Research Article

Optimal Power Allocation for Cooperative Pattern Division Multiple Access Systems

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This study focuses on the power allocation (PA) problem in code division multiple access (PDMA) networks with amplify-and-forward (AF) relays. We provide two wireless communication technical performance indexes, which are system throughput and outage probability. A multiobjective version of particle swarm optimization is proposed to solve Pareto-optimal solutions for optimal PA problems. A novel programming model is built based on improvement of constraint functions, and the accuracy and efficiency of solution can be improved via compact constraints. The technique for order preference by similarity to an ideal solution is proposed to balance the performance indicators, which include outage probability and system throughput. It has been calculated that the proposed approach for optimal PA is verified and performs better than a genetic algorithm approach.

1. Introduction

Renewable energy has become a trend in smart grid development. Wind power and photovoltaic are representatives of renewable energy. To address the randomness of wind power, robust sliding mode control [1], maximum power point tracking control [2, 3], and passivity-based sliding-mode control [4] are presented to maximize the availability of wind power. Maximum power point tracking is also used in the photovoltaic system, which can get the maximum power output under partial shading condition [5, 6]. The reliability of the renewable energy communication system has significant engineering significance for optimization and control in distribution networks integrated with renewable energy.

With the development of 5G networks, wireless communication technology will support the intellectualization of the renewable energy system. 5G networks can deliver superfast speeds and support extremely low-latency connections. Power communication adopts both optical fiber communication and wireless communication, which are

applied to new energy monitoring systems. 5G networks can meet the real-time data acquisition and transmission and realize data measurement, state awareness, and scheduling control. Nonorthogonal multiple access (NOMA) has emerged as a key component of 5G networks and has attracted extensive attention and research for its superior spectral efficiency performance [7]. The core concepts of NOMA are to service multiple users on the same resource simultaneously by utilizing power allocation (PA) and to separate multiplexed users at the receiver side by using the successive interference canceller (SIC) technique [8]. Different from the traditional orthogonal transmission, NOMA uses nonorthogonal transmission at the transmitter and actively introduces interference information. At the receiving end, the correct demodulation is realized by a SIC technology. Huawei, ZTE, and Datang Telecom have presented their own multiple access technologies, which are called sparse code multiple access (SCMA) [9], multiuser shared access (MUSA) [10], and pattern division multiple access (PDMA) [11], respectively. Although these technical details are different, they basically belong to NOMA

schemes. SCMA, MUSA, and PDMA [11] have been studied in both academia and industry. PDMA is a multicarrier NOMA scheme that has attracted significant attention due to its unequal diversity design at the transmitting side, and its ability to obtain almost equal or approximately equal diversity benefits at the receiving side. PDMA combined with relay technology can enhance system performance [12]. PDMA is a significant NOMA technology, which defines sparse mapping from data to a great sum of resources. Compared with other multiple access technologies, such as SCMA and MUSA, the advantage of PDMA is that PDMA patterns provide unequal classification to meet the communication requirements of different users [13]. Different diversity orders are provided for multiple users to alleviate the error propagation problem of the SIC receiver in PDMA-based systems.

The programming problem is a common problem in wireless communication systems, including optimal parameter setting and optimal power allocation (OPA). Bae and Han joined power and time allocation to minimize system outage probability for two-way cooperative NOMA [14]. Cao et al. [15] presented two PA schemes to improve the secrecy of wireless transmissions in a NOMA system. One scheme jammed eavesdropping attempts, and the other optimized the PA power. Zhu et al. presented a PA method to achieve max-min fairness, weighted sum rate maximization, sum rate maximization with quality of service (QoS) constraints, and energy efficiency maximization with weights or QoS constraints under a given channel assignment in NOMA systems [16]. Cui et al. investigated PA in multicell multicarrier NOMA (MC-NOMA) networks by considering maximizing the sum mean opinion scores (MOSs) of users and proposed a low-complexity suboptimal approach based on successive convex approximation techniques, which attained a good computational complexity-optimality trade-off [17]. Ni et al. developed a centralized minimum power control algorithm to minimize the total transmit power by considering the user data rate requirements for multicell MC-NOMA networks where the user assignment is fixed [18]. Khan et al. presented an iterative local optimal solution to calculate the optimal PA and enhance the sum capacity, which considered the transmission power in sending node, the user PA, and the minimum rate requirements per user [19]. Zhao et al. presented a joint problem of spectrum allocation and power control to maximize the sum rate of small-cell users in a NOMA network by considering user fairness. The PA problem used sequential convex programming to update the result iteratively. The spectrum allocation problem used a many-to-one matching game with peer effects [20]. Song et al. presented a PA algorithm based on a bisection search algorithm and a gradient value to maximize the energy efficiency in downlink NOMA networks with imperfect channel state information. The nonconvex problem was transformed to a convex problem by sequential convex programming, and the PA factors were attained by the Lagrangian multiplier method [21]. He et al. presented a deep reinforcement learning framework where PA and channel assignment were combined to allocate resources to users in a near optimal way.

Specifically, an attention-based neural network was exploited to perform the channel assignment [22]. Xiao et al. presented an improved PSO algorithm to improve the energy efficiency of the systems while guaranteeing the spectral efficiency [23]. Except GA, particle swarm optimization (PSO) is another artificial intelligence algorithm that can be used for wireless communication system optimization [24]. From the point of view of the programming solution method, the following comparison can be summarized [24], and the proposed methods are artificial intelligence algorithms. The main difference between this study and [24] is that, in this study, OPA is a multiobjective optimization problem rather than a single-objective optimization problem as in [24]. High system throughput is a major target in [24]. Both high system throughput and low outage probability are targets in this study. We not only improve the constraint functions in [24] but also propose an effective method for multiobjective programming.

The existing OPA methods only consider a single performance objective, that is, the system throughput, but single-objective optimization cannot meet the requirements of multiple performance indicators of wireless communication. Beside system throughput, outage probability is another important index to measure the performance of the communication system. Multiobjective optimization can make power allocation meet the requirements of different performance indexes of PDMA at the same time, that is, the significance of this work. Multiobjective optimization is of vital importance in a wireless communication system, but it is more complex and time-consuming than single-objective optimization. This motivates us to find an OPA algorithm in amplify-and-forward (AF) relaying with PDMA (AF-PDMA) networks to improve multiple system performances. The first challenge is that OPA is a nonconvex problem, which cannot be solved effectively by the gradient descent method. The second challenge is that how to balance the optimization needs of different system performance indicators. It was proved that different performance objectives make the optimization problem become a constrained multiobjective optimization problem in PDMA systems [25].

