Synthesis of Radiation Patterns of Arrays with Defined Sidelobe Structure Using Accelerated Particle Swarm Optimization

P. A. Sunny Dayal, G. S. N. Raju, S. Mishra and V. K. Varma Gottumukkala

***Abstract*— Pattern synthesis from array antennas has become a commonly problem to address. Several standard and conventional techniques are available in the literature for the above purpose. Depending on the desired shape of the pattern, the methods are chosen for example, Taylor considered a continuous line sources and generated narrow beams with the desired sidelobe levels of equal height close to the main beam. Elliot has reported a method to generate unsymmetrical patterns. There are some applications where the restricted sidelobes in the mid of the sidelobe region are required. To generate such patterns, no work is available in the literature. In view, of this intensive investigations are carried out to generate such patterns. Accelerated Particle Swarm Optimization is applied to optimize the above patterns. The simulated patterns are presented for both small and large arrays.**

***Index Terms*— Linear arrays, Accelerated Particle Swarm Optimization, Pattern synthesis, Sidelobe Level (SLL)**

I. Introduction

IN antenna design pattern synthesis is one of the important problems to solve. Each applications starting from communications, radars, and radiation therapy systems, demand a specific type of radiation beam shape. For example, point to point communication requires pencil beams, ground mapping and airborne surveillance radars require cosecant patterns, search radars require flat and sector beams, IFF radars require sum and difference patterns, and Marine radars require asymmetric patterns. Some users require low first sidelobe levels. Some other requires low sidelobes in mid-sidelobe region. It is also often required to generate patterns with low sidelobes at the far end of the visible region. Interestingly some applications of communications require multiple beams with the equal height of the main beam [1]-[3].

To meet the above requirements and applications, several methods are reported in the literature. Some of them are Dolph-Chebyshev method, standard distributions like Taylor's method, Fourier Transform, Laplace Transform, Woodward method, Modified Taylor's method, Bayliss method etc [4]-[7].

The above methods are applied to produce patterns of different shapes. Taylor reported [8] a method of generation of sum patterns from continuous line sources. It has been possible to maintain required number of sidelobes of equal height by the selection of $\bar{n}$. This variable provides $(\bar{n}-1)$ number of equal sidelobes close to the main beam. The remaining sidelobes taper exponentially. Taylor's modified method is used to produce symmetric sum patterns. These patterns are useful in marine radars to overcome roll and pitch due to turbulent sea.

Sometime, perturbation techniques [9] are also used to synthesize a few typical shapes. It is difficult to use this technique to generate complex shaped patterns as it leads to convergence problems.

However, no work is reported in open literature, to produce low sidelobes in the middle of sidelobe region. In view of this, an attempt is made to produce beam using Accelerated Particle Swarm Optimization. The patterns of present interest are of symmetric nature. Accelerated Particle Swarm Optimization algorithm is simultaneously applied to generate the desired pattern accurately. The data presented in this paper is entirely useful for the array designers.

II. Optimization Techniques

Optimization of a specific parameter is very important in every field of human life. These include agricultural, product design, product sales, aircraft design, all industrial products, satellite design, radar and antenna design etc. Specific parameter is optimized within the given constraints, the number of constraints vary from parameter to parameter. Over the last several decades techniques and methods of optimization are reported in the open literature. Some of the useful techniques that are frequently used are Gradient, Random, Perturbation, Iterative, Simplex, Systematic Search, Genetic Algorithm, Simulated Annealing, Particle Swarm Optimization, Accelerated Particle Swarm Optimization, etc.

The Gradient technique is a very quick local optimization technique and it provides local optima rather than global. It is often used in the applications, where the point is required. In order to calculate gradient, first step specifies numerical

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approximation of the gradient of the cost function due to the dynamic range of the variable to be optimized it lies between 0 and 1.

Perturbation technique is used when the initial value is well defined. It involves incremental values till the parameter is optimized. The time consumed for optimization depends on incremental value and convergence.

