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Accelerated genetic algorithm based on real number coding for solving mobile communication network site planning

Jiawei Luo[1], Jialu Wang[2], Bo Wen[3], Yu Yan[4], Zebin Ma[1], Ruihan Chen[1,*], Minhua Ye[5], Xuewen Chen[1], Yueyang Wu[1], Di Ning[6]

[1]*School of Mathematics and Computer, Guangdong Ocean University, Zhanjiang, 524088, China*
[2]*College of Applied Mathematics, Chengdu University of Information Technology, Chengdu, 610225, China*
[3]*School of Information and Communication Engineering, North University of China, Taiyuan, 030000, China*
[4]*College of Communication Engineering, Chengdu University of Information Technology, Chengdu, 610225, China*
[5]*College of Ocean Engineering and Energy, Guangdong Ocean University, Zhanjiang, 524088, China*
[6]*School of Economics, Guangdong Ocean University, Zhanjiang, 524088, China*
[*]*Corresponding author: Ruihan_chen2003@163.com*

Abstract: *The advancement of 5G networks has sparked widespread interest in effectively strategizing the placement of communication base stations within areas of weak network coverage. Addressing this pertinent topic, this paper aims to enhance service coverage and reduce the construction costs associated with base stations in such areas. Specifically, we conduct a comprehensive analysis by selecting base station sites within a given area comprising 2500×2500 points, taking into account both ideal and real-world conditions. To ensure practical applicability, we strive to develop an optimal base station site selection scheme for 5G construction enterprises. This is accomplished through the construction of a multi-objective planning model that considers multiple constraints. By building upon this foundation, we further refine and optimize the conditions of the multi-objective planning model. This step enables us to obtain a new multi-objective planning model that aligns with the real-life requirement of fan-shaped base station communication coverage. To effectively solve the listed multi-objective planning model and obtain an optimized station site plan, we employ an accelerated genetic algorithm based on real number coding. Furthermore, to provide visual representation and analysis of the base station solution, this paper utilizes Python and ArcGIS, facilitating the visualization of the results. Through this approach, we can effectively explore and demonstrate the efficacy of the proposed base station placement strategy.*

Keywords: *Accelerated genetic algorithm based on real number encoding, Multi-objective planning, Mobile communication network site planning, ArcGIS*

1. Introduction

The deployment of 5G networks continues to enhance the convenience in people's lives, making it imperative for social workers to extend the reach of 5G connectivity to every household. Since wireless networks rely on communication base stations, our focus lies in strategically determining the locations for mobile communication networks based on the coverage range and the cost associated with constructing these stations [1].

In this study, we address the problem of site selection within a specific area. To tackle this issue, we employ a 0-1 planning approach, which enables us to determine whether to opt for a macro base station or a micro base station. Our objective is to achieve a 90% coverage of areas with weak network connectivity. However, we also aim to enhance the practicality of our model in real-world applications. Therefore, we propose a multi-objective planning model that maximizes the coverage of areas with weak network connectivity while simultaneously minimizing the costs associated with constructing new sites. To ensure the model's applicability, we introduce two additional conditions that align with real-world scenarios [2].

ISSN 2616-5775 Vol. 6, Issue 7: 124-130, DOI: 10.25236/AJCIS.2023.060716

2. Model notation

Important notations used in this paper are listed in Table 1.

Table 1: Notations

Notations	**Symbol Description**
i,j	Weak coverage point number
X_i	Horizontal coordinates of the site
Y_i	Vertical coordinate of the site
$Acer\ Station_i$	0-1 variable to determine if a macro base station is built at point i
$Micro\ Station_i$	0-1 variable to determine if a microbase station is built at point i
A_{ij}	0-1 variable to determine if site j is covered by macro base station i
M_{ij}	0-1 variable to determine if site j is covered by microbase station i
Tra_j	j point business volume
Z_{ij}	Coordinate matrix of the distance between base station i and base station j (base stations - including macro and micro base stations)
$Dist_{ij}$	The distance between i and j
β_I	The angle corresponding to the main direction of the sector
α	Relative change angle of the main direction of the sector
r_α	Radius of coverage corresponding to the relative change angle of the main direction of the sector
label	Base Station Type
R_{label}	Radius of coverage in the main direction of the corresponding base station type sector

3. Model construction and solving

3.1. Multi-objective planning model

The objective function of the problem[3].

$$\frac{\max\left(\frac{\sum_{j=1}^{n} Tra_j \sum_{i=1}^{n}\left(A_{ij}+M_{ij}\right)}{\left(A_{ij}+M_{ij}\right)}\right)}{\sum_{j=1}^{n} Tra_j} \tag{1}$$

Binding Conditions.

