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Research Article

Power Allocation for 5G Mobile Multiuser Cooperative Networks

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With the fifth generation (5G) communication technology, the mobile multiuser networks have developed rapidly. In this paper, the performance analysis of mobile multiuser networks which utilize decode-and-forward (DF) relaying is considered. We derive novel outage probability (OP) expressions. To improve the OP performance, we study the power allocation optimization problem. To solve the optimization problem, we propose an intelligent power allocation optimization algorithm based on grey wolf optimization (GWO). We compare the proposed GWO approach with three existing algorithms. The experimental results reveal that the proposed GWO algorithm can achieve a smaller OP, thus improving system efficiency. Also, compared with other channel models, the OP values of the 2-Rayleigh model are increased by 81.2% and 66.6%, respectively.

1. Introduction

Recently, the increasing provision of multiuser services, the ever-increasing number of devices, and the continuous growth of data pose significant challenges to massive mobile multiuser connectivity. Fifth generation (5G) mobile communication networks are very important in achieving massive mobile multiuser connectivity [1, 2]. To meet this requirement, the boom of 5G mobile communications has resulted in the emergence of many new technologies [3–5]. Nonorthogonal multiple access and millimeter-wave communications are key aspects of 5G technology [6]. However, the complex multiuser communication environment makes the 5G mobile communication challenging.

As an alternative way to ensure reliable multiuser communication, cooperative communication has sparked a great deal of research [7]. Secrecy performance of multiple-relay cooperative communication was investigated in [8]. In [9], cooperative cognitive relaying was employed to provide secure communications. Xu et al. [10] studied the incremental decode-and-forward (DF) cooperative relay network.

To improve the multiuser cooperative communication, power allocation plays a key role [11]. Xu et al. employed the passive beamforming to improve energy efficiency optimization in [12]. In [13], with multicarrier division, Li et al. investigated resource allocation problem. Filomeno et al. proposed two power allocation algorithms in [14].

To further improve the power allocation performance, various swarm intelligence optimization methods have been used to optimize the parameters [15]. To solve the multi-UAV task allocation problem, an improved genetic algorithm (GA) was proposed in [16]. An adaptive firefly algorithm (FA) algorithm was proposed to enhance data security in [17]. By using the golden section (GS) algorithm, Cuevas et al. optimized the evolutionary computation in [18].

However, research on power allocation optimization of mobile multiuser communications is very rare. Therefore, we investigate power allocation optimization over the 2-Rayleigh model. The main contributions are as follows:

(1) With transmit antenna selection (TAS), we analyze the OP performance of mobile multiuser networks. New OP expressions are derived. These results are more complex than those in the Rayleigh model.

(2) To improve the OP performance, we propose an intelligent power allocation optimization method

based on grey wolf optimization (GWO), which reduces computational complexity.

(3) Compared with Nakagami and Rayleigh channel models, the 2-Rayleigh model has an increase of 81.2% and 66.6% in OP values, respectively. We also test the firefly algorithm (FA), the genetic algorithm (GA), and the golden section (GS) algorithm. Compared with these algorithms, our proposed GWO method achieves a smaller OP.

Table 1 shows the notations in our paper.

2. System Model

In Figure 1, N_t and N_r antennas are installed at mobile source (MS) and mobile relay (MR), respectively. There are L mobile users (MUs). The channel coefficient h follows 2-Rayleigh distribution [19]. The energy E is allocated by K. $W_{\{\mathrm{SU}il,\mathrm{RU}jl\}}$ are the position gains of $\mathrm{MS}_i \longrightarrow \mathrm{MU}_l$ and $\mathrm{MR}_j \longrightarrow \mathrm{MU}_l$, respectively.

Firstly, MU_l and MR_j receive the signals as

$$r_{SUil} = \sqrt{W_{SUil}KE}h_{SUil}x + N_{SUil}, \tag{1}$$

$$r_{SRij} = \sqrt{KE}h_{SRij}x + N_{SRij}, \tag{2}$$

where $N_{\mathrm{SR}ij}$ and $N_{\mathrm{SU}il}$ are Gaussian noises.

