Optimization of NOMA Downlink Network Parameters under Harvesting Energy Strategy Using Multi-Objective GWO

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Abstract. *Non-orthogonal multiple access technique (NOMA) is based on the principle of sharing the same physical resource, over several power levels, where user's signals are transmitted by using the superposition-coding scheme at the transmitter and these users signals are decoded by the receiver by means of successive interference cancellation technique (SIC). In this work, performance of NOMA Downlink network under Rayleigh fading distribution is studied, in the power domain where a power beacon (PB) is used to help a base station (BS) to serve distant users, by Wireless Power Transfer (WPT). The harvested energy permits by the BS, supports information signal transmission to NOMA users. This concept can be an effective way to power Internet of Things (IoT) devices, reduce battery dependency, and promote energy sustainability and may be used in SWIPT systems and vehicular networks. To improve the key performance indicators of the system expressed by the outage performance of NOMA users and system throughput, a Multi-Objective Grey Wolf Optimizer algorithm (MOGWO) is used to find optimal values of several influencing parameters. These parameters are partition time expressing the harvesting energy time, the power conversion factor and power allocation coefficients.*

Keywords

Base station, outage probability, power beacon, throughput, wireless power transfer, multi-objective optimization, Grey Wolf Optimizer (GWO), Multi-Objective Grey Wolf Optimizer (MOGWO), Pareto optimal solutions

1. Introduction

NOMA system is broadly considered a solution to the growing user's demands in cellular communication systems such as 5G and 6G, and resolve the spectral efficiency problem and difficulties met in traditional orthogonal systems such as OFDMA [1–4].

NOMA technique is based on the principle of sharing the same physical resource, over several power levels, where user's signals are transmitted by using the superposition-coding scheme at the transmitter and these user's signals are decoded by the receiver by means of successive interference cancellation technique (SIC) [5–8].

In the literature [9], Y. Liu et al. examined the integration of simultaneous wireless information and power transfer (SWIPT) with non-orthogonal multiple access (NOMA) networks catering to users located at random positions. They proposed a new co-operative SWIPT NOMA protocol, where the nearer NOMA user to the source acts as energy-harvesting relay to aid distant NOMA users. The findings confirm that the adaptable use of node positions for user selection can lead to low outage probability and higher throughput compared to random selection scheme. Energy harvesting is increasingly seen as a viable way to produce minor amounts of electrical power, thereby potentially replacing traditional power sources for wireless networks and extending their lifespan. Employing time switching (TS) or power switching (PS) ensures optimal power decoding and energy harvesting at the receiver side.

In the reference [10], H. T. Van et al. investigated a half-duplex (HD) relaying cooperative NOMA network by means of decode-and-forward (DF) transmission mode with energy harvesting (EH) capacity, where they assumed that NOMA destination (D) is capable of receiving two data symbols in two continuous time slots which leads to obtain higher transmission rate than traditional relaying networks.

While in the literature [11], authors considered an hybrid time switching (TS) and power splitting (PS) simultaneous wireless information and power transfer (SWIPT) protocol design in a full-duplex (FD) massive MIMO system. In their proposed model system, an FD base station

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(BS) serves a set of half-duplex (HD) users and a set of fixed HD sensors. Their simulation results displayed the advantage of the proposed protocol on spectral efficiency, in comparison to conventional massive MIMO SWIPT protocol.

Moreover, there are studies using intelligent optimization algorithms to improve the performance of NOMA systems [12–14]. In the literature [12], the author examined a downlink multiuser NOMA system with optimized energy efficiency (EE) and spectral efficiency (SE), by means of a power allocation algorithm based on two-layer optimization, consisting of the transformation of the original multi-objective optimization problem into a univariate problem through the linear weighted sum method.

His simulation results display that this algorithm always converges within few iterations and can realize the compromise between EE and SE.

While in the literature [13], the authors presented a power allocation algorithm in NOMA based on particle swarm optimization (PSO) in the aim to improve the system's energy efficiency.

The authors in [14] studied the power allocation optimization by introducing a Modified Artificial Bee Colony (MABC) algorithm, in order to obtain optimal powers amongst multiplexed users on every sub-channel.

In this paper, a network under Rayleigh fading distribution is considered. The system is composed of a Power Beacon (PB), a base station (BS) two random users (*UEi*) with identically independent distributed (i.i.d) channel. It is assumed that, the total transmission time T is segmented into two slots; in the first time slot, the BS harvests energy transmitted by the PB by Wireless Power Transfer (WPT), then the BS transmits information signal to users (*UEi)*, in the second slot. Furthermore, we investigate the optimization problem of NOMA downlink network using MOGWO algorithm [15]; one of the most recent meta-heuristic optimization technology that mimics the hunting behavior of grey wolves in multi-objective search spaces. In fact, this algorithm is used as an optimization process to obtain optimal values of the partition time expressing the harvesting energy time, the power conversion factor and power allocation coefficients.

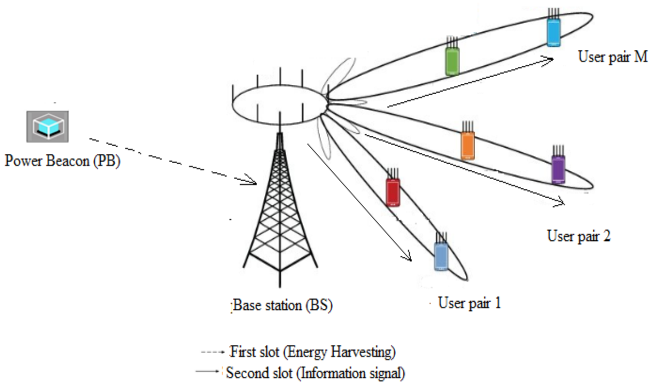

Fig. 1. Presentation of system model.

