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Green Deployment Method of Micro Base Station for Ultra-Dense Heterogeneous Cellular Networks Based on Constrained Dolphin Swarm Algorithm

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ABSTRACT This paper proposes a green deployment method for micro base stations for ultra-dense heterogeneous cellular networks to balance network energy efficiency and electromagnetic radiation and meet certain user service quality. Firstly, a constrained multi-objective mathematical model for the green deployment of the micro base station is established for the two-dimensional communication scenario, with the user rate as the constraint, aiming at maximizing the network energy efficiency and minimizing the average electromagnetic radiation. Then, a multi-objective dolphin swarm algorithm which considering the evolutionary advantages of excellent infeasible solutions and feasible solutions, improving the individual search mechanism in the dolphin group algorithm, combined with the improved two-population strategy is proposed and tested on the CTP test set. It shows that compared with the other three methods, the method has certain advantages in convergence and distribution. Finally, a green deployment method for micro base stations based on constrained multi-objective dolphin swarm algorithm is established. Experiments on nine communication scenarios show that the proposed method can balance network energy efficiency and electromagnetic radiation.

INDEX TERMS Constrained multi-objective optimization, dolphin swarm algorithm, micro base station deployment, ultra-dense heterogeneous cellular networks.

I. INTRODUCTION

Ultra-dense heterogeneous cellular networks (UDHCN) are one of the key technologies of 5G [1]. It is implemented by densely deploying micro base stations within the coverage area of the macro base station or at the edge of the cell, in order to increase the network throughput and signal reception strength, thereby meeting the increasing speed and capacity requirements. However, UDHCN brings about serious electromagnetic pollution at the same time. In order to achieve sustainable development, the green deployment problem of micro base stations in UDHCN, that is, satisfying certain user service quality, maximizing network energy efficiency and minimizing electromagnetic radiation intensity, has become an extremely complicated yet challenging problem.

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At present, research on the deployment of micro base stations focuses on improving network energy efficiency or reducing electromagnetic pollution. Representative research results are as follows: In 2013, Garcia-Diaz *et al.* proposed the use of evolutionary algorithms to deploy mobile networks, and considered the control of electromagnetic radiation of base stations as one of the key design parameters [2]. The proposed evolution method is a variable-length algorithm that can be deployed for base stations of different numbers of sizes. In the same year, Eunsung Oh *et al.* proposed a dynamic solution to adjust the coverage and sleep status of the base station according to the load [3]. The mathematical model is used to build the least energy consumption model. This method can get better base station deployment, but for the management of large-scale network base stations the algorithm has a poor response speed. In 2014, Salcedo-Sanz optimized the goal of minimizing electromagnetic pollution, and proposed a coral reef optimization algorithm (CRO) to solve the problem of mobile network deployment [4]. Its convergence speed is obviously better than that of particle swarm algorithm and harmony search algorithm. In 2015, Chung Y L *et al*. proposed a micro base station deployment scheme [5]. A macro base station is located in the center of the area and covers the entire target area, while the micro base station is deployed around the macro base station. In the same year, HY Lateef *et al*. proposed an energy-saving and quality of service-aware dynamic cell scaling algorithm for dense heterogeneous networks [6]. By real-time scaling of macro base stations and micro-area coverage areas to reduce network energy consumption through actual traffic conditions. Zhang Yingjie *et al.* considered the electromagnetic radiation and used the improved immune algorithm to select the base station site [7]. Ruchi Sachan *et al.* used a real-coded genetic algorithm (RGA) to optimize the optimal configuration of base stations, to achieve the purpose of reducing network energy consumption, and have a good response speed for large-scale network base station management [8]. In 2016, Chen Dengzhao achieved the goal of energy saving by mathematically modeling the relationship between users and base stations, and solving problems through particle swarm optimization algorithms [9]. However, due to the shutdown of the base station, as the number of users increases, the quality of service of the user will decrease. After the base station is activated, the quality of service of the user will return to normal levels. In 2017, Zhang Yangyang *et al*. proposed a High Energy Efficient Deployment Algorithm (HEEDA) with quality of service constraints to reduce network energy consumption while ensuring user service quality, but did not study the dynamic load micro base station sleep method [10].

On the basis of the above research, in 2017, Chun-Cheng Lin *et al*. comprehensively considered network energy efficiency and electromagnetic pollution, and integrated the two according to a certain weight to deploy a one-dimensional base station on the expressway to a hybrid genetic difference [11]. The algorithm proposes a green deployment strategy for micro base stations in heterogeneous cellular networks.

In summary, the deployment of micro base stations has evolved from a single performance requirement to a comprehensive consideration. At present, its related research is still in the exploration stage, and there are still two major defects in the following two aspects: First, the existing results focus on the pursuit of only the largest network energy efficiency or the minimum electromagnetic radiation intensity. The comprehensive consideration of the two is only a one-dimensional linear scene facing the highway, which does not meet most practical application scenarios [11]–[15]. Second, from the perspective of mathematics, the green deployment of micro base stations belongs to the constrained multi-objective optimization problem. The current deployment strategy is to convert the constrained multi-objectives into linearly weighted and then into the constrained single-objective problem, because the weight selection is related to the importance of the target. Therefore, it is impossible to achieve comprehensive consideration of network energy efficiency and electromagnetic pollution [16]. Similar to the two performance indicators in the fields of intelligent tracking, DOA estimation, resource allocation, *etc.*, only the constrained multi-objective algorithm can solve the real balance between the two [17]–[23]. However, the existing constrained multi-objective algorithm has obvious shortcomings such as low convergence precision and easy to fall into local optimum because of its own evolutionary strategy, which leads to its obvious convergence and distribution. A large number of literatures have confirmed that compared with evolutionary algorithms such as genetic [24], particle swarm [25], [26], and bee colony [27], the Dolphin Swarm Algorithm (DSA) proposed in 2016 performs better on single-objective problems [28]. Then the constrained multi-objective algorithm based on the Dolphin Swarm Algorithm is expected to get better performance than the existing constrained multi-objective algorithms.

To this end, we propose a green deployment method for micro base stations based on the constrained multi-objective dolphin swarm algorithm. The specific work is as follows: Firstly, with reference to the established single network energy efficiency model and electromagnetic pollution model that meet the actual communication scenario, a mathematical model for the green deployment of micro base stations is established. Secondly, the update mechanism of the infeasible solution and the feasible solution in the two-population search mechanism is improved. According to the characteristics of the constrained multi-objective problem, the location update strategy of the dolphin swarm algorithm is improved, and the constrained multi-objective algorithm based on the dolphin swarm algorithm is proposed. Thirdly, a two-stage green deployment method for micro base stations based on constrained multi-objective dolphin swarm algorithm is proposed. The simulation of the communication scenario including low load, medium load and high load shows that the proposed deployment method has certain advantages in network energy efficiency, electromagnetic radiation and user speed.

The remaining chapters of this paper are organized as follows. Section II establishes a mathematical model for the green deployment method of micro base stations in ultra-dense heterogeneous cellular networks. Section III introduces the principle of the proposed multi-objective dolphin swarm algorithm. Section IV introduces the principle of green deployment method of micro base station based on constrained multi-objective dolphin swarm algorithm. Section V gives experimental simulation and analysis, and summarizes the full text at the end.

II. RELATED WORK

Maximizing network energy efficiency and minimizing electromagnetic radiation intensity while ensuring the quality of individual user services is the purpose of researching the green deployment of ultra-dense network micro base stations. In order to establish its corresponding mathematical model,

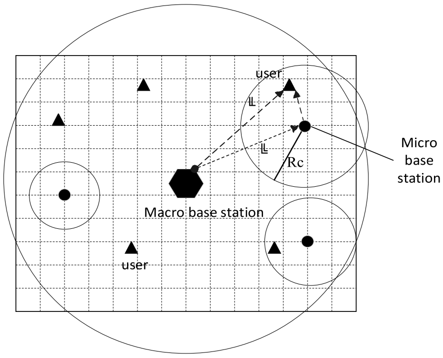


FIGURE 1. **Two-layer heterogeneous cellular network architecture.**

referring to the wireless sensor model [29] , [30], the relevant research model, the definition of user service quality, network energy efficiency and electromag-netic radiation intensity are given.

