Adaptive beamforming for uniform circular arrays

Tong Van Luyen*, Nguyen Thi Van Anh

Hanoi University of Industry
**Corresponding author E-mail: luyentv@haui.edu.vn*
DOI: https://doi.org/10.64032/mca.v29i2.259

Abstract

Beamforming in smart antennas is a highly effective technique that utilizes the flexible adjustment of antenna radiation characteristics, including main beam direction, interference nulling, and sidelobe level control. This paper proposes an adaptive beamforming solution based on the hybrid optimization algorithm combining Particle Swarm Optimization Grey Wolf Optimizer (HPSOGWO) and Bat Algorithm (BA) for Uniform Circular Arrays (UCA). The proposed approach demonstrates the ability to place nulls at interference directions and steer the main beam toward the desired direction. The modeling of circular antenna arrays, objective function, and evaluation scenarios will be presented. Additionally, the cumulative distribution function (CDF) and signal-to-noise ratio (SNR) will be addressed to assess system performance.

***Keywords**: Uniform circular arrays; Hybrid particle swarm optimization and grey wolf optimizer; Bat algorithm; Adaptive beamforming.*

1. Introduction

In the context of the Fourth Industrial Revolution, the rapid advancement of information and communication technology has significantly increased the demand for high-performance, reliable, and high-speed wireless communication systems. Fifth generation (5G) mobile networks are gradually becoming the new standard, offering considerable advantages in terms of speed, bandwidth, and latency compared to previous generations. Furthermore, the continuous expansion of wireless devices and the rise of the Internet of Things (IoT) present a major challenge: supporting millions of simultaneous connections.

Smart antennas have emerged as a promising solution, offering the capability to suppress interference, direct energy toward desired directions, optimize spectrum utilization, and enhance the overall quality of communication services [1]. In smart antenna systems, beamforming is implemented by adjusting the phase and amplitude of signals across the antenna elements. This technique improves system performance by: (i) steering the beam toward the desired direction; (ii) suppressing sidelobe levels below a predefined threshold; and (iii) minimizing undesired signals in other directions (interference) [2], [3], [4].

In beamforming, the optimization algorithm plays a crucial role in determining the optimal weights for the antenna elements. These weights define the radiation pattern and directly affect the system's performance. Recently, nature-inspired optimization algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Bat Algorithm (BA) have been widely applied to antenna array optimization problems [5–13]. These algorithms are adaptive and capable of learning from environmental changes or previous search experiences, making them suitable for dynamic and complex optimization tasks. Moreover, they offer robustness in avoiding local optima and increase the likelihood of achieving globally optimal solutions.

Among these, the Hybrid Particle Swarm Optimization and Grey Wolf Optimizer (HPSOGWO) algorithm-which combines the strengths of PSO and GWO-has demonstrated enhanced stability, faster convergence, and improved global search capabilities. While PSO is known for its exploratory search driven by particle interactions, GWO excels at exploiting solutions by simulating the hunting behavior of grey wolves. The hybridization in HPSOGWO effectively balances exploration and exploitation, resulting in superior optimization performance [5].

This paper investigates a beamforming approach for Uniform Circular Arrays (UCAs) using nature-inspired optimization algorithms, specifically HPSOGWO and BA. The objective is to suppress interference and concentrate energy in the desired direction-an essential capability for next-generation wireless communication systems. The effectiveness of the proposed beamformer is validated through its ability to place nulls, improve signal-to-noise ratio (SNR), and enhance cumulative distribution function (CDF) performance.

2. Problem Formulation

2.1. Array Factor

Uniform Circular Array (UCA) is a structure comprising antenna elements arranged in a circular configuration. UCA is often used in telecommunications and radar systems due to its ability to generate highly directional beams and perform omnidirectional angle scanning [2], [14]. The paper considers a circular array consisting of N antenna elements, radius a, placed on the Oxy plane as shown in Figure 1. Array Factor of UCA can be written [14],[15]:

Received: 11 December 2024; Revised: 23 May 2025; Accepted: 23 May 2025.

$$AF(\theta,\phi)=\sum_{n=1}^{N} w_n e^{j[ka\sin\theta\cos(\phi-\phi_n)]} \quad (1)$$

$$w_n = a_n e^{j\varphi_n} \quad (2)$$

where: w_n is n^{th} weight, $\phi_n = 2\pi(\frac{n}{N})$ is the angular position of the n^{th} element on the plane.

a_n , φ_n are the excitation amplitude and excitation phase of the n^{th} element.