The rest of this paper is structured as follows: Section 2 presents the analysis system model, consisting of a downlink system, composed of a power beacon, a base station and two NOMA users, description, while in Sec. 3, the analysis of outage probability performance is achieved, and the expressions of outage probabilities of NOMA users are derived. However, Section 4 presents the multi-objective GWO for NOMA downlink network parameters optimization. Subsequently, Section 5 provides simulation and results discussion and Section 6 completes with a conclusion which comments and reviews the important results.

2. Analysis of System Model

Let us study a downlink communication system composed of a power beacon (PB), a single base station (BS) acting as a cell center and serving a wireless channel to N users (*UEi*) located randomly inside the cell, and having a single antenna by means of M orthogonal sub-channels.

Channels are assumed i.i.d subject to Rayleigh distribution described by a complex fading channel coefficient (see Fig. 1). Let us consider the first slot time of BS harvesting energy from PB is μT where T is the total transmission time and μ is a factor given as $0 < \mu < 1$ and the second slot time of information transmission from the BS to UE_i is $(1 - \mu) T$. So that, the transmission strategy is described as follows.

2.1 Wireless Power Transfer Process

Wireless power transfer (WPT) is an encouraging solution to provide convenient and perpetual energy supplies to wireless networks. In practice, for energy harvesting, WPT is conceivable by various technologies such as inductive coupling; magnetic resonate coupling, and electromagnetic (EM) radiation. The radio frequency to DC energy conversion is characterized by an efficiency factor $\alpha \in (0,1)$.

In this phase, a cell network (CN) at the BS needs the support of the power beacon to serve the N users. The amount of harvested energy at CN in the first slot time is expressed by

$$E_s = \alpha\mu P_{PB} |h_s|^2 T \tag{1}$$

where P_{PB} is the power beacon transmit power, h_s PB to BS channel coefficient is assumed followed by Rayleigh fading distribution.

While the average received power by CN from PB during the second slot time is given by

$$P_s = \frac{\alpha\mu P_{PB} |h_s|^2}{1-\mu}. \tag{2}$$

In this model, we suggest the user-pairing scheme given by M. B. Shahab et al. [12], in which each sub-channel

Parameter	Description
μT	EH slot time of BS from PB
E_s	The amount of harvested energy at CN
P_{PB}	The power beacon transmit power to the BS
P_s	The average received power by CN from PB
P_0	The power allotted to each pair user

Tab. 1. Summary of WPT process.

serves only two users denoted by $UE_{f,j}$ (farthest user with weak channel gain in the sub-channel j) and $UE_{n,i}$ (nearby user with strong channel gain in the sub-channel j). Assume that P_s is equally divided between all M sub-channels, and for each pair user a same power P_0 is allotted ($P_0 = P_s / M$). The parameters describing WPT process are summarized in Tab. 1.

2.2 Information Transmission Process

In the second phase, during the second slot time, by means of the harvested energy, the information is transmitted by the BS to the NOMA pair users in the sub-channel j and can be expressed as

$$z_j = \sqrt{a_{n,j} P_0} x_{n,j} + \sqrt{a_{f,j} P_0} x_{f,j} \tag{3}$$

where $x_{n/f,j}$ is information symbol of user $UE_{n/f}$ in the sub-channel j, $a_{n/f,j}$ power allocation coefficient of user $UE_{n/f}$ in the sub-channel j; with $a_{n,j} + a_{f,j} = 1$, and $a_{f,j} > a_{n,j}$.

Moreover, the composite received signal received by user $UE_{n/f}$ is written as

$$y_{n/f,j} = \left(\sqrt{a_{n,j} P_0} x_{n,j} + \sqrt{a_{f,j} P_0} x_{f,j} \right) h_{n/f,j} + n_{n/f,j} \tag{4}$$

where $n_{n/f,j}$ is additive white Gaussian noise at the receiver having zero mean and variance equal to one ($\sigma_{n/f,j}^2 = \sigma_j^2 = 1$), and for simplicity purpose, we suppose that $E\{|x_{n/f}|^2\} = 1$.

The signal-to-interference plus noise ratio (SINR) at $UE_{f,j}$ to decode signal $x_{f,j}$ is expressed as

$$\gamma_{f,x_{f,j}} = \frac{\left|h_{f,j}\right|^2 a_{f,j} P_0}{\left|h_{f,j}\right|^2 a_{n,j} P_0 + 1}. \tag{5}$$

Replacing (2) into (5), we obtain this SINR expressed as

$$\gamma_{f,x_{f,j}} = \frac{\mu\alpha \left|h_{f,j}\right|^2 \left|h_s\right|^2 a_{f,j} \rho}{\mu\left(\alpha \left|h_{f,j}\right|^2 \left|h_s\right|^2 a_{n,j} \rho - 1\right) + 1}, \tag{6}$$

with $\rho = P_0 / \sigma_j^2$, presenting the transmit signal to noise ratio (SNR).