Then, MR_j employs DF scheme and transmits signal to MU_l as

$$r_{RUjl} = \beta\sqrt{W_{RUjl}(1-K)E}h_{RUjl}x + N_{RUjl}. \tag{3}$$

The SNR $\gamma_{\mathrm{SR}ij}$ at MR_j is given as

$$\begin{aligned}\gamma_{SRij} &= \frac{K\left|h_{SRij}\right|^2 E}{N_0}\\ &= K\left|h_{SRij}\right|^2\overline{\gamma}.\end{aligned} \tag{4}$$

If $\gamma_{\mathrm{Sr}i} < \gamma_{\mathrm{th}}$, MU_l cannot receive the signal from MR. $\gamma_{\mathrm{Sr}i}$ is given as

Table 1: Notations.

Notations	Designation
K	Power allocation coefficient
W	The position gain
SNR	Signal-to-noise ratio
N_t	The transmit antennas
N_r	The receive antennas

$$\gamma_{SRi} = \max_{1\le j\le N_r}\left(\gamma_{SRij}\right). \tag{5}$$

MU_l receives the SNR γ_{il} aswhere

$$\begin{aligned}\gamma_{SUil} &= KW_{SUil}\left|h_{SUil}\right|^2\overline{\gamma},\\ \gamma_{RUil} &= (1-K)W_{RUil}\left|h_{RUil}\right|^2\overline{\gamma},\end{aligned} \tag{6}$$

where $\overline{\gamma}$ is the average SNR.

The best user is chosen from L mobile users:

$$\gamma_i = \max_{1\le l\le L}\left(\gamma_{il}\right). \tag{7}$$

The TAS is employed to select w as

$$\begin{aligned}w &= \max_{1\le i\le N_t}\left(\gamma_i\right)\\ &= \begin{cases}\max\limits_{1\le i\le N_t, 1\le l\le L}\left(\gamma_{SUil}\right), & \text{if } |C| = 0,\\ \max\limits_{1\le i\le N_t, 1\le l\le L, j\in C}\left(\gamma_{SUil}, \gamma_{RUjl}\right), & \text{if } |C| \ne 0,\end{cases}\end{aligned} \tag{8}$$

where C is given as

$$C = \left\{1\le i\le N_t | \gamma_{SRi} \ge \gamma_{th}\right\}. \tag{9}$$

3. OP Performance with TAS

We obtains the OP as

$$F = Q_1 + Q_2, \tag{10}$$

where

$$\begin{aligned}Q_1 &= \left(G_{1,3}^{2,1}\left[\frac{\gamma_{th}}{K\overline{\gamma}}\Big|_{1,1,0}^{1}\right]\right)^{N_t\times N_r} \times \left(G_{1,3}^{2,1}\left[\frac{R_{th}}{KW_{SU}\overline{\gamma}}\Big|_{1,1,0}^{1}\right]\right)^{N_t\times L},\\ Q_2 &= \sum_{n=1}^{N_t}\binom{N_t}{n}\left(G_{1,3}^{2,1}\left[\frac{\gamma_{th}}{K\overline{\gamma}}\Big|_{1,1,0}^{1}\right]\right)^{(N_t-n)\times N_r}\left(1-\left(G_{1,3}^{2,1}\left[\frac{\gamma_{th}}{K\overline{\gamma}}\Big|_{1,1,0}^{1}\right]\right)^{N_r}\right)^n\\ &\quad\times\left(G_{1,3}^{2,1}\left[\frac{R_{th}}{KW_{SU}\overline{\gamma}}|1,1,0_1\right]\right)^{N_t\times L}\left(G_{1,3}^{2,1}\left[\frac{R_{th}}{(1-K)W_{RU}\overline{\gamma}}|1,1,0_1\right]\right)^{n\times L},\end{aligned} \tag{11}$$

where R_{th} is a given threshold.

