Improved AP Deployment Optimization Scheme Based on Multi-objective Particle Swarm Optimization Algorithm

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Abstract

Deployment of access point (AP) is a problem that must be considered in network planning. However, this problem is usually a NP-hard problem which is difficult to directly reach optimal solution. Thus, improved AP deployment optimization scheme based on swarm intelligence algorithm is proposed to research on this problem. First, the scheme estimates the number of APs. Second, the multi-objective particle swarm optimization (MOPSO) algorithm is used to optimize the location and transmit power of APs. Finally, the greedy algorithm is used to remove the redundant APs. Comparing with multi-objective whale swarm optimization algorithm (MOWOA), particle swarm optimization (PSO) and grey wolf optimization (GWO), the proposed deployment scheme can reduce AP's transmit power and improves energy efficiency under different numbers of users. From the experimental results, the proposed deployment scheme can reduce transmit power about 2%-7% and increase energy efficiency about 2%-25%, comparing with MOWOA. In addition, the proposed deployment scheme can reduce transmit power at most 50% and increase energy efficiency at most 200%, comparing with PSO and GWO.

Keywords: Deployment, Energy Efficiency, MOPSO, Redundancy Elimination

1. Introduction

Network planning is a classical and important problem in the network. The main content is to obtain the optimal location and configurations of access point (AP) by considering the rate requirements, AP capacity and quality of service (QoS) of users. In order to achieve this objective, the task of network planning is to obtain the number and location of deployed APs, and adjust the transmission power of APs according to the above constraints. The problem requires some parameters such as the distribution of users or the interference from other AP as inputs to the solution of the problem, which increases the complexity of the problem.

This problem has been studied by many scholars. The NP-hard problem generated in the base station placement was solved by using genetic approaches [1]. Tugrul et al. classified the base station deployment problems and provided solutions for these problem [2]. An intensive learning-based approach was proposed by Dai et al. to solve AP deployment problem with multi-objective [3]. Wang et al. combined the greedy search algorithm and distributed motion algorithm to deploy the base stations (BS) [4]. Ghazzai et al. used the algorithms based on swarm intelligence to get optimal locations with minimum number of BS in a given area [5]. To achieve the objective of coverage maximization, Hanh et al. proposed a novel metaheuristic in the form of a genetic algorithm [6]. In addition, a novel particle swarm optimization (PSO) was proposed to obtain minimum number and maximum coverage, which is based on the negative velocity [7].

In order to obtain optimal location, improve communication capacity and provide better service for users, some studies for the location of AP have been proposed. Wu et al. proposed a priority-based AP deployment scheme to increase user throughput in the WIFI convergence network [8]. Fu et al. presented a novel architecture of AP deployment, which was consisted of control layer, processing layer and access layer, to improve the service efficiency of AP [9]. Additionally, the 3D position optimization of drone-BS based on maximizing the number of serviced users is studied [10]. Zhang et al. deployed the AP from the perspective of the operator without affecting the profit of the operator [11]. An optimization model based on a maximizing algorithm was proposed to decrease the number of drone AP and ensure their optimal positions by [12]. But these works only consider the location in the area and do not consider the power of the AP.

Other studies on AP power adjustment have also been proposed. A hybrid access point (H-AP) realizes the improvement of ap energy efficiency based on the mixed transmission of energy and information [13]. Garcia et al. researched on the distribution of channels and power and proposed heuristic algorithm [14]. Similarly, an AP deployment scheme through power control and partial channel multiplexing is proposed by Tewari and Ghosh [15]. Hsu and Su considered the minimum deployment number and maximum coverage of APs and proposed an AP deployment scheme based on a greedy algorithm [16]. The above works only consider the power adjustment of the AP and do not comprehensively consider the location and coverage of the AP.

In summary, most of the current schemes do not consider both AP location and AP transmit power. Because those schemes ignore the transmit power when determining the location of the AP, the energy efficiency (EE) of the AP is not high. Thus, in order to improve the EE of AP, the location and the transmit power of AP are considered simultaneously.

In this paper, improve AP deployment optimization scheme based on swarm intelligence algorithm is proposed to find the maximum EE, minimum transmit power and optimal location of APs. Meantime, in view of three important constraints, including area coverage constraint, AP capacity constraint and transmit power constraint, this paper tries to exploit swarm

intelligence algorithm to solve the combinatorial optimization problem. The main contributions of this paper can be summarized as follows:

1) In this paper, the objective of AP deployment is to obtain the minimum transmit power and maximum energy efficiency, which guarantees the energy consumption and transmit rate of the communication network.

2) A random geometric algorithm is used to estimate the capacity of a single AP and calculate the maximum number of APs according to the user's service requirements.

3) The proposed deployment scheme first introduces multi-objective particle swarm optimization (MOPSO) algorithm to obtain the location of AP and then applies greedy algorithm to reduce redundant AP.

In section 2, related works are introduced. In section 3, the system model is presented. In section 4, the method for estimating the number of APs based on the random geometry, the AP deployment scheme based on MOPSO algorithm and the greedy algorithm for reducing the redundancy of APs are proposed. In section 5, the performance of the proposed scheme is evaluated by comparing with other algorithms. A conclusion and discussion of future work are described in section 6.

2. Related Works

In this paper, the proposed AP deployment optimization scheme based on swarm intelligence algorithm contains two main points: 1) Modeling AP using stochastic geometry theory; 2) Application of MOPSO algorithm.

Around the challenging points, there has been many research results in the past decades. In these results, the application of stochastic theory is significant for the challenging points. Andrews used stochastic geometry to develop new general models to evaluate the multi-cell signal-to-interference-plus-noise ratio (SINR) [17]. Nie et al. proposed the ergodic rate expression by the stochastic geometry [18], which can effectively address the problem how to design appropriate cooperative radius. In the same way, the model of user association radius and base station ergodic rate was obtained by using random geometric theory [19]. Sun et al. proposed an extended point process to simulate the distribution of the interfering body sensor networks by using stochastic geometry [20]. Thus, the stochastic geometry theory can be used to estimate the number of APs deployed and compute the capacity of a single AP, which can save a lot of computing time.

The MOPSO algorithm [21] was first proposed by Carlos et al. to solve the optimization problem with mutual influence among multiple goals. Zhang et al. applied the MOPSO to solve antenna deployment problem [22]. Yang et al. used the MOPSO algorithm to complete the deployment of radar BSs to meet the requirements of coverage and energy signals [23].

In this paper, two objective functions are composed of minimum transmit power and maximum energy efficiency. In order to reach these two objectives, the MOPSO algorithm is designed to complete the deployment of AP location and transmit power. Because the AP deployment problem is generally a NP-hard problem and other evolutionary algorithms, including MOEA/D, NGSAII, et al. are more complicated with heavy computation and difficult to solve the large-scale AP and unlimited groups of AP deployment problem. It is simpler to update the population position and velocity in the evolution process in MOPSO algorithm. Thus, the MOPSO is simple for handling large-scale combinatorial optimization problems. In addition, the proposed deployment scheme considers both the power and energy efficiency of AP and the deployment scheme continuously changes the user's location and the

transmit power of each AP in iterations, and finally ensures the entire system to obtain minimum transmit power and maximum energy efficiency.