Similarly, the SINR to decode $x_{f,j}$ signal at UE_n is expressed by

$$\gamma_{n,x_{f,j}} = \frac{\mu\alpha \left|h_{n,j}\right|^2 \left|h_s\right|^2 a_{f,j} \rho}{\mu\alpha \left|h_{n,j}\right|^2 \left|h_s\right|^2 a_{n,j} \rho + (1-\mu)}. \tag{7}$$

At $UE_{n,j}$, by performing successive interference cancellation (SIC) to decode signal $x_{n,j}$, the signal to noise ratio is given by

$$\gamma_{n,x_{n,j}} = \frac{\mu\alpha \left|h_{n,j}\right|^2 \left|h_s\right|^2 a_{n,j} \rho}{(1-\mu)}. \tag{8}$$

3. Performance Analysis

Based on the system model described in the above section, we derived the outage probability at users $UE_{n/f}$ and general throughput system performance.

The considered downlink communication system is composed of a BS and two users where each one is characterized by multipath communication identified as Rayleigh fading channel that can be described by a complex fading channel coefficient.

So, h_s, $h_{n,j}$ and $h_{f,j}$ are followed by Rayleigh fading distribution and their probability density function (pdf) is expressed as

$$f_{|h_\theta|}(x) = \frac{x}{\Omega_\theta^2} e^{-\frac{x^2}{2\Omega_\theta^2}} \tag{9}$$

where $h_\theta \in \{h_s, h_{n,j}, h_{f,j}\}$ and $\Omega_\theta \in \{\Omega_s, \Omega_n, \Omega_f\}$, are the respective complex channel coefficient and scale parameter.

However, Rayleigh distribution of the squared magnitude is written as

$$f_{|h_\theta|^2}(x) = \frac{1}{\Omega_\theta} e^{-\frac{x}{\Omega_\theta}}. \tag{10}$$

In the other hand, the outage probability at $UE_{f,j}$ signifying that this receiver decodes unsuccessfully the received signal is expressed by

$$P_{f,j}^{out} = 1 - \Pr(\gamma_{f,x_{f,j}} > th_{f,j}, \gamma_{n,x_{f,j}} > th_{f,j}) \tag{11}$$

where $th_{n/f} = 2^{\frac{2R_{n/f}}{(1-\mu)}} - 1$, signifies the SINR threshold and $R_{n/f}$ is the target rate of $UE_{n/f}$.

For simplicity, we assume that $th_{n,j} = th_n$ and $th_{f,j} = th_f$ for $j \le M$.

Using SINR expressions previously evaluated we obtain the outage probability at $UE_{f,j}$ given by

$$P_{f,j}^{out} = 1 - \Pr\left(\begin{array}{l} \dfrac{Q\left|h_{f,j}\right|^2 \left|h_s\right|^2}{T\left|h_{f,j}\right|^2 \left|h_s\right|^2 + V} > th_f, \\ \dfrac{T\left|h_{n,j}\right|^2 \left|h_s\right|^2}{Q\left|h_{n,j}\right|^2 \left|h_s\right|^2 + V} > th_f \end{array} \right) \tag{12}$$

where $Q = \mu\alpha a_{f,j}\rho$, $T = \mu\alpha a_{n,j}\rho$ and $V = (1-\mu)$.

Expression (12) can be developed according to the complex fading channel coefficients, and written as

$$P_{\mathrm{f},j}^{\mathrm{out}} = 1-\Pr\left(\begin{array}{l}\left|h_{\mathrm{f},j}\right|^2 > \dfrac{th_{\mathrm{f}}V}{\left(Q-th_{\mathrm{f}}T\right)\left|h_{\mathrm{s}}\right|^2},\\ \left|h_{\mathrm{n},j}\right|^2 > \dfrac{th_{\mathrm{f}}V}{\left(T-th_{\mathrm{f}}Q\right)\left|h_{\mathrm{s}}\right|^2}\end{array}\right) = 1-\int_0^\infty f_{\left|h_{\mathrm{s}}\right|^2}\left(x\right)\int_{\frac{\phi_{\mathrm{n}}}{x}}^\infty f_{\left|h_{\mathrm{n},j}\right|^2}\left(y\right)\int_{\frac{\phi_{\mathrm{f}}}{x}}^\infty f_{\left|h_{\mathrm{f},j}\right|^2}\left(z\right)\mathrm{d}z\mathrm{d}y\mathrm{d}x, \tag{13}$$

with $\phi_{\mathrm{n}} = \dfrac{th_{\mathrm{f}}V}{\left(T-th_{\mathrm{f}}Q\right)}$, and $\phi_{\mathrm{f}} = \dfrac{th_{\mathrm{f}}V}{\left(Q-th_{\mathrm{f}}T\right)}$.

Since channels are characterized by Rayleigh fading distribution, the final expression of the outage probability at $UE_{\mathrm{f},j}$ can be written as

$$P_{\mathrm{f},j}^{\mathrm{out}} = 1-\frac{1}{\Omega_{\mathrm{s}}\Omega_{\mathrm{n}}\Omega_{\mathrm{f}}}\int_0^\infty \mathrm{e}^{-\frac{x}{\Omega_{\mathrm{s}}}}\int_{\frac{\phi_{\mathrm{n}}}{x}}^\infty \mathrm{e}^{-\frac{y}{\Omega_{\mathrm{n}}}}\int_{\frac{\phi_{\mathrm{f}}}{x}}^\infty \mathrm{e}^{-\frac{z}{\Omega_{\mathrm{f}}}}\mathrm{d}z\mathrm{d}y\mathrm{d}x = 1-\sqrt{\frac{\xi_1}{\psi_1}}K_1\left(\sqrt{\xi_1\psi_1}\right), \tag{14}$$

with $\xi_1 = 4\left(\dfrac{\phi_{\mathrm{f}}}{\Omega_{\mathrm{f}}}+\dfrac{\phi_{\mathrm{n}}}{\Omega_{\mathrm{n}}}\right)$, $\psi_1 = \dfrac{1}{\Omega_{\mathrm{s}}}$, and $K_1(\cdot)$ is the Bessel function of first order [17].