In Iterative technique the time consumed depends on number of iterations required for the convergence of the parameter to be optimized.

The Simplex algorithm provides robust local optimized solution if the initial optimization parameter values exist in the vicinity of the solution, it provides the best option. It has initial step between 0 and 1. It is possible to prescribe in this technique the tolerance for the coordinate (optimization variable) and tolerance for the cost function [10].

Genetic Algorithm (GA) is frequently used to optimize the parameters using Darwinian evolution principle [11]. It provides the survival of the fittest. It is one of the most robust universal algorithms for optimization. It takes care of many optimization variables and huge optimization spaces. It is not preferred local optimization due to its slow convergence properties. It consists of the following parameters, they are algorithm type (continuous or binary), number of bits, pareto genetic algorithm, population size, number of surviving, crossover probability, mutation probability, total number of generations, keep from previous generation, probability of keeping, end calculations, specified tolerance for function, total number of populations, swap entities, and probability of swapping.

Simulated Annealing (SA) is used to optimize any quantity by simulating the annealing process [12]. It is also a robust universal algorithm, unlike Genetic Algorithm, which can be used for local optimization also. It has following parameters, they are starting temperature, cooling scheme, and number of iterations per generation.

Particle Swarm Optimization (PSO) optimizes any quantity by simulating the movement of a bird flock, fish school. It is a very useful technique to address optimization problems with about 4 to 5 variables [13]. It has the following parameters, they are number of particles in the swarm, inertia, cognitive coefficient, social rate, maximal velocity, end calculations if swarm converged, and relative tolerance with absolute tolerance for the cost-function.

Accelerated Particle Swarm Optimization (APSO) which was developed by Yang, et.al., [14]-[15]. In accelerated particle swarm optimization, it is possible to accelerate the convergence of the algorithm using the global best only [16]-[23]. Virtual mass is introduced to stabilize the motion of the particles, and hence convergence occurs quickly.

III. Accelerated Particle Swarm Optimization APSO

If $\mathbf{x}_i$ is a position vector and $\mathbf{v}_i$ is velocity vector of the i^{th} particle, new velocity vector is obtained from the following

$$\mathbf{v}_i^{k+1} = \mathbf{v}_i^k + \alpha\varepsilon_1(\mathbf{g}^* - \mathbf{x}_i^k) + \beta\varepsilon_2(\mathbf{x}_i^* - \mathbf{x}_i^k) \qquad (1)$$

Here, ε_1 and ε_2 are random vectors each entry takes the values between 0 and 1. α and β are acceleration constants, they are approximately ≈ 2.

In order to extend particle swarm optimization algorithm, inertia function $y(k)$ is used. Here $\mathbf{v}_i^k$ can be replaced by $y(k)\mathbf{v}_i^k$. That is

$$\mathbf{v}_i^{k+1} = y\mathbf{v}_i^k + \alpha\varepsilon_1(\mathbf{g}^* - \mathbf{x}_i^k) + \beta\varepsilon_2(\mathbf{x}_i^* - \mathbf{x}_i^k) \qquad (2)$$

Here, $y \in (0,1)$. However typically y varies between 0.5 and 0.9. This is equivalent to introducing a virtual mass and stabilizes the motion of the particles to have fast convergence.

The current global best, $\mathbf{g}^*$ and the individual best, $\mathbf{x}_i^*$ are used in particle swarm optimization. Individual best increases the diversity in the best solution, where the diversity is simulated with randomness. The individual best is used only when the parameter to be optimized is non-linear and multimodal.

