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NPSO-based Pattern Synthesis of Uniformly Spaced Circular Array Antenna

T.V.S Jyothi Swaroop | P. Hari Venkat | T. Gopi Hemanth | Sk. Fatema Tabassum Hassan

Department of Electronics and Communication Engineering, RVR&JC CE, Guntur, Andhra Pradesh, India.

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ABSTRACT

This paper presents Novel Particle Swarm Optimization (NPSO) for uniformly spaced circular antenna pattern synthesis, aiming to minimize interference by reducing sidelobe levels. NPSO, an evolution of Particle Swarm Optimization (PSO), introduces enhancements to improve convergence speed and solution quality. Through comparative analysis and experimental validation, NPSO demonstrates superior performance in generating optimized antenna patterns with minimized sidelobes. Additionally, the developed algorithm utilizing NPSO is rigorously tested for 12 and 20 element Circular Antenna Arrays (CAA), showcasing its adaptability and efficacy across different array configurations.

Keywords: Circular array antenna, SLL Reduction, Pattern Synthesis.

1. INTRODUCTION

Antenna arrays emerge as a necessity in modern wireless communication systems, driven by the ever-growing demand for enhanced performance and reliability across a multitude of applications. Unlike single antennas, antenna arrays offer unparalleled capabilities in shaping and directing electromagnetic radiation patterns, enabling functionalities such as beamforming, spatial diversity, and interference mitigation. In scenarios where traditional antennas fall short in terms of range, coverage, or signal quality, antenna arrays rise to the occasion, providing tailored solutions to address specific challenges. Whether in radar systems requiring precise target detection, satellite communications necessitating robust link establishment, or wireless networks striving for increased data throughput and seamless connectivity, antenna arrays prove indispensable. Moreover, the versatility of antenna arrays extends beyond communication to fields such as remote sensing, radio astronomy, and medical imaging, where their ability to extract valuable information from the electromagnetic spectrum finds wide-ranging applications. As technology continues to evolve and communication requirements become increasingly demanding, antenna arrays stand poised to play a pivotal role in shaping the future of wireless connectivity and information exchange.

A circular antenna array employing microstrip patch antennas as its array elements presents a sophisticated yet efficient solution for modern wireless communication systems. Leveraging the compactness and versatility of microstrip patch antennas, this configuration offers a multitude of advantages, including enhanced directivity, beamforming capabilities, and reduced profile. By arranging these antennas in a circular fashion, the array achieves omnidirectional coverage, making it well-suited for applications such as satellite communication, radar systems, and wireless networks.

Circular array antennas are pivotal across various domains, facilitating robust satellite communication, precise radar detection, and optimized wireless networks. They ensure reliable data transmission for weather monitoring and telecommunications, enhance situational awareness in defense, and empower smart antennas for beamforming and interference mitigation in urban environments. Their significance underscores versatility, driving innovation in communication technologies[5].

Pattern synthesis in antenna design involves shaping the radiation pattern to meet specific performance criteria. By adjusting the amplitude and phase of signals across array elements, pattern synthesis enables precise control over the antenna's radiation characteristics, such as beam steering, spatial coverage optimization, and interference suppression. This process plays a crucial role in enhancing communication system efficiency, flexibility, and adaptability, making it indispensable in modern antenna design.

This paper aims to conduct Pattern synthesis on circular arrays using a Novel Particle Swarm Optimization (NPSO) technique, an advancement over traditional Particle Swarm Optimization methods. It considers the amplitude and phase of excitation currents as optimizing variables with the objective of minimizing interference by reducing sidelobe levels

2. PSO ALGORITHM

Particle Swarm Optimization (PSO), introduced by Eberhart and Kennedy in 1995, is a metaheuristic algorithm inspired by the collective behavior of social organisms, such as birds and fish. In PSO, a population of candidate solutions, or particles, explores the solution space iteratively, adjusting their positions based on personal experience and the collective knowledge of the swarm. This self-organizing approach mimics the collaboration and information exchange observed in nature, leading to efficient exploration and convergence toward optimal solutions. PSO's inherent simplicity, scalability, and ability to handle high-dimensional search spaces make it a popular choice across various fields, serving as a versatile tool for tackling complex optimization challenges in engineering, economics, and machine learning. Eberhart and Kennedy's seminal work paved the way for numerous advancements and extensions in the realm of swarm intelligence, solidifying PSO's status as a fundamental optimization technique with widespread applicability.