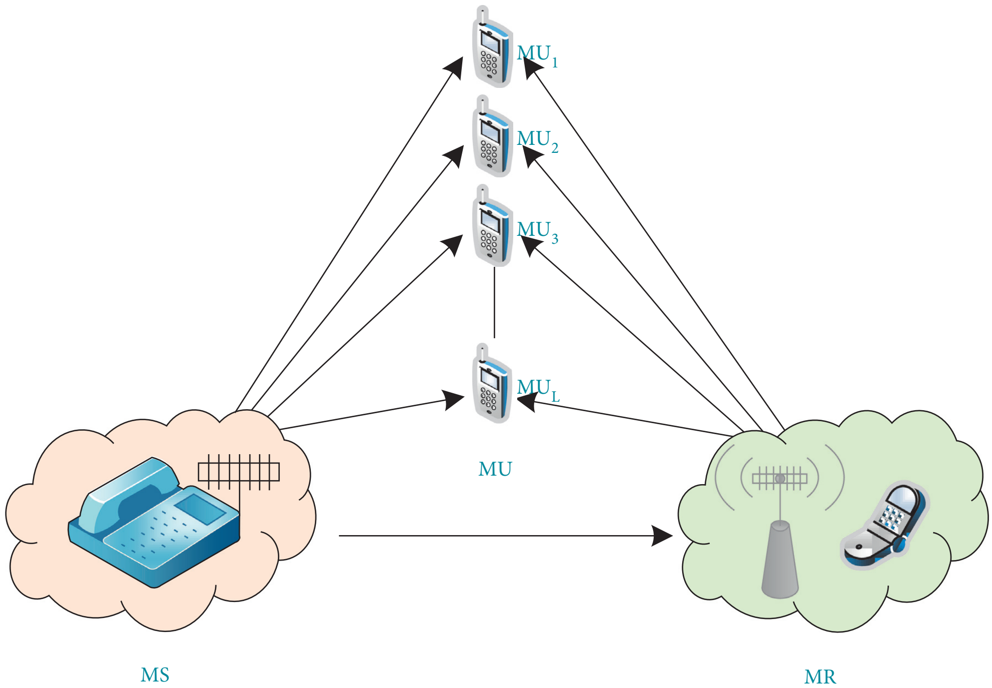

FIGURE 1: The system model.

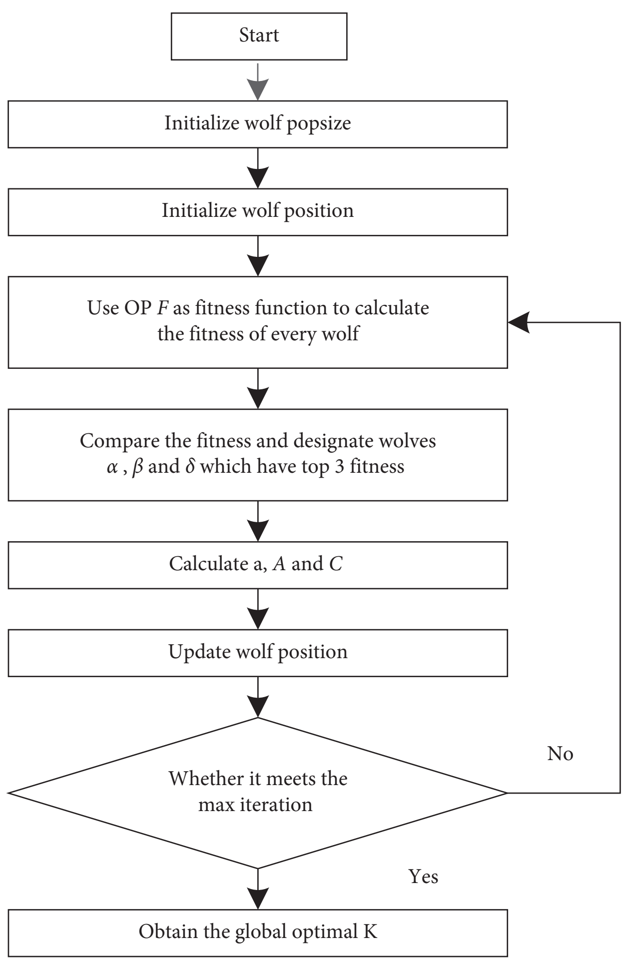

FIGURE 2: GWO algorithm.