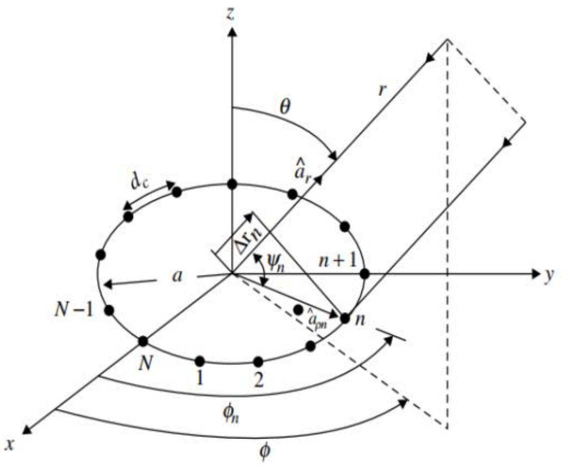

Figure 1: N-elements uniform circular array.

2.2. Objective Function

Radiation pattern synthesis for antenna arrays is an optimization problem to determine the optimal location and orientation of antennas in an antenna array. A mathematical optimization problem is often expressed as:

$$\begin{array}{ll} \text{minimize/maximize} & f_0(x) \\ \text{subject to} & f_i(x) \le b_i, i=1,\dots,I \end{array} \quad (3)$$

where $f_i(x)$ is the radiation in the interference directions, and $f_0(x)$ is the radiation in the remaining (desired) directions.

Mapping the general optimization problem to the circular antenna array (UCA) optimization problem involves defining the objective function while considering various constraints such as main lobe, NULLS, sidelobes.

One of the ways to solve constrained optimization problems is to use the Penalty Method [16]. Therefore, the objective function can be written:

$$O=\sum_{\theta=90^0,\phi=-90^0,\phi\neq\phi_i}^{\phi=90^0} \left|P_0(\theta,\phi)-P_d(\theta,\phi)\right|^2+\xi\sum_{i=1}^{I}\left|P(\theta_i,\phi_i)\right|^2 \quad (4)$$

where: $P_0(\theta,\phi)$ is the optimal pattern obtained by the optimization algorithms at (θ,ϕ);

$P_d(\theta,\phi)$ is a pre-specified radiation pattern at (θ,ϕ);

$P_0(\theta_i,\phi_i)$ is the optimal pattern at (θ_i,ϕ_i);

I is the total of interferences;

(θ_i,ϕ_i) is the i^{th} interference direction, $i=1,2,\dots,I$

3. The Proposed Beamformer

ABF uses an objective function to find a suitable set of weights, corresponding to the optimal radiation pattern of the array. As a result, the main beam direction is maintained in the direction of the SOIs, and the NULLS are placed in the direction of the SNOIs. The ABF sets based on the metaheuristic algorithm are all implemented through the following steps:

(I) Initialize the initial parameters: Number of antenna elements N, Direction of the interference signals, Number of loops/Stopping conditions, Radiation pattern of the antenna element. Determine the objective function. Map the optimal weights to the position of X in the optimization through the metaheuristic algorithm.

(F) Search for the optimal solution based on the metaheuristic algorithm.

(B) Build the array element weights and model the radiation pattern.

Accordingly, the steps applied to develop adaptive beamformers based on the HPSOGWO algorithm are shown in the block diagram in Figure 2.

