Multi-objective Optimization Deployment Algorithm for 5G Ultra-Dense Networks

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Abstract. Due to insufficient spectrum resources, B5G and 6G will adopt millimeter waves for data transmission. Due to the poor physical characteristics of millimeter-wave diffraction ability, a large number of base stations are required for deployment, forming ultra-dense networks. Regarding the deployment of base stations, the first problem faced by operators is how to optimize the deployment of base stations in consideration of deployment costs, coverage rates and other factors. This research focuses on multi-objective three-dimensional (3D) small cell deployment optimization for B5G mobile communication networks (B5G). An optimized deployment mechanism based on NSGA-II is proposed. The simulation results show that, compared with NSGA-II, the deployment cost of this method is slightly higher, but it has achieved better results in terms of coverage and RSSI indicators.

Keywords: Multi-objective optimization · 3D base station deployment · NSGA-II

1 Introduction

With the rapid development of wireless communication, the frequency spectrum resources within 30 GHz are almost exhausted. To meet the requirements of 5G, it is necessary to solve the problem of insufficient spectrum. Therefore, the 5G New Radio (NR) [1] has determined to mainly use two frequencies, including the Frequency Range 1 (FR 1) band and the FR 2 band. The frequency range of the FR1 band is from 450 MHz to 6 GHz, also called the sub 6 GHz band; the frequency range of the FR 2 band is from 24.25 GHz to 52.6 GHz, also called mmWave [2,3]. The atmosphere will selectively absorb electromagnetic waves of

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certain frequencies (wavelengths) in radio waves propagation, causing the path loss of these electromagnetic waves to be particularly serious. Electromagnetic waves are mainly absorbed by oxygen and water vapor. The resonance caused by water vapor absorbs electromagnetic waves between 22 GHz and 183 GHz, and the resonance absorption of oxygen affects electromagnetic waves between 60 GHz and 120 GHz.

Therefore, no matter which organization allocates mmWave resources, it needs to avoid the frequency bands around these four frequencies. In addition, mmWaves above 95 GHz are not considered for use due to technical difficulties. Although the use of mmWave can provide greater bandwidth and higher transmission rate, it has the problem of too large path loss and too small coverage [4], which makes the deployment of 5G base stations more difficult. In addition, the penetration of radio waves comes from the diffraction characteristics of radio waves. Generally speaking, the low-frequency signal has a diffraction effect because of its longer wavelength. The diffraction allows us to receive signals through the wall but mmWave signals have relatively low wall penetration due to high frequency, short wavelength, and short diffraction radius. For the above reasons, a large number of 5G base stations will be deployed and an Ultra-Dense Heterogeneous Network (UDHN) architecture will be formed [5–7]. In order to effectively reduce the deployment cost. This study formulated deployment problem of 5G cellular network as a multi-objective optimization problem, considering deployment cost, Received Signal Strength Indication (RSSI), coverage to achieve optimal deployment. Furthermore, we also considered the interference of obstacles and proposed a 3D deployment algorithm based on NSGA-II.

The rest of this dissertation is organized as follows. In Sect. 2, we introduce the current study of small cell deployment. Then, the problem definition is shown in Sect. 3. Section 4 presents improved NSGA-II algorithm for deployment problem. The results analysis is shown in Sect. 4.2. Section 5 provides conclusion.

2 Background and Related Works

For deployment problems, coverage is often used as an objective function [8–10] pointed out that the deployment density of 5G ultra-dense cellular networks will affect RSSI. The too sparse deployment will lead to coverage holes but too dense will increase interference between cells. [11] uses a single-objective genetic algorithm to deploy wireless sensor nodes. The largest coverage area minus the overlapping area of coverage is taken as the objective function. The single-target problem is difficult to optimize the trade-off relationship between different parameters. Therefore, [12] proposed a multi-target deployment problem, considering the ratio of deployment cost, signal, interference, and coverage. Then, they choose the best deployment plan from the set of candidate positions. [13] proposed a method for optimizing base station deployment based on deployment costs. They consider three network nodes, including Macro cell, Pico cell, and relay node, and select the best location from the candidate locations. In [14], the difference from the above method is that there is no candidate location design. The deployment location can be arbitrarily selected, providing a greater degree of freedom and making the location of the base station closer to the best solution.

