Multi-Verse Optimization algorithm for the Optimal Synthesis of Phase-only reconfigurable linear array of mutually coupled parallel half-wavelength dipole antennas placed at finite distances from the ground plane

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Abstract

Researchers on antenna arrays usually neglect the effect of mutual coupling of antennas placed in proximity to each other. The interchange of electromagnetic energy happening between an antenna and a far field point depends not only on the transmitting antenna, but also from its neighboring antennas. This effect is referred to as mutual coupling between dipole antenna elements and it is considered here in the synthesis of phase only reconfigurable antenna arrays. The main objective of this work is to produce desired Side Lobe Level and Voltage Standing Wave Ratio in addition to few other radiation pattern parameters. Multiverse Optimization algorithm is employed for the purpose of generating voltage amplitude and discrete phase distributions in the dipole elements for the generation of flat-top beam/pencil beam patterns. These two patterns share the common amplitude distributions and differ in phase distributions. Results obtained from simulations prove that this algorithm accomplished its task successfully and is also found to be superior over other algorithms like Particle Swarm Optimization, Grey Wolf Optimization and Imperialist Competitive Optimization algorithms.

Keywords

Reconfigurable linear array antenna, Multiverse Optimization algorithm, Mutual Coupling, Voltage Standing Wave Ratio, Particle Swarm Optimization, Grey Wolf Optimization, Imperialist Competitive Optimization algorithms.

1. Introduction

Recent developments in the field of communications demand a more flexible and an easy approach for the provision of multi-beam patterns. In this regard, antenna arrays [1, 2] guarantee them by providing certain common excitations and certain differing excitations. These arrays are referred to as reconfigurable arrays [1-9] and the corresponding excitations can be amplitudes, phases, positions, etc. Literature review reports many methods of generating these beams like projection approach [3], Woodward Lawson synthesis [4], and other methods using evolutionary algorithms [5-8], etc.

There are concerns that hinder the effective generations of these beams. One of these is mutual coupling [10-13], which plays a prominent role in diminishing the radiation pattern of any antenna array. This mutual coupling refers to the electromagnetic interactions within the neighboring elements existing in an antenna array. In simple words, it can be said that the electric field generated by an antenna element affects the neighboring elements in such a way that the total pattern gets deviated from the desired one. In addition to it, the relative separation between the elements as well as the orientation of the elements also influences the mutual coupling effects.

To add to the concern above, an effective mismatch between an antenna and the feeding network hinders perfect transreception. A mismatch between the antenna and the feeder line or the subsequent components results in return loss. Necessary care is taken in this paper to include both the mutual coupling effects as well as sustained Standing Wave Ratio.

Simulations are done with the inclusion of ground plane and analysis is done on the effect of the distance between the ground plane and the antenna array.

To undergo this process, evolutionary algorithms are used here to generate voltage amplitudes that can hold values between 0 and 1, and current amplitudes are calculated using the mutual impedance matrix. These algorithms also generate the phase excitations that can vary between -180° and 180° in discrete steps using a 6-bit phase shifter [5].

Multiverse Optimization algorithm [14-22] is used here in generating the required amplitudes as well as the phase excitations. The reason for choosing Multiverse Optimization algorithm is due to its immense success in providing solutions to problems related to antenna arrays, and especially in the synthesis of large arrays. The performance of this algorithm is investigated numerically and compared with few other standard popular algorithms, namely, Particle Swarm Optimization (PSO) [23-24], Imperialist Competitive algorithm (ICA) [25-29] and Grey Wolf Optimization (GWO) [30-33]. All the algorithms used in this paper are run to minimize the fitness value in the weighted fitness functions in order to achieve the desired pattern.

The novelty in this paper is that Voltage Standing Wave Ratio is considered simultaneously for both the flat-top and pencil beams. Mutual coupling effect is taken into account along with the ground plane effects. Also, the phase excitations are controlled by discrete phase shifters which greatly reduce the complexity in feed networks.

