# Nature-Inspired Algorithms-Based Beamforming for Advanced Antenna Systems

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**Abstract.** In pursuit of enhancing the signal processing capabilities of antenna arrays for directed signal transmission and reception in spatial contexts, novel methodologies have been developed for advanced antenna systems. Leveraging cutting-edge technologies such as beamforming (BF) and multiple-input and multiple-output (MIMO) within smart antenna systems has emerged as a compelling strategy for elevating the quality of service, capacity, and coverage in mobile information systems. This paper presents a comparison, wherein algorithms inspired by natural processes are applied to amplitude-only controlled beamforming techniques. Subsequently, a comprehensive assessment is undertaken to discern the merits and demerits of the weight control methodologies employed. Specifically, this study delves into the application of bat algorithms, multi-verse optimization, hybrid particle swarm optimization, and gray wolf optimization in various scenarios.

**Keywords:** Beamforming · ULA · Bat Algorithm · Multi-Verses Optimization · Hybrid Particle Swarm Optimizer and Gray Wolf Optimizer

## 1 Introduction

In wireless communication systems, highly directional antennas are often used to take advantage of their advantages. Combining a variety of radiating elements (an antenna array) creates highly directional antennas. Beamforming is the technique of combining radio signals from a set of separate antennas to create an equivalent directional antenna system. This directional antenna system (advanced antenna) has the ability to focus on radiating energy or receiving signals in a predetermined direction in space. In order to improve radio signal spectrum efficiency, reduce interference, and save energy, beamformers are frequently utilized in radar, sonar, and wireless communication systems. Additionally, adaptive beamformers have the ability to provide the correct weights for antenna arrays in order to produce desired patterns [1]. In addition, the growing proliferation of wireless devices has led to significant congestion within the electromagnetic propagation environment. Consequently, directional antenna systems emerge as a favorable approach for mitigating interference in radar, sonar, and wireless communication [10].


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Amplitude-only controllers [4–6] change the excited amplitude at each array element. This method has been used and proven to work for adaptive beamformers using the metaheuristics algorithm to manage and turn off the ULA antenna in research [7]. A method of global search and optimization known as metaheuristics was created based on testing random solutions or searching in the search space of the problem. Specifically, the metaheuristic algorithms used and evaluated in this study are BA (Bat Algorithm), HPSOGWO (Hybrid Particle Swarm Optimizer and Gray Wolf Optimizer), and MVO (Multi-Verse Optimizer). Based on the behavior and hunting methods of bats, gray wolves, and particles in general, or based on multiverse theory to search for and optimize solutions through two processes of exploration and exploitation.

This study aims to evaluate the advantages and disadvantages of the recommendations in research [7–9] with consistent suggestions for each scenario while maintaining the highest and most stable level of performance. Specifically, five simulation scenarios, including convergence rate, optimized samples with single nulls, multiple nulls, and broad nulls, will be implemented through different excitation weight control techniques.

The rest of this paper is organized as follows: In Sect. 2, the problem is defined, in which the antenna array coefficients and the formation of the objective function are presented. Section 3 gives the general characteristics of nature-inspired algorithms. Section 4 describes in detail the three algorithms mentioned in the article. Simulation results with different scenarios for the amplitude-only beam generator are presented in Sect. 5. Section 6 is the conclusion.

## 2 Beamforming Approach Formulation

In advanced antenna systems, although there are different array geometries, the principle of signal processing techniques shares some common points. Therefore, for simplicity, only linear arrays will be analyzed in this section.

### 2.1 Array Factor of ULA Antenna

The 2N isotropic ULA antenna is utilized as an example and shown in Fig. 1. The array is symmetrically arranged along the x axis, and the array factor is [4]:

$$AF(\theta) = \sum_{n=-N}^{N} \omega_n e^{jndksin(\theta)} \tag{1}$$

where: $\omega_n = \omega_n^{re} + j\omega_n^{im} = a_n e^{j\delta_n}$ is the complex weight of n$^{\text{th}}$ array element; λ is wave length; $k = \frac{2\pi}{\lambda}$ is the wave number; d is the distance between adjacent elements.

