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Energy-Efficient Resource Allocation for Downlink Non-Orthogonal Multiple Access Systems

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Abstract: With the rapid popularization of intelligent terminals and the explosive growth of wireless communication service demand, future mobile communication technology will face many challenges. Non-orthogonal multiple access (NOMA) technology for 5G can provide many connections and effectively improve the frequency spectrum and energy efficiency compared to traditional orthogonal multiple access technologies. Therefore, in recent years, NOMA technology has become one of the research hotspots of numerous scholars. However, the resource allocation problem in the NOMA system, as a high-dimensional nonlinear programming problem, has not been well studied. In addition, the particle swarm optimization algorithm can also effectively find the optimal solution for complex and constrained problems. Still, at the same time, it is easy to fall into local optimal defects. In this context, we decouple the high-dimensional nonlinear programming problem to maximize system energy efficiency into sub-problems: subchannel and power allocation. Firstly, a low-complexity greedy algorithm based on the principle of worst-case subchannel priority matching is proposed to solve the subchannel assignment problem. In addition, we further apply the modified particle swarm optimization algorithm to allocate power to the NOMA downlink system, aiming to improve the energy efficiency of the communication system as much as possible under the premise of ensuring the quality of service (QoS). Simulation results show that our proposed scheme has low complexity and can significantly improve the energy efficiency of the NOMA system and achieve better user fairness.

Keywords: non-orthogonal multiple access; energy efficiency; greedy algorithm; particle swarm optimization

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1. Introduction

1.1. Preliminaries

With the continuous explosion of traffic and the increasing number of intelligent devices, the 5th generation (5G) technology is being driven to develop at high speed [1–3]. The first four generations of mobile communication systems adopted orthogonal multiple access (OMA) technology to keep the receiving cost low and achieve good system throughput. The interference between users in an orthogonal multiple access scheme is relatively small, and user detection is convenient. However, different users need to have orthogonality when sharing communication resources, which significantly restricts the number of users carried by the system, resulting in low spectral efficiency. Compared with 4G, 5G will increase spectrum efficiency by 100–1000 times, increase capacity by 10–100 times, and support diverse QoS. To adapt to the requirements of 5G ultra-high spectrum efficiency and system capacity, experts and scholars from various countries have actively studied advanced wireless communication technologies [4,5]. Among these technologies, non-orthogonal multiple access (NOMA) technologies have become one of the candidates for the next-generation communication system due to their excellent performance [6–10]. The main idea of NOMA technology is to use power multiplexing technology at the transmitter end and actively introduce interference, multiplex superimposed signals for transmission. It eliminates the multiple-access interference through the serial interference canceling (SIC) receiver [11], thus achieving correct demodulation for multiple users. However, interference between users in NOMA can significantly affect system performance. Based on ensuring user access fairness, using reasonable user grouping and power allocation algorithm can improve the total rate of the NOMA system [12,13]. Therefore, studying NOMA technology's critical technology and resource allocation algorithm can effectively enhance resource utilization and system capacity, which has important significance and application value.

1.2. Related Work

Since 5G is committed to achieving communication with higher speed, larger capacity, and ultra-low delay, in previous studies, many scholars have devoted themselves to studying how to improve the system rate. To further enhance the spectral efficiency, the author in [14] combined multiple input multiple output (MIMO) technology with a non-orthogonal multiple access system. Furthermore, they transformed the weighted sum rate maximization problem, constructed auxiliary variables, and proposed an iterative algorithm. Compared with the MIMO-NOMA system with an equal power allocation algorithm, the MIMO-NOMA system with the proposed algorithm has a higher weighted sum rate. The authors in [15] studied multi-user systems and rate maximization under perfect CSI. Firstly, the author proposed a sub-optimal low complexity subchannel allocation scheme to allocate each user to the appropriate subchannel. Secondly, the fractional transmit power allocation (FTPA) algorithm was used between subchannels, and the closed form solution of power allocation of multiplexing users was obtained by constructing the Lagrange function in subchannels. Aiming to maximize the weighted sum rate, some scholars studied the subchannel and the power allocation of the multi-carrier non-orthogonal multiple access (MC-NOMA) system in [16,17].

In recent years, the wireless network energy consumption has been enormous, and effectively using resources to achieve green communication is imminent [18]. The author of [19], taking into account the incomplete CSI, transformed the probability problem of maximizing the energy efficiency of the downlink NOMA heterogeneous network into a non-probability problem. They obtained the approximate solution of the power allocation factor through the dichotomous search algorithm and convex sequence programming. In [20], the authors proposed multi-objective joint optimization problems, such as improving spectral efficiency, meeting transmission power constraints, and improving energy efficiency. In addition, the dual technique was used to solve the problem. However, when evaluating the performance of this scheme, the authors only introduced the implementation effect separately. There were no comparisons and explanations with other methods. Aiming to maximize the energy efficiency of the NOMA system, the authors solved the non-convex optimization problem by subchannel-user matching and power allocation step by step in [21]. Based on the matching theory, this paper proposes a suboptimal sub-channels bidirectional matching algorithm with users. The main idea of the algorithm is that the user, according to the channel gain of each channel on the descending sequence to the highest priority sub-channels, post-matches the request according to whether the current maximum subchannels reject or accept based on the energy efficiency. Although the algorithm can obtain good matching results, the user can only passively select the sub-channel with poor channel quality at the later stage of the user and sub-channel assignment.

Due to the relatively high complexity and high computational overhead of previous resource allocation schemes, many researchers have begun to apply heuristic algorithms with increased flexibility and low complexity to the resource allocation problem [22–24]. Compared with exact algorithms, heuristic algorithms are not guaranteed to find the best solution. However, they can discover near-optimal solutions with appropriate resources. Among them, the particle swarm optimization algorithm (PSO), which was first proposed by Dr. Eberhart and Dr. Kennedy in the study of the flight foraging behavior of birds, is a swarm intelligence optimization algorithm [25,26]. In [27], the authors proposed to apply the particle swarm optimization algorithm to the orthogonal frequency division multiplexing access (OFDMA) adaptive resource allocation problem. In addition, this paper creatively presented a re-selection mechanism to solve the problem that PSO is prone to fall into the local optimum so that the users with more significant channel gain can match subchannels with greater probability. In [28], aiming at the device-to-device (D2D) underlying cellular network, the author proposed a PSO algorithm to reasonably allocate user power to ensure the minimum user rate. Compared with the random and fixed power allocation algorithms, the proposed algorithm can maximize the throughput of cellular networks. However, the application of this algorithm in multi-cell scenarios remains to be studied. In [29], to ensure the system's spectral efficiency and maximize the system's energy efficiency, the author combined the cycle strategy rotation with the particle swarm optimization algorithm to allocate the downlink power of the NOMA system. In [30], the authors studied how to distribute power to maximize the throughput of a single input single output (SISO) NOMA system. In this paper, the authors proposed a power allocation scheme that distributed power equally to the subchannels and used a particle swarm optimization algorithm to allocate power to the subchannels. The two methods significantly improve system throughput and fairness between users compared to the water-filling-based method. Because the Doppler frequency shift easily exists in the downlink MIMO-OFDM high-speed railway system, it is necessary to consider the inter-carrier interference to maximize the system throughput under this background. For this mixed integer nonlinear programming problem, the author in [31] proposed to use the quantum-behaved particle swarm optimization (QPSO) algorithm to find the sub-optimal solution. In [32], that particle swarm optimization algorithm was also applied to the power allocation of uplink NOMA millimeter-wave (mmWave) communications. The NOMA mmWave system of the proposed solution performs significantly better than OMA, but the practical value of the approach is not high due to the two-user setup. In [33], the author improved the particle swarm optimization algorithm by adding a genetic algorithm to the particle swarm optimization algorithm and used it to solve the adaptive resource allocation problem of the cognitive radio system. The simulation results show that this novel power allocation algorithm has a better resource allocation effect and can adapt to the adaptive task of cognitive radio in different communication scenarios.