The PSO algorithm begins by initializing the positions and velocities of each particle randomly within the D-dimensional search space. Subsequently, each particle navigates towards the target region, dynamically adapting its position based on both its individual experiences and the collective knowledge shared by its neighboring particles within the topology. This collaborative exchange of information allows particles to efficiently explore the solution space, gradually converging towards optimal solutions.

Every i-th particle's position and velocity are represented as $X_i = (x_{i1}, x_{i2,\dots} x_{iD})$ and $V_i = (v_{i1}, v_{i2,\dots} v_{iD})$ respectively. Every particle's corresponding previous location is stored and denoted as $P_i = (p_{i1}, p_{i2,\dots} p_{iD})$. The symbol "g" denotes the index corresponding to the best-performing particle among all particles in the swarm[4]. The positions and velocities of the particles undergo updates governed by the following equations:

$$v_i^{k+1} = w* v_i^k + c_1*rand(\,)*(p_i^k - x_i^k) + c_2*rand(\,)*(p_g^k - x_i^k); \qquad (2.1)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \qquad (2.2)$$

where w = Inertia weight

c_1, c_2 = Acceleration constants and both are positive.

$rand(\,)$ = Random number in range [0,1] used as r1, r2.

k = Iteration count

3. Novel Particle Swarm Optimization Algorithm

The modification outlined below significantly enhances the global search capacity of the classical Particle Swarm Optimization (PSO), resulting in an improved variant termed NPSO. In classical PSO, the random parameters r_1 and r_2 in Equation (2.1) are dependent. If both parameters are large, there's a risk of overusing individual and collective experiences, potentially leading to the particle being misled towards a local optimum. Conversely, if both parameters are small, there's underutilization of these experiences, slowing down convergence. To address this, instead of independently selecting r_1 and r_2, a single random number r_1 is chosen, where $(1- r_1)$ behaves inversely. To further control the process, another random value r_2 is introduced. Drawing inspiration from fish schooling behavior, where individuals may adjust their direction after a change in location, a sign(r_3) term is introduced to guide the particle towards promising regions. This adjustment ensures a balance between exploration and exploitation by adapting both the individual and social components of the algorithm.

The update equation for velocity of ith particle is expressed as shown in equation 3.1

$v_i^{k+1} = r_2 * sign(r_3) * v_i^k + (1-r_2)*c_1*r_1*(p_i^k-x_i^k)+ (1-r_2)*c_2*(1-r_1)*(g_i^k-x_i^k)$ [2](3.1)

Where c_1, c_2 = local acceleration coefficients

g = Global acceleration Constant of particle

r_1, r_2, r_3 = Random numbers in range [0,1]

x_i^k = In kth iteration, ith particle position

p_i^k = Particle's local best in ith iteration

g_i^k = Global best of all particles in kth iteration.

The starting location within the solution space can be altered using the sign(r_3) function, where r_3 is a random parameter. This function is defined as follows:

$sign(r_3) = -1$ when $r_3 \le 0.05$

$+1$ when $r_3 > 0.05$

4. DESIGN EQUATIONS

Envision a scenario where N isotropic sources are arranged in a circular array (CA) within the x-y plane, as depicted in Figure 1, each located at a radial distance 'a' from the center. Suppose we're observing a point P in the far field. To characterize the radiation pattern of this non-uniform circular array (CAA), we turn to its array factor. This factor, a fundamental descriptor of the circular array's behavior, illuminates how radiation is distributed across its constituent elements. The array factor for the above mentioned Circular array is expressed as follows:

$$AF(\Theta, \Phi) = \sum_{n=1}^{N} I_n e^{j[ka\ \sin\Theta \cos(\phi - \phi_n) + \alpha_n]}$$

[1](4.1)

Where

$ka = 2\pi a/\lambda$ (4.2)

λ = operating wavelength

Θ = Elevation angle

Φ = Azimuthal angle

a = Radius of the circular array

I_n = Amplitude of Excitation Current of nth Element

Φ_n = Angular position of nth Element

$\phi_n = (2\pi/ka) \sum_{j=1}^{n} d_j$ (4.3)

