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# Particle swarm optimization for beamforming design in a cognitive radio

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**ABSTRACT**

Beamforming is essential for improving transmission in wireless sensor networks (WSNs), particularly in cognitive radio networks (CRNs) with several secondary users (SU) equipped with transmitting antennas. Optimizing beamforming while minimizing interference with primary users (PU) is of great interest. This study proposes an improved particle swarm optimization (PSO) algorithm to enhance beamforming performance. This approach aims to maximize the power of the beam directed to the SU receiver while controlling interference in the PU protection region. The results show that this algorithm constantly improves beam focus and signal-to-noise ratio to effectively optimize beamforming. Firstly, beam focusing becomes narrower as the number of antenna elements increases, generating optimal transmission conditions. Secondly, the algorithm achieves a considerable improvement in signal-to-noise ratio as the number of antenna elements increases. Furthermore, optimization performance improves as the number of antenna elements increases, as shown by the best fitness values. The simulations also illustrate the performance of the proposed method.



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## 1. INTRODUCTION

By the end of 2025, it is estimated that wireless communications will serve nearly 75 billion mobile devices, and each person will be surrounded by more than nine devices on average [1], leading to the scarcity of the spectrum. Moreover, most of the spectrum for wireless communications is licensed, and some of the unlicensed spectrum is filling up fast. According to federal communications commission (FCC) measurements [2], most licensed frequencies are underutilized.

Cognitive radio networks (CRNs) are emerging as a solution to increase spectrum utilization by using unused or less-used spectrum in radio environments. The basic idea is to allow unlicensed users, usually called secondary users (SUs), access to licensed spectrum under the condition that the interference perceived by the licensed users, usually called primary users (PUs), is based on three scenarios: overlay, interweave and underlay [3]-[7]. In the first approach, SUs cooperates with PUs by relaying data from PUs to enable them to transmit their data. In the second method, the SUs send their data into the spectral holes of the PUs. SUs must therefore detect free channels by applying spectrum detection algorithms. In the last mode, SUs coexist with PUs with the limited interference induced from SU transmitters to PU receivers. To preserve quality of service (QoS) in CRN, SU should not interfere with the communications of PU [8].

Beamforming is an important part of network signal processing and is widely used in wireless communications, microphone array signal, and radar systems [9]-[11].

In an antenna array, multiple antennas (called elements) are connected together and arranged in various geometric patterns, such as linear, planar, or circular configurations [12]. The key idea behind beamforming is to combine the radio frequency (RF) waves emitted by each element in a constructive or destructive form. By adjusting the phase and amplitude of the signals transmitted to each element, beamforming improves the radiated power in the desired direction while minimizing it in other directions. This allows for more efficient communication and better signal reception, as shown in Figure 1. For more details on these sensors, we refer the interested reader to a part of the literature where the detection takes place by beamforming technology [13], [14].

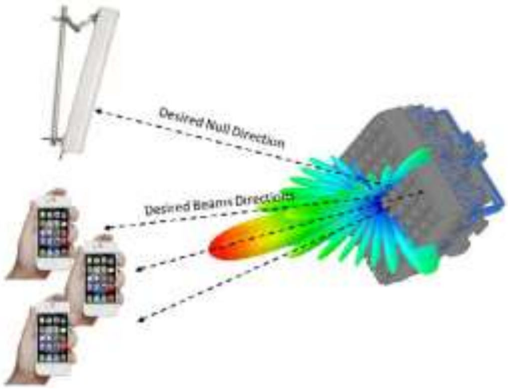



Figure 1. The beamforming signals

In the context of CRNs, beamforming offers significant advantages: improved signal strength, increased system capacity, and reduced interference. Optimizing its parameters to achieve the best possible performance requires sophisticated tools. This is where particle swarm optimization (PSO) comes into play.