In our study, the imaginary parts of weight $\omega_n^{im} = 0$ và $\omega_{-n}^{re} = \omega_n^{re}$; Therefore, the array factor in (1) can be rewritten as:

$$AF(\theta) = 2\sum_{n=1}^{N} \omega_n^{re} cos(ndksin(\theta)) \tag{2}$$

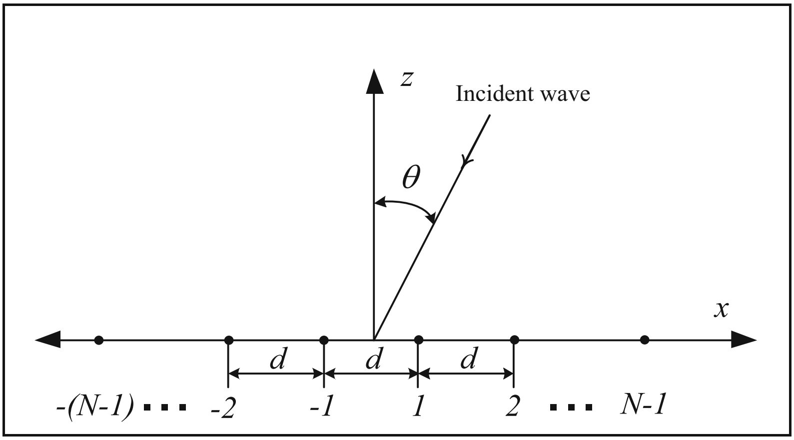


**Fig. 1.** The ULA antenna of 2N isotropic elements

The weights are real and symmetrical around the center of the array. As a result, the array layout is symmetrical around the major lobe at = 0 and the number of attenuators and calculation time are both cut in half. However, this approach still requires attenuators and amplitude controllers for practical phased array systems.

### 2.2 Objective Function

One of the ways to solve this optimization problem is to apply the penalty method [2]. Based on this method, a new objective function F is given as follows (3):

$$O = \begin{cases} \xi \sum_{i=1}^{I} \left[ |AF_o(\theta_i)|^2 \right], for \theta = \theta_i \\ \sum_{\theta=-90^0}^{90^0} \left[ |AF_o(\theta) - AF_d(\theta)|^2 \right], elsewhere \end{cases} \quad (3)$$

where: $F_0$ is used to reduce SLL and to keep beamwidth of main lobe within a maximum allowable change; $F_d$ is for placing the null points; $\theta$ is angle of elevation.

However, choosing appropriate values for the penalty parameters can help solve the problem effectively. If the penalty parameters are too small, they can lead to under-leveling penalties for violations; conversely, when the penalty parameters are too large, they can lead to excessive penalties, thus the solution oversatisfies the condition. Constraint functions instead of minimizing the objective function [3]. This article chooses the penalty parameter $\xi = 10000$.

## 3 Nature Inspired Optimization

### 3.1 Inspiration of Optimization

A metaheuristic algorithm is a search and optimization method with the goal of finding the best solution in a large and complex search space [14, 16]. A common feature of metaheuristic algorithms is their ability to perform searches that may not be globally optimal, but they can find near-optimal solutions in reasonable time. Nature-inspired algorithms are a subset of metaheuristic algorithms that draw their inspiration from natural processes and mechanisms in nature. In order to solve optimization problems, these algorithms frequently simulate or draw inspiration from natural phenomena. Scientists have looked to a variety of natural sources for inspiration, including fish, birds, mammals, plants, ants, bees, bats, fish, and physical and chemical systems. As a result, numerous algorithms with varying functionalities and degrees of performance have emerged [17, 18]. The combination of nature-inspired optimization algorithms, computational electromagnetics, and computer processing is a promising tool to address the challenges of smart antennas in wireless communications [17] and [18].