α_n = The nth element excitation phase

$\alpha_n = -ka\cos(\phi - \phi_n)$ (4.4)

The complete array factor can be computed from the equations (4.1) and (4.4) as follows:

$$AF(\Theta, \Phi) = \sum_{n=1}^{N} I_n e^{j[ka\sin\Theta\cos(\phi-\phi_n) - k a\cos(\phi_0 - \phi_n)]}$$

[1](4.5)

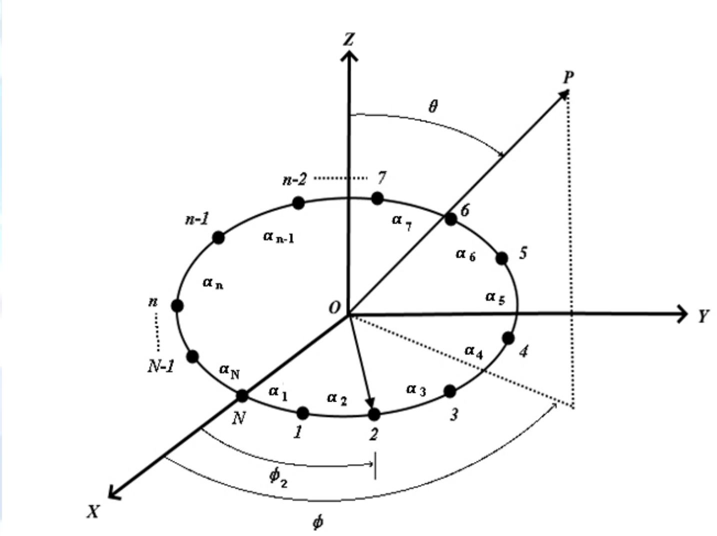

Figure 1. Diagram depicting a uniform circular array scanning at a designated point P with N isotropic elements

$I=[I_1, I_2, I_3, \ldots I_N]$ and $\alpha=[\alpha_1, \alpha_2, \alpha_3, \ldots\ldots \alpha_N]$ the terms I_n and α_n denotes the nth excitation element and phase of excitation of the array respectively. The primary goal of this study is to achieve an array pattern characterized by the best possible minimization of Side Lobe Level (SLL) and First Null Beam Width (FNBW) in the intended direction φ. To accomplish this, the focus lies on identifying the ideal combination of I_n and α_n values, which serve as crucial parameters in modifying the antenna design. Following this identification phase, the subsequent step involves the formulation of the minimized objective function. This objective function, denoted as f, plays a pivotal role in quantifying the optimization criteria. It encapsulates various performance metrics and constraints, ultimately guiding the optimization process towards the desired array pattern with enhanced directional characteristics.The minimized objective function is expressed as

$$f=W_1*|AF(\phi_{maxsl},I_n)|/|AF(\phi_0, I_n)|+ W_2*(FNBW(computed)-FNBW|I_n=1) \quad [3](4.6)$$

Where, ϕ_{maxsl}denotes the main beam's side lobe angle on either side reaches its maximum side lobe $AF(\phi_{maxsl},I_n)|$. Weighting factors W_1 and W_2 are selected to ensure that the optimal value of the side lobe level (SLL) holds more significance than that of the first null beam width (FNBW), while also ensuring that the objective function f remains non-negative throughout the optimization process. The FNBW values, both computed (FNBW(computed)) and for I_n=1 ($FNBW|I_n$=1), are expressed in radians and serve as crucial indicators of array performance under non-uniform and uniform excitation conditions, respectively. Equation (4.6) guides the retention of the active population, where solutions of I_n and α_n are retained only if they satisfy the condition $FNBW$(computed) <$FNBW|I_n$=1; otherwise, they are discarded. Leveraging the NPSO technique, the optimization process focuses on minimizing the objective function f by tuning the values of I_n and α_n.