1.3. Contributions and Structure of the Paper

Based on the above research, to ensure the quality of service of users and satisfy the transmission power constraint, we propose a novel resource allocation scheme to maximize the energy efficiency of the NOMA downlink system. First, to ensure users' fairness and improve the data rate of users with poor channel quality, we propose a low complexity greedy algorithm to allocate subchannels. Secondly, given the problem that the existing particle swarm optimization algorithm is prone to fall into local optimization and the later search accuracy is not high, we modify the algorithm. Finally, we use the modified particle swarm optimization algorithm to solve the power allocation problem between and within subchannels.

The subsequent arrangement of the article is as follows. Section 2 introduces the NOMA downlink system model and proposes the optimization problems we need to solve. In Section 3, we first introduce our proposed low complexity subchannel allocation algorithm. Then we explain the improvement measures of the particle swarm optimization algorithm. Finally, we present how to use the improved particle swarm optimization algorithm for power allocation. In Section 4, we analyze the simulation results of the proposed scheme. Finally, Section 5 is the conclusion of this paper.

2. System Model and Problem Formulation

2.1. System Model

We consider a single-cell multiuser NOMA downlink system in which the base station is located in the center of the cell, and the users are distributed randomly. The system model diagram is shown in Figure 1. In this system, M users are allocated to N subchannels, and the maximum number of users multiplexed per subchannel is $M_n = M/N$. The total bandwidth of the system is equally divided into orthogonal subchannels; that is, the bandwidth of each subchannel is $B_s = B/N$. Additionally, the mth user is denoted as U_m, while the nth subchannel is denoted as SC_n. $U_{m,n}$ represents the mth user on SC_n. In this NOMA system, we assume that the channel state information can be obtained by channel estimation, and the superposition information sent to each subchannel is independent. Then the transmitted superposed signal by the BS on SC_n is

$$x_n = \sum_{m=1}^{M_n} \sqrt{p_{m,n}} x_{m,n} \tag{1}$$

where $p_{m,n}$ is the power allocated to $U_{m,n}$, $x_{m,n}$ is the signal sent by user U_m on SC_n. $p_n = \sum\limits_{m=1}^{M_n} p_{m,n}$ indicates the transmit power on the subchannel n. When the superimposed signal is transmitted to the receiving end through the channel, the received signal of $U_{m,n}$ is given by

$$y_{m,n} = h_{m,n} x_n + z_{m,n} = \sqrt{p_{m,n}} h_{m,n} x_{m,n} + h_{m,n} \sum_{i=1, i \neq m}^{M_n} \sqrt{p_{i,n}} x_{i,n} + z_{m,n} \tag{2}$$

where $h_{m,n}$ is the channel gain from the base station to $U_{m,n}$. The additive white Gaussian noise (AWGN) is represented by $z_{m,n}$ with zero mean and σ_n^2 variance, that is, $z_{m,n} \sim \mathcal{CN}(0, \sigma_n^2)$.

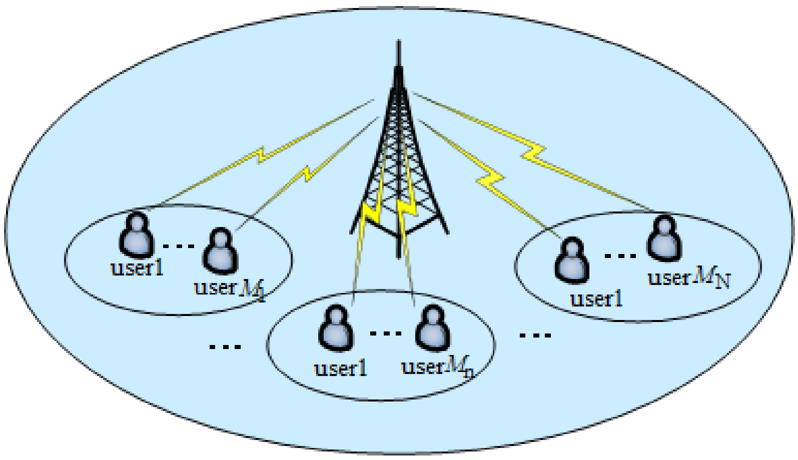

Figure 1. Downlink multicarrier NOMA system model.

Since NOMA multiplexes several users on the same sub-channel, multiple users are not orthogonal to each other. Therefore, co-channel interference between users is inevitable. In this case, each user eliminates interference from other users' signals through SIC at the receiving end. Due to the users' fairness, the base station allocates less power to users with good channel conditions and more power to users with poor channel conditions. The SIC performs data decisions on a plurality of users according to the user power in the received signal. In this process, once the SIC demodulates a user, the interference caused by the signal is subtracted. This operation is generally performed according to the increasing order of channel response normalized by noise (CRNN). In this system, we assume that

$|H_{1,n}| \geq |H_{2,n}| \geq \cdots \geq |H_{m,n}| \geq |H_{m+1,n}| \geq \cdots \geq |H_{M_n,n}|$ and $H_{m,n} = |h_{m,n}|^2/\sigma_n^2$. After SIC demodulation, in accordance with Shannon's capacity law, the swallow volume of $U_{m,n}$ can be written as

$$R_{m,n} = B_s \log_2\left(1 + \frac{p_{m,n}H_{m,n}}{1 + H_{m,n}\sum_{i=1}^{m-1} p_{i,n}}\right) = B_s \log_2(1 + SINR_{m,n}) \tag{3}$$