PSO is one of the most commonly used algorithms in a lot of engineering applications. It has been extensively applied to solve diverse wireless communications optimization problems in different areas such as electrical power systems and signal processing [15], [16], wireless sensor networks (WSNs) [17], [18], CRNs [19], [20] and antenna design [21], [22]. PSO was initially introduced by Kennedy and Eberhart [23].

Beamforming is widely investigated in the literature in the context of CRNs, Barjoei *et al.* [24], within the framework of a transmission scheme using beamforming technology, propose an improved performance for solving the problem of non-linear multi-objective optimization and coherent power allocation based on PSO. The algorithm is used to find optimal beamforming weights by minimizing the transmission power of each terminal. Power is controlled by the measured signal-to-interference-plus-noise ratio (SINR), which contains gain and interference information. Their simulations show the convergence behavior of the proposed algorithm and the efficiency of the proposed scheme with a dynamic cost function. in [25], a robust beamforming scheme for reconfigurable intelligent surface (RIS) enhanced transmission in CRN is proposed. The scheme addresses non-convex optimization problems with interruption constraints using Schur complement approaches and alternative optimization with semi-definite relaxation methods. The simulation results show the robustness of the proposed BF algorithm and the superiority of RIS-enhanced wireless transmission. Khodier and Saleh [26] proposes a design scheme for distributed power control by beamforming in cognitive radio. An algorithm is proposed that, on the one hand, minimizes interference between cognitive users and, on the other hand, maximizes the capacity of SUs. The PSO is used to solve a nonlinear multi-objective optimization problem with constraints. The main objective of this work is to determine the optimal beamforming weight vector and the maximum transmission power of each node. They illustrate the advantages of using beamforming in conjunction with power control, and the effectiveness of the optimization technique adopted. Zamiri-Jafarian and Jannat-Abad [27], proposed a new cooperative algorithm for beamforming and power allocation in the downlink of a CRN. The main objective of this study is to maximize the total SINR of the SU, while respecting the total transmit power constraints of the base station and the SINR of the PU. The transceiver design was developed using an iterative procedure. Jannatabad and Khoshbin [28], a new scheme for cooperative beamforming and relay selection in CRNs was proposed. In this scheme, a pair of SUs communicates with the help of some multiple-antenna relay nodes.

The objective of this algorithm is to maximize the SINR of each SU, subject to limitations on the interference caused to the PU receiver and the power constraints of the relay nodes.

Due to the dynamic nature of the network's parameters and constraints, as well as the large number of users, it would be interesting to study the application of an algorithm that can be used to solve the network utilization problem, taking into account various constraints. To increase the performance of beamforming in CRN, we use our improved metaheuristic method: PSO, and we employed it to optimize beamforming parameters, especially, antenna weight.

The aim of this study is to improve beamforming in CRNs using an improved PSO algorithm. Wireless channels are evaluated taking into consideration key performance metrics such as SINR. The PSO fitness function incorporates the SINR ratio, which evaluates the transmitted signal power as a function of interference and noise, to guide the algorithm towards maximizing signal power and minimizing interference.

In this research we use improved PSO capabilities to address CRN challenges, such as dynamic network conditions and user constraints. By adjusting antenna weights, the algorithm ensures the correct orientation of signals, thereby reducing interference and improving overall network performance. This method offers significant advances over conventional optimization techniques, making it extremely relevant for 5G systems. Based on the above, the main contributions of this paper are to exploit an improved PSO algorithm for beamforming in CRNs. This algorithm optimizes antenna weights to maximize beam power for SUs, while minimizing interference with PU, improving SINR and beam focus, under different changing network conditions, for faster convergence and better overall network performance.

This paper is organized as follows: section 2 contains a description of the model used and outlines the basic idea and procedure of the improved PSO and specifies the required parameters. Finally, the simulation results and the analysis of some scenarios, as well as the conclusions, are presented in sections 3 and 4, respectively.