3 Problem Definition

The defined planning problem of 5G small cell deployment is called a Signal Quality Maximization (SQM) problem. The SQM problem aims to maximize the signal quality of each served user by avoiding interference from buildings. Then, the SQM problem has been reduced and mapped to a well-known NP-complete problem, such as the Knapsack problem. Therefore, the SQM problem is proved as an NP-complete problem [14].

Small cell deployment problems can be close to an actual environment by using the results of traffic prediction. The scenario of this dissertation is in the 5G wireless backhaul network. There are K base stations, P users. Where B_k represents the k^{th} base station and U_p represents the p^{th} user. The wireless frequency of communication between B_k and U_p is represented by f. The topic of this dissertation is how to design a base station deployment scheme that meets the requirements of operators and users. Therefore, the coverage rate, RSSI, and deployment cost of the base station are considered. However, these three factors have a trade-off problem. In fact, when other factors remain unchanged, the number of base stations is reduced, which can intuitively reduce the deployment cost of the base station but it may also lead to a reduction in coverage or RSSI. Therefore, the location of the base station is relatively important because the same base station in different locations may cause different coverage. The base station at the appropriate location can reduce deployment costs. The evaluation function of the deployment strategy of the base station based on the above problems is defined in this dissertation.

Before evaluating the RSSI and coverage rate, the following values must be known the relative distance between base stations, the signal strength received by the indoor user, and the relative distance between the building and the base station. Figure 1 shows the distance relationship between the user and the building. If the user is inside the building, the distance between the outside and inside of the building needs to be additionally considered.

$$D_{k,p}^{3D} = d_{k,b}^{3D} + d_{b,p}^{3D} \tag{1}$$

$$D_{k,p}^{2D} = d_{k,b}^{2D} + d_{b,p}^{2D} \tag{2}$$

$$D_{k,p}^{3D} = \sqrt{D_{k,p}^{2D} + (H_k^{b,s} - H_p^{u,s})} \tag{3}$$

Where $d_{k,b}^{3D}$is the distance between B_k and the outside of building in three-dimensional, $d_{b,p}^{3D}$ is the distance between U_p and the inside of building in three-dimensional, $d_{k,b}^{2D}$ is the distance between B_k and the outside of building in two-dimensional, $d^{2D}_{b,p}$ is The distance between U_p and the inside of building in two-dimensional, $H^{b,s}_k$ indicates the height of B_k, and $H^{u,s}_p$ is the height of U_p. The above units are all meters, used to describe the distance relationship between the base station, users, and buildings.

3.1 Received Signal Strength Indicator

RSSI is used to estimate the signal strength in a wireless network environment, affected by the interference of neighboring channels and obstacles. Neighboring channel interference means that when there are neighboring base stations with the neighboring channel, the generated radio waves will interfere with the user's signal. However, in current or future base station deployment planning, base stations with different frequencies will be arranged next to any base station as far as possible to avoid the above-mentioned neighboring channel interference. In addition, when a user enters an environment with a wireless network, there may be multiple base stations that can be connected. Usually, users will be connected to the base station which has the best reception. The RSSI received by the device can be calculated by Eq. (4).

$$f_{RSSI} = \frac{\sum_{p=1}^{N} R_p}{N}, R_p = \begin{cases} T_k - P_{k,p}, & \text{if } C_{k,p} = 1 \\ 0 & \text{otherwise} \end{cases}, \tag{4}$$

Where N is the number of UEs. R_p is received signal strength indicator, defined as the signal power at the transmitter minus the path loss. T_k is the Transmitter Signal Strength Indicator (TSSI) of B_k with dBm unit. $P_{k,p}$ is path loss between B_k and U_p with dBm unit. $C_{k,p}$ is a Boolean value and indicates whether U_p is covered by B_k as shown in Eq. (5).

$$C_{q,k} = \begin{cases} 1, & \text{if } D^{3D}_{k,p} < TH_D \text{ and } R_p > TH_R \\ 0, & \text{otherwise} \end{cases}, \tag{5}$$

In addition to considering the distance between the user and the base station, the RSSI actually received by the user also needs to larger than the threshold TH_R. Where $D^{3D}_{k,p}$ is the distance between B_k and U_p in three-dimensional, TH_D is a threshold, indicating the longest distance that the base station communicates with the user in LOS.

$$P_{k,p} = p^{\alpha}_{k,p} + p^{\beta}_{k,p} + p^{\gamma}_{k,p} \tag{6}$$

Where $P_{k,p}$ is path loss between B_k and U_p, $p^{\alpha}_{k,p}$ is basic path loss, $p^{\beta}_{k,p}$ is penetration loss, and $p^{\gamma}_{k,p}$ is indoor path loss.