The threshold for the distance between the new site and the existing site is 10.

$$Z_{ij} \geqslant 10, \quad i,j = 1,2,\dots,53249 \tag{2}$$

Only one type of base station can be established at point i, i.e.

$$\text{Acer Station}_i + \text{Micro Station}_i \leqslant 1, \quad i = 1,2,\dots,53249 \tag{3}$$

According to Euler's formula, it is known that

$$Dist_{ij} = \sqrt{\left(X_j^2 - X_i^2\right) + \left(Y_j^2 - Y_i^2\right)} \tag{4}$$

Establishing a macro base station or a micro base station at point i has the limitation of coverage, i.e.

$$\begin{gathered} Dist_{ij} \times A_{ij} \leqslant 30 \times AcerStation_i, \quad i,j=1,2,\dots,53249 \\ Dist_{ij} \times M_{ij} \leqslant 10 \times MicroStationi, \quad i,j=1,2,\dots,53249 \end{gathered} \tag{5}$$

The correlations between the four sets of decision variables, namely.

$$\begin{gathered} AcerStation_i \geqslant A_{ij}, i,j=1,2,\dots,53249 \\ MicroStation_i \geqslant M_{ij}, \quad i,j=1,2,\dots,53249 \end{gathered} \tag{6}$$

$$\begin{gathered} AcerStation_i = A_{ii}, \quad i=1,2,\dots,53249 \\ MicroStation_i = M_{ii}, \quad i=1,2,\dots,53249 \end{gathered} \tag{7}$$

ISSN 2616-5775 Vol. 6, Issue 7: 124-130, DOI: 10.25236/AJCIS.2023.060716

3.2. Improved multi-objective planning model

Assuming a complete circular coverage area for the base station, the reasonable site planning involving 829 macro base stations and 1246 micro base stations achieves an impressive coverage rate of 98.4% for the total service volume of weak coverage points. However, considering the real-life scenario where the communication coverage of base stations follows a fan-shaped pattern, it is crucial to assess whether a minimum coverage rate of 90% for the total service volume of weak coverage points can still be achieved. To address this, two practical conditions are introduced [4].

Firstly, each base station comprises three coverage sectors with a linearly decreasing coverage radius from the main direction towards 120°. This configuration ensures a comprehensive and balanced coverage distribution.

Secondly, to prevent signal overlap and interference, the angle between the main directions of any two sectors of each base station must not be less than 45°. This constraint guarantees the effective utilization of resources while minimizing interference.

By incorporating these practical conditions, the study aims to assess the impact on the coverage radius of the base station and evaluate the feasibility of achieving the desired coverage rate for the total service volume of weak coverage points.

$$r_\alpha = R_{\text{label}} \cdot \left(1 - \frac{\alpha}{120^\circ}\right) \tag{8}$$

α is the relative change angle with respect to the main direction of the sector, and r_α is the corresponding radius. We visualize the actual coverage range of the base station in one direction. Actual coverage area of base station in one direction is shown in Figure 1.

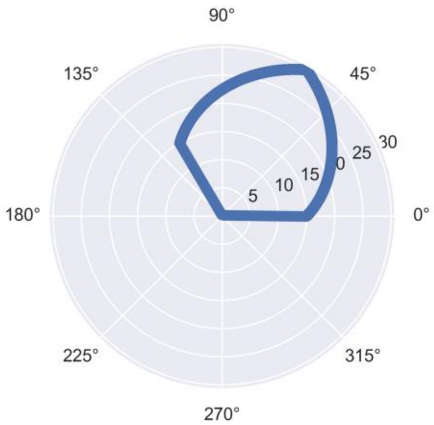

Figure 1: Actual coverage area of base station in one direction

When each sector of the base station is spaced at 120◦ in the main direction, we visualize its coverage area as shown in Figure 2.

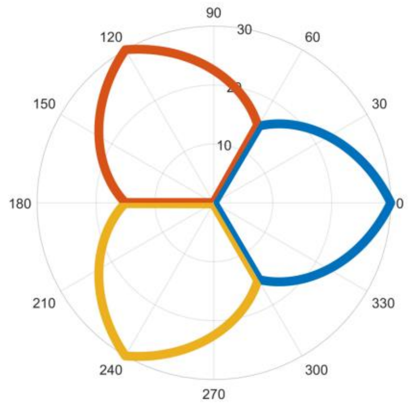

Figure 2: Coverage diagram of communication base stations under specific conditions

In summary, a multi-objective planning model for mobile communication network site planning problem is established.

