Contents lists available at YXpublications

International Journal of Applied Mathematics in Control Engineering

Journal homepage: http://www.ijamce.com

Research on GA-PSO Algorithm in MIMO NOMA Network with SWIPT

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ARTICLE INFO

Article history:
Received 15 April 2020
Accepted 15 June 2020
Available online 20 June 2020

Keywords：
NOMA
SWIPT
PSO

ABSTRACT

This paper studies the application of simultaneous wireless information and power transfer (SWIPT) in non-orthogonal multiple access (NOMA) and combines multi-input and multi-output (MIMO) technology. A new cooperative MIMO-SWIPT-NOMA protocol is proposed, which uses the near-end user with strong channel conditions as the energy harvesting relay to help the far-end user with poor channel conditions, and the near-end users adopt the power splitting (PS) receiving mechanism. This paper maximizes the transmission rate of the far-end user on the premise of satisfying the transmission of the near user. For the constructed multi-variable non-convex optimization problem, traditional optimization methods are difficult to solve. An improved particle swarm optimization (PSO) algorithm combined with genetic algorithm is proposed to solve the studied optimization problem. Experiments show that the proposed algorithm is more effective than the existing improved PSO algorithms.

1. Introduction

The rapid rise in traffic demands has driven the incentive for the research and development of the next generation of mobile networks, known as 5G [1]. Expected to be commercially available in early 2020s, 5G network will need to deliver high spectral efficiency (SE) to pave the way for future ultra highrate applications and the Internet-of-Things (IoT) era, which aims for massive machine type communication (mMTC) and ultra-reliable low-latency communications (uRLLC). Since the conventional orthogonal multiple access (OMA) techniques are not able to meet the demand of higher SE, non-orthogonal multiple access (NOMA) has emerged as a candidate for 5G networks for its superior SE performance [2]–[4].

The basic idea of non-orthogonal multiple access technology (NOMA) is to adopt non-orthogonal transmission at the transmitter, which introduces interference information actively, and then the successive interference cancellation (SIC) is used at the receiver, so as to realize correct demodulation. The sub-channel transmission of NOMA is still using orthogonal frequency division multiplexing (OFDM) technology, which is orthogonal between sub-channels and does not interfere with information transmission. Meanwhile, a certain sub-channel is no longer only assigned to a single user, but is shared by multiple users. Due to non-orthogonal transmission between different users on the same sub-channel, inter-user interference will be generated, which is the purpose of adopting SIC technology to conduct multi-user detection at the receiver. At the transmitter, the power multiplexing technology is used to send information to different users on the same sub-channel. And the signal power of different users is allocated according to the relevant algorithm, so that the signal power of each user at the receiver is different. SIC receiver can eliminate interference in a certain order according to the signal power of different users to realize correct demodulation, and at the same time achieves the purpose of distinguishing users. Another benefit of NOMA technology is that communication networks does not rely on the Channel state information which users feedback. In most communication networks nowadays, due to some special reasons such as user mobility and feedback processing delay, it is often difficult for users to timely feedback effective network channel state information to the transmitter according to the changes of network environment. At present, although there are a lot of technology is no longer of excessive dependence on user feedback channel state information, one can get stable performance gain, but adopted the technology of SIC NOMA scheme can better adapt to this kind of situation, so as to make the NOMA technology can be in high speed mobile user scenarios to obtain better performance, and can form a better mobile node backhaul links.

Unlike OMA, the key idea behind NOMA is to serve multiple users in the same resource block, i.e., time slot or subcarrier, and hence improve SE [2]. The better optimum sum rate performance for NOMA systems than OMA systems is proved with consideration

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of user fairness. The comparison is investigated from an optimization point of view and the advantages of NOMA over OMA were showed in practical Rayleigh fading channels. To be more practical, a downlink NOMA transmission with dynamic traffic arrival for spatially random users of different priorities was considered in [4]. By using tools from queueing theory and stochastic geometry, it was proved that the proposed NOMA scheme achieves larger stable throughput regions than OMA. The pairing between users is a problem worthy of attention in NOMA systems [5], [6]. In [5], the impact of user pairing on the performance of two NOMA systems, i.e., NOMA with fixed power allocation (F-NOMA) and cognitiveradio-inspired NOMA (CR-NOMA), has been considered. A novel low-complexity suboptimal user scheduling algorithm was proposed to maximize the system energy efficiency in [6].