3. System Model

This paper considers multiple APs with a specific number of users within a given area. The entire area is divided into $N_{subarea}$ subareas with N users. The system model is shown in **Fig. 1**. The acreage of subarea k is $A(k)$ and the total area is A_T. Thus, it can be obtained that:

$$\sum_{k=1}^{N_{subarea}} A(k) = A_T, k = 1, 2, \cdots\cdots, N_{subarea} \tag{1}$$

Let the user distribution density in each subarea k be $D(k)$. The users obey uniform distribution. Note that different subarea is with different user density. The goal of the deployment scheme is to find the number of APs, AP's best position (x, y) and transmit power P_b, which should satisfy the coverage constraint, capacity constraint and transmit power constraint.
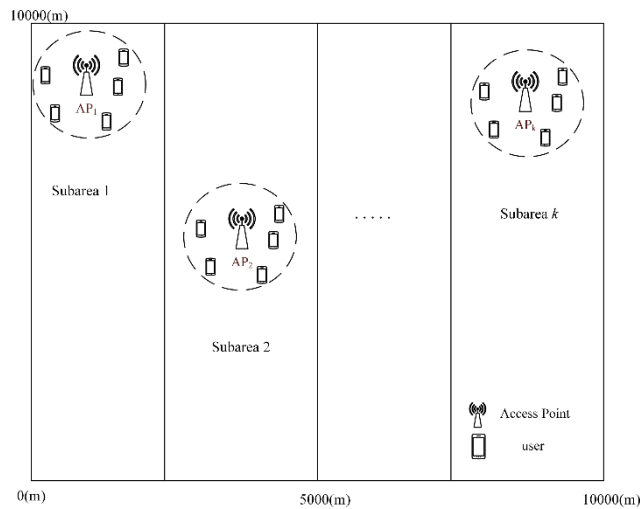

Fig. 1. System model

The capacity constraint: Define area ratio variable $\rho_{m,k}$ which depends on the mutual area and the total area, can be expressed as:

$$\rho_{m,k} = \frac{a_{m,k}}{S_{AP_m}}, m = 1, 2, ..., N_{AP} \tag{2}$$

Where AP_m is the mth AP, $a_{m,k}$ is the mutual area between AP_m and subarea k, S_{AP_m} is the total area of AP_m and $0 \leq \rho_{m,k} \leq 1$. The N_{AP} is the number of deployed APs, which is introduced in subsection 4.1.

To satisfy the capacity constraint, (3) should be satisfied, where η is tolerance parameter which is used to relax the capacity constraint.

$$\sum_{m=1}^{N_{AP}} N_{user} \rho_{m,k} \geq \eta D(k) A(k), 0 \leq \eta \leq 1 \tag{3}$$

where N_{user} is the maximum number of users that can be served by an AP, which is introduced in subsection 4.1.

The coverage constraint: The paper states that when users with a proportion of σ get services, the coverage constraints can be satisfied. Let $N_{ref} = \sigma N$ define binary variable γ_n which is used to express the user status.

$$\gamma_n = \begin{cases} 1 & \text{if user } n \text{ is covered by at least one AP} \\ 0 & \text{if user } n \text{ is not covered by any AP} \end{cases}, n = 1,\ 2,\ ...,N \tag{4}$$

Therefore, when the entire area meets the coverage constraint, the following equation should be satisfied:

$$\sum_{n=1}^{N} \gamma_n \geq N_{ref} \tag{5}$$

It should be noted that the values γ_n and $\rho_{m,k}$ are related to the AP position coordinates (x, y).

The transmit power constraint: The transmit power constraint also should be satisfied:

$$P_m \leq P_{threshold}, m \in 1, 2, \cdots\cdots, N_{AP} \tag{6}$$

where P_m is the transmit power of mth AP, $P_{threshold}$ is the transmit power threshold. In summary, the problem of AP deployment can be expressed as follows:

$$f_1 : \min_{(x,y),P_m} \sum_{m=1}^{N_{AP}} P_m \qquad f_2 : \min_{(x,y),P_m} (-\text{EE}) \tag{7}$$

Subject to

$$\sum_{m=1}^{N_{BS}} N_{user} \rho_{m,k} \geq \eta D(k) A(k), k = 1, 2, \cdots\cdots, N_{subarea} \tag{7a}$$

$$\sum_{n=1}^{N} \gamma_n \geq N_{ref} \tag{7b}$$

$$P_m \leq P_{threshold}, m \in 1, 2, \cdots\cdots, N_{AP} \tag{7c}$$

The (7) represents the optimization goal of the AP deployment scheme which consists of two sub-goals. f_1 is to make the deployment solution have the lowest energy consumption, and f_2 ensures that each user has the optimal EE. In order to ensure the entire problem to be a minimized problem, the value of EE is reversed and the maximum value is converted to the minimum value. This paper uses the average EE of users who are served by AP to represent the EE of current AP. The equation is as follows:

$$\text{EE} = \overline{u/P_r} \tag{8}$$

where u is the throughput of each user and P_r is the received power of each user.

4. AP Deployment Scheme

In this section, an AP deployment scheme based on user distribution is proposed. The process of scheme is shown in **Fig. 2**. First, the scheme uses random geometry to pre-estimate the number of deployed APs, which will be introduced in subsection 4.1. Second, the scheme uses the MOPSO algorithm to obtain the AP location and the transmit power in subsection 4.2. Then, the scheme uses the greedy algorithm to eliminate redundant APs in subsection 4.3.
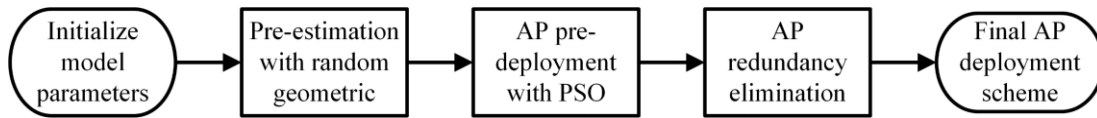

Fig. 2. AP deployment scheme process

4.1 Pre-estimation with random geometric

In this section, random geometry method is selected to evaluate the performance of a single AP because the performance of each AP in the network affects the deployed number of APs which influence the overall communication network greatly. The AP follows the assumptions including: the AP follows a distribution of Poisson point process (PPP) with intensity of λ and have a common cell radius of R_{th}; A user can be covered by multiple APs but only one AP can provide the service for this user; Interference only exists between APs.

Considering a propagation channel model containing pathloss and Rayleigh fading, the receiving SINR of a user associating with the AP within R_{th} is as follows:

$$\text{SINR}(i) = \frac{P_b g_i r_i^{-\alpha}}{\sum_{j \in \Psi/\{i\}} P_b g_j R_j^{-\alpha} + N_0} \tag{9}$$

where P_b is the transmit power of AP, g_i, g_j are the Rayleigh fading factor of AP_i and AP_j respectively, AP_i is the AP that provides services to user, AP_j is the interference AP. i, j is the index of APs in the area, α is the pathloss factor, r_i is the distance from user to AP_i, R_j is the distance from user to AP_j, $\sum_{j \in \Psi/\{i\}} P_b g_i R_j^{-\alpha}$ is the interference from other APs except AP_i, Ψ is the set of all APs, $\Psi/\{i\}$ excludes AP_i from Ψ and N_0 is the thermal noise power. Then (9) can be rewritten as:

$$\text{SINR}(i) = \frac{I_{\Phi_s}}{I_{\Phi_s'} + N_0} \tag{10}$$

$$I_{\Phi_s}(i) = P_b g_i r^{-\alpha} \tag{10a}$$

$$I_{\Phi_s'}(j) = \sum_{j \in \Psi/\{i\}} P_b g_j R_j^{-\alpha} \tag{10b}$$

According to random geometry theory, the total throughput u can be expressed as:

$$u = \frac{B}{\ln 2} \ln(1 + \text{SINR}(i)) \tag{11}$$

where the logarithm can be rewritten in (12):

$$\ln\left(1+\mathrm{SINR}\left(i\right)\right)=\int_0^\infty \frac{1}{s}e^{-sN_0^2}L_{\Phi_s'}\left(s\right)\left(1-L_{\Phi_s}\left(s\right)\right)ds \tag{12}$$

where the $L_{\Phi_s'}\left(s\right)$ and $L_{\Phi_s}\left(s\right)$ are the Laplace transform of $I_{\Phi_s'}\left(j\right)$ and $I_{\Phi_s}\left(i\right)$.