ISSN 2616-5775 Vol. 6, Issue 7: 124-130, DOI: 10.25236/AJCIS.2023.060716

$$Z=F(X)=\begin{bmatrix} \max \dfrac{\left(\dfrac{\sum_{j=1}^{n}\mathrm{Tra}_j \sum_{i=1}^{n}\left(A_{ij}+M_{ij}\right)}{A_{ij}+M_{ij}}\right)}{\sum_{j=1}^{n}\mathrm{Tra}_j} \\ \min\left(\sum_{i=1}^{n} 10\times \text{ Acer Station }_i+\sum_{i=1}^{n} \text{ Micro Station }_i\right) \end{bmatrix} \tag{9}$$

$$\text{s.t. } \varphi(X)=\begin{cases} Z_{ij}\geqslant 10, i,j=1,2,\dots,53249 \\ \text{Acer Station }_i+\text{ Micro Station }_i\leqslant 1, \quad i=1,2,\dots,53249 \\ \text{Dist }_{ij}\times A_{ij}\leqslant 30\times \text{ Acer Station }_i, \quad i,j=1,2,\dots,53249 \\ \text{Dist }_{ij}\times M_{ij}\leqslant 10\times \text{ Micro Station } i, \quad i,j=1,2,\dots,53249 \\ \beta_I-\beta_J\geqslant 45^\circ, I,J=1,2,3 \text{ and } I\neq J \\ \text{Acer Station }_i\geqslant A_{ij}, \quad i,j=1,2,\dots,53249 \\ \text{Micro Station }_i\geqslant M_{ij}, \quad i,j=1,2,\dots,53249 \\ \text{Acer Station }_i=A_{ii}, \quad i=1,2,\dots,53249 \\ \text{Micro Station }_i=M_{ii}, \quad i=1,2,\dots,53249 \\ \text{Acer Station }_i, \text{Micro Station }_i=0 \text{ or } 1, \quad i=1,2,\dots,53249 \\ A_{ij},\ M_{ij}=0 \text{ or } 1, \quad i,j=1,2,\dots,53249 \end{cases} \tag{10}$$

3.3. Model solving - accelerated genetic algorithm based on real number coding

3.3.1. accelerated genetic algorithm based on real number coding

Genetic algorithms are probabilistic optimization algorithms rooted in Darwin's theory of evolution and Mendel's theory of heredity. They employ the concept of biological evolution to search for global optimum solutions. By employing straightforward coding techniques and algorithmic mechanisms, genetic algorithms can effectively simulate intricate optimization processes [5].

The Standard Genetic Algorithm (SGA) relies on binary coding; however, it exhibits limitations such as a predisposition to converge on local optima, high computational demands, and diminished solution accuracy. In contrast, the Real Number Coding-based Accelerated Genetic Algorithm (RAGA) addresses these challenges by adopting a real number coding representation and employing accelerated loops to expedite the problem-solving process. This modification enhances various aspects of the SGA and allows for improved performance. Thus, this paper proposes the utilization of the RAGA to tackle the established multi-objective planning model [6].

The solution steps of the Real Number Coding-based Accelerated Genetic Algorithm (RAGA) are outlined as follows:

Step 1: Encoding.Traditionally, the standard genetic algorithm employs binary encoding, which often leads to increased computational effort and a higher likelihood of generating redundant optimal solutions. In contrast, the Real Number Coding-based Accelerated Genetic Algorithm (RAGA) utilizes real number encoding, introducing a linear transformation to represent the encoding process. This transformation allows for a more efficient and effective solution representation, improving the overall performance of the algorithm.

$$aj = \underline{aj} + yj\left(\overline{aj} - \underline{aj}\right)(j = 1 \cdots n) \tag{11}$$

where$\left[\underline{aj}, \overline{aj}\right]$is the domain of definition of the decision variable aj The transformation can be viewed as encoding the solution direction $a=(a_1,a_2,\dots,a_n)$ into the chromosomal form of $y=(y_1,y_2,\dots,y_n)$, and for any j, there is $y_1\in[0,1]$.

Step 2: Initialize the population. Let the number of initialized populations be M. The initial coding sequence $\{y_{i,i}^{(0)}\}(j=1\cdots n, i=1\cdots M)$ is obtained by substituting it into the real number coding in Step 1, and the initial coding sequence $\{y_{i,i}^{(0)}\}(j=1\cdots n, i=1\cdots M)$ is obtained after the real number coding in Step 1, respectively, in the definition domain [M group primitive solution direction $\{dre_{j,i}^{(0)}\}(j=1\cdots n, i=1\cdots M)$ The sequence is then substituted into the objective function $Q(a)$ to find the objective function value $\{f_i^{(0)}\}(i=1\cdots M)$ of each individual in the population, and the individuals are sorted in ascending order according to the magnitude of the objective function value, and the top $Num(Num<M)$ individuals are selected as the best individuals.

