Journal of Computers Vol. 34 No. 3, June 2023, pp. 179-193
doi: 10.53106/199115992023063403013

LS-DN Algorithm Based User Matching and Power Minimization in NOMA Disaster Communication

Chengcheng Zou[1], Damin Zhang[1*], Linna Zhang[2]

[1] School of Big Data and Information Engineering, Guizhou University, Guizhou, Guiyang, 550025, China
2537582170@qq.com, 1203813362@qq.com

[2] School of Mechanical Engineering, Guizhou University, Guizhou, Guiyang, 550025, China
zln770808@163.com

Received: 29 June 2022; Revised 12 October 2022; Accepted 11 December 2022

Abstract. To address the limited and time delay disaster communication, a joint optimization scheme integrates the advantages of differential evolution algorithm (DE) and naked mole- rat algorithm (NMR), and proposes Lévy and sigmoidal DE-NMR, namely LS-DN. LS-DN applies the Lévy flight parameters of adaptive features and sigmoidal selection factor (λ) to the worker of NMR phase, and optimizes the crossover rate (CR) and variation parameter (F) in the DE algorithm, to obtain a balance the exploration and development capabilities. The proposed LS-DN algorithm is used to optimize the user aggregation scheme, since an effect aggregation of disaster victims can reduce power consumption and improve system performance. An value of power external function (C_n^f) is defined for each disaster victim, which is expressed as the system power consumption value for each disaster victim under different aggregation schemes. To minimize the microcell power without deteriorating the quality of service (QoS), it is demonstrated by analyzing the relevant characteristics of non-orthogonal multiple access（NOMA）disaster communication that the power consumption strongly depends on user aggregation method and power allocation. The significance of joint optimization for improving the performance of NOMA disaster communication systems is also emphasized. Simulation results show that LS-DN is able to significantly reduce the power consumption of the system. With the application of LS-DN, the throughput of NOMA system increases by 65% compared to the conventional orthogonal multiple access (OMA) system.

Keyword: LS-DN, NOMA, QoS, disaster communication, user matching, power allocation

1 Introduction

When natural disasters occur, timely and stable disaster communications can save thousands of families. As global temperatures rise, polar glaciers melt and floods devastate, many people become homeless [1]. According to the United Nations Disaster Risk Reduction (UNDRR), extreme natural disasters such as: floods, earthquakes, and droughts have severely affected human life, and in the worst cases, on average, a large number of people lose their lives every year [2]. When such extreme disasters occur, many injured lives can be saved if first responders can provide timely rescue, and this decision relies on the timely positioning of the injured at the point of occurrence, which is achieved by the injured sending a large number of distress signals through mobile network devices at the point of occurrence [3]. The reliability, delay and power loss of signal transmission of many mobile facilities can be closely related to this. The destruction of a local or central part of a communication device by a natural disaster is the most common in natural disasters. In most cases, many sacrifices can be prevented if the mobile communication equipment can maintain the lowest power consumption, so saving infrastructure power consumption with multi-user access systems is one of the core issues in disaster communication.

In mobile communications, the use of appropriate wireless access access technology can effectively increase system capacity and reduce system power consumption. Currently, compared with traditional orthogonal multiple access (OMA) technology, non-orthogonal multiple access (NOMA) technology has the advantages of high capacity, low power consumption, low latency and high reliability. NOMA is more suitable for disaster communication [4]. At the receiving end, successive interference cancellation (SIC) demodulation. To achieve high spectrum utilization the complexity of SIC [5-6]. The application of orthogonal techniques between sub-channels and

* Corresponding Author

non-orthogonal techniques within sub-channels allows users to be grouped and paired to improve performance gains using rational and efficient power allocation algorithms [7]. Therefore, user group pairing and power allocation become hot issues for transmitting information in disaster communication using NOMA technology.

At present, for these two hot issues, relevant researchers have done a lot of research to improve the performance of NOMA. In [8], the authors use the Unified Channel Gain Difference (UCGD) method to focus on the intermediate users of the cell, where the user with the largest channel gain in a group is matched with the user with the next intermediate value, and so on until all users are matched. Although this method is suitable for the aggregation of intermediate users, it increases the system capacity. In [9], the authors consider the problem of co-layer user interference in real communication environments. The vertical user pairing scheme is analyzed for reducing the co-layer interference situation by matching the users to overcome the inter-user interference from the perspective of reducing the channel gain difference. In [10], the authors match three users i.e., one edge user with any two users in any two cells in order to achieve channel fairness between intermediate and edge users in the cell, which ultimately improves the overall performance of the edge users.

And for system power allocation is often solved by water injection method, graph theory method, game theory, convex function solving method and intelligent optimization algorithm. In [11], to make the power allocation algorithm simple, the authors aim at maximizing the system energy efficiency by selling the transmit power with the base station as the seller and letting the strong and weak user pairs that have been successfully matched compete with each other as buyers. The paper accomplishes power allocation in a simple and feasible way while guaranteeing a fair average and rate for the user pairs. However, it does not consider user quality of service (QoS) and has a single application scenario. In [12], the authors consider the QoS of strong and weak users with minimum sum rate as a constraint and maximize the base station revenue and user utility using a Stackelberg game strategy that solves the system non-convex revenue function in three steps. It brings better sum rate for communication users, but also increases the complexity of the algorithm. In [13-14], the authors artificially systematically identify different fading factors to reduce algorithmic complexity without guaranteeing fairness to edge users

Solving the minimum power allocation under user QoS constraints can be easily considered as a class of optimization algorithm problems [15-18]. In this case, meta-heuristic intelligent optimization algorithms with high accuracy and low complexity are suitable solutions. Among them are cuckoo search algorithm (CS), whale optimization algorithm (WOA), particle swarm algorithm (PSO), DE, genetic algorithm (GD) and gray wolf optimization algorithm (GWO), etc. PSO is applied in [18] to achieve user matching with minimum power transmission. However, the best user matching was not achieved leading to waste of certain channel resources. Genetic Algorithm (GA) is also applied to achieve different power allocation values for different objective functions under user QoS constraints and it is proved that NOMA system achieves higher users and rates than OMA system, which has low complexity as well as susceptibility of premature maturity [19]. To reduce the power consumption of disaster communication, this paper proposes a robust, computational speed and low complexity meta-heuristic intelligent algorithm to solve the convex optimization equation based on the analysis of the strong dependence between user QoS, microcellular network number and power consumption. In this paper, LS-DN is to optimize power allocation in disaster communication. The poor exploration property of naked mole-rat algorithm (NMRA) in its worker phase easily leads to local optimum, and LS-DN makes use of variation and crossover of DE to compensate for its deficiency [20]. Simultaneously，it incorporates adaptive parameters, which aim to eliminate the influence of solution parameters. LS-DN is applied to disaster communication and compared with DE, PSO and NMR in simulation experiments.