## 2. METHOD

### 2.1. System model and problem statement

In this section, we consider a system model consisting of a network of wireless CR transmitters communicating with a SU receiver. The network operates in the presence of a PU and must avoid any form of interference. It is assumed that the location of the SUs is known in advance in relation to their origin. SUs communicate directly with each other without the need for a central or controlling node. We consider N SU transmitters distributed uniformly in a circle of radius R. We use a polar coordinate system designated by $(d_n, \varphi_n)$, and we also assume that the SUs transmit the same power level, as shown in Figure 2.

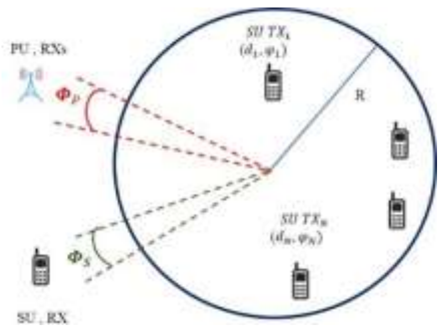



Figure 2. CRNs model

Where $\Phi_S$ is the region of the SU receiver and $\Phi_p$ is the region of the PU receiver. If φ denotes the azimuth angle, the array factor at angle φ can be expressed as follows:

$$F(\varphi) = \left[e^{jkd_1\cos(\varphi-\varphi_1)}, \dots , e^{jkd_N\cos(\varphi-\varphi_N)}\right] \tag{1}$$

where k=2π/λ is the propagation constant in free space and λ is the wavelength. In beamforming technology, finding a weight vector is an essential step for directing the signal towards the desired use, this weighting vector can be formulated as follows:

$$w = [w_1, w_2, \dots, w_N] \tag{2}$$

were $w_k$ is the k-th node's transmission weight, assuming that a signal arrives at the angle of $\theta_0$, and if we note:$t_k$ the time arrival of the signal for each element, then the element weight for each element can be obtained as follow:

$$w_k = \frac{1}{N} e^{j\omega t_k \theta_0} \quad (3)$$

where $\omega$ is the frequency in radian. If we pose; $\beta_k = \omega t_k \theta_0$, the weight can be rewritten as follows:

$$w_k = \frac{1}{N} e^{j\beta_k} \quad (4)$$

from the distribution of the above-mentioned distributed model, and under the assumption that we have oriented the beamforming in the direction of the desired user, we can then calculate the power, or variance, of the output signal as follows:

$$P(\varphi) = |F.w'|^2 \quad (5)$$

the CRN uses beamforming to direct a zero to the PUs. To protect PUs we consider a range of azimuth angles which we will call PU regions.

In order to maximize the beam power in the direction of the SU receiver while limiting interference in the PU protection region, we consider an instantaneous beampattern and spread nulls in order to provide arbitrarily large protection to the PU network. If the SU is located in $\varphi \epsilon \Phi_S$ and if we write $\Phi_P$ the PU protection region, a nonlinear optimization problem can be formulated as follows:

$$\mathrm{Max}_{\beta_1;\, \beta_2;\ldots;\beta_N} |F.w'|^2 \;\; ; \;\; \varphi \epsilon \Phi_S \quad (6)$$

subject to:

$$|F.w'|^2 \; \leq \gamma_p \;\; ; \;\; \varphi \epsilon \Phi_P \quad (7)$$

where $\gamma_p$ is the limit on the interference in the PU protection region $\Phi_P$ (a threshold to protect the PU communication).

The expression in (6) is the fitness function, whose role is to maximize the power directed at the regions of the SU $\Phi_S$ receiver, while, the constraint function (7) ensures that the maximum power within the PU protection region is limited to $\gamma_p$. To evaluate this scenario using the PSO approach, we evaluate the effectiveness of PSO in the Beamforming approach through the signal-to-interference-and-noise ratio (SINR). This ratio is defined as follows:

$$\mathrm{SINR} = \frac{P_{\mathrm{target}}}{\sum_{n=1}^{N} P_{\mathrm{interference\_n}} + \mathrm{Noise}} \quad (8)$$

where $P_{target}$ is the power of target user, $P_{interference}$ is the power of interference, and $n$ is the number of interference sources. This ratio expresses the QoS guarantees resulting from the requirements imposed by applications running on user terminals.