This paper studies a two-layer heterogeneous cellular network consisting of a macro base station (***BS***) and a small cell base station (***SC***), as shown in Fig. 1, and based on the following assumptions and definitions.

a. In the center of the rectangular field, there is a ***BS*** that provides services for the entire cell.
b. m users are randomly distributed within the cell, and the number and distribution status of users vary with time.
c. All active users always transmit data and can only access one base station at a time.
d. There are generally two communication methods for users in the area. If the user terminal is in the coverage area of the SC, the user terminal communicates with the base station at the highest signal-to-noise ratio, that is, using SINR association; otherwise, it communicates directly with the BS.
e. The N micro base stations distributed in the cell are all in a two-dimensional space.

$$\boldsymbol{SC} = (sx_1, \cdots, sx_i, \cdots sx_N, sy_1, \cdots, sy_i, \cdots sy_N)$$

where $\mathrm{sx_i}$ and sy_i are the horizontal and vertical coordinates of the i-th base station.

The coverage radius Rc_i of each micro base station may take values within Rc_{min} and Rc_{max} and may be different from each other.

A. USER SERVICE QUALITY MODEL

In order to ensure the user's data transmission rate, we use the user rate as the evaluation standard of user service quality. Assuming that the total bandwidth of the system is W, the ***BS*** and the ***SC*** share a section of spectrum, so there is inter-layer interference between the macro base station and the micro base station, and there is intra-layer interference between the micro base station and the micro base station due to the use of resources of the same frequency. All user terminals are allocated to the same bandwidth resources on different carrier frequencies, so interference between user terminals can be ignored. Therefore, the user rate *C(u,n) (bit/s)* of the user u communicating with the base station n can be written as:

$$C(u,n) = W_u \times \log_2\left(1+\gamma_{u,n}\right), \tag{1}$$

where $\gamma_{u,n}$ is the SINR of the user u communicating with the base station n being formulated as:

$$\gamma_{u,n} = \frac{P_n \times d_{un}^{-\alpha}}{\sum\limits_{n' \in BS \cup SC, n' \neq n} P_{n'} \times d_{un'}^{-\alpha} + n_0 \times W_u}, \tag{2}$$

where P_n is the transmission power of the base station n, the channel gain mainly considers the path loss, d_{un} is the distance from the user u to the base station n, α is the path loss factor, generally takes 2, n_0 is the noise power spectral density, and W_u represents the bandwidth of the user u.

B. NETWORK ENERGY EFFICIENCY MODEL

In general, energy efficiency is defined as the ratio of the total rate of the system to the total power consumed, which is the number of bits that can be transmitted in energy per unit of joule, in *bits/ J*. The power consumption of the base station includes static energy consumption P_0 and dynamic energy consumption P_t, wherein P_0 is the energy consumed by the circuit of the base station itself, regardless of the working state of the base station, and P_t is the transmitting power of the base station. Obviously, the network energy efficiency of the system involved at a certain moment in this paper is shown as:

$$\eta_{EE} = \frac{\sum\limits_{u \in U} C(u,n)}{P_{B0} + P_{Bt} + N \times P_{b0} + \sum\limits_{i=1}^{N} P_{it}}, \tag{3}$$

where N is the number of small cell base station ***SC***, P_{B0} and P_{Bt} represent the static energy consumption and dynamic energy consumption of the macro base station, respectively, P_{b0} represents the static energy consumption of the micro base station, P_{it} is the transmission power of the i-th micro base station, and U represents the user set in the network.

C. ELECTROMAGNETIC RADIATION INTENSITY MODEL

In the system model of this paper, each user terminal is an observation point. In order to facilitate comparison with the electromagnetic communication standard of mobile communication, the average electromagnetic radiation intensity is used in this paper. The electromagnetic radiation intensity can be written as:

$$S = \frac{10^{(P_t+G-30)/10}}{4\pi d^2} 100, \tag{4}$$

where d is the distance between the base station and the observation point, G is the antenna gain (multiplier), and P_t is the transmission power of the base station. Generally, the transmission power of the macro base station is fixed, and the transmission power P_{it} of the i-th micro base station as:

$$P_{it} = P_0 \left(\frac{Rc_i}{Rc_0} \right)^{1.69}, \tag{5}$$

where P_0 and Rc_0 are the nominal transmit power and corresponding coverage radius of the base station.

The calculation formula of the average electromagnetic radiation intensity in the whole area is shown as:

$$S = \frac{\sum_{i=1}^{m_0} \left(\frac{10^{(P_{Bt}+G_B-30)/10}}{4\pi d_i^2} 100 \right) + c \sum_{i=1}^{N} \sum_{j=1}^{m_i} \left(\frac{10^{(P_{it}+G_s-30)/10}}{4\pi d_{ij}^2} 100 \right)}{m_0 + \sum_{i=1}^{N} m_i} \tag{6}$$

where P_{Bt} is the transmission power of the macro base station, which is a constant, m_0 is the number of users falling in the coverage area of the macro base station (which is the number of observation points), and m_i is the number of users falling in the coverage area of the i-th micro base station.

D. MODEL ESTABLISHMENT

As described above, when the micro base station is deployed, it is necessary to maximize the network energy efficiency and minimize the electromagnetic radiation intensity while ensuring the quality of the individual user. Considering that in real communication, due to the mobility of users, the distribution density of users in different time periods is different, and the deployment of micro base stations should be able to meet the user rate coverage requirements under different user distributions. Therefore, we are inspired by [31]–[33], this paper divides the user distribution of one day into k different time periods, each time period appears with a certain different probability, and proposes a green deployment model of the micro base station as:

$$\begin{aligned} &\max \eta_{EE} = \sum_{k \in K} \rho_k \times \eta_{EE_k} \\ &\min S = \sum_{k \in K} \rho_k \times S_k \\ &s.t. \begin{cases} C_k(u, n) \geq \lambda \times C_k \\ Rc_{\min} \leq R_i \leq Rc_{\max} \end{cases} \end{aligned} \tag{7}$$

where K is the set of user distributions in different time periods; ρ_k is the probability of occurrence of the k-th distribution; η_{EEk} is the energy efficiency of the system network under the k-th user distribution, and the calculation method is as shown in (3); η_{EE} is comprehensive consideration of all users. The network energy efficiency obtained by the distribution; for the same reason, S_k is the average electromagnetic radiation intensity under the k-th user distribution, and the calculation method is as shown in (6); S is the electromagnetic radiation intensity obtained by comprehensively considering all user distributions; $C_k(u, n)$ is the user rate of the user u communicating with the base station n under the kth distribution; C_k is the user rate at which only the macro base station is deployed under the kth distribution; and λ is the rate multiplier of the expected boost (here, 1.5).

III. CONSTRAINED DOLPHIN SWARM ALGORITHM

As shown in (7), the mathematical nature of the green deployment model of heterogeneous cellular network micro-base station is a complex constrained multi-objective problem. In order to obtain better deployment effect, a constrained dolphin swarm algorithm is proposed.

A. DOLPHIN SWARM ALGORITHM

The key steps of the DSA are as follows:

1) POPULATION INITIALIZATION

In the optimization problem, each dolphin individual $Dol_i = [x_{i1}, x_{i2}, \cdots, x_{iD}]$ $(i = 1, 2, \cdots, Num)$ represents a solution, where Num is the population number, D is the dimension of the optimization problem, and x_{ij} represents the value of $\boldsymbol{Dol_i}$ in the j-th dimension, which is randomly generated as:

$$x_{i,j} = F_j + rand \times \left(H_j - F_j \right), \tag{8}$$

where H_i and F_i is the upper and lower limits of the search range of the j-th dimension, and $rand$ is a random number between [0, 1].