The main contributions are as follows:

1. In the simulated disaster communication, when the base station is damaged, the microcellular network is used to cluster the victims within the physical distance and find the cluster head as the standby base station to ensure communication.

2. Considering that the performance of NOMA strongly depends on user matching and power allocation, this paper proposes a joint optimization scheme for low power transmission scenarios based on the analysis of user related characteristics and channel gain difference to meet the requirements of high capacity, low power consumption and low delay.

3. In heterogeneous networks, a hybrid optimization problem with low power consumption as the objective function and interference constraints is established to ensure the QoS of users and minimize the transmission power at the same time. The improved NMRA algorithm is used to achieve this.

4. Considering the goal of low power consumption, we define an external impact function for each victim user, which represents the power consumption value required by the victim to meet the minimum QoS requirements, and also shows the interference to other communication users.

5. Combine the efficient exploration ability in DE algorithm with the powerful development ability in NMRA to minimize the impact of their shortcomings.

6. Lévy flight random walk strategy provides a rich population for the algorithm. At the same time, the S-type function changes slowly but the entire algorithm is always declining. Their introduction in the early stage of NMRA is expected to improve the optimization accuracy.

7. Adaptive parameter adjustment is introduced to avoid the random uncertainty of the solution.

By simulating the damage of the base station in disaster communication, this paper adopts the pseudo base station of micro cellular network and cluster to solve the difficult communication problem. Starting from the actual problem (insufficient power supply of user equipment), establish a hybrid optimization scheme with low power consumption and high access as the goal, while ensuring user QoS and reducing interference of different and same layers.

The paper is organized as follows:

The literature of the related work has been presented in the first section.

Section 2 presents the disaster communication model and the user's minimum transmission power and total system power consumption optimization formula under QoS constraints.

Section 3 demonstrates the optimization of important parameters affecting the exploration and development capabilities of LS-DN and applying them to the disaster victims aggregation scheme.

Section 4 analyzes the simulation results of LS-DN algorithm for disaster aggregation and the related performance and comparison with other algorithms.

Section 5 concludes the paper and proposes directions for future research.

2 Disaster Communication Model

The disaster communication model simulates a communication disaster scenario, as shown in Fig. 1. The mobile communication exchange center (base station) is not working properly due to communication obstruction or restricted stable energy between itself and the destination of information delivery, thus the disaster victims cannot get help through the base station. The following assumptions are taken into consideration:

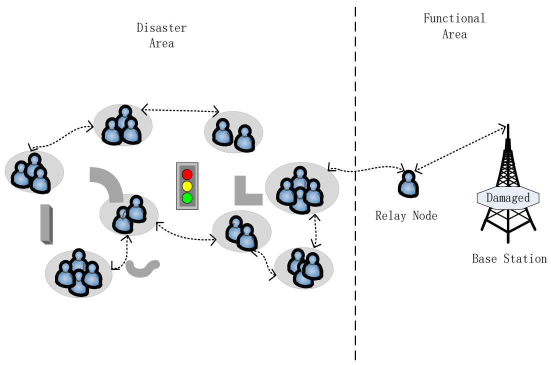


Fig. 1. Disaster communication

1. Disaster victims who are close to each other form clusters one by one, and the clusters including a small number of users within a small range can be considered as microcells.

2. Each cluster has single cluster head (CH), which temporarily acts as part of the base station (pseudo-base station) and manages the radio channel resources of the disaster within its microcell, and we assume that there are F microcellular networks.

3. There are N disaster victims' communication equipment, with the transmitter as the center, Poisson distribution within the radius of R.

Considering that each cluster is composed of disaster victims whose communication is blocked, the first task is to aggregate the number of disaster victims, the NOMA technique multiplexes multiple users in the same sub-channel to economize channel resources. Assume the available bandwidth in the downlink system in this model is B/Hz, then the bandwidth of each sub-channel will be B/F/HZ (the number of sub-channels is the same as the number of micro-cellular networks); The number of disaster victims N, is divided into F clusters, and let the number of disaster victims in each cluster be T; let the sub-channel coefficient $h = g\sqrt{d^{-a}}$, where g is the small-scale Rayleigh distribution and a is the path fading coefficient, and d is the linear distance between the disaster victims and the pseudo-base station. According to the principle of NOMA technology, the nth disaster victims of the fth microcell and fth sub-channel superimposed transmit signal code is

$$x_n^f = \sqrt{p^{\mathrm{f}}} \sum_{n=1}^{N} \alpha_n^f S_n^f \ . \tag{1}$$

$$\| \mathrm{x}_i \|^2 = 1 \ . \tag{2}$$

$$\sum_{n=1}^{N} \alpha_n^f = 1 \ . \tag{3}$$

where S_n^f is the modulated signal of the disaster victims, α_n^f is the power allocation factor of the pseudo-base station to the disaster victims on its corresponding microcell network, and p^f is the power allocated by the pseudo-base station to the micro-cell network. Then the received signal of the nth disaster victims is.

$$y_n^f = h_n^f \sqrt{p^{\mathrm{f}}} \sum_{n=1}^{\mathrm{T}} \sqrt{\alpha_n^f} S_n^f + \eta_n^f \ . \tag{4}$$

$$\eta_n^f \sim CN(0, \sigma^2) \ . \tag{5}$$

Eq. (4) is the noise interference from other weak disaster victims in the same microcell, Eq. (5) is the noise suffered by disaster victims when transmitting distress signals on sub-channel f (mean 0, variance $\sigma^2 = BN_0$), disaster victims are sorted by channel gain coefficient from largest to smallest, i.e. $h_1^f \geq h_2^f \geq \dots$.

