Research Article

Power Allocation Intelligent Optimization for Mobile NOMA Communication System

Xiaobin Fu, Zhen Tang, and Pingping Xiao

College of Physical Science and Engineering, Yichun University, Yichun 336000, Jiangxi, China

Correspondence should be addressed to Xiaobin Fu; fxb8508457@163.com

Received 16 March 2022; Revised 17 April 2022; Accepted 26 April 2022; Published 10 May 2022

1. Introduction

Recently, the number of mobile users has increased rapidly. With the rapid growth of wireless communication data, the available spectrum becomes more and more crowded, and the space in the electromagnetic spectrum will become more and more scarce [1]. To meet the high-quality communication and large-scale user access, 5G mobile communication technology has attracted extensive attention [2]. 5G mobile communication technology has been rapidly popularized with ultrahigh bandwidth, ultralarge capacity, ultralow delay, and ultrasmall energy consumption, which has brought far-reaching impact and change to people’s life, work, and national economic development [3, 4].

Non-orthogonal multiple access (NOMA) technology has good fairness and considerable spectral efficiency, and it is regarded as a key technology of 5G mobile communication [5–7]. A novel deep learning method was proposed to cut down the computation complexity of NOMA multiuser detection in [8]. In [9], a multiagent deep learning method was proposed to solve the complex NOMA optimization problem, which considered user fairness and decoding complexity. The authors in [10] proposed a trusted NOMA model and maximized the secure rate at the near user by using KKT conditions. To improve the NOMA system performance, the authors in [11] proposed a joint queue-aware and channel-aware scheduling to reduce traffic delay.

Power allocation can improve the NOMA performance in [12–14]. The authors in [15] constructed a multicarrier NOMA system and proposed a power allocation algorithm to reduce computational complexity. In [16], considering an unmanned aerial vehicle (UAV)-assisted NOMA system, user grouping and power allocation were used to reduce the relative distance between users and UAV. The authors in [17] obtained the error probability to fairly allocate power to different users of the NOMA system. Considering vehicle mobility, the authors in [18] proposed a sequence-based power allocation algorithm for NOMA UAV-aided vehicular platooning. However, there are some problems in these schemes, such as large amount of calculation, poor energy efficiency performance, insufficient power utilization, and unable to balance the fairness and service quality of users.

In order to obtain the best power allocation coefficient, the swarm intelligence optimization algorithm has been widely used in [19, 20]. In [21], artificial fish swarm algorithm (AFSA) optimized a wireless sensor network coverage problem, which can reduce the energy consumption. With simplified propagation and firefly algorithm (FA), an
improved power point tracking system is composed of a source S, a far user Df, and an near user Dn. This figure is the mobile NOMA communications system model.

Therefore, we investigate the mobile power allocation optimization. The main contributions of this paper are as follows:

1. A mobile NOMA communication system model is established. For ideal communication conditions, we derive the exact expressions for OP and analyze the relationship between OP and power allocation coefficients.

2. Considering the system efficiency and user fairness, we have established the optimization objective function. Employing monarch butterfly optimization (MBO), an intelligent optimization algorithm is proposed. MBO can reduce the computing parameters. The power allocation optimization algorithm employing MBO has good convergence performance and optimization performance.

3. Compared with FA and AFSA, the MBO algorithm can obtain the shortest time, which is 18.7063s, while AFSA is 48.9128s, and FA is 23.6096s. The efficiency of MBO is increased by 20.7%, which can better improve the OP performance of the mobile NOMA system.

### 2. System Model

Figure 1 is the mobile NOMA communications system. The system is composed of a source S, a far user Df, and a near user Dn. hi represents the channel gains of $S \rightarrow Df$ and $S \rightarrow Dn$, $i = |S, Dn, S, Df|$. hi is expressed as follows [24]:

$$h = \sum_{i=1}^{N} a_i,$$

where $a_i$ is a Nakagami variable.

$S$ transmits $\sqrt{a_1 P_1 x_1} + \sqrt{a_2 P_2 x_2}$ to Df and Dn. $P_s$ is the transmission power. $a_1$ and $a_2$ are power allocation coefficients of Df and Dn, respectively. $a_1 + a_2 = 1$, and $a_1 > a_2$.

The signals received at Df and Dn are as follows [25, 26]:

$$y_{Df} = h_{SDf} (\sqrt{a_1 P_1 x_1} + \sqrt{a_2 P_2 x_2} + \eta_{SDf}) + \eta_{SDf},$$

$$y_{Dn} = h_{SDn} (\sqrt{a_1 P_1 x_1} + \sqrt{a_2 P_2 x_2} + \eta_{SDn}) + \eta_{SDn},$$

where $\eta_{SDf}$ and $\eta_{SDn}$ are AWGN of Df and Dn, respectively, and $\eta_{SDf}$ and $\eta_{SDn}$ are the distortion noise from the transmitter.