Then, the sum rate of the SC_n can be written as

$$R_n = B_s \sum_{i=1}^{M_n} \log_2(1 + \mathrm{SINR}_{i,n}) \tag{4}$$

2.2. Problem Formulation

For the downlink NOMA network, this paper considers the case that any subchannel only allocates two users. Let the multiplexing user on SC_n be $U_{1,n}$ with good channel condition and $U_{2,n}$ with poor channel condition respectively, and $|H_{1,n}| \geq |H_{2,n}|$. In this case, the throughput of $U_{1,n}$ and $U_{2,n}$ can be expressed as

$$R_{1,n} = B_s \log_2(1 + \alpha_n p_n H_{1,n}) \tag{5}$$

$$R_{2,n} = B_s \log_2\left(1 + \frac{(1-\alpha_n)p_n H_{2,n}}{1 + \alpha_n p_n H_{2,n}}\right) = B_s \log_2\left(\frac{1 + p_n H_{2,n}}{1 + \alpha_n p_n H_{2,n}}\right) \tag{6}$$

where $\alpha_n \in (0,1)$ is the power distribution scaling factor of $U_{1,n}$. Then, the throughput of subchannel SC_n is expressed as

$$R_n = R_{1,n} + R_{2,n} \tag{7}$$

Therefore, we formulate the energy efficiency optimization problem of the NOMA downlink system as follows:

$$\eta : \max_{p_n > 0} \sum_{n=1}^{N} \left(\frac{R_{1,n} + R_{2,n}}{p_n + p_c}\right) \tag{8}$$

$$\begin{aligned} s.t. \quad & C_1 : R_{m,n} \geq R_{\min}, \forall m \in M_n, n \in N \\ & C_2 : \sum_{n=1}^{N} p_n \leq P_{tot}, \forall n \in N \end{aligned} \tag{9}$$

Among them, p_c represents the power loss of the subchannel, and P_{tot} represents the total transmit power of the base station. The constraint C_1 indicates the minimum data rate for each user to meet the quality of service (QoS) requirements, and C_2 guarantees the maximum transmission power limit of the base station. It can be seen that the problem is non-convex and NP-hard, so it is difficult to find the optimal global solution directly. In order to solve this problem efficiently, we decouple it into two subproblems: subchannel allocation and power allocation. We use a stepwise approach to find the suboptimal solution of the problem.

3. Proposed Algorithm

3.1. Subchannel Assignment Algorithm (SAA)

The exhaustive search algorithm, as everyone knows, is the best performance for confident channel assignment. However, it needs to traverse all users; that is, the complexity increases exponentially with the increase in the number of users and the number of subchannels. High complexity in exchange for performance optimization is not desirable in practical applications. Inspired by [34], to reasonably allocate users and subchannels, we propose a low-complexity greedy algorithm that can not only maximize the energy efficiency of subchannels, but also improve the data rate of weak users and ensure user fairness.

To simplify the calculation, we assume that the initial power of all subchannels is equal, and the fractional power allocation algorithm is used to allocate power among the multiplexed users on each subchannel. When allocating subchannels, we propose an algorithm that first sorts the subchannels in ascending order according to the magnitude of the user's worst channel gain on each subchannel and then arranges the matching order of subchannels. When a subchannel matches, it matches the user with the most substantial channel gain on the local channel. In the following matching process, the matched users are excluded from consideration in the matching process. According to the sorting of subchannels, the next subchannel selects only the user with the best channel quality on this channel among the unmatched users. Based on the above matching principle, the remaining users will perform the next round of matching with the subchannel when all the subchannels have reached a user. This subchannel allocation algorithm ensures that the channel gain of the two matched users is as high as possible, thus helping to improve user fairness and reduce the probability of disruption. The detailed flow of the proposed subchannel allocation algorithm is shown in Algorithm 1.

Algorithm 1 Proposed Subchannel Allocation Algorithm.

Construct a channel gain matrix with M users $m \in \{1, 2, \cdots, M\}$ and N subchannels $n \in \{1, 2, \cdots, N\}$.
Construct the set $U_{unmatch}$ to record unmatched users.
while $\{U_{unmatch}\}$ is not empty **do**
    for $n = 1$ to N **do**
        To compare the channel gain of users on each sub-channel and to select the worst channel gain.
        Sort the matching order of each subchannel and the ascending order is based on the N worst channel gains selected.
    end for
    if then$|U_{unmatch}| > M/2$
        for Sorted n subchannel **do**
            Match the sorted subchannels to the user with the best channel quality on the subchannel.
            Remove the matched users from $U_{unmatch}$
        end for
    end if
    if then$|U_{unmatch}| \leq M/2$
        for Sorted n subchannel **do**
            Match the sorted subchannels to the the remained user of $U_{unmatch}$ with the best channel quality on the subchannel.
            Remove the matched users from $U_{unmatch}$
        end for
    end if
end while

In addition, to clarify the subchannel assignment algorithm in detail, we take the NOMA system with four subchannels and two users for each subchannel as an example. Assume that the channel gain matrix of four subchannels and eight users is

$$H_{4\times 8} = \begin{bmatrix} 1.32 & 5.78 & 0.67 & 1.21 & 1.06 & 4.37 & 2.15 & 2.23 \\ 0.07 & 3.21 & 0.87 & 3.54 & 1.12 & 5.01 & 1.87 & 4.33 \\ 2.38 & 1.33 & 4.20 & 2.68 & 0.84 & 1.93 & 1.70 & 1.39 \\ 1.55 & 1.96 & 5.84 & 1.02 & 3.21 & 2.10 & 1.46 & 2.79 \end{bmatrix} \quad (10)$$

where we take $SC_n \in \{SC_1, SC_2, SC_3, SC_4\}$ as the subchannel, that is, each row of the channel gain matrix. $U_m \in \{U_1, U_2, \ldots, U_8\}$ is expressed as the user, that is, each column of the channel gain matrix. The subchannel matching process is as follows:

Step 1: The channel gain of users in SC_1 is compared. The user with the worst channel gain is U_3, whose channel gain is 0.67. Similarly, the user with the worst channel gain in SC_2 is U_1, and the channel gain is 0.07. In SC_3, the user with the worst channel gain is U_5, with a channel gain of 0.84. In SC_4, the user with the worst channel gain is U_4, and the channel gain is 1.02. After the channel gain matrix has gone through the operational process in step 1, we note it as $H1$, as shown below. Similarly, after steps 2, 3 and 4, the channel gain matrix is denoted as $H2$, $H3$ and $H4$, respectively.