The contributions of this study can be outlined as follows. (1) We present a multiobjective PSO algorithm considering a Pareto-optimal solution to solve the complicated PA solution problems in an AF-PDMA network. The benefit is that the feasible region of the PSO algorithm is greatly reduced by modifying the original constraint functions, and the convergence efficiency is greatly improved. The iteration in the infeasible region is also avoided. (2) We analyse the relationship of user outage probabilities and system throughput from which a trade-off between the outage probability of a single user and system throughput is attained. The benefit is that different requirements of users and systems on OPA are taken into consideration, and the proposed multiobjective evaluation theory can be extended to other wireless communication systems for equilibrium optimization.

Notation: the notation $\odot$ represents the dot multiple. $(\cdot)^{-1}$ denotes the matrix inversion. $(\cdot)^{H}$ denotes the matrix

conjugate transpose. $\mathbf{I}_N$ represents an identity matrix with an $N \times N$ vector.

2. System Model

In this section, we consider an AF-PDMA downlink network as outlined in [26]. A PDMA pattern matrix $\mathbf{G}_{\text{PDMA}}^{N,K} = [\mathbf{g}_1, \mathbf{g}_2, \ldots, \mathbf{g}_K]$ denotes a K pattern with $\mathbf{g}_i$ mapping on N resources, where $\mathbf{g}_i$ is the ith user's PDMA pattern.

The transmission powers for the BS and relaying node are equal ($P_s = P_r = P$). The channel coefficients among the BS, the kth user, and the AF relaying node are denoted as h_{mn_k}, ($\text{mn}_k \in \{\text{bu}_k, \text{br}, \text{ru}_k\}$), in which $h_{\text{mn}_k} \sim \text{CN}(0, \mu_{\text{mn}_k})$. $n_{\text{br}} \sim \text{CN}(0, N_0)$ and $n_{\text{bu}_k} \sim \text{CN}(0, N_0)$ represent additive white Gaussian noise at the relaying node and the kth user, respectively. $\gamma \triangleq (P/N_0)$ is a transmit SNR.

The received signals at k^{th} user from the BS or relaying node are denoted as follows:

$$
\mathbf{y}_{\text{bu}_k} = \mathbf{h}_{\text{bu}_k} \odot \sum_{i=1}^{K} \sqrt{\alpha_i P} \mathbf{g}_i x_i + \mathbf{n}_{\text{bu}_k} = \sum_{i=1}^{K} \sqrt{\alpha_i P} \widetilde{h}_{\text{bu}_k} x_i + \mathbf{n}_{\text{bu}_k} = H\mathbf{x} + \mathbf{n}_{\text{bu}_k},
$$

$$
\mathbf{y}_{\text{ru}_k} = G\widetilde{h}_{\text{ru}_k} \odot \left(\mathbf{h}_{\text{br}} \sum_{i=1}^{K} \sqrt{\alpha_i P} \, \mathbf{g}_i x_i + \mathbf{n}_{\text{br}} \right) + \mathbf{n}_{\text{ru}_k},
$$

(1)

where $\mathbf{y}_{\text{bu}_k}$ and $\mathbf{y}_{\text{ru}_k}$ are the signals from the BS or relaying node, respectively. $\mathbf{n}_{\text{bu}_k}$ and $\mathbf{n}_{\text{ru}_k}$ are the noises from the BS and relaying node, respectively. $\widetilde{\mathbf{h}}_{\text{bu}_k}$ and $\widetilde{\mathbf{h}}_{\text{ru}_k}$ are the channel responses from the BS and relaying node, respectively. $\widetilde{\mathbf{h}}_{\text{bu}_k} = \mathbf{h}_{\text{bu}_k} \odot \mathbf{g}_k$, $\widetilde{\mathbf{h}}_{\text{ru}_k} = \mathbf{h}_{\text{ru}_k} \odot \mathbf{g}_k$, and $\widetilde{H}$ is the PDMA equivalent channel response matrix. x_i is the ith user's signal. α_i is the PA coefficient, where $\alpha_1 + \alpha_2 + \cdots + \alpha_K = 1$. $\mathbf{x} = \begin{bmatrix} \sqrt{\alpha_1 P} x_1 & \sqrt{\alpha_2 P} x_2 & \cdots & \sqrt{\alpha_K P} x_K \end{bmatrix}^T$ is the modulated symbol. G is the amplifying gain factor in which $G = \sqrt{P/(P|\widetilde{h}_{\text{br}}|^2 + N_0)}$.

The corresponding SINR for the kth user who receives a signal from the BS is represented as follows:

$$
\gamma_{\text{bu}_k} = P_k \left(\widetilde{\mathbf{h}}_{\text{bu}_k} \right)^H \left(N_0 \mathbf{I}_N + \sum_{i=k+1}^{K} P_i \widetilde{\mathbf{h}}_i \left(\widetilde{\mathbf{h}}_i \right)^H \right)^{-1} \widetilde{\mathbf{h}}_{\text{bu}_k}. \quad (2)
$$

$P_k = \alpha_k P$ denotes the kth user's transmit power.

