



Reduce side lobes using linear Antenna Arrays by comparing PSO, GA, and FPA algorithms

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Abstract

Linear Antenna Arrays (LAAs) are widely used electromagnetic systems in modern wireless communication, and Metaheuristics algorithms have been utilized to reduce side lobe level SLL and reach the optimal solution. This paper employs three algorithms: the first, Particle Swarm Optimization PSO, the second, Genetic Algorithm GA, and the third, Flower Pollination Algorithm FPA. Each test consists of $N = 8, 16, 32, 64, 128,$ and 256 antenna array elements. To reduce SLL and the concentration of radioactive energy in the main lobe, each algorithm compares the beam pattern to the theoretical beam pattern. In addition, the algorithms were compared with the existence of the theoretical beam pattern, and it was discovered that there is a superior algorithm for each number of antenna elements; in $N = 8$, when comparing FPA to other algorithms, it was discovered that FPA reduced SLL by a value of -20.8492dB , which was superior to the other algorithms. SLL decreased by -27.2992dB when comparing PSO with other algorithms at $N = 16$. When $N = 32, 64$ represents FPA more accurately than other algorithms where the SLL plummeted to -28.3071dB and -28.0148dB , respectively. GA is superior to other algorithms when $N = 128, 256$, reducing SLL by -28.5568 dB and -28.6204 dB , respectively.

Keywords: Linear Antenna Arrays, particle swarm optimization, genetic algorithm, Flower pollination algorithm, side lobe level, beam pattern.



1. INTRODUCTION

Antenna arrays play a vital role in modern wireless communications due to their advantages and design diversity in terms of employing one or more antenna elements for high gains and steering and employing them in a variety of beam pattern formation processes [1].

Phased arrays can direct energy in a specific direction, which is crucial for antenna architects, as this is accomplished by minimizing side lobes [2]. The process of collecting signals from beam formation direction elements is referred to as the array containing multiple antenna elements that collect signals for all element arrays. Producing a steering beam and maintaining a very low level of lateral lobe reduces interference with other beam patterns [3], which is essential for synthesizing its array. Numerous intensive studies have been conducted to synthesize the linear antenna arrays described in the references [4,5].

To bring the radiation pattern closer to the intended pattern, the physical design of the antenna array must be modified. Synthesis techniques aim to reduce SLL, maintain the gains and direction of the primary radiation, and reduce interference and confusion. The distance between antenna elements is a crucial element of design for pneumatic arrays, and it is governed by the design.

Numerous Metaheuristics algorithms, such as the genetic algorithm GA [6], particle swarm optimization PSO [7], Grey Wolf optimization GWO [8], cat swarm optimization CSO [9], Ant colony optimization ACO [10], flower pollination algorithm [11], differential search algorithm [12], and cuckoo search algorithm [13], have been successful in designing antennas for arrays.

In this paper, we investigate the effect of the algorithms and use each individually in LAA to find the optimal solution. We also compare algorithms with others and conclude that, for a given number of antenna elements, the GA algorithm is superior to other algorithms.

1. LINEAR ANTENNA ARRAY

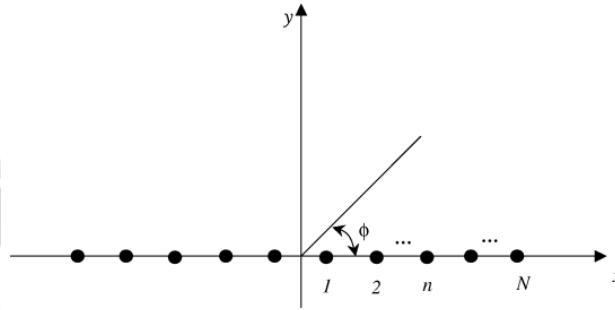


Fig. 1. The 2N-element symmetric linear arrays x-axis placement's geometry.

The excitation distribution of linear arrays was designed using PSO, GA, and FPA algorithms [14], which were also used to increase the distances between linear array components, build a radiation pattern with minimal SLL, and regulate blank mode. The array geometry is shown in Figure 1. With 2N isotropic radiators, it is presumed that the x-axis is aligned symmetrically. Due to symmetry, the array factor in the azimuth plane (x-y plane) can be expressed as follows:

$$AF(\phi) = 2 \sum_{n=1}^N I_n \cos[kx_n \cos(\phi) + \varphi_n] \quad (1)$$

Where φ_n , I_n , k , and x_n are the phase, excitation amplitude, wavenumber, and location of the n^{th} element respectively. If we additionally assume that there is uniform amplitude and phase excitation ($\varphi_n = 0$ and $I_n = 1$), the array factor can be expressed as:

$$AF(\phi) = 2 \sum_{n=1}^N \cos[kx_n \cos(\phi)] \quad (2)$$

The purpose of this research is to implement the methods for determining the optimal element positions x_n , obtaining an array pattern with minimal SLL, and arranging the nulls in the requisite directions. In linear antenna arrays, it is vital to position antennas accurately. If the antennas are placed too closely or too far apart from one another, the grating lobes will be affected.

2. Particle Swarm Optimization

It is one of the algorithms metaheuristics used in many applications, including in optimization techniques where the population must be considered to solve problems solving global optimization. PSO has many parameters, and each has several characteristics, such as access to convergence speed and met with adjustment and others [15]. This algorithm has many parameters used to evaluate particle fitness functions, such as beam pattern, direction, size, etc., as it does not work with coding parameters but with an actual number.