### 2.2. Improved PSO algorithm

PSO is classified as a metaheuristic algorithm. It is considered one of the most reputed swarm-based algorithms in the literature [16]. PSO is inspired by the swarming and gathering behaviors observed in fish and birds. Each solution to an optimization problem is considered a member of a figurative swarm, communicating with the other solutions. Under the influence of the best individuals, the positions of the solutions are adjusted, which has proved extremely effective. This success is demonstrated by the numerous applications of PSO in real-life problems, contributing significantly to its popularity [29].

PSO is a robust algorithm with fast convergence. It stands out for its simplicity and ease of implementation on software platforms. It should also be noted that it does not consume much memory. Likewise, it can be used to solve multimodal, non-differential and non-linear problems [29].

In the PSO algorithm, each solution to the optimization problem is considered as a "bird" and is called a "particle" in the search space. The entire population of the solution is called a "swarm," and all particles are searched by following the best particle in the swarm. Each particle uses its own information, as well as that of its neighbors, to adjust its position in the search space. It is assumed that the strength of PSO comes from the cooperation between particles, unlike other evolutionary algorithms (EA).

Each particle $i$ has two characteristics:

– $x_i$: is the position which determines the fitness value of the particle.
– $v_i$: is the velocity which determines the direction and distance of the search.

At iteration t (t is a positive integer), to avoid confusion, the position and velocity of the particle $i$ are usually denoted as $x_i(t)$ and $v_i(t)$. Each particle follows two "best" positions:

– $p_{i\,best}\,(t)$: is the best position found by the particle itself so far.
– $g_{best}\,(t)$: is the best position found by the entire swarm so far.

When the algorithm finishes, $g_{best}\,(t)$ is declared as the solution to the problem in question. The position and velocity of every population member are updated via the following formula:

$$v_i(t+1) = wv_i(t) + c_1r_1\big(p_{i\,best}\,(t) - x_i(t)\big) + c_2r_2\big(g_{best}\,(t) - x_i(t)\big) \tag{9}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{10}$$

here, $w$ denotes the inertia weight, while $r_1$ and $r_2$ are variables distributed according to a uniform probability distribution in [0,1], $c_1$ and $c_2$ are cognitive and social coefficient, respectively [23].

In this work, an improved PSO algorithm is applied; this improvement is implemented for parameters (w, $c_1$, $c_2$) to make them more dynamic. To help particles explore broadly in the initial stages and converge efficiently towards optimal solutions, making the algorithm more effective for complex optimization problems [30]. Dynamic parameters $c_1$ and $c_2$ utilized in the algorithm are as follow:

$$c_1 \;=\; \left(c_{upper} -\; c_{low}\right) \times \frac{maxiter - iter}{maxiter} \;+\; c_{low} \tag{11}$$

$$c_2 \;=\; \left(c_{upper} -\; c_{low}\right) \times \frac{iter}{maxiter} \;+\; c_{low} \tag{12}$$

and the dynamic parameter w utilized in the algorithm is as follow:

$$w \;=\; (w_1 - w_2) \times \frac{maxiter - iter}{maxiter} \;+\; w_2 \tag{13}$$

here, the iter is the current number of iterations, and maxiter is the maximum number of iterations $c_{upper}$ and $c_{low}$ are the upper and lower bounds of the learning factors, respectively. $w_1$ *and* $w_2$ are the upper and lower bounds of w, respectively. The values of $\mathrm{c_{upper}}$, $\mathrm{c_{low}}$, $w_1$ and $w_2$ are recalled in the simulation section.

These modifications will result in better performance because it induces more dynamic behavior than that of a standard PSO. We also note that the PSO implementation uses only primitive mathematical operators, which makes the algorithm inexpensive in terms of memory and speed. The flowchart in Figure 3 shows the optimization steps mentioned above.