However, in accelerated particle swarm optimization, the global best is only used. Keeping this fact in view, the velocity vector is generated from

$$\mathbf{v}_i^{k+1} = \mathbf{v}_i^k + \alpha\varepsilon_n + \beta(\mathbf{g}^* - \mathbf{x}_i^k) \qquad (3)$$

Here, ε_n is taken from $M(0,1)$. As a result, we have

$$\mathbf{x}_i^{k+1} = \mathbf{x}_i^k + \mathbf{v}_i^{k+1} \qquad (4)$$

Updating the location to improve the convergence, we have

$$\mathbf{x}_i^{k+1} = (1-\beta)\mathbf{x}_i^k + \alpha\varepsilon_n + \beta\mathbf{g}^* \qquad (5)$$

In most of the application, $\alpha = 0.1$ and $\beta = 0.1 \sim 0.7$. It is evident that accelerated particle swarm is the simplest and it has only two parameters instead of having more parameters like in particle swarm optimization. The accelerated particle swarm optimization reduces the randomness when the iterations are taken place. Hence it is possible to use a monotonically decreasing function like

$$\alpha = \alpha_0 e^{-\gamma t} \qquad (6)$$

Here γ is in range 0 and 1. In the above expression k represents number of iterations. As γ is the controlling parameter α can be written as $\alpha = 0.7^k$, where $k \in [0, k_{max}]$ and k_{max} is the maximum of iterations.

IV. Array Design Using Accelerate Particle Swarm Optimization Algorithm

Considering a linear array of N isotropic antennas, antenna elements are equally spaced at distance d apart from each other along the x axis. The free space far-field pattern $E(u)$ is given by.

$$E(u) = 2\sum_{n=1}^{N} A(n)\cos[k(n-0.5)du] \qquad (7)$$

Here,

$k =$ wave number $= 2\pi/\lambda$

$\lambda =$ wave length , $\theta =$ angle of observer

$u = \sin\theta$ $d =$ element spacing

$A(n) =$ excitation of the nth element on either side of the array, array being symmetric

Normalized radiation in dB is given by:

$$E(u) = 20\log_{10}\left[\frac{|E(u)|}{|E(u)|_{\max}}\right] \quad (8)$$

A typical uniform linear array is shown in Fig.1.

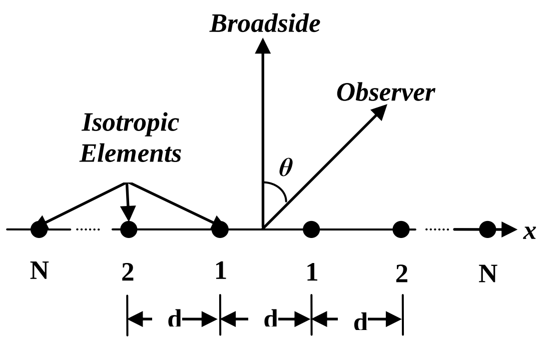

Fig. 1. Geometry of Linear Array with equal spacing.

In the design of array, amplitude distribution is considered to be optimized keeping phase and space parameters constant, for a specified sidelobe level, $A(n)$ is computed for $d = \frac{\lambda}{2}$ and excitation phase = 0.

$$\textit{Fitness Function} = PSLL_o - PSLL_d$$

$$\text{for } u \in \text{sidelobe región} \quad (9)$$

Case 1	$PSLL_d$	$= -30\,dB$	$0.4 \le u \le 0.6$
		$= -45\,dB$	*elsewhere*
Case 2	$PSLL_d$	$= -35\,dB$	$0.4 \le u \le 0.6$
		$= -50\,dB$	*elsewhere*
Case 3	$PSLL_d$	$= -40\,dB$	$0.4 \le u \le 0.6$
		$= -55\,dB$	*elsewhere*

Here,

$PSLL_o$ = Peak Sidelobe level obtained

$PSLL_d$ = Peak Sidelobe level desired

V. Results and Discussion

Using the expression Eq. 3-9, amplitude distributions are computed for desired sidelobe ranging -30 to -55 dB. The results are presented in Tables I-III and Figs. 2, 4, and 6. The excitation levels so obtained are introduced for the array element and their radiation patterns are computed and presented in Figs. 3,5,and 7. The elements are considered to be isotropic and the element pattern is uniform. The data obtained from the patterns, the resultant first sidelobe level, null to null beam width for different arrays are presented in Tables IV-VI.