The corresponding SINR for the kth user who receives the signal from the relaying node is represented as follows:

$$
\gamma_{\text{ru}_k} = \alpha_k \gamma^2 \left(\widetilde{\mathbf{h}}_{\text{ru}_k} \odot \widetilde{\mathbf{h}}_{\text{br}_k} \right)^H \left[\mathbf{K}_{Z_k} \right]^{-1} \left(\widetilde{\mathbf{h}}_{\text{ru}_k} \odot \widetilde{\mathbf{h}}_{\text{br}_k} \right), \quad (3)
$$

where Z_k is the noise plus the interference from the relaying node. $\mathbf{K}_{Z_k}$ is the covariance of Z_k, which is calculated as follows:

$$
\mathbf{K}_{Z_k} = \gamma^2 \sum_{i=k+1}^{K} \alpha_i \left(\widetilde{\mathbf{h}}_{\text{ru}_i} \odot \widetilde{\mathbf{h}}_{\text{br}_i} \right) \left(\widetilde{\mathbf{h}}_{\text{ru}_i} \odot \widetilde{\mathbf{h}}_{\text{br}_i} \right)^H + \gamma \widetilde{\mathbf{h}}_{\text{ru}_k} \left(\widetilde{\mathbf{h}}_{\text{ru}_k} \right)^H
$$
$$
+ \gamma \widetilde{\mathbf{h}}_{\text{br}} \left(\widetilde{\mathbf{h}}_{\text{br}} \right)^H + \mathbf{I}_N.
$$

(4)

The metrics are defined as follows. Generally, outage probability is defined as the probability by which SINR is smaller than a specified threshold value in both BS-to-user and relay-to-user channels. An outage occurs if neither the direct nor the relay transmission succeeds [24]. System throughput is defined as the product of the transmission rate and the probability of successful transmission [27].

To simplify the outage expressions, we define function $G_k(x)$ as (5).

$$
G_k(x) = \begin{cases} 1 - e^{-(x/\gamma)\left(\left(1/\mu_{\text{br}}\right) + \left(1/\mu_{\text{ru}_k}\right)\right)} \sqrt{\dfrac{4x(x+1)}{\mu_{\text{br}}\mu_{\text{ru}_k}\gamma}} K_1 \left(\dfrac{4\phi(x+1)}{\mu_{\text{br}}\mu_{\text{ru}_k}\gamma} \right), & x \neq 0, \\ \\ 0, & x = 0, \end{cases}
$$

(5)

where $K_1(\cdot)$ is the first-order modified Bessel function of the second type, and μ_{mn_k} is the channel coefficient where $\text{mn}_k \in \{\text{bu}_k, \text{br}, \text{ru}_k\}$.

The matrix with two rows ($N = 2$) and three columns ($k = 3$) is the most representative matrix with the minimum degree of unequal diversity. Other larger dimension matrices can be extended similarly. The PSO algorithm has a good applicability. When the number of users and channels change, we only need to modify the PSO parameters, constraints, and objective functions, rather than the

algorithm mechanism. Taking the PDMA pattern matrix $G_{\text{PDMA}}^{2,3}$ as an example, the outage expressions for users are as follows:

$$
\begin{aligned}
\mathscr{O}_1 &= \begin{cases} \left(1 - e^{-\tau_1/\mu_{\text{bu}_1}} + e^{-\tau_2/\mu_{\text{bu}_1}}\right) \times \left(1 + G_1\left(\tau_1\right) - G_1\left(\tau_2\right)\right), & \text{if } a < 0, \\ \left(e^{-\tau_1/\mu_{\text{bu}_1}} - e^{-\tau_2/\mu_{\text{bu}_1}}\right) \times \left(G_1\left(\tau_2\right) - G_1\left(\tau_1\right)\right), & \text{if } a > 0, \end{cases} \\
\mathscr{O}_2 &= \begin{cases} \left(1 - e^{-\varsigma_1/\mu_{\text{bu}_2}} + e^{-\varsigma_2/\mu_{\text{bu}_2}}\right) \times \left(1 + G_2\left(\varsigma_1\right) - G_2\left(\varsigma_2\right)\right), & \text{if } a < 0, \\ \left(1 - e^{-\varsigma/\mu_{\text{bu}_2}} + e^{-\varsigma_1/\mu_{\text{bu}_2}} - e^{-\varsigma_2/\mu_{\text{bu}_2}}\right) \times \left(G_2\left(\varsigma\right) - G_2\left(\varsigma_1\right) + G_2\left(\varsigma_2\right)\right), & \text{if } a > 0, \end{cases} \\
\mathscr{O}_3 &= \begin{cases} \left(1 - e^{-\xi_1/\mu_{\text{bu}_3}} + e^{-\xi_2/\mu_{\text{bu}_3}}\right) \times \left(1 + G_3\left(\xi_1\right) - G_3\left(\xi_2\right)\right), & \text{if } a < 0, \\ \left(1 - e^{-\xi/\mu_{\text{bu}_3}} + e^{-\xi_1/\mu_{\text{bu}_3}} - e^{-\xi_2/\mu_{\text{bu}_3}}\right) \times \left(G_3\left(\xi\right) - G_3\left(\xi_1\right) + G_3\left(\xi_2\right)\right), & \text{if } a > 0, \end{cases}
\end{aligned}
\tag{6}
$$

where $\tau_1 = \max\{0, x_1\}$, $\tau_2 = \max\{0, x_2\}$, $\varsigma = (\phi_2/\alpha_2\gamma)$, $\varsigma_1 = \max\{(\phi_2/\alpha_2\gamma), x_1\}$, $\varsigma_2 = \max\{(\phi_2/\alpha_2\gamma), x_2\}$, $\psi_1 = \max\{x_1, (\phi_2/\alpha_2\gamma), (\phi_3/\alpha_3\gamma)\}$, $\psi_2 = \max\{x_2, (\phi_2/\alpha_2\gamma), (\phi_3/\alpha_3\gamma)\}$, $\psi = \max\{(\phi_2/\alpha_2\gamma), (\phi_3/\alpha_3\gamma)\}$, and $a = [\alpha_1(\alpha_2 + \alpha_3) - \alpha_2\alpha_3\phi_1]\gamma^2$.

ϕ_k is the targeted SNR of the kth user; x_1 and x_2 stand for different values of $|h_{\text{bu}_1}|^2$, and they can be obtained by solving the following equation.

$$
\begin{aligned}
&[\alpha_1(\alpha_2 + \alpha_3) - \alpha_2\alpha_3\phi_1]\gamma^2 |h_{\text{bu}_1}|^4 \\
&+ [2\alpha_1 - (\alpha_2 + \alpha_3)\phi_1]\gamma |h_{\text{bu}_1}|^2 - \phi_1 = 0.
\end{aligned}
\tag{7}
$$

The AF-PDMA system throughput expression is denoted as

$$
\mathscr{R}_{\text{sum}} = \mathscr{R}_1\left(1 - \mathscr{O}_1\right) + \mathscr{R}_2\left(1 - \mathscr{O}_2\right) + \mathscr{R}_3\left(1 - \mathscr{O}_3\right).
\tag{8}
$$

3. Optimal Power Allocation

The optimal PA is mathematically equivalent to the optimal PA factor setting. Multiobjective programming is an effective way to solve complicated PA problems.

