, is changed to the desired value at the same time. The value of each element in the binary mask could be adjusted to suit the actual function.

### 2.3 Multi-objective planning modeling

#### 2.3.1 Determination of the objective function

The coverage range of the macro base station was 30 and the cost was 10, the coverage range of the micro base station was 10 and the cost was 1. Therefore, the multi-objective planning model had two optimization objectives, the first optimization objective was the total cost of macro base stations and micro base stations should be as low as possible, the mathematical expression was:

$$\min \left\{ \sum_{i=1}^j 10h_i + \sum_{i=1}^k w_i \right\} \quad (1)$$

Where  $h_i, w_i$  denoted the  $i^{\text{th}}$  macro base station and the  $i^{\text{th}}$  micro base station, respectively, and  $j, k$  denote the corresponding number of stations.

The second objective to be optimized was for the base station to cover the weak coverage area with the highest possible total service volume, expressed as:

$$\max \frac{1}{S} \left( \sum_{i=1}^j 900\pi h_i + \sum_{i=1}^k 100\pi w_i \right) \quad (2)$$

where  $S$  was the total business volume in the weak coverage area.

To apply the algorithm better, a certain simplification of the objective function was needed to reduce the dual objective to a single objective, which was handled by dividing the total cost by the proportion of business volume covered to obtain an expression for the unit cost under the coverage proportion.

$$\min \left\{ S \frac{\sum_{i=1}^j 10h_i + \sum_{i=1}^k w_i}{\sum_{i=1}^j 900\pi h_i + \sum_{i=1}^k 100\pi w_i} \right\} \quad (3)$$

### 2.3.2 Determination of Constraints

The threshold distance not only limited the distance between the new base station and the original base station to no less than 10, but also includes the distance between the new base station and the new base station to no less than 10, from which the following constraints could be obtained.

$$\sqrt{h_i^2(x_1, y_1) + h_j^2(x_2, y_2)} > 10 \quad (4)$$

$$\sqrt{h_i^2(x_1, y_1) + w_j^2(x_2, y_2)} > 10 \quad (5)$$

$$\sqrt{h_i^2(x_1, y_1) + w_j^2(x_2, y_2)} > 10 \quad (6)$$

## 2.4 Differential Evolution (DE) algorithm

The DE algorithm was a heuristic random search algorithm based on population differences. The basic principle of this algorithm was similar to the genetic algorithm. Meanwhile, it could avoid to some extent the shortcomings of the genetic algorithm variant approach. The DE algorithm process could be summarized in four steps: initialization, mutation, crossover and selection.

### 2.4.1 Initializing the population

Let the population be:  $\{X_1(t), X_2(t), \dots, X_N(t)\}$ , where  $N$  was the number of population;

### 2.4.2 Variation operations

The mutation operation was an extremely important part of the DE algorithm. It was the signature difference compared to the genetic algorithm, which first randomly selected two individuals from the population to perform the following operation.

$$V_{ij}(t+1) = X_{ij}(t) + F(X_{im}(t) - X_{in}(t)) \quad (7)$$

Where  $i, j$  was the  $j^{\text{th}}$  individual of the dimension and  $m, n$  are two random integers in the range 1 and  $N$ .

### 2.4.3 Crossover operation

$$U_{ij}(t) = \begin{cases} V_{ij}(t) & \text{rand}(0,1) \leq CR, \text{ or } j = \text{rand}(i, n) \\ X_{ij}(t) & \text{otherwise} \end{cases} \quad (8)$$

#### 2.4.4 Select operation

$$\begin{cases} U_i(t+1) & f(U_i(t+1)) < f(X_i(t)) \\ X_i(t) & \text{otherwise} \end{cases} \quad (9)$$

The specific flow chart of the algorithm is as follows.