$$H1 = \begin{bmatrix} 1.32 & 5.78 & 0.67 & 1.21 & 1.06 & 4.37 & 2.15 & 2.23 \\ 0.07 & 3.21 & 0.87 & 3.54 & 1.12 & 5.01 & 1.87 & 4.33 \\ 2.38 & 1.33 & 4.20 & 2.68 & 0.84 & 1.93 & 1.70 & 1.39 \\ 1.55 & 1.96 & 5.84 & 1.02 & 3.21 & 2.10 & 1.46 & 2.79 \end{bmatrix} \tag{11}$$

Step 2: According to the ascending order of channel gain, the order of matching users of each subchannel is sorted. The matching sequence is SC_2, SC_1, SC_3, and SC_4. This gives the following results.

$$H2 = \begin{bmatrix} 0.07 & 3.21 & 0.87 & 3.54 & 1.12 & 5.01 & 1.87 & 4.33 \\ 1.32 & 5.78 & 0.67 & 1.21 & 1.06 & 4.37 & 2.15 & 2.23 \\ 2.38 & 1.33 & 4.20 & 2.68 & 0.84 & 1.93 & 1.70 & 1.39 \\ 1.55 & 1.96 & 5.84 & 1.02 & 3.21 & 2.10 & 1.46 & 2.79 \end{bmatrix} \tag{12}$$

Step 3: Each subchannel matches the user with the best channel quality in the sub-channel according to the sorting order as the strong user. SC_2 takes the lead in selecting user U8 with the strongest gain on the local channel. Since U_8 has been chosen as a strong user on SC_2, we exclude U_8 before matching the user to the next subchannel. Next, select U_2 for SC_1, U_3 for SC_3, and U_5 for SC_4. At this point, a strong user has been matched on all subchannels. The matching results are shown below.

$$H3 = \begin{bmatrix} 0.07 & 3.21 & 0.87 & 3.54 & 1.12 & 5.01 & 1.87 & \underline{4.33} \\ 1.32 & \underline{5.78} & 0.67 & 1.21 & 1.06 & 4.37 & 2.15 & 2.23 \\ 2.38 & 1.33 & \underline{4.20} & 2.68 & 0.84 & 1.93 & 1.70 & 1.39 \\ 1.55 & 1.96 & 5.84 & 1.02 & \underline{3.21} & 2.10 & 1.46 & 2.79 \end{bmatrix} \tag{13}$$

Step 4: The four users that have already been matched are excluded. In the order of sub-channel matching, the remaining users are again matched to the sub-channel with the highest channel gain. Finally, SC_1 multiplexes U_2 and U_7, SC_2 multiplexes U_6 and U_8, SC_3 multiplexes U_3 and U_4, and SC_4 multiplexes U_1 and U_5. The result after matching two users per sub-channel is as follows.

$$H4 = \begin{bmatrix} 0.07 & 3.21 & 0.87 & 3.54 & 1.12 & \underline{5.01} & 1.87 & \underline{4.33} \\ 1.32 & \underline{5.78} & 0.67 & 1.21 & 1.06 & 4.37 & \underline{2.15} & 2.23 \\ 2.38 & 1.33 & \underline{4.20} & \underline{2.68} & 0.84 & 1.93 & 1.70 & 1.39 \\ \underline{1.55} & 1.96 & 5.84 & 1.02 & \underline{3.21} & 2.10 & 1.46 & 2.79 \end{bmatrix} \tag{14}$$

To illustrate the complexity of the algorithm, we take the NOMA downlink system with M users and N subchannels $(M = 2N)$ as the background. In order to complete the subchannel allocation, the exhaustive search algorithm needs to perform $\frac{(2N)!}{2^N}$ operations with complexity of $\mathcal{O}\left(\frac{(2N)!}{2^N}\right)$. In our proposed algorithm, the subchannel needs $\sum_{\text{n}=1}^{N}(M - 1) = N(M-1)$ operations to find the user with the worst gain. Next, sorting all subchannels according to the selected channel gain ascending order requires 2NlnN operations. The subchannel needs $\left(2 * \sum_{\text{n}=1}^{N} \frac{(M-1)}{2} = N(M-1)\right)$ operations to match two users. That is, the algorithm needs a total of $(2N \ln N + 2N(M-1))$ operations to complete subchannel allocation, and the complexity is $\mathcal{O}(N^2)$. From the above analysis, we can see that the proposed subchannel allocation algorithm has low complexity and can greatly shorten the operation time.

3.2. Power Allocation Algorithm

In this section, we first introduce the basic particle swarm. Subsequently, we modify the particle swarm optimization algorithm. Our work is mainly reflected in the following aspects. We add random adjustment numbers that follow beta distribution to inertial weights. Then, we introduce mutation and crossover operations in differential evolution to update the position of particles. Finally, the suboptimal solution of power allocation is obtained by iterative search.

3.2.1. Particle Swarm Optimization (PSO)

We suppose the particle swarm is D dimensional and the number of particles is K. The position of the particles i during the ith iteration can be represented by vector $X_i(t) = \left[x_i^1(t), x_i^2(t), \ldots, x_i^D(t)\right]^T$. We can express the velocity of the particle i during the ith iteration in terms of vector $V_i(t) = \left[v_i^1(t), v_i^2(t), \ldots, v_i^D(t)\right]^T$. When particle i reaches the historical optimum position in the iterative process, the particle is called the individual optimum particle, which can be expressed as

$$\mathrm{Pbest}_i(t) = \left[pbest_i^1(t), pbest_i^2(t), \ldots, pbest_i^D(t)\right]^T \tag{15}$$

Similarly, the global optimal position of all particles in the particle swarm traversing, namely the global optimum value, is expressed as

$$\mathrm{Gbest}(t) = \left[gbest^1(t), gbest^2(t), \ldots, gbest^D(t)\right]^T \tag{16}$$

The iterative formulas for updating the moving speed and position of each particle are as follows:

$$v_i^j(t+1) = \omega \cdot v_i^j(t) + c_1 \cdot r_1 \cdot \left(pbest_i^j(t) - x_i^j(t)\right) + c_2 \cdot r_2 \cdot \left(gbest^j(t) - x_i^j(t)\right) \tag{17}$$

$$x_i^j(t+1) = x_i^j(t) + v_i^j(t+1) \tag{18}$$

where ω is the inertia weight coefficient, and c_1 and c_2 are both acceleration coefficients, which usually take a constant. r_1 and r_2 are random variables uniformly distributed on the interval (0, 1). The specific flow of particle swarm optimization is shown in Figure 2 below.

3.2.2. Modified Particle Swarm Optimization (MPSO)

Firstly, for the basic particle swarm, we improve the inertia weight.