3.1. Programming Model.
Two typical objectives, based on system throughput and outage probability, have been proposed for optimal PA in a downlink network. Hence, the PA allocation problem is an optimization problem with two objective functions, and it can be formulated as

$$
\min f(\boldsymbol{\alpha}, \boldsymbol{\theta}) = [\mathscr{O}_3(\boldsymbol{\alpha}, \boldsymbol{\theta}), -R_{\text{sum}}(\boldsymbol{\alpha}, \boldsymbol{\theta})],
\tag{9}
$$

where $\boldsymbol{\alpha}$ is the three PA coefficients (i.e., α_1, α_2, and α_3), $\boldsymbol{\theta}$ is a system parameter vector in the downlink network, $\mathscr{O}_3$ is the outage probability of the third user, the significance ensures the reliability of single-user communication, and R_{sum} is the system throughput.

The inequality constraints are given as follows:

$$
1 > \alpha_1 > \alpha_2 > \alpha_3 > 0.
\tag{10}
$$

The equality constraint is given as follows:

$$
\alpha_1 + \alpha_2 + \alpha_3 = 1.
\tag{11}
$$

The challenge of PSO is that once the initial value and update particles are not in the feasible region, all the particles may be updated in the infeasible region. We propose a new approach to address this issue by revising the existing constraints through logic. After the constraint conditions are modified, the decision variables are changed from three coefficients to two coefficients. The third coefficient is calculated as a parameter by (11). The inequality constraints are improved as follows:

$$
\frac{1}{3} < \alpha_1 < 1,
\tag{12a}
$$

$$
0 < \alpha_2 < \frac{1}{2},
\tag{12b}
$$

$$
0 < \alpha_2 < \alpha_1,
\tag{12c}
$$

$$
1 - \alpha_1 - \alpha_2 < \alpha_2.
\tag{12d}
$$

Equations (13) and (14) are broad constraints, but (12a)–(12d) make the constraints narrow. The point is that the constraint conditions are very important for the efficiency and accuracy of the evolutionary algorithm. With respect to PSO, the programming model based on (13) and (14) is easy to iterate in the infeasible region, but the model based on (12a)–(12d) can avoid this problem.

3.2. PSO Theory.
PSO exhibits strong randomness and covers most solution spaces to avoid reaching a local optimum [28]. The advantage of an artificial intelligence algorithm is that it is amenable to almost all stochastic programming models. Its disadvantage is that it cannot guarantee that a global optimal solution can be found. Even if the global optimal solution is found, it is impossible to provide a strict mathematical proof. In addition, adjusting the parameters, including the step size and penalty coefficients, is difficult. Reasonable parameters are necessary conditions for obtaining the optimal solution, and the PSO parameters in this study are listed in Table 1.

TABLE 1: Simulation parameters for PSO.

Item	Value
The PSO particle size	30
The PSO iteration number	15
The penalty function factor	10^6

3.3. Pareto Frontier.

The Pareto frontier is a key to solving the multiobjective programming problem [29]. A Pareto-optimal solution can include a noninferior solution set, a nondominated solution set, and a nondominant solution set. Based on the Pareto dominance, we present a multiobjective PSO algorithm considering a Pareto-optimal solution. The procedure of the multiobjective PSO algorithm is given as follows: Algorithm 1.

3.4. TOPSIS.

The technique for order preference by similarity to an ideal solution (TOPSIS) is an effective double benchmark evaluation method [30] that can be used to balance the outage probability of a single user and system throughput. TOPSIS can calculate the positive and negative ideal solutions of each index (i.e., outage probability of a single user or system throughput). The relative closeness of each evaluation object to positive and negative ideal solutions can be used to evaluate the comprehensive performance of the system. The optimal TOPSIS should be close to the positive ideal solution, and the distance from the negative ideal solution should be large. The decision problem of two objectives is shown in Figure 1.

$A+$ and $A-$ denote the positive ideal solution and negative ideal solution, respectively. The feasible solution A_1 is closest to the ideal solution $A+$ but not the farthest solution from the negative ideal solution $A-$. The feasible solution A_2 is further away from the negative ideal $A-$. The disadvantage of TOPSIS is that the weight is not reflected in the distance calculation. The calculated Euclidean distance can be weighted using an entropy-weighing method to overcome this shortcoming.

The calculation steps of an entropy TOPSIS method are as follows. A standard treatment of the evaluation matrix data using 0-1 transformation is implemented.

When the index is positive, the following formula is used for standardized transformation.

$$b_{ij}^* = \frac{b_{ij} - \min_j b_{ij}}{\max_j b_{ij} - \min_j b_{ij}}, \quad 1 \le i \le m, \ 1 \le j \le n, \tag{13}$$

where b_{ij} is an optimal system throughput in step 3 in section C, and n is equal to two. When the index is an inverse index, the following formula is used for standardized transformation.

$$b_{ij}^* = \frac{\max_j b_{ij} - b_{ij}}{\max_j b_{ij} - \min_j b_{ij}}, \quad 1 \le i \le m, \ 1 \le i \le n, \tag{14}$$

where b_{ij} is an optimal outage probability in step 3 in section C.

According to the standardized decision matrix, the characteristic proportion of the jth index and the ith evaluation sample can be calculated using

$$cp_{ij} = \frac{b_{ij}^*}{\sum_{i=1}^m b_{ij}^*}. \tag{15}$$

The entropy of the index is calculated using

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^m cp_{ij} \ln cp_{ij}, \quad 1 \le j \le n. \tag{16}$$

Note that when $cp_{ij} = 0$, we set $\ln (cp_{ij})$ equal to zero. The entropy weight formula is

$$w_j = \frac{1 - e_j}{\sum_{i=1}^n 1 - e_j}, \quad 1 \le j \le n. \tag{17}$$

From here, it follows that

$$\begin{aligned} c_{ij} &= w_j \times b_{ij}, \quad i = 1, 2, \ldots, m; \ j = 1, 2, \ldots, n, \\ C^+ &= \max c_{ij}, \quad 1 \le i \le m, \\ C^- &= \min c_{ij}, \quad 1 \le i \le m, \end{aligned} \tag{18}$$

where $C = (c_{ij})_{m \times n}$ is the weighted normal matrix, C^+ is the set of positive ideal solutions, and C^- is the set of negative ideal solutions.