2. Theory

Figure 1. A linear array of parallel half-wavelength dipole antennas with ground plane placed at a distance *h* behind the array.

The free space far field pattern of a linear array constructed of N half-wave dipoles separated from each other by a distance d in azimuth plane with $\varnothing$ being the azimuth angle measured from the *x*-axis as shown in Figure 1 is given by

$$F(\varnothing) = \sum_{n=1}^{N} I_n e^{j(n-1)kdcos\varnothing} * EP(\varnothing) \tag{1}$$

In the above equation, k is the wave number, $EP(\varnothing)$ is the element pattern, I_n is the complex current excitation obtained from the product of impedance matrix and the voltage excitation matrix of the elements. $[I]_{N*1} = [Z]^{-1}{}_{N*N}\,[V]_{N*1}$, where $[Z]$ is the impedance matrix (size $N * N$) and $[V]$ is the voltage excitation matrix (size N *1) of the elements.

The element pattern of the dipole elements is assumed to be omnidirectional in the plane considered, i.e., $EP(\varnothing) = 1$. From the currents calculated using the voltage excitations as well as the impedance matrix, a sum pattern is generated in the broadside direction.

Since mutual coupling effects are included in this paper, the customary equations related to it are shown as follows. The mutual coupling includes both the self-impedance of the elements as well as the mutual impedances among elements [2]. The relationship between the voltages V and impedances are given by

$$V_p = I_p Z_{pp} + \sum_{p \neq q} I_q Z_{pq} \tag{2}$$

where Z_{pp} refers to self-impedance of dipole p and Z_{pq} refers to mutual impedance between p and q. The active impedance is given by

$$Z_p^{Ac} = Z_{pp} + \sum_{p \neq q} (I_{q/} I_p) Z_{pq} \tag{3}$$

In case, when a ground plane [2] is kept at a distance *h* behind the array, the new active impedance is calculated taking into account the image principles in obtaining the impedances of the elements.

In the impedance matrix, self-impedance is replaced by $(Z_{pp} - Z_{pp}*)$ and mutual impedance is replaced by $(Z_{pq} - Z_{pq}*)$, where $Z_{pp}*$ is the impedance between the p^{th} dipole and its image, and $Z_{pq}*$ is the impedance between the p^{th} dipole and image of the q^{th} dipole. If h is the distance between the array and the ground plane and if the element factor is $\left[\sin\left(khsin\varnothing\right)\right]$, then the new far field expression taking the ground plane into effect is given by

$$F\left(\varnothing\right) = \sum_{n=1}^{N} \left[\sin\left(khsin\varnothing\right)\right] I_n e^{j(n-1)kdcos\varnothing} \tag{4}$$

$$\text{Normalized absolute far field} = \frac{\left|F\left(\varnothing\right)\right|}{max\left|F\left(\varnothing\right)\right|} \tag{5}$$

Voltage Standing Wave Ratio (VSWR) is calculated as (1+ Γ)/(1- Γ), where Γ is the Reflection Coefficient being equal to $(Z_p^{Ac} - Z_0)/(Z_p^{Ac} + Z_0)$. Z_0 is the characteristic impedance with a value of 50 **Ω**. A low value of VSWR denotes good matching condition of the array.

The weighted fitness function is given by

$$F = \sum_{i=1}^{3} w_i \left(F_i\right)^2 + \sum_{j=1}^{2} w_j \left(F_j\right)^2 \tag{6}$$

The first term in the RHS of the above equation is written as below:

$$F_i = \begin{cases} F_i^{flat} - F_{i,d}^{flat}, \; if \; F_i^{flat} > F_{i,d}^{flat} \\ 0, \; if \;\; F_i^{flat} \leq F_{i,d}^{flat} \end{cases} \tag{7}$$

where F_i represents the flat-top beam parameters and $i = 1, 2 \text{ and } 3$ refers to the parameters, namely, Side Lobe Level (SLL) in dB, Ripple in dB and maximum VSWR (no unit).