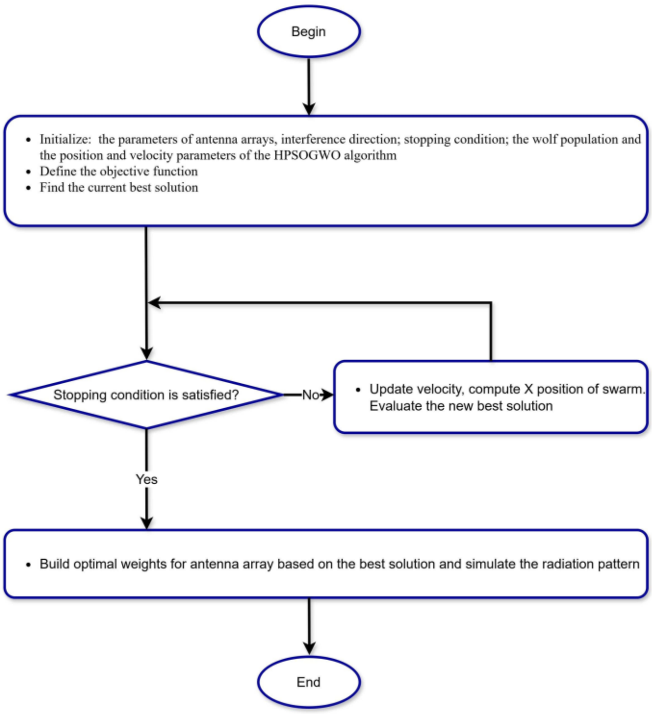

Figure 2: Beamformer based on HPSOGWO.

Adjusting the parameters of the algorithm, calculating the positions of X1, X2, X3, updating the velocity, calculating the X position of the swarm are calculated based on the formulas presented in [5].

4. Numerical Results

This section presents the results obtained after validating the proposed beamforming solution through the scenarios: convergence characteristics, ability to place nulls at interference directions and calculation of CDF and SNR.

The simulation results were obtained after 200 Monte Carlo iterations, running on the same environment (Laptop Intel(R) Core(TM) i5-8265U CPU @ 1.60GHz (8 CPUs), ~1.8GHz and Pycharm2021). The general parameters for the scenarios are as follows: UCA consists of 20 elements, the optimal algorithm with 50 populations, and 100 iterations (except section 4.1). To satisfy the NULLS setting criteria, the penalty parameter value $\xi = 1500$ is chosen. Parameters HPSOGWO: $C_1 = C_2 = C_3 = 0.5$; $w = 0.5$; Parameters for BA: $A = r = 0.5$; $f_{\min} = 0$; $f_{\max} = 2$; The parameters used for the HPSOGWO and BA algorithms are taken from the original studies [5] and [17], which are cited in the reference list.

4.1. Convergence Characteristic

The convergence rate can indicate whether the optimization algorithm is capable of finding a good solution or not. In this scenario, authors consider the convergence ability of the HPSOGWO algorithm in the cases of placing NULL at $\phi = -20^0$ with different numbers of individuals. Figure 3 gives the details of the objective function values in the cases of populations 5, 10, 50, 100 and 500, respectively.

Where pops = 5 and pops = 10, the objective function value decreases rapidly in the first iterations but converges more slowly as it approaches the best value and tends to converge at higher objective function values, while pops = 50, 100, 500, the convergence rate in the first iterations is relatively fast and reaches a stable value better.

However, the number of individuals and the number of iterations affect the computation time and computational complexity, so the number of iterations is chosen between 100 and 50 individuals to use for simulating the following scenarios.

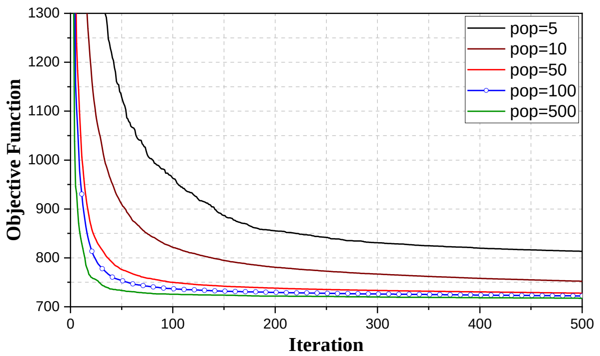

Figure 3: Convergence rate.

During the simulation, a threshold value is defined at which the objective function is considered to have converged. The execution times required for convergence by the BA and HPSOGWO algorithms are comparable, recorded at 2.68 seconds and 2.56 seconds, respectively.