Then, the weighted Euclidean distances from each evaluation object to the positive and negative ideal solutions are calculated separately.

$$d_i^+ = \sqrt{\sum_{j=1}^n w_j^2 (c_{ij} - c_j^+)^2}, \quad i = 1, 2, \ldots, m,$$

$$d_i^- = \sqrt{\sum_{j=1}^n w_j^2 (c_{ij} - c_j^-)^2}, \quad i = 1, 2, \ldots, m, \tag{19}$$

$$f_i = \frac{d_i^-}{d_i^+ + d_i^-}, \quad i = 1, 2, \ldots, m,$$

where f_i is the evaluation result of the comprehensive performances. One can find the best solution at the Pareto frontier by finding the greatest f_i.

The implementation process of the proposed algorithm is shown in Figure 2.

4. Results and Discussion

4.1. Subheadings.

We use a step-by-step validation method to demonstrate the power optimization method for AF-PDMA in a downlink network. First, we compare GA with the proposed PSO algorithm. Then, system throughput performance and the minimum outage probability of the third user are taken as planning objectives, and different

Step 1. Single-objective optimization

 (i) Find the optimal solution of the maximum system throughput using the PSO algorithm
(ii) Find the optimal solution of the minimum outage probability of user3 using the PSO algorithm

Step 2. Probability distribution calculation

 (i) Calculate the system throughput using the solutions, which ensures the minimum outage probability of user3
(ii) Generate a row vector of m linearly equally spaced points between the optimal system throughput and the system throughput, which is solved in the last step

Step 3. Obtain the Pareto frontier

 (i) Add inequality constraint $R_{sum}(\alpha, \theta) > a$, which is an element of the above equally spaced points. For each solution, a constraint is added in order.
(ii) Find the optimal solution of the minimum outage probability of user3 using the PSO algorithm based on the above added inequality constraint
(iii) Repeat the above process m times to obtain m groups of optimization target values

ALGORITHM 1: Process for multiobjective optimization.
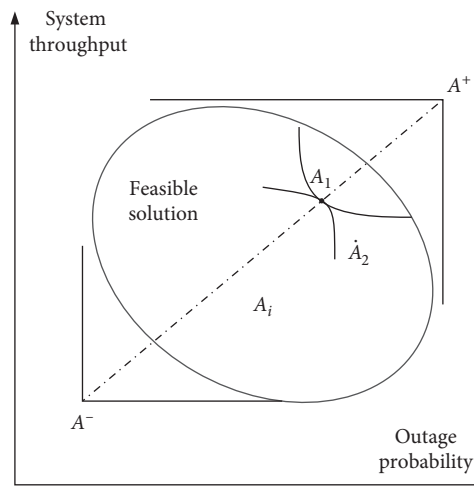
FIGURE 1: Positive ideal solution and negative ideal solution.

FIGURE 2: Implementation process of the proposed algorithm.

solutions for OPA are derived. To balance the need for system throughput with the desire to minimize outage probabilities, a Pareto frontier consisting of a set of possible solutions is found. The Pareto solutions are further evaluated with the TOPSIS approach to help the decision-maker find the desired OPA solution. The simulation in this study is performed on a Lenovo laptop with an Intel(R) Core (TM) i7-1065G7 CPU operating at 1.30 GHz with 15.7 GB of available memory.

An internal function of MATLAB, i.e., a GA solver for mixed-integer or continuous-variable optimization, constrained or unconstrained, is used to solve the OPA problem. Because GA internal function is installed in Matlab, the solution performance is reliable and can be used to verify the accuracy and effectiveness of the proposed PSO algorithm.