2) SEARCH

Dolphin $\boldsymbol{Dol_i}$ randomly emits sound waves in M directions. The new position that the Dolphin $\boldsymbol{Dol_i}$ searches for in time is X_{ijt}, which can be written as:

$$\boldsymbol{X_{ijt}} = \boldsymbol{Dol_i} + \boldsymbol{V_j} \times t \tag{9}$$

where $t = 1, 2, 3 \ldots T_1$, $V_i = [v_1, v_2, \ldots, v_D]^T (i = 1, 2, \ldots, M)$ is a sound wave emitted by the dolphin in the j-th direction, satisfying $||V_i|| = speed$, and $speed$ is a constant of speed.

The individual optimal solution L_i and the neighborhood optimal solution K_i found by $\boldsymbol{Dol_i}$ in the maximum search time T_1 are obtained. Among them, K_i is the optimal position found by $\boldsymbol{Dol_i}$ and other neighboring individuals, (individuals within the maximum search radius $R_{s1} = T_1 \times speed$), and K_i is updated as:

$$K_i = \begin{cases} L_i, & if\ fitness\,(L_i) < fitness\,(K_i) \\ K_i, & otherwise \end{cases} \tag{10}$$

3) CALL AND RECEPTION

The call and reception phases are performed simultaneously for K_i. The acoustic wave transmission takes time, defining the N × N transmission time matrix TS, $TS_{i,j}$ is the remaining propagation time of the acoustic wave from $\boldsymbol{Dol_j}$ to $\boldsymbol{Dol_i}$, the initial value is the maximum transmission time T_2 (man-made setting), the algorithm $TS_{i,j}$ minus 1 per iteration, means that the sound wave propagates in one unit time. In each iteration, when $\boldsymbol{Dol_j}$'s neighborhood optimal solution K_j is better than $\boldsymbol{Dol_i}$'s neighborhood optimal solution K_i and $TS_{i,j}$ is

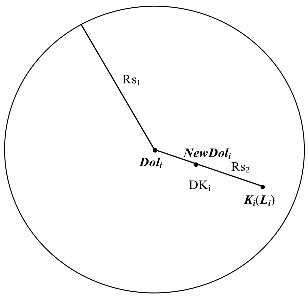


FIGURE 2. Doli's neighborhood optimal solution Ki is within the search range.

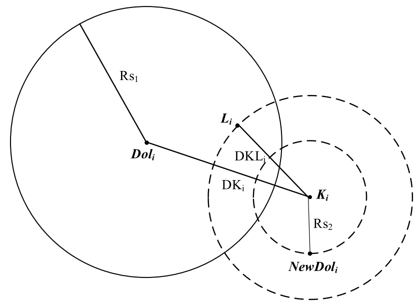


FIGURE 3. Doli's neighborhood optimal solution Ki is outside the search range and Li is closer to Ki.

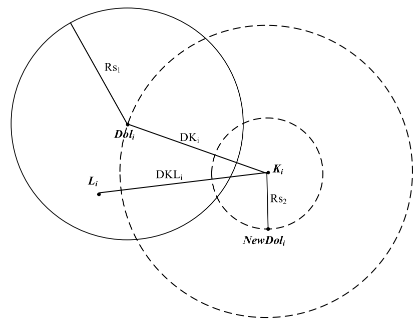


FIGURE 4. Doli's neighborhood optimal solution Ki is outside the search range and the Doli is closer to Ki.

greater than the acoustic propagation time $\left[\frac{DD_{i,j}}{A\times speed}\right]$ between the two, $TS_{i,j}$ is updated as:

$$TS_{i,j} = \begin{cases} \left[\dfrac{DD_{i,j}}{A \times speed}\right], & if\ fitness\left(K_j\right) < fitness\left(K_i\right)\ and \\ & TS_{i,j} > \left[\dfrac{DD_{i,j}}{A \times speed}\right] \\ TS_{i,j}, & otherwise \end{cases} \tag{11}$$

where DD_{ij} is the distance between $\boldsymbol{Dol_i}$ and $\boldsymbol{Dol_j}$, $DD_{ij} = ||Dol_i - Dol_j||, i, j = 1, 2, \ldots, Num, i \neq j$. A is an acceleration constant that adjusts the speed of sound wave propagation.

After $TS_{i,j}$ is updated, if $TS_{i,j} = 0$, the sound wave emitted by $\boldsymbol{Dol_j}$ has been received by $\boldsymbol{Dol_i}$. At this time, $TS_{i,j}$ is reassigned to T_2, and the better one of $\boldsymbol{K_i}$ and $\boldsymbol{K_j}$ is selected to update $\boldsymbol{Ki}$, which is shown as:

$$K_i = \begin{cases} K_j, & if\ TS_{i,j}=0\ and\ fitness\left(K_j\right) < fitness\left(K_i\right) \\ K_i, & otherwise \end{cases} \tag{12}$$

4) HUNTING

According to the positional relationship between $\boldsymbol{Dol_i}$, $\boldsymbol{L_i}$ and $\boldsymbol{K_i}$ and the size of R_{s1}(where the distance between $\boldsymbol{Dol_i}$ and $\boldsymbol{K_i}$ and between $\boldsymbol{K_i}$ and $\boldsymbol{L_i}$ are $DK_i = ||Dol_i - K_i||$ and $DKL_i = ||L_i - K_i||$, respectively), the following three situations are carried out to obtain the new position of the dolphin $\boldsymbol{newDol_i}$, which is compared with the optimal solution $\boldsymbol{K_i}$ of $\boldsymbol{Dol_i}$'s neighborhood, if $fitness(\boldsymbol{newDol_i}) < fitness(\boldsymbol{K_i})$, then update $\boldsymbol{K_i}$, which is $\boldsymbol{K_i} = \boldsymbol{newDol_i}$, otherwise, $\boldsymbol{K_i}$ does not change.

a. $DK_i < R_{s1}$, as shown in Fig. 2, indicates that the neighborhood optimal solution $\boldsymbol{K_i}$ of $\boldsymbol{Dol_i}$ is within the search range. At this time, $K_i = L_i$, the new position obtained by Dolphin $\boldsymbol{Dol_i}$ is shown as:

$$\begin{cases} \boldsymbol{newDol_i} = \boldsymbol{K_i} + \dfrac{\boldsymbol{Dol_i} - \boldsymbol{K_i}}{DK_i} \times Rs_2 \\ Rs_2 = \left(1 - \dfrac{2}{e}\right) \times DK_i \end{cases} \tag{13}$$

where e>2 is the radius attenuation coefficient, usually 3 or 4.

b. $DK_i > Rs_1$ and $DK_i > DKL_i$, as shown in Fig. 3, indicates that the neighborhood optimal solution $\boldsymbol{K_i}$ of $\boldsymbol{Dol_i}$ is outside the search range, and $\boldsymbol{L_i}$ is closer to $\boldsymbol{K_i}$ than $\boldsymbol{Dol_i}$, and the new position obtained by $\boldsymbol{Dol_i}$ is shown as:

$$\begin{cases} \boldsymbol{newDol_i} = \boldsymbol{K_i} + \dfrac{\boldsymbol{random}}{\|\boldsymbol{random}\|} \times Rs_2 \\ Rs_2 = \left(1 - \dfrac{\frac{DK_i}{fitness(\boldsymbol{K_i})} + \frac{DK_i - DKL_i}{fitness(\boldsymbol{L_i})}}{e \times DK_i \times \frac{1}{fitness(\boldsymbol{K_i})}}\right) \times DK_i \end{cases} \tag{14}$$

c. $DK_i > Rs_1$ and $DK_i < DKL_i$, as shown in Fig. 4, indicates that the neighborhood optimal solution $\boldsymbol{K_i}$ of Dolphin $\boldsymbol{Dol_i}$ is outside the search range, and $\boldsymbol{Dol_i}$ is closer to $\boldsymbol{K_i}$ than $\boldsymbol{L_i}$, and the new position obtained by Dolphin $\boldsymbol{Dol_i}$ is shown as:

$$\begin{cases} \boldsymbol{newDol_i} = \boldsymbol{K_i} + \dfrac{\boldsymbol{random}}{\|\boldsymbol{random}\|} \times Rs_2 \\ Rs_2 = \left(1 - \dfrac{\frac{DK_i}{fitness(\boldsymbol{K_i})} + \frac{DKL_i - DK_i}{fitness(\boldsymbol{L_i})}}{e \times DK_i \times \frac{1}{fitness(\boldsymbol{K_i})}}\right) \times DK_i \end{cases} \tag{15}$$

Repeat the above search, call and reception, and hunting phases until the iteration termination condition is reached.