Since users are sharing the same channel in NOMA system, the privacy and security in wireless networks need attention. Recently, physical-layer security has been proposed to achieve the information-theoretical security [7], [8]. In particular, the resource management scheme in [7] makes an important contribution to the field of secure communication, and the proposed analysis on the secrecy capacity and secrecy outage probability in [7], [8] provides critical guidance to the research of secure communications. In [9], cooperative jamming (CJ) was exploited to enhance the achievable secrecy energy efficiency (EE) for NOMA two-way relay wireless networks. Besides, the research on NOMA has been extended to multiple-input multiple-output (MIMO) systems [10], millimeter-wave (mmWave) communications [11] and mobile edge computing (MEC) [12].

Meanwhile, 5G application scenarios such as blockchain based IoT ecosystem and smart city require long life battery to support the demand of high data rate services [13]. Recent progress in the research on wireless power transfer (WPT) provides the possibility of improving the lifespan of energy constrained wireless devices [14]. Furthermore, it is known that the radio frequency (RF) signals are the carriers of both information and energy, which makes it possible to combine WPT and wireless information transmit (WIT) in wireless communications systems. Motivated by this, an advanced technology named simultaneous wireless information and power transfer (SWIPT), has emerged recently, aiming to achieve the parallel transmission of information and energy. Based on this idea, an information-theoretic study on SWIPT was first investigated in [15]. Energy harvesting technology is one of the key technologies of SWIPT. In recent years, scholars from all over the world have carried out active exploration and research on EH technology from theory to equipment, and the designed model also jumps from single node to multiple nodes, striving to seek an adaptive perceptive energy harvesting model, so as to complete revolutionary transformation of energy storage mode. The nonlinear relationship between the outputs DC power of EH device and the input RF signal power is verified through the data analysis of the actual energy harvesting circuit. However, the linear EH model is still applicable to low input power devices. The main reasons are as follows: First, when EH devices are assigned low or high input power respectively, the nonlinear EH model can be approximated as piecewise linear model. Under this assumption, the linear EH model has better accuracy. Second, smart IoT devices are usually exposed to an electromagnetic environment full of low RF signal power.

Despite being insightful, current technologies for energy harvesting are not yet able to decode the carried information directly due to the fact that the information and energy receivers sensitivities are fundamentally different, and hence such theoretical bounds are not practically feasible. Because of this, two new receiver structures were developed where information decoding (ID) and energy harvesting were separated through the time domain and the power domain, namely time switching (TS) scheme and power splitting (PS) scheme [16]. In [17], both of these practical receiving schemes have been studied in a relaying-assisted uRLLC network, where a tradeoff between the PS and TS protocols was introduced to improve the performance. With independent splitting control, the authors in [18] proposed a joint subcarrier and power allocation-based SWIPT scheme by assuming the received OFDM sub-carriers are partitioned into two groups which are used for either ID or EH. In [19], the authors considered TS-based SWIPT for a small-cell network, where the joint optimization of spatial precoding and TS ratios was addressed in order to maximize the data rates and harvested energy of all UEs simultaneously. In [20], the authors considered an EH efficiency maximization problem for both linear and non-linear model in multi-cell multiple-input single-output (MISO) networks. In [21], EE optimization was studied in MIMO two-way amplify-and-forward relay networks, where the sources, relay precoding matrices and the PS ratio are jointly optimized. Besides, SWIPT techniques have also attracted great interest in cognitive radio (CR) networks [22].

Due to the immense potential SWIPT and NOMA, the combination of these two techniques has aroused great interest. The work in [23] considered a wireless-powered NOMA communication system and focused on the joint design of downlink energy transfer and uplink information transmission. Two schemes namely the “fixed decoding order” and the “time sharing” scheme were proposed for proportional fairness improvement and individual optimization. It was demonstrated that the system performance could be significantly improved through the integration of SWIPT and NOMA. Considering the wireless powered networks are exposed to the effect of the cascaded near-far problem, the authors in [24] maximized the downlink/uplink users rate by utilizing corresponding priority weights. In addition, the cooperative NOMA scheme has been widely used in the SWIPT-enabled NOMA system, in which near NOMA users that were close to the source acted as energy harvesting relays to help far NOMA users with poor channel conditions [25], [26]. In [25], the authors aimed at maximizing the data rate of the “strong user” while satisfying the QoS requirement of the “weak user” by jointly optimizing the PS ratios and the beamforming vectors. In [26], the performance of the cell-edge user in terms of outage probability and diversity gain was investigated with the hybrid TS/PS SWIPT NOMA architecture. The results demonstrated the achievable performance improvements of the proposed schemes in comparison to that of the OMA systems. To optimize the SE and EE, a MISO SWIPT-enabled NOMA CR network was considered based on a non-linear EH model [27], where robust beamforming and power splitting ratio were jointly designed for minimizing the transmission power. Furthermore, a SWIPT-enabled NOMA mmWave massive MIMO system was studied in [28] where an iterative optimization algorithm was developed to maximize the achievable sum rate.