PSO and GA are used to solve the OPA problem to obtain the maximum system throughput. As shown in Figures 3–5, the performances of this method are better than those of the GA. It should be noted that it is important to adjust parameters in an artificial intelligence algorithm
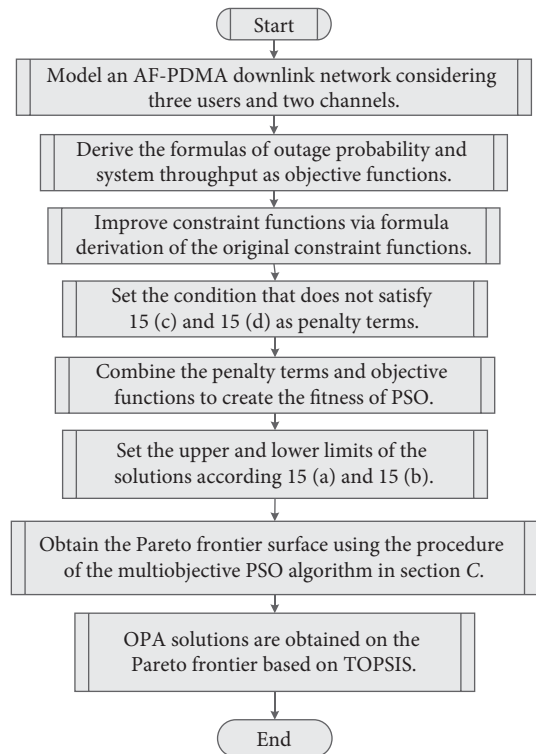
according to the programming model. The simulation results do not demonstrate that PSO is more efficient and accurate than GA but demonstrate that the solution performance of the artificial intelligence algorithm depends on the parameter setting. Noted that the PSO algorithm uses the modified constraints, the GA uses the constraints before modification. The feasible region of GA solution is original and broad, and the solution is limited by (13)-(14). The feasible region of the PSO algorithm is modified and compact, and the solution is limited by (12a)–(12d). It will greatly improve the efficiency and accuracy of the solution via transforming (10)-(11) to (12a)–(12d). With respect to
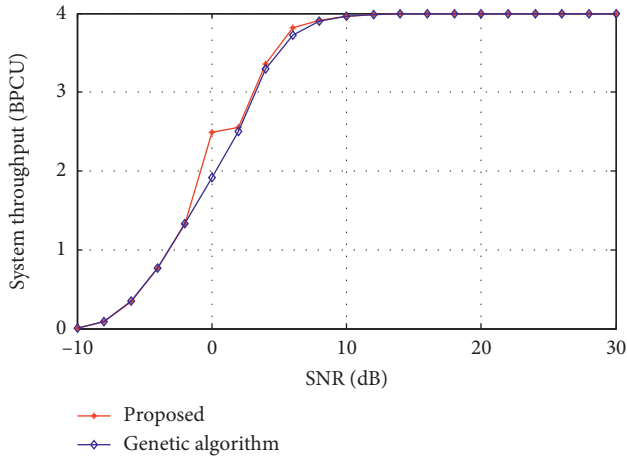
Figure 3: System throughput (BPCU) versus SNR (dB) using different solutions.
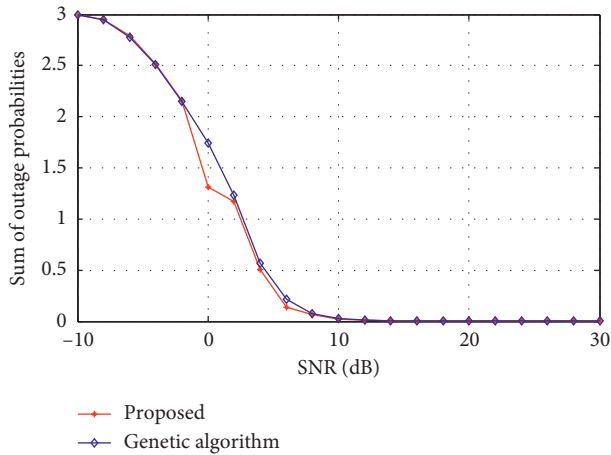

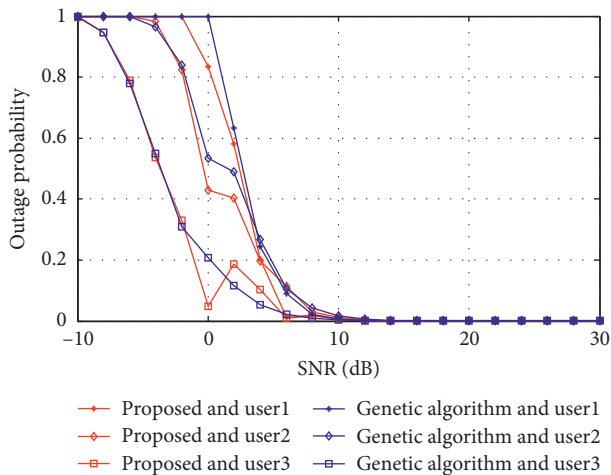Figure 4: Sum of outage probabilities versus SNR (dB) using different solutions.

Figure 5: Outage probabilities versus SNR (dB) using different solutions.

the proposed method, the feasible regions of α_1 and α_2 have been reduced to improve the calculation efficiency. α_3 is no longer used as a solution, and it is directly calculated using α_1 and α_2. The benefit of such a treatment is that the equality constraint (11) is avoided when generating fitness function. This result shows that rigorous mathematical derivations and reductions of the feasible region are important for an intelligent optimization algorithm.

Figures 3–5 show the different evaluation metrics, but their optimization objectives are the same. System throughput is taken as the single-objective function. According to the formulas for outage probabilities and system throughput, there is no contradiction between them. When the outage probability is very low, the system throughput performance can be guaranteed. However, this does not mean that the outage probability of each user is completely consistent with the system throughput performance of the downlink network. It has been calculated that the individual user may be sacrificed to maximize the system throughput. With the increasing of outage probability (power reduction) of the individual user, the total outage probability and system throughput may be improved. Although some GA results are better than the PSO results for user3, system throughput of GA optimization is definitely worse than that of the proposed PSO optimization. There exist balance and game problems between system throughput performance and a user outage probability. To illustrate this problem, the outage probability of user3 is taken as the objective function, and the proposed PSO method is used to solve the OPA.

As shown in Figures 6–8, the system performances vary depending on the target functions. It can be seen that the optimal system throughput performance does not guarantee the best performance for every user. Even if multiple users have the lowest total outage probability, there is no guarantee that each user will have the lowest outage probability. With regards to the solution results, it should be noted that it is difficult for an artificial intelligence algorithm to find the global optimal solution. In terms of few individual points, the system throughput of the curve targeting the best system throughput can be less than that of the curve targeting the best user3. Also, these locally optimal solutions are few and reasonable when PSO is used. To solve the biobjective programming problem, we use the weighted ideal method to evaluate Pareto frontier using 500 solutions, which is shown in Figure 9.

At the Pareto frontier, user3 outage probability and system throughput performances need to be balanced. OPA should balance the two to achieve a balance of the two indicators.