Due to the Rayleigh fading factor g_i/g_j follows the exponential distribution, the $L_{\Phi_s'}\left(s\right)$ and can be expressed in (13) and (14):

$$\begin{aligned}
L_{\Phi_s'}\left(s\right)&=E\left[e^{-sI_{\Phi_s'}\left(j\right)}\right]=E_{R_j,g_j}\left[e^{-s\sum_{j\in I_{\Phi_s}/\{i\}}P_b g_j R_j^{-\alpha}}\right]\\
&=\exp\left\{-2\pi\lambda\int_r^\infty\left(1-E_{g_j}\left[\exp\left\{-sP_b g_j r^{-\alpha}\right\}\right]\right)rdr\right\}\\
&=\exp\left\{-2\pi\lambda\int_r^\infty\left(1-\frac{1}{1+sP_b r^{-\alpha}}\right)rdr\right\}
\end{aligned} \tag{13}$$

$$L_{\Phi_s}\left(s\right)=E\left[e^{-sI_{\Phi_s}\left(i\right)}\right]=\exp\left\{-\frac{2}{R_{th}^2}\int_0^{R_{th}}\left(1-\frac{1}{1+sP_b r^{-\alpha}}\right)rdr\right\} \tag{14}$$

Let $\alpha=4$, (13) and (14) can be rewritten as:

$$L_{\Phi_s'}\left(s\right)=\exp\left\{-\pi\lambda\sqrt{sP_b}\arctan\frac{\sqrt{sP_b}}{r^2}\right\} \tag{15}$$

$$L_{\Phi_s}\left(s\right)=\exp\left\{-\frac{1}{R_{th}^2}\sqrt{sP_b}\arctan\frac{R_{th}^2}{\sqrt{sP_b}}\right\} \tag{16}$$

According to (12), (15) and (16), (11) can be rewritten as:

$$u=\int_0^\infty\frac{1}{s}e^{-sN_0^2}\exp\left\{-\pi\lambda\sqrt{sP_b}\arctan\frac{\sqrt{sP_b}}{r^2}\right\}\left(1-\exp\left\{-\frac{1}{R_{th}^2}\sqrt{sP_b}\arctan\frac{R_{th}^2}{\sqrt{sP_b}}\right\}\right)ds \tag{17}$$

When deploying APs, the paper first estimates the number of APs needed. Due to the limited coverage of a single AP, user coverage and AP capacity should be considered simultaneously for the entire coverage area.

According to the COST-231-HATA model, the pathloss which can be denoted as PL is:

$$\begin{aligned}
\mathrm{PL}=&46.33+\left(44.9\text{-}6.55\lg\left(h_t\right)\right)\lg\left(d\right)+33.9\lg\left(f\right)\\
&-\left(\left(1.1\lg\left(f\right)-0.7\right)h_r-1.56\lg\left(f\right)+0.8\right)-13.82\lg\left(h_t\right)+3.
\end{aligned} \tag{18}$$

where h_r is the height of receiving antenna, h_t is the height of transmit antenna, f is operating frequency. Let the minimum rate for each user be u_{th}, the maximum allowed pathloss be ML [5]. According to the PL and ML, the coverage radius of a single AP is:

$$R_{th}=d\,|_{\mathrm{PL=ML}} \tag{19}$$

Then the number of APs based on AP coverage can be calculated according to (19), which can be expressed as N_{AP}^{COV} :

$$N_{AP}^{COV} = \frac{A_T}{\pi R_{th}^2} \tag{20}$$

The number of APs based on AP service capacity can be calculated, which can be expressed as N_{AP}^{CAP} :

$$N_{AP}^{CAP} = \sum_{k=1}^{N_{subarea}} \frac{D(k)A(k)}{N_{user}} \tag{21}$$

where N_{user} is the maximum number of users that are served by an AP, which can be expressed as:

$$N_{user} = \frac{u}{u_{th}} \tag{22}$$

where u_{th} is the minimum throughput threshold for each user. In order to ensure the coverage constraint and the capacity constraint at the same time, the number of APs is estimated as follows:

$$N_{AP} = \max\left(N_{AP}^{COV}, N_{AP}^{CAP}\right) \tag{23}$$

4.2 AP pre-deployment with MOPSO

Generally, this AP deployment optimization problem for EE and transmit power is a multi - dimensional and multi-objective problem. In this paper, the changes of two objectives including f_1 and f_2 affect each other, which means that an achievement of one objective will affect another objective. In some algorithms, it always sacrifices one objective to achieve another objective and obtains the solution that satisfies only one of the objectives [5, 6]. It is necessary to find a group of solutions that can satisfy the f_1 and f_2 rather than to find a solution which satisfies only one of them. MOPSO can be applied to deal with this kind of optimization problem [24].

In this paper, a group of solutions that satisfy all objectives are generated with MOPSO method to a front (REP). Each group of solutions in REP represents an AP deployment scheme. Finally, the deployer selects a best deployment scheme from REP.

Step 1, the algorithm first generates L particles, each particle is donated by $W^{(l)}$ (l=1, 2, ..., L) with the length of $3N_{AP}$ elements to form an initial population. $W^{(l)}$ consists of AP position coordinates and transmit power, which can be expressed as:

$$W^{(l)} = \left\{ x_1^{(l)} \cdots x_{N_{AP}}^{(l)}, y_{N_{AP}+1}^{(l)} \cdots y_{2N_{AP}}^{(l)}, p_{2N_{AP}+1}^{(l)} \cdots p_{3N_{AP}}^{(l)} \right\} \tag{24}$$

where x, y and p are randomly generated.

$$\begin{cases} x_i^{(l)} = x_{\min} + \left(x_{\max} - x_{\min}\right) \cdot rand() \\ y_i^{(l)} = y_{\min} + \left(y_{\max} - y_{\min}\right) \cdot rand() \end{cases}, i = 1, 2, \cdots\cdots, 2N_{AP} \tag{25}$$

$$p_i^{(l)} = P_{threshold} \cdot rand(), i = 2N_{AP} + 1, 2N_{AP} + 2, \cdots\cdots, 3N_{AP} \tag{26}$$

where (25) represents the AP coordinate point that is initially generated. x_{max} , y_{max} , x_{min} and y_{min} are the range of deployment area, *rand*() returns a random number uniformly distributed in the range of (0,1).

Step 2, generate the speed $V_w^{(l)}$ (w=1, 2, ..., $3N_{AP}$) of each particle and initialize the $V_w^{(l)}$=0.

Step 3, the MOPSO algorithm needs to calculate objective (f_1, f_2) of every particle and store the positions of the particles that satisfy all objectives in REP.

Step 4, let the optimal position of each particle $W^{(l,local)}$ be the initial position of these particles.

Step 5, generate hypercubes of the search space explored so far as a coordinate system to locate the particles whose coordinates are defined according to the values of its objective functions (f_1 and f_2).

Step 6, the hypercubes which contain more than one particle will be generated a fitness value. This value is the result of dividing any number which is more than 1 by the number of particles that the hypercube contains. Then, the paper uses roulette wheel selection to select the hypercube according to these fitness values. Once, the hypercube is selected, the algorithm selects randomly a particle from them as the global optimal position $W^{(global)}$.

Step 7, update the position of each particle $W^{(l)}$ and $V^{(l)}$ as follows: In each iteration, $W^{(global)}$ and $W^{(l,local)}$ are updated. The velocity and location of the particles are calculated based on these two variables. The velocity term $V_w^{(l)}$, is updated in each iteration t as follows:

$$V_w^{(l)}(t) = \varphi V_w^{(l)}(t-1) + c_1\phi_1\left(W_w^{(l,local)}(t-1) - W_w^{(l)}(t-1)\right)$$
$$+ c_2\phi_2\left(W_w^{(global)}(t-1) - W_w^{(l)}(t-1)\right) \tag{27}$$

where φ is the inertia weight that controls the speed of convergence, which is usually chosen between 0.8 and 1.2. c_1 and c_2 are the size of step that the particle in each iteration for local learning coefficients and global learning coefficients. In this paper, let $c_1 = c_2 = 2$. ϕ_1 and ϕ_2 are the positive number for each w (i.e., the element of vector $W_w^{(l)}$). Then $W_w^{(l)}$ is updated as follows:

$$W_w^{(l)}(t) = W_w^{(l)}(t-1) + V_w^{(l)}(t-1) \tag{28}$$

Step 8, recalculate the objective function (f_1, f_2) of each particle. If the new solution dominates the $W^{(l,local)}$ of the particle itself, the $W^{(l,local)}$ will be replaced. If the new solution is independent of the $W^{(l,local)}$ of the particle itself, the $W^{(l,local)}$ will random select one solution from them.

Step 9, this paper uses the adaptive grid method [25] to update REP and selects the solution that minimizes the objective functions f_1 and f_2 as the $W^{(global)}$ from REP.