In real world, most of practical engineering problems are multimodal functions [29-31] whose optimization is still one of the most challenging tasks due to many local optima. Several evolutionary algorithms, such as particle swarm optimization (PSO) [32], ant colony optimization (ACO) [33], differential evolution (DE) algorithm [34], cooperative co-evolution (CC) algorithm [35] and estimation of distribution algorithm (EDAs) [36], have been proposed to solve the multimodal optimization problems. Among these algorithms, PSO which imitates the foraging behavior of bird flocks [37] is one of the most outstanding population-based evolutionary algorithms. It becomes popular not only because it is easy to implement, but also due to its strong optimization ability. Its efficiency in solving benchmark functions and complex optimization problems attracts numerous attentions [38-45].

For the optimization of multimodal functions where many local optima exist, the optimization algorithm should try to avoid trapping into local optima, which is a difficult issue for many heuristic algorithms [46]. As a typical metaheuristic algorithm, the standard PSO algorithm indeed has the drawback of premature convergence and easily trapping into local optima. Many improved PSO variants focus on solving the problem of trapping into local minima when used for minimizing multimodal functions, which aim to improve the global search ability of PSO. Much progress has been made. Some studies aim to avoid premature convergence by maintaining or increasing population diversity. There are many such means, e.g., dynamic clustering [47], [48], [49], [50] supervised learning [51].[52], historical memory [53] and adopting different learning strategies [54], [55]. Researches have been done to improve the global search ability by combining PSO with other intelligent algorithms [56]

- In this paper, a new network model is constructed and explored using NOMA technology in MIMO SWIPT networks. In this network, the near-end users with strong channel conditions act as an energy harvesting relay to help the far-end users with poor channel conditions. Furthermore, the optimization problem of far-end user rate maximization is constructed under the condition of near-end user rate constraint.
- In this paper, the standard particle swarm optimization is improved and the advantages of genetic algorithm are introduced. In the iterative optimization process, chromosome hybridization and gene mutation in genetic algorithm are referred in this paper to increase the population diversity of particle swarm so as to successfully avoid particles falling into local optimal.
- In this paper, the feasibility of the proposed algorithm is verified by simulation results, and the effectiveness of the proposed algorithm is verified by comparison with other baseline algorithms.

The rest of the paper is organized as follows: Section 2 introduces the system model and problem formulation. In this section, the optimization problem of transmission rate maximization of the remote user is formulated. In Section 3, a GA-PSO algorithm is introduced to solve the proposed problem. Section 4 shows the simulation results and performance comparisons. Section 5 concludes the paper.

Notations: In this paper, boldface uppercase represents the matrix, and boldface lowercase represents the vector. The set of *n*-by-*m* complex matrices is denoted by $C^{n\times m}$. For a given matrix $\mathbf{A}$, $\mathbf{A}^H$ represents the complex conjugate transpose of that matrix, and $\mathbf{A}\succ\mathbf{0}$ is a positive matrix. The symbol $\mathbf{I}$ denotes the identity matrix and $\mathbf{0}$ denotes a zero vector or matrix.

2. System model and problem formulation

A. System Model

Consider a downlink MIMO network model with a base station and two users, user 1 and user 2. Suppose that the channel condition of user 1 is worse than that of user 2. Therefore, to ensure the QoS requirements of user 1, user 2 can assist user 1 as EH relay. BS and users have M and N antennas respectively.

The SWIPT NOMA transport for this article is divided into two phases. In the first phase, user 1 receives the signal directly from BS and user 2 performs SWIPT. The signals received by user 2 are respectively used for information decoding and energy harvesting through PS, in which the information decoding needs to extract the signals of user 1 through serial interference elimination. In the second stage, user 2 uses the harvested energy to forward the information to user 1, who merges the signals received in the two stages and decodes them. The specific process is as follows.