However, at $UE_{\mathrm{n},j}$, using (8), the outage probability is given by

$$P_{\mathrm{n},j}^{\mathrm{out}} = 1-\Pr(\gamma_{\mathrm{n},x_{\mathrm{n},j}} > th_{\mathrm{n}}). \tag{15}$$

This leads to obtain the expression

$$P_{\mathrm{n},j}^{\mathrm{out}} = 1-\Pr\left(\left|h_{\mathrm{n},j}\right|^2 > \frac{V}{T\left|h_{\mathrm{s}}\right|^2}th_{\mathrm{n}}\right) = 1-\int_0^\infty f_{\left|h_{\mathrm{s}}\right|^2}\left(x\right)\int_{\frac{Vth_{\mathrm{n}}}{Tx}}^\infty f_{\left|h_{\mathrm{n},j}\right|^2}\left(y\right)\mathrm{d}y\mathrm{d}x. \tag{16}$$

Using (16), the final expression of the outage probability at $UE_{\mathrm{n},j}$ is given as follows

$$P_{\mathrm{n},j}^{\mathrm{out}} = 1-\frac{1}{\Omega_{\mathrm{s}}\Omega_{\mathrm{n}}}\int_0^\infty \mathrm{e}^{-\frac{x}{\Omega_{\mathrm{s}}}}\int_{\frac{Vth_{\mathrm{n}}}{Tx}}^\infty \mathrm{e}^{-\frac{y}{\Omega_{\mathrm{n}}}}\mathrm{d}y\mathrm{d}x = 1-\sqrt{\frac{\xi_2}{\psi_1}}K_1\left(\sqrt{\xi_2\psi_1}\right), \tag{17}$$

with $\xi_2 = \dfrac{4Vth_{\mathrm{n}}}{T}$.

After evaluating outage performance system, for given target rates $R_{\mathrm{n/f}}$, the general system throughput of all sub-channels is given by

$$Thp = \sum_{j=1}^{M}\left\{R_{\mathrm{n}}\left(1-P_{\mathrm{n},j}^{\mathrm{out}}\right)+R_{\mathrm{f}}\left(1-P_{\mathrm{f},j}^{\mathrm{out}}\right)\right\}. \tag{18}$$

4. Multi-Objective GWO for NOMA Downlink Network Parameters Optimization

4.1 Problem Formulation

Efficient power allocation is very important for improving the NOMA system's performance expressed by the outage probabilities of NOMA users and system throughput. Consequently, we formulate the following two objective optimization problem:

Find $a_{\mathrm{f},j}$, $a_{\mathrm{n},j}$, α and μ so that

$$\mathrm{Max}\left(f_1(\mathbf{x}) = \gamma_{\mathrm{f},x_{\mathrm{f},j}}(\mathbf{x}), f_2(\mathbf{x}) = \gamma_{\mathrm{n},x_{\mathrm{n},j}}(\mathbf{x})\right), \tag{19}$$

subject to:

$$a_{\mathrm{f},j} + a_{\mathrm{n},j} = 1, \tag{20}$$

$$a_{\mathrm{f},j} > a_{\mathrm{n},j}, \tag{21}$$

$$0 < \alpha < 1 \quad \text{and} \quad 0 < \mu < 1 \tag{22}$$

where $\gamma_{\mathrm{f},x_{\mathrm{f},j}}$ and $\gamma_{\mathrm{n},x_{\mathrm{n},j}}$ represents the SINR at the farthest and the nearby users respectively given by (6) and (8) and $\mathbf{x} = [\alpha, \mu, a_{\mathrm{n},j}, a_{\mathrm{f},j}]$ is the vector of decision variables.

4.2 Solution Using Multi-Objective GWO

In contrast to single-objective optimization problem, there is no unique optimal solution when considering multi-objective optimization problem. In this case, the problem is characterized by various trade-offs between the objectives and, thus, its optimal solution becomes a set called Pareto optimal solution set.

Without loss of generality, a multi-objective optimization problem with a number of competing objectives can be formulated as a minimization problem with vector-valued objective function:

$$\mathrm{Min}\, f\left(\mathbf{x}\right) = \left(f_1\left(\mathbf{x}\right),\ldots,f_m\left(\mathbf{x}\right)\right),\ m \geq 2 , \tag{23}$$

subject to:

$$g_i\left(\mathbf{x}\right) \leq 0,\ i = 1,\ldots,k, \tag{24}$$

$$h_i\left(\mathbf{x}\right) = 0,\ i = 1,\ldots,p, \tag{25}$$

$$L_i \leq x_i \leq U_i,\ i = 1,\ldots,n \tag{26}$$

where $\mathbf{x} = [x_1,x_2,\ldots,x_n]$ is the vector of decision variables, f_i: $\mathbb{R}^n \to \mathbb{R}$, $i = 1,\ldots m$ are the objective functions, g_i: $\mathbb{R}^n \to \mathbb{R}$ are the inequality constraints, h_i: $\mathbb{R}^n \to \mathbb{R}$, $i = 1,\ldots p$ are the equality constraints and $[L_i, U_i]$ are the boundaries of the ith decision variable.

