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A power allocation method based on particle swarm algorithm for NOMA downlink networks

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Abstract. Non-orthogonal multiple access (NOMA) is now considered as one of the most promising technologies in multiple access technologies in 5G mobile communications. In this paper, we provided a power allocation algorithm in NOMA based on particle swarm optimization (PSO). PSO is an intelligent algorithm that starts from a random solution and finds the optimal solution through iteration. The simulation results show that the PSO-based power allocation method can greatly improve the system’s energy efficiency.

1. Introduction

With the rapid development of new mobile Internet services and the popularity of IoT (Internet of Things) technologies, people have found that existing wireless mobile communication technologies in 3G and 4G have become increasingly difficult to meet growing demands. As a result, the new generation of mobile communication system of 5G has become the focus of worldwide attention. In ITU’s (International Telecommunication Union) requirement of 5G to achieve a leap-forward increase in transmission speed since 2020’s, each 5G base station should provide at least 20 Gb/s downlink and 10 Gb/s uplink bandwidth transmission performance [1]. The most critical technology above all is non-orthogonal multiple access technology (NOMA).

NOMA technology has become a research hotspot of 5G multiple access technology as it can make multiple users share one time-frequency resource unit, which has a higher spectral efficiency. Sparse code multiple access (SCMA) [3], multiuser shared access (MUSA) [4], pattern division multiple access (PDMA) [5] and NOMA proposed by NTT DOCOMO [6] are four mainstream technologies currently. In this paper, we mainly discuss NOMA based on power domain multiplexing.

2. The theoretical basis of NOMA

2.1. The Principle of NOMA

Compared with the traditional OFDM research focusing on time domain and frequency domain, NOMA introduces the concept of power domain multiplexing. Unlike in OFDM, where one user occupies a time-frequency resource block alone. In NOMA, a specific power allocation algorithm is
adopted for multiple users according to the different channel gains of each user and multiple users occupy the same time-frequency resource block [7].

NOMA has higher spectral efficiency and system throughput than OFDM. In addition, NOMA also has the advantages of improving the network’s anti-interference capability and not being limited by channel state information and so on. However, multiple users using the same time-frequency resource block by allocating different powers are equivalent to actively introducing interference signals at the transmitting end. This will cause severe multiple access interference to the receiver’s signal detection. Therefore, serial interference cancellation (SIC) detection needs to be introduced at the receiving end to solve the problem of multiple access interference [8].

2.2. NOMA Downlink System Model
Assume that a cell using a single antenna for both base station and user equipment has \( K \) users in total. The total system bandwidth is assumed to be \( B \) and is divided into \( N \) sub-bands. We assume that \( S_k \) denotes transmit signal of the total of \( k \) users superimposed in sub-band \( n \). It can be described by

\[
S_k = \sum_{i=1}^{k} \sqrt{p_{i,n} S_{i,n}}
\]

where \( S_{i,n} \) denotes the transmit signal of user \( i \) in sub-band \( n \), \( p_{i,n} \) denotes the power that user \( i \) is allocated in sub-band \( n \). The received signal of user \( i \) in sub-band \( n \) can be described by

\[
y_{i,n} = h_{i,n} S_k + I_n + W_n
\]

where \( h_{i,n} \) denotes channel response from base station to users in sub-band \( n \), \( I_n \) and \( W_n \) denote the inter-cell interference and additive white Gaussian noise with a mean of 0 and a variance of \( \sigma_n^2 \). SIC detection for users in sub-band \( n \) to eliminate intra-cell interference and improve current user’s SINR (Signal to Interference plus Noise Ratio). Before SIC detection processing [9], SINR of user \( m \) in sub-band \( n \) is

\[
\text{SINR}^\text{pre} = \frac{p_{m,n} \beta_{m,n}}{1 + \sum_{i=1, i\neq m}^{k} p_{i,n} \beta_{i,n}}
\]

where \( \beta_{m,n} = |h_{m,n}|^2 / \sigma_n^2 \) denotes carrier to interference noise ratio. After SIC detection processing, SINR of user \( m \) in sub-band \( n \) is

\[
\text{SINR}^\text{post} = \frac{p_{m,n} \beta_{m,n}}{1 + \sum_{i=1, i\neq m}^{k} p_{i,n} \beta_{i,n}}
\]