Step 10, the algorithm needs to calculate the following fitness function U for each particle l at each iteration. U is related to U_1, U_2 and U_3:

$$U_1 = -\sum_{k=1}^{N_{subarea}}\left(\sum_{m=1}^{N_{AP}} N_{user}\rho^{(l)}_{m,k} - \eta D(k)A(k)\right), l=1,2,\cdots\cdots,L \tag{29}$$

$$U_2 = \begin{cases} -\sum_{n=1}^{N}\gamma_n & \text{if (3) is satisfied by each } l \\ 0 & \text{else} \end{cases} \tag{30}$$

$$U_3 = p_i - P_{threshold}, i = 2N_{AP} + 1, 2N_{AP} + 2, \cdots\cdots, 3N_{AP} \tag{31}$$

U_1 function calculates the difference between the number of users served by particle l and the minimum number of users that must be served. In order to ensure that there is sufficient service capacity, the value of U_1 should be less than 0. U_2 function calculates the number of users served by AP. If the AP capacity constraint expressed in (3) is not satisfied, U_2 is equal to 0. According to the (7b), U_2 should be less than $-N_{ref}$. U_3 function ensures that the AP's transmit power is not higher than the given power threshold and the value of U_3 should be less than 0. The update process of U is shown as **Fig. 3**.
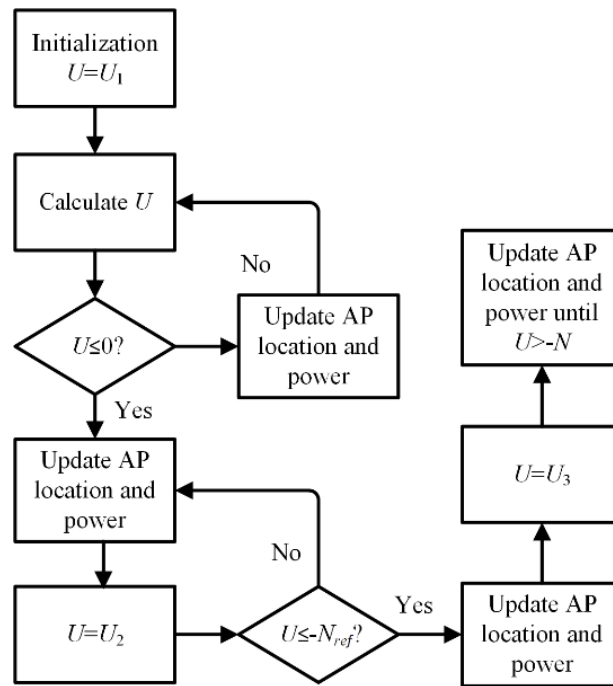

Fig. 3. Update process of fitness function U

Step 11, the above process is repeated until the target is reached. Otherwise, the process will jump to step 6. In addition, this paper also sets the maximum number of iterations. If the maximum number of iterations is reached, the process also will be stopped. Finally, the optimal solution of AP location and power $W^{(global)}$ can be obtained through the REP.

4.3 AP redundancy elimination

After determining the position and transmit power of the APs using MOPSO, greedy algorithm for elimination of redundant APs will be proposed. If all the capacity of system, coverage, and user's energy efficiency constraints are not affected, the AP should be removed. In other words, if any optimization problem constraint (i.e. (29), (30) and (31)) is affected by the removed AP, the AP must be kept and assumed indispensable for a safe network operation.

The parameter ϖ is used to represent the status of each AP and the length is N_{AP}. The set K is used to store the removed AP. In addition, the algorithm first assumes that all the APs cannot be removed (i.e., $\varpi = [1, 1, \cdots\cdots, 1]$). In the next step, it removes an AP from these APs and then checks whether the constraints are still satisfied or not at each time. If the mth AP can be

removed, let the value of ϖ_m be 0 and place it in set K. Otherwise, the value is 1. After checking all the APs, the next step only needs to check whether the APs in set K can be completely removed and then set their corresponding ϖ_m to 0.

All APs should not be removed from set K at the same time. Indeed, it may happen that more than one AP in set K can support each other to satisfy the coverage constraint, cell capacity constraint and energy efficiency constraint. Thus, the APs which have the least influence on served users from set K will be removed. The method of removing is as follows:

$$j^* = \arg \max \sum\nolimits_{k=1}^{N_{subarea}} \sum\nolimits_{m=1, m \neq j^*}^{N_{AP}} \left(N_{user} \rho_{m,k} - \eta D(k) A(k) \right) \tag{32}$$

Equation (32) obtains AP_{j^*} with the smallest removal impact in set K. In other words, when AP_{j^*} is removed, the remaining APs still have the biggest difference between the number of users served and the minimum number of users that must be served. The entire process of getting ϖ_m and K is repeated until K=∅. Details of greedy algorithm for redundancy elimination of APs in Algorithm 1.

Algorithm 1 Greedy algorithm for elimination of redundant APs.

1. t=0.

2. Input the location (x, y) and transmit power of AP which are obtained from section 4.2.

3. Initialize all APs are activated $\varpi(t)$=[1,1,······ ,1], K=[]

4. **for** m=1, 2, ······, N_{AP} **then**

5.   Check the cell capacity, coverage and energy efficiency constraints as expressed in (3), (5) and (6), respectively.

6.   **if** (3), (5) and (6) are satisfied **then**

7. AP_m can be eliminated and place m into set K

8.   else

9. AP_m cannot be eliminated.

10. **end if**

11. **end for**

12. Find AP_{j^*} by (32).

13. K=K/$\{j^*\}$, and find the position j of AP_{j^*} in $\varpi(t)$.

14. $\varpi_{j^*}(t)$=0.

15. t=t+1

16. repeat step3 - step13 until K=∅.

17. Output the final location (x, y) and transmit power of AP.

5. Results and Analysis

In this section, the performance of the deployment scheme based on MOPSO algorithm and greedy algorithm in section 4 are compared with the multi-objective whale swarm optimization algorithm (MOWOA) [26, 27], PSO, grey wolf optimization (GWO) [5] and heuristic algorithm [28]. Otherwise, in order to ensure the fairness between multiple goals and single goal, the deployment scheme of PSO and GWO with the power adjustment can be used to compare with MOPSO. The deployment scheme of PSO and GWO with the power adjustment can be denoted as PSO_A and GWO_A respectively.

First, the paper uses the (19) to compute the cell radius R_{th} and then the paper obtains the total throughput according to the random geometry theory. The parameters used in the algorithm are given in **Table 1**.

Table 1. Simulation parameters

| Parameters	Value
P_b	46 dBm
λ	$10^{-5}\,m^2$
N_0	-174 dBm
R_{th}	1.2 km
α	4

The total throughput of single AP is shown in **Fig. 4**. As shown in **Fig. 4**, the numerical value can be used to estimate the number of AP service users because the numerical value is roughly consistent with the simulated value. The results show that the total throughput u=18 Mbits when the radius is 1.2 km.
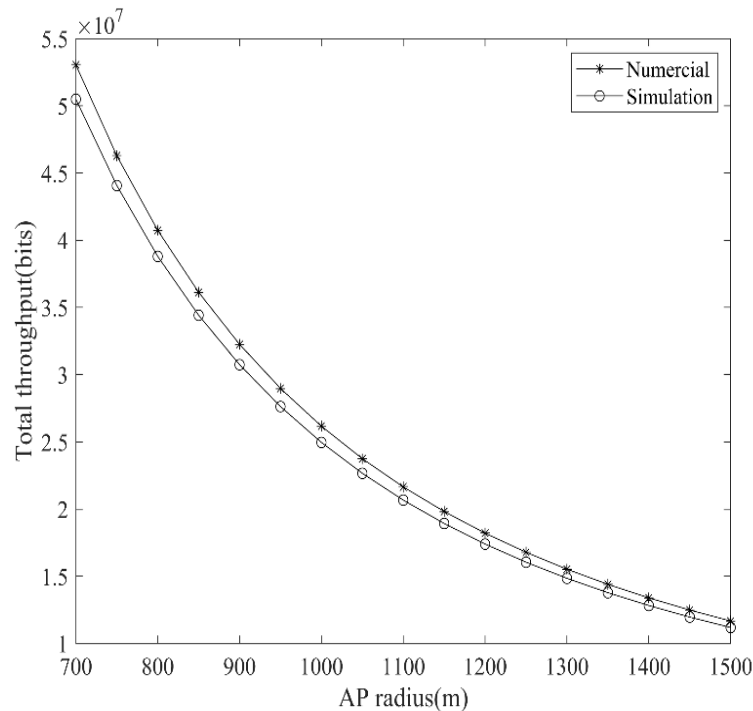
Fig. 4. Numerical and simulation value of total throughput

This paper considers a 10000×10000 (m^2) coverage area to deploy APs to serve N users. This paper defines μ as the proportion of user distribution, which represents the percentage of users to the total number in different areas. In this paper, the total area is divided into two subareas. μN users are placed in subarea1 and $(1-\mu)N$ users are placed in subarea2. Assume that the system bandwidth B is equal to 10 MHz, the range of P_b is 23 dBm - 46 dBm. In this paper, let u_{th} be 1 Mbits and N_{user} be 18.