## 3.2 Characteristics of Nature Inspired Optimization

The two primary categories of metaheuristic optimization approaches are population search optimization methods (PSOMs) and local search optimization methods (LSOMs) [19]. LSOMs start with a single solution and use neighborhood mechanisms to try to improve that single candidate agent [20]. Evolutionary computation and swarm intelligence are examples of PSOMs [21] and [22]. The nature-inspired optimization method uses this approach to manage the constrained exploration area: If an agent is far from the exploration area, it will adjust the values that disturbed the limits to its previous preferences in order to turn back toward the potential exploration area. The flowchart of the basic nature-inspired optimization algorithm is shown in Fig. 2.

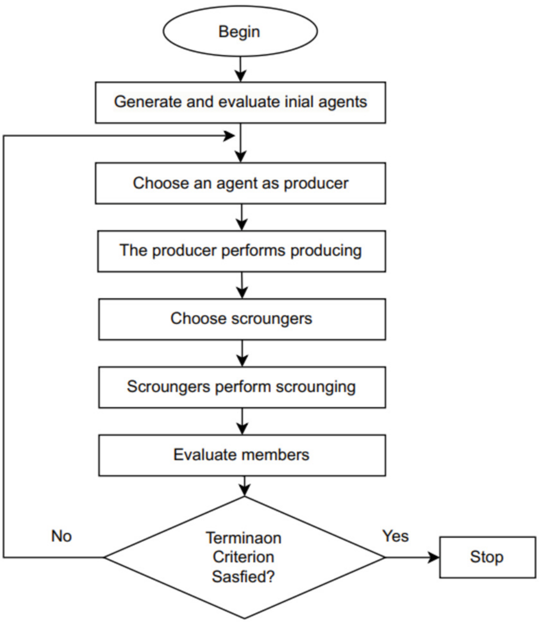


**Fig. 2.** Flowchart of the basic nature inspired optimizer algorithm

## 4 Evaluated Beamforming

Beamforming is based on the Nature-inspired optimization; specifically, in this paper, three algorithms (BA [11], HPSOGWO [12], MVO [13]) are used, taking advantage of amplitude-only control for interference suppression applications. They were constructed, and their flow diagram is shown in Figs. 3, 4 and 5.

Null-steering adaptive beamformers emerge as a promising solution for interference suppression in wireless communications and radar applications. We will develop algorithm-based adaptive beamformers for interference suppression applications in the following ways:

- Based on the idea that is introduced in Sects. 2 and 3;
- Applied for pattern nulling of ULAs, such as a single null, multiple nulls, and a broad null at directions of interference;
- Capable of maintaining the direction of the main lobe and the beamwidth while suppressing the sidelobes.