It can be seen that SINR is related to the actual channel conditions and power of each user. After SIC detection processing, throughput of user \( m \) in sub-band \( n \) is

\[
R_{m,n} = \frac{B}{N} \log_2(1 + \text{SINR}^\text{post})
\]

And the total capacity of sub-band \( n \) is

\[
R_n = \frac{B}{N} \sum_{k=1}^{K} S_k \log_2(1 + \text{SINR}^\text{post})
\]

It can be seen that the throughput of a user in a single sub-band is closely related to the user combination manner in the sub-band and the size of the transmit power of the superposed user.

In wireless communication systems, downlink energy efficiency is defined as the number of bits per Joule that can be transmitted. Base station power consumption consists of two aspects: the power consumption of the power amplifier and the power loss of the circuit. Assuming that the system transmits data at a rate of \( R \) bit/s in \( T \) seconds, the power consumed by the base station during transmission is \( P_{\text{tot}} \). Energy efficiency of the system can be described by

\[
\eta = \frac{R \times T}{P_{\text{tot}} \times T}
\]
\[ P_{\text{tot}} = \zeta P + P_c \]  
where \( \zeta \) is power amplification factor, \( P \) is system transmit power, \( P_c \) is the power loss of the circuit. According to throughput of user \( m \) in sub-band \( n \) mentioned before, we can learn that the energy efficiency of the NOMA system is

\[
\eta_{\text{NOMA}} = \frac{\sum_{n=1}^{N} \sum_{m=1}^{K} R_{m,n}}{\zeta \sum_{n=1}^{N} \sum_{m=1}^{K} P_{m,n} + P_c}
\]

### 3. Power allocation based on PSO

PSO (Particle Swarm Optimization) is a kind of evolutionary algorithm. Similar to the simulated annealing algorithm, it also starts from a random solution and finds the optimal solution through iteration [10]. It also evaluates the quality of the solution through fitness. However, compared with the genetic algorithm, it does not have “crossover” and “mutation” operations, but instead seeks the global optimum by following the current searched optimal value. Since the PSO algorithm has efficient search capability and it is beneficial to obtain the optimal solution under multiple objectives, it can be used to solve the power allocation problem of NOMA system under the condition of user grouping in sub-bands that have been identified.

According to the previous analysis of the NOMA downlink capacity model and energy efficiency model, suppose there are only two users \( u_1 \) and \( u_2 \) in sub-band \( n \), and their corresponding CINRs are \( \beta_{1,n} \) and \( \beta_{1,n} \), the power allocated in sub-band \( n \) is \( P_n \), and the power allocation ratio of sub-band \( n \) is \( \Psi \).

We can get the throughput of sub-band \( n \) as

\[
R_n = \frac{B}{N} \left\{ \log_2 \left( 1 + \psi P_n \beta_{1,n} \right) + \log_2 \left[ 1 + \frac{P_n \beta_{2,n}}{1 + \psi P_n \beta_{2,n}} \right] \right\}
\]