PSO interferes with social life, such as fish flow, evolutionary calculation, etc. It can simulate stampede movement within an area of specific dimensions. A certain velocity characterizes each particle v_x . Each particle has a location that represents the best location for $p_{best}x$ as well as the best location for all $g_{best}x$ particles and is given the following relationships [16]:

$$v_x = v_x + 2rand(p_{best}x - x) + 2rand(g_{best}x - x) \quad (3)$$

$$x = x + v_x \quad (4)$$

Updates to particle velocity are made by adjusting particle velocity via the proportional positions of the present particles affecting how fast they move p_{best} and g_{best} When the directions are determined by the parameter w , within the range (0, 1), and thus, called inertia, the most significant initial velocity at a given weight that can be fitness is achieved through Eq. 5. This equation also determines the extent to which the particle reaches the best state and the world of the best positions. If w is linearly decreased with iterations starting at 0.9 and linearly ending at 0.4 at the last iteration, it is demonstrated that the PSO method converges more quickly. The particle can be easily moved to its following location. The new coordinates for each dimension are derived using the following equation once the speed has been determined:

$$V_{i,t+1}^d = V_{i,t}^d + C_1rand(P_{i,t}^d - X_{i,t}^d) + C_2rand(P_{g,t}^d - X_{g,t}^d) \quad (5)$$

$$X_{i,t+1}^d = X_{i,t}^d + V_{i,t+1}^d \quad (6)$$

Where $V_{i,t+1}^d$ and $X_{i,t+1}^d$ It represents the speed after the movement of the particle and the best position of the particle respectively. Fig.2. Flowchart shows the PSO algorithm steps.

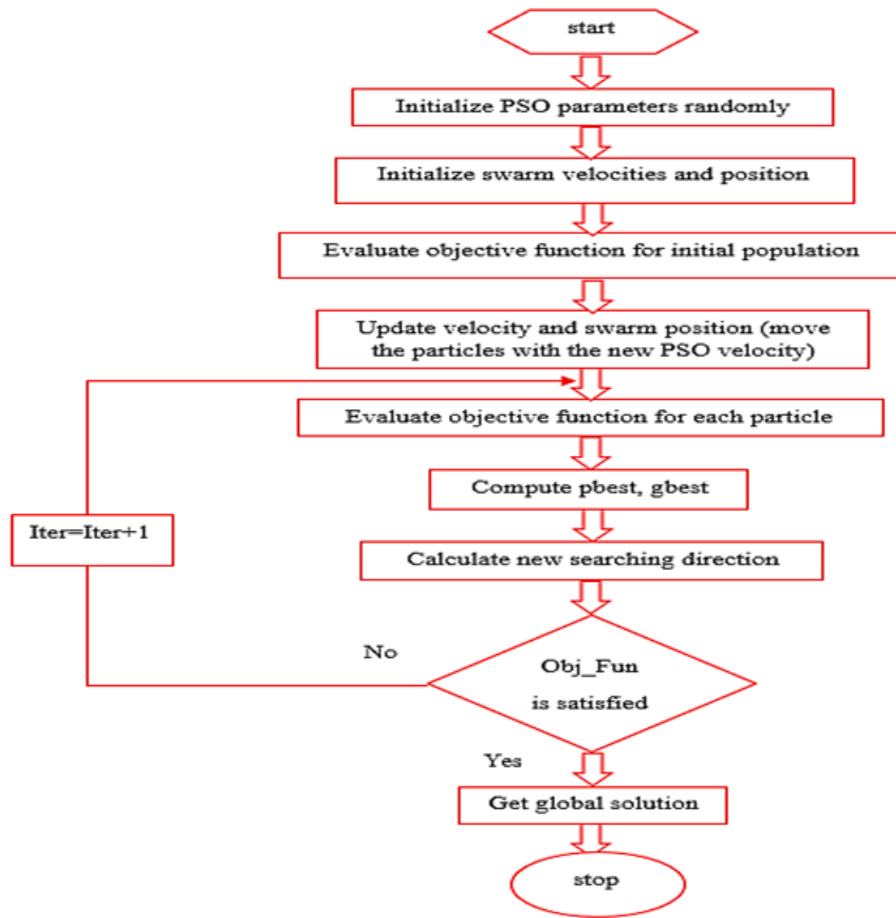


Fig. 2. Flowchart of PSO Algorithm.

3. Genetic Algorithm

The genetic algorithm is a research algorithm that relies on artificial evolution [17]. The research mechanisms that have been adopted often depend on the pursuit of adaptation with modifications to the original algorithm, and the efficiency of this algorithm depends on the search and which depends on its formulas. This algorithm has previously been applied to several scientific aspects, including pipeline design. While others used this algorithm to improve the discharge of a straight network such as natural gas [18]. It is one of the evolutionary technologies proposed and developed by the scientist John Holland, and its working mechanism consists of a set of encrypted symbols and a chromosomal-shaped token that is superior to using each symbol individually to obtain optimal solutions for a given group [19]. These include steps in form Fig. 3: initiation, evaluation, and selection for reconstruction. The last three are the main steps. Starting with the first step is that the chromosomes are selected randomly to determine the number of the population, after which

the assessment will be made; the unique fitness of each mosque will be determined and reassembled where the original (parents) and depending on the fitness (children) representing the new chromosome will be identified, two points considered essential in genetic algorithms are mutation and crossover.

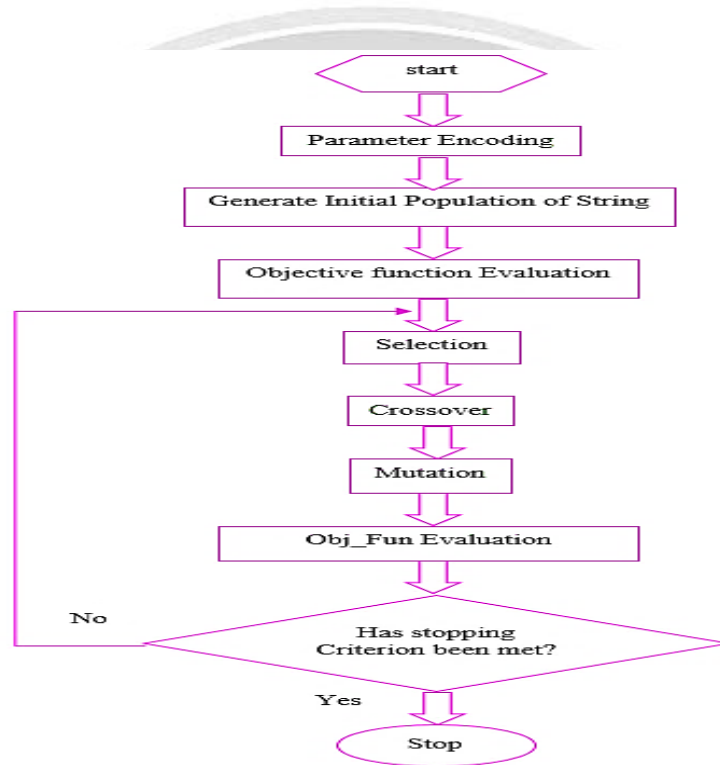


Fig. 3. Flowchart of GA Algorithm.