4.2. Ability to set nulls on the pattern

The proposed beamforming solution is capable of placing nulls at interference directions including single interference, multiple interference and a broad interference while steering main lobe. Figures 4, 5, 6 demonstrate the ability to place nulls at single interference $\phi = -20^0$, multiple interference $\phi = -30^0; 48^0$ and a broad interference $\phi = [30^0; 50^0]$, respectively.

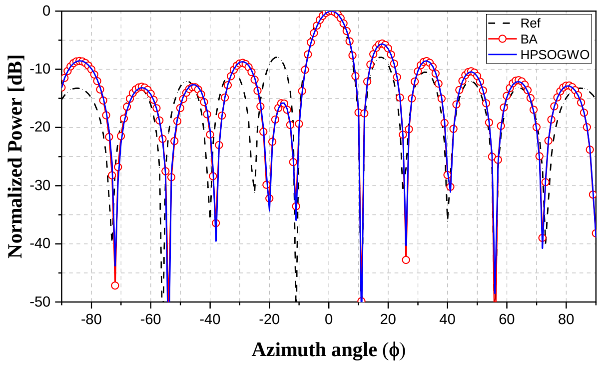

Figure 4: A single null pattern.

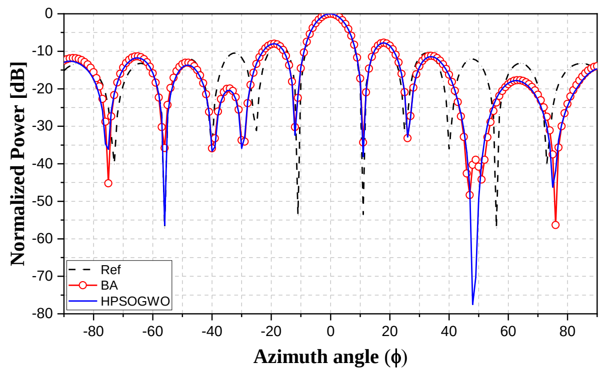

Figure 5: Multiple nulls pattern.

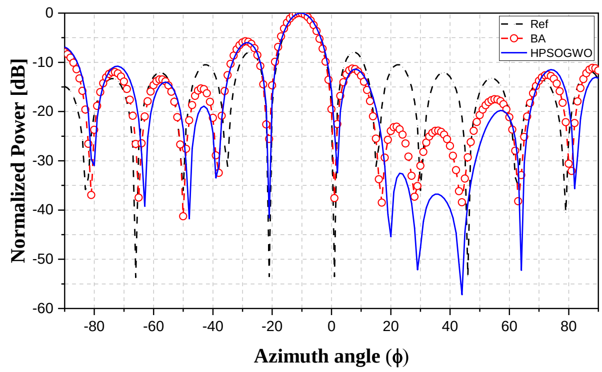

Figure 6: A broad null and steering main beam pattern.

Overall, the efficiency of the beamformer based on the optimization algorithm can be seen compared to the reference one. In addition, ABF-HPSOGWO (H) shows better NULLS placement ability than ABF-BA (B) in all three noisy cases.

Details of the nulls depth level and SNR are presented in Table 1.

Table 1: Details of the NDL and SNR of scenarios

		Single null	Multiple nulls		Broad null
Interference directions		$\phi = -20^0$	$\phi = -30^0$	$\phi = 48^0$	$\phi = [20^0; 40^0]$
NDL (dB)	H	-34.8	-35.8	-77.5	[-53; -32]
	B	-32.1	-33.7	-48.4	[-37; -23]
SNR (dB)	Ref	9.1	11.9		15.6
	H	34.8	56.65		38.8
	B	32.1	41.05		26.8

4.3. Cumulative Distribution Function

Figures 7 and 8 show the cumulative distribution function (CDF) of the side lobe level (SLL) for three methods: Ref, BA, and HPSOGWO in the case of a single null and a broad null (presented in Section 4.2). This function helps to compare the performance of the methods in minimizing the side lobe level, an important factor in antenna system design and optimization.