Suppose two victims are aggregated into a cluster, according to the principle of step-by-step demodulation of SIC in NOMA technology, to ensure the communication stability of the weak disaster victims (whose channel gain is below average), during demodulation of the disaster victims signal at the receiving end, it is preferred to demodulate the weak disaster victims signal, before the strong, In this sense, the strong disaster victims signal acts as an interference to the weak disaster victims signal, then the transmission rate of the disaster victims is.

$$\mathrm{R}_n^{\mathrm{f}} = \log_2 \left(1 + \frac{\mathrm{P}_n^f \, | h_2^f |^2}{| h_{\mathrm{n}}^f |^2 \sum_{\mathrm{n}=1}^{\mathrm{T}} \mathrm{P}_n^f + \sigma^2}\right) . \tag{6}$$

where $P_n^f = p^f \alpha_n^f$, the disaster victims QoS constraint requires that the transmission rate should be greater than the minimum transmission rate, then the inequality for satisfying QoS per disaster victims can be obtained as follows

$$\mathrm{R}_{\mathrm{n}}^{\mathrm{f}} \geq \mathrm{R}_{\mathrm{n,min}}^{\mathrm{f}} \ . \tag{7}$$

The minimum power required for per microcell is summed as

$$P_{tot}^f = \sum_{n=1}^{T} P_n^f \ . \tag{8}$$

The analysis above yields the combination of users of the disaster victims that satisfies the minimum power allocation. Let G be the sparse matrix of pairs of disaster victims of N × F, $G=\left\{g_{i,j}^{f}\left|g_{i,j}^{f}\in\{0,1\}\right.\right\}_{N\times F}$, if disaster victim i is in microcell network j, the $g_{i,j}^{f}=1$, otherwise $g_{i,j}^{f}=0$, the specific equation of the minimum power allocation for the disaster victims is as in equation (9).

$$\min_{G} P_{tot}^{f}. \tag{9a}$$

$$\text{s.t.}\quad \mathrm{R}_{\mathrm{n}}^{\mathrm{f}}\geq \mathrm{R}_{\mathrm{n,min}}^{\mathrm{f}}\quad \forall\, i=1\ldots\mathrm{N}. \tag{9b}$$

$$\sum_{j=1}^{F} g_{i,j}^{f}=1\quad \forall\, i=1\ldots\mathrm{N}. \tag{9c}$$

Eq. (9a) denotes the sum of the minimum power required by all disaster victims; Eq. (9b) denotes the QoS requirements satisfied by each disaster victims; and Eq. (9c) denotes that each user can only be aggregated in a microcellular network. In this paper, the improved NMRA is applied to obtain the optimal solution, since it achieves a better balance between solution accuracy and complexity.

Question Formulation

OMA is used between different sub-channels, so there is no inter-group interference. Substituting equation (6) into equation (7) yields.

$$\log_2\left(1+\frac{p_n^{f}\,|h_{2,m}^{f}|^2}{\sum_{n=1}^{N} p_n^{f}\,|h_{\mathrm{n},m}^{f}|^2+\sigma^2}\right)\geq \mathrm{R}_{\mathrm{n,min}}^{\mathrm{f}}. \tag{10}$$

By satisfying the QoS power allocation principle, the disaster victims with larger power values affects the power value of the disaster victims with smaller power values in the same microcell network. Defining this effect as $\omega_{n,m}^{f}$ [15], we have

$$P_{\mathrm{n,min}}^{f}\geq\left(2^{\mathrm{R}_{\mathrm{n,min}}^{\mathrm{f}}}-1\right)\left(\frac{\sigma^2}{|h_{\mathrm{n}}^{f}|^2}+\sum_{i=1}^{\mathrm{n-1}}P_i^{f}\right). \tag{11}$$

$$P_{n+1,\min}^{f}\geq\left(2^{\mathrm{R}_{n+1,\min}^{\mathrm{f}}}-1\right)\left(\frac{\sigma^2}{|h_{n+1}^{f}|^2}+P_{\mathrm{n,min}}^{f}+\sum_{i=1}^{n-1}P_i^{f}\right)\geq\left(2^{\mathrm{R}_{n+1,\min}^{\mathrm{f}}}-1\right)\left(\frac{\sigma^2}{|h_{n+1}^{f}|^2}+\sum_{i=1}^{n-1}P_j^{f}\right)+P_{\mathrm{n,min}}^{f}\left(2^{\mathrm{R}_{n+1,\min}^{\mathrm{f}}}-1\right). \tag{12}$$

$$\begin{aligned}P_{n+2,\min}^{f}&\geq\left(2^{\mathrm{R}_{n+2,\min}^{\mathrm{f}}}-1\right)\left(\frac{\sigma^2}{|h_{n+2}^{f}|^2}+P_{n+1,\min}^{f}+P_{\mathrm{n},\min}^{f}+\sum_{i=1}^{n-1}P_i^{f}\right)\\&\geq\left(2^{\mathrm{R}_{n+2,\min}^{\mathrm{f}}}-1\right)\left(\frac{\sigma^2}{|h_{n+2}^{f}|^2}+\left(2^{\mathrm{R}_{n+1,\min}^{\mathrm{f}}}-1\right)\left(\frac{\sigma^2}{|h_{n+1}^{f}|^2}+\sum_{i=1}^{n-1}P_i^{f}\right)+\sum_{j=1}^{i-1}P_j^{f}\right)\\&\quad+\left(2^{\mathrm{R}_{n+2,\min}^{\mathrm{f}}}-1\right)\left(P_{\mathrm{n}\,\min}^{f}\times\left(2^{\mathrm{R}_{n+1,\min}^{\mathrm{f}}}-1\right)+P_{\mathrm{n}\,\min}^{f}\right)\end{aligned}. \tag{13}$$

Note that the minimum allocated power of the strongest disaster victims in a microcellular network $P_{1,\min}^{f}=\mathrm{G}\frac{\sigma^2}{|h_{1,m}^{f}|^2}$, from Eq. (12) and Eq. (13), the power ($P_{1,\min}^{f}=G\frac{\sigma^2}{\left|h_m^{f}\right|^2}$) of the ith disaster victims in the same microcellular network allocation affects the power allocation value of the (i+1)th and subsequent disaster victims in the same microcell network, and this external influence is designated as $\omega^f_{n,n+1}, \omega^f_{n,n+2}\cdots$

$$\omega^f_{\mathrm{n,n+1}} = P^f_{\mathrm{n,min}}(2^{\mathrm{R}^f_{n+1,\min}} - 1)\ . \tag{14}$$

$$\begin{aligned}\omega^f_{\mathrm{n,n+2}} &= (2^{\mathrm{R}^f_{n+2,\min}} - 1)\\ &\quad * \left(P^f_{\mathrm{n}\ \min} \times (2^{\mathrm{R}^f_{n+1,\min}} - 1) + P^f_{\mathrm{n},\ \min}\right)\ .\\ &= P^f_{\mathrm{n}\ \min} \times 2^{\mathrm{R}^f_{n+1,\min}}(2^{\mathrm{R}^f_{n+2,\min}} - 1)\end{aligned} \tag{15}$$