In addition, the MOPSO algorithm is applied under the following settings: The initial population size L is 24, the η and σ are all 0.95. Moreover, the value of $V_w^{(l)}$ is between $-V_{max}$ and V_{max}. When $w \in [0, 2N_{AP}]$, let V_{max} be 500. When $w \in [2N_{AP}, 3N_{AP}]$, let be 2.7. Let $c_1=c_2=2$, ϕ_1 and ϕ_2 be the positive number and $\varphi = 0.8$. After the proposed deployment scheme, the location of APs can be shown in **Fig. 5**.

(a) $N=1000, \mu=0.8$ (b) $N=1000, \mu =0.6$
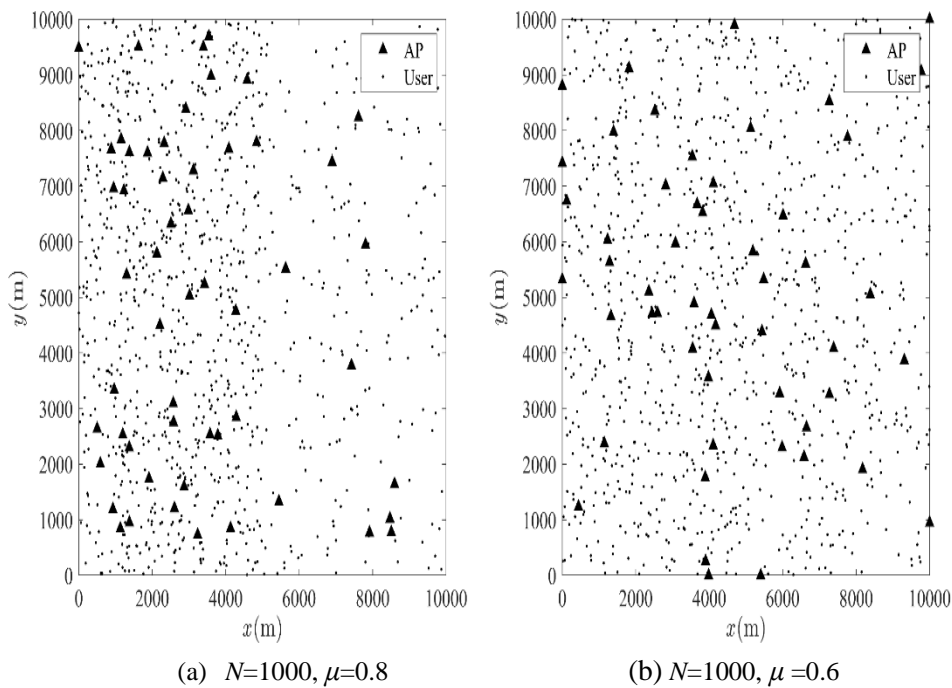
Fig. 5. AP and user location distribution with different proportion of user distribution

As shown in **Fig. 5(a)** and **Fig. 5(b)**, the proposed algorithm can deploy APs according to the density of users. 80% users are placed in the subarea1 in **Fig. 5(a)** and 60% users are placed in this area in **Fig. 5(b)** and the conclusion can also be obtained that 80% of APs are deployed in the subarea1 in **Fig. 5(a)** and 60% of APs are deployed in this area in **Fig. 5(b)** in the proposed scheme.
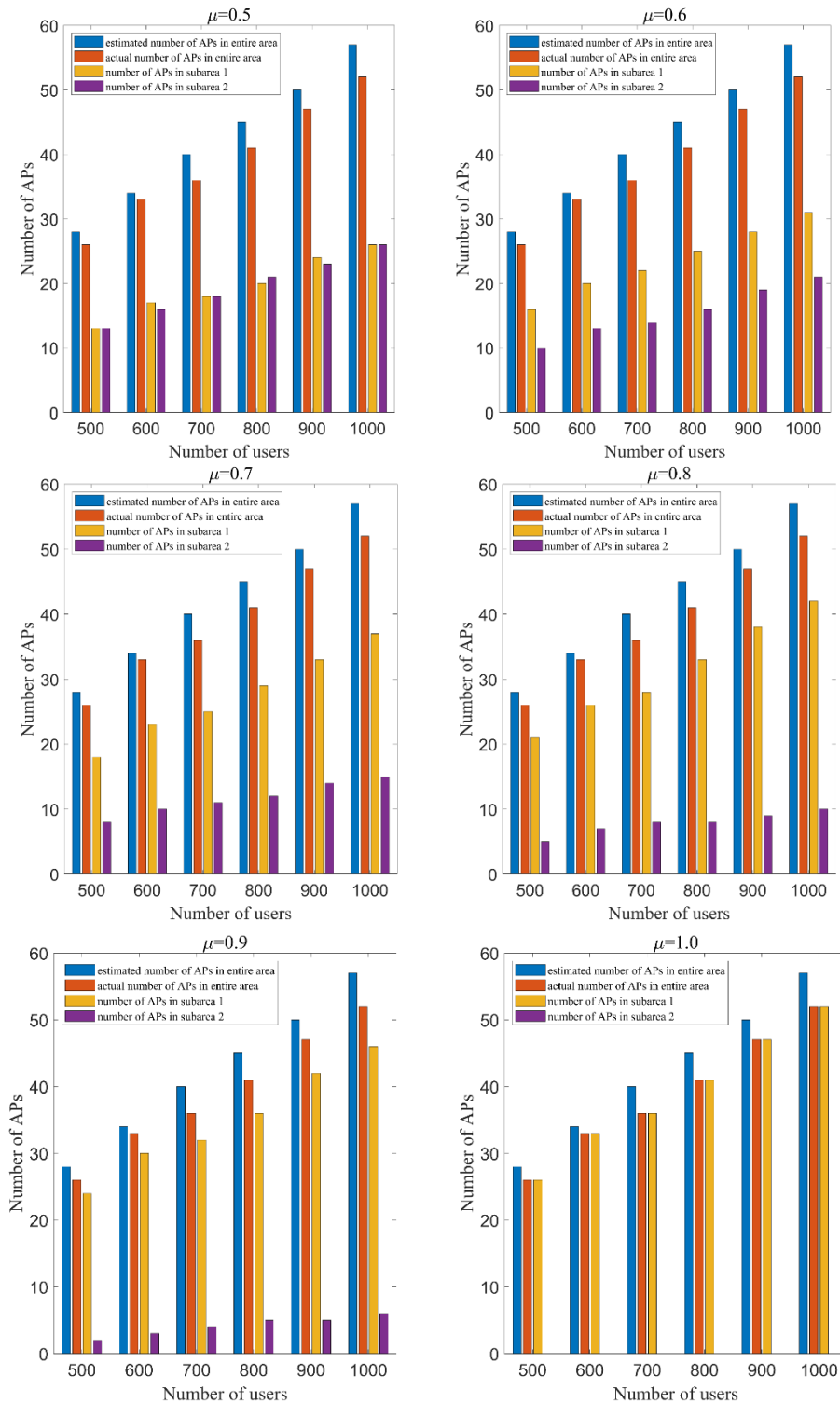
Fig. 6. Number of APs in different areas

Fig. 6 shows the number of deployed APs with different user proportion. It contains the number of estimated deployed APs, the actual number of deployed APs and the number of