Multi-objective optimization techniques are based on the following Pareto dominance and Pareto optimality concepts:

- Suppose that there are two decision vectors **x** and **x'**, **x** is said to dominate **x'** iff:

$$\forall i \in \{1,\ldots,m\},\quad f_i(\mathbf{x}) \le f_i(\mathbf{x}') \wedge \exists j \in \{1,\ldots,m\}, f_j(\mathbf{x}) < f_j(\mathbf{x}'). \tag{27}$$

- A decision vector $\mathbf{x} \in X$ is called Pareto optimal if it is non-dominated by any other decision vector in the feasible region X:

$$\nexists \mathbf{x}' \in X \mid f(\mathbf{x}') < f(\mathbf{x}). \tag{28}$$

- The non-dominated solutions set is called Pareto-optimal set P and it is defined by:

$$\mathrm{P_S} = \{\mathbf{x} \in X \mid \mathbf{x} \text{ is Pareto optimal}\}. \tag{29}$$

- The Pareto front is a set containing the value of objective functions for Pareto-optimal set:

$$\mathrm{P_f} = \{f(\mathbf{x}) \mid \mathbf{x} \in \mathrm{P_S}\}. \tag{30}$$

Over the past two decades, many evolutionary algorithms have been proposed to deal with multi-objective optimization problems. The literature shows that these algorithms are able to effectively approximate the true Pareto optimal solutions of a given problem. Some of the most well-known multi-objective evolutionary optimization techniques proposed are: Non-dominated sorting genetic algorithm II (NSGA-II) [18], Multi-Objective Particle Swarm Optimization (MOPSO) [19], Multi-Objective Ant Colony Optimization (MOACO) [20], Multi-Objective Artificial Bee Colony Algorithm (MOABCA) [21], Multi-Objective Bat Algorithm (MOBA) [22] and Multi-Objective Grey Wolf Optimizer algorithm (MOGWO) [15], [23].

In this study, the MOGWO algorithm with certain modifications is applied to settle the multi-objective problem set in the previous section. MOGWO is a multi-objective version of GWO proposed by Mirjalili et al. [15]. The GWO algorithm [24] mimics the dominance hierarchy and hunting behavior of grey wolves in nature. Indeed, these animals have a strict social hierarchy that includes the alpha, beta, delta, and omega classes. The solutions in GWO algorithm are distributed as per the grey wolf social order. The (α) wolf is the fittest solution, followed by the second and third best solutions named (β) and (δ) wolves. The rest of solutions are considered to be (ω) wolves. In the GWO algorithm, the hunting (optimization) is guided by the optimal solutions α, β and δ. The ω wolves follow these three wolves in the search for the global optimum.

The hunting process of the gray wolf pack involves three main steps: encircling, hunting and attacking [24]. The algorithm starts with an arbitrary generated positions of a given number of grey wolves. Encircling behavior is mathematically modeled by the following equations:

$$\mathbf{X}(t+1) = \mathbf{X}_p(t) - \mathbf{A} \times \mathbf{D}, \tag{31}$$

$$\mathbf{D} = \left|\mathbf{C} \times \mathbf{X}_p(t) - \mathbf{X}(t)\right| \tag{32}$$

where t indicates the current iteration, **X** is the position vector of a grey wolf, $\mathbf{X}_p$ indicates the position vector of the prey and **A** and **C** are coefficient vectors given by $\mathbf{A} = 2\mathbf{a} \times \mathbf{r}_1 - \mathbf{a}$, and $\mathbf{C} = 2\mathbf{r}_2$, where $\boldsymbol{r}_1$ and $\boldsymbol{r}_2$ are random vectors generated from the interval [0, 1]. Components of **a** are linearly reduced from 2 to 0 and are given by $a = 2 - t(2/t_{\max})$, with $t_{\max}$ is the maximum number of iterations.

To simulate the hunting mechanism and find promising regions of the search space, the position of each wolf is updated by averaging the positions of the α, β and δ grey wolves (best solutions). The following equation is considered for this purpose:

$$\mathbf{X}(t+1) = \frac{\mathbf{X}_1 + \mathbf{X}_2 + \mathbf{X}_3}{3} \tag{33}$$

where

$$\begin{aligned} \mathbf{X}_1 &= \mathbf{X}_\alpha(t) - \mathbf{A}_1 \times \mathbf{D}_\alpha, & \mathbf{D}_\alpha &= \left|\mathbf{C}_1 \times \mathbf{X}_\alpha - \mathbf{X}\right|, \\ \mathbf{X}_2 &= \mathbf{X}_\beta(t) - \mathbf{A}_2 \times \mathbf{D}_\beta, \quad \text{and} & \mathbf{D}_\beta &= \left|\mathbf{C}_2 \times \mathbf{X}_\beta - \mathbf{X}\right|, \\ \mathbf{X}_3 &= \mathbf{X}_\delta(t) - \mathbf{A}_3 \times \mathbf{D}_\delta, & \mathbf{D}_\delta &= \left|\mathbf{C}_3 \times \mathbf{X}_\delta - \mathbf{X}\right|. \end{aligned}$$

The GWO algorithm first starts the optimization process by generating an initial random grey wolf population. During optimization, an objective function is calculated for each solution and the best three are considered to be α, β and δ. The algorithm is then iteratively updating the position of wolves according to (33) while updating the time-varying parameters *a, A* and *C*. At any point in time, if a solution becomes better than alpha, beta, and delta, they have to be replaced by the new solution. The GWO algorithm stops when an end criterion is satisfied [25].