Similarly, there are

$$\omega^f_{\mathrm{n,k}} = \begin{cases} P^f_{\mathrm{n}\ \min} \times (2^{\mathrm{R}^f_{\mathrm{k,min}}} - 1) & k = n+1 \\ P^f_{\mathrm{n}\ \min} \times \left((2^{\mathrm{R}^f_{\mathrm{k,min}}} - 1) \times \prod_{i<k<j} 2^{\mathrm{R}^f_{\mathrm{k,min}}}\right) & k > n+2 \end{cases}\ . \tag{16}$$

Define the external influence function C^f_n and the external influence factor W^f_n with.

$$C^f_n = P^f_n + W^f_n\ . \tag{17}$$

$$W^f_n = \sum_{j=i+1} \omega^f_{n,j} = P^f_{n,\min} \prod_{j=i+1} 2^{R^f_{j,\min}} - P^f_{n,\min}\,. \tag{18}$$

3 The Proposed Method

NMRA simulates the process of a group of naked mole rats assisting each other to complete a task to find the optimal solution. In general, a group of naked mole rats consists of a number of 50 to 295. The members are divided into three types: queen, breeder and worker, each of which performing a different task. The worker with the optimal solution becomes the breeder, and eventually the optimal breeder mates with the queen to complete the reproduction task. The task of the algorithm is to find the optimal mates (breeders) to mate with the queen. The original NMRA has a simple structure and cannot cope with complex practical problems because in the worker stage, two similar solutions take up a relatively large portion of the new solution and cannot search the whole space of solutions comprehensively. The variation parameter (*F*) and **crossover rate** (CR) in the DE improve the search ability of the algorithm, which can make up for the lack of exploration ability of the naked mole rat algorithm. In this paper, we also optimize parameter λ in the naked mole-rat algorithm and adopt the breeding probability (*bp*) to facilitate the adjustment of the algorithm's exploration and mining ability. The original naked mole rat algorithm and the main parts of the specific optimization are described below.

NMRA

1. Initialization stage

Let $G_{N\times F}$ be the naked mole rat matrix and $g^f_{i,j}$ is each naked mole rat, and its value is only 0 and 1. Each naked mole rat is initialized according to equation (19).

$$x_{\mathrm{i,j}} = x_{\min,j} + U(0,1) \times (x_{\max,j} - x_{\min,j})\ . \tag{19}$$

where, $i \in [1,2,3,\ldots\mathrm{N}]$, $\mathrm{j} \in [1,2,3,\ldots\mathrm{D}]$, $\mathrm{S_{i,j}}$ denote the ith solution in the jth dimension. U(0,1) is a random solution between 0 and 1, and $x_{\max,j}$, $x_{\min,j}$ are the upper and lower boundary values of the solution.

2. Worker stage

The optimal worker will be selected to become the breeder in the worker phase, and the transfer probability is controlled by λ and two very similar solutions, and the exploration function of the algorithm is mainly performed in this stage. It is given by equation (20).

$$x_i^{t+1} = x_i^t + \lambda(x_j^t - x_k^t) . \quad \textbf{(20)}$$

where x is the solution at the worker stage, the left side of the equation is the new solution, the first term on the right side of the equation is the solution at this point, λ is the selection factor, and the other two terms in the equation are two similar random solutions.

3. Breeder stage

The breeder stage was similar to the worker stage, where the best breeders were selected as mates and the worst were returned as workers, as given in equation (21).

$$y_i^{t+1} = (1-\lambda)\,\mathrm{y}_i^t + \lambda(\mathrm{y}_{best} - \mathrm{y}_i^t) . \quad \textbf{(21)}$$

Similar to the worker stage, y is the solution at the worker stage, the left side of the equation is the new solution, the first term on the right side of the equation is the solution at this point, λ is the selection factor, and the other two terms in the equation are two similar random solutions.

Optimization improvements

1. Integration with DE algorithms

The Lévy flight trajectory mechanism makes the flight step to search with small probability and large stride search with small probability, satisfying the heavy-tailed distribution and expanding the population diversity to improve the exploration ability of the algorithm [15]. The specific Lévy equation is shown in equation (22).

$$\mathrm{Levy(d)} = 0.01 \times \frac{r_1 \times \sigma}{|r_2|^{1/\beta}} . \quad \textbf{(22)}$$

$Levy(d)$ is the number with d-dimensional Lévy flight; $r_1, r_1 \in [0,1]$; $\beta \in (0,2)$, which generally takes a fixed constant value of 1.5, so take $\beta = 1.5$. σ is given by Eq. (23) [21].

$$\sigma = \left(\frac{\Gamma(1+\beta)\sin(\frac{\pi\beta}{2})}{\Gamma(\frac{1+\beta}{2})\beta 2^{(\frac{n-1}{2})}} \right) . \quad \textbf{(23)}$$

where $\Gamma(\mathrm{x}) = (\mathrm{x}-1)!$; experimental studies proved that Lévy flight has better results in balancing exploration and exploitation capabilities. Applying it to the worker phase of the NMRA, keeping the feeder phase equation constant.

2. Self-adaptive capability

The CR in the DE algorithm provides a larger search space for the algorithm and brings the NMRA one step closer to the optimal solution [15]. In this paper, the adaptive parameter CR is introduced through literature [22] to improve the exploration capability of NMR. The specific expression of CR is given by equation (24).

$$\mathrm{CR} = (1-a)^{2a} , \quad a = \frac{t}{t_{\max}} . \quad \textbf{(24)}$$

$$v_i^t = \begin{cases} x_{r1}^t + F.(x_{r1}^t - x_{r2}^t); \text{ "}DE/rand/1 \\ x_{best}^t + F.(x_{r1}^t - x_{r2}^t); \text{ "}DE/best/1 \\ x_i^t + F.(x_{best}^t - x_i^t) + F.(x_{r1}^t - x_{r2}^t); \text{ "}DE/currenttobest/1 \\ x_{best}^t + F.(x_{r1}^t - x_{r2}^t) + F.(x_{r3}^t - x_{r4}^t); \text{ "}DE/best/1 \\ x_{r1}^t + F.(x_{r1}^t - x_{r2}^t) + F.(x_{r4}^t - x_{r5}^t); \text{ "}DE/rand/1 \end{cases}. \quad \textbf{(25)}$$

The working phase of the NMRA is mainly controlled by the variation and crossover parameters in the DE algorithm. The specific equation of the working phase is shown in equation (25).