Figure 3. Improved PSO flowchart

## 3. RESULTS AND DISCUSSION

In this section, simulation results are provided to evaluate the performance beamforming in a CRN using improved PSO, the simulations were performed using the MATLAB environment. Table 1 show the improved PSO parameters used in our simulation. In order to estimate the performance of the PSO algorithm in the transmission scenario considered in this work, we would like to measure the effect of the number of SUs within a radius of 4×λ (λ=1.25 m), on the behavior of the network factor; the direction of interest is set to 60°, the threshold to protect the PU communication $\gamma_p$ is fixed at -20dB, we will take into account the interference constraints power (or threshold) for PU, the corresponding numerical results are processed. As a general rule, a large population size allows rapid convergence, so we set it at 2000, as shown in Table 1. Initially, by varying the number of SUs, we want to get an idea of the behavior of the beampattern. Figure 4 shows this diagram as a function of angle with different numbers of antennas (N=8, N=16 and N=24).

Table 1. Improved PSO parameters

| Parameter | Description | PSO |
|---|---|---|
| $N$ | Population size | 2000 |
| $t_{max}$ | Maximum iteration | 100 |
| $c_{upper}$ | Upper bounds of the learning factors | 2.5 |
| $c_{low}$ | Lower bounds of the learning factors | 1.2 |
| $c_1$ | Cognitive coefficient | Equation (11) |
| $c_2$ | Social coefficient | Equation (12) |
| $w_1$ | Upper bounds of w | 0.9 |
| $w_2$ | Lower bounds of w | 0.4 |
| $w$ | Weight | Equation (13) |
| $r_1$ | Random cognitive coefficient | Uniform random value in [0; 1] |
| $r_2$ | Random social coefficient | Uniform random value in [0; 1] |

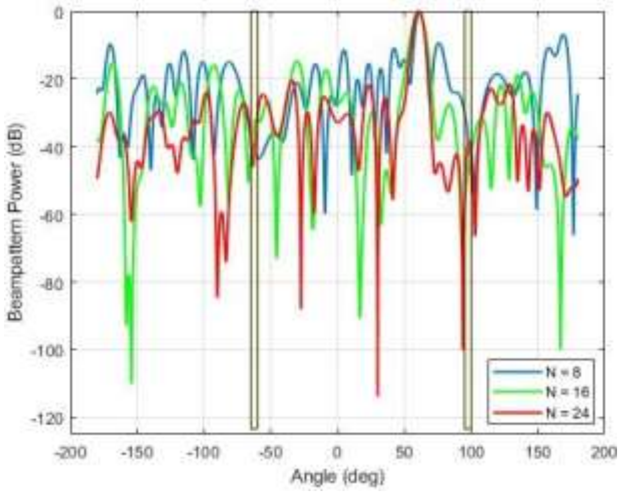
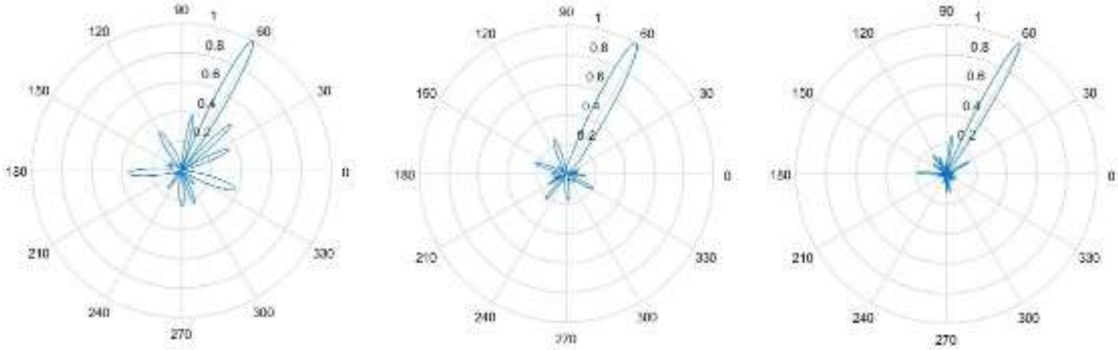