As described above, the pseudocode of logistic map can be described as below.

B. CONSTRAINED MULTI-OBJECTIVE DOLPHIN SWARM ALGORITHM

The dolphin swarm algorithm itself does not have the ability to deal with multi-objective optimization problems. To this end, we improve it and combine it with the dual-population

Algorithm 1 Pseudocode of the Standard DSA Algorithm

Input: swarm size $\boldsymbol{Num}$, swarm dimension $\boldsymbol{D}$, upper search range $\boldsymbol{H}$, lower search range $\boldsymbol{F}$, speed constant $\boldsymbol{speed}$, the maximum number of iterations $\boldsymbol{G_{max}}$, and other parameters.

Process:

1. Randomly initialize the dolphins of swarm $\boldsymbol{Dol_i}$.
2. $g = 1$.
3. **while** $g < G_{max}$ **do**
4. Find the individual optimal solution $\boldsymbol{L_i}$ and neighborhood optimal solution $\boldsymbol{K_i}$ in the maximum search time $\boldsymbol{T_1}$.
5. Update $\boldsymbol{K_i}$ by (10).
6. Define the transmission time matrix $\boldsymbol{TS}$ and update $\boldsymbol{TS_{ij}}$ by (11).
7. Update $\boldsymbol{K_i}$ by (12).
8. Calculate DK_i and DKL_i.
9. **if** $DK_i < Rs_1$ **then**
10. Update $\boldsymbol{newDol_i}$ by (13).
11. **else if** $DK_i > Rs_1$ and $DK_i > DKL_i$
12. Update $\boldsymbol{newDol_i}$ by (14).
13. **else if** $DK_i > Rs_1$ and $DK_i < DKL_i$
14. Update $\boldsymbol{newDol_i}$ by (15).
15. **end if**
16. Find Global optimal solution $gbest$.
17. $g = g + 1$.
18. **end while**

Output: $gbest$ as the final optimal solution.

search mechanism to propose a constrained multi-objective dolphin swarm algorithm.

1) IMPROVED DUAL-POPULATION SEARCH MECHANISM

The dual-population search mechanism means that in addition to the iterative population, additional populations are added to retain some feasible solutions and infeasible solutions, and are updated with iterations. In order to improve the optimization effect, this paper improves the update of the feasible solution set and the infeasible solution set as follows:

a: IMPROVEMENT OF THE UPDATE MECHANISM OF FEASIBLE SOLUTION SET

The existing dual-population search mechanism usually adopts the following methods to perform feasible solution set updating: First, the feasible solution set is merged with the newly generated feasible solution, and the population is sorted by fast non-dominated sorting; then, the scale is from small to large. The order sequentially puts each level of individuals into a new feasible solution set until the total number of individuals of the previous several levels exceeds the capacity N_1 of the feasible solution set; finally, the individuals with smaller crowding distances are removed until the number of feasible solutions reaches N_1.

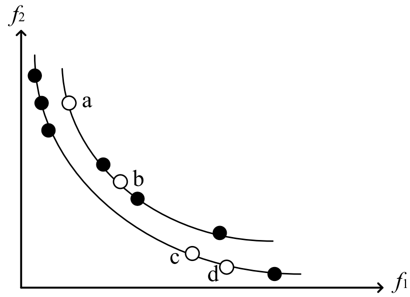


FIGURE 5. Individual distribution map.

As shown in Fig. 5, the above final step has certain defects: First, for two individuals a and b of the same dominant level, sorting according to the crowded distance will delete the individual b while retaining the individual a, but from the overall distribution of the population. In view, the individual a is more dense around, should delete a; second, for individuals c and d, they have the same crowded distance, so they will be deleted or retained at the same time. If they are deleted, the overall distribution will not improve. Instead, it will fall.

Studies have shown that Harmonic distance can better reflect the degree of crowding between individuals, so as to solve the problem that the crowded distance ignores the distribution of other ranks, so the Harmonic distance is used instead of the crowded distance [28]. However, the calculation of Harmonic distance is too complicated, and it does not highlight the difference between the different levels of individuals. For this reason, the Harmonic distance is improved, and shown as:

$$hd_i = \frac{PN_{i1}}{\frac{1}{d_{i,1}} + \frac{1}{d_{i,2}} + \cdots \frac{1}{d_{i,PN_{i1}}}} + \frac{PN_{i2}}{\frac{1}{d_{i,1}} + \frac{1}{d_{i,2}} + \cdots \frac{1}{d_{i,PN_{i2}}}} \tag{16}$$

where $PN_{i1} = PN_{i2} = [PN_i/2]$, PN_i is the number of Pareto rank individuals in which individual x_i is located, $d_{i,1}, d_{i,2} \cdots, d_{i,PN_{i1}}$ represents the Euclidean distance of PN_{i1} individuals closest to individual x_i, and $d_{i,1}, d_{i,2} \cdots, d_{i,PN_{i2}}$ represents the Euclidean distance of PN_{i2} individuals closest to individual x_i in individuals whose Pareto rank is not inferior to x_i.

It can be seen from (16) that only the PN_i individuals who are closer to themselves and the PN_{i2} individuals with better Pareto are selected for the improved Harmonic distance, which eliminates the miscalculation of the degree of congestion of distant individuals. Accurately reflect the distribution of the population and is more conducive to the retention of elite individuals.

In addition, considering the influence of the deleted crowd with small crowding distance on the remaining individuals, referring to the cyclic crowding distance strategy, propose a cyclic Harmonic distance deletion strategy instead of the final step in the feasible solution set update, as follows: Step 1, according to (16), calculate the Harmonic distance of the individual to be screened; Step 2, delete the individual with the smallest Harmonic distance; Step 3, repeat steps 1 and 2 until the number of remaining individuals meets the requirements.

b: UNFEASIBLE SOLUTION SET UPDATE

The infeasible solution set update method in the dual-population mechanism only considers the constraint condition and retains the individuals with less constraint violation. However, individuals with less constraint violations are likely to have poor objective function values, that is, not at the edge of the feasible domain, and it is difficult to provide excellent information for individual evolution, thus failing to promote the convergence of the population to the feasible domain edge. Therefore, when selecting the infeasible solution, individuals who are close to the feasible domain edge and have better target values should be selected. Hence, this section comprehensively considers the constraints and target values to improve the ways of comparing the inferior individual's advantages and disadvantages. The specific judgment methods are as follows: Suppose $N(x_i)$ represents the number of violations of the individual x_i, and $G(x_i)$ represents the constraint violation of the individual x_i. If the vector $X_i = (N(x_i), G(x_i), f_1(x_i), f_2(x_i), \cdots, f_m(x_i))$ Pareto is better than $X_i = \left(N\left(x_j\right), G\left(x_j\right), f_1\left(x_j\right), f_2\left(x_j\right), \cdots, f_m\left(x_j\right)\right)$, the infeasible solution x_i is better than the infeasible solution x_j.