The crossover operation of the worker phase is shown in equation (26).

$$x_i^t = \begin{cases} v_i^t & if\,(rand_j[0,1] \le CR), j = 1,2,...,n \\ x_i^t & otherwise \end{cases}. \quad \textbf{(26)}$$

3. Selection factor improvement

In the breeder stage, the selection factor plays a decisive role in the selection of the best mates. The dynamic inertia weights of the selection factors are exponential inertia weight, logarithmic inertia weight, random inertia weight and sigmoidal inertia weight [23]. Because the sigmoidal decreasing inertia weights change their values from large to small as the algorithm starts to finish, the algorithm gradually changes from global search capability to local search capability to achieve the best balance between exploration and exploitation capability. The specific sigmoidal decreasing inertia weight is given by equation (27) [24].

$$\lambda = \frac{\alpha_{\min} - \alpha_{\max}}{1 + e^{-l \times (t - i \times j)}} + \alpha_{\max} \qquad \text{i, j} \in rand[0,1]. \quad \textbf{(27)}$$

$$l = 10^{\ln(\text{gen}) - 2}. \quad \textbf{(28)}$$

4. Greedy choice

In this paper, the best naked mole rat is selected by comparing the fitness value of each solution, and the solution with the optimal fitness value is picked at each iteration, and equation (9a) is used as the fitness function to pick the best naked mole rat; this greedy idea picks the optimal solution for the optimal NMR algorithm. The specific greedy selection equation is shown in Eq. (29).

$$x_{new}^{t+1} = \begin{cases} x_{new} & if\ fit(x_{new}) < fit(x_i^t) \\ x_i^t & other \end{cases}. \quad \textbf{(29)}$$

Comprehensive analysis, the pseudo-code for LS-DN-based disaster victims matching and power allocation optimization is shown in Algorithm 1.

Algorithm 1. LS-DN-based user matching and power allocation

1. Initialization: algorithm parameters F, CR, λ, maximum number of iterations t_{max}
2. Initializing the population G, each user is formed into a corresponding microcellular network by random assignment, satisfying the constraint of Eq. (9).
3. Set n=1
4. While n≤N do
5. Calculate the fitness value for each naked mole rat using equation (9a) P_{tot}^f
6. End while
7. Record the solution with the best fitness value G_{best} and P_{tot}^f
8. For t=1

9. Worker Phase:
10. The variation operation was performed for each naked mole rat using equation (26)
11. Breeder Phase:
12. Crossover manipulation of naked mole rats using equation (27)
13. Greedy Phase:
14. The optimal solution is selected by greedy comparison selection of the fitness values in step 5 using equation (29).
15. Using equation (22) to update F
16. Using equation (24) to update CR
17. Using equation (27) to update
18. Update G_{best} and P_{tot}^f
19. $t = t + 1$
20. until $t < t_{max}$
21. return G_{best} and P_{tot}^f

4 Results and Discussion

To illustrate the optimizing problem in disaster victims minimum power allocation, this paper focuses on three aspects. Firstly, the proposed LS-DN in this paper is compared with other swarm intelligence algorithms and traditional user pairing algorithms in terms of external influence, QoS requirements, number of users and SNR, etc.; secondly, the significance for disaster communication is verified by extracting the characteristics of optimized transmit power minimization. Finally, the importance of optimal NOMA user pairs for power reduction (especially in disaster communication environments) is emphasized, where. Power efficiency (PE) is used as an evaluation metric, i.e., $PE_i^f = \frac{P_{av,PSO}^f - P_{av,LS-DN}^f}{P_{av,LS-DN}^f}$ ($P_{av,PSO}^f$ is the average power value of PSO user aggregation, and $P_{av,LS-DN}^f$ is the average power value of LS-DN user aggregation). It is shown the LS-DN algorithm obtains a better power reduction aggregation scheme compared to PSO (QoS = 5bps/HZ for the disaster victims in the experiment).

Table 1 and Table 2 show the experimental parameters related to LS-DN algorithm and disaster communication respectively

Table 1. LS-DN algorithm parameters

Parameters	Value
Number of populations N	60
Dimension D	10
Maximum number of iterations t_{max}	200
Reproduction probability bp	0.05
λ Related parameters	$\alpha_{\max} = 0.9$ $\alpha_{\min} = 0.5$ gen = 51

Table 2. Disaster communication network parameters

Parameters	Value
Cellular radius	200m
Total bandwidth (B)	25MHz
Number of microcells (F)	[25:50]
QoS Boundary	[1bps/Hz:5 bps/Hz]
Noise power spectral density (N0)	-172dBm/Hz
Path decay coefficient (a)	2

As shown in Fig. 2, the achievable throughput of users under disaster communication is plotted for OMA and NOMA under QoS requirements. The throughput increases as the power value increases, while the NOMA disaster victims throughput is higher than that of OMA under the same conditions. At a transmission power of 30dBm, the throughput of NOMA disaster victims pairs is about 18% higher than that of OMA. NOMA uses power difference to aggregate multiple disaster victims on the same sub-channel, and the pairing of strong disaster victims with weak disaster victims helps to increase the channel gain difference, thus improving the performance advantage. In contrast, NOMA can improve the system throughput and spectrum efficiency; the superiority of NOMA can ensure more disaster victims to communicate normally in case of uneven channel conditions of disaster victims, which is more suitable for disaster communication.

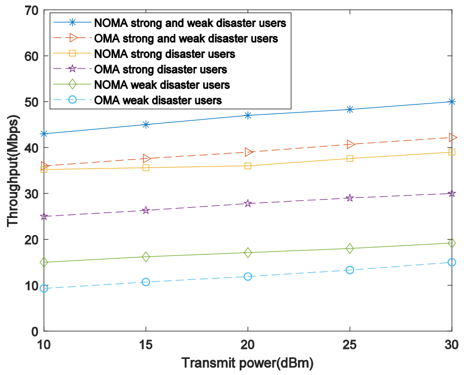


Fig. 2. Comparative analysis of the throughput of OMA-NOM disaster victims at different transmission powers

Fig. 3 simulates and compares several classical algorithms with LS-DN under disaster communication environment of NOMA, showing the total system power achievable by different smart algorithms based on the number of users per microcell network in disaster communication. In the disaster victims matching, the intelligent algorithms provide more candidate solutions, so they bring lower total transmission power than random solutions. PSO, DE and NMR depend strongly on local optimal solutions and are prone to fall into local optima. LS-DN optimizes disaster user pairing by integrating DE algorithms and optimizing selection parameters in the exploration phase, sacrificing time complexity to improve algorithm exploration and development, so that the total power value required for user matching in disaster communication is significantly lower than the other four algorithms when the number of microcell networks is 2, 3, 4, and 5. In particular, when there are 5 microcell networks, the total power value required by LS-DN is 25%, 20%, 6.67%, and 10% lower in comparison, respectively. Note that the disaster communication environment is harsh, so low transmit power is more likely to succeed. Therefore, the LS-DN algorithm proposed in this paper is more beneficial for low-power implementation.