Figure 4. Beampattern with varying N, $\Phi_{P1}$= [-65° -60°], $\Phi_{P2}$= [95° 100°]

Next, to characterize the directivity of the radiation in the scenario under consideration, we plot the polar curve in Figure 5. For more details, Figure 5(a) depicts the polar diagram of the beampattern with N=8, Figure 5(b) shows this polar diagram for N=16, and finally, Figure 5(c) plots the same diagram for a number of users equal to 24. From Figures 4 and 5, it is clear that the beampattern becomes increasingly narrow and centered on the desired user (SU) at 60° as the number of antennas increases, from 8 to 24, which can ensure well-directed signal transmission. On the other hand, a few antennas (N=8) are more than sufficient to achieve limited deep cancellation in the main user's region. We also note that as the number of antennas increases (N=16, N=24), cancellations are improved and become deeper and more effective at suppressing interference in the PU user regions.

Next, we analyzed the performance of the proposed algorithm in terms of convergence speed for different numbers of SUs. Figure 6 shows the convergence curves of the fitness function under $\gamma_p = -20dB$ with differents number of antenna elements. It can be seen from Figure 6 that increasing the number of SUs from 8 to 24 significantly improves PSO optimization performance, as illustrated by the lower values of the best fitness values obtained for smaller numbers of iterations. Indeed, For N=8, the best fitness value first rapidly declines and then stabilizes at around -0.92 within about 20 iterations, while it rapidly declines to around -0.98 within 10 iterations and remains stable for N=16, and rapidly declines to around -0.98 within 15 iterations before slightly decreasing and stabilizing around -0.99 after 30 iterations for N=24. Overall, performance for 16 and 24 users is significantly better than for 8 users at $\gamma_p = -20dB$.



(a) (b) (c)

Figure 5. The polar plot of the beampattern, $\Phi_{P1}$=[-65° -60°], $\Phi_{P2}$=[95° 100°] with varying N: (a) N=8, (b) N=16, and (c) N=24

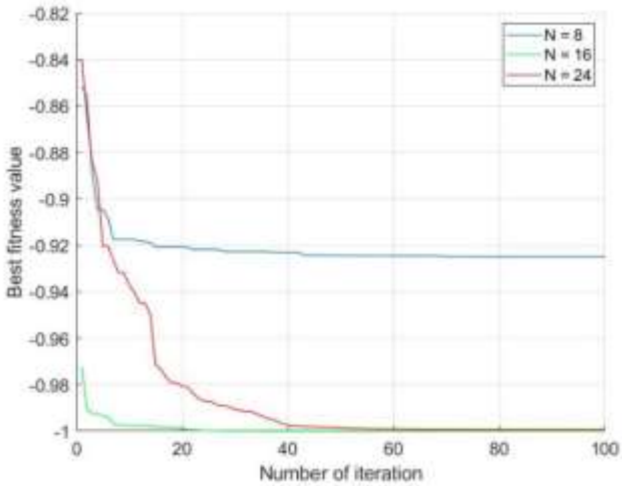



Figure 6. Fitness function convergence curves ($\gamma_p = -20dB$)

Unlike Barjoei *et al.* [24], who transform the nonlinear constrained problem into an unconstrained one by using the penalty method, the present work applies the improved PSO algorithm directly to the problem in question, thus pursuing an investigation of the possibilities offered by PSO algorithms. The performance improvement resulting from the increase in the number of SU is explained by the essence of the PSO algorithm. Basically, the PSO algorithm takes advantage of the cooperation and information sharing between individuals in the group to find an optimal solution. More precisely, PSO starts by finding the objective function and then searches for a local optimum that ensures convergence of the objective function by optimizing the speed and displacement parameters. Finally, it's worth noting that the time required to perform the fitness calculations can dominate the total calculation time when applying PSO to real-world problems.