5. COMPUTATIONAL RESULTS

This section presents the simulation results obtained through the utilization of the Novel Particle Swarm Optimization (NPSO) technique, focusing on the minimization of both the Side Lobe Level (SLL) and the First Null Beam Width (FNBW) across a range of Circular Array Antenna (CAA) designs. The radiation pattern of the CAA is a central consideration in this analysis, particularly with respect to the orientation of the major lobe at φ_0 = 0 degrees. Specifically, we examine two distinct scenarios involving uniform CAAs, one comprising 12 elements and the other comprising 20 elements. Throughout the simulation process, the NPSO algorithm is executed for a total of 400 iterations, with a fixed population size of 120 individuals for each array configuration. The initialization of the NPSO algorithm involves the assignment of random values to the control parameters. These control settings, integral to the performance of the NPSO algorithm, are detailed in Table 1, providing insights into the configuration and behavior of the optimization process. Through this thorough examination, weseek to understand how well the NPSO technique can enhance the directional performance of CAA designs. This exploration sheds light on its potential uses in improving antennas.Figures 2,3 indicates the comparision between non-uniform and uniform circular array's radiation pattern. Fig2 demonstrates the argument for number of elements as 12. It is tabulated in table-2 using an NPSO technique the I_n and α_n set is obtained that produces a radiation pattern containing -16.57dB SLL and 62.28 degrees FNBW, which is a maximum SLL and FNBW reduction compared to -7.8dB SLL for a 12-element Circular Antenna Array (CAA) with uniform excitation current and excitation phase.

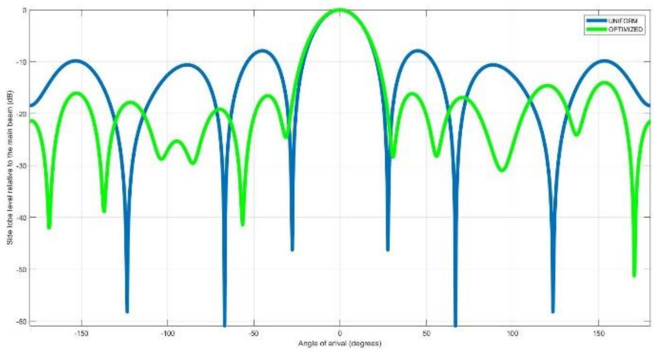

Figure 2. Array pattern obtained by NPSO for non-uniform 12- elements circular array.

Fig3 demonstrates the argument for number of elements as 20. It is tabulated in table-2 using an NPSO technique the I_n and α_n set is obtained that produces a radiation pattern containing -17.04dB SLL and 60.84 degrees FNBW, which is a maximum SLL and FNBW reduction compared to -7.9dB SLL for a 20-element Circular Antenna Array (CAA) with uniform excitation current and excitation phase.

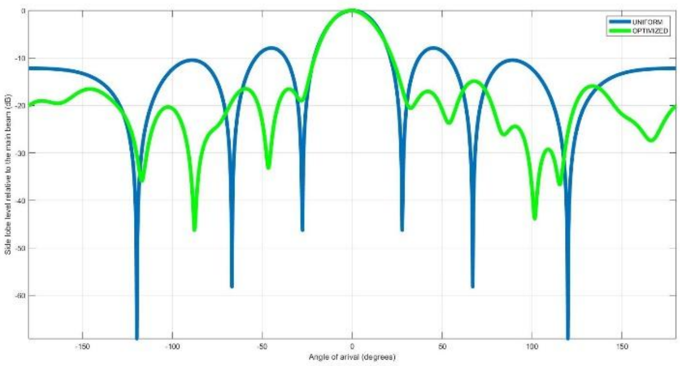

Figure 3Array pattern obtained by NPSO for non-uniform 20- elements circular array.

Table I:CONTROL PARAMETER OF NPSO

PARAMETERS	**Valuesfor Number of Elements**	
	12	**20**
Population Size	120	120
Number of Iterations	400	400
c1=c2	1.5	1.8