In the basic particle swarm optimization algorithm, the inertia weight ω is a fixed constant. However, the value of fixed inertia weight ω has certain limitations on the optimization ability of the algorithm [35]. At the beginning of the iteration, the global search speed of the algorithm needs to be accelerated, so the large inertia weight needs to be used. In addition, at the end of the iteration, particle swarm optimization usually needs to use a small inertia weight to enhance the local search ability. Through this strategy, the coordination between global search and local optimal search can be enhanced. For this reason, we propose a strategy of dynamic adjustment of inertia weight. The improved inertia weight parameter is modified as

$$\omega = \omega_{\min} + (\omega_{\max} - \omega_{\min}) * \mathrm{e}^{-\frac{t}{t_{max}/10}} + \sigma * \mathrm{B}(p, q) \tag{19}$$

where $\omega_{\max}$ and $\omega_{\min}$ are the maximum and minimum values of inertia weight, respectively. t represents the current number of iteration. In this equation, $\omega_{\min} + (\omega_{\max} - \omega_{\min}) * e^{-\frac{t}{t_{\max}/10}}$ are changed by the exponential function $e^{-\frac{t}{t_{max}/10}}$. By adding this item, the inertia weight of the early stage can be made larger. With the continuous iteration of particle swarm, the inertia weight can be reduced nonlinearly. In the third term, B is a random number generator in MATLAB, which can generate random numbers in accordance with beta distribution and $p = 1, q = 3$. The beta distribution can be used to adjust the overall value distribution of ω. δ is the inertia adjustment factor, which is added to control the deviation degree of inertia weight.

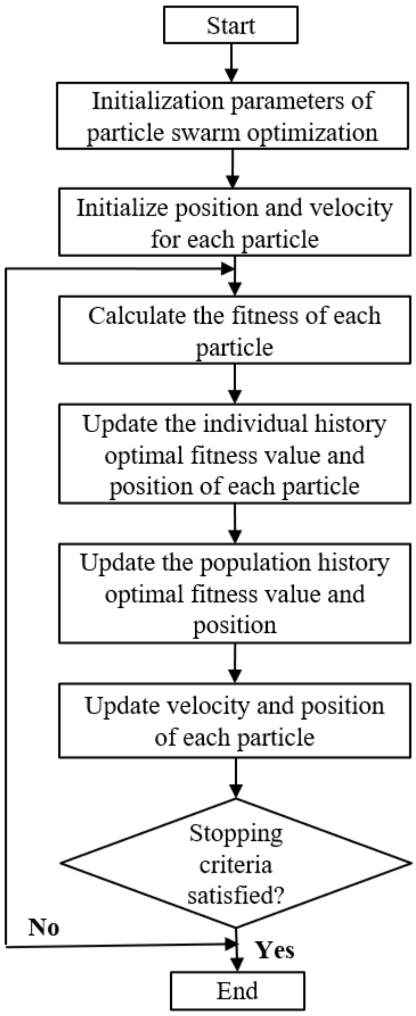

Figure 2. Flow chart of particle swarm optimization.

Secondly, we no longer use a fixed constant for the acceleration coefficient.

It must be mentioned that in the initial stage of particle search, the ideal particle state should be traversed in the solution space as far as possible to obtain the diversity of particles. At the end of the search, the particle should maintain a constant velocity to avoid the interference of the local extremum. In order to obtain better algorithm performance, this chapter will adopt the time-varying acceleration coefficient (TVAC) [36].

$$c_1 = (c_{\max} - c_{\min}) \times \frac{t}{t_{\max}} + c_{\min} \tag{20}$$

$$c_2 = (c_{\min} - c_{\max}) \times \frac{t}{t_{\max}} + c_{\max} \tag{21}$$

In the process of the acceleration factor change, $c_{\max}$ and $c_{\min}$ are used in the initial search, which makes the particles less affected by other particles in the population and enhances the global search ability. With the progress of iteration, the decrease in $c_{\max}$ and the increase in $c_{\min}$ are more conducive to the optimal solution.

Thirdly, we combine the advantages of differential evolution algorithm to introduce mutation and crossover operation.

Particle swarm optimization is prone to decreasing population diversity and falling into the local optimization in the late iteration. Considering that the differential evolution algorithm has the advantages of tracking and adjusting the search in time, in order to increase the diversity of the population, we combine it with particle swarm optimization algorithm to achieve co evolution. Mutation and crossover operations are added to update the position of particles, and the position update expression is

$$u_{i,j} = \begin{cases} x_{r_1,j} + F\left(x_{r_2,j} - x_{r_3,j}\right) & \text{rand } < C_R \\ x_{r_1,j} & \text{rand } \geqslant C_R \end{cases} \tag{22}$$

where x_{r_1}, x_{r_2}, x_{r_3} are random individuals and $r_1 \neq r_2 \neq r_3 \neq i \in [1 \ldots M]$. F is a scalar value, and we take $F = 0.5$. *rand* can generate random numbers in the range [0, 1]. $C_R \in [0,1]$ is the crossover probability. When the random number is less than the crossover probability, the mutation operation is used to update the particle position. When the random number is greater than the crossover probability, it remains constant.

3.3. Power Allocation Problem Based on MPSO

On the premise of obtaining the subchannel allocation, in this section, we use the MPSO algorithm to solve the optimization problem of power allocation between subchannels and user power allocation within subchannels. Since our objective function is a constrained nonlinear programming problem, we introduce a penalty function to transform the original problem into an unconstrained optimization problem. Then according to the constraint conditions of the original objective function, the penalty function can be obtained as

$$\phi = \left(\max\left(\sum_{\text{n}=1}^{N} p_n - P_{tot}, 0\right)\right)^2 + (\max(R_{\min} - R_{m,n}, 0))^2 \tag{23}$$

Then, the fitness function of MPSO can be expressed as

$$f = -\sum_{n=1}^{N}\left(\frac{B_s \log_2(1 + \alpha_n p_n H_{1,n}) + B_s \log_2\left(\frac{1+p_n H_{2,n}}{1+\alpha_n p_n H_{2,n}}\right)}{p_n + p_c}\right) + \phi \tag{24}$$

In addition, we set the particle dimension to 2D. The first D-dimensional particle represents the power value allocated to the subchannel, and the second D-dimensional particle represents the power allocation factor of the secondary user in the channel. The optimal solution is determined by the iterative results of MPSO algorithm, which can be recorded as vector $\Psi = (p_1, p_2, \cdots, p_N, \alpha_1, \alpha_2, \cdots, \alpha_N)$. The detailed process of power allocation strategy can be referred to in Algorithm 2.

In MPSO, we improve the calculation method of the inertia weight and acceleration coefficient but do not increase the algorithm time. In addition, when the crossover operator is used to update the particle position, we only add a linear step of computation in the inner loop. Therefore, for the convenience of calculation, we assume that the total number of PSO is K, the particle dimension is D, and the number of iterations is T. Through the description of the optimization process and improvement measures of particle swarm optimization algorithm, we know that the time complexity of the basic PSO algorithm is $O(K * D * T)$, and the time complexity of the MPSO algorithm is also $O(K * D * T)$.