The second term in the RHS of equation (7) is written as below:

$$F_j = \begin{cases} F_j^{pen} - F_{j,d}^{pen}, if\ F_j^{pen} > F_{j,d}^{pen} \\ 0,\ if\ \ F_j^{pen} \le F_{j,d}^{pen} \end{cases} \tag{8}$$

where F_j represents the pencil beam parameters and $j\ = 1 \text{and} 2$ refers to the parameters, SLL in dB and maximum VSWR (no unit).

Moreover, in the above equations, the superscript pen represents the specifications for the pencil pattern and the superscript $flat$ represents the specifications for the flat-top pattern. The term F_{id}, F_{jd} represents the expected/desired value and $F_{i,}$, F_j represents the obtained value for each specification parameter. The weights *w* are chosen to be equal to 1 suggesting that equal importance is given to all the parameters during the optimization process.

3. Multi-Verse Optimization algorithm

Multi-Verse Optimization (MVO) algorithm is one of the recently introduced algorithms and is influenced by the multi-verse theory concepts. As per the concepts dealing with this algorithm, our Universe may be one of the infinite numbers of Universes that can exist. The theory underlying this relies on white holes, black holes and wormholes. In this algorithm, the worm holes are responsible for the exploitation part and the combined white and black holes control the exploration part. Here, a solution refers to a Universe, a variable refers to an object in it, the inflation rate refers to the solution's fitness values and finally the term *time* refers to the iteration. The rules that are used in this algorithm are:

(i) The higher the inflation rate indicates the situation having more white holes than black holes.

(ii) The universes with more inflation rate move the objects through the white holes and the universes with less inflation rate accept the objects via the black holes.

(iii) The objects in all the universes move randomly towards the Best Universe via wormholes ignoring the effect of the inflation rate.

The objects travel between universes through the white or black hole tunnels. During the creation of a tunnel between two universes, the universe with the higher inflation rate is treated as a white hole and the other one as a black hole. Then the objects are allowed to move from the white holes of one universe to the black holes of the other. Thus exchange of objects can easily take place without any hassle. It is also assumed that when the inflation rate is more, the probability of having white holes will also be more.

Wormholes appear in a random manner in any of the universes irrespective of the inflation rate. This ensures more diversity of universes during iterations. The tunnels require the universes to change in an abrupt manner thus guaranteeing exploration of the search within the allotted space. These changes also help in relieving any local optimum stagnation. The wormholes also indulge in re-span of few of the variables around the best obtained solution in a random way, thus ensuring exploitation around the most promising region.

The mathematical modeling of the interchange of the objects between the Universes and the white and black hole tunnels is done using a roulette wheel selection. At the end of every iteration, one Universe is chosen as the best one. With *d* as the number of variables and no is the number of Universes, the set of solution *U* is formulated as:

$$U = \begin{bmatrix} x_1^1 & x_1^2 & x_1^3 & \dots & x_1^d \\ \vdots & \vdots & \vdots & \dots & \vdots \\ \vdots & \vdots & \vdots & \dots & \vdots \\ \vdots & \vdots & \vdots & \dots & \vdots \\ x_{no}^1 & x_{no}^2 & x_{no}^3 & \dots & x_{no}^d \end{bmatrix} \tag{9}$$

If *Um* is the m^{th} universe, *NIr(Um)* is the normalized inflation rate of the m^{th} universe, then

$$x_m^n = \begin{cases} x_k^n & ran1 < NIr(U_m) \\ x_m^n & ran1 \geq NIr(U_m) \end{cases} \tag{10}$$

Where $ran1$ is a random number between 0 and 1, and x_k^n is the n^{th} parameter of k^{th} Universe selected by the selection method used. To use the facility to avail the changes locally for every Universe and to upgrade the inflation rate, the wormhole tunnels are created between a Universe and the *Best Universe* obtained till that *time*, and the following equation is used for the same.