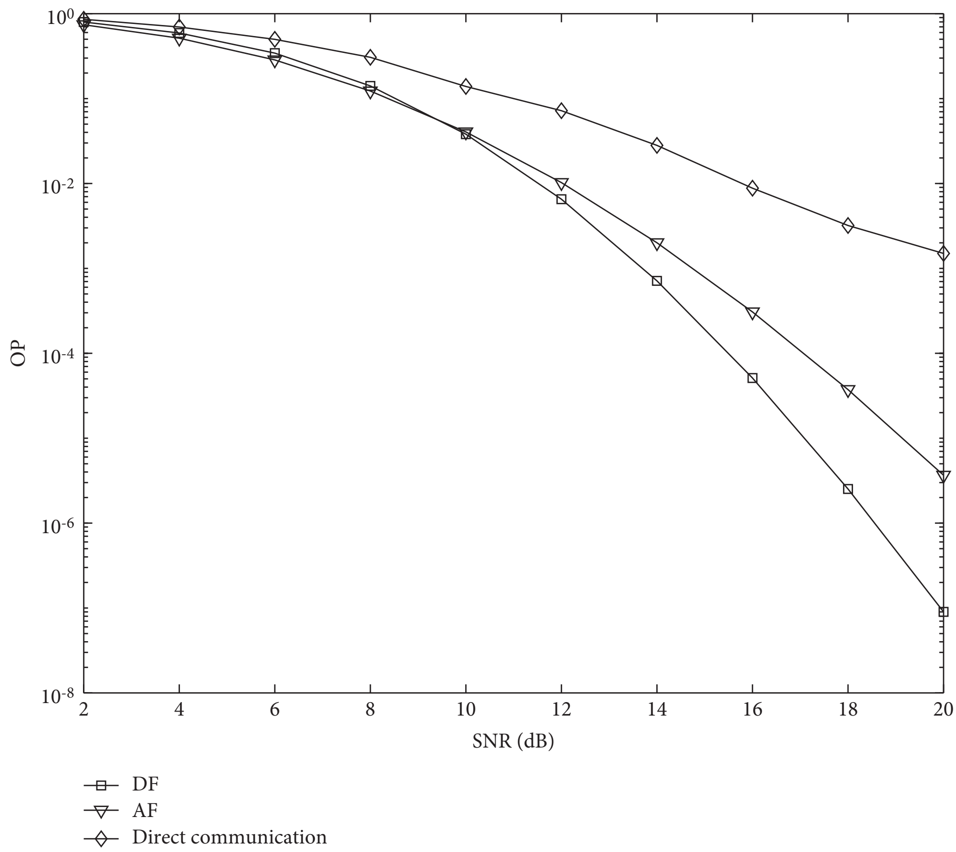

Figure 3: OP comparison with different schemes.

4. Power Allocation Intelligent Optimization

According to [20–22], the GWO algorithm is divided into the following parts.

4.1. Encircling. The encircling process is expressed as

$$\begin{aligned} D\,D &= \left|C \cdot XX_p(t) - XX(t)\right|, \\ XX(t+1) &= XX_p(t) - A \cdot DD, \\ A &= 2a \cdot r_1 - r_2, \\ C &= 2 \cdot r_2, \end{aligned} \tag{12}$$

where r_1, $r_2 \in [0, 1]$ and $a \in [0, 2]$.

4.2. Hunting. The wolves renew their positions as

$$XX(t+1) = \frac{XX_1 + XX_2 + XX_3}{3}, \tag{13}$$

where

$$\begin{aligned} XX_1 &= XX_\alpha(t) - A_\alpha \cdot DD_\alpha, \\ XX_2 &= XX_\beta(t) - A_\beta \cdot DD_\beta, \\ XX_3 &= XX_\delta(t) - A_\delta \cdot DD_\delta, \\ DD_\alpha &= \left|C_\alpha \cdot XX_\alpha(t) - XX(t)\right|, \\ DD_\beta &= \left|C_\beta \cdot XX_\beta(t) - XX(t)\right|, \\ DD_\delta &= \left|C_\delta \cdot XX_\delta(t) - XX(t)\right|. \end{aligned} \tag{14}$$

4.3. Attacking. The wolves attack the prey. The maximum iteration is *ter*. a is given as

$$a = 2 - \frac{2t}{\text{ter}}. \tag{15}$$

Figure 2 shows the GWO algorithm.

5. Performance Results

Figure 3 illustrates the comparison of amplify-and-forward (AF), DF, and direct communication schemes. Table 2 shows

Table 2: Parameters of Figure 3.