Algorithm 2 Power Allocation using MPSO

for $i = 1$ to K **do**
    initialize the position $x_i(t)$ and the velocity $v_i(t)$ within the search range randomly;
end for
Evaluate each particle
Set the best position of the current particle (pbest) to its initial position
Set the current best position of the entire population (gbest) to its initial position
while $t \leq t_{max}$ **do**
    Update ω, c_1 and c_2 by (19), (20), (21) respectively
    for $i = 1$ to K **do**
        Update the velocity $v_i(t+1)$ by (17)
        Generate a random number *rand* in [0,1]
        if $rand < C_R$ **then**
            Update the position $x_i(t+1)$ by (22)
        end if
        if $rand \geq C_R$ **then**
            Update the position $x_i(t+1)$ by (18)
        end if
        Evaluation fitness of particle $x_i(t+1)$
        if $f(x_i(t+1)) > f(pbest_i)$ **then**
            Set $pbest_i = x_i(t+1)$
        end if
        if $f(pbest_i) > f(gbest)$ **then**
            Set $gbest = pbest_i$
        end if
    end for
end while

4. Simulation Results

In this section, we use MATLAB to simulate the performance of the above power distribution strategy. We assume that the channel states are known and the channels are independently uniformly distributed Rayleigh fading channels. The radius of the cell is 500 m. The base station is located in the center of the cell. We set the minimum distance between users, and the base station is 50 m. The bandwidth of the NOMA systems is 5 MHz. The circuit power consumption is $p_c = 27$ dBm. For the MPSO algorithm, we set the population size of $K = 100$ particles. The specific simulation parameters can be detailed in Table 1.

To further evaluate the system performance of our proposed scheme (SSA-MPSO), we compare it with a scheme using the combination of the subchannel allocation algorithm in [34] and the power allocation algorithm proposed in this paper (SOMSA-MPSO), as well as a scheme combining our proposed subchannel allocation algorithm and the fractional transmission power allocation [37] (SSA-EPA-FTPA), a method combining the random matching algorithm and the the fractional transmission power allocation (Random-EPA-FTPA), and an OFDMA-based scheme. In addition, when allocating power, the FTPA algorithm must vary the power allocation factor to adjust the given power for each user, considering the different channel conditions. When the power allocation factor is zero, all users on the subchannel will receive equal power. As the power allocation factor increases, users with low channel gain will receive more power. For this reason, a power allocation factor of 0.2 is taken as a reference value for the initial allocation.

Table 1. Simulation parameters for downlink NOMA systems.

Parameter	Value
Maximum number of users	40
Number of subchannels	20
System bandwidth	5 MHZ
BS maximum transmission power	40 dBm
Cell radius	500 m
Min distance between user and BS	50 m
Circuit power consumption	27 dBm
AWGN power density	−174 dBm/Hz
Rayleigh fading coefficient	1
PSO population size	100
PSO maximum iterations	100
Inertia weight	$\omega_{\max} = 0.9$, $\omega_{\min} = 0.4$
Inertia adjustment factor	0.1
Acceleration coefficient	$c_{\max} = 2.5$, $c_{\min} = 0.5$
Crossover probability	1

Figure 3 shows the system's energy efficiency versus the number of iterations. We take the base station's transmit power to be 40 dBm and the number of users to be 20. It can be observed that the energy efficiency of the system keeps increasing with the number of iterations. Although the convergence speed is slower with the improved particle swarm algorithm, the power allocation algorithm based on the enhanced particle swarm algorithm is simple compared to the traditional power allocation algorithm on the one hand. Moreover, the modified PSO algorithm has a higher global search capability due to the differential evolution operation we introduce.

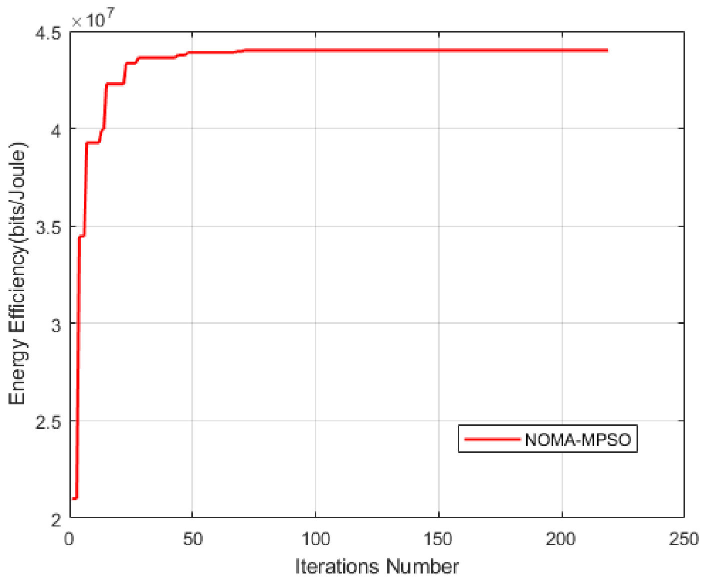

Figure 3. System energy efficiency versus the number of iterations.

For P_{tot} = 40 dBm, with a fixed total transmit power of d base stations, we can see in Figure 4 that the system's energy efficiency gradually increases with the increasing number of users. Although the overall trend is the same, the NOMA system with all four resource allocation schemes outperforms the conventional OFDMA system due to the higher diversity gain achieved by NOMA compared to conventional OFDMA. In addition, the modified particle swarm algorithm for inter- and intra-subchannel power allocation schemes is more global than the ETP-FTPA algorithm, resulting in a more energy efficient NOMA system. Further, the performance of the NOMA system using the SSA-MPSO scheme is slightly better than that using the SOMSA-MPSO strategy. This is because the subchannel allocation algorithm proposed in this paper ensures that the subchannels are not matched to users with poor channel gain and that the channel gain of the paired users is as high as possible, which can help to increase the system rate.