ISSN 2616-5775 Vol. 6, Issue 7: 124-130, DOI: 10.25236/AJCIS.2023.060716

Step 3: Adaptability evaluation. Since the smaller the value of the objective function, the higher the fitness of the individual, and considering the case where the value of the objective function is 0, the fitness function is defined as

$$S_i = \frac{1}{\left(f_i^{(0)}\right)^2 + 0.001} \tag{12}$$

Step 4: Perform the selection operation to generate the 1st offspring population $\{y_{j,i}^{(0)}\}(j = 1 \cdots n, i = 1 \cdots M)$. The probability of the ith individual being selected is $E = \frac{S_i}{\sum_{i=1}^{M} S_i}$, and defining $\{p \mid p_i = \sum_{k=1}^{i} E_i\}$, then p divides the interval [0,1] into M subintervals $\{[0, p_1], (p_1, p_2] \cdots (p_M, 1]\}$. Then randomly generate (M- Num) a random number $Rand \in R^{M-Num}$, then the individuals are selected in the following way:

$$y_{j,k}^{(0)} = y_{j,i}^{(0)} \quad R^k \in (p_{i-1}, p_i) \tag{13}$$

For the remaining Num five individuals, the best individuals from the previous generation are used to directly supplement the population, i.e. the 1st offspring population.

Step 5: Perform the hybridisation operation to produce the 2nd offspring population $\left\{y_{j,i}^{(2)}\right\}(j = 1 \cdots n, i = 1 \cdots M)$. Based on the selection probability Ei obtained in step IV, a pair of individuals $y_{j,k1}$ and $y_{j,k2}$ are randomly selected for hybridization, and because of the limitation of the coding method, the following random linear combination of individuals $y_{j,i}^{(2)}$ is used to obtain the offspring individuals in this paper:

$$\begin{cases} y_{j,i}^{(2)} = r_1 \times y_{j,i}^{(0)} + (1 - r_1) \times y_{j,i}^{(0)} & r_3 < 0.5 \\ y_{j,i}^{(2)} = r_2 \times y_{j,i}^{(0)} + (1 - r_2) \times y_{j,i}^{(0)} & r_3 \geq 0.5 \end{cases} \tag{14}$$

where r_1, r_2, r_3 are random numbers in the interval [0,1].

Step6: Perform the mutation operation to generate the 3rd offspring population $\{y_{j,i}^{(3)}\}(j = 1 \cdots n, i = 1 \cdots M)$. Using n random numbers with probability pmi = 1 - Ei in place of the $y_{j,i}$th individual for variation:

$$\begin{cases} y_{j,i}^{(3)} = r_4 & r_5 < pm_i \\ y_{j,i}^{(3)} = y_{j,i}^{(0)} & r_5 \geq pm_i \end{cases} \tag{15}$$

where r_4 and r_5 are random numbers in the interval [0,1].

Step 7: Evolutionary Iteration. Following the acquisition of individuals from steps 4 to 6, they are sorted based on their fitness in ascending order. The top M individuals are then selected to form a new population. This new population replaces the previous one and undergoes reproduction in step 3, continuing the evolutionary process.

Step 8: Accelerated Cycle. The Real Number Coding-based Accelerated Genetic Algorithm (RAGA) employs an accelerated cycle to further enhance performance. This cycle involves utilizing the variable change interval derived from the best individuals obtained in the first and second evolutionary iterations. The new initial change interval is determined, and the algorithm re-enters step 1 to initiate a new iteration. This cycle continues until the preset number of accelerations, N, is reached, at which point the iteration concludes.

3.3.2. Solution results

In the ongoing execution of the Real Number Coding-based Accelerated Genetic Algorithm (RAGA), the Pareto front, representing the non-inferior solutions, undergoes continuous updates as the number of iterations progresses. In this particular run, the data from the last iteration of evolution is extracted, with the Pareto front organized in descending order. This data is then utilized to generate a linear plot, where the last few sets of data points are plotted against the coverage metric. The resulting plot, illustrating the linear relationship between the data and the coverage, is presented in Figure 3.