It is well known that uniform amplitude distribution for the arrays of discrete patterns with first sidelobe level -13.5 dB. There is no control in the sidelobe structure. However, it is often required to reduce the sidelobes in the mid-region in EMI environment in order to meet this requirement arrays are designed using state of art algorithms. The results are very optimum and significant as the realized patterns will meet the specifications. Moreover the designed excitation levels are realistic for practical implementation. As the designed amplitude distribution is symmetric the number of sources required are also reduced.

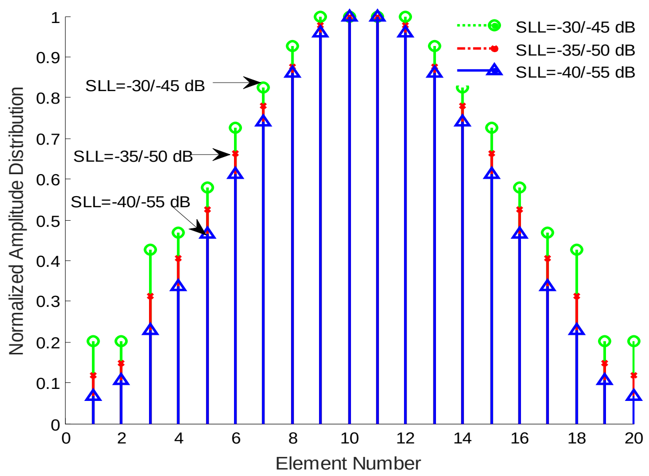

Fig. 2. Element amplitude weights obtained by APSO method for N=20, SLL=-30/-45dB, SLL=-35/-50dB, and SLL=-40/-55dB.

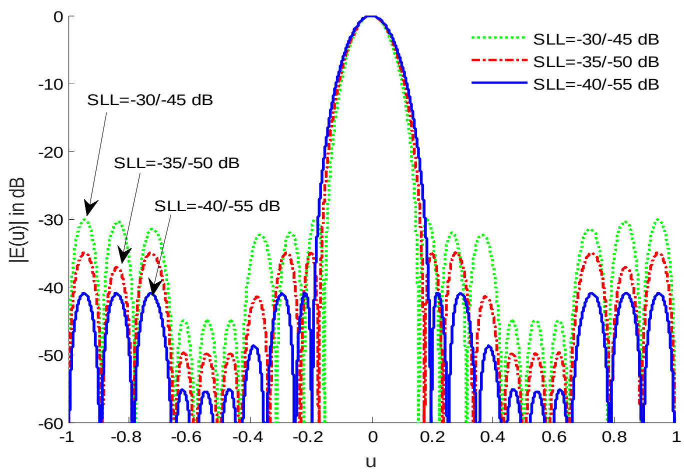

Fig. 3. Optimized Sum Pattern by APSO method for N=20, SLL=-30/-45dB, SLL=-35/-50dB, and SLL=-40/-55dB.

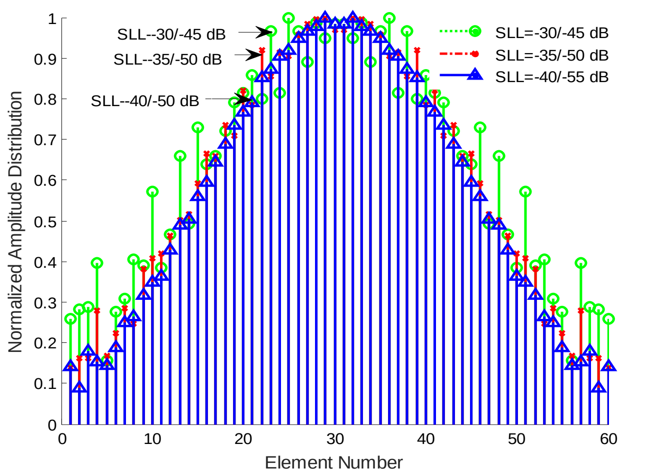

Fig. 4. Element amplitude weights obtained by APSO method for N=60, SLL=-30/-45dB, SLL=-35/-50dB, and SLL=-40/-55dB.