$$x_m^n = \begin{cases} \begin{cases} X_n + TDR((Ur_n - Lr_n)ran4 + Lr_n) & ran3 < 0.5 \\ X_n - TDR((Ur_n - Lr_n)ran4 + Lr_n) & ran3 \geq 0.5 \end{cases} & ran2 < WEP \\ x_m^n & ran2 \geq WEP \end{cases} \tag{11}$$

where X_n is the n^{th} parameter of the *Best Universe* obtained so far, *TDR* is the travelling distance rate, *WEP* is the work hole existence probability, Lr_n and Ur_n are the lower and upper bounds of n^{th} variable, x_m^n is the n^{th} parameter of the m^{th} Universe and *ran2, ran3* and *ran4* are random numbers between 0 and 1. *WEP* is given by

$$WEP = mn + l\left(\frac{mx - mn}{\text{Max\_Iters}}\right) \tag{12}$$

$$TDR = 1 - \frac{l^{1/p}}{\text{Max\_Iters}^{1/p}} \tag{13}$$

where *mn* is set to 0.2, *mx* is set to 1, *l* is the current iteration, Max_Iters refers to the maximum iterations and *p* is the accuracy of the process of exploitation over the iterations. The pseudo code is found below:

Pseudo Code
1: Initialization
Creation of random Universes *U*
Initialization of WEP, TDR, and Best Universe
time = 0
2: Sorting of Universes and Normalization of the fitness values of the Universes
SUs = Sorted Universes and *NIr* = Normalization of the inflation rate of the Universes
BHI = Black hole Index and *WHI* = white hole index

```
3: Process of Iteration
while time < Max_Iters
        The fitness values of all the Universes Um, m = 1, 2, 3,…, n are evaluated.
  for each universe Um
        Update WEP and TDR
        BHI= m;
        for each object n
           ran1 = random value between 0 and 1;
           if ran1<NIr(Um)
           WHI = Roulette Wheel Selection (-NIr);
           U(BHI, n) = SUs(WHI, n);
           end if
              ran2 = random value between 0 and 1;
           if ran2< WEP
           ran3 = random value between 0 and 1;
           ran4 = random value between 0 and 1;
           if ran3<0.5
             U(m, n) = Best Universe (n) + TDR * ((Ur(n)- Lr(n)) * ran4 + Lr(n ));
           else
             U(m, n) = Best Universe (n) —TDR * ((Ur(n)-Lr(n )) * ran4 + Lr(n ));
             end if
             end if
        end for
  end for
time = time+1
end while
4: Stop
Output the values of Best Universe and NIr(Best Universe)
```

4. Simulation results and discussions

A total of 20 elements are used in this simulation process. Because of symmetry, it is made customary for the algorithms to generate only 10 elements excitations. Here, the amplitudes are kept common to both the beams, whereas the generated discrete phases are used to produce a flat-top beam and zero phases to produce a pencil beam. The amplitudes range from 0 to 1 and the phases range from -180° to 180°. The algorithm is run for a maximum of 200 iterations. The dipoles used here have a length of 0.5λ and a radius of 0.005λ. The distance between the dipoles is kept at 0.5λ. The ground plane is taken into consideration for various distances of 0.10λ, 0.20λ and 0.25λ for simulation purposes. The population size and maximum number of iterations are kept same for all the algorithms. A total of five runs are used for the algorithms and the best out of the five runs based on the lowest fitness values are chosen as the final generated values of excitations. Tables 1, 2 and 3 show the parameter values for the linear array at a distance of 0.10λ, 0.20λ and 0.25λ from the ground plane. Figures 2, 3 and 4 show the Normalized Power Pattern in dB vs ϕ in degrees for the linear array with a distance of 0.10λ, 0.20λ and 0.25λ from the ground plane. Table 4 shows the corresponding Voltage and phase distributions. Figure 5 shows the VSWR values for all the algorithms at different distances between the array and the plane. Table 5 shows the fitness values and computation times. Figure 6 shows the Fitness values versus iteration numbers.