(1) User 1 direct connection and user 2 SWIPT phase

At this stage, the transmission signal of BS can be expressed as $\mathbf{x}=\mathbf{w}_1x_1+\mathbf{w}_2x_2$, $x_1, x_2\in C$ are the standard transfer symbols to user 1 and user 2, respectively. $\mathbf{w}_1$ and $\mathbf{w}_2$ are the weight vectors of x_1 and x_2, $\mathbf{w}_1,\mathbf{w}_2\in C^{M\times 1}$. Each component represents the weight of the corresponding antenna on x_1 and x_2 during transmission, and it needs to meet the power constraint $\|\mathbf{w}_1\|^2+\|\mathbf{w}_2\|^2\le 1$. We can then get the signals that user 2 receives at this stage.

$$\mathbf{y}_{U_2}^{(1)}=\sqrt{P_S}\mathbf{G}_1^H(\mathbf{w}_1x_1+\mathbf{w}_2x_2)+\mathbf{I}_n\mathbf{n}_1^{(1)}\,. \tag{1}$$

where P_S is the transmission power of BS, $\mathbf{G}_1\in C^{M\times N}$ is the channel coefficient between BS and user 2, $\mathbf{n}_1^{(1)}\sim CN(0,\sigma_1^2)$ is user 2's additive white gaussian noise (AWGN). User 2 performs SWIPT through power splitting and uses SIC to detect $x1$. Signals used for information decoding and energy harvesting at user 2 can be respectively expressed as:

$$\mathbf{y}_{U_2,\mathrm{ID}}=\sqrt{(1-\rho)}\left(\sqrt{P_S}\mathbf{G}_1^H(\mathbf{w}_1x_1+\mathbf{w}_2x_2)+\mathbf{I}_n\mathbf{n}_1^{(1)}\right)+\mathbf{n}^{(1)}$$

$$\mathbf{y}_{U_2,x_1,\mathrm{EH}}=\sqrt{\rho}\sqrt{P_S}\mathbf{G}_1^H(\mathbf{w}_1x_1+\mathbf{w}_2x_2)$$

where $\mathbf{n}^{(1)}\sim CN(0,\sigma_1^2)^{N\times 1}$ is signal processing noise. For convenience, the noise power a is assumed that $\sigma_1^2=\sigma^2$.

Its signal-to-noise ratio (SINR) about x_1 can be expressed as:

$$\gamma_{U_2,x_1}=\frac{(1-\rho)P_S\|\mathbf{G}_1^H\mathbf{w}_1\|^2}{(1-\rho)P_S\|\mathbf{G}_1^H\mathbf{w}_2\|^2+[n(1-\rho)+1]\sigma^2}\,. \tag{2}$$

where $\rho\in[0,1]$ is the power splitting factor. The remaining signal-to-noise ratio (SNR) of x_2 on the received signal of user 2 is:

$$\gamma_{U_2,x_2}=\frac{(1-\rho)P_S\|\mathbf{G}_1^H\mathbf{w}_2\|^2}{[n(1-\rho)+1]\sigma^2}\,. \tag{3}$$

The transmit power of user 2 in the assist transmission phase is:

$$P_{U_2}=\frac{\alpha}{1-\alpha}\eta\rho P_S(\|\mathbf{G}_1^H\mathbf{w}_1\|^2+\|\mathbf{G}_1^H\mathbf{w}_2\|^2)\,. \tag{4}$$

where η is the energy conversion efficiency. The signal received by user 1 in the first stage is:

$$\mathbf{y}_{U_1}^{(1)}=\sqrt{P_S}\mathbf{G}_2^H(\mathbf{w}_1x_1+\mathbf{w}_2x_2)+\mathbf{n}_2^{(1)}\,. \tag{5}$$

where $\mathbf{G}_2\in C^{M\times N}$ is the channel coefficient matrix between BS and user 1. $\mathbf{n}_2^{(1)}\sim CN(0,\sigma_1^2)^{N\times 1}$ is user 1's AWGN. Its SNR for x_1 is:

$$\gamma_{U_1,x_1}^{(1)}=\frac{P_S\|\mathbf{G}_2^H\mathbf{w}_1\|^2}{P_S\|\mathbf{G}_2^H\mathbf{w}_2\|^2+n\sigma^2} \tag{6}$$