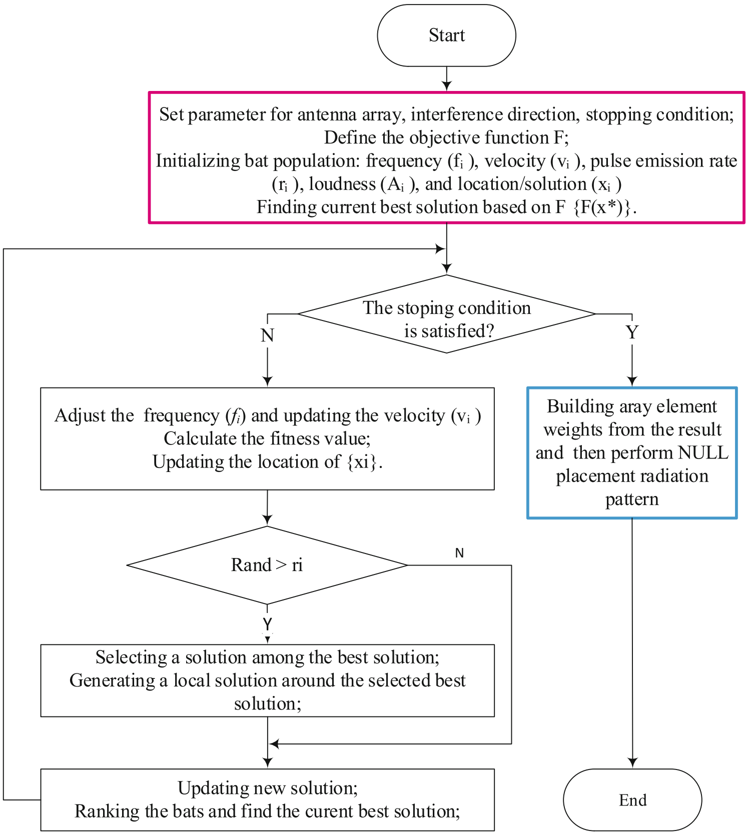


**Fig. 3.** Flow diagram of the BA-based beamformer

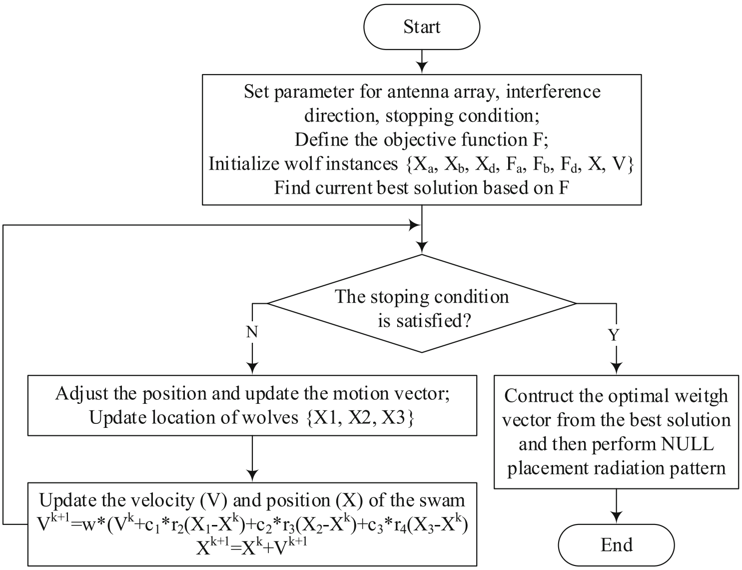


**Fig. 4.** Flow diagram of the HPSOGWO-based beamformer

# 5 Numerical Results

To demonstrate the variety and capability of sidelobe suppression and null steering techniques, five scenarios are examined. For equally spaced arrays, it is well known that the Chebyshev array weight distribution provides the best pattern in terms of the trade off between the sidelobe level and the main lobe's first-null beamwidth [15]. In order to manage the sidelobe level and beamwidth, the array factor of the Chebyshev array has been selected as the desired one in this research. The initial pattern has been a −30 dB Chebyshev array pattern for 20 isotropic elements with $\lambda/2$ inter-element spacing, with the exception of scenario 5, which employs 40 antennas.

The parameters of all investigation scenarios were initialized as boundary frequency values: $f\_min = 0$ and $f\_max = 1$; step size of the random size is 0.01; the jump of the theta angle is 1°; All simulation results run on desktop (with an Intel i5–5300 CPU, 8GB of RAM, and Pycharm 2021) are the average of 20 Monte Carlo simulations for all scenarios.

Initial parameters for the algorithm: The search value x(i) has been set as: (i) the amplitude of the weights is limited from 0 to 1, and (ii) all stages of weight are 0; population size (pop) is 150; and the number of iterations is 20 except for the first scenario in Sect. 5.1.