The signal-to-interference noise ratios of Df and Dn are as follows [25, 26]:

$$\gamma_{SDn} = \frac{|h_{SDn}|^2 a_2 y}{|h_{SDn}|^2 y + y + 1}.$$

$$\gamma_{SDf} = \frac{|h_{SDf}|^2 a_1 y}{|h_{SDf}|^2 a_2 y + y + 1}.$$

where $y = P_s / N_0$ is the transmit signal-to-noise (SNR) ratio at S.

### 3. OP Performance Analysis

#### 3.1. OP of Df

The OP of Df is expressed as

$$\text{OP}_{Df} = \Pr (\gamma_{SDf} < \gamma_{thf})$$

$$= \Pr \left( \frac{|h_{SDf}|^2 a_1 y}{|h_{SDf}|^2 a_2 y + y + 1} < \gamma_{thf} \right)$$

$$= \Pr \left( |h_{SDf}|^2 < \frac{[y + 1] \gamma_{thf}}{a_1 y - a_2 \gamma_{thf}} \right)$$

$$= \int_0^{[y + 1] \gamma_{thf}} f(y) dy$$

$$= F \left[ |h_{SDf}|^2 \left( \frac{[y + 1] \gamma_{thf}}{a_1 y - a_2 \gamma_{thf}} \right) \right]_{0}^{1}.$$

where $\gamma_{thf}$ is the interrupt threshold of Df.

#### 3.2. OP of Dn

The OP of Dn is given as

$$\text{OP}_{Dn} = \Pr (\gamma_{SDn} < \gamma_{thn})$$

$$= \Pr \left( |h_{SDn}|^2 < \frac{[y + 1] \gamma_{thn}}{a_1 y - a_2 \gamma_{thn}} \right),$$

where $\gamma_{thn}$ is the interrupt threshold of Dn.

To simplify the integration process, we define the following variables:
\[
\begin{align*}
    \tau_1 &= \frac{(y+1)\gamma_{thf}}{a_1 y - a_2 y\gamma_{thf}} \\
    \tau_2 &= \frac{(y+1)\gamma_{thn}}{a_2 y - \gamma\gamma_{thn}} \\
    \tau &= \max(\tau_1, \tau_2).
\end{align*}
\]

Bringing the above variables into (11), we obtain that
\[
\begin{align*}
    OP_{dn} &= \Pr(|h_{sln}|^2 < \tau_1, |h_{nln}|^2 < \tau_2) \\
    &= \Pr(|h_{sln}|^2 < \max(\tau_1, \tau_2)) \\
    &= \Pr(|h_{sln}|^2 < \tau) \\
    &= F_\gamma_{\text{bar}}\left((y)\gamma_0\right) \\
    &= G_{1,3}^{2,1}\left[\tau_{1,0,0}^1\right].
\end{align*}
\]

4. Intelligent Power Allocation Optimization Employing MBO Algorithm

Here, we employ the MBO algorithm to optimize the mobile power allocation.

4.1. Optimization Objective Function. To achieve high efficiency and user fairness, we should ensure $\min|OP_{df} + OP_{dn}|$ and $\min|OP_{df} - OP_{dn}|$. Therefore, the optimization objective function is

\[
\begin{align*}
    \min \left( G_{1,3}^{2,1}\left[\frac{(y+1)\gamma_{thf}}{a_1 y - a_2 y\gamma_{thf}} 1_{1,0,0}^1\right] + G_{1,3}^{2,1}\left[\tau_{1,0,0}^1\right] + G_{1,3}^{2,1}\left[\frac{(y+1)\gamma_{thn}}{a_2 y - \gamma\gamma_{thn}} 1_{1,0,0}^1\right] - G_{1,3}^{2,1}\left[\tau_{1,0,0}^1\right] \right).
\end{align*}
\]

4.2. MBO Intelligent Optimization Algorithm. Therefore, employing the MBO algorithm, an intelligent power allocation optimization algorithm is proposed. In [27], it presents the MBO algorithm.

4.2.1. Population Initialization. The number of the monarch butterfly population is $N$. The number of iterations is $MaxGen$, and the adjustment rate is $BAR$.

4.2.2. Fitness Evaluation. The fitness value of each monarch butterfly individual is calculated and sorted. The sorted population is divided into two subpopulations $NP_1$ and $NP_2$, respectively. They have $N_1$ and $N_2$ individuals, respectively.