(2) Assisted transmission phase

At this stage, user 2 transmits x_1 to user 1 using the harvested RF energy. Therefore, the signal got by user 1 is:

$$\mathbf{y}_{U_1}^{(2)} = \sqrt{P_{U_2}}\mathbf{G}_3^H\mathbf{w}_3 x_1 + \mathbf{I}_n\mathbf{n}_3^{(2)} . \quad (7)$$

where $\mathbf{G}_3 \in C^{N\times N}$ is the channel coefficient between user 1 and user 2. $\mathbf{w}_3$ is the weight vector of user 2 in the second phase of assisted transmission. $\mathbf{n}_3^{(2)} \sim CN(0,\sigma_1^2)^{N\times 1}$ is AWGN. In the second stage, the SNR of user 1 about x_1 is:

$$\begin{aligned}\gamma_{U_1,x_1}^{(2)} &= \frac{P_{U_2}\|\mathbf{G}_3^H\mathbf{w}_3\|^2}{n\sigma^2} \\ &= \frac{\alpha\eta\rho P_S(\|\mathbf{G}_1^H\mathbf{w}_1\|^2+\|\mathbf{G}_1^H\mathbf{w}_2\|^2)\|\mathbf{G}_3^H\mathbf{w}_3\|^2}{(1-\alpha)n\sigma^2} .\end{aligned} \quad (8)$$

At the end of the second phase, user 1 calculates the sum rate within the entire transmission cycle, and as the two transmission stages have equal duration, 0.5 is weighted respectively.

$$R_{U_1} = \alpha\log_2(1+\gamma_{U_1,x_1}^{(1)}) + (1-\alpha)\log_2(1+\gamma_{U_1,x_1}^{(2)}) . \quad (9)$$

B. Problem Formulation

The goal of this paper is to maximize the transmission rate of the remote user while satisfying the requirements of the near user. The optimization problem can be expressed mathematically as follows. We assume that the user's transmission rate requirements are all R_0.

$$\mathbf{P1}: \max_{\mathbf{w}_1,\mathbf{w}_2,\mathbf{w}_3,\alpha,\rho} R_{U_1} \quad (10a)$$

$$s.t.\alpha\log_2(1+\gamma_{U_2,x_1}) \ge R_0 \quad (10b)$$

$$\alpha\log_2(1+\gamma_{U_2,x_2}) \ge R_0 \quad (10c)$$

$$0 \le \|\mathbf{w}_1\|^2 + \|\mathbf{w}_2\|^2 \le 1 \quad (10d)$$

$$0 \le \|\mathbf{w}_3\|^2 \le 1 \quad (10e)$$

$$0 < \rho < 1 \quad (10f)$$

$$\mathbf{w}_1,\mathbf{w}_2,\mathbf{w}_3 \succ \mathbf{0} \quad (10g)$$

where (10b) and (10c) indicate that user 2 detects in phase 1 that the effective transfer rate for x_1 and x_2 needs to be greater than the threshold. (10d) and (10e) are transmission power constraints. We assume that the transmission power threshold is 1W.

Since the objective function (10a) and the constraints (10b), (10c) contain product terms of variables , so **P1** is a non-convex optimization problem. For non-convex optimization problems, there is no effective method to find the optimal solution. Fortunately, we find that $\mathbf{w}_3$ can be optimized separately, being not coupled to the rest of the variables. In the case that $\mathbf{G}_3$ is known, the maximum value of $\|\mathbf{G}_3^H\mathbf{w}_3\|^2$ is easy to find, so we can suppose that the maximum value is θ.

Then, optimization problem **P1** can be further equivalently converted into optimization problem **P2**.

$$\mathbf{P2}: \begin{aligned}&\max_{\mathbf{w}_1,\mathbf{w}_2,\alpha,\rho} \alpha\log_2\left(1+\frac{P_S\|\mathbf{G}_2^H\mathbf{w}_1\|^2}{P_S\|\mathbf{G}_2^H\mathbf{w}_2\|^2+n\sigma^2}\right)+ \\ &(1-\alpha)\log_2\left(1+\frac{\alpha\eta\rho P_S(\|\mathbf{G}_1^H\mathbf{w}_1\|^2+\|\mathbf{G}_1^H\mathbf{w}_2\|^2)\theta}{(1-\alpha)n\sigma^2}\right)\end{aligned} \quad (11a)$$

$$s.t.\alpha\log_2\left(1+\frac{(1-\rho)P_S\|\mathbf{G}_1^H\mathbf{w}_1\|^2}{(1-\rho)P_S\|\mathbf{G}_1^H\mathbf{w}_2\|^2+[n(1-\rho)+1]\sigma^2}\right) \ge R_0 \quad (11b)$$