Under the condition of satisfying the user’s service quality and total power limitation, the system energy efficiency is maximized through a reasonable power distribution scheme. This is a nonlinear programming problem with constraints

\[
\begin{align*}
\max & \quad \frac{\zeta \sum_{n=1}^{N} P_n + P_c}{B \left\{ \log_2 \left( 1 + \psi P_n \beta_{1,n} \right) + \log_2 \left[ 1 + \frac{P_n \beta_{2,n}}{1 + \psi P_n \beta_{2,n}} \right] \right\}} \\
\text{s.t.} & \quad C_1 : \sum_{n=1}^{N} P_n \leq P_{\text{max}} \\
& \quad C_2 : \sum_{n=1}^{N} \log_2 \left( 1 + \frac{P_n \beta_{m,n}}{\sum_{i=1, i \neq n}^{N} P_i \beta_{m,n} + 1} \right) \geq D_k, k \in \{1, 2, ..., K\}
\end{align*}
\]

where \( D_k \) indicates user minimum rate and \( P_{\text{max}} \) indicates maximum transmit power. The PSO algorithm mainly adopts the method of guaranteeing the rationality of the solution when dealing with constraint conditions, which is optimizing within the range of feasible solutions. Under the constraint conditions, the fitness function of the PSO algorithm can be expressed as

\[
f(\psi, P_n) = \frac{\zeta \sum_{n=1}^{N} P_n + P_c}{B \left\{ \log_2 \left( 1 + \psi P_n \beta_{1,n} \right) + \log_2 \left[ 1 + \frac{P_n \beta_{2,n}}{1 + \psi P_n \beta_{2,n}} \right] \right\}}
\]

In the PSO, if the inertia weight is large, it helps the algorithm to jump out of the local optimum for global search; and if the inertia weight is small, it helps the algorithm to perform a local search accurately. In order to improve the speed of searching for the optimal solution, a larger inertia weight
is needed in the early stage of the search to determine the general position of the optimal solution, and a smaller inertia weight is needed in the later stage of the search to determine the exact position of the optimal solution. To balance the local search with the global search, the inertia weight selection in the PSO algorithm will adopt the linear decrement weight method. The change of the inertia weight is

\[ W^k = W_{\text{max}} - \frac{k \times (W_{\text{max}} - W_{\text{min}})}{k_{\text{max}}} \]  

(13)

In the formula, \( k \) represents the current number of iterations and \( k_{\text{max}} \) represents the maximum number of iterations.

In particle swarm optimization, the accelerating constants \( c_1 \) and \( c_2 \) allow the particles to have the ability to self-learn and socially learn, making them close to the individual optimal position and global optimal position. The use of larger \( c_1 \) and smaller \( c_2 \) in the early stage of the search makes the particles less affected by other particles and enhances the global search ability. As the iteration progresses, \( c_1 \) decreases and \( c_2 \) increases, which helps the algorithm converge to the optimal solution. The change formulas for \( c_1 \) and \( c_2 \) are

\[ c_1^k = c_{1,j} + \frac{k \times (c_{1,f} - c_{1,j})}{k_{\text{max}}} \]

\[ c_2^k = c_{2,j} + \frac{k \times (c_{2,f} - c_{2,j})}{k_{\text{max}}} \]  

(14)

where \( c_{1,j} \) and \( c_{2,j} \) represent the initial values of \( c_1 \) and \( c_2 \), \( c_{1,f} \) and \( c_{2,f} \) represent the iterative final values of \( c_1 \) and \( c_2 \). Combined with the above analysis, the particle swarm algorithm is used to complete the power allocation. The position \( x_i \) of the particle corresponds to a group of feasible solutions in the power allocation problem, and the optimal value obtained by the particle swarm algorithm is the optimal power allocation scheme. The specific steps of the NOMA system power allocation scheme based on PSO are as follows:

**Step 1**: Set each parameter required by the algorithm and set the iteration number \( k=0 \).

**Step 2**: Randomly initialized the speed and position of each particle.

**Step 3**: The fitness of each particle is calculated according to the fitness function, which it is taken as the local optimal value of each particle, and the position of the local optimal value of each particle is initialized.

**Step 4**: Compared the fitness values of all particles and find the maximum fitness value as the global optimal value of the current population.

**Step 5**: If the maximum number of iterations is reached, the global optimal value of the population and its location are output and the algorithm terminates; if not, the algorithm continues.

**Step 6**: Calculated the inertia weight \( w \), acceleration constants \( c_1 \) and \( c_2 \) during the current iteration.