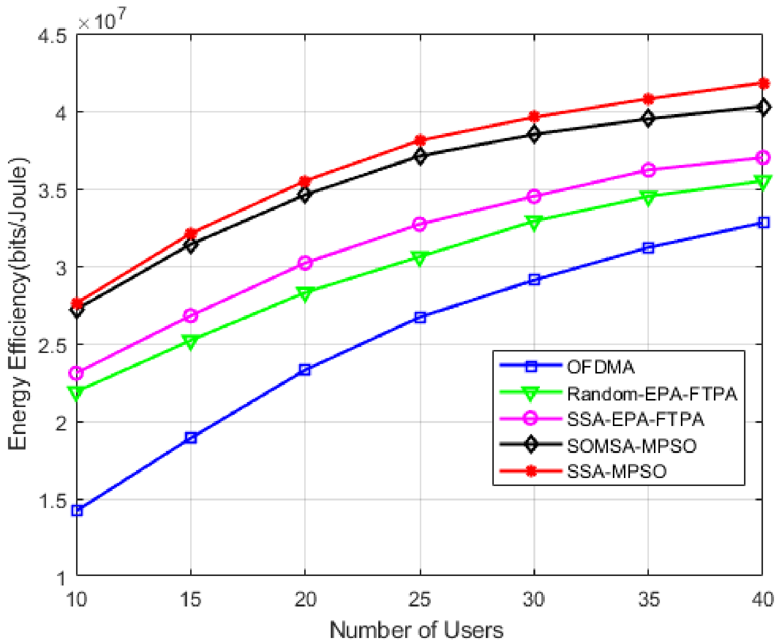

Figure 4. Energy efficiency versus the number of users.

We took 10 users randomly distributed in the cell. Figure 5 shows the system energy efficiency trend as the base station's total transmission power increases. We can clearly see that the system energy efficiency increases in the early stage as the power of the base station increases. However, the system energy efficiency is most excellent when the base station's total transmission reaches 33 dBm. After that, even if the transmitting power of the base station is increased, the system's energy efficiency no longer grows and tends to decrease gradually. This is because the total transmission power of the base station puts a significant constraint on the system's energy efficiency at the beginning. Still, the base station consumes more power as the available power increases. This phenomenon shows that increasing the available power does not guarantee an increase in system energy efficiency; on the contrary, it may lead to a waste of resources.

To assess the fairness of our proposed SSA-MPSO scheme and other NOMA schemes and OFDMA allocation among users, we introduce Jain's fairness index F from [38] to characterize the fairness per pair of users.

$$\mathrm{F} = \frac{\left(\sum_{n=1}^{N} R_n\right)^2}{N\sum_{n=1}^{N} R_n^2} \tag{25}$$

In Figure 6, we first observe that the system's fairness becomes progressively smaller as the number of users increases, both with the NOMA system scheme and OFDMA. In particular, due to subchannels being assigned to only one user, OFDMA-based systems lose access to many subchannels. Therefore, all NOMA system solutions are higher than OFDMA solutions. In addition, the SOMSA-MPSO scheme selects the user with the best channel conditions at each step of the sub-channel matching process. It ensures that the user with the best channel gain matches the subchannel. However, users in the later matching order tend to lose the right to choose, which may result in the combination of the user with the worst channel gain and the subchannel. On the other hand, our proposed subchannel assignment algorithm avoids matching the worst subchannel to a user with low channel gain.

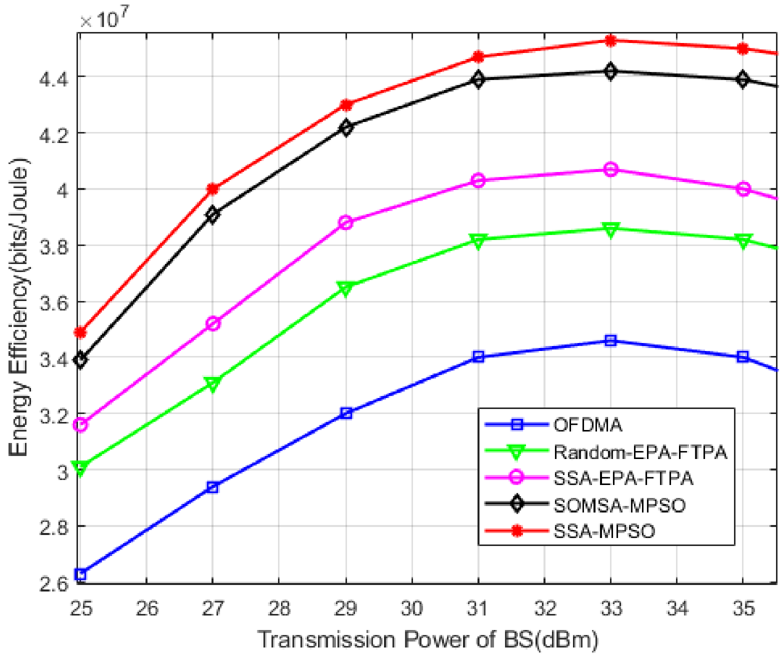

Figure 5. Energy efficiency versus maximum transmission power of BS.

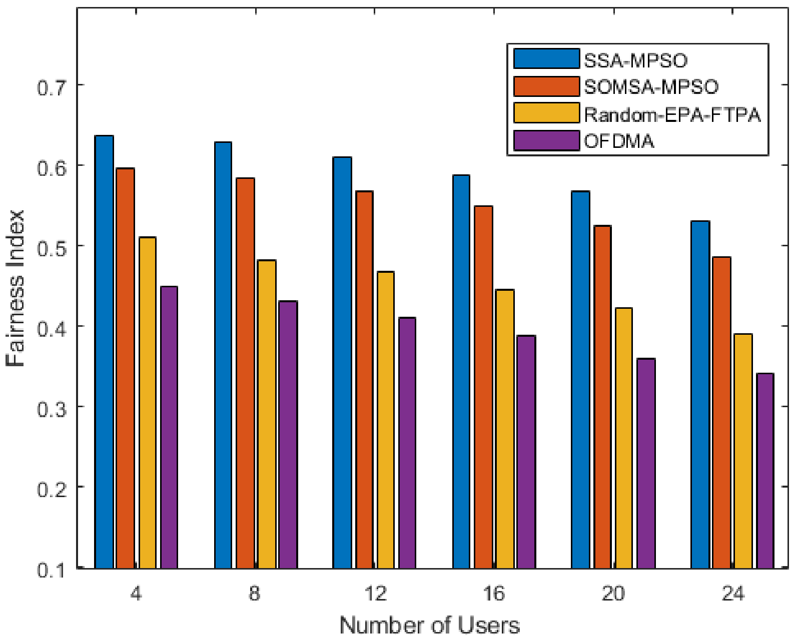

Figure 6. The fairness index versus SNR.

Figure 7 shows the probability of interruption versus SNR for a user count of 36. It is known that the lower the interruption probability, the better the system performance. From Figure 7, we can observe that the outage probability of applying our proposed sub-channel assignment algorithm is better than that of the random matching algorithm and OFDMA. This is because, when matching subchannels to users, we prioritize the worst subchannel to avoid reaching the worst subchannel to a user with low channel gain and check the user with high channel gain on the current subchannel. This operation helps to increase the data rate of the paired users. In addition, by looking at Figure 8, we can see that our proposed SSA-MPSO scheme has the best BER performance. The BER performance of the Random-EPA-FTPA scheme is slightly better than that of the OFDMA but much worse than the BER performance of our proposed method. This is because the Random-EPA-FTPA scheme may result in some users with close channel gains being assigned to the same subchannel. This will make it more difficult for the receiver to decode.