In order to further determine the more representative excellent infeasible solutions, the update method of the infeasible solution set is improved as follows: First, the newly generated infeasible solution is combined with the original infeasible solution, and the above judgment method is not feasible. The solution is sorted and retained in the new infeasible solution set from small to large according to the level. If the number of new infeasible solution sets is greater than N_2, Equation (16) is changed to (17), and the cycle deletion strategy based on Harmonic distance is used. Delete the number of new infeasible solution sets to N_2.

$$hd_i = \frac{N_3}{\frac{1}{d_{i,1}} + \frac{1}{d_{i,2}} + \cdots \frac{1}{d_{i,PN_3}}} \tag{17}$$

where $d_{i,1}, d_{i,2}, \cdots, d_{i,N_3}$ is the Euclidean distance of the N_3 individual closest to the infeasible solution x_i in the target space.

2) IMPROVEMENT OF THE SEARCH MECHANISM OF DOLPHIN SWARM ALGORITHM

In order to make the dolphin swarm algorithm better solve the constrained multi-objective problem, the search mechanism of the dolphin swarm algorithm search and hunting is improved as follows.

a: IMPROVEMENT OF THE LOCATION UPDATE MECHANISM IN THE SEARCH PHASE

The position update which in (9) of the search phase can be described as: new position = base vector + sound wave × search time, in which the sound wave direction is random, the size is a constant, and the search time is a positive integer constant.

For the characteristics of constrained multi-objective problems, the following improvement is made to (9): First, some excellent infeasible solutions in constrained multi-objective problems play an important role in promoting population convergence and increasing population diversity. The excellent infeasible solution has the opportunity to participate in the composition of the basis vector. Second, the length of the sound wave determines the search step size of the base vector itself, but the algorithm has different requirements in different evolutionary periods: in the early stage of evolution, each dolphin individual is far apart, The global search ability of the enhanced algorithm can use a larger sonic length, so that the dolphins can search in a larger area; in the later stage of the search, the dolphins are in the vicinity of the optimal non-dominated front, and if the search range is too large. Not conducive to the even distribution of dolphin population, resulting in invalid search. Therefore, the length of the sound wave should gradually decrease as the number of iterations increases. Specifically, it is shown as:

$$\boldsymbol{X}_{ijt} = \begin{cases} \boldsymbol{F}_i + \boldsymbol{V}_j(g) \times t, & \text{if } rand > p \\ \boldsymbol{IF}_i + \boldsymbol{V}_j(g) \times t, & \text{otherwise} \end{cases} \tag{18}$$

where F_i is the i-th feasible solution; IF_i is the individual randomly selected in the infeasible solution set; $V(g)$ adaptively changes according to (19); p is the selection probability, and considering the late evolutionary stage, the algorithm generally converges to the optimal Near the pareto level, if it is not feasible to participate in evolution, it will greatly affect the convergence speed of the algorithm. For this reason, p adaptively changes according to (20).

$$\begin{cases} \left\|\boldsymbol{V}_j(g)\right\| = \boldsymbol{V}_{j\min} + \left\|\boldsymbol{V}_j(g-1)\right\| \times \alpha \\ \alpha = \exp\left(-\beta \times \left(\frac{g}{G_{\max}}\right)^s\right) \end{cases} \tag{19}$$

where V_{jmin} is the minimum value of the length of the sound wave, and its value is determined by the distance between the individuals in the later stage of the analysis algorithm after multiple experiments, g is the current number of iterations, G_{max} is the maximum number of iterations, and the initial value $||V(1)||$ of the length of the sound wave is set to $max_j = 1, 2, \ldots, D(H_j - F_j)/4$, α is a nonlinear time-varying function, β and s are constant values, which can be set according to specific problems. If there is no special requirement, generally when β and s take 30 and 5 respectively, better results can be obtained.

$$p(t) = \begin{cases} 0.5 - \frac{g}{G_{\max}}, & g \le G_{\max}/2 \\ 0, & g > G_{\max}/2 \end{cases} \tag{20}$$

b: IMPROVEMENT OF LOCATION UPDATE MECHANISM IN HUNTING STAGE

In the hunting stage of the dolphin swarm algorithm, according to the relationship between Rs_2, DK_i and DKL_i, it is divided into three kinds of position update strategies. It is necessary to compare the fitness value, but the constrained multi-objective problem has multiple targets, and it is impossible to judge the individual superiority directly through the fitness value. Therefore, we consider the particularity of constraining the multi-objective problem and propose a new search strategy as shown in (21).

$$newDol_i = \begin{cases} \left(\frac{1}{pareto\left(F_i\right)}\right) \times F_i + \left(1 - \frac{1}{pareto\left(F_i\right)}\right) \\ \times K_i' + c\left(r_1 - 0.5\right) \times \left(r_2 \times K_i' - F_i\right), \\ \quad if\ rand > p \\ r \times IF_i + (1-r) \times K_i' + c\left(r_1 - 0.5\right) \\ \times \left(r_2 \times K_i' - IF_i\right), \\ \quad otherwise \end{cases} \tag{21}$$

where pareto($\boldsymbol{F}_i$) represents the non-dominated ranking of the feasible solution $\boldsymbol{F}_i$, and $\boldsymbol{K}_i^{'}$ represents the individuals randomly selected in the optimal ranking. r is a random number on [0, 1], *rand* is a random number on [0, 1], and p is taken as (20).

Analysis (21) can be seen: First, in view of the fact that the dolphin swarm algorithm sets three search strategies to match different optimization problems, (21) retains this idea, provides two search strategies, and automatically selects one to explore the new location according to the change of p; Second, using the characteristics of the constrained multi-objective problem, that is, there are multiple non-dominated sorting solutions in the early stage of evolution, that is, most solutions are not close to the real Pareto frontier, and most solutions are in the optimal sorting level in the late stage of evolution. In (21), in the early stage of evolution, most individuals with poor grades learn from the better grades, and can quickly approach the real Pareto front, while at the same time let the excellent infeasible solutions participate in evolution to increase population diversity; By applying variability perturbations to individuals with superior levels, more excellent solutions can be explored, making them evenly distributed at the front of Pareto.

In addition, since the call and reception phases are only used to update the neighborhood optimal solution $\boldsymbol{K_i}$ in a single-objective DSA, the CMDSA algorithm will no longer calculate the call and reception phases.

3) STEPS TO CMDSA

Based on the above analysis, the specific steps of the CMDSA algorithm are as follows:

Step 1: Parameter initialization and population initialization, setting initial parameters including population size N, dimension of optimization problem, feasible solution set size N_1, infeasible solution set size N_2, maximum search time T_1, maximum transmission time T_2, upper and lower bounds $\boldsymbol{H}$ and $\boldsymbol{F}$ of search problems, function maximum call times Callmax, time transfer matrix $\boldsymbol{TS}$, etc.

Step 2: Calculate individual fitness values and constraint violations.

Step 3: Search phase. Perform the search phase according to (18)-(20) and update the feasible solution set and the infeasible solution set according to the section III.

Step 4: Hunting phase. Update the position of the dolphin individual $\boldsymbol{Dol_i}$ according to (21), and update the feasible solution set and the infeasible solution set according to the section III.

Step 5: Determine if the termination condition is reached. If it is reached, the Pareto optimal solution in the feasible solution set is output, and the algorithm terminates; otherwise, return to Step 2 and continue searching.