Two new components are added when extending GWO to multi-objective optimization:

- An archive; it is created in order to store non-dominated solutions that have been found in the search process. The archive contains two main parts:
  - The archive controller; this module controls the entering solutions to the archive, i.e. which solutions that should be stored in the archive and which ones should be removed from it at each iteration.
  - The grid; it is used when the archive is full, it divides the objective space into segments and finds the most crowded segment to remove one of its solutions to make a space for the new solution. The crowdedness of each segment is defined by the number of solutions that it holds.
- A leader selection approach; a mechanism applied to choose the best solutions being α, β and δ from the elements of the least crowded segments in the grid. This choice makes it possible to direct the other search agents towards favorable unexplored areas of

the search space, expecting to find a solution close to the global optimum.

Pseudo code of MOGWO applied to our two objective trade-off problem is given in Fig. 2 [15].

Problem definition: Define Vector of decision variables $\mathbf{x} = [\alpha,\mu,a_{n,j},a_{f,j}]$ and working space boundaries of decision variables.
MOGWO parameters: Number of iterations *(Maxit)*, Population size*(nPop)*, Archive size*(Asize)*, Grid Inflation Parameter*(Gi)*, Number of Grids per each Dimension *(nGrid)*, Leader Selection Pressure Parameter*(Lsp)*, Extra Repository Member Selection Pressure*(Esp)*.
Initialize *(Pop)*: Initialize the grey wolf population xi (i = 1, 2,..., $nPop$) with random combinations of $[\alpha,\mu,a_{n,j},a_{f,j}]$
Evaluate *(Pop)*: Calculate the fitness values of all population.
Find the non-dominated solutions and create the archive with them.
Xα, Xβ, Xδ = ***SelectLeaders*** *(archive)*
It = 1;
While *(it < Maxit)* **do**
For *(i* = 1 to *nPop)* **do**
Update the position of the current search agent by (33)
End for
Calculate the fitness values of all search agents
Find the non-dominated solutions
Update (archive): Update the archive with respect to the obtained non-dominated solutions
If (the archive is full) **then**
Apply the grid mechanism;
Add the new solution to the archive
End if
If (any of the new added solutions is located outside the Hypercubes) **then**
Update the grids;
End if
Xα, Xβ, Xδ = **SelectLeaders** (archive)
It = *it* + 1
End while
Return **archive**

Fig. 2. Pseudo code of MOGWO algorithm.

5. Simulation Results and Discussion

In order to assess the effectiveness of the presented algorithm, MATLAB simulations are shown in this section. As stated before, the goal of the MOGWO algorithm is to find optimal values of the partition time expressing the harvesting energy time (μ), the power conversion factor (α) and power allocation coefficients ($a_{f,j}$, $a_{n,j}$) subject to constraints (20) and (21), such that $\mathrm{Max}(f_1,f_2)$ where $f_1 = \gamma_{f,x_{f,j}}$ and $f_2 = \gamma_{f,x_{n,j}}$.

This problem is recast as a minimization problem:

$$\mathrm{Min}(fit_1, fit_2) \tag{34}$$

where fit_i indicates the fitness functions given by

$$fit_1 = \frac{10}{1+|f_1|}, \text{ and } fit_2 = \frac{10}{1+|f_2|}. \tag{35}$$

Parameter	Value
Population size (*nPop*)	100
Number of iterations (*Maxit*)	1 000
Archive size (*Asize*)	100
Grid inflation (*Gi*)	0.1
Number of grids (*nGrid*)	10
Leader selection pressure (*Lsp*)	4
Extra Repository Member Selection Pressure(*Esp*)	2

Tab. 2. MOGWO parameters.

The parameters of the MOGWO algorithm are detailed in Tab. 2. The whole set of solutions obtained at the last generation is plotted in Fig. 3. It shows clearly that the multi-objective GWO algorithm succeeds to find a Pareto-optimal set of solutions.

Thus, a number of non-dominated solutions have been found, each solution presents a trade-off between the two fitness functions (objectives).The two objectives are contradicted; one solution being better in (f_1) is accordingly worst in (f_2) and vice-versa. Now, one solution that offers a good trade-off between both objectives has to be chosen. The remarkable extracted solutions on the Pareto-front are as indicated in Tab. 3.

Figure (4) and Figure (5) present outage probabilities $P_{n,j}^{out}$ and $P_{f,j}^{out}$ of the two users respectively. It is clear and

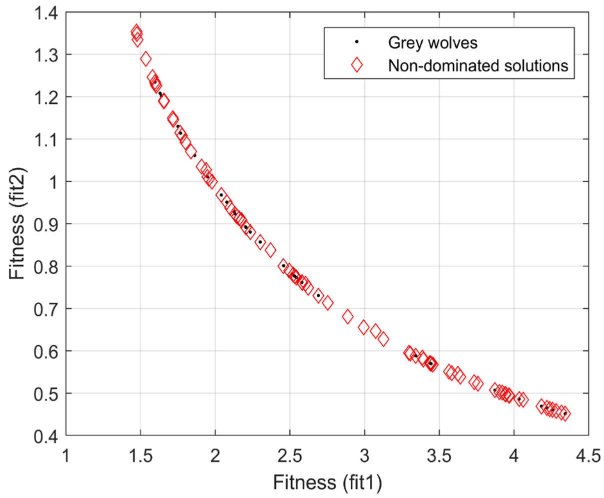

Fig. 3. Distribution of the population of the last generation.