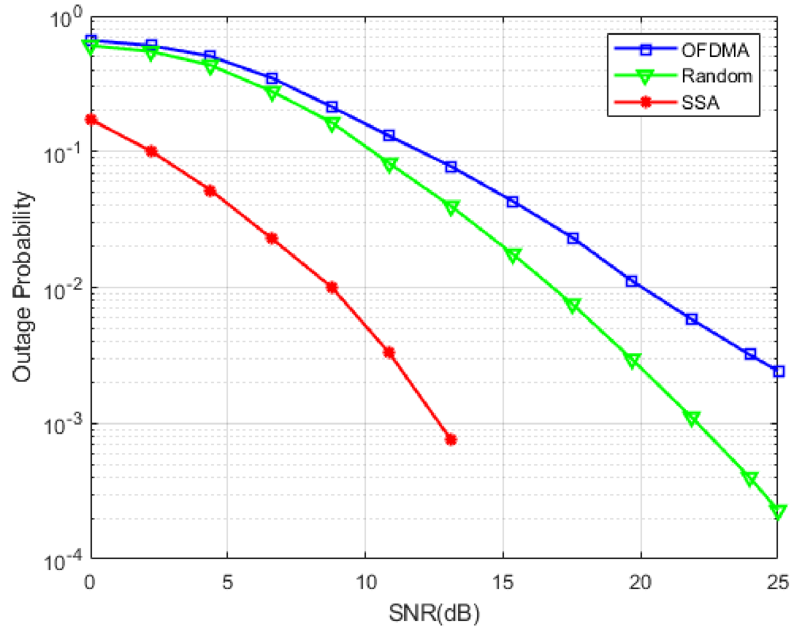

Figure 7. Outage probability versus SNR.

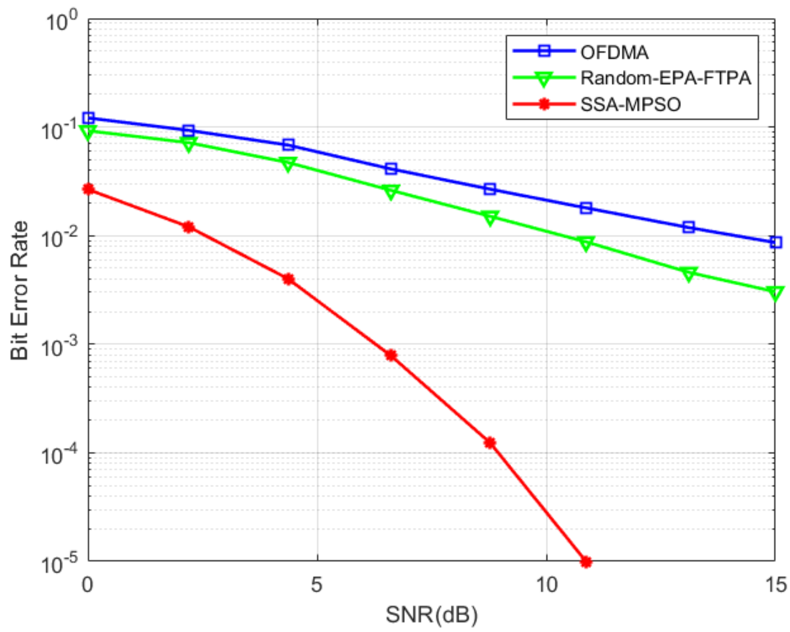

Figure 8. Bit error rate versus SNR.

Figure 9 illustrates the decreasing energy efficiency of the system as the user minimum data rate gradually increases, regardless of the resource allocation scheme adopted. In particular, we can see that our proposed SSA-MPSO scheme achieves a higher energy efficiency compared to Random-EPA-FTPA, SOMSA-MPSO, and SSA-EPA-FTPA. In addition, all NOMA schemes can still meet the user requirements at a minimum data rate of 0.5 Mbps, but OFDMA cannot continue to work.

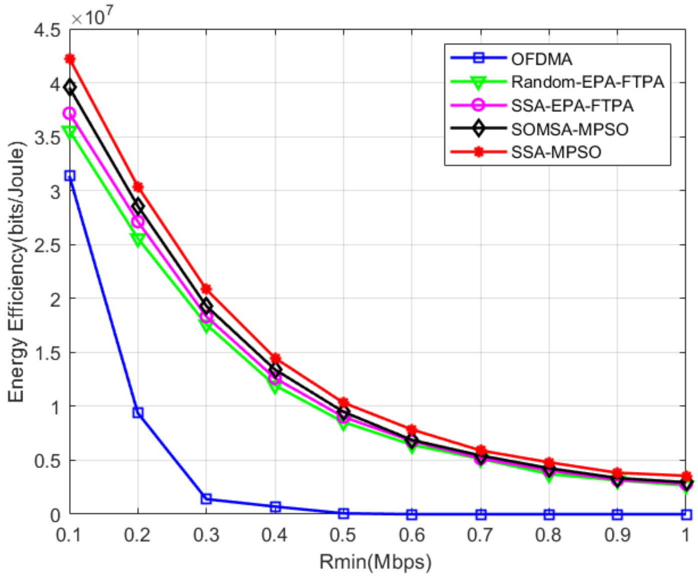

Figure 9. Energy efficiency versus minimum data transmission rate requirements.

5. Conclusions

This paper investigates the allocation of downlink resources in a multi-user NOMA system based on base station power transmission and minimum user rate constraints, intending to maximize energy efficiency. The NOMA system transmits signals from multiple users superimposed on the same subchannel, so the user grouping scheme will significantly impact the system performance. We consider that the optimal user grouping scheme obtained by exhaustive enumeration has high algorithmic complexity and is unsuitable for practical applications. In this paper, a low-complexity greedy algorithm based on the principle of worst-case subchannel priority matching is proposed to solve the subchannel assignment problem. In addition, we propose a power allocation strategy based on a modified particle swarm optimization algorithm that combines subchannel power allocation and inter-user power allocation for a joint optimization solution. Meanwhile, we add a beta distribution to the inertia weights to address the problem that particle swarm optimization tends to fall into local optimization and poor search accuracy. This improvement allows the algorithm to be dynamically tuned and gives the algorithm good global convergence capability. In addition, we use variation and crossover operations in the differential evolution algorithm to update the particles' positions, increasing the population's diversity. Finally, the simulation results show that our proposed scheme not only significantly improves the energy efficiency of the NOMA system, but also ensures the high fairness of the fire usage.

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