Table 1. Parameter values for the linear array at a distance of 0.10λ from the ground plane.

From Table 1, it is seen that the MVO showed its supremacy in delivering the best excitation values to produce the parameter values well under the expected criteria. These parameter values include SLL and VSWR in pencil beam and SLL and VSWR in the flat-top beam. There is a deficit of 0.07652 dB in the ripple in flat-top beam. GWO succeeded in producing all the parameter values to the expected level except VSWR and Ripple in flat-top beam. But in overall, PSO and ICA results are not good as compared with the remaining algorithms. Except PSO, expected SLL value is reached by all algorithms for the pencil beam. Figure 2 shows the Normalized Power in dB vs ϕ in degrees for the linear array with a distance of 0.10λ from the ground plane.

Figure 2. Normalized Power in dB vs ϕ in degrees for the linear array placed at a distance of 0.10λ from the ground plane.

Table 2. Parameter values for the linear array at a distance of 0.20λ from the ground plane.

From Table 2, it is seen that the MVO algorithm has succeeded in producing the SLLs well within the expected values for both the beams. The ripple in dB is very close to the expected value with a deficit of 0.2899 dB. It faced a tough competition with GWO algorithm, as it succeeded in producing the best VSWR in pencil beam, whereas it lost to the same in flat-top beam.

Figure 3. Normalized Power in dB vs ϕ in degrees for the linear array placed at a distance of 0.20λ from the ground plane.

Table 3. Parameter values for the linear array at a distance of 0.25λ from the ground plane.

From Table 3, it is found that MVO algorithm again succeeded in producing the best outputs, espeically over GWO in VSWRs of both the beams. But, GWO slightly edged better over MVO by 0.2558 dB in the ripple portion in flat-top beam.

Figure 4. Normalized Power in dB vs ϕ in degrees for the linear array placed at a distance of 0.25λ from the ground plane.

Table 4. Voltage amplitude and Phase distributions (in degrees) of the elements for various distances from the ground plane

Figure 5. VSWR values versus algorithms

Table 5. Fitness values and Computation time details

Table 5 shows that the fitness values of MVO algorithm are very low when compared to other algorithms for all the values of the distance between the array and the ground plane. It also shows the computational time taken by MVO is lesser in most of the places over other algorithms.

Figure 6. Fitness values versus Number of Iterations

Figure 6 shows the plot between fitness values and number of iterations. It is very clear from this figure that MVO algorithm has performed better in terms of convergence speed as well as lowest fitness values over other algorithms. Overall, it is found that MVO has performed better than the other algorithms. The reasons for the success of this algorithm are that, abrupt changes increase the exploration of the search space and it also resolves the problem of the stagnation of local optima. Since wormholes randomly re-span some of the variables of the around the best optimum solution, there is a good level of guarantee in exploitation around the most promising region. Adaptive *WEP* increases the probability of the availability of wormholes and adaptive *TDR* increases the accuracy of the local search. All the above reasons helped this algorithm to show its superiority over other algorithms.

Analysis:

Effect of distance on the pattern:

To study the effect of the inter-element distance of the array on the radiation pattern parameters, simulations are done for various inter-element distances using the obtained excitations from MVO algorithm. The results are shown in Table 6 for various inter-element distances.

Table 6. Parameter values for the linear array for various inter-element distances.

Table 6 clearly shows that when the distances are either more or less than 0.5λ, all the parameter values obtained are not under the desired limit. For instance, when *d*=0.6λ, it's the ripple value in dB which is affected and when *d*=0.4λ, it's the VSWR values and the SLL in dB in the flat-top beam that are affected.