There are three values for θ venom, longitude, radial distance, R (Equal to about 6378100 meters, the value of the Earth's radius), used to build Spherical coordinates of the point. Using the formula below [20].

$$X = R \times \sin \theta \times \cos \emptyset \quad (7)$$

$$Y = R \times \sin \theta \times \sin \emptyset \quad (8)$$

$$Z = R \times \cos \theta \quad (9)$$

Chromosomal parameters X , Y , and Z can manufacture images using 2D Fourier conversion is separate. In reference [21], where $u-v$ was used $n(n-1)$ through the presence of particle swarms applied to them for improvement arrays composition, the increasing frequency and reducing SLL for the evolutionary algorithm were used to scale up Antennas. The initial stage of the GA genetic algorithm is the beginning, which works on Constructing



chromosomes randomly between higher and lower length points to achieve appropriate annexation. Then the assessment process begins to reach the required physical fitness, afterwards the process of identification and reconstruction is selected through part of the chromosomes between them based on the probability of crossover and mutations in the next generation.

1. Crossover: The crossover operator creates a new chromosome by randomly cutting Chromosomes in one or more locations (X, Y, or Z). Single or multiple-point intersection is possible. While the Intersection does not lead to the production of new materials Within the population, it creates new chromosomes by blending two Existing ones, improving average fitness in the next generation.

2. Mutation: The evolutionary algorithm randomly alters the chromosome gene; the mutation can change X, Y, Z, or maybe More than one. The mutation adds new chromosomes to the population to increase the size of the solution space. Using random modifications to the gene on chromosomes Discover new sites that may improve the problem [19].

4. Flower Pollination Algorithm

It is one of the Metaheuristics algorithms inspired by the pollination of flowering plants and developed in 2012 by Xin-She Yang [22]. It has been used extensively and is based on four basic rules: cross-vaccination and bioavailability are global vaccinations, but for local inoculation, it uses biological and subjective pollination, as well as probability p , which represents the ratio of local vaccination substitution and global inoculation.

FPA contains core parameters of population size (N), Switching Probability p , Levy-flights based step size $L(\beta)$, scaling factor γ , and $\varepsilon \in (0,1)$ and is uniform distribution often used in local inoculation [11].

Global and local inoculation is determined by choosing a random number if it is less likely to switching probability p , a global inoculation is performed and otherwise the inoculation is local.

The following equations provide a mathematical depiction of flower constancy and global pollination:

$$x_i^{t+1} = x_i^t + \gamma L(g_{best} - x_i^t) \quad (10)$$

Where g_{best} is the current best solution, and x_i^t is the solution vector x_i at iteration t . γ is a scaling factor to control step size, L denotes the Levy flights-based step size, this is a measure of the pollination intensity.

The below mathematical formula is used to represent local pollination:

$$x_i^{t+1} = x_i^t + \varepsilon(x_j^t + x_k^t) \quad (11)$$

Where x_k^t and x_j^t are pollination from various flowering of the same flowering plants. If x_j^t and x_k^t are This is similar to a local random walk because it was chosen from the same population and was drawn from a uniform distribution in (0,1). The flowchart above shows the fundamental FPA steps in Fig. 4.

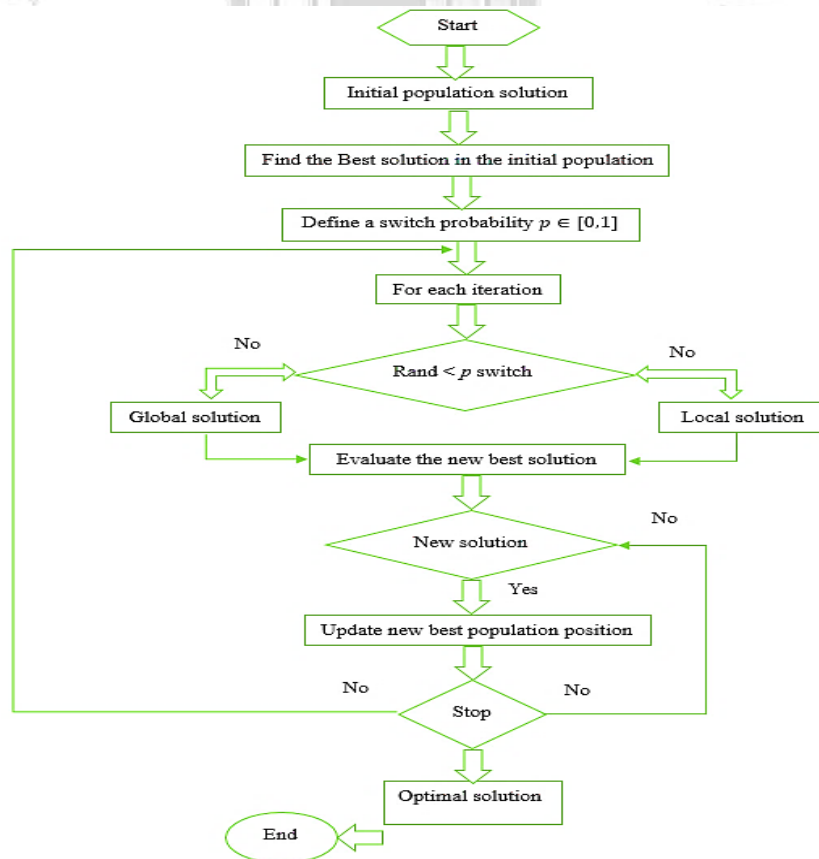


Fig. 4. Flowchart of FPA Algorithm.