APs deployed in each subarea. The first two indicators represent the total number of deployed APs in the entire area. The last indicator represents the number of deployed APs in the subarea. When the value of μ is small, it means that users are relatively evenly distributed in the subarea1 and subarea2. For example, when $\mu=0.5$, it means that users are completely evenly distributed in the two areas. This situation leads to that the number of APs in subarea1 is almost equal to the number of APs in subarea2. When μ is large, it means that the user distribution is mainly concentrated in subarea1. This situation will bring greater service pressure to APs because of large users in this area. Thus, the service rate that users get will become lower and the Qos also becomes worse in this area. In order to improve the Qos of users, the proposed scheme deploys more APs in the area where the μ is large. For example, when $\mu=0.8$, the number of APs are 43 in subarea1. This number is more than the deployed number when $\mu=0.6$. At the same time there is an extreme situation in **Fig. 6**. When $\mu=1.0$, all users are concentrated in subarea1 and no user in subarea2. Thus, all APs are placed in subarea1 and the number of APs deployed in subarea1 is equal to the actual number of deployed APs. In addition, the total number of deployed APs is less than the estimated value. For example, when $N=1000$, $\mu=0.6$ and $\mu=0.8$, the actual number of deployed APs is 54 and 53, but the estimated number of deployed APs is 57.
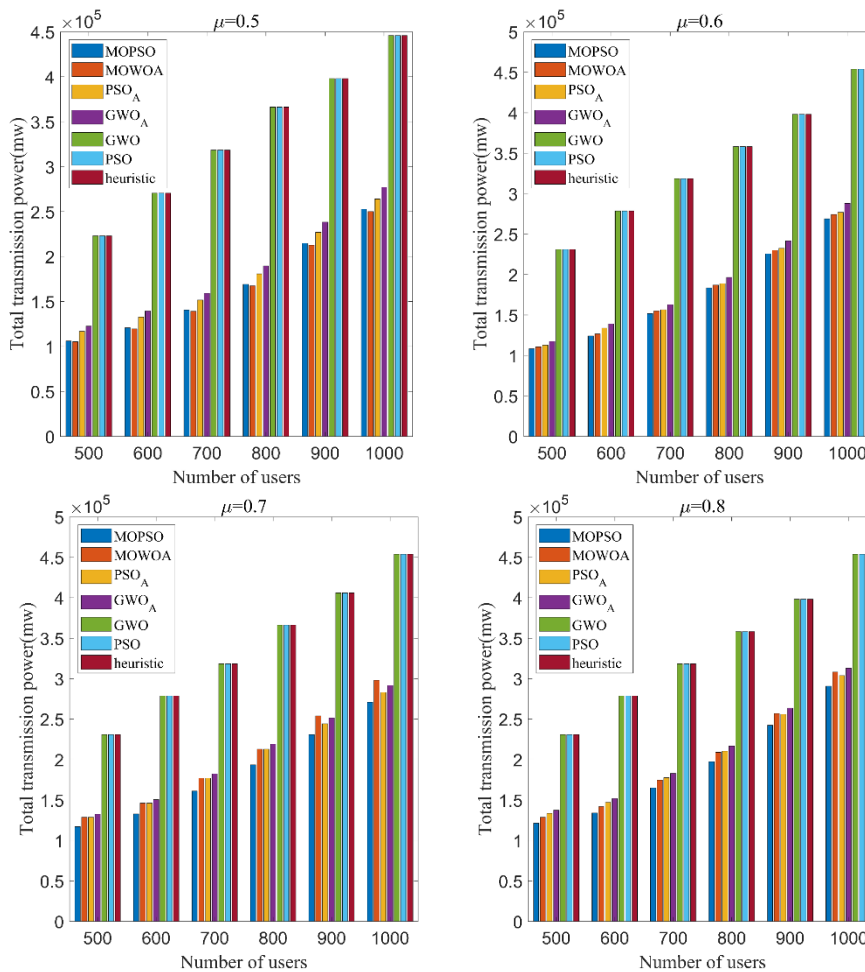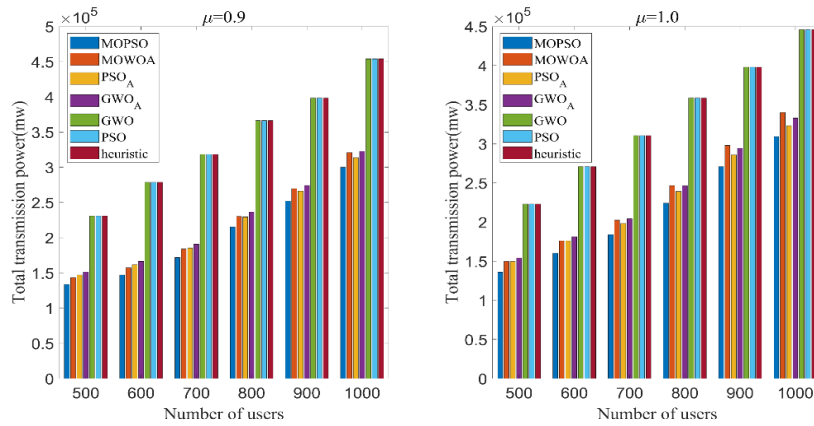
Fig. 7. Comparison of the total transmit power in different AP deployment schemes

Fig. 7 shows total transmit power in the MOPSO, MOWOA, GWO, PSO, PSO$_A$, GWO$_A$ and heuristic algorithm. Because the GWO, PSO and heuristic algorithm deployment solutions only consider the AP's capacity constraint and coverage constraint without considering the AP's transmit power constraint, the total transmit power of PSO, GWO and heuristic algorithm remain constant and the values are equal.

With the increasement of users, the total power increases to ensure user service in different schemes under different values of μ. As shown in **Fig. 7**, the total power shows an increasing trend in all deployment schemes. But the MOPSO, MOWOA, PSO$_A$ and GWO$_A$ consider the power of AP according to the AP location in the iteration, which adjust the transmit power to satisfy the energy efficiency objective and the total power objective. This method can accurately find the minimum transmit power threshold of each AP. Thus, compared with GWO, PSO and heuristic algorithm, the deployment schemes with the power adjustment have lower total power under different values of μ. Although the transmit power of PSO$_A$ and GWO$_A$ only reach one of the goals and cannot reach the above two optimization goals at the same time. Thus, the solution of the transmit powers in PSO$_A$ and GWO$_A$ is not optimal solution. As shown in **Fig. 7**, the total powers of PSO$_A$ and GWO$_A$ are reduced to a certain extent compared with the PSO and GWO, but compared with MOPSO and MOWOA, their total transmit powers are still higher. It also can be seen from **Fig. 7** that the deployment scheme with MOPSO has lower total transmit power by comparing with the MOWOA.