	Solution (X_1) corresponding to best fitness (fit_1)	Solution (X_2) corresponding to best fitness (fit_2)
fit_1	1.473	4.342
fit_2	1.353	0.4517
f_1	5.7888	1.3030
f_2	6.3909	21.13858
α	0.8971	0.9
μ	0.9	0.9
a_{fj}	0.8698	0.5776
a_{nj}	0.1302	0.4224

Tab. 3. Simulation results of MOGWO.

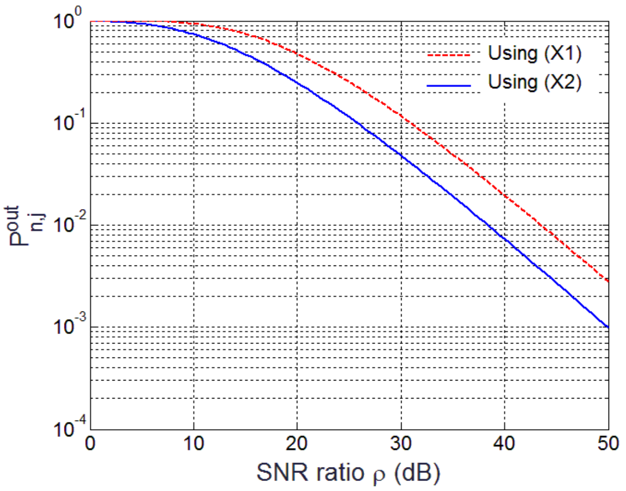

Fig. 4. Outage probability of UE_{nj}.

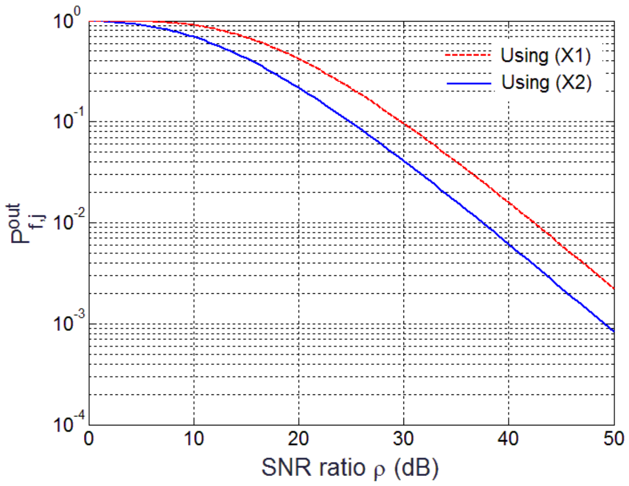

Fig. 5. Outage probability of UE_{fj}.

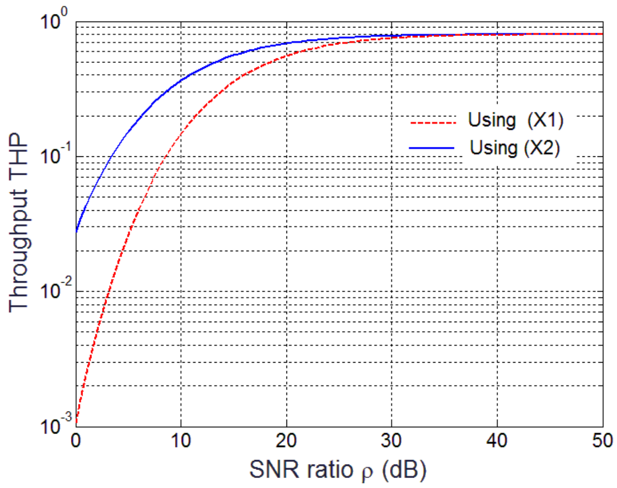

Fig. 6. Throughput system performance vs. SNR ratio.

logical that less outage probability is obtained for high portion time μ, permitting the BS to harvest more energy. In addition, low levels of $P_{n,j}^{out}$ and $P_{f,j}^{out}$ are obtained in the case of high values of power allocation coefficient (a_{nj}) of the nearest user to the BS. It means that outage performance is essentially related to UE_{nj} (nearby user) power allocation. Thus, the best extracted solution on the Pareto-front is (*X2*) which corresponds to Max(f_2). Figure (6) gives the evolution of the system throughput versus SNR ratio. It confirms the result obtained previously, which reveals again that the system throughput is directly influenced by the power allocation coefficient of the stronger user (nearby user).

The significance of the proposed MOGWO method is determined by comparing its results to two single-objective meta-heuristic optimization methods; Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). Both algorithms were studied utilizing the control parameters summarized in Tab. 4.

The best solutions obtained by both GA and PSO methods are as indicated in Tab. 5 where f is the fitness function to be maximized calculated by the weighted aggregation of the two objective functions f_1 and f_2 and given by

$$f = w_1 f_1 + w_2 f_2 \tag{36}$$

where w_1 and w_2 are weights which allows to define the importance of objectives.

GA		PSO	
Parameter	**Value**	**Parameter**	**Value**
nPop	100	*nPop*	100
Maxit	100	*Maxit*	100
Crossover percentage (*Pc*)	0.7	Inertia weight (*w*)	1
Mutation percentage (*Pm*)	0.1	c_1	1.5
		c_2	2

Tab. 4. Parameters of GA and PSO.

	GA	PSO
f	15.6516	15.4124
α	0.9	0.9
μ	0.9	0.9
a_{fj}	0.7398	0.7463
a_{nj}	0.2602	0.2537

Tab. 5. Simulation results of PSO and GA.