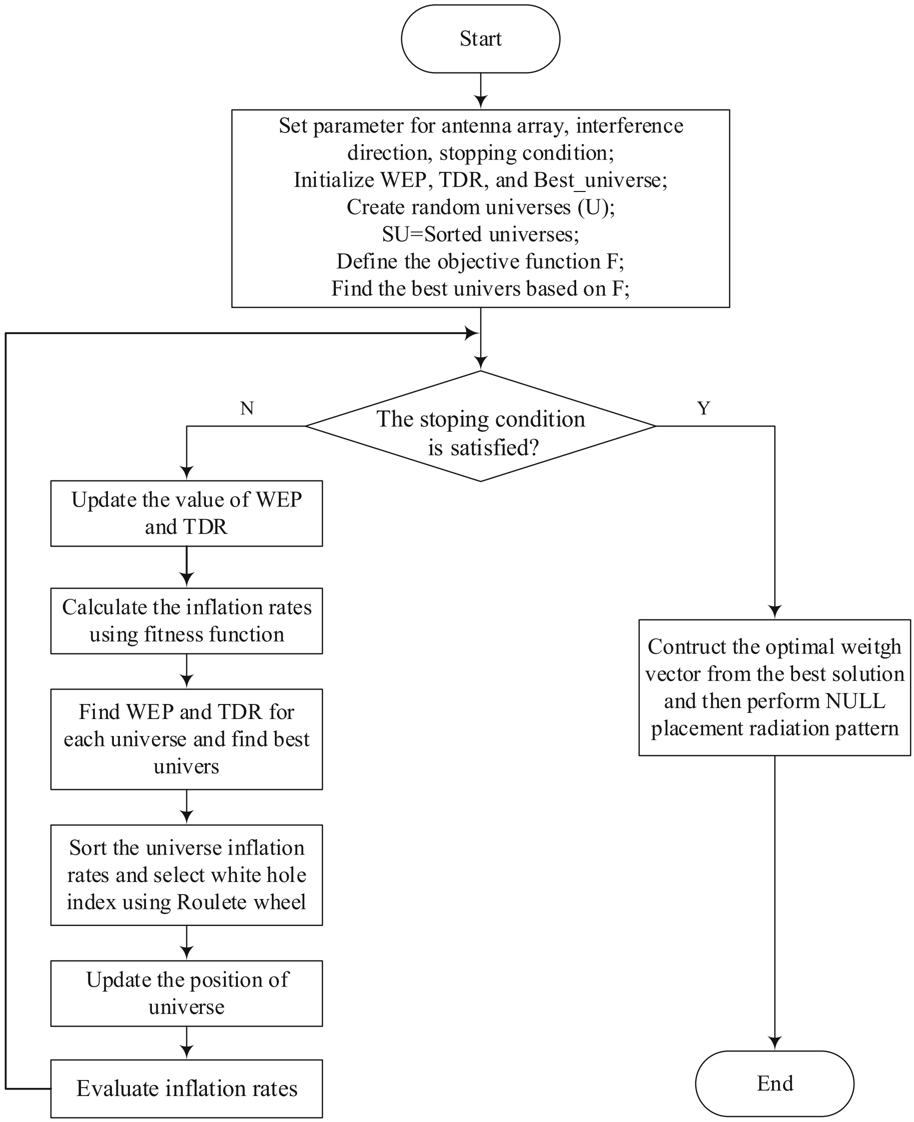


**Fig. 5.** Flow diagram of the MVO-based beamformer

### 5.1 Convergence Characteristic

In the first scenario, the convergence speed of the beamformer based on the proposed BA was studied. In order to do that, the −30 dB Chebyshev array pattern, the intended optimization pattern, was obtained by applying these beamformers. Furthermore, there are 100 repetitions and a random beginning bat population generation. In Fig. 6, their convergence rate is shown. It is evident that the BA-based beamformer with more bats has a faster rate of convergence.