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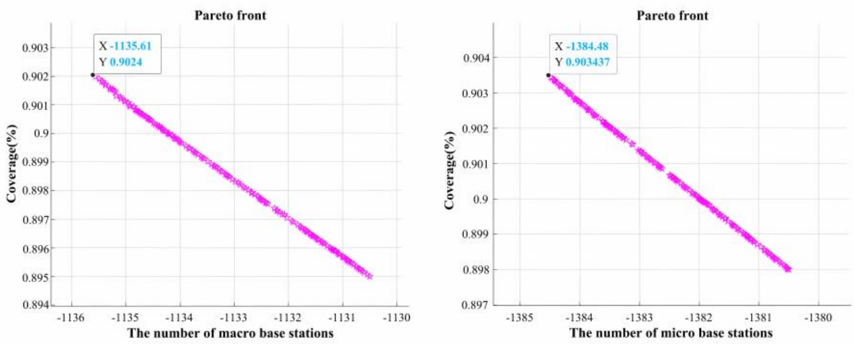

Figure 3: Diagram of the iterative process of solving the number of macro base stations (left) and micro base stations (right) based on the accelerated genetic algorithm for real number coding

The Real Number Coding-based Accelerated Genetic Algorithm yields the following results: 1136 macro base stations, 1384 micro base stations, a total cost of 12774, and a coverage rate of 90.84%.

Following the above analyses, this paper employs Python programming language to visualize the base station planning scheme. The visualization provides a graphical representation of the planned base station locations, illustrating their spatial distribution and coverage. The resulting visualization is presented in Figure 4.

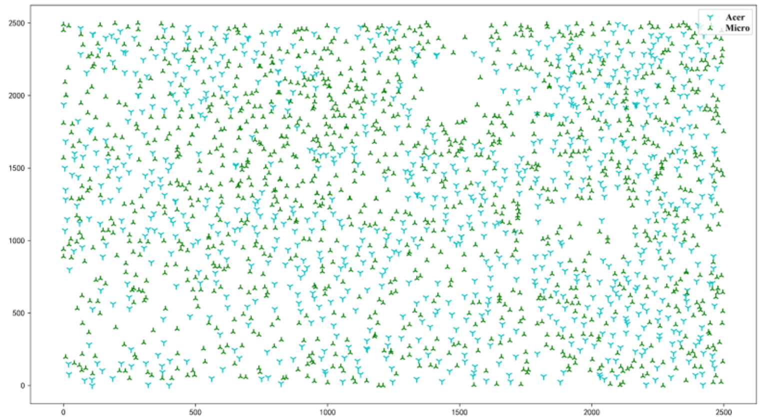

Figure 4: Base station location visualisation

To further analyze the distribution of the base stations, a visualization is created. Using ArcGIS software, the distribution of both macro and micro base stations is displayed. Additionally, the kernel density analysis is conducted individually for macro and micro base stations, generating heat maps that depict the intensity of base station distribution. The resulting visualization is presented in Figure 5.

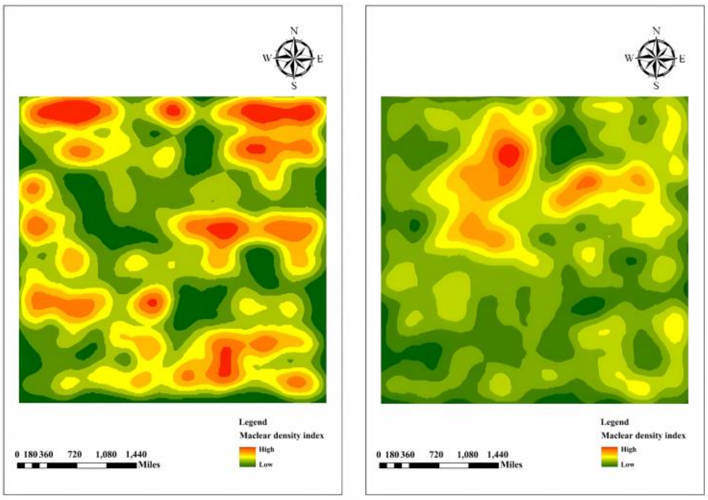

Figure 5: Heat map of the distribution of macro-communication base stations (left) and micro-communication base stations (right)

ISSN 2616-5775 Vol. 6, Issue 7: 124-130, DOI: 10.25236/AJCIS.2023.060716

4. Conclusions

The multi-objective planning model developed in this study demonstrates a strong alignment with real-world scenarios, particularly focusing on the perspective of 5G construction companies [7]. This approach enhances the model's applicability and increases its generalizability, ensuring its relevance across various contexts.

Moreover, the model is solved utilizing a multi-objective genetic algorithm based on the accelerated genetic algorithm for real number coding. This advanced algorithmic approach is relatively novel, allowing for more realistic, objective, and accurate solutions. By incorporating this state-of-the-art method, the model produces results that are closely connected to reality, further enhancing its effectiveness and practicality.

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