Further to verify the outputs, the whole array is simulated using FEKO software. Using FEKO, the array is simulated with a random choice of a distance equal to 0.10λ. Figure 7 shows the Normalized Power Pattern in dB vs ϕ in degrees for the linear array placed at a distance of 0.10λ from the ground plane using MATLAB simulated outputs and FEKO generated outputs. From the outputs obtained, the value of SLL obtained for the flat-top pattern is found to be -21.8761 dB and the SLL for the pencil beam is found to be -22.0078 dB. There is a small deficit of 0.1239 dB of SLL in the flat-top pattern from the desired value. Otherwise, it is a very good agreement when compared with the values obtained using MATLAB outputs using MVO algorithm.

Figure 7. Normalized Power in dB vs ϕ in degrees for the linear array placed at a distance of 0.10λ from the ground plane using MATLAB simulated outputs and FEKO generated outputs.

5. Conclusion

This paper dealt with the application of Multiverse Optimization algorithm in reconfigurable antenna arrays. The algorithm showed its capability in successively generating the necessary excitations in the generation of dual beams. Discrete phase shifters were used for the purpose of reducing the complexity of the feed networks. Mutual coupling had been taken into account. The effect of ground plane on the radiation pattern had been studied here. Moreover, real antennas were used instead of isotropic ones. Simulation results proved that MVO algorithm was better than the compared algorithms in terms of the fitness function parameters, convergence speed, etc.

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7 Figures and 6 Tables

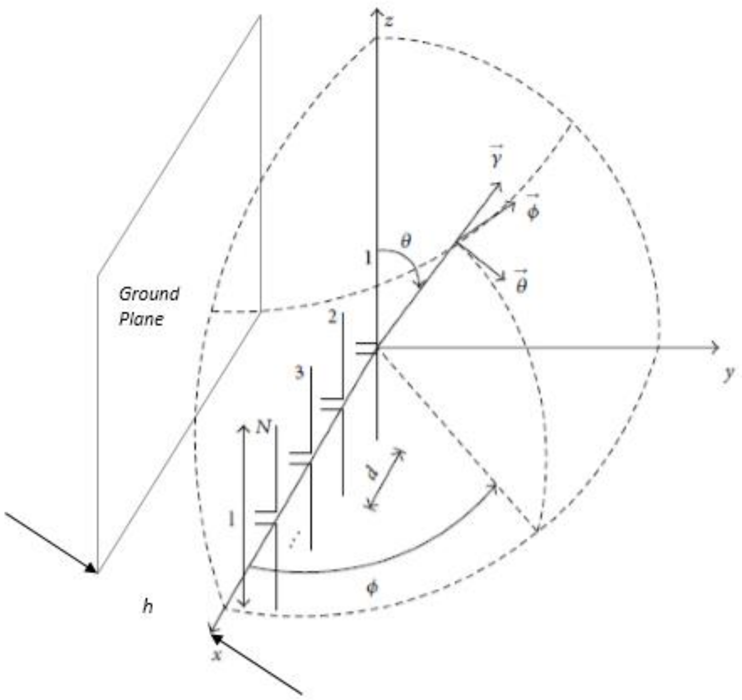

Figure 1. A linear array of parallel half-wavelength dipole antennas with ground plane placed at a distance *h* behind the array.

Table 1. Parameter values for the linear array at a distance of 0.10λ from the ground plane.

Patterns	**Parameters**	**Desired values**	**Obtained values**			
			MVO	**GWO**	**PSO**	**ICA**
Pencil beam	SLL in dB	-22	-22.0934	-22.0222	-21.8158	-22.1674
	VSWR	1.3	1.2359	1.2621	1.2233	1.374
Flat-top beam	SLL in dB	-22	-23.1407	-22.1199	-21.9791	-21.7364
	VSWR	1.3	1.2444	1.526	1.8901	1.4504
	Ripple in dB (75° < ϕ <105°)	0.5	0.57652	0.73797	1.7995	1.3535