4.2.3. New Subpopulation Generation. At the current iteration $t$, the $NP_1$ and $NP_2$ generate two new subpopulations, respectively. For $NP_1$, it uses the migration operator to generate a new subpopulation, which is expressed as follows:

\[
\begin{align*}
    x_{i,k}^t &= \begin{cases} 
    x_{i,k}^t & \text{if } r \leq \rho, \\
    x_{i,k}^t & \text{else},
    \end{cases}
\end{align*}
\]

where $x_{i,k}$ and $x_{i,k}^t$ represent the $k$th element of $r_1$ and $r_2$ that is the newly generated position of $r_1$ and $r_2$, respectively. $r_1$ and $r_2$ are randomly selected from $NP_1$ and $NP_2$, respectively. $r$ is a random number.
For NP2, it uses the adjustment operator to generate a new subpopulation, which is expressed as follows:

\[
\begin{align*}
    x_{i,k}^{t+1} &= x_{\text{best},k}, & r &\leq p, \\
    x_{i,k}^{t+1} &= x_{r_3,k}, & \text{else,}
\end{align*}
\]  

(10) where \(x_{\text{best}}\) represents the position of the globally optimal individual and \(x_{r_3}\) represents the location of \(r_3\), which is randomly selected from \(NP_2\).

\[\text{rand} \text{ is between } [0, 1]. \text{ If } \text{rand} > \text{BAR}, \text{ NP}_2 \text{ updates } x_{i,k}^{t+1} \text{ again. The process is as follows:}
\]

\[
\begin{align*}
    x_{i,k}^{t+1} &= x_{i,k}^t + \beta \ast (dx_k - 0.5), \\
    dx &= \text{Levy}(x_{i,k}^{t+1}),
\end{align*}
\]  

(11) where \(\beta\) is the weight factor and \(dx\) represents the step size which is calculated by the Levy function.

Table 2: Four test functions.

| Function  | Ranges             | Dimension |
|-----------|--------------------|-----------|
| Griewank  | \(F_1 = \sum_{i=1}^{d} x_i^2 / 4000 - \prod_{i=1}^{d} \cos (x_i / \sqrt{i}) + 1\) | 20        |
| Rastrigin | \(F_2 = 10 \ d + \sum_{i=1}^{d} |x_i^2 - 10 \ \cos (2 \pi x_i)|\) | 20        |
| Sphere    | \(F_3 = \sum_{i=1}^{d} x_i^2\) | 20        |
| Schwefel  | \(F_4 = 418.9828 \ d - \sum_{i=1}^{d} x_i \sin (\sqrt{|x_i|})\) | 20        |

Figure 4: The convergence performance of different algorithms on \(F_1\)–\(F_4\). (a) \(F_1\). (b) \(F_2\). (c) \(F_3\). (d) \(F_4\).
4.2.4. New Subpopulation Mergence. It merges the two newly generated subpopulations and calculates the fitness of the new population. Repeat above process, and when the number of iterations reaches MaxGen, the best solution is obtained.

5. Performance Analysis

This section will analyze the OP performance and optimize the power allocation using MBO, AFSA, and FA algorithms.

Table 1 gives the simulation parameters. For the ideal case, the residual hardware impairment $k = 0$, and the incomplete channel state information $\sigma = 0$. Figure 2 shows the OP performance with different $m$. From Figure 2, when the power allocation coefficient is constant, the system OP performance becomes better with the increase in SNR and $m$. The OP performance with different $N$ is shown in Figure 3. As $N$ is decreased, it can minimize the system OP.

We select four test functions, which are shown in Table 2. Figure 4 shows the convergence performance of different algorithms. For $F_1$–$F_4$ functions, the MBO is the best.

| Parameter       | Value       |
|-----------------|-------------|
| Iteration       | 1000        |
| Population number | 100        |
| Dimension       | 1           |
| Range           | [0.5, 0.9] |

Table 3: Simulation parameters for power allocation.

| Parameter       | Value       |
|-----------------|-------------|
| Iteration       | 1000        |
| Population number | 100        |
| Dimension       | 1           |
| Range           | [0.5, 0.9] |

Table 4: Power allocation optimization comparison.

| Parameter Value |
|-----------------|
| Iteration 1000  |
| Population number 100 |
| Dimension 1 |
| Range [0.5, 0.9] |

Table 5: Power allocation optimization comparison.

| Optimal power allocation coefficient | Time (s) |
|--------------------------------------|----------|
| MBO 0.56768                          | 18.7063  |
| FA 0.56768                            | 23.6096  |
| AFSA 0.56768                          | 48.9128  |