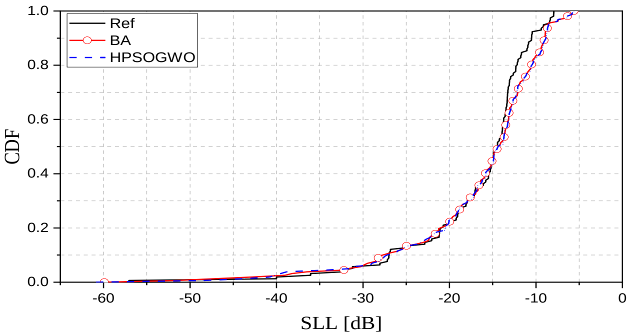

Figure 7: CDF in a single null scenario

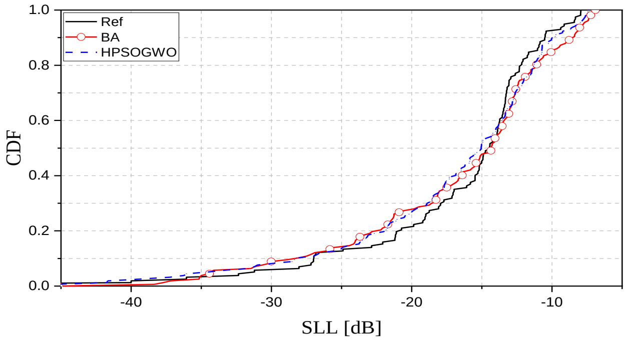

Figure 8: CDF in a broad null scenario

Both HPSOGWO and BA optimization methods have similar performance in reducing sidelobe levels, but the difference is not too significant. At CDF ≈0.5, Ref achieves a lower SLL than BA and HPSOGWO. The Ref reference pattern does not place NULLS at the interference directions, while the radiation pattern based on HPSOGWO and BA algorithms completely place NULLS in the cases where interference occurs, in exchange for having a sidelobe level exceeding the reference pattern.

The simulation results have demonstrated the high performance of the proposal. However, in order to apply this proposal in real applications such as 5G advanced antennas phased array radar, some future challenges will be addressed:

Hardware Feasibility:

Precision and cost: Metaheuristic beamforming designs often assume ideal element control. Real-world implementations face: (i) Limited phase-shifter resolution; (ii) Nonlinearities in power amplifiers; (iii) Calibration errors in antenna arrays (especially in UCA).

Computational complexity: Algorithms like HPSOGWO and BA may be computationally expensive for real-time beam adaptation. Embedding them in FPGAs or DSPs requires optimization or simplification.

Real-World Signal Environments:

Multipath fading and NLOS propagation can degrade beamforming performance, especially in cluttered urban environments.

Interference*:* Unlike simulations, real systems face co-channel interference, which may require adaptive interference cancellation.

Channel estimation errors can reduce the accuracy of metaheuristic-optimized beam directions.

5. Conclusion

This paper proposed an adaptive beamforming approach for Uniform Circular Arrays using a hybrid optimization strategy combining HPSOGWO and the Bat Algorithm. The approach aims to steer the main lobe precisely while placing nulls in interference directions. Simulation results across multiple scenarios showed significant improvements in null depth level, signal-to-noise ratio, and sidelobe suppression. Cumulative distribution function analysis further confirmed its effectiveness. Despite the promising results, real-world implementation faces challenges such as hardware limitations and computational complexity. Future research will focus on optimizing algorithm efficiency and robustness under dynamic signal environments. The proposed approach shows strong potential for advanced wireless communication systems, including 5G networks and beyond.

References

[1] R. W. Heath, N. González-Prelcic, S. Rangan, W. Roh and A. M. Sayeed (2016), "An Overview of Signal Processing Techniques for Millimeter Wave MIMO Systems," in *IEEE Journal of Selected Topics in Signal Processing*, 10(3), pp. 436-453, doi: 10.1109/JSTSP.2016.2523924.

[2] C.A. Balanis, 2016. *Antenna theory: Analysis and design.* John Wiley and Sons.