$$\alpha\log_2\left(1+\frac{(1-\rho)P_S\|\mathbf{G}_1^H\mathbf{w}_2\|^2}{[n(1-\rho)+1]\sigma^2}\right) \ge R_0 \quad (11c)$$

$$0 \le \|\mathbf{w}_1\|^2 + \|\mathbf{w}_2\|^2 \le 1 \quad (11d)$$

$$0 < \rho < 1 \quad (11e)$$

$$\mathbf{w}_1,\mathbf{w}_2 \succ \mathbf{0} . \quad (11f)$$

Optimization problem **P2** is still a non-convex optimization problem. Due to the coupling between optimization variables, **P2** is difficult to be converted into a solvable optimization problem form in the traditional way.

Modern swarm intelligent optimization algorithm provides an excellent solution to the optimization problem of multivariable coupling, and has great reference significance. Therefore, modern swarm intelligence optimization algorithm is considered to solve the problem.

3. Proposed Optimal Solution

A. Basic overview of PSO

Particle swarm optimization is a kind of swarm intelligence algorithm, which is designed by simulating the predatory behavior of birds, and has been widely used in many fields. Assuming that there is only one food in the region, which is regarded as the optimal solution in the usual optimization problem, the task of the flock is to find this food source. In the whole process of searching, the birds send their own information to each other to let other birds know their location. Through such cooperation, they judge whether they have found the optimal solution or not, and at the same time, they transmit the information of the optimal solution to the whole birds. In the end, the whole flock can gather around the food source, which is what we call the optimal solution. In other words, the problem converges. In a word, particle swarm optimization algorithm makes use of swarm intelligence to search cooperatively and find the optimal solution in the solution space finally.

PSO algorithm starts from the random solution and searches for the optimal solution through the iterative process. The algorithm evaluates the quality of the solution by fitness, and the algorithm design rules are more simple and direct. It determines the global optimal solution by following the maximum fitness found in the current search. This algorithm has attracted the attention of academic circles for its easy implementation, high precision and fast convergence, and has shown its superiority in solving practical problems.

In PSO, each individual bird can be regarded as a search particle in the N-dimensional search space. Each particle has two special properties: velocity and position. Velocity represents how fast or slow it is moving, and position represents the direction it is moving in. The particle's flight represents the individual's search process. The velocity of the particle can be dynamically adjusted according to the historical optimal position of the particle and the historical optimal position of the population. The current position of the particle is a candidate solution to the corresponding optimization problem. The optimal solution searched for each particle individually is called individual extremum, and the optimal individual extremum in the particle swarm is seen as the current global optimal solution. Particle swarm optimization often requires constant iteration, updating velocity and location. Finally, the optimal solution satisfying the termination condition is obtained.

The initial solution is generated at the beginning of the algorithm, that is, the population $Y = \{Y_1, Y_2, Y_3, \cdots Y_m\}$ composed of m particles is randomly initialized in the feasible solution space, and the initial position of each particle can be defined as $Y_i = \{y_{i1}, y_{i2}, y_{i3}, \cdots y_{in}\}$. Each position of the particle corresponds to a candidate solution of the optimization problem, and the new solution would be calculated and searched according to the objective function. During each iteration, the particle updates itself according to two "extreme values": one is the optimal solution searched by the particle itself, called the current local optimal solution, and the other is the optimal solution searched by the entire population, called the current global optimal solution. In addition, the velocity vector of each particle can be expressed as $V_i=\{v_{i1},v_{i2},v_{i3},\cdots v_{in}\}$. When the current local optimal solution and the current global optimal solution are determined, the velocity and position of each particle are updated according to the following iterative equation:

1) Iteration formula of velocity vector:

$$V_i=\omega[V_i+\lambda_1\gamma_1(\mathbf{pbest}_i-Y_i)+\lambda_2\gamma_2(\mathbf{gbest}_i-Y_i)]$$

2) Iteration formula of velocity Position:

$$Y_i=Y_i+V_i$$

where the parameter ω is called the inertia factor of PSO and is a non-negative constant. By adjusting the size of ω, global optimization performance and local optimization performance can be adjusted. λ_1 and λ_2 are learning factors, in which λ_1 is the individual learning factor of each particle and λ_2 is the social learning factor of each particle. In general, $\lambda_1=\lambda_2\in[0,4]$. Both λ_1 and λ_2 are random probability values between [0,1].