6. Conclusion

This paper studies the power allocation optimization for the mobile NOMA communication system. Firstly, the mobile NOMA model is built, and the OP expressions for $Df$ and $Dn$ are derived. Then, the optimization objective function is established, and a power allocation optimization algorithm is proposed. Finally, it can obtain the best power allocation coefficient. The efficiency of the MBO algorithm is improved by 20.7%.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon reasonable request and with permission of funders.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This project was supported by the National Natural Science Foundation of China (No. 11664043).
References

[1] P. K. Hota, S. Thapar, and D. Mishra, R. Saini and A. Dubey, "Ergodic performance of downlink untrusted NOMA system with imperfect SIC," *IEEE Communications Letters*, vol. 26, no. 1, pp. 23–26, 2022.

[2] J. Nightingale, P. Salva-Garcia, J. M. A. Calero, and Q. Wang, "5G-QoE: QoE modelling for ultra-HD video streaming in 5G networks," *IEEE Transactions on Broadcasting*, vol. 64, no. 2, pp. 621–634, 2018.

[3] E. Garro, M. Fuentes, J. L. Carcel et al., "5G mixed mode: NR multicast-broadcast services," *IEEE Transactions on Broadcasting*, vol. 66, no. 2, pp. 390–403, 2020.

[4] L. Chettri and R. Bera, "A comprehensive survey on internet of things (IoT) toward 5G wireless systems," *IEEE Internet of Things Journal*, vol. 7, no. 1, pp. 16–32, 2020.

[5] X. W. Li, Z. Xie, Z. Chu, V. G. Menon, S. Mumtaz, and J. H. Zhang, "Exploiting benefits of IRS in wireless powered NOMA networks," *IEEE Transactions on Green Communications and Networking*, vol. 6, no. 1, 2022.

[6] Z. Hong, G. Li, Y. Xu, and X. Zhou, "User grouping and power allocation for downlink NOMA-based quadrature spatial modulation," *IEEE Access*, vol. 8, no. 2020, pp. 38136–38145, 2020.

[7] Y. Sun, D. W. K. Ng, Z. Ding, and R. Schober, "Optimal joint power and subcarrier allocation for full-duplex multicarrier non-orthogonal multiple access systems," *IEEE Transactions on Communications*, vol. 65, no. 3, pp. 1077–1091, 2017.

[8] Y. Bai, W. Chen, B. Ai, Z. Zhong, and J. J. Wassell, "Prior information aided deep learning method for grant-free NOMA in mMTC," *IEEE Journal on Selected Areas in Communications*, vol. 40, no. 1, pp. 112–126, 2022.

[9] X. Xu, Q. Chen, X. Mu, Y. Liu, and H. Jiang, "Graph-embedded multi-agent learning for smart reconfigurable THz MIMO-NOMA networks," *IEEE Journal on Selected Areas in Communications*, vol. 40, no. 1, pp. 259–275, 2022.

[10] I. Amin, D. Mishra, R. Saini, and S. Aissa, "QoS-aware secrecy rate maximization in untrusted NOMA with trusted relay," *IEEE Communications Letters*, vol. 26, no. 1, pp. 31–34, 2022.

[11] Y. Liu, W. Chen, and J. Lee, "Joint queue-aware and channel-aware scheduling for non-orthogonal multiple access," *IEEE Transactions on Wireless Communications*, vol. 21, no. 1, pp. 264–279, 2022.

[12] M. Alibeigi, A. Taherpour, and S. Gazor, "Improving secrecy rate and social welfare by NOMA technique in D2D communications network," *IEEE Transactions on Green Communications and Networking*, 2021, https://ieeexplore.ieee.org/document/9638994.

[13] L. W. Xu, X. P. Zhou, Y. Li, F. Cai, X. Yu, and N. Kumar, "Intelligent power allocation algorithm for energy-efficient mobile internet of things (IoT) networks," *IEEE Transactions on Green Communications and Networking*, 2022.

[14] H. Wang, P. Xiao, and X. Li, "Channel parameter estimation of mmWave mimo system in urban traffic scene: a training channel-based method," *IEEE Transactions on Intelligent Transportation Systems*, pp. 1–9, 2022.

[15] E. C. Cejudo, H. Zhu, and J. Wang, "Resource allocation in multicarrier NOMA systems based on optimal channel gain ratios," *IEEE Transactions on Wireless Communications*, vol. 21, no. 1, pp. 635–650, 2022.

[16] G. Q. Li, J. Z. Lin, Y. J. Xu, Z. W. Huang, and T. Liu, "User grouping and power allocation algorithm for UAV-aided NOMA network," *Journal on Communications*, vol. 41, no. 9, pp. 21–28, 2020.