3.2 Coverage Rate

Coverage rate is an important indicator for users. If an operator can provide a networked service anytime and anywhere, users will naturally choose this operator. Therefore, in addition to signal power, coverage is also the key for operators to attract users. Equation (7) is the calculation of coverage.

$$f_{coverage} = \frac{\sum_{p=1}^{N} C_v}{N}, C_v = \begin{cases} 1, & \text{if } \sum_{k=1}^{Q} C_{k,p} \neq 0 \\ 0, & \text{otherwise} \end{cases}, \tag{7}$$

Q represents the number of the base stations. $C_{k,p}$ is a Boolean value which means whether U_p is covered. In other words, it represents whether the user is covered by any base station. C_v represents the sum of covered U_p. If C_v is equal to 0, it means that U_p is not covered by any B_k. Finally, dividing all C_v by the total number of users P to get the coverage rate for users.

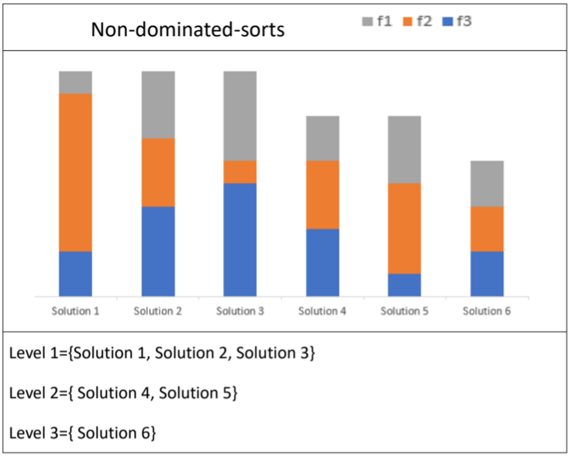

Fig. 1. The schematic diagram of Non-dominated-sort classification.

3.3 Deployment Cost

Deployment cost is very important for the operator. The deployment of the base station may result in the same cost but different coverage or RSSI due to the location. Therefore, in addition to coverage and RSSI, the deployment cost must be considered. The main deployment cost of the wireless network comes from the base station. We define the main cost as follows Eq. (8). Where f_{cost} is the objective function of deployment cost and Lis the set of deployment cost with$L = \{l^{MC}, l^{SC1}, l^{SC2}, l^{SC3}\}$. l^{MC} is deployment cost of Macro cell, l^{SC1} is deployment cost of type 1 small cell, l^{SC2} is deployment cost of type 2 small cell, and l^{SC3} is deployment cost of type 2 small cell. A, B, C, and D are the sum of cells. c_0,c_1, c_2, and c_3 are the number of cells.

$$f_{cost} = \sum_{c_0=1}^{A} l^{MC} + sum_{c_0=1}^{B} l^{SC1} + sum_{c_0=1}^{V} l^{SC2} + sum_{c_0=1}^{D} l^{SC3}, \tag{8}$$

$$A + B + C + D = K \tag{9}$$

The deployment of base stations needs to be considered from the perspective of users and operators to provide low RSSI, high coverage, and low deployment costs. Therefore, this dissertation formulates the deployment problem as a Multi-Objective Optimization (MOO) problem according to the above three factors, as shown in Eq. (10).

$$f(x)\begin{cases}\text{Max } f_{RSSI}(x)\\ \text{Max } f_{coverage}(x)\\ \text{Min } f_{cost}(x)\end{cases} \tag{10}$$

$$R_p > -100\,\text{dBm} \tag{11}$$

$$1.5\,\text{m} < H_p^{ue} < 22.5\,\text{m} \tag{12}$$

In order to meet the requirements of the real environment, we define some restrictions. Where x is the deployment solution. Equation (11) is used to limit RSSI of U_k. It must be larger than −100 dBm. Equation (12) is used to limit the height of U_k between 1.5 m to 22.5 m according to 3GPP standard [15].