The index of outage probability is an inverse index and has a cost type attribute. The smaller the outage probability value is, the better the system performance. The index of system throughput is positive and has a benefit type attribute. The larger the index value, the better the system performance. According to formulas (9) and (10), the system throughput and outage probability values in Figure 9 are standardized. The weight matrix is determined by the entropy weight method, and the matrix is
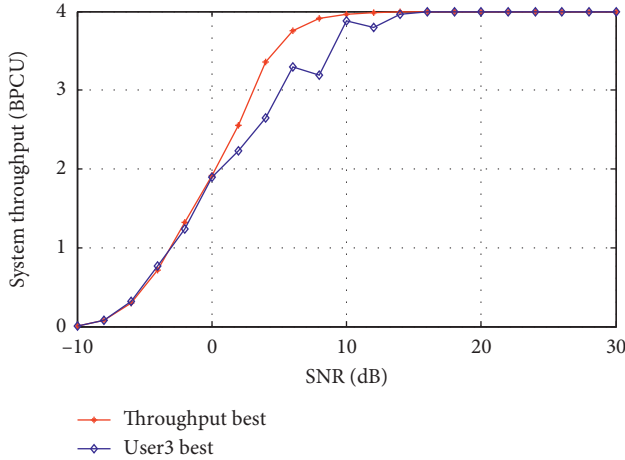
FIGURE 6: System throughput (BPCU) versus SNR (dB) considering different optimization objectives.
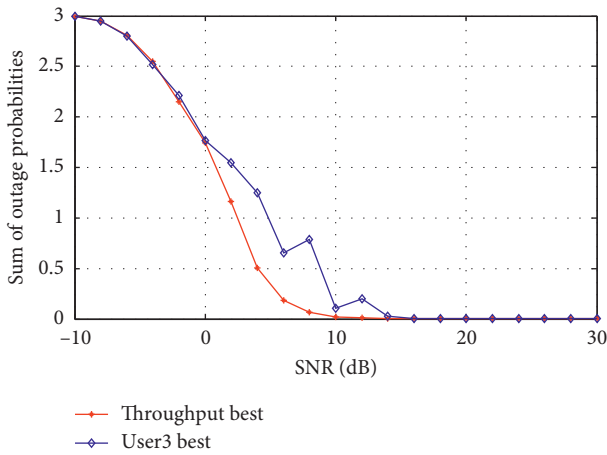

FIGURE 7: Sum of outage probabilities versus SNR (dB) considering different optimization objectives.
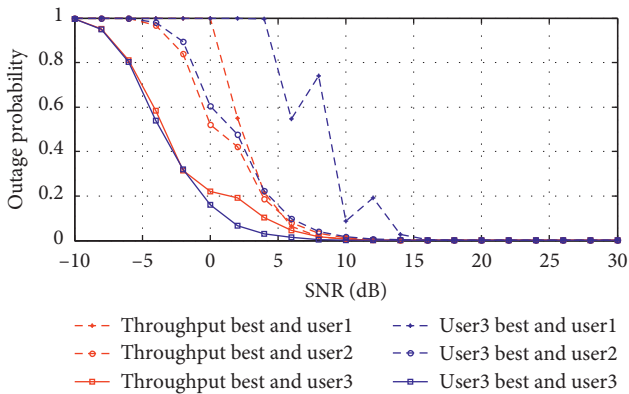

FIGURE 8: Sum of outage probabilities versus SNR (dB) considering different optimization objectives.

[0.1408, 0.8592]. The TOPSIS approach is a double benchmark that can reduce the probability of the same evaluation results. We can obtain the best power distribution
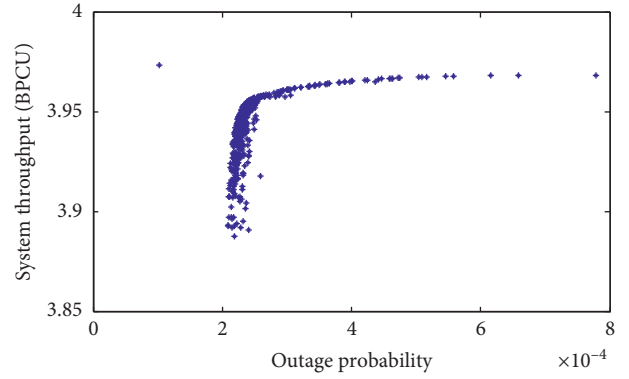

FIGURE 9: Pareto frontier for user3 outage probability versus system throughput with SNR = 10.

TABLE 2: System performances of TOPSIS.

Item	System throughput	Outage probability
Lower boundary	3.88	0.0010
Upper boundary	3.97	0.0078
TOPSIS	3.96	0.0011

scheme using the method combining entropy weight and TOPSIS, and the solution of PA coefficients is [0.7, 0.2, 0.1]. The optimal system throughput and outage probability of TOPSIS is listed in Table 2. It can be seen that each index of TOPSIS is not the best, but there is a balance between the two indexes.

Although PSO can be applied to solve nonconvex multiobjective optimization problems, it cannot avoid the complexity of parameter setting and program debugging. The setting of PA initial values and particle moving speed will affect the PSO performance. In practical programming, the biggest challenge is that the particle swarm can be updated in the infeasible region. With respect to the proposed optimization method, the updating of particle swarm is strictly limited in the feasible region via putting strict constraints on the feasible region instead of setting the penalty term in the fitness function. Of course, multiobjective will bring about the complexity problem, which can be dealt with by Pareto frontier and an effective comprehensive evaluation method.

5. Conclusion

The entropy method is used to determine the weight of a system index (system throughput and outage probability), which avoids the subjectivity of multifactor weight determination. Through the analysis of the comprehensive evaluation results of the system performance of a downlink network, the effectiveness and rationality of the TOPSIS approach for OPA are verified. TOPSIS can calculate the weighted distance and overcome the shortage of comprehensive evaluation results caused by the use of a single standard. The simulation results ensure that the outage probability of a single user is low, and the system throughput performance is good.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

References

[1] B. Yang, T. Yu, H. Shu, J. Dong, and L. Jiang, "Robust sliding-mode control of wind energy conversion systems for optimal power extraction via nonlinear perturbation observers," *Applied Energy*, vol. 210, pp. 711–723, 2018.

[2] B. Yang, X. Zhang, T. Yu, H. Shu, and Z. Fang, "Grouped grey wolf optimizer for maximum power point tracking of doubly-fed induction generator based wind turbine," *Energy Conversion and Management*, vol. 133, pp. 427–443, 2017.

[3] B. Yang, L. Jiang, L. Wang, W. Yao, and Q. H. Wu, "Nonlinear maximum power point tracking control and modal analysis of DFIG based wind turbine," *International Journal of Electrical Power & Energy Systems*, vol. 74, pp. 429–436, 2016.

[4] B. Yang, T. Yu, H. Shu et al., "Passivity-based sliding-mode control design for optimal power extraction of a PMSG based variable speed wind turbine," *Renewable Energy*, vol. 119, pp. 577–589, 2018.

[5] B. Yang, L. Zhong, X. Zhang et al., "Novel bio-inspired memetic salp swarm algorithm and application to MPPT for PV systems considering partial shading condition," *Journal of Cleaner Production*, vol. 215, pp. 1203–1222, 2019.