Table II :RESULTS COMPARISON OF NPSO WITH UNIFORM EXCITATION

No. of Elements	**SLL Uniform excitation**	**SLL Optimized**	*[I_1, I_2, I_3,… I_N];* *[α_1, α_2, α_3…α_N]* *in radians*
12	**-7.78dB**	**-16.57dB**	**[0.2959,0.0784, 0.4454,0.0292, 0.3571,0.5250, 0.2211,0.1965, 0.4627,0.1492, 0.2460,0.5052]; [1.2597,0.3738, -0.9722,2.4881, 2.8519,2.3444, 2.2387,0.4983, -1.0572,-2.7731, 2.0253,1.9164];**
20	**-7.9dB**	**-17.04dB**	**[0.6655,0.5875, 0.3624,0.4818, 0.4497,0.2069, 0.2150,0.1167, 0.7212,0.5280, 0.6041,0.6164, 0.1389,0.3457, 0.2629,0.1273, 0.3836,0.3385, 0.5779,0.2119]; [-1.5369,1.3799, -1.5566,1.0044, 2.0626,-2.6384, -1.6807,1.3063, -1.7418,0.6080, -1.7131,0.8702, -1.5822,1.4983, 2.2602,0.8889, -2.8293,-0.7645, -2.2396,0.0820];**

6. THE CONVERGENCE CURVES OF NPSO

To monitor the convergence progress of each array's optimization process, we plotted the minimum values of the cost function against the number of iteration cycles. Figures 4 and 5 offer detailed visual representations of the convergence curves, specifically focusing on CAAs with 12 and 20 elements, respectively. These curves provide valuable insights into how the optimization algorithms perform over time, illustrating the trends in improvement and stabilization. The programming aspect of this analysis involved utilizing the MATLAB R2021B language, executed on a computing system powered by an AMD Ryzen 5 5500U CPU running at 2.10 GHz, with 16 GB of RAM. This computational environment ensured efficient execution and accurate representation of the optimization results.

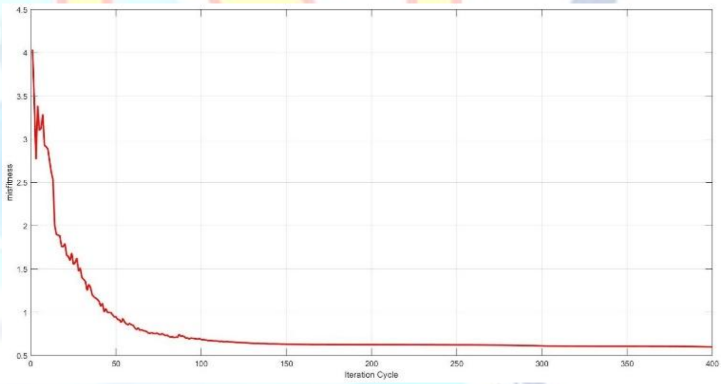

Figure 4. Convergence curve for uniformly spaced 12-elements circular array.

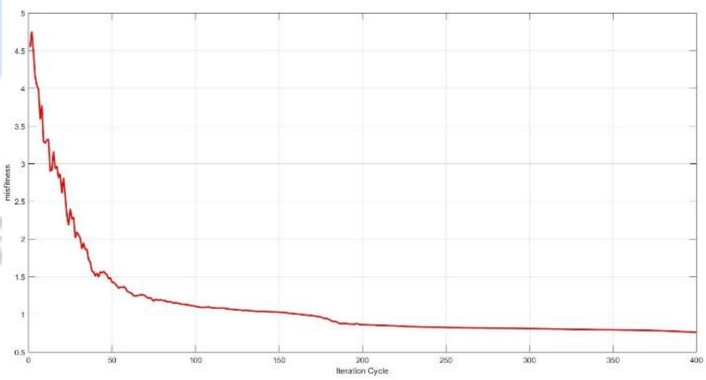

Figure 5. Convergence curve for uniformly spaced 20-elements circular array

7. CONCLUSION

This paper delves into the design modeling techniques applied to uniform Circular Array Antennas (CAAs) with the primary objective of achieving a substantial reduction in the Side Lobe Level (SLL). To address this design challenge effectively, the proposed approach leverages the Nature-inspired Particle Swarm Optimization (NPSO) technique. By meticulously identifying the optimal set of excitation phases and current excitations, the method aims to craft a radiation pattern characterized by minimal side lobe levels and an enhanced initial null beamwidth. The experimental results presented in the paper serve to juxtapose the performance of uniform excitation with that of NPSO-optimized results, offering valuable insights into the effectiveness of the proposed methodology. Looking ahead, future research endeavors are planned to encompass the exploration of different array geometries, including hexagonal and concentric circular structures. Moreover, there are plans to extend the investigation towards minimizing the side lobe level and First Null Beam Width (FNBW) of these structures using a diverse range of evolutionary algorithms.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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