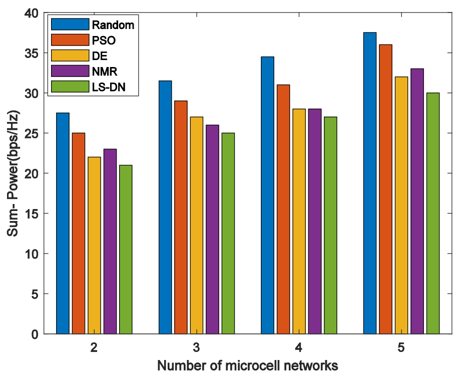


Fig. 3. Comparative analysis of the total power of different intelligent algorithms

The corresponding C_n^f curves are presented in the Fig. 4. Fig. 4 compares the C_n^f of disaster victims under different algorithms, C_n^f is the total power consumption brought by the user to the microcellular network, and the C_n^f value is the difference between the power value when the disaster victims n is in the microcell and when it is not. If the pairing scheme for a disaster victims is changed arbitrarily, the difference value before and after C_n^f of the disaster victim can accurately give the power comparison difference value of the microcellular network. Every three disaster victims are matched in a microcell network, and the difference value of C_n^f of the user is calculated respectively. Random algorithm C_n^f variance value is the most unstable, analyzing the external function values from the perspective of disaster victim 1, LS-DN is optimized by 44.4%, 39.2%, 23.5% and 11% with the random algorithm, PSO, DE and NMR respectively. Lévy flight is introduced in the worker phase of NMR and the parameters are optimized in the breeder phase, drawing on the advantages of other intelligent algorithms to improve the adverse effects of differences in candidate solution sets. By appropriately increasing the number of users and reasonable user matching and considering user interference and QoS constraints, LS-DN has relatively good performance in reducing power consumption. Because of the lower transmission power difference, it proves that LS-DN is more suitable for user matching in disaster communication.

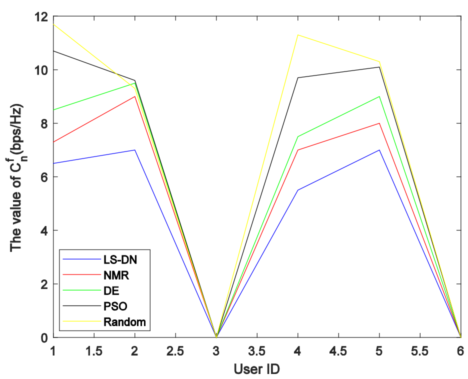
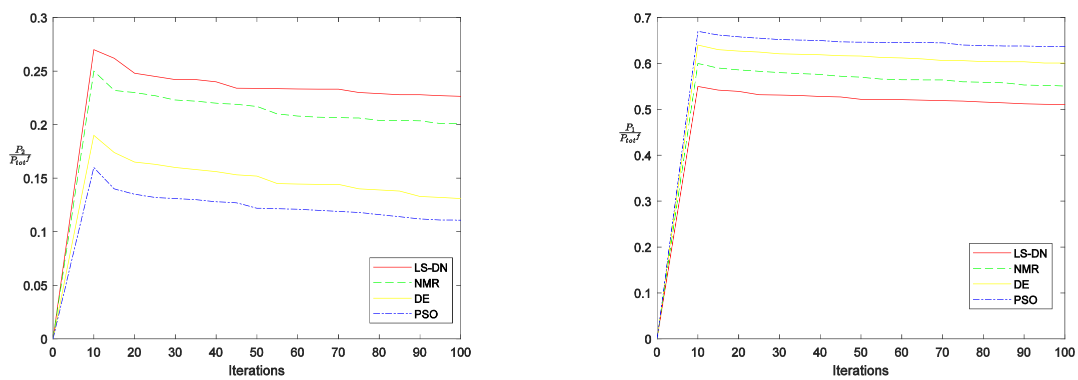


Fig. 4. Comparison of the difference in power external function for users with different algorithms

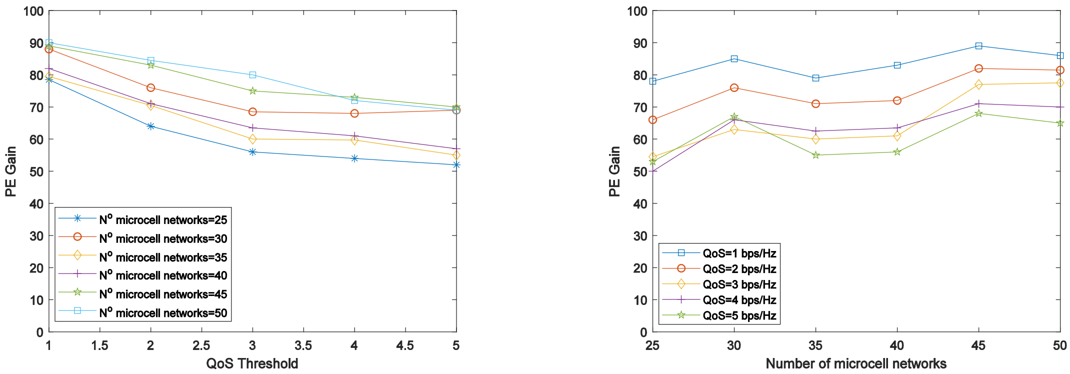


(a) Power allocation share of strong disaster victims with different algorithms (b) Power allocation share of weak disaster victims with different algorithms

Fig. 5. Power allocation with different algorithms

Fig. 5 also presents the value of the power saved by user matching under this algorithm, which depicts the power share values of the disaster victims pairs ($\frac{P_1}{P_{tot}^f}$ and $\frac{P_2}{P_{tot}^f}$), within the communication range of the pseudo-base station, expressed as the average power value of all disaster users in each NOMA pair, further highlighting the power allocation between LS-DN and other algorithms in NOMA pairs. To facilitate the experimental comparison, it is specified that each group of user pairs has only two disaster victims. It is evident that the proposed algorithm is more power-efficient compared to other algorithms. Compared with the strong disaster victim, the weak disaster victim gets more power allocation to ensure normal communication, i.e., the occurrence of $h_1^f \geq h_2^f$ case, the constraint $P_2 < P_1$ can also guarantee the error-free SIC for weak disaster victims.