5. Results and Discussion

Using MATLAB simulation shows the following forms represent the two-dimensional beam pattern obtained using LAAs containing a different number of elements at ($N = 8, 16, 32, 64, 128, \text{ and } 256$) each to improve the solution, gain the highest and width range of the main lobe, and the lowest amount of side lobes.

Compared to the theory of many antenna elements, the 2D package pattern shows optimization results obtained using the PSO algorithm. The best beam pattern was found in $N = 256$ with a value of up to -28.5405dB , as shown in Fig.5. In addition, the same results were inferred when compared to the same algorithm and with the numbers of different elements as in the Fig.6.

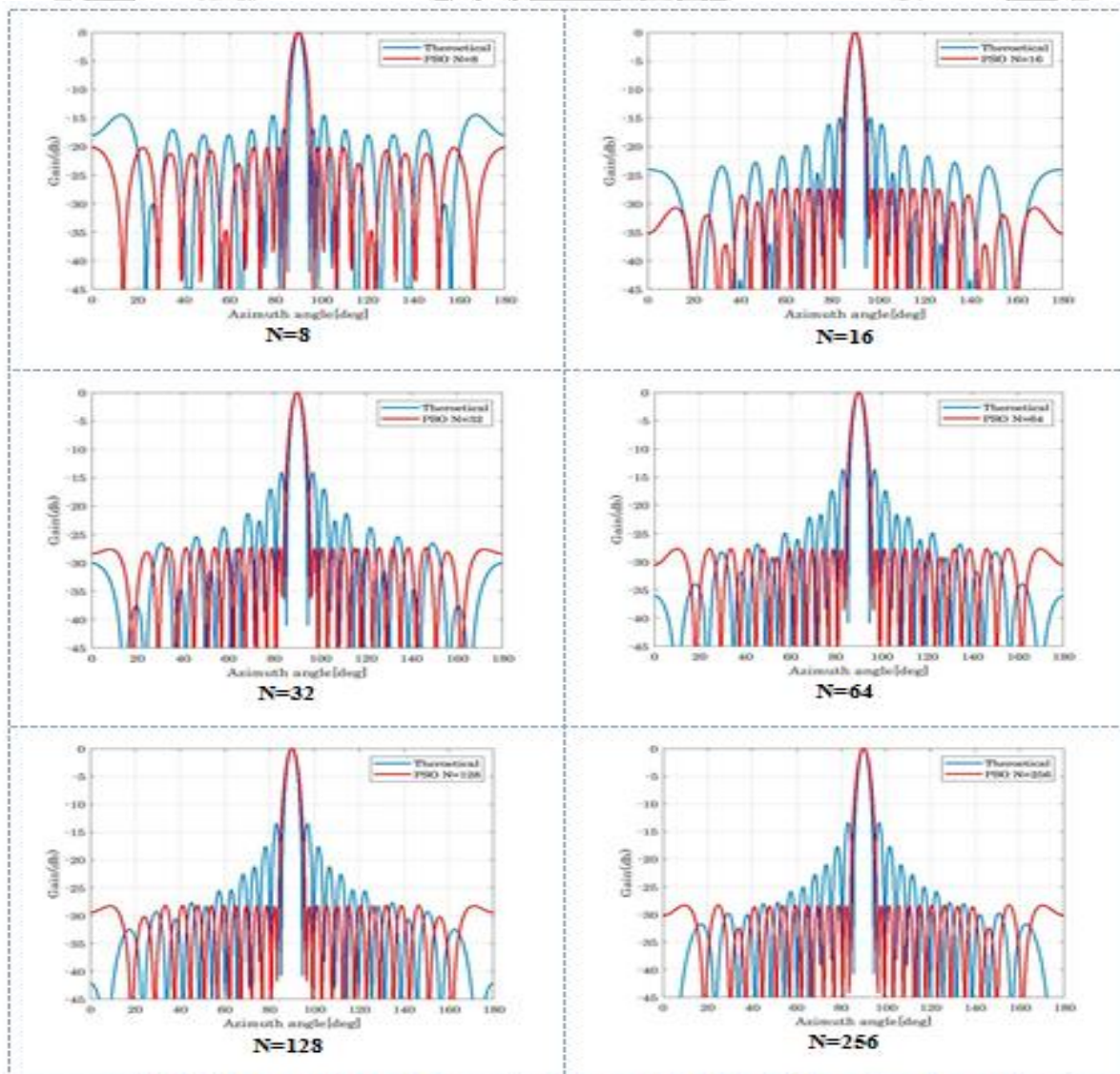


Fig.5. PSO comparison with theoretical beam pattern for a different number of elements.