**Step 7**: Updated the speed and position of each particle during the current iteration and calculated the current fitness value of each particle.

**Step 8**: The local optimal value and position of each particle are updated, and the global optimal value and position of the population are updated.

**Step 9**: Updated iteration number \( k=k+1 \), skip to Step 5.

The position of the global optimal value in the population of the final output of the algorithm is the optimal solution of the power allocation problem of the NOMA system based on energy efficiency.

**4. Simulation evaluations**

We compare two schemes to verify the performance of the algorithm: the power allocation scheme using equal power allocation-fractional transmit power allocation (EPA-FTPA) algorithm and power allocation scheme using particle swarm optimization.

The parameters in PSO algorithm are as follows: The size of the particle swarm is 50, maximum inertia weight \( w_{\text{max}}=0.9 \); minimum inertia weight \( w_{\text{min}}=0.4 \); acceleration constants \( c_{1,f}=2.75, c_{1,j}=0.5, c_{2,f}=2.25, c_{2,j}=1.25 \); the maximum number of iterations \( k_{\text{max}}=30 \). The simulation parameters are shown in Table 1, which is compliant with the LTE/LTE-Advanced specifications [11-14].
From Figure 1, we can see that when using the EPA-FTPA algorithm, as the maximum transmit power of the base station continues to increase, the energy efficiency experiences an increase and then decrease and it is because the maximum transmit power of the base station initially imposes greater constraints on the system energy efficiency. Increasing the power can improve the system energy efficiency. However, as the available power is increased, the base station will continue to consume power, and the energy efficiency of the system tends to decrease.

Table 1. Simulation parameter settings

| Simulation parameters                  | Parameter value |
|---------------------------------------|-----------------|
| Cell radius                           | 1000m           |
| Number of sub-bands                   | 128             |
| Base station maximum transmit power   | 33dBm           |
| Sub-band bandwidth                    | 15kHz           |
| Overlay users                         | 2               |
| Cell users                            | 20              |
| Delay extension                       | 5us             |
| Circuit loss                          | 2w              |
| Power amplification factor            | 4               |
| Noise power spectral density          | -174dBm/Hz      |
| Maximum Doppler shift                 | 30Hz            |
| User minimum rate                     | 500b/s          |
| Channel estimation                    | Ideal           |

When we using the PSO algorithm, as the maximum transmit power of the base station continues to increase, the energy efficiency of the system just begins to rise within a certain range. When the maximum transmission power of the base station reaches 25 dBm, the energy efficiency of the system no longer increases, but basically remains unchanged. This is because at the beginning, the maximum transmission power of the base station imposes greater constraints on the system’s energy efficiency. With the increase of the maximum transmission power of the base station, the base station has found an optimal value by constantly optimizing the system’s energy efficiency. In the power allocation scheme, if the available power increases continuously, the base station will not consume excess power, resulting in constant energy efficiency. And it can be seen that using this algorithm has higher energy efficiency form above Figure 1 and 2.
From Figure 2, we can find that with the increase of radius of the cell, the energy efficiency of the system will gradually decrease. This is because when the cell radius becomes larger, the base station needs more power to overcome the actual path loss. In addition, it can be seen that the PSO algorithm has higher energy efficiency than the EPA-FTPA algorithm.

5. Conclusions
This paper mainly introduces a NOMA power allocation algorithm based on particle swarm optimization, which is mainly optimized for the system’s energy efficiency. We build an energy-efficient NOMA system downlink optimization model and propose a power allocation optimization problem for a given user grouping. We use PSO algorithm as a solution to this problem because it has the characteristics of fast convergence speed and strong global optimization ability in solving nonlinear continuous optimization problems. The simulation results show that the algorithm mentioned in this paper has greatly improved the energy efficiency of the NOMA system and the energy efficiency optimization problem of NOMA system under the condition of satisfying the minimum user speed is solved.

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