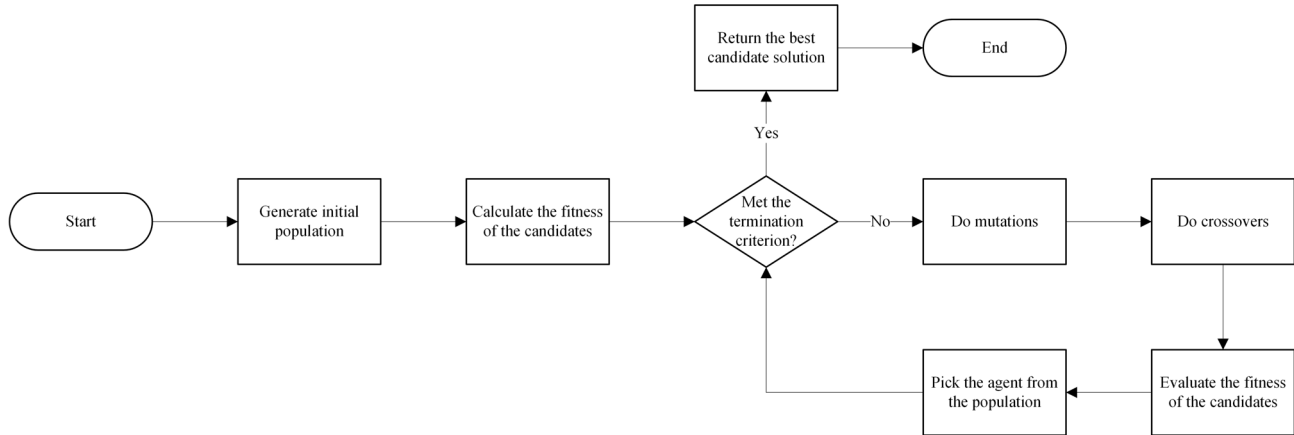


Figure 2. Flow chart of differential evolution algorithm

The differential evolution algorithm had several advantages over traditional optimization algorithms.

- Good generality and ease of integration with multiple models to create better models for better processing results.
- The relatively small number of control parameters and the relative simplicity of the DE principle made it easier to implement and operate accordingly.
- The algorithm was highly adaptable, robust and had excellent global search capabilities.
- There was a certain degree of parallelism within the algorithm, so that the DE algorithm was able to demonstrate superior computational efficiency when performing large-scale processing, greatly reducing the time cost of solving the problem.

#### 2.4.5 Monte Carlo simulation

The Monte Carlo method is a statistical test method that is widely used in the field of stochastic simulation[6]. When we needed to solve a physical problem, a mathematical problem, an engineering problem, a production management problem, etc. Firstly, we built a stochastic process or a probabilistic model so that its parameters were equal to the solution of the problem, and then calculated the characteristics of the parameters by sampling tests or by observing the process of the mode. Finally, find the approximate value of the solution.

The Monte Carlo method for generating random numbers required a random number generator that could generate equal probability densities in the interval [0,1]. And then, convert the random numbers in [0,1] into what satisfied the requirements of the differential evolution algorithm, which was then applied to the model.

### 3. SITE SELECTION MODEL SOLVING

#### 3.1 Data filtering

The siting of new base stations should be based on the existing network base station layout. The same grid could not be used to establish more than one base station at the same time, and the distance between the different base stations must be greater than the threshold 10. Therefore, we needed to filter the points in the area using the coordinates of the existing base stations to get all the coordinates of all the base stations that could be set up under the threshold conditions.

First, a 21\*21 binary mask matrix was defined based on the length of the threshold at a distance of 10. Because the threshold limits the original base station to a circle with a radius of 10, the matrix was defined as having the center point

as the origin, with all elements at a radius of 10 units as 0, and elements at the other edges as 1. In terms of a 5\*5 matrix, this was roughly expressed as:

$$\begin{pmatrix} 1 & 1 & 0 & 1 & 1 \\ 1 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 \\ 1 & 1 & 0 & 1 & 1 \end{pmatrix} \quad (10)$$

Create a 2,500\*2,500 area matrix, where all elements were initialized to 1. Set the coordinates of all existing base stations to all the centroids in the area matrix and overlap them with the binary mask centroids, then perform logical sum operations by bit, at which the points with a value of zero were the unreasonable points screened out by the threshold condition that could not be built with new base stations. At last, name the matrix as the threshold matrix  $A_M$ .

### 3.2 Screening results

After calculation, we found 418,417 unreasonable points. The number of points that can build a new base station is a total of 5,831,583 points, which greatly reduces the amount of computation we need to build and solve the model next. To make the data more intuitive, we have visualized the results as follows.

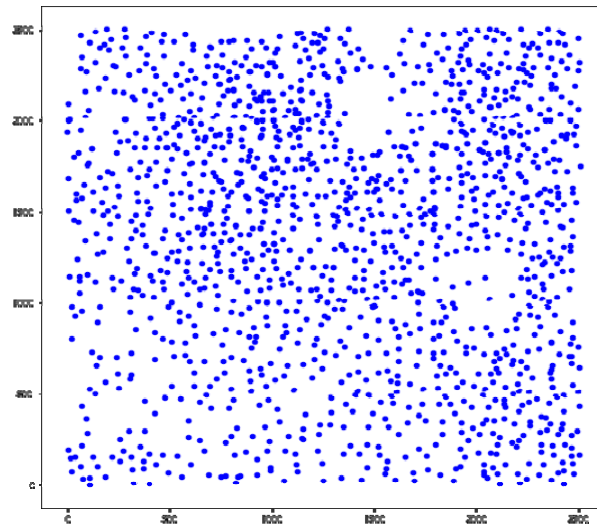


Figure 3. Diagram of the threshold range of existing network base stations

Where the blue dots indicate the area covered by the original base station, then all the points in the blank area were the points where a new base station could be established after filtering.