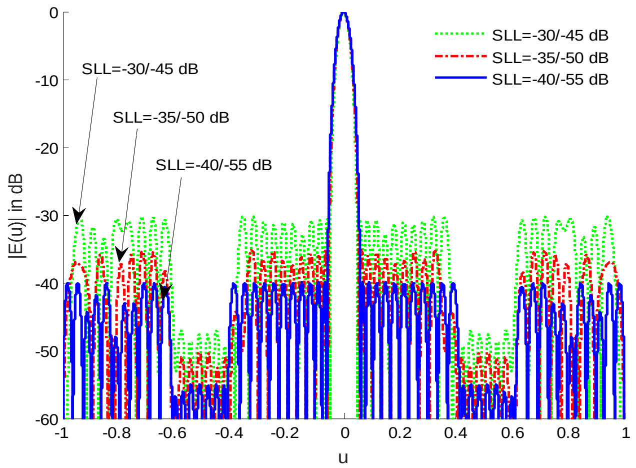

Fig. 5. Optimized Sum Pattern by APSO method for N=60, SLL= -30/-45dB, SLL=-35/-50dB, and SLL= -40/-55dB.

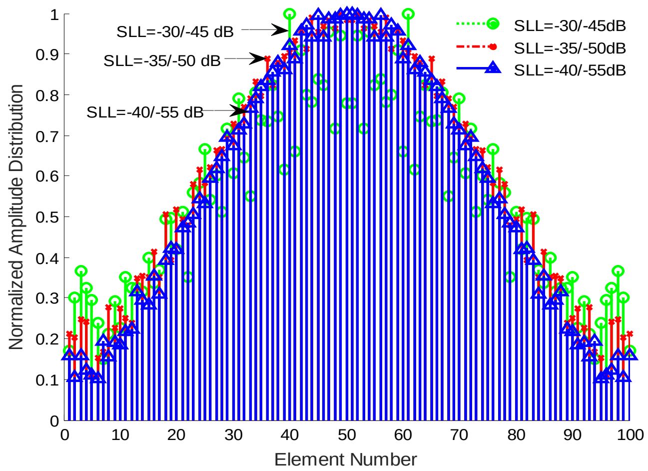

Fig. 6. Element amplitude weights obtained by APSO method for N=100, SLL= -30/-45dB, SLL=-35/-50dB, and SLL= -40/-55dB.

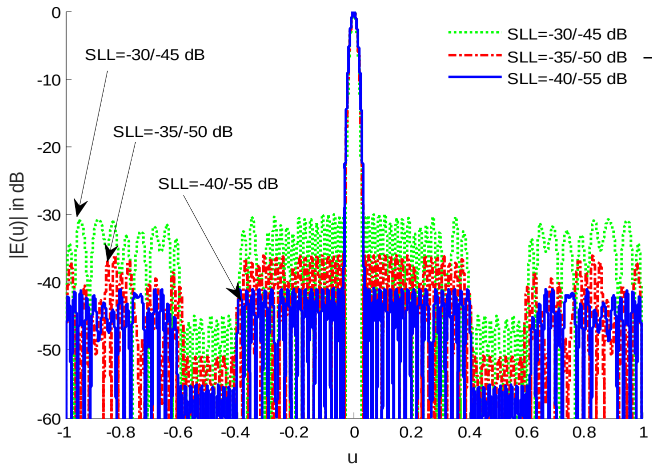

Fig. 7. Optimized Sum Pattern by APSO method for N=100, SLL=-30/-45dB, SLL=-35/-50dB, and SLL=-40/-55dB.