μ	0 dB
K	0.5
γ_{th}	5 dB
R_{th}	5 dB
N_{t}	2
N_{r}	2
L	2

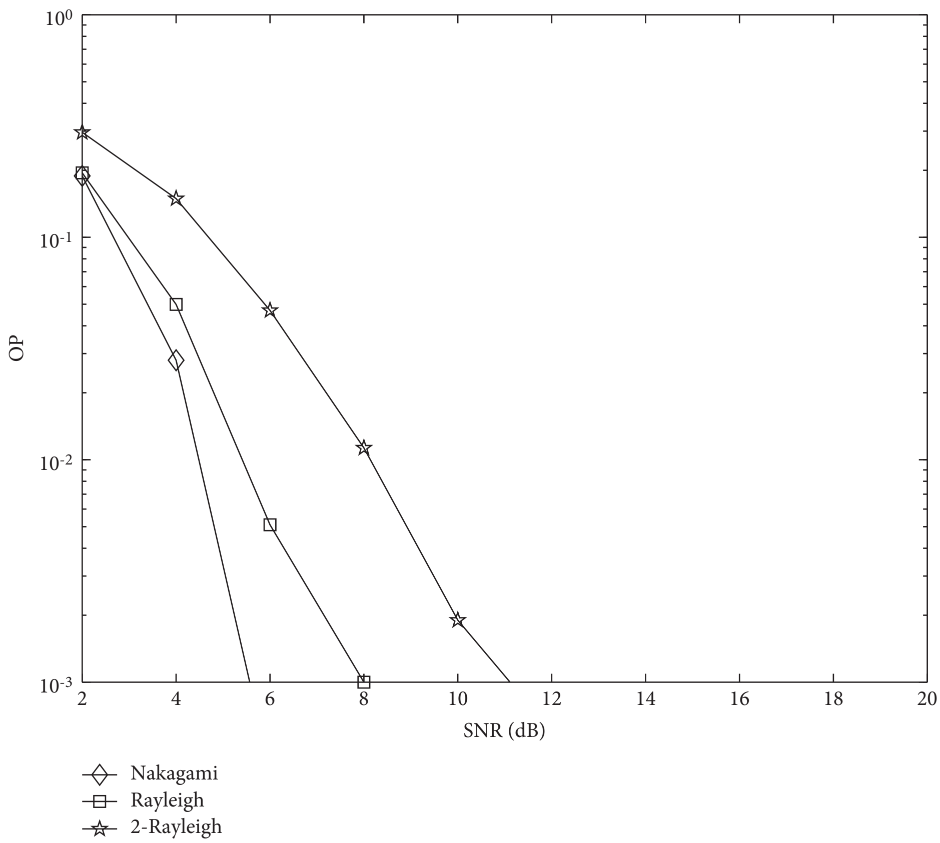

Figure 4: OP comparison with different channel models.

the corresponding parameters. The DF scheme is superior to AF and direct communication schemes. This means that with the increase of SNR, the cooperative communication condition becomes good, which reduces the OP. Compared with direct transmission, it also shows that cooperative transmission always reduces the OP.

Figure 4 presents the OP performance comparison under Nakagami, Rayleigh, and 2-Rayleigh models. The parameters are given in Table 3. We can see that the OP performance of the Nakagami model is better than that of Rayleigh and 2-Rayleigh models. When SNR = 4 dB, the OP values are 0.0280, 0.0499, and 0.1492, respectively. Compared with Nakagami and Rayleigh channel models, the 2-Rayleigh model has an increase of 81.2% and 66.6% in OP values, respectively.

Table 3: Parameters of Figure 4.

μ	0 dB
K	0.6
γ_{th}	5 dB
R_{th}	5 dB
N_t	2
N_r	2
L	2

In Figures 5–8, we obtain the optimum K for the GWO, GS, GA, and FA methods. The parameters are given in Table 4. Compared with GS, GA, and FA, GWO achieves a smaller OP (0.0005). This is due to the fact that GWO has a simple structure and a strong convergence performance, which is easy to implement.

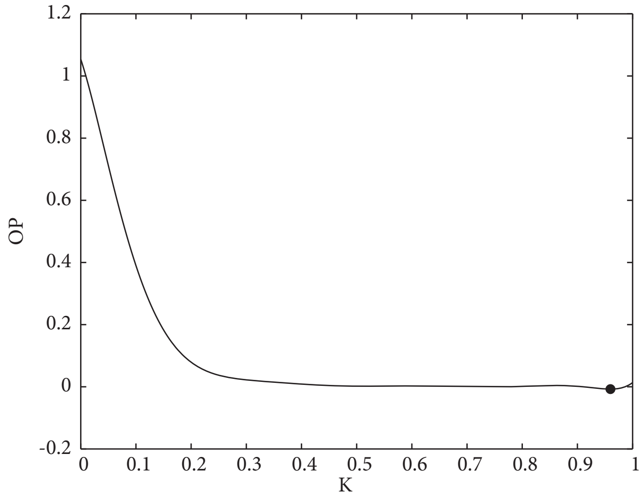

Figure 5: Optimum K of GWO.