B. GA-PSO algorithm

Although particle swarm optimization is fast, efficient, simple and suitable for real value processing, it is not good at discrete optimization and easy to fall into local optimization. In order to overcome the shortcoming of standard PSO which is easy to converge to the local optimal solution, scholars have made many attempts. The most important direction is to increase the diversity among particles to achieve better optimization results. In this paper, we refer to chromosomal crossing and gene mutation in genetic algorithm to increase the population diversity of particle swarm during iterative optimization process, so as to avoid particles falling into local optimal.

First, in order to facilitate the setting of particle coordinates, **P2** is transformed through variable substitution.

$$\mathbf{P3}:\ \max_{\substack{a_i,b_i,\alpha,\rho\\ i=1,2,\dots,M}}(1-\alpha)\log_2\Big(1+\frac{\alpha}{1-\alpha}\eta\rho\theta P_S\sum_{i=1}^{M}\dot{h}_i(a_i+b_i)\Big)+\alpha\log_2\Big(1+\frac{P_S\sum_{i=1}^{M}\dot{k}_ib_i}{P_S\sum_{i=1}^{M}\dot{k}_ia_i+n\sigma^2}\Big) \tag{12a}$$

$$s.t.\ \alpha\log_2\Big(1+\frac{(1-\rho)P_S\sum_{i=1}^{M}h_ia_i}{(1-\rho)P_S\sum_{i=1}^{M}h_ib_i+[n(1-\rho)+1]\sigma^2}\Big)\ge R_0 \tag{12b}$$

$$\alpha\log_2\Big(1+\frac{(1-\rho)P_S\sum_{i=1}^{M}h_ib_i}{[n(1-\rho)+1]\sigma^2}\Big)\ge R_0 \tag{12c}$$

$$0\le\sum_{i=1}^{M}h_i(a_i+b_i)\le 1 \tag{12d}$$

$$0<\rho<1 \tag{12e}$$

$$0<a_i,b_i\le 1 \tag{12f}$$

where, a_i and b_i are squared components of $\mathbf{w}_1$ and $\mathbf{w}_2$, and h_i and k_i are squared sum of channel coefficients from the i-th receiving antenna.

In PSO, constraints are generally added to the main function by penalty factors and become penalty functions. In the iterative process, when the particle coordinates do not meet the constraints, the penalty term plays a role in setting the size according to the specific situation, so that the value of the objective function of the particle this time will not interfere with other particles. In this way, (12b) and (12c) can be combined with (12a).

$$f_1=(1-\alpha)\log_2\Big(1+\frac{\alpha}{1-\alpha}\eta\rho\theta P_S\sum_{i=1}^{M}\dot{h}_i(a_i+b_i)\Big)+\alpha\log_2\Big(1+\frac{P_S\sum_{i=1}^{M}\dot{k}_ib_i}{P_S\sum_{i=1}^{M}\dot{k}_ia_i+n\sigma^2}\Big) \tag{13}$$

$$f_2=\alpha\log_2\Big(1+\frac{(1-\rho)P_S\sum_{i=1}^{M}h_ia_i}{(1-\rho)P_S\sum_{i=1}^{M}h_ib_i+[n(1-\rho)+1]\sigma^2}\Big)-R_0 \tag{14}$$

$$f_3=\frac{1}{2}\log_2\Big(1+\frac{(1-\rho)P_S\sum_{i=1}^{M}h_ib_i}{[n(1-\rho)+1]\sigma^2}\Big)-R_0 \tag{15}$$

Then the objective function of PSO can be expressed as:

$$F=f_1+\varphi_1f_2+\varphi_2f_3 \tag{16}$$

where φ_1 and φ_2 are the penalty factor. When f_2 and f_3 are non-negative, set φ_1 and φ_2 to 0. Otherwise set them to appropriate values to make F small enough.

The updating formula of PSO:

$$\mathbf{v}'=w[\mathbf{v}+c_1r_1(\mathbf{gbest}-\mathbf{p})+c_2r_2(\mathbf{pbest}-\mathbf{p})] \tag{17}$$

$$\mathbf{p}'=\mathbf{p}+\mathbf{v}' \tag{18}$$

where c_1 and c_2 are the acceleration factor. r_1 and r_2 are random numbers. w is the contraction factor.

In order to solve the transformed optimization problem, we summarize the solution as Algorithm 1.

Algorithm 1: GA-PSO Algorithm

(1) Initializes the coordinates and velocities of the particles: $\mathbf{p}_j^0(a_{ji},b_{ji},\rho_j)$, $\mathbf{v}_j^0$. Calculate θ. The superscript on the right is the number of iterations. j is the particle number and i is the dimension.