As shown in **Fig. 7**, because the proposed scheme considers each AP, it flexibly provides the user required power to satisfy the rate threshold. Generally speaking, the more uniform the distribution of users, the more balanced the load on the AP. It is not easy to happen that some APs serve massive users and others serve little users. The number of users who are served by each AP is almost equal and the AP load is more balanced. The users will get better service rate from AP. Thus, when the value of μ is small, the AP can be configured with lower transmit power to satisfy the user's requirements for APs. For instance, when $\mu=0.6$, the value of total transmit power based on MOPSO is almost 40%-50% less than the value of comparison scheme based on PSO, GWO and heuristic algorithm. The value of total transmit power obtained by MOPSO can be reduced by almost 2%-4%, 3%-5%, 5%-7%, comparing with MOWOA, PSO$_A$ and GWO$_A$, respectively. However, if the $\mu=0.8$, the value of total transmit power based on MOPSO is almost 35%-47% less than the value of comparison scheme based on PSO, GWO and heuristic algorithm. The value of total transmit power obtained by MOPSO can be reduced by almost 4%-6%, 5%-6%, 5%-7%, comparing with MOWOA, PSO$_A$ and GWO$_A$, respectively.
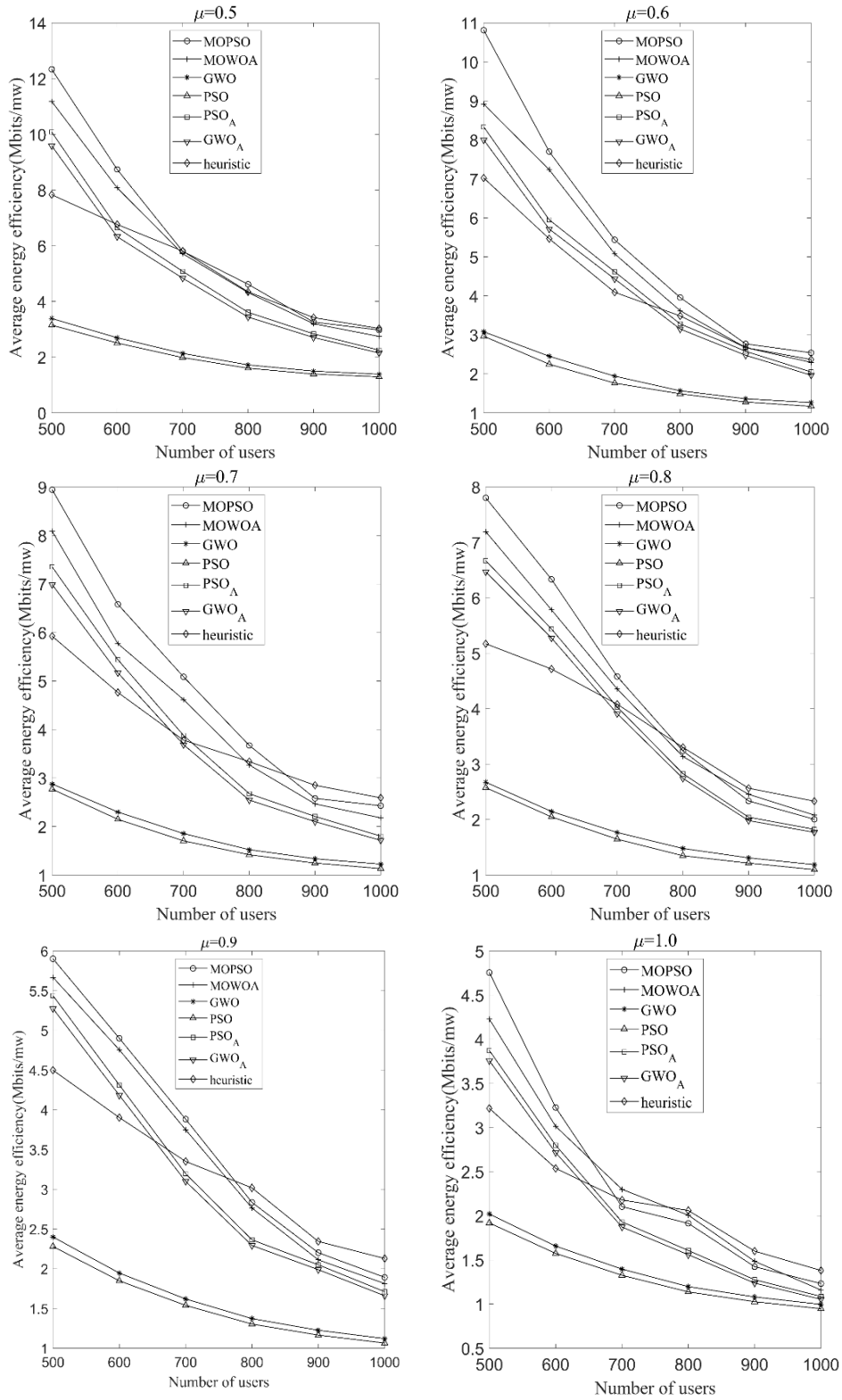
Fig. 8. Comparison of the energy efficiency in different AP deployment schemes

Fig. 8 shows the average EE in different deployment schemes. It is noted that this value of the EE is the average of each user's EE. With the increasement of users, the AP needs more energy to provide users with the same service, which is the reason of the decrease of energy efficiency.

As shown in **Fig. 8**, the EE of MOPSO deployment scheme is higher than the MOWOA, GWO, PSO, PSO_A and GWO_A deployment scheme under different user distribution ratios. If the users served in the AP is small, the improvement in energy efficiency is huge. When the number of users are equal to 500, the EE increases almost 100%-200% compared with the GWO and PSO. However, when the number of users is equal to 1000, the EE increases almost 10%-40% compared with the GWO and PSO under different user distribution ratios. Under the same number of users, the EE increases 5%-10% compared with PSO_A and GWO_A. This is because the number of users increases and the load on the AP also increases. Thus, the average transmit rate obtained by users decreases and affects the value of EE.

From the comparison results between MOPSO deployment scheme and MOWOA deployment scheme, when the number of users is equal to 500, the EE of MOPSO increases about 7%-25%, comparing with the MOWOA. When the the number of users is equal to 1000, the EE increases about 1%-2%. Thus, the performance of the proposed scheme is higher than the MOWOA deployment scheme**.**

It also can be seen from **Fig. 8** that the EE of MOPSO is also different under the different user distribution ratios. When μ=1.0, all users are distributed in one area and the situation of AP's load imbalance happened. Since the users are too concentrated, the scheme will deploy a large number of APs in the area. In addition, the users always choose APs that are closer to themselves and have better signal strength. It is easy to cause the situation that the choosen AP has served massive users and influenced the data rate obtained by users. APs in this area need more energy to provide services for these users. That is the reason that the user's EE will decrease if the value of μ is large. As decreases, the users are distributed evenly and the load of APs is gradually balanced, meantime, the EE of user gradually increase.

From the comparison results between MOPSO and heuristic algorithm, when the number of users is less than 800, the EE of MOPSO is higher than the heuristic algorithm and the total transmit power of MOPSO is lower than the heuristic algorithm under different values of μ. It is because that two algorithms have different ways to find the optimal solution. The heuristic algorithm deploys AP based on its coverage. The entire area is divided into many small areas and each small area has an AP. Because the distribution of APs is proportional to μ in MOPSO, the smaller the μ is, the more even APs distribution is. When μ is small, the distributions of APs in MOPSO and heuristic algorithm are even, the pathloss of transmit power is similar. But the heuristic algorithm cannot adjust the transmit power, the power is higher than the MOPSO as shown in **Fig. 7**. Due to the number of users is small, the APs in MOPSO use a lower power value to satisfy the needs of users compared with heuristic algorithm. Thus, the EE of MOPSO is higher when the number of users is less than 800.

However, when the number of users is more than 800, the EE of MOPSO is lower or equal to EE of the heuristic algorithm. As shown in **Fig. 8**, when the μ is less than 0.7, the EE of MOPSO is equal to the heuristic algorithm under the number of users is more than 800. When the μ is more than 0.7, the EE of MOPSO decreases by 5%-7% compared with the heuristic algorithm under the same number of users. One reason is that the distribution of APs in MOPSO is concentrated as the value of μ increases and the interference from other AP becomes larger compared with heuristic algorithm. That leads to a reduction in the transmit power which is obtained by users. Otherwise, the transmit power of heuristic algorithm is always higher than the MOPSO. Thus, the power obtained by users in MOPSO is less than it

obtained in heuristic algorithm. When the number of users is large, the heuristic algorithm can provide more power to serve users and the users obtain higher rate than that of MOPSO. Thus, the EE of MOPSO is lower than the heuristic algorithm when the number of users is more than 800.

In summary, the proposed deployment scheme based on MOPSO is superior to MOWOA, PSO, GWO and heuristic algorithm deployment scheme in terms of power consumption and energy efficiency. The proposed deployment scheme can reduce transmit power about 2%-7% and increase energy efficiency about 2%-25%, comparing with MOWOA. The proposed deployment scheme reduces transmit power at most 50% and increases energy efficiency at most 200%, comparing with PSO and GWO. Although the EE of MOPSO decreases by 5%-7%, comparing with the heuristic algorithm when the number of users is large, the total power consumption of the heuristic algorithm is 40%-50% higher than that of MOPSO.

6. Conclusion and Future Work

This paper introduces a novel AP deployment optimization scheme based on swarm intelligence algorithm. First, the random geometry theory is selected to evaluate the performance of a single AP and estimate the number of APs that need to be deployed in the given area. Then, the proposed scheme obtains the optimal position and optimal transmit power based on the MOPSO algorithm. Finally, in order to reduce the redundancy of APs, a greedy algorithm is used.

The performance of the AP deployment scheme based on MOPSO algorithm and greedy algorithm is validated by comparing with the scheme based on MOWOA, PSO, GWO and heuristic algorithm. From the analysis results, the proposed scheme has lower transmit power and higher energy efficiency.