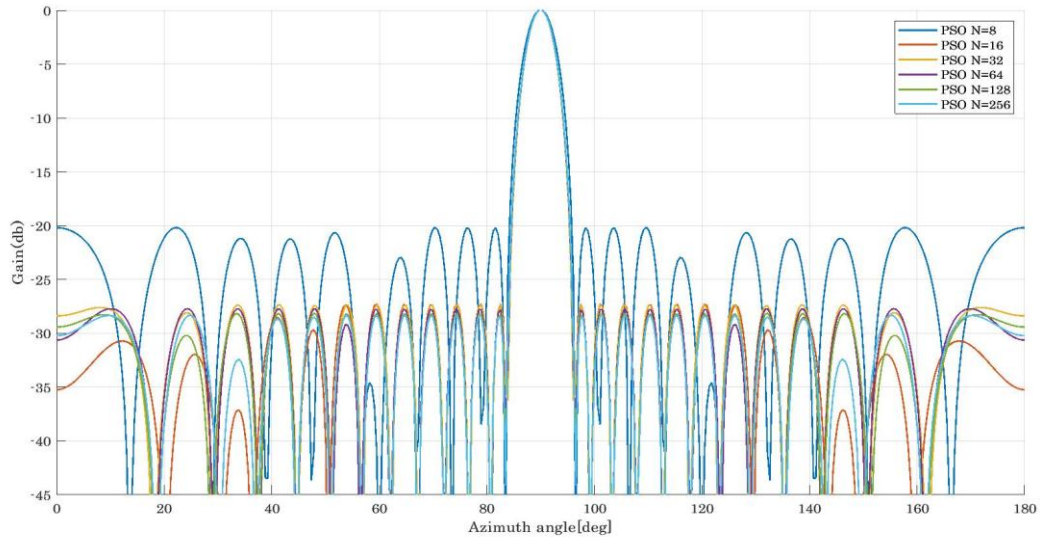
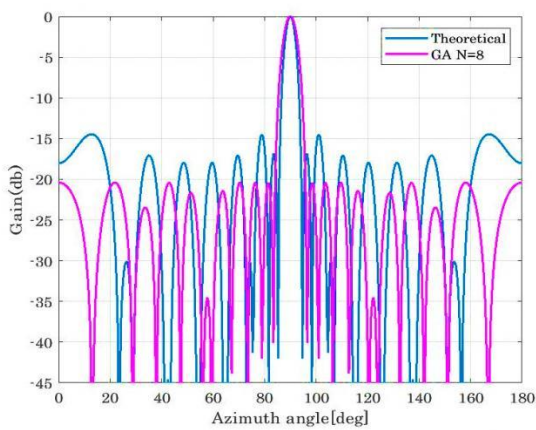
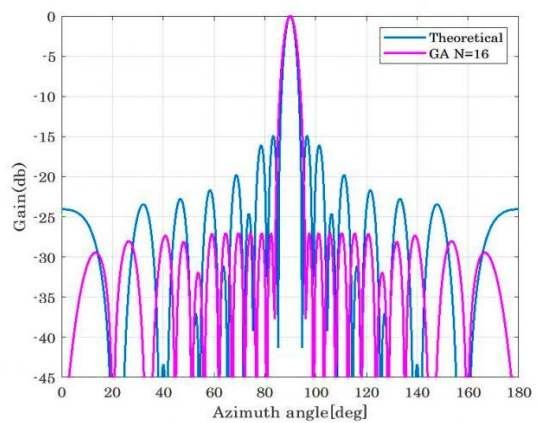


Fig.6. Shows PSO comparison by the number of elements

The following Fig.7. shows us the GA algorithm with LAA, the best optimization of the beam pattern was obtained when the array antenna is 256 elements as the optimization amount is -28.6204dB as the SLL was reduced and the bandwidth of the required main beam pattern was obtained. Also, the same conclusions were reached using the same algorithm and the same number of distinct elements as shown in the Fig.8.



N=8



N=16

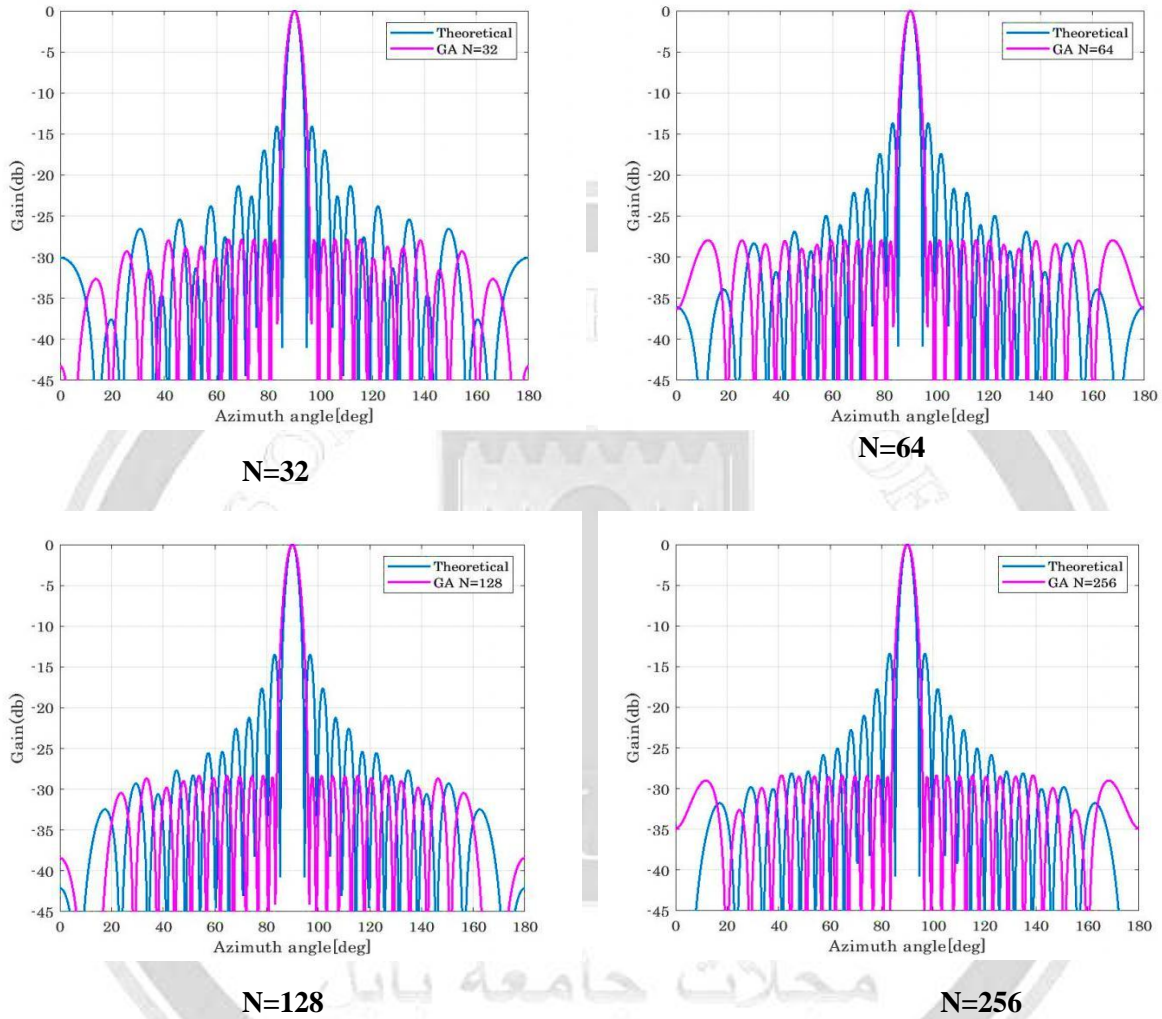


Fig.7. GA comparison with theoretical beam pattern for a different number of elements.