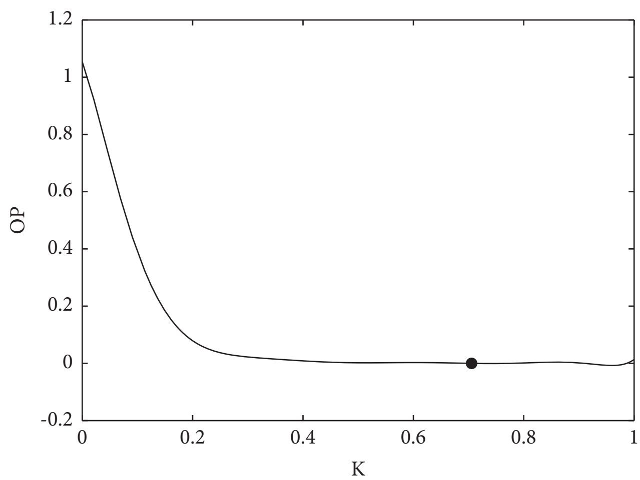

Figure 6: Optimum K of GA.

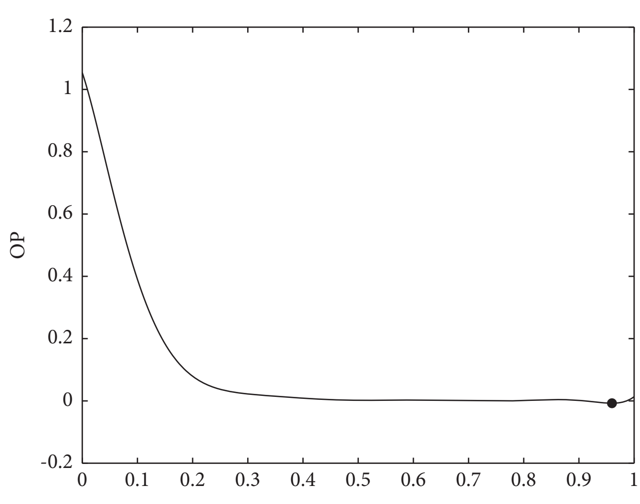

Figure 7: Optimum K of FA.

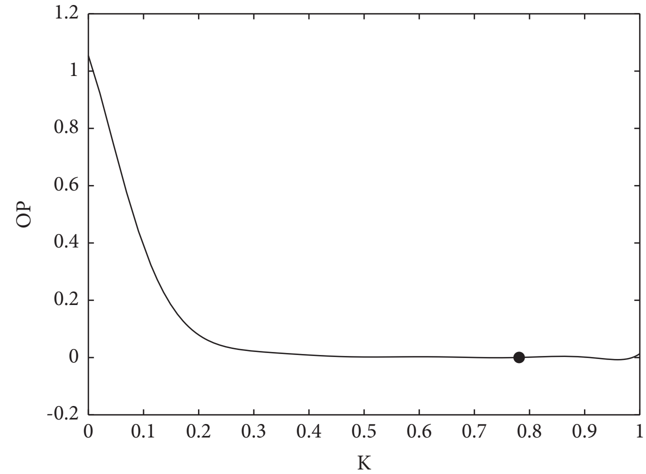

Figure 8: Optimum K of GS.

Table 4: Simulation parameters for the 4 methods.

Algorithm	Simulation parameters
GWO	$psize = 50,\ ter = 1000$
GS	$a = 0,\ b = 1,\ \varepsilon = 0.2$
GA	$psize = 50,\ ter = 1000$
FA	$psize = 50,\ \alpha = 0.5,\ \beta = 0.2,\ \gamma = 1,\ ter = 1000$

6. Conclusions

In this paper, the power allocation optimization of mobile multiuser networks was investigated. Based on the GWO method, we proposed a power allocation optimization algorithm. The simulation results showed that compared with GS, GA, and FA algorithms, GWO algorithm can obtain better OP performance results. Compared with Nakagami and Rayleigh channel models, the 2-Rayleigh model has an increase of 81.2% and 66.6% in OP values, respectively.

In future studies, we will consider using artificial intelligence to obtain the optimal K value.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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