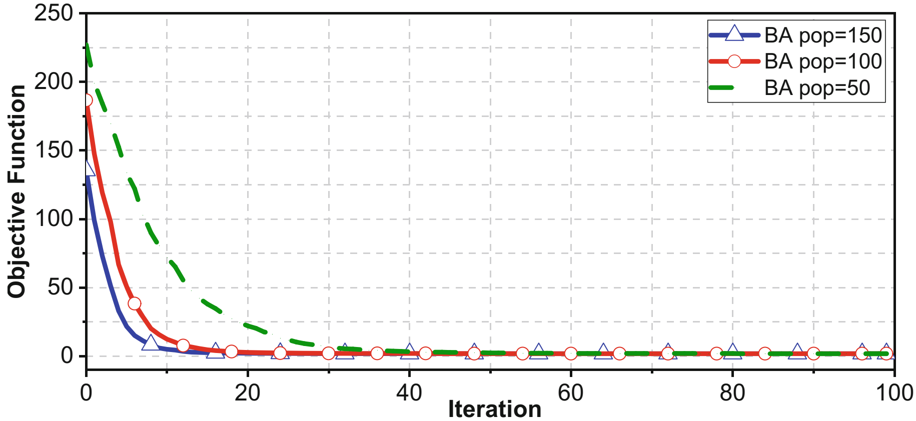


**Fig. 6.** Compare the objective function of BA with different numbers of individuals.

Based on the convergence characteristics of the bat algorithm, the article chooses the parameters for the BA bat algorithm as: number of iterations ite = 20, number of individual bats pop = 150 to investigate for the next scenarios. They ensure that the algorithm has the ability to find solutions, and the speed of finding solutions is the best.

Figure 7 describes the convergence characteristics of three beamformers based on three algorithms: BA, HPSOGWO, and MVO. It can be seen that the convergence speed of all 3 beamformers is not much different, with BA and HPSOGWO converge faster.

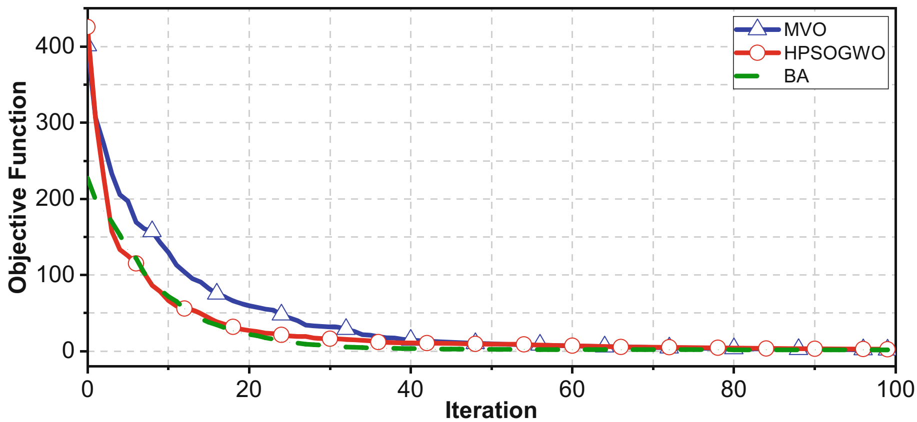


**Fig. 7.** Objective function comparisons of BA, HPSOGWO and MVO

## 5.2 Single Null

The second scenario illustrates the improved patterns with a single null. This null is arbitrary and set at any angle; in this test scenario, it is selected at the peak of the second sidelobe ($14^0$). Initialized with −30 dB Chebyshev array weights, the population. The majority of the properties of the original Chebyshev sample, such as almost half the power beam width (HPBW = $6.6^0$) and the sidelobe level being nearly −30 dB, with the exception of the first sidelobe level, are maintained by the suggested beamformer-optimized sample, as shown in Fig. 8.

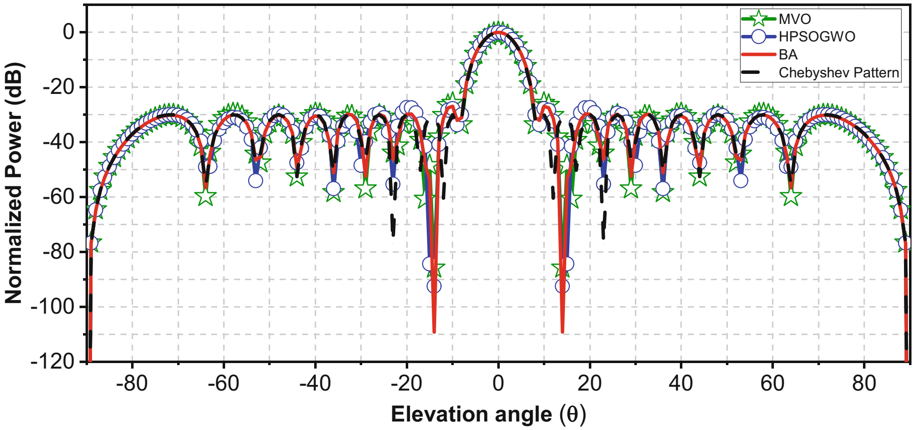


**Fig. 8.** Optimized pattern with a single null at 14°

Figure 8 presents optimized patterns with single null obtained by BA, HPSOGWO and MVO. It indicates that the single null-pattern optimized by the BA is better than that of the HPSOGWO and MVO in terms of NDL at the desired null point. They are presented in detail in the following table:

| | BA | HPSOGWO | MVO |
|---|---|---|---|
| Max SideLope | −27dB | −27.8dB | −25.8dB |
| Null Depth Level | −109dB | −92.5dB | −85.8dB |

## 5.3 Multiple Null

Figure 9 shows the optimal patterns imposed in the third case with multiple nulls set at $14^0$, $26^0$, and $33^0$. It is evident that the optimized pattern's nulls were precisely located in the designated direction. The BA pattern shows advantages over the HPSOGWO and MVO patterns in terms of NDL and SLL.

| | | BA | HPSOGWO | MVO |
|---|---|---|---|---|
| Max SideLope | | −19.9dB | −14.3dB | −13.5dB |
| Null Depth Level | $14^0$ | −85.8dB | −79.8dB | −63.4dB |

(*continued*)

(*continued*)

| | | BA | HPSOGWO | MVO |
|---|---|---|---|---|
| | $26^0$ | −72.7dB | −71.5dB | −89.5dB |
| | $33^0$ | −74.5dB | −58.2dB | −64.7dB |

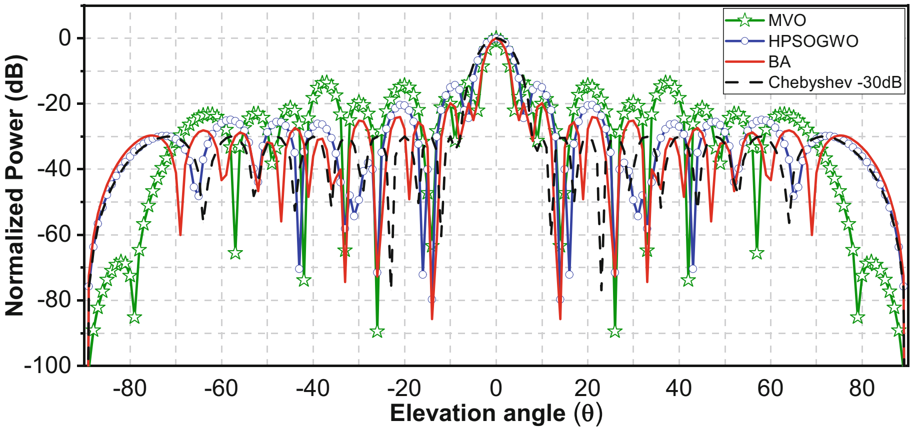


**Fig. 9.** Optimized pattern with a multiple null at $14^0$, $26^0$, $33^0$.

## 5.4 A Broad Null

In interference suppression applications, a broad null is necessary if the directions of undesirable interferences' arrival vary significantly over time or are not precisely known, or if a null is continually guided to achieve the desired signal-to-noise ratio. In the fourth scenario, the pattern has an imposed broad null to show the capability of broad interference suppression [$20^0$,$40^0$]. In terms of NDL and SLL, the BA pattern performs better than the HPSOGWO and MVO patterns. It is evident that a broad null on the BA pattern at the target broad has been obtained, with a minimum NDL of $< -8.5$ dB and a maximum NDL of −105 dB. There are no appreciable changes to the BA beamwidth, and the maximum SLL is −13.2 dB. Meanwhile, the NDL of MVO beamwidth is −68.5dB and that of HPSOGWO beamwidth is −75.5 dB but the SLL of them are −15.6 dB and −14 dB (Fig. 10).