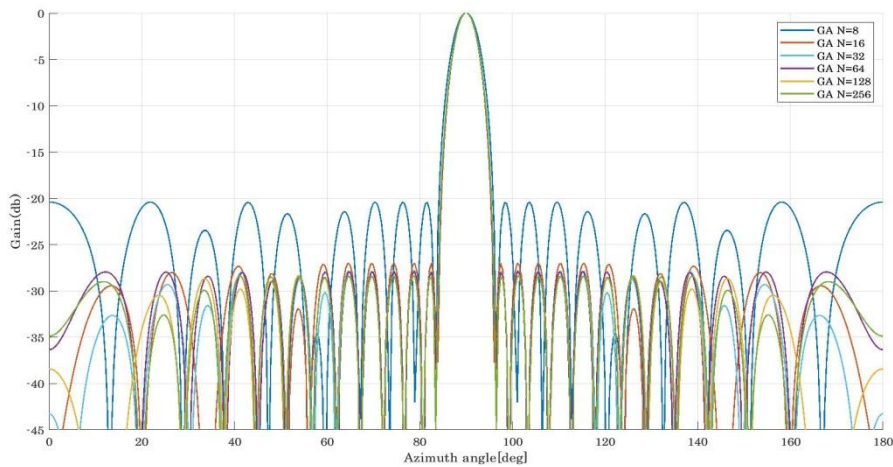


Fig.8. Shows GA comparison by the number of elements

In Fig.9. the FPA algorithm was used with LAA and when compared with the theoretical for a different number of antenna elements. The best optimization was reached at 32-element with a gain of -28.3071dB. The SLL decreased and was a good percentage. Furthermore, identical results were deduced if applied to the same algorithm and with the same number of distinct elements as illustrated in the Fig.10.

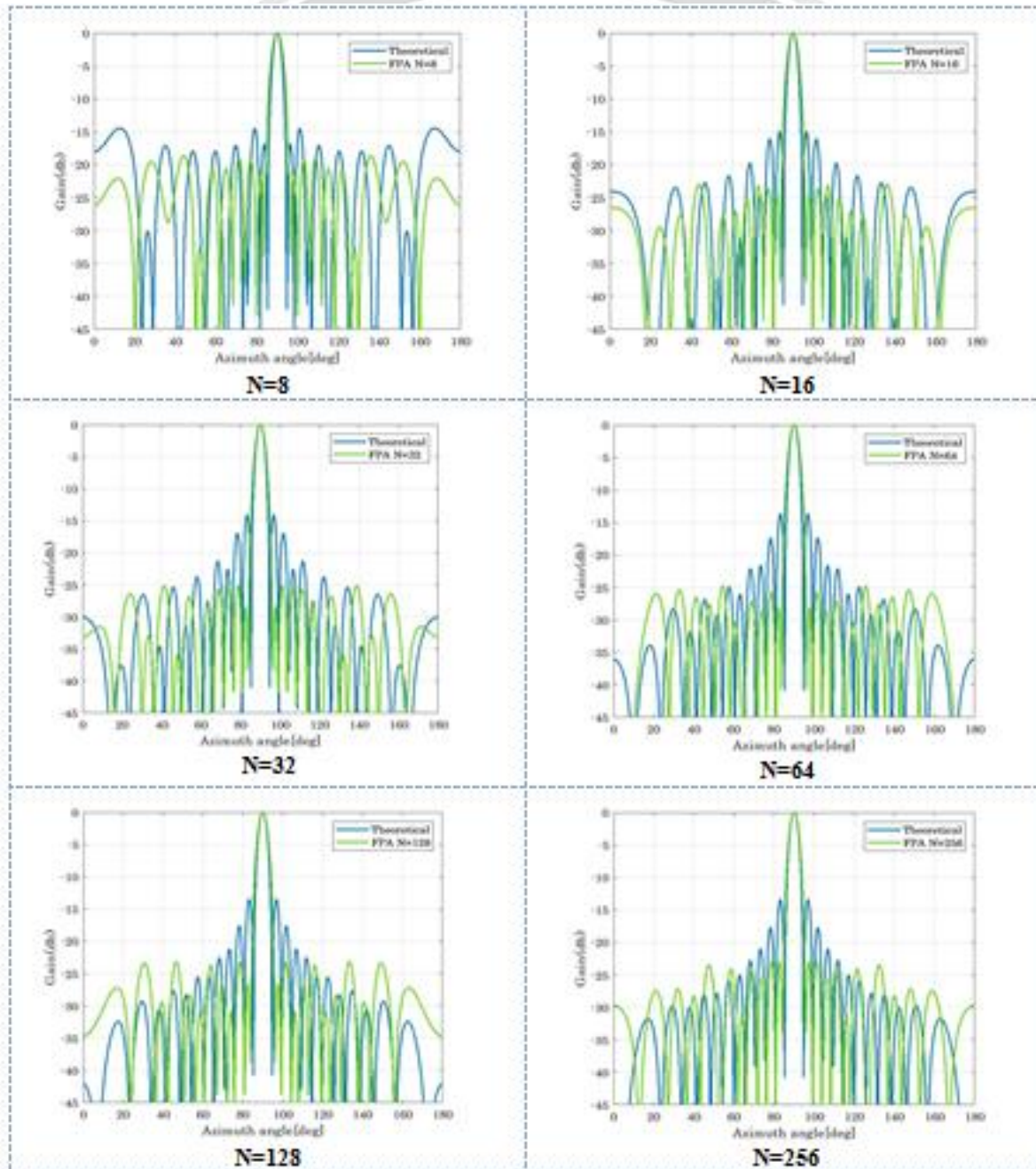


Fig.9. FPA comparison with theoretical beam pattern for a different number of elements