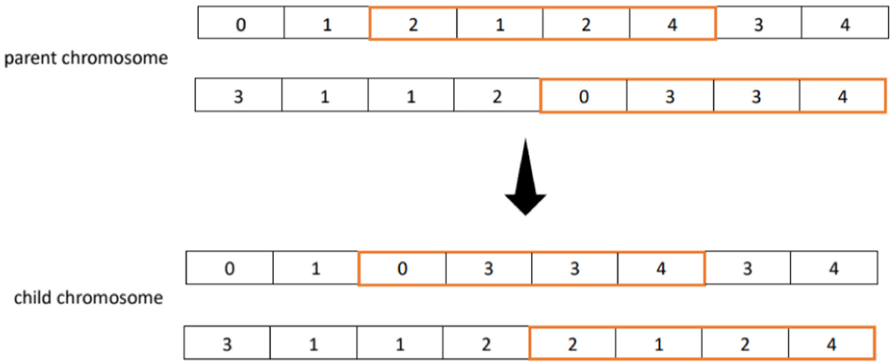

Fig. 2. Schematic diagram of crossover step.

3.4 Improved Non-dominated Sorting Genetic Algorithm II

The key to the multi-objective optimization problem is to find the best solution set of Pareto. Many algorithms have been proposed based on the concept of Pareto improvement, the most classic of which is the NSGA-II proposed by Kalyanmoy Deb and others in 2000 [16]. This algorithm is applied to multi-objective problems based on the genetic algorithm. The algorithm uses the concept of mating and mutational biomimetic evolution of the genetic algorithm, combined with the Non-dominated-sort method to reduce the complexity of the calculation.

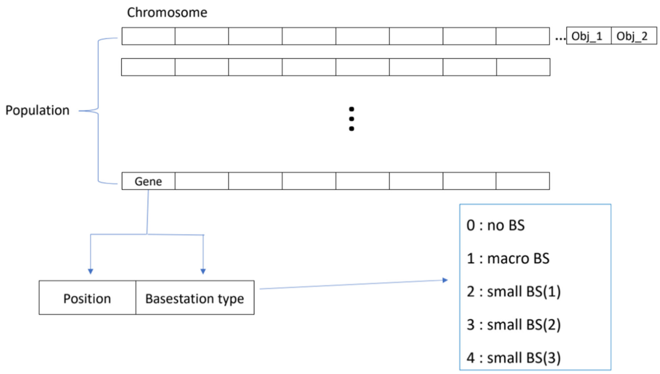

Fig. 3. Schematic diagram of chromosomes and genes.

Then NSGA-II adopts the elite strategy and merges the parent and offspring populations to ensure that excellent solutions can continue to participate in the algorithm and improve the optimization results in terms of results. In addition, NSGA-II introduces the calculation of crowding distance to compare solutions of the same Pareto level with large differences to ensure the diversity of the next generation and avoid similar results from mating with each other. The concept is like avoiding inbreeding and losing diversity.

In addition, NSGA-II also has the advantages of fast operation speed and good convergence performance. NSGA-II's Non-dominated- sort is to classify the solution set according to the function of each solution for each goal to obtain $s_l.s_l$ represents the set of solutions of level l after a Non- dominated-sort. This is a cyclical process of grading according to the target value. First, find the Non-dominated solution set in the group, which is counted as s_1, and remove it from the entire set S. Then continue to find the Non-dominated solution set in the next level group and record it as s_2. This process is repeated until all classifications are completed. Figure 1 is a schematic diagram of Non-dominated-sort classification.

The meaning of crowded distance is to find a solution with large differences. As the mixing of parent and children in NSGA-II will exceed the number of original chromosomes, after mixing the population, they need to be classified by Non-dominated-sort ($S = \{s_1, s_2, \ldots, s_l\}$). Then, according to the classification results, put s_l in order until the s of a certain level cannot be completely put into the new solution set. At this time, the solution to be put in priority should be selected according to the solution's Crowding distance. The calculation of crowding distance is shown in Eq. (13). The crowded distance of the solutions is after non- domination-sort, the objective function gap between the solutions j at the first level and the adjacent solutions$j+1$ and $j-1$.

$$w_s = \frac{m_{s+1} - m_{s-1}}{m_{max} - m_{min}}, \tag{13}$$

w_s represents the crowded distance of any solution s. First, according to the objective function, sort the solutions at the same level in ascending order. Then, get the relative crowded distance according to the maximum value m_{max} and the minimum value m_{min} of this function, the target value m_{s+1}, and the distance ratio between m_{s-1} between two solutions. Finally, arrange the solutions according to the crowded distance and put them into the new group in sequence.