In a final simulation, in Figure 7, we consider the same noisy environment, setting the interference limit in the user protection zone to -20dB. It will be useful to get an idea of the evolution of the SINR over time. We will also vary the number of SU involved in this scenario. Based on a result in [26], where the average SINR received is characterized as a function of the number of mobile users, we consider in the present research the instantaneous SINR values as a function of the evolution of the resolution, i.e., as a function of the number of iterations, varying the number of SUs.

In Figure 7, the instantaneous values of signal to-interference plus noise ratio are taken into account to analyze channel quality for future deployment of a transmission scheme. For N=16, the SINR converges rapidly to a steady state around 15 dB in around five iterations. Similarly, for N=24, it shows a more gradual increase, reaching stability just above 15 dB around iteration 20. For N = 8, it improves steadily until stabilizing just below 15 dB after around 30 iterations.

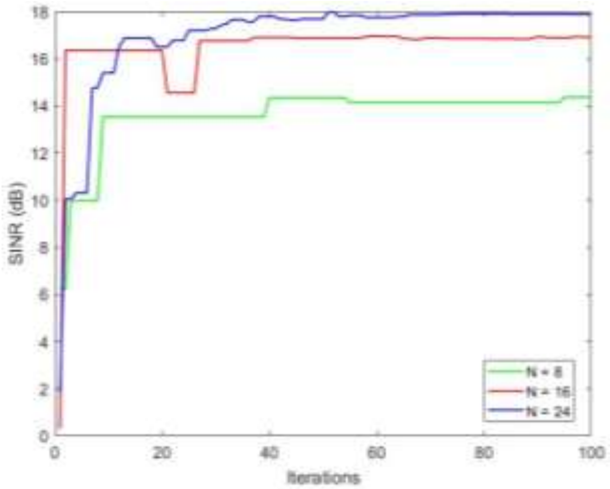



Figure 7. SINR versus number of iterations ($\gamma_p = -20$dB)

The results obtained in this simulation have been examined in relation to existing work detailed in [31]. Indeed, it is clear from Figure 7 that a relatively small number of iterations can achieve a high SINR, up to 17 dB in just 20 iterations. In contrast, previous work required more than 100 iterations to reach 16 dB. However, it should be noted that in [31] the number of iterations increases with decreasing permissible interference level and uncertainty variance.

In terms of complexity, the study [25] proposes a robust beamforming approach using reconfigurable smart surfaces (RIS), requiring the solution of non-convex optimization problems. Which results in high computational complexity, estimated at $O(n^3)$, which can be particularly challenging for large-scale systems with many antennas or RIS elements. In contrast, the improved PSO method presented in this study has a much lower computational complexity, on the order of $O(n \times p)$, where n represents the number of particles and p the number of iterations.

## 4. CONCLUSION

In this work, we explored beamforming techniques within CRNs by employing an improved PSO algorithm. The improved PSO algorithm demonstrated rapid convergence and efficiently navigated large solution spaces to identify optimal beamforming configurations due to dynamic PSO's parameters that adapt during the optimization process. Our simulations achieved a balance between focusing the signal on the desired user and minimizing interference to PU, resulting in significant improvements in SINR even under severe interference conditions.

Overall, the advances achieved represent a major step forward in the field of WSNs, in particular CRNs, improving the current performance of beamforming techniques and opening up new research perspectives. Future studies could explore hybrid approaches, combining PSO with other algorithms such as genetic algorithms or reinforcement learning, to further optimize performance in increasingly complex scenarios, such as full-duplex communications and mmWave frequencies. In addition, the development of low-power versions of the PSO algorithm could significantly reduce energy consumption, making it more suitable for practical applications in regional communication networks.

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