However, this paper only considers the deployment scheme of the AP's location and transmit power. In terms of actual deployment, the change in power will also cause the delay to change. In the future, the impact of transmit delay can be considered to optimize the AP deployment.

References

[1] Y. Liu, W. Huangfu, H. Zhang, H. Wang, W. An, and K. Long, "An efficient geometry-induced genetic algorithm for base station placement in cellular networks," *IEEE Access*, vol. 13, pp. 108604-108616, Aug. 2019. Article (CrossRef Link)

[2] C. T. Cicek, H. Gultekin, B. Tavli, and H. Yanikomeroglu, "UAV base station location optimization for next generation wireless networks: Overview and future research directions," in *Proc. of the 1ˢᵗ International Conference on Unmanned Vehicle Systems-Oman*(*UVS*), pp. 1-6, 2019. Article (CrossRef Link)

[3] H. Dai, H. Zhang, B. Wang, and L. Yang, "The multi-objective deployment optimization of UAV-mounted cache-enabled base stations," *Physical Communication*, vol. 34, pp. 114-120, June 2019. Article (CrossRef Link)

[4] H. Wang, H. Zhao, W. Wu, D. Ma, and J. Wei, "Deployment algorithms of flying base stations: 5G and beyond with UAVs," *IEEE Internet of Things Journal*, vol. 6, no. 6, pp. 10009-10027, Dec. 2019. Article (CrossRef Link)

[5] H. Ghazzai, E. Yaacoub, M. S. Alouini, Z. Dawy, and A. Abu-Dayya, "Optimized LTE cell planning with varying spatial and temporal user densities," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 3, pp. 1575-1589, Mar. 2016. Article (CrossRef Link)

[6] N. T. Hanh, H. T. T. Binh, N. X. Hoai, and M. S. Palaniswami, "An efficient genetic algorithm for maximizing area coverage in wireless sensor networks," *Information Sciences*, vol. 488, pp. 58-75, July 2019. Article (CrossRef Link)

[7] A. Anurag, R. Priyadarshi, A. Goel, and B. Gupta, "2-D coverage optimization in WSN using a novel variant of particle swarm optimization," in *Proc. of the 7th International Conference on Signal Processing and Integrated Networks*(*SPIN*), pp. 663-668, 2020. Article (CrossRef Link)

[8] D. Wu, Z. Kong, S. Cen, and X. Jin, "Novel access point deployment method in WIFI convergence network," *Journal of Zhe Jiang University* (*Engineering Science*), vol. 53, no. 9, pp. 1805-1814, Sep. 2019. Article (CrossRef Link)

[9] Z. Fu, X. Hu, X. Wang, C. Chen, and J. Li, "AP MATRIX: A new access point architecture for reliable public Wi-Fi services," in *Proc. of the International Conference on Computing, Networking and Communications*(*ICNC*), pp. 1-5, 2016. Article (CrossRef Link)

[10] H. Huang, A. V. Savkin, M. Ding, and M. A. Kaafar, "Optimized deployment of drone base station to improve user experience in cellular networks," *Journal of Network and Computer Applications*, vol. 144, pp. 49-58, Oct. 2019. Article (CrossRef Link)

[11] C. Zhang, Z. Liu, B. Gu, K. Yamori, and Y. Tanaka, "Wireless LAN access point deployment and pricing with location-based advertising," in *Proc. of the 13th International Conference on Network and Service Management*(*CNSM*), pp. 1-7, 2017. Article (CrossRef Link)

[12] H. Huang, C. Huang, and D. Ma, "A method for deploying the minimal number of UAV base stations in cellular networks," *IEEE/CAA Journal of Automatica Sinica*, vol. 7, no. 2, pp. 559-567, Mar. 2019. Article (CrossRef Link)

[13] Y. Zhao, D. Wang, J. Hu, and K. Yang, "H-AP deployment for joint wireless information and energy transfer in smart cities," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 8, pp. 7485-7496, Aug. 2018. Article (CrossRef Link)

[14] G. Garcia, H. I. D. Monego, M. E. Pellenz, R. D. Souza, A. Munaretto, and M. S. P. Fonseca, "An iterative heuristic approach for channel and power allocation in wireless networks," *Annals of Telecommunications*, vol. 73, no. 5, pp. 293-303, June 2018. Article (CrossRef Link)

[15] B. P. Tewari and S. C. Ghosh, "Efficient AP Placement Through Power Control and Partially Overlapping Channel Assignment," *Wireless Personal Communications*, vol. 110, no. 1, pp. 223-244, Jan. 2020. Article (CrossRef Link)

[16] F. T. Hsu and H. J. Su, "When does the AP deployment incentivize a user to offload cellular data: An energy efficiency viewpoint," in *Proc. of the 6th International Symposium on Communications, Control and Signal Processing*(*ISCCSP*), pp. 210-213, 2014. Article (CrossRef Link)

[17] J. G. Andrews, F. Baccelli, and R. K. Ganti, "A tractable approach to coverage and rate in cellular networks," *IEEE Transactions on Communications*, vol. 59, no. 11, pp. 3122-3134, Nov. 2011. Article (CrossRef Link)

[18] W. Nie, X. Wang, F. C. Zheng, and W. Zhang, "Energy-efficient base station cooperation in downlink heterogeneous cellular networks," in *Proc. of the IEEE Global Communications Conference*, pp. 1779-1784, 2014. Article (CrossRef Link)

[19] L. Pei, J. Huilin, P. Zhiwen, and Y. Xiaohu, "Energy-delay tradeoff in ultra-dense networks considering BS sleeping and cell association," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 1, pp. 734-751, August 2017. Article (CrossRef Link)

[20] W. Sun, Y. Ge, Z. Zhang, and W. C. Wong, "An analysis framework for interuser interference in IEEE 802.15. 6 body sensor networks: A stochastic geometry approach," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 10, pp. 8567-8577, Nov. 2015. Article (CrossRef Link)

[21] C. A. C. Coello, G. T. Pulido, and M. S. Lechuga, "Handling multiple objectives with particle swarm optimization," *IEEE Transactions on Evolutionary Computation*, vol. 8, no. 3, pp. 256-279, June 2004. Article (CrossRef Link)

[22] T. Zhang, J. Liang, Y. Yang, G. Cui, L. Kong, and X. Yang, "Antenna deployment method for multistatic radar under the situation of multiple regions for interference," *Signal Processing*, vol. 143, pp. 292-297, Feb. 2018. Article (CrossRef Link)

[23] Y. Yang, T. Zhang, W. Yi, L. Kon, X. Li, B. Wang, and X. Yang, "Deployment of multistatic radar system using multi-objective particle swarm optimisation," *IET Radar, Sonar & Navigation*, vol. 12, no. 5, pp. 485-493, May 2018. Article (CrossRef Link)

[24] N. A. B. Ab Aziz, A. W. Mohemmed, and M. Y. Alias, "A wireless sensor network coverage optimization algorithm based on particle swarm optimization and Voronoi diagram," in *Proc. of the International Conference on Networking, Sensing and Control*, pp. 602-607, 2009. Article (CrossRef Link)

[25] J. D. Knowles and D. W. Corne, "Approximating the nondominated front using the Pareto archived evolution strategy," *Evolutionary Computation*, vol. 8, no. 2, pp. 149-172, June 2000. Article (CrossRef Link)

[26] P. Jangir and N. Jangir, "Non-dominated sorting whale optimization algorithm (NSWOA): a multi-objective optimization algorithm for solving engineering design problems," *Global Journal of Research in Engineering*, vol. 17, Sep. 2017. Article (CrossRef Link)

[27] M. M. Ahmed, E. H. Houssein, A. E. Hassanien, A. Taha, and E. Hassanien, "Maximizing lifetime of large-scale wireless sensor networks using multi-objective whale optimization algorithm," *Telecommunication Systems*, vol. 72, no. 2, pp. 243-259, Mar. 2019. Article (CrossRef Link)

[28] S. Zhang and N. Ansari. "3D drone base station placement and resource allocation with FSO-based backhaul in hotspots," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 3, pp. 3322-3329, Jan. 2020. Article (CrossRef Link)

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