[6] B. Yang, T. Yu, X. Zhang et al., "Dynamic leader based collective intelligence for maximum power point tracking of PV systems affected by partial shading condition," *Energy Conversion and Management*, vol. 179, pp. 286–303, 2019.

[7] Y. Ye, R. Q. Hu, G. Lu, and L. Shi, "Enhance latency-constrained computation in MEC networks using uplink NOMA," *IEEE Transactions on Communications*, vol. 68, no. 4, pp. 2409–2425, 2020.

[8] Z. Ding, Y. Liu, J. Choi et al., "Application of non-orthogonal multiple access in LTE and 5G networks," *IEEE Communications Magazine*, vol. 55, no. 2, pp. 185–191, 2017.

[9] L. Lu, Y. Chen, W. Guo, H. Yang, Y. Wu, and S. Xing, "Prototype for 5G new air interface technology SCMA and performance evaluation," *China Communications*, vol. 12, pp. 38–48, 2015.

[10] ZTE, *Discussion on Multiple Access for New Radio Interface 3GPP TSG RAN WG1 Meeting 84bis, Doc.R1–162226*, ZTE, Busan, Korea, 2016.

[11] X. Dai, Z. Zhang, B. Bai, S. Chen, and S. Sun, "Pattern division multiple access: a new multiple access technology for 5G," *IEEE Wireless Communications*, vol. 25, no. 2, pp. 54–60, 2018.

[12] B. Ren, Y. Wang, X. Dai, K. Niu, and W. Tang, "Pattern matrix design of PDMA for 5G UL applications," *China Communications*, vol. 13, no. Supplement2, pp. 159–173, 2016.

[13] S. Chen, B. Ren, Q. Gao, S. Kang, S. Sun, and K. Niu, "Pattern division multiple access-a novel nonorthogonal multiple access for fifth-generation radio networks," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 4, pp. 3185–3196, 2017.

[14] J. Bae and Y. Han, "Joint power and time allocation for two-way cooperative NOMA," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 12, pp. 12443–12447, 2019.

[15] Y. Cao, S. Wang, M. Jin et al., "Power optimization for enhancing secrecy of cooperative user relaying NOMA networks," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 7, pp. 8008–8012, 2020.

[16] J. Zhu, J. Wang, Y. Huang, S. He, X. You, and L. Yang, "On optimal power allocation for downlink non-orthogonal multiple access systems," *IEEE Journal on Selected Areas in Commun*, vol. 35, no. 12, pp. 2744–2757, 2017.

[17] J. Cui, Y. Liu, Z. Ding, P. Fan, and A. Nallanathan, "Qoe-based resource allocation for multi-cell NOMA Networks," *IEEE Transactions on Wireless Communications*, vol. 17, no. 9, pp. 6160–6176, 2018.

[18] D. Ni, L. Hao, Q. T. Tran, and X. Qian, "Transmit power minimization for downlink multi-cell multi-carrier NOMA networks," *IEEE Communications Letters*, vol. 22, no. 12, pp. 2459–2462, 2018.

[19] W. U. Khan, Z. Yu, S. Yu, G. A. S. Sidhu, and J. Liu, "Efficient power allocation in downlink multi-cell multi-user NOMA networks," *IET Communications*, vol. 13, no. 4, pp. 396–402, 2019.

[20] J. Zhao, Y. Liu, K. K. Chai, A. Nallanathan, Y. Chen, and Z. Han, "Spectrum allocation and power control for non-orthogonal multiple access in hetNets," *IEEE Transactions on Wireless Communications*, vol. 16, no. 9, pp. 5825–5837, 2017.

[21] X. Song, L. Dong, J. Wang, L. Qin, and X. Han, "Energy efficient power allocation for downlink NOMA heterogeneous networks with imperfect CSI," *IEEE Access*, vol. 7, pp. 39329–39340, 2019.

[22] C. He, Y. Hu, Y. Chen, and B. Zeng, "Joint power allocation and channel assignment for NOMA with deep reinforcement learning," *IEEE Journal on Selected Areas in Communications*, vol. 37, no. 10, pp. 2200–2210, 2019.

[23] H. Xiao, Y. Wang, Q. Cheng, and Y. Wang, "An improved PSO-based power allocation algorithm for the optimal EE and SE tradeoff in downlink NOMA systems," in *Proceedings of 2018 IEEE 29th Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*, pp. 1–5, Bologna, Italy, September 2018.

[24] X. Zhang, S. Kang, and X. Fu, "Pattern division multiple access featuring amplify-and-forward relaying in an uplink network," *IEEE Access*, vol. 8, pp. 85656–85663, 2020.

[25] J. Tang, Y. Yu, D. So, G. Chen, X. Zhang, and M. Huang, "Multi-objective optimization of joint power allocation and splitting control for SWIPT-enabled NOMA systems," in *Proceedings of 2019 International Conference on Computing, Networking and Communications (ICNC)*, pp. 491–496, Honolulu, HI, USA, February 2019.

[26] X. Zhang, S. Kang, X. Fu, and W. Tang, "Performance analysis of cooperative PDMA with AF relaying over Rayleigh fading channels," *IET Communications*, vol. 14, no. 13, pp. 2166–2175, 2020.

[27] J. Choi, "Joint rate and power allocation for NOMA with statistical CSI," *IEEE Transactions on Communications*, vol. 65, no. 10, pp. 4519–4528, 2017.

[28] X. Fu, Q. Guo, and H. Sun, "Statistical machine learning model for stochastic optimal planning of distribution networks considering a dynamic correlation and dimension reduction," *IEEE Transactions on Smart Grid*, vol. 11, no. 4, pp. 2904–2917, 2020.

[29] X. Fu, H. Chen, R. Cai, and P. Yang, "Optimal allocation and adaptive VAR control of PV-DG in distribution networks," *Applied Energy*, vol. 137, pp. 173–182, 2015.

[30] X. Fu, H. Chen, and X. Jin, "Study on effectiveness evaluation of the siting of DG based on a TOPSIS method-based approach," in *Proceedings of 2013 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC)*, pp. 1–6, Kowloon, Kerala, 2013, November.