TABLE I
OPTIMIZED ELEMENT AMPLITUDE WEIGHTS FOR $N = 20$

N Element Number	*A(n)* for SLL=-30/-45dB using APSO	*A(n)* for SLL=-35/-50dB using APSO	*A(n)* for SLL=-40/-55dB using APSO
1 & 20	0.2014	0.1173	0.0682
2 & 19	0.2025	0.1496	0.1077
3 & 18	0.4252	0.3115	0.2294
4 & 17	0.4700	0.4061	0.3356
5 & 16	0.5805	0.5251	0.4651
6 & 15	0.7270	0.6646	0.6131
7 & 14	0.8243	0.7794	0.7423
8 & 13	0.9262	0.8766	0.8620
9 & 12	0.9991	0.9776	0.9581
10 & 11	1.0000	1.0000	1.0000

TABLE II
OPTIMIZED ELEMENT AMPLITUDE WEIGHTS FOR $N = 60$

n Element Number	*A(n)* for SLL=-30/-45dB using APSO	*A(n)* for SLL=-35/-50dB using APSO	*A(n)* for SLL=-40/-55dB using APSO
1 & 60	0.2601	0.1382	0.1421
2 & 59	0.2819	0.1626	0.0895
3 & 58	0.2880	0.1628	0.1806
4 & 57	0.3963	0.2797	0.1541
5 & 56	0.1551	0.1676	0.1447
6 & 55	0.2756	0.2246	0.1878
7 & 54	0.3092	0.2854	0.2495
8 & 53	0.4037	0.2478	0.2632
9 & 52	0.3914	0.3829	0.3185
10 & 51	0.5704	0.4085	0.3481
11 & 50	0.3841	0.4192	0.3633
12 & 49	0.4666	0.4624	0.4288
13 & 48	0.6600	0.5019	0.4889
14 & 47	0.4922	0.5166	0.5040
15 & 46	0.7304	0.5916	0.5594
16 & 45	0.6389	0.6646	0.5951
17 & 44	0.6601	0.6603	0.6449
18 & 43	0.7194	0.7366	0.6886
19 & 42	0.7902	0.7095	0.7356
20 & 41	0.8149	0.8208	0.7669
21 & 40	0.8576	0.7840	0.7899
22 & 39	0.7992	0.9207	0.8518
23 & 38	0.9665	0.8545	0.8718
24 & 37	0.8154	0.9152	0.9061
25 & 36	1.0000	0.9036	0.9203
26 & 35	0.9663	0.9582	0.9482
27 & 34	0.8915	0.9833	0.9667
28 & 33	0.9873	0.9950	0.9784
29 & 32	0.9484	1.0000	1.0000
30 & 31	0.9829	0.9684	0.9844

TABLE III
OPTIMIZED ELEMENT AMPLITUDE WEIGHTS FOR $N = 100$

n Element Number	*A(n)* for SLL=-30/-45dB using APSO	*A(n)* for SLL=-35/-50dB using APSO	*A(n)* for SLL=-40/-55dB using APSO
1 & 100	0.1719	0.2124	0.1600
2 & 99	0.3008	0.2021	0.1066
3 & 98	0.3673	0.2485	0.1590
4 & 97	0.3255	0.2407	0.1239
5 & 96	0.2953	0.1114	0.1101
6 & 95	0.2394	0.1527	0.1036
7 & 94	0.1513	0.1668	0.1937
8 & 93	0.2110	0.2762	0.1560
9 & 92	0.2937	0.2279	0.1913
10 & 91	0.2282	0.2738	0.1845
11 & 90	0.3517	0.2499	0.2169
12 & 89	0.3252	0.2380	0.2234
13 & 88	0.3260	0.3481	0.3175
14 & 87	0.3165	0.3556	0.2953
15 & 86	0.3998	0.3505	0.2824
16 & 85	0.3357	0.4140	0.3545
17 & 84	0.3705	0.3522	0.3107
18 & 83	0.4926	0.5049	0.3927
19 & 82	0.4961	0.3940	0.4229
20 & 81	0.4212	0.5171	0.4202
21 & 80	0.5114	0.4942	0.4742
22 & 79	0.3521	0.4802	0.4838
23 & 78	0.5588	0.5802	0.5053
24 & 77	0.5817	0.6163	0.5439
25 & 76	0.6656	0.5817	0.5312
26 & 75	0.5411	0.6211	0.5949
27 & 74	0.5996	0.6637	0.6181
28 & 73	0.5131	0.6674	0.6476
29 & 72	0.7171	0.6927	0.6949