Fig. 6 depicts the PE gain values corresponding to different QoS values with microcells under the algorithm LS-DN. Intuitively, the values of the vertical coordinates of Fig. 6(a) and Fig. 6(b) are distributed within 60% to 90%, with a 20% increase in the minimum value of PE gain compared to the literature [16]. It is verified again that LS-DN can find the best NOMA pair under the premise of ensuring the QoS of each disaster victims user and aiming at the minimum transmission power. Fig. 6 shows two ways of increasing PE gain: increasing the number of microcell networks or decreasing in the user QoS constraint. An increase in the QoS threshold leads to a sharp increase in the transmission power for all disaster users, and a decrease in the number of microcell networks allows more disaster victims to aggregate in the same network, which also leads to an increase in the minimum transmission power. Then the total system power increases. In this sense, the efficiency of LS-DN is verified in finding the best NOMA pair that is compatible with any environment to ensure that the QoS constraint of each disaster victims is satisfied using the lowest power value.



(a) Comparison of PE gain for different QoS values

(b) Comparison of PE gain with different number of microcells

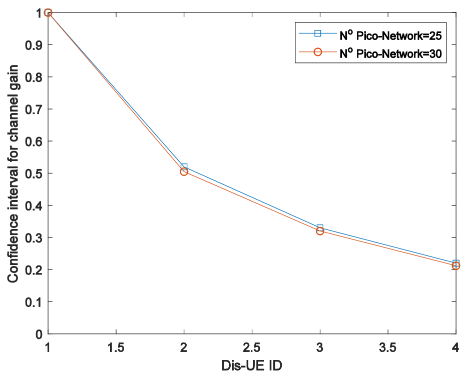
Fig. 6. Comparison with different number of microcells

Table 3. Number of microcellular network aggregated disaster victims

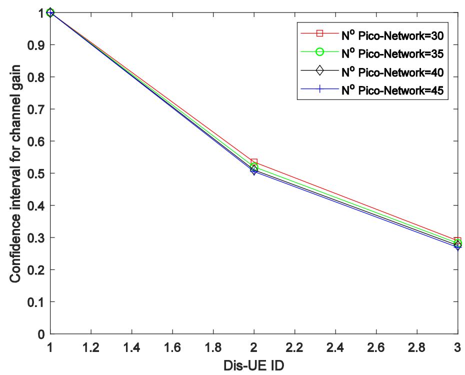
N° microcell networks	2 Disaster victims	3 Disaster victims	4 Disaster victims
25	-	-	25
30	-	20	10
35	8	28	-
40	23	18	-
45	38	8	-
50	40	-	-

Suppose in this disaster communication there are 100 users with 25 to 50 microcell networks. The aggregation results are shown in Table 3, where 2 to 4 disaster victims are aggregated in each microcell network. LS-DN algorithm intends to reduce the minimum transmission power with increasing the spectral efficiency to make an effort to reduce the number of aggregated users by increasing the number of microcell networks.

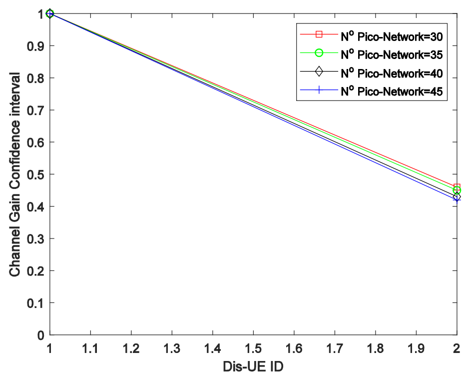
For the aggregation results of disaster victims in Table 3, Fig. 7 plots the channel gain ratios when the number of aggregated users is 2, 3 and 4, respectively. The impact of the change in the number of microcell networks on the channel gain ratio is analyzed. Each of the graphs is sorted by the channel gain ratio of the disaster victims from highest to lowest, i.e., disaster victims 1 is the highest, disaster victims 2 is the second highest, and so on. Although each user may not be aggregated in the same microcellular network, each user is within the QoS mean constraint and ultimately within the 95% confidence interval for the simulation experiments. The confidence interval variation of the channel gain ratio for most users in the figure is smaller than 4%, indicating that the user's QoS constraint limits do not cause large fluctuations in their channel gain ratio. The reason for the variation range higher than 4% is that there are fewer users aggregated together, resulting in no sufficient reliable source of statistics. For Fig. 7(a) to Fig. 7(c), the number of microcell networks varies, but the confidence interval of channel gain ratio for their disaster victims hardly changes. That is, the confidence intervals of channel gain ratio for the second, third and fourth disaster victims are: 50%, 30% and 20%.



(a) 4 disaster victims per microcell network



(b) 3 disaster victims per microcellular network



(c) 2 disaster victims per microcell network

Fig. 7. Different disaster victims per microcell network

Fig. 8 depicts the average transmission power consumption of each cluster in different schemes, which can well select the low-power solution suitable for disaster victim information transmission in disaster communication. In this paper, the stochastic scheme uses the random selection of the appropriate initial test power proposed by algorithm 2 [25] to maintain a uniform distribution across all clusters. Therefore, the power value in the random scheme is concentrated at 60, because the spectrum utilization is increased by increasing the power consumption, so the power consumption value gradually increases, but most of it is lower than the value in the random solution. The power consumption values of FTPA, FPA and PSO schemes are higher than those proposed in this article, and the fading factors of FTPA and FPA are not fixed, so the power consumption values are greatly affected. PSO and the LS-DN intelligent optimization algorithm in this paper are influenced by natural inspiration and combined with convex optimization regulations to jointly optimize the low-power solution of user matching and power distribution. PSO converges quickly and prematurely, lacks population diversity, and cannot find the optimal user matching and power distribution scheme. Through experimental comparison, the LS-DN in this paper meets the low-power requirements of disaster communication transmission by introducing Lévy flight and S-type weight attenuation.

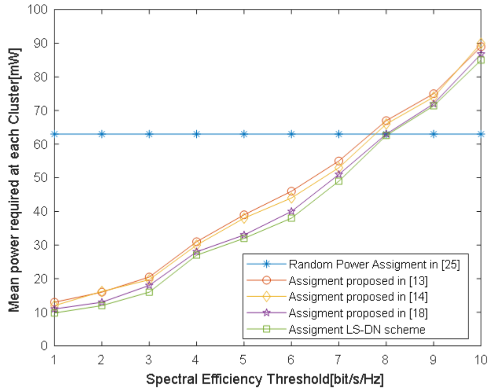


Fig. 8. Mean power required by each cluster under different schemes

5 Summary

This paper presents joint optimization scheme LS-DN algorithm, which aims at the minimum microcell power to ensure the QoS of each disaster victims while accomplishing the best user matching and power allocation. LS-DN performs joint optimization in two aspects, namely the worker phase incorporates Lévy flight and S-type inertia weights to improve the exploration capability. And the feeder phase optimizes the CR and λ of D, to enhance the exploitation capability. Simulation results show that LS-DN applied in the NOMA system improves the system throughput by about 65% compared to the conventional OMA system, which is more favorable for disaster victims to send distress signals. Evaluated by the per-user power external function, the power consumption is reduced by at least 10% compared with the random algorithm, PSO, DE and NMR, further verifying that LS-DN optimizes the disaster victims matching and reduces the total system power consumption. In future work, the research can be extended to the uplink to improve the reliability and effectiveness of data transmission in emergency situations, as well as applying the algorithm in a variety of power-constrained environments such as UAV communications.