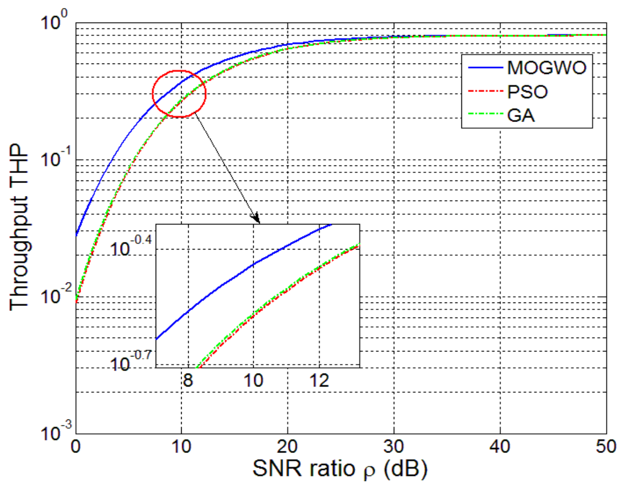

Fig. 7. Throughput system comparison between MOGWO, PSO and GA vs. SNR ratio.

Figure 7 displays the throughput system comparison between MOGWO, PSO and GA. Accordingly; it is clearly explicit that MOGWO delivers better performance than the GA and PSO optimization methods.

The followings draw some main advantages and contributions of this research:

1. Integrating energy harvesting (EH) strategies into NOMA systems have the following primary advantages:

- EH is a key technology for green wireless communications, which aim to reduce the environmental impact of wireless networks. By using harvested energy to power network devices, we can decrease the use of traditional energy sources.
- EH eliminates or reduces the costs associated with regular battery replacement, charging infrastructure, or cabled power supplies. This aspect is particularly beneficial in large-scale deployment of wireless sensor networks or Internet of Things (IoT) devices, where frequent battery replacements or charging are impractical or costly.
- EH can significantly extend the overall network lifetime by supplying a near-infinite energy source to individual nodes, contributing to a self-sustaining network.
- By leveraging the NOMA principle of serving multiple users in the same frequency band but with different power levels, EH can balance energy usage across the network. Devices with better channel conditions can harvest more energy, ensuring the equitable distribution of resources.
- With energy harvesting, NOMA networks can perform SWIPT (Simultaneous Wireless Information and Power Transfer), allowing devices to harvest energy and receive data from the same radio signal, increasing the efficiency of resource usage.

2. Optimizing the parameters of a NOMA downlink network with EH strategy using MOGWO presents several advantages. Here are a few:

- Multi-objective Grey Wolf Optimizer algorithm (MOGWO), which we can describe as more efficient than the algorithms used in the studies in the literature, is applied on NOMA Downlink Network with EH Strategy for the first time.
- The performance of a NOMA network depends on several parameters. By optimizing these parameters, we can improve key performance indicators such as system throughput, latency and reliability.
- By formulating the problem of optimizing a NOMA network as a multi-objective optimization problem, we can flexibly choose which objectives to prioritize (e.g., maximizing energy harvesting, maximizing throughput, minimizing latency) and adapt the network's design to meet the changing needs of its users. This approach can also help the network scale up to serve more users without degrading its performance or increasing its energy consumption.
- Because of the derived outage probabilities and throughput expression's complexity, we employ the MOGWO to jointly optimize the partition time expressing the EH time, the power conversion factor and power allocation coefficients for achieving SINR maximization (outage probabilities minimization and throughput maximization). The simulation results show that the MOGWO is perfect for optimizing performance of the proposed NOMA system rather than conventional methods which often require derivative information [26], [27].
- The optimization process is performed with four parameters compared to the studies in the literature where only the power allocation factors are optimized [26–28].
- The MOGWO algorithm also has several advantages as compared to single-objective optimization (SOO) methods [25]. Firstly, MOGWO provides a set of optimal solutions (known as Pareto-optimal solutions), instead of a single one. This set of solutions offers different options that we can choose from, according to our preferences. Secondly, the set of Pareto optimal solutions used and improved in each iteration in MOGWO algorithm is smaller than that in SOO methods. Therefore, the algorithm does not waste computational resources searching in non-promising regions of the search space. Finally, through comparing with other single-objective advanced meta-heuristic algorithms, we confirm the correctness and effectiveness of the MOGWO algorithm by simulation results.

6. Conclusion

Taking into account the performance of NOMA downlink network in the power domain, a PB is used to help a base station to serve distant users, by WPT, and the harvested energy by the BS is employed to support information signal transmission to NOMA users. The performance of this system such as outage probabilities of NOMA users and system throughput are improved through a power allocation optimization issue. For this purpose, multi-objective GWO algorithm has been used to find optimal values of certain influencing parameters that maximize two objective functions (f_1, f_2) representing the SINR at the farthest and the nearby users. Simulation results illustrate that the algorithm succeeded to find the Pareto optimal set of solutions. Two remarkable solutions extracted from the Pareto front are tested; one solution being better in (f_1) but worst in (f_2) and vice-versa.

The simulation findings revealed an interesting result, which is the impact of the power amount allocated to the nearby user on the system performance. As consequence, *UEi* perform less outage probability and higher throughput in the case of higher power allocation coefficient, allotted to the stronger user, as well more important portion time reserved to energy harvesting leads to reduce outage probability. Through comparing with other advanced metaheuristic SOO algorithms used in simulations, it can be said that MOGWO has the best performance.

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