4) PERFORMANCE VERIFICATION OF CMDSA

In order to further investigate the performance of CMDSA, we compare it with the current NSGA-II [34], BB-MOPSO algorithm [35] and dual-group differential evolution algorithm (called B algorithm) [36] with better constraint effect on the CTP test set. We select the general SP and GD as the test standard, but since the optimal frontiers of CTP3, CTP4 and CTP5 are discrete points, it is not suitable for evaluating the distribution with SP. Therefore, we only use GD to evaluate the convergence performance of each algorithm on CTP3, CTP4 and CTP5. The parameters of CMDSA are set to $N_1 = 100$, $N_2 = 20$, T=1000, $T_1 = 3$, $T_2 = 1000$, speed=1, $A = 5$, $M = 3$, e=4, c=2, $\mu = 0.5$, $\lambda = 0.001$, $V_{min} = 0.0002$, the para-meter settings of other algorithms can be found in the corre-sponding references. Among them, the values of T_1, T_2, speed, A, M, and e in CMDSA are exactly the same as those in DSA algorithm in reference [11], and the other parameters are the values corresponding to the relatively excellent optimization effect after a large number of experiments.

Tables 1 and 2 show the mean and variance of the SP and GD obtained by each algorithm running 30 times independently, as follows:

We observed that the GD values obtained by CMDSA are significantly better than other algorithms on all test functions, indicating that CMDSA has the best convergence. The SP standard value of the CMDSA algorithm on CTP6 is slightly inferior to that of NSGA-II. On the functions CTP1 and CTP7, the SP of the CMDSA algorithm is equal to BB-MOPSO and NSGA-II, respectively, and the SP values obtained by CMDSA on other issues are lower than other algorithms show that the distribution of CMDSA is optimal compared to several other algorithms. B algorithm, BB-MOPSO, CMO-DSA obtained all the discrete points of the real frontier of CTP3, and the standard deviation is 0, reflecting the superior ability of the algorithm to maintain diversity, and the average value of discrete points found by NSGA-II. It is 13.58, which also reflects the lack of capacity of the crowd to maintain the diversity of the population. On CTP4 and CTP5, CMDSA obtains all discrete points of the real frontier, which indicates that the distribution of CMDSA is better than the other three algorithms.

In summary, CMDSA has certain advantages in distribution and convergence compared with other three algorithms. We have reason to believe that the CMDSA algorithm can better solve the complex constrained multi-objective

TABLE 1. Performance indicators on the CTP part test function.

Set	Algorithm	SP		GD	
		Mean	Standard deviation	Mean	Standard deviation
CTP1	B algorithm	5.7e-001	1.0e-001	2.1e-004	3.0e-004
	BB-MOPSO	9.8e-003	**5.7e-005**	2.3e-003	1.2e-004
	NSGA-II	5.7e-001	1.8e-001	1.7e-003	1.3e-003
	CMDSA	**1.8e-003**	**3.2e-005**	**1.6e-004**	**1.7e-009**
CTP2	B algorithm	7.4e-003	2.7e-005	5.6e-004	7.0e-007
	BB-MOPSO	7.6e-003	3.9e-005	2.3e-003	1.2e-004
	NSGA-II	2.4e-003	1.4e-004	3.7e-004	1.1e-005
	CMDSA	**1.8e-003**	3.2e-005	**1.6e-004**	**1.7e-010**
CTP6	B algorithm	1.1e-001	7.7e-002	9.6e-004	8.1e-005
	BB-MOPSO	1.4e-001	3.5e-001	8.0e-004	6.0E-008
	NSGA-II	1.3e-001	**9.6e-004**	8.5e-004	6.5E-005
	CMDSA	**5.3e-003**	1.5e-003	**6.2e-004**	**1.5e-008**
CTP7	B algorithm	2.5e-002	3.7e-004	9.9e-004	4.6e-006
	BB-MOPSO	5.1e-001	1.9e+000	6.4e-002	4.8e-005
	NSGA-II	2.3e-002	**3.7e-004**	9.8e-004	4.6e-006
	CMDSA	**1.9e-004**	**3.5e-008**	**1.4e-005**	**3.6e-008**

problem of the micro-base station green deployment problem as described in (7).

IV. ALGORITHM IMPLEMENTATION

In this part we use CMDSA to solve (7), the specific steps are as follows:

A. INITIALIZATION

Initialization consists of three parts, parameter initialization, network initialization, and population initialization.

Parameter initialization: number of micro base stations N, maximum number of iterations G_{max}, feasible solution set size N_1, infeasible solution set size N_2, maximum search time T_1, maximum transmission time T_2, time transfer matrix $\boldsymbol{TS}$, etc.

Network initialization: The macro base station BS is arranged at the center of the rectangular area of length X_0 and width Y_0, and the coverage radius is R_B, and the user distribution of 9 different scenarios is created: three kinds of

TABLE 2. Performance indicators on the CTP part test function.

Set	Algorithm	SP		GD	
		Mean	Standard deviation	Mean	Standard deviation
CTP3	B algorithm	14	0	6.9e-003	3.2e-008
	BB-MOPSO	14	0	2.3e-003	**2.5e-008**
	NSGA-II	13.58	7.6e-001	2.4e-003	7.1e-004
	CMDSA	**14**	0	**3.0e-004**	4.2e-008
CTP4	B algorithm	13.33	3.0e-001	2.8e-003	1.8e-006
	BB-MOPSO	13.67	2.3e-001	2.9e-003	**2.1e-007**
	NSGA-II	12.30	1.8e+00 0	**2.5e-003**	7.8e-004
	CMDSA	**14**		**2.5e-003**	3.3e-007
CTP5	B algorithm	14.27	2.0e-01	9.2e-004	3.4e-008
	BB-MOPSO	13.80	5.8e-001	8.8e-004	4.8e-008
	NSGA-II	13.52	2.4e+00 0	8.0e-004	8.8e-005
	CMDSA	**15**		**3.1e-004**	**2.5e-008**

low load, three medium loads and three high loads, the three cases are equally likely to occur. The number of low-load, medium-load, and high-load active users is m_1, m_2, and m_3, respectively. All users are distributed uniformly, and all users and base stations adopt SINR correlation.

Population initialization: The initial population POP is randomly generated. The $1\sim N$ dimension of the individual represents the abscissa of the location of the micro base station, and the $N+1\sim 2N$ dimension represents the ordinate of the location of the micro base station, respectively, and the $2N+1\sim 3N$ represent the coverage radius of the micro base station, respectively.

B. CALCULATE FITNESS VALUES AND CONSTRAINT VIOLATIONS

a. Considering the k-th scene distribution, calculating the distance between all users and the micro base station and the macro base station, and the user rate C_k when only the macro base station is deployed.

b. According to the distance and the coverage radius R_i of each base station, it is determined which base stations are covered by the user and the number of users covered by each micro base station, the number of users covered by the micro base station i is m_i, and the number of users covered by the macro base station is m_0.

c. Calculate the average electromagnetic radiation intensity under scene k according to (6).

d. If the user is not covered by any micro base station, the user rate and the constraint violation degree of the user are directly calculated. Otherwise, calculate the signal to interference and noise ratio SINR of the user and all the base stations, select the base station communication with the largest signal-to-noise ratio, and calculate the user rate and constraint violation degree of the user.

e. Calculate the network energy efficiency under scene k according to (1) and (3), and accumulate the constraint violation degree of all users.

f. Considering all the distribution scenarios, the network energy efficiency and the average electromagnetic radiation intensity are calculated in the form of probability weighting according to (7).

C. SEARCH PHASE

Perform the search phase according to (18)-(20), and calculate the fitness value and constraint violation degree of each body, and update the feasible solution set $\boldsymbol{F}$ and the infeasible solution set $\boldsymbol{IF}$ according to Section III.

D. HUNTING PHASE

According to (21), the deployment scheme of the micro base station is updated, and the fitness value and the constraint violation degree of each body are calculated, and the feasible solution set $\boldsymbol{F}$ and the infeasible solution set $\boldsymbol{IF}$ are updated according to Section III.

E. TERMINATION CONDITION

Determine whether the termination condition is satisfied. If yes, output the Pareto optimal solution in the feasible solution set, and the algorithm terminates. Otherwise, return to search phase and continue searching.

In summary, the CMDSA-based heterogeneous cellular network micro-base station green deployment algorithm flow chart is shown in Fig. 6.