Acknowledgements

This work was supported by the National Natural Science Foundation of China under Grant 62062021 and 61872034, the Natural Science Foundation of Guizhou Province under Grant [2020] 1Y254, the Natural Science Foundation of Guizhou Province under Grant [2019] 1064.

References

[1] A. Kumbhar, F. Koohifar, I. Güvenç, B. Mueller, A Survey on Legacy and Emerging Technologies for Public Safety Communications, IEEE Communications Surveys and Tutorials 19(1)(2017) 97-124.
[2] Y.F. Djoumessi, L.B.E. Mbongo, An analysis of information Communication Technologies for natural disaster management in Africa, International Journal of Disaster Risk Reduction 68(2022) 102722.
[3] K. Ali, H.X. Nguyen, Q.-T. Vien, P. Shah, Disaster management communication networks: Challenges and architecture design, in: Proc. 2015 IEEE International Conference on Pervasive Computing and Communication Workshops (PerCom Workshops), 2015.
[4] Y.-J. Pei, X.-W. Yue, Y.-Y. Yao, X.-H. Li, H. Wang, D.-T. Do, Secrecy communications of intelligent reflecting surfaces aided NOMA networks, Physical Communication 52(2022) 101691.
[5] P. Gandotra, R.K. Jha, A survey on green communication and security challenges in 5G wireless communication networks, Journal of Network and Computer Applications 96(2017) 39-61.
[6] Z. Song, Q. Ni, X. Sun, spectrum and energy efficient resource allocation with QoS requirements for hybrid MC-

NOMA 5G systems, IEEE Access 6(2018) 37055-37069.
[7] A.B.M. Adam, X.-Y. Wan, Z.-Q. Wang, User scheduling and power allocation for downlink multi-cell multi-carrier NOMA systems, Digital Communications and Networks 9(1)(2023) 252-263.
[8] M.B. Shahab, M. Irfan, M.F. Kader, S.Y. Shin, User pairing schemes for capacity maximization in non-orthogonal multiple access systems, Wireless Communications and Mobile Computing 16(17)(2016) 2884-2894.
[9] Z.Q. Al-Abbasi, D.K. So, User-pairing based non-orthogonal multiple access (NOMA) system, in: Proc. 2016 IEEE 83rd Vehicular Technology Conference, 2016.
[10] D. Wan, M. Wen, Y. Liu, F. Ji, H. Yu, F. Chen, User pairing strategy: a novel scheme for non-orthogonal multiple access systems, in: Proc. 2017 IEEE Globecom Workshops, 2017.
[11] A.K. Lamba, R. Kumar, S. Sharma, Power allocation for downlink multiuser hybrid NOMA-OMA systems: an auction game approach, International Journal of Communication Systems 33(7)(2020) e4306.
[12] Z. Wang, C. Wen, Z. Fan, X. Wan, A novel price-based power allocation algorithm in non-orthogonal multiple access networks, IEEE Wireless Communications Letters 7(2)(2018) 230-233.
[13] M.-R. Hojeij, J. Farah, C.A. Nour, C. Douillard, Resource Allocation in Downlink Non-Orthogonal Multiple Access (NOMA) for Future Radio Access, in: Proc. 2015 IEEE 81st Vehicular Technology Conference (VTC Spring), 2015.
[14] J.A. Oviedo, H.R. Sadjadpour, A Fair Power Allocation Approach to NOMA in Multiuser SISO Systems, IEEE Transactions on Vehicular Technology 66(9)(2017) 7974-7985.
[15] F. Guo, H. Lu, D. Zhu, H. Wu, Interference-aware User Grouping Strategy in NOMA Systems with QoS Constraints, in: Proc. IEEE INFOCOM 2019-IEEE Conference on Computer Communications, 2019.
[16] J. Wu, B. Cheng, M. Wang, J. Chen, Energy-efficient bandwidth aggregation for delay-constrained video over heterogeneous wireless networks, IEEE Journal on Selected Areas in Communications 35(1)(2017) 30-49.
[17] H. Zhang, M. Feng, K. Long, G.K. Karagiannidis, V.C.M. Leung, H.V. Poor, Energy Efficient Resource Management in SWIPT Enabled Heterogeneous Networks With NOMA, IEEE Transactions on Wireless Communications 19(2)(2020) 835-845.
[18] A. Masaracchia, D.B. Da Costa, T.Q. Duong, M.-N. Nguyen, M.T. Nguyen, A PSO-Based Approach for User-Pairing Schemes in NOMA Systems: Theory and Applications, IEEE Access 7(2019) 90550-90564.
[19] X. Ma, J. Wu, Z. Zhang, Z. Zhang, X. Wang, X. Chai, L. Dai, X. Dai, Power allocation for downlink of non-orthogonal multiple access system via genetic algorithm, in: Proc. International Conference on 5G for Future Wireless Networks, 2017.
[20] R. Salgotra, U. Singh, G. Singh, N. Mittal, A.H. Gandomi, A self-adaptive hybridized differential evolution naked mole-rat algorithm for engineering optimization problems, Computer Methods in Applied Mechanics and Engineering 383(2021) 113916.
[21] R. Salgotra, U. Singh, Application of mutation operators to flower pollination algorithm, Expert Systems with Applications 79(2017) 112-129.
[22] M. Probert, Book Review: Engineering Optimization: an Introduction with Metaheuristic Applications, by Xin-She Yang, Contemporary Physics 53(3)(2012) 271-272.
[23] A. Faramarzi, M. Heidarinejad, S. Mirjalili, A.H. Gandomi, Marine predators algorithm: A nature-inspired metaheuristic, Expert Systems with Applications 152(2020) 113377.
[24] J. Zhang, A.C. Sanderson, JADE: adaptive differential evolution with optional external archive, IEEE Transactions on Evolutionary Computation 13(5)(2009) 945 -958.
[25] A. Masaracchia, L.D. Nguyen, T.Q. Duong, M.-N. Nguyen, An Energy-Efficient Clustering and Routing Framework for Disaster Relief Network, IEEE Access 7(2019) 56520-56532.