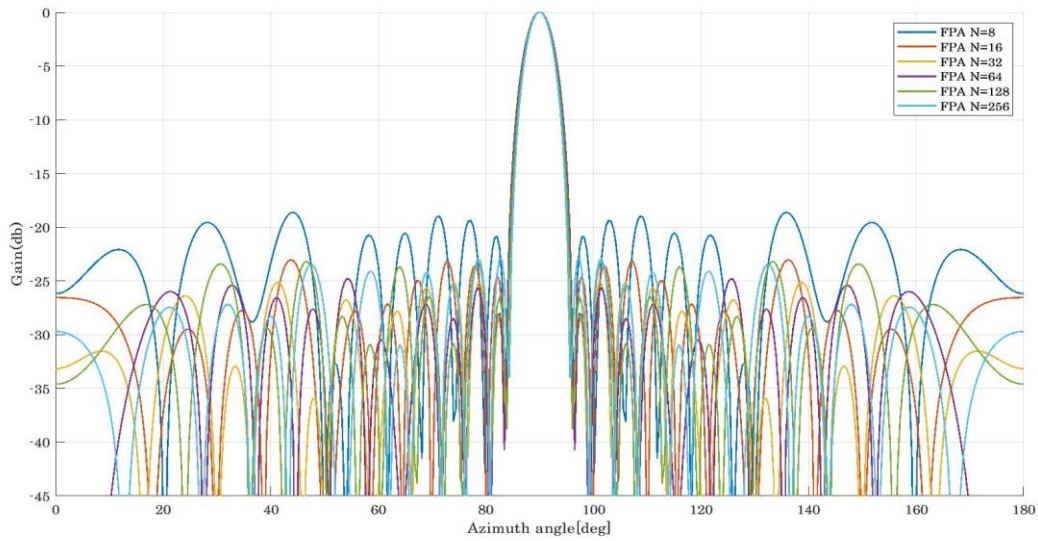


Fig.10. Shows FPA comparison by the number of elements

The following shown in Fig.11. is the comparison of PSO, GA, and FPA algorithms with each other and with the theoretical, as the FPA algorithm in the antenna arrays with 8-element is found to be better than other algorithms because the optimization process has reduced SLL more than other algorithms. When the number of antenna elements is 16-element, the PSO algorithm beats GA and FPA with a value of -27.2992dB . When the number of antenna elements is 32 and 64, the FPA algorithm is better than other algorithms due to the SLL drop as low as possible as the values reached -28.3071dB and -28.0148dB , respectively.

When the number of antenna elements is 128-element and 256-element, GA is the best algorithm, reducing the amount of SLL to -28.5568dB and -28.6204dB , respectively. After comparing the algorithms, it was concluded that the best algorithm in which SLL reduction occurred in GA when the number of elements is 256-element. Table.1. Compare algorithms with each other with the best function value.

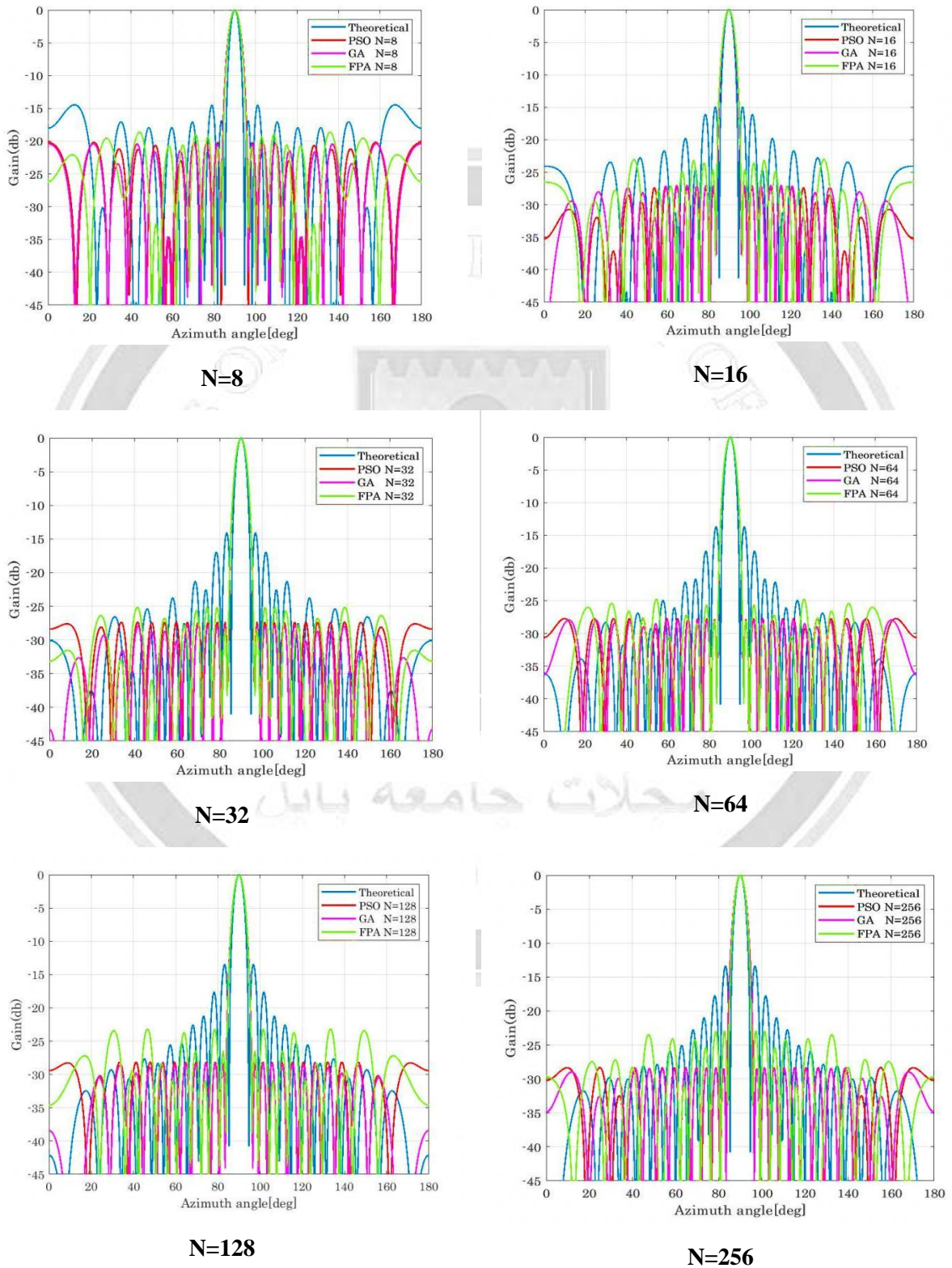


Fig.8. Compare PSO, GA, and FPA algorithms with theoretical beam patterns for a different number of elements.