30 & 71	0.6057	0.7291	0.6740
31 & 70	0.7921	0.7225	0.7135
32 & 69	0.6462	0.7695	0.7295
33 & 68	0.5497	0.7897	0.7656
34 & 67	0.8044	0.8338	0.7921
35 & 66	0.7368	0.7966	0.8194
36 & 65	0.7341	0.8893	0.8349
37 & 64	0.8228	0.8246	0.8553
38 & 63	0.7468	0.8792	0.8809
39 & 62	0.6157	0.8935	0.8612
40 & 61	1.0000	0.9023	0.9226
41 & 60	0.6590	0.9320	0.8885
42 & 59	0.9097	0.9563	0.9557
43 & 58	0.8010	0.9120	0.9723
44 & 57	0.7808	0.9883	0.9419
45 & 56	0.8372	0.9533	0.9966
46 & 55	0.8221	0.9679	0.9408
47 & 54	0.9543	0.9842	0.9870
48 & 53	0.7176	0.9623	0.9857
49 & 52	0.9448	1.0000	0.9951
50 & 51	0.1719	0.2124	0.1600

TABLE IV
FIRST NULL BEAMWIDTH FOR OPTIMIZED SUM PATTERN USING ACCELERATED PARTICLE SWARM OPTIMIZATION (APSO)

N Number of Elements	SLL=-30/-45dB using APSO	SLL=-35/-50dB using APSO	SLL=-40/-55dB using APSO
20	17.82°	19.89°	22.36°
60	5.71°	6.38°	6.88°
100	3.36°	3.78°	4.17°

TABLE V
FIRST SIDE LOBE LEVEL FOR OPTIMIZED SUM PATTERN USING ACCELERATED PARTICLE SWARM OPTIMIZATION (APSO)

N Number of Elements	SLL=-30/-45dB using APSO	SLL=-35/-50dB using APSO	SLL=-40/-55dB using APSO
20	-30.00 dB	-35.00 dB	-40.93 dB
60	-30.69 dB	-35.23 dB	-40.00 dB
100	-30.16 dB	-35.82 dB	-40.88 dB

TABLE VI
INNER CLOSED SIDE LOBE LEVEL FOR OPTIMIZED SUM PATTERN USING ACCELERATED PARTICLE SWARM OPTIMIZATION (APSO)

N Number of Elements	SLL=-30/-45dB using APSO	SLL=-35/-50dB using APSO	SLL=-40/-55dB using APSO
20	-45.00 dB	-50.00 dB	-55.10 dB
60	-45.93 dB	-50.18 dB	-55.01 dB
100	-45.00 dB	-50.88 dB	-55.17 dB

VI. CONCLUSION

Accelerated Particle Swarm Optimization algorithm is found to be very useful for the optimization of desired patterns. The convergence has become simple compared to Particle Swarm Optimization. From the amplitude distribution presented, it is found that it exhibits a gradual taper from the centre to the end with symmetric behavior. As the number of elements is increased in the array the beamwidth is found to be decreased without much change in sidelobe levels. It has been possible with the present work to synthesis the required patterns using Accelerated Particle Swarm Optimization successfully.

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