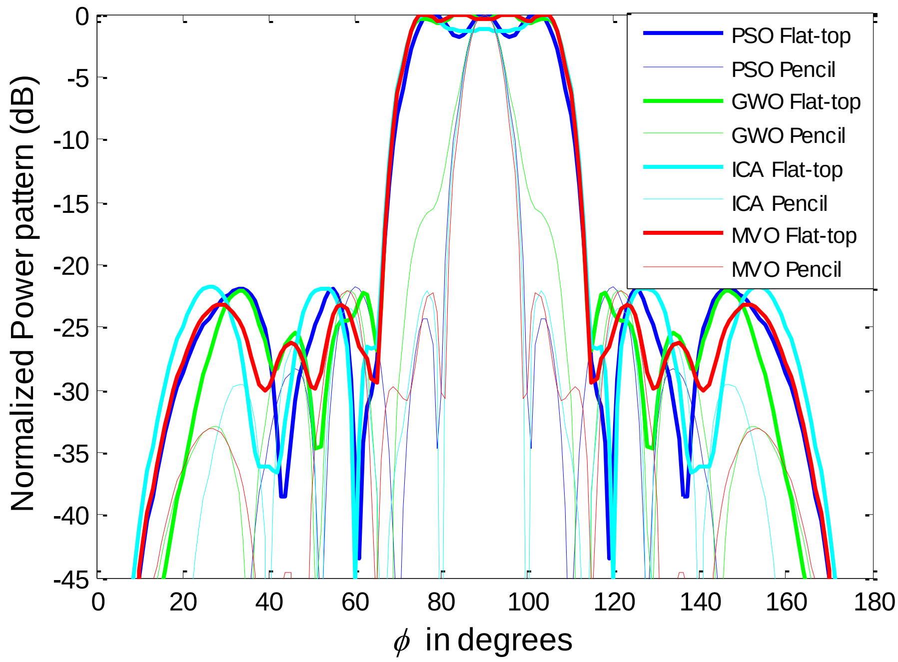

Figure 2. Normalized Power in dB vs ϕ in degrees for the linear array placed at a distance of 0.10λ from the ground plane.

Table 2. Parameter values for the linear array at a distance of 0.20λ from the ground plane.

Patterns	Parameters	Desired values	Obtained values			
			MVO	GWO	PSO	ICA
Pencil beam	SLL in dB	-22	-22.029	-22.0996	-21.8788	-22.1899
	VSWR	1.3	1.2221	1.3269	2.0011	1.9924
Flat-top beam	SLL in dB	-22	-23.3714	-22.468	-21.9851	-22.4286
	VSWR	1.3	2.0504	1.2497	2.1046	2.1249
	Ripple in dB (75° < ϕ <105°)	0.5	0.7899	0.5378	0.97112	1.3829