The differential evolution algorithm required initialization of the population and was sensitive to the initial values, requiring us to randomize the site selection state. We decided to use a Monte Carlo model with the idea of binary mask for this step.

1. Create a 2,500\*2,500 matrix;
2. A Monte Carlo model was used to randomize a numerical element at each location, where the values of the elements include 0, 1 and 2, with 1 indicating a micro-base station at the point, 2 indicating a macro-base station at the point and 0 indicating no new base station at the point and the number of 1s and 2s specified as a total of 1,000. The probability of three random numbers was specified as  $P(0)=0.99424$ ,  $P(1)=P(2)=0.00029$ .

The resulting new matrix was multiplied with the matrix  $A_m$  by the corresponding bits to exclude the coordinate points where the new base station cannot be built. This matrix was named the station building matrix  $A_j$ .

3. Create a 21\*21 micro-base station binary mask and a 61\*61 binary mask, assigning a value of 1 to the circular area and 0 to the edge area. Cover the two binary masks with the corresponding coordinates of the station building matrix, and perform a bitwise or operation on the corresponding points to obtain the matrix of the coverage area of the new base station, named the coverage matrix  $A_f$ .
4. Multiply the points in the coverage matrix with the business volume of each point in Annex I to obtain the business volume matrix  $A_y$ .
5. The initial value of this time could be obtained by dividing the cost of all the build matrices in the business volume matrix by the sum of the business volumes.
6. Repeat steps 1 to 5 to obtain the initial values for different random cases, and take the station building matrix corresponding to the smallest value as the initial value of the DE algorithm.

### 3.3 Confirmation of the initial value of the DE algorithm

The differential evolution algorithm required initialization of the population and was sensitive to the initial values, requiring us to randomize the site selection state. We decided to use a Monte Carlo model with the idea of binary mask for this step.

### 3.4 Solution of the differential evolution algorithm

The optimal initial value was used as the initialized population of the differential evolution algorithm. The final result after optimization was obtained based on the constraint and objective function iterative variation operation, crossover operation and selection operation for a total of 186 micro-base stations and a total of 1930 macro-base stations, for a total of 2116 new base stations, as shown below.

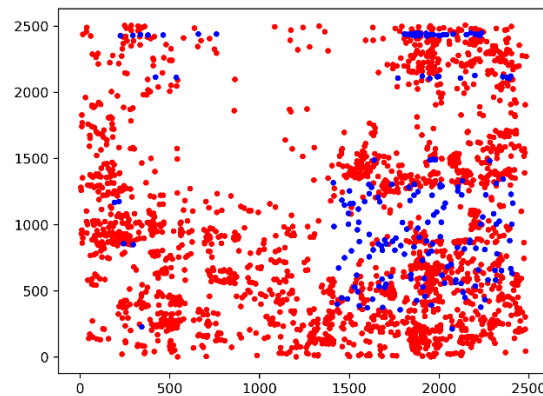


Figure 4. Scatter plot of new base stations

Where red dots indicate macro base stations and blue dots indicate micro base stations. The site selection results were obtained to verify the coverage requirement of 90% of the total service volume of the weak coverage points, at which point we again used the binary mask idea used in the data screening. The new macro base station and the micro base station were assigned a binary mask matrix according to their respective coverage areas. However, unlike the data screening, the circular area was assigned a value of 1 and the edge area was assigned a value of 0. Then the binary mask was logically oriented with the new base stations in the area by bit, so that even if there were duplicate coverage areas, they were only assigned a value of 1, avoiding duplicate summation of data. At the end of the operation, the points with a value of 1 in the whole area were added up and divided by the total number of services, giving a coverage of 91.2% of the total number of services.

## 4. SUMMARIZATION

This paper designs a new 5G base station planning model based on the idea of "mask" in image processing, combining differential evolution algorithm and Monte Carlo simulation to solve the signal coverage problem in the weak coverage area of existing network. Meanwhile, a relatively complete 5G base station siting scheme is obtained by considering the coverage and cost attributes of macro base stations and micro base stations. The result shows that the differential evolution algorithm converges faster and gives better results under the same cost constraint, and the communication

volume covered by the given scheme reaches 91.2% of the total coverage, which can meet the actual production and living needs.

In addition, the model in this paper can be further researched and optimized in practice, such as considering the characteristics of terrain distribution, labor cost, and crowd distribution in different regions, and making appropriate adjustments to the model with the actual situation of the region. In addition, there will be certain interference factors in the actual propagation of the signal from the base station, and it will be the next research direction of this paper to avoid the signal interference to the greatest extent while ensuring the maximum coverage and minimizing the cost of the service.

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