(2) Calculate f_2 and f_3 for each particle, and then F. Update individual history best coordinate **pbest** and group best coordinate **gbest**.

(3) The particle mutates with probability p_1:

$$\mathbf{v}_j^t=\mathbf{v}_j^t+r\Delta\mathbf{v}_0 \tag{19}$$

where r is a random number. $\mathbf{v}_0$ is fixed.

(4) Some pairs of particles are randomly selected to cross chromosomes with probability p_2:

$$\mathbf{child}_1=p_2\times\mathbf{parent}_1+(1-p_2)\times\mathbf{parent}_2 \tag{20}$$

$$\mathbf{child}_2=(1-p_2)\times\mathbf{parent}_1+p_2\times\mathbf{parent}_2 \tag{21}$$

Intersections include coordinates and velocities.

(5) To further ensure the diversity of particle swarm, count the average distance between the particle $\bar{S}$ and maximum distance $S_{\max}$.

When $\bar{S}<p_3\times S_{\max}$, it represents the overconcentration of particles. The global optimal solution cannot be found well in this case. We need to adjust the updating formula:

$$\mathbf{v}_j^{t+1}=w^t[\mathbf{v}_j^t+c_3c_1r_1(\mathbf{gbest}-\mathbf{p}_j^t)+c_2r_2(\mathbf{pbest}-\mathbf{p}_j^t)] \tag{22}$$

$$\mathbf{p}_j^{t+1}=\mathbf{p}_j^t+\mathbf{v}_j^{t+1} \tag{23}$$

When the particles are concentrated, c_3 is set to -1 to make the particle swarm away from the current swarm. Otherwise it's set to 1.

(6) Repeat step (2) until convergence.

(7) Set n particle swarms at the same time to improve the accuracy.

4. Simulation Results

In this section, simulation results are provided in order to validate the performance of the proposed joint power allocation and splitting control algorithms in the SWIPT enabled NOMA systems. Rayleigh Fading is considered in this paper. The source transmitting power P_S is 1W. Rate threshold R_0=1bit/s/Hz. energy conversion efficiency $\eta = 0.6$.

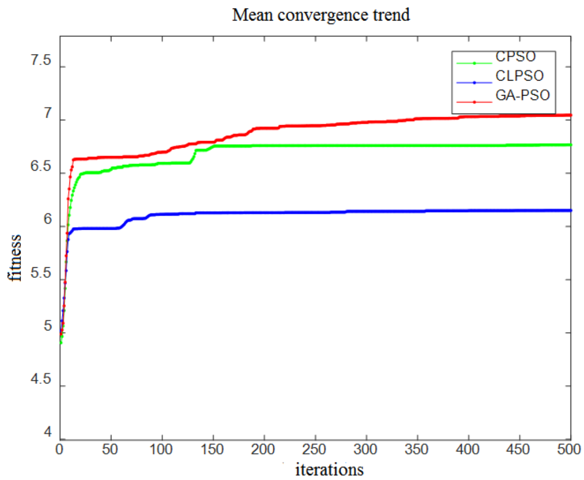

Fig. 1.The mean convergence trend of the algorithms

Fig. 1 shows the comparison between the proposed algorithm and other algorithms when M=12 and N=6. Experimental data show that GA-PSO algorithm has better effect in solving the problem mentioned in the paper.

5. Conclusion

In this paper, a genetic learning scheme for PSO algorithm has been proposed, which adopts genetic operators, specifically, crossover, mutation, and selection, to construct exemplars. The crossover utilizes the particles' historical information pbests and gbest to generate high-quality offspring, whereas the mutation injects diverse information into the offspring to enhance global exploration. Moreover, the selection operation ensures that each exemplar evolves directionally generation by generation. This way, the bred exemplars are well diversified and highly qualified, which are capable of providing improved guidance for the evolving particles. The proposed GA-PSO algorithm performs better in solving the problem.

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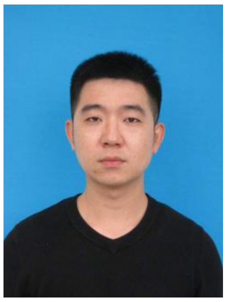

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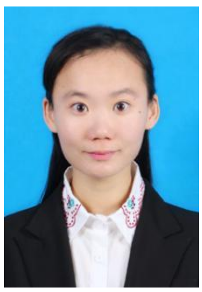

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