V. EXPERIMENTAL SIMULATION AND PERFORMANCE ANALYSIS

In order to fully prove the effectiveness of the CMDSA-based heterogeneous cellular network micro-base station green deployment algorithm, the algorithm is compared with two other excellent algorithms. Due to the green deployment of micro base stations, most scholars only study a single object. Therefore, this paper selects the constrained single-objective HEEDA algorithm [10] and B algorithm which have better performance.

In this section, a simulation area of 1km × 1km is used. There is a macro base station in the center. It is assumed that there are 9 different scenarios, 3 low loads, 3 medium loads, and 3 high loads. The number of users is 30, 100 and 200 respectively. All of these scenes are subject to uniform distribution. The experimental parameters are shown in Table 3.

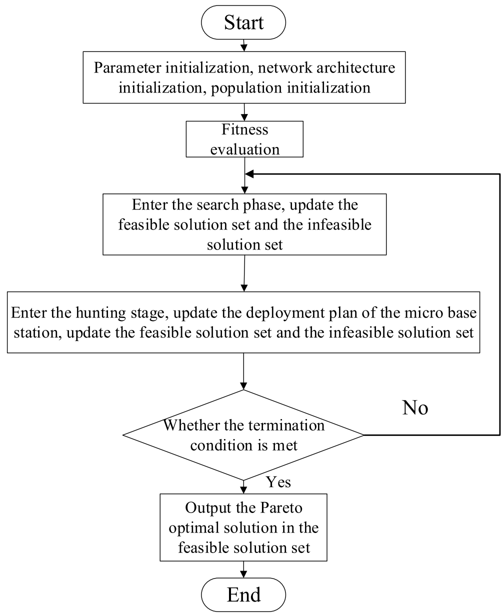


FIGURE 6. Flow chart of green deployment algorithm for hetero-geneous cellular network micro base station based on CMO-DSA.

TABLE 3. Simulation parameter.

Parameter	Value
Macro base station static power P_{B0}	56.2dBm
Macro base station transmit power P_{Bt}	46dBm
Macro base station coverage radius Rc_B	1km
Macro base station antenna gain G_B	14 dBi
Micro base station static power P_{i0}	45dBm
Micro base station nominal transmit power P_0	38dBm
Micro base station nominal coverage radius Rc_0	400m
Micro base station minimum coverage radius $Rc_{\min}$	100m
Micro base station maximum coverage radius $Rc_{\max}$	500m
Micro base station antenna gain G_S	14 dBi
Network bandwidth W	20MHz
Noise power spectral density n_0	-174dBm/Hz

A. COMPARISON WITH THE OPTIMIZATION SCHEME OF HEEDA ALGORITHM

Consider the distribution of users under low load, medium load, and high load, respectively. The number of micro base stations is 30, the number of population is 100, and the maximum number of iterations is 200. Other parameters are consistent with the above. Since the HEEDA algorithm belongs to the constrained single-objective algorithm for optimizing network energy efficiency, this experiment first optimizes the algorithm and HEEDA algorithm on the network energy efficiency model, and then calculates the average electromagnetic radiation intensity by using the optimal solution optimized by HEEDA algorithm. Fig. 7 shows the relationship between the network energy efficiency of this algorithm and HEEDA algorithm with the number of iterations under three load scenarios. The objective function values corresponding to the optimal solution obtained by the HEEDA algorithm are shown in Table 4.

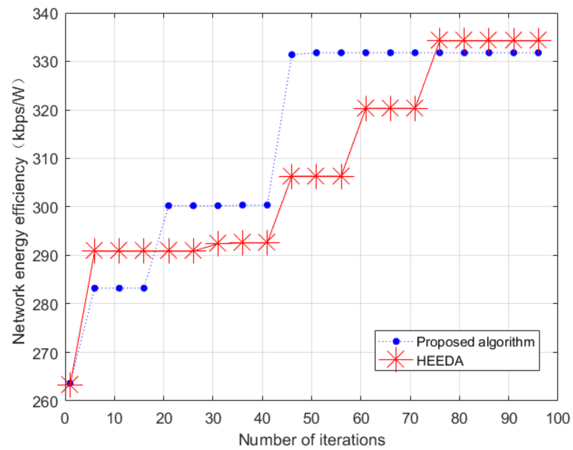
A comprehensive analysis of Fig. 7 and Table 4 can be drawn: First, under the same user distribution, the network energy efficiency of the algorithm is slightly lower than that of the HEEDA algorithm. This is because the algorithm is limited by the intensity of electromagnetic radiation and needs to consider two indicators comprehensively. HEEDA only considers network energy efficiency factors when optimizing the deployment of micro base stations. Second, under the same user distribution, the electromagnetic radiation intensity of the proposed algorithm is significantly lower than that of the HEEDA algorithm, and the average user rate of the proposed algorithm is higher than the HEEDA algorithm. Therefore, the algorithm of this paper can comprehensively consider two evaluation indexes of network energy efficiency and electromagnetic radiation intensity under the condition of guaranteeing user speed, which has practical application value. Third, with the in-crease of the number of users, the network energy efficiency of the two algorithms increases to a stable level, which also indicates that the algorithm optimization scheme can better adapt to the traffic demand under high load.

B. COMPARISON WITH THE OPTIMIZATION SCHEME OF B ALGORITHM

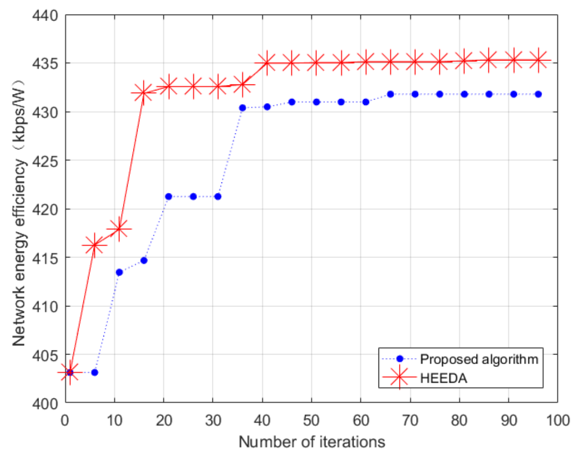
The parameter setting is consistent with the previous one. The proposed algorithm and B algorithm optimize the deployment of the micro base station respectively, and obtain two sets of Pareto optimal solutions. The multi-objective decision is used to select the better three sets of schemes. The specific results are shown in Table 5.

It can be seen from Table 5 that the algorithm can obtain higher network energy efficiency when the number of micro base stations is the same. The electromagnetic radiation intensity is similar to or slightly higher than the B algorithm, but both are within the safe range. The rate has a certain advantage over the B algorithm, and the network energy efficiency can be improved by up to 9.9% compared with the B algorithm.

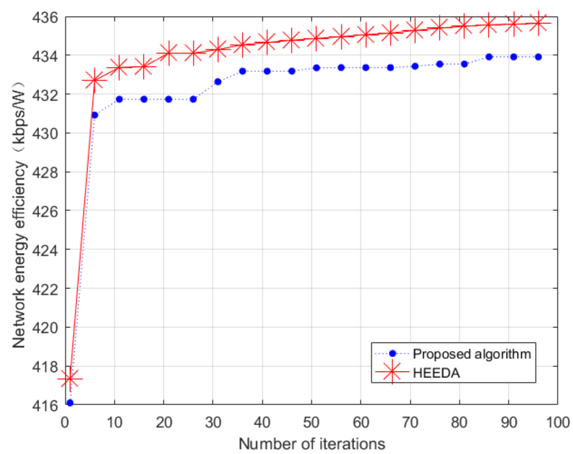
In summary, the green deployment method for heterogeneous network micro base stations proposed in this paper has certain advantages.