After completing the above steps, the next step is the flow of the genetic algorithm. The genetic algorithm (GA) is originated derived from the evolutionary theory of biology. It can be divided into three steps, including selection, crossover, and mutation, which are introduced separately below. The first is the selection step. GA will select excellent chromosomes from the solution space and put them into a crossover pool. There are many selection methods has proposed. This dissertation uses the roulette method according to the objective function value of each chromosome that gives the corresponding selection probability. In NSGA-II, the roulette rate is based on the solution that belongs to which F_t. Therefore, the roulette rate is determined after the chromosome is selected into the crossover pool. Then, steps of crossover and mutation are performed in sequence according to the crossover rate and mutation rate. The crossover step is to randomly take two chromosomes for partial chromosome exchange, as shown in Fig. 2. The mutation step is to randomly select a gene from the chromosome to change.

The following describes the 3D small cell deployment algorithm proposed by this research. First, each chromosome represents a deployment solution (CS). Figure 3 is a schematic diagram of chromosomes and genes. Genes represent the type and position coordinates of each base station. There are two parameters in each gene, including position and type of the base station. The number 1 is a Macro cell, the numbers 2 to 4 are three different types of small cells, and the number 0 means there is no base station at this location. In addition, the location of the base station may be located in the building, at the top of the building, or on the telephone pole.

Therefore, when the gene is changed by steps of crossover or mutation, it means that the type or location of the corresponding base station in the deployment plan has changed. For the convenience of storage and calculation, the objective function is stored at the end of the chromosome.

However, the NSGA-II algorithm may cause too long computational time due to complicated calculations on the base station deployment problem, making the solution difficult to converge. Therefore, this dissertation uses the annealing mechanism of the simulated annealing algorithm to change the length of crossover and mutation. In the beginning, the algorithm has a strong search space. As the number of iterations increases, the search space in the latter part of the algorithm will shrink, prompting the results to gradually converge. The length of crossover and mutation is based on Eq. (14).

$$CL_m - CL_{m-1} \times (1 - \frac{m}{M}), \tag{14}$$

Where m indicates the m^{th} iteration, M is the total number of iterations, CL_m is the length of the gm^{th} crossover. According to Eq. (14) as the iteration increases, the length of crossover will become shorter and shorter.

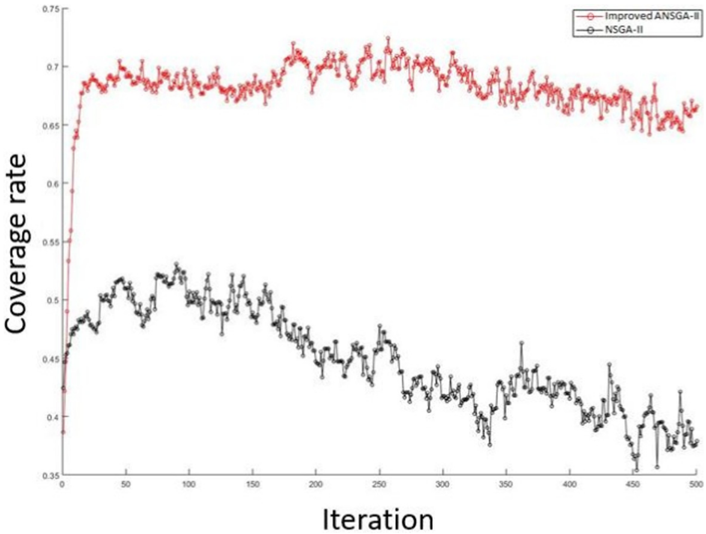

Fig. 4. Comparison of coverage rate.

4 Experimental Results

4.1 Experimental Setup

This experiment uses java 8 for encryption algorithm implementation and uses Intel i7 8700h processor as the main computing platform. In order to maintain high fairness, we use the original DES algorithm published on GitHub [2]. The existing work [1] used GA-based encryption which adopted the same hardware setting with this study as well as the GA parameter uniformly uses 12 size parent population and executes 16 rounds. Each round is executed 200 times. The selection operation of GA adopts tournament selection. The crossover and mutation triggering ratios are 95% and 50% respectively.