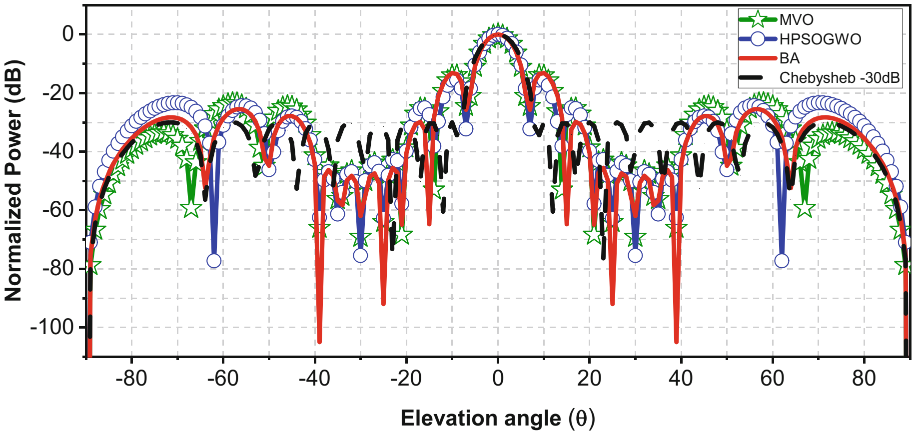


**Fig. 10.** Optimized pattern with a broad null from $20^0$ to $40^0$.

### 5.5 Change the Number of Antennas

In fact, changing the number of antennas can be done to achieve a number of different goals: increase service capacity, expand coverage, improve signal quality, etc. Figure 11 illustrates the optimized partern of all three algorithms when changing the number of antenna elements from 20 to 40. With a single null at $14^0$, it is easy to see that in this case, the null suppression ability of the MVO algorithm (NDL $= 121.9$ dB) is much better than the other 2 algorithms ($NDL_{HPSOGWO} = -108.2$ dB and $NDL_{BA} = -97.7$ dB) while still ensuring SLL at $< -28.3$ dB.

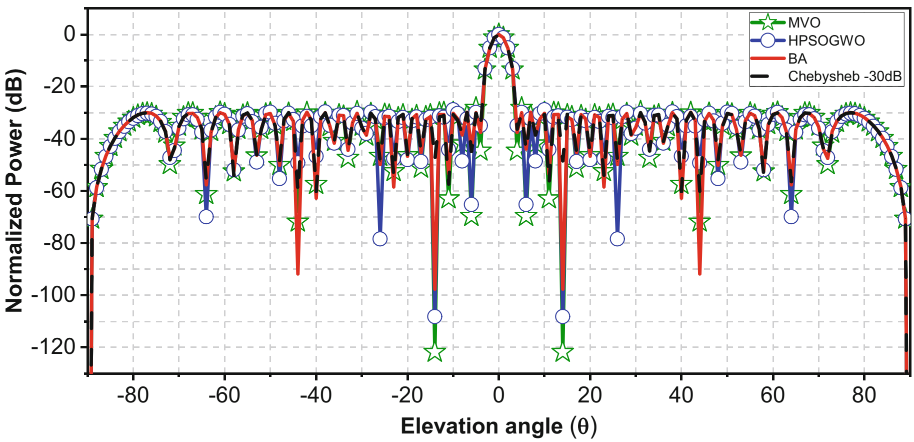


**Fig. 11.** Optimized pattern for a single null at 14° with 40 antennas

## 6 Conclusion

In this study, the bat algorithm beamformer with amplitude-only control technique was evaluated for its advantages and disadvantages compared with the multi-verse optimizer, the hybrid particle swarm optimizer, and the grey wolf optimizer. Through all the simulation scenarios mentioned above, the results have been evaluated and analyzed in detail to have appropriate recommendations to apply in each scenario to achieve greater efficiency.

– Regarding convergence ability, all three beamformers based on three algorithms show uniform and equivalent convergence speeds.
– The beamformer based on the bat algorithm has better interference suppression ability than the other two algorithms in the cases of single null, multiple null, and broad null.
– The beamformer based on the MVO algorithm shows superiority in interference suppression ability when the number of antennas is 40.
– The biggest advantage of the nature-inspired beamformers is their ability to adaptively suppress interference without losing the mainlobe.

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