**Table.1. Conclusive Values of Three Algorithms with Theoretical Patterns**

Algorithm	Number of Element	8	16	32	64	128	256	Gain(dB)
	Theoretical	-16.847dB	-14.8815dB	-14.0977dB	-13.6939dB	-13.4779dB	-13.3727dB	
	PSO	-20.1984dB	-27.2992dB	-27.3525dB	-27.8289dB	-28.3277dB	-28.5405dB	
	GA	-20.4335dB	-26.9987dB	-27.8764dB	-28.0044dB	-28.5568dB	-28.6204dB	
	FPA	-20.8492dB	-24.5472dB	-28.3071dB	-28.0148dB	-26.4663dB	-23.0646dB	

The Table.1. above shows the conclusive values of the theoretical beam pattern and comparison with the three algorithms where it was found that these values were deduced at an objective function and that these values could change depending on that function.

Table.2. Results of Previous Studies

References	Type of Antenna and Connecting Technique	The Technique Applied for Optimization	Best Result
[23]	Time-Modulated linear array TMA.	PSO, IWO	The results showed that IWO reduced SLL to -40.53dB, while PSO decreased SLL by -25.49dB. When comparing algorithms, IWO was found to be better than PSO.
[11]	Linear antenna array synthesis.	FPA, PSO, ACO, CSO	FPA is better than other algorithms, followed by CSO, ACO, and PSO, where they all retained SLL at specific values but FPA outperformed different algorithms where the value reached -23.45dB, at a certain number of antenna elements.
[24]	Non-Uniform circular antenna arrays.	PSO, GA	In the reference, PSO outperformed GA results, as SLL reduced as much as possible and used non-uniform circular antenna arrays.

The results of this paper are contingent on a particular objective function and initialization values, with each algorithm differing based on the values introduced. There is no algorithm that is superior to others based on the number of elements and the objective function when compared to the findings of other studies.



6. Conclusion

It is possible to conclude that minimal side lobes are achieved in order to achieve the highest possible direction of the radiation pattern when the three algorithms PSO, GA, and FPA are applied to different numbers of elements of the antenna array. It was discovered that the best SLL value when using PSO occurs when the number of antenna elements is 256, and its value is -28.5405dB. When using GA, the optimal antenna has 256 elements and a value of -28.6204dB. When using FPA, the optimal SLL is achieved when the number of elements is 32, with values reduced to -28.3071dB.

Comparing algorithms with one another and for various numbers of antenna elements, the study demonstrated that the optimal algorithm was employed when the number of antenna elements was 256-element GA, where SLL was minimized as much as possible. Other algorithms also reduced SLL, but when applied to this objective function, GA outperformed the other algorithms.

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تقليل الفصوص الجانبية باستخدام مصفوفات الهوائي الخطية عن طريق مقارنة خوارزميات

FPA و GA و PSO

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الخلاصة

ان مصفوفات الهوائي الخطي هي نظام كهرومغناطيسي يستخدم على نطاق واسع في الاتصالات اللاسلكية الحديثة، وقد تم استخدام خوارزميات الميتاهوريستس لتقليل مستوى الفص الجانبي والوصول إلى الحل الأمثل. يستخدم هذه البحث ثلاث خوارزميات: الأولى، تحسين سرب الجسيمات، والثانية، الخوارزمية الجينية، والثالثة، خوارزمية تلقیح الزهور. يتكون كل اختبار من عدد العناصر ١٦ و ٣٢ و ٦٤ و ١٢٨ و ٢٥٦. عنصراً من مجموعة عناصر الهوائي. لتقليل مستوى الفص الجانبي وتركيز الطاقة المشعة في الفص الرئيسي، تقارن كل خوارزمية نمط الحزمة بنمط الحزمة النظرية. بالإضافة إلى ذلك، تمت مقارنة الخوارزميات بوجود نمط الحزمة النظرية، وتم اكتشاف وجود خوارزمية فائقة لكل عدد من عناصر الهوائي؛ في $n=8$ عند مقارنة خوارزمية التلقیح بالخوارزميات الأخرى، تم اكتشاف أنها قللت مستوى الفص الجانبي بقيمة 20.8492 - ديسبل، والتي كانت متفوقة على الخوارزميات الأخرى. انخفض مستوى الفص الجانبي بمقدار 27.2992 - ديسبل، عند مقارنة خوارزمية تحسين سرب الجسيمات مع الخوارزميات الأخرى عند $n=16$ ، عندما $n=32,64$ يمثل خوارزمية تلقیح الجسيمات بشكل أكثر دقة من الخوارزميات الأخرى حيث انخفض الفص الجانبي إلى 28.3071 -ديسبل و 28.0148 - ديسبل، على التوالي. ان الخوارزمية الجينية متفوقة على الخوارزميات الأخرى عندما $n=128$ و 256 ، مما يقلل الفصوص الجانبية بنسبة 28.5568 - ديسبل - 28.6204 - ديسبل، على التوالي.

الكلمات الدالة: المصفوفات الهوائي الخطية، خوارزمية تحسين سرب الجسيمات، الخوارزمية الجينية، خوارزمية تلقیح الزهور، مستوى الفصوص الجانبية، نمط الشعاع.