4.2 Results Analysis

In this study, MATLAB is adopted as a simulated tool to construct the proposed algorithms. In simulations, users and buildings are randomly deployed in our scenario of 1,000 m $\times$ 1,000 m. There are three types of small cells, called small cell 1, small cell 2, and small cell 3. They are divided according to cost and coverage.

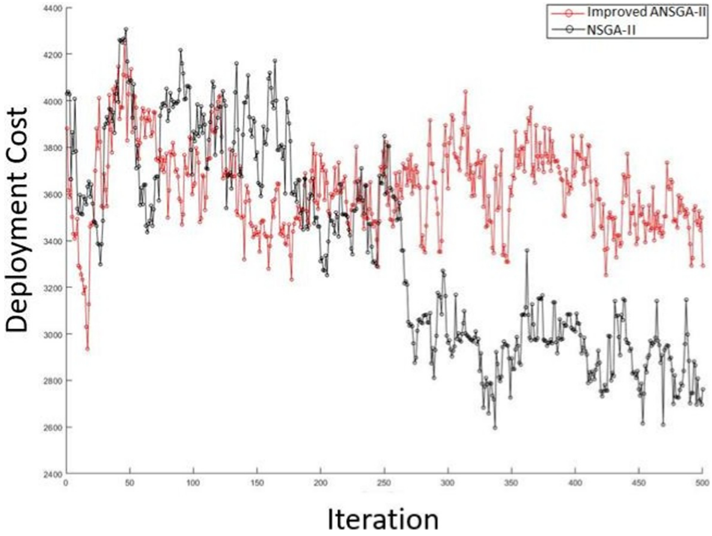

Fig. 5. Comparison of average deployment cost.

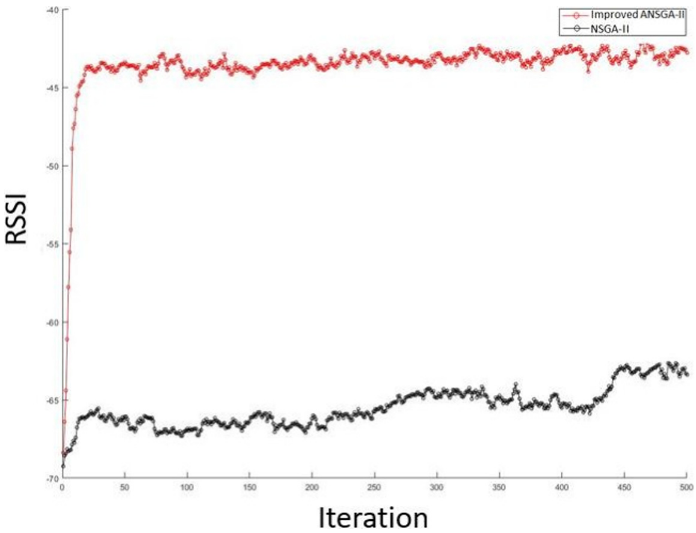

Fig. 6. Comparison of RSSI.

Macro cells and small cells form a wireless backhaul network in our scenario. To test the impact of the number of different users on the deployment performance, the number of users from 1,000 to 10,000 with 1,000 as a gap.

Figure 4, Fig. 5, and Fig. 6 are comparisons of coverage rate, deployment cost, and RSSI. The X-axis is the number of iterations and the Y-axis is three kinds of metrics. Falling into the local optimum. Compared with NSGA-II, although the deployment cost of this method is higher than that of NSGA-II, the RSSI and coverage are significantly better than NSGA-II. The reason is that when there are no candidate nodes, the solution is difficult to converge. For NSGA-II, although the deployment cost and RSSI have gradually improved, the coverage rate has also decreased significantly.

5 Conclusion

In this study, we formulated the 3D deployment problem as a MOO problem to optimize coverage, deployment cost, and RSSI. In addition, we proposed a three-dimensional small cell deployment algorithm based on NSGA-II. The simulation results show that although the deployment cost of the proposed method is higher than NSGA-II, it has better coverage and RSSI. It has a better effect on the balance of multi-objective problems.

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