[3] Holland, J. H. (1992). Genetic algorithms. *Scientific american*, *267*(1), 66-73, doi: 10.1038/scientificamerican0792-66.

[4] H. Steyskal, R. A. Shore, and R. L. Haupt, (1986), "Methods for null control and their effects on the radiation pattern", *IEEE Trans. Antennas Propagat*. vol. 34, pp. 404–409, doi: 10.1109/TAP.1986.1143816.

[5] Singh, N., & Singh, S. B. (2017). Hybrid algorithm of particle swarm optimization and grey wolf optimizer for improving convergence performance. *Journal of Applied Mathematics*, *2017*(1), 2030489, doi: 10.1155/2017/2030489.

[6] Mirjalili, S., Mirjalili, S. M., & Lewis, A. (2014). Grey wolf optimizer. *Advances in engineering software*, *69*, 46-61, 10.1016/j.advengsoft.2013.12.007.

[7] T. V. Luyen and T. V. B. Giang (2017), "Interference Suppression of ULA Antennas by Phase-Only Control Using Bat Algorithm", *IEEE Antennas and Wireless Propagation Letters*, 16, pp. 3038–3042, doi: 10.1109/LAWP.2017.2759318.

[8] Khanduja, N., & Bhushan, B. (2021), "Recent Advances and Application of Metaheuristic Algorithms: A Survey (2014–2020)", *Metaheuristic and Evolutionary Computation: Algorithms and Applications*, pp. 207-228, doi: 10.1007/978-981-15-7571-6_10.

[9] Abhinav Sharma (2022) "Antenna Array Pattern Synthesis Using Metaheuristic Algorithms: A Review, IETE Technical Review", doi: 10.1080/02564602.2022.2051616.

[10] Tong, L., Nguyen, C., Le, D. (2022). An Effective Beamformer for Interference Mitigation. In: Anh, N.L., Koh, SJ., Nguyen, T.D.L., Lloret, J., Nguyen, T.T. (eds) Intelligent Systems and Networks. Lecture Notes in Networks and Systems, vol 471. Springer, Singapore, doi: 10.1007/978-981-19-3394-3_73.

[11] Luyen, T. V., Kha, H. M., Tuyen, N. V., & Giang, T. V. B. (2020). An efficient ULA pattern nulling approach in the presence of unknown interference. *Journal of Electromagnetic Waves and Applications*, *35*(1), 1–18, doi: 10.1080/09205071.2020.1819442.

[12] Tong, V.L., Hoang, M.K., Duong, T.H., Pham, T.Q.T., Nguyen, V.T., Truong, V.B.G. (2020). An Approach of Utilizing Binary Bat Algorithm for Pattern Nulling. In: Solanki, V., Hoang, M., Lu, Z., Pattnaik, P. (eds) Intelligent Computing in Engineering. Advances in Intelligent Systems and Computing, vol 1125. Springer, Singapore, doi: 10.1007/978-981-15-2780-7_101.

[13] K. -X. Thuc, H. M. Kha, N. Van Cuong and T. Van Luyen, "A Metaheuristics-Based Hyperparameter Optimization Approach to Beamforming Design," in *IEEE Access*, vol. 11, pp. 52250-52259, 2023, doi: 10.1109/ACCESS.2023.3277625.

[14] Ioannides, P., & Balanis, C. A. (2005). Uniform circular and rectangular arrays for adaptive beamforming applications. *IEEE antennas and wireless propagation letters*, *4*, 351-354, doi: 10.1109/LAWP.2005.857039.

[15] Ioannides, P., & Balanis, C. A. (2005). Uniform circular arrays for smart antennas. *IEEE Antennas and propagation magazine*, *47*(4), 192-206, doi: 10.1109/MAP.2005.1589932.

[16] Yeniay, Ö. (2005). *Penalty function methods for constrained optimization with genetic algorithms. Mathematical and computational Applications*, 10(1), 45-56, doi:10.3390/mca10010045.

[17] Yang, Xin-She. "A new metaheuristic bat-inspired algorithm." *Nature inspired cooperative strategies for optimization (NICSO 2010)*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2010. 65-74, doi: 10.1007/978-3-642-12538-6_6.