(a) Network energy efficiency under low load



(b) Network energy efficiency under medium load



(c) Network energy efficiency under high load

FIGURE 7. Network energy efficiency comparison under different loads.

VI. DISCUSS

It can be seen from the above coding method that the number of micro base stations affects the size of the population and directly affects the complexity of the algorithm. Combining (3) and (6), the impact of the number of micro

TABLE 4. Comparison with the optimal scheme of HEEDA algorithm.

Evaluation index	User distribution	Algorithms	HEEDA
Network energy efficiency（kpbs/W）	Low load	331.7846	334.6827
	Medium load	431.3515	436.2410
	High load	434.8498	436.4006
Electromagnetic radiation intensity(W/m^2)	Low load	0.1315	0.1410
	Medium load	0.1310	0.1450
	High load	0.1312	0.1315
Average user rate(Mbit/s)	Low load	14.6667	13.2670
	Medium load	13.3333	12.5890
	High load	12.1222	11.9670

TABLE 5. Comparison with the optimal scheme of B algorithm.

Program	method	Network energy efficiency（kpbs/W）	Electromagnetic radiation intensity(W/m^2)
1	CMDSA	406.0611	0.1310
	B algorithm	369.4952	0.1310
2	CMDSA	406.6104	0.1316
	B algorithm	370.0727	0.1311
3	CMDSA	403.1443	0.1313
	B algorithm	371.6673	0.1311

base stations on the deployment result described in (7) is further analyzed: after the micro base station is deployed, some users of the macro base station are offloaded to the micro base station, and the distance between the user and the micro base station is closer, and the corresponding path loss and interference are reduced. In addition, since the micro base station and the macro base station share the bandwidth, the user who communicates with the micro base station obtains more bandwidth resources, the user rate thereof also increases, and the user rate of the same macro base station is also improved, and therefore, the average user of the entire network. The rate will increase, and the power consumption of the micro base station is small, so the network energy

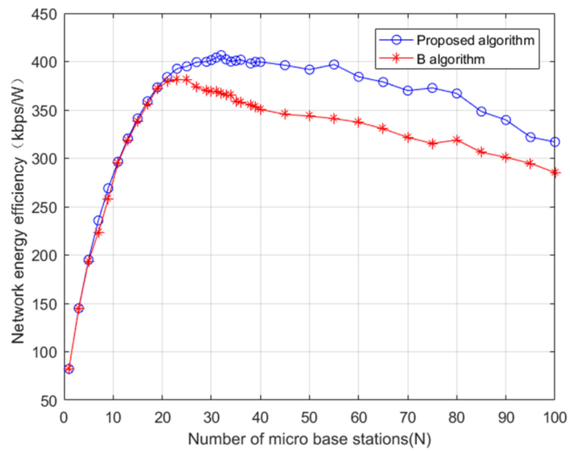


FIGURE 8. The number of micro base stations deployed by the two algorithms and the energy efficiency relationship of the network.

efficiency will be improved. As the number of deployments of micro base stations continues to increase, the interference between them increases, and the gain brought by the micro base stations will be offset by the inter-layer interference, resulting in an average user rate will be stable, while network power consumption continues to increase, so the network energy efficiency will decline. In short, when the number of micro base stations is a certain number, the network energy efficiency of the system will be maximized. If the number is exceeded, the energy efficiency of the network will decrease and the electromagnetic radiation will continue to rise.

To further verify the above analysis, we experimented with the scenario described in the experimental part: changing the number of micro base stations, using the method and algorithm B to deploy, and obtaining the relationship between the number of micro base stations and the network energy efficiency and electromagnetic radiation. The parameters are set as follows: the number of populations is 100, the maximum number of iterations T is 200, and other parameter settings are consistent with Section 3. The algorithm runs independently 20 times, and the average value of the objective function is calculated.

Fig. 8 shows the relationship between the number of micro base stations deployed in the network and the network energy efficiency of the proposed algorithm and B algorithm.

It can be seen from Fig. 8 that as the number of deployed micro base stations increases, the network energy efficiency of both algorithms increases first and then decreases, which is consistent with the theoretical analysis in Section 4. For any number of micro base stations, the CMDSA optimized network energy efficiency is better than the B algorithm, and when the number of micro base stations is around 30, the energy efficiency of the algorithm network is the largest, the energy efficiency of the B algorithm is improved by 8.7%, and the network energy efficiency can be increased by 18.19%. Therefore, this also shows that the proposed algorithm performs better than the B algorithm in optimizing the deployment problem of the micro base station.

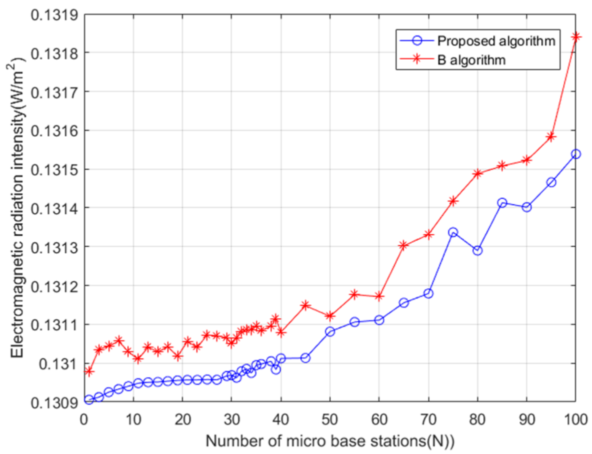


FIGURE 9. Relationship between the number of tiny base stations and electromagnetic radiation intensity.

Fig. 9 shows the relationship between the number of micro base stations and the intensity of electromagnetic radiation.

It can be seen from Fig. 9 that as the number of micro base stations increases, the intensity of electromagnetic radiation also increases. This is because the micro base stations are deployed in the coverage area of the macro base station, and the electromagnetic radiation of the micro base stations is increased on the basis of the original electromagnetic radiation. The intensity of electromagnetic radiation also increases. For the number of any micro base stations in Fig. 9, the electromagnetic radiation intensity of the proposed algorithm is lower than that of the B algorithm. This proves that the proposed algorithm and the B algorithm have better micro base station position and coverage radius under the same number of micro base stations. Although the intensity of electromagnetic radiation has been increasing, the growth rate is very slow and has been below 0.4 W/m2, so it is within the safe range.

In summary, when the number of micro base stations is 30, the maximum network energy efficiency and the micro electromagnetic radiation can be obtained. For the green deployment problem of the above micro base stations, the number of the micro base stations is 30, and the result is optimal. In the next study, we can determine the optimal number of micro base stations by some method, without manually setting the number of multiple micro base stations, and then determining the optimal number of micro base stations according to the target.

VII. CONCLUSION

For the ultra-dense heterogeneous cellular network oriented to two-dimensional communication scenarios, this paper establishes a constrained multi-objective mathematical model for the green deployment of micro base stations, and improves the search mechanism and dual-population strategy of the dolphin swarm algorithm, and proposes a constrained multi-objective dolphin swarm algorithm. Finally, the constrained multi-objective dolphin swarm algorithm is used to solve the problem of green deployment of micro base stations. Simulation of 9 communication scenarios shows that the proposed method can balance network energy efficiency and electromagnetic radiation. Next we will study how to determine the optimal number of tiny base stations and reduce the complexity of deployment problems.

In the next step, we can conduct further research in the following aspects: First, how to determine the optimal number of micro base stations and reduce the complexity of deployment problems. Second, because we do not have data on actual user distribution, we use a uniform distribution to simulate user distribution in this paper. If there is data on actual user distribution, it will better reflect the network status and facilitate the practical application of the algorithm. Third, when establishing a constrained multi-objective model for micro base station deployment, economic factors such as deployment costs and site rental costs can be taken into account.

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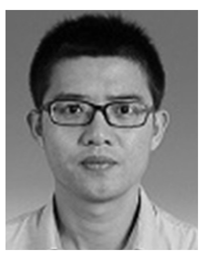

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