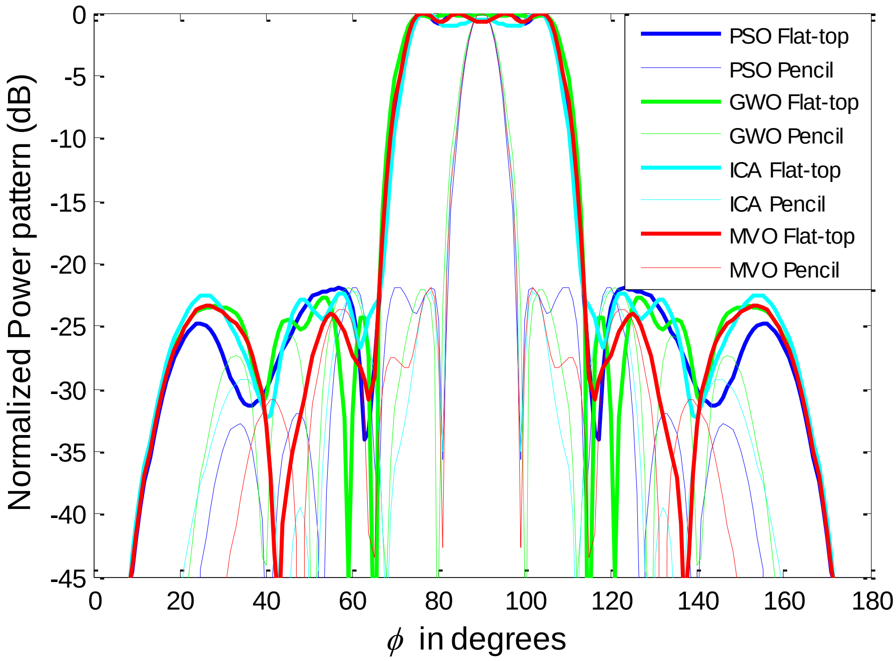

Figure 3. Normalized Power in dB vs ϕ in degrees for the linear array placed at a distance of 0.20λ from the ground plane.

Table 3. Parameter values for the linear array at a distance of 0.25λ from the ground plane.

Patterns	**Parameters**	**Desired values**	**Obtained values**			
			MVO	**GWO**	**PSO**	**ICA**
Pencil beam	SLL in dB	-22	-22.2765	-22.1221	-21.843	-21.0699
	VSWR	1.3	2.0704	2.1706	2.378	2.3361
Flat-top beam	SLL in dB	-22	-23.6803	-24.4325	-21.5715	-20.8859
	VSWR	1.3	2.1817	2.3451	3.1563	2.3944
	Ripple in dB (75° < ϕ <105°)	0.5	0.7977	0.5419	2.376	2.5608

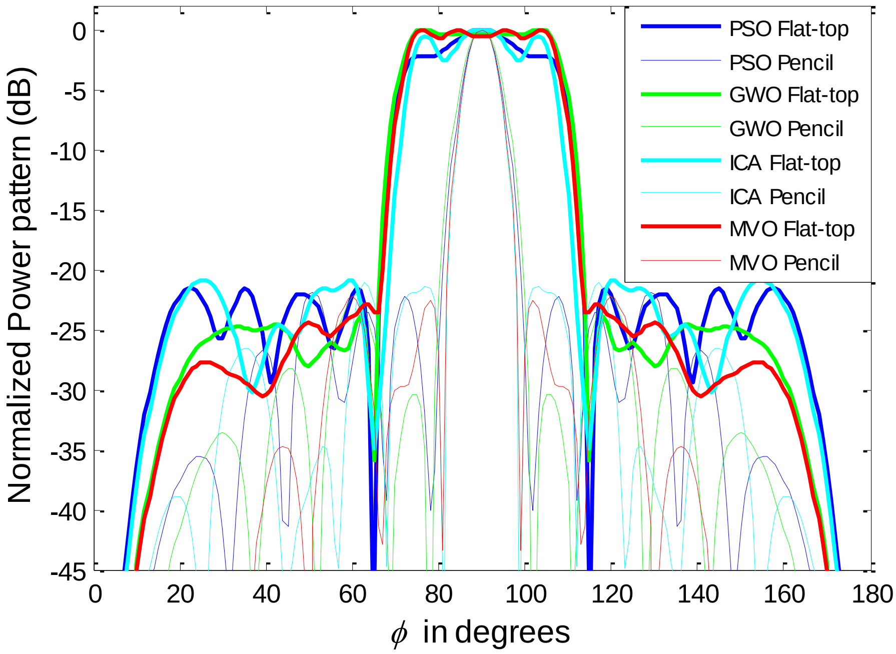

Figure 4. Normalized Power in dB vs ϕ in degrees for the linear array placed at a distance of 0.25λ from the ground plane.

Table 4. Voltage amplitude and Phase distributions (in degrees) of the elements for various distances from the ground plane

Element Number	*h*=0.10λ Distribution		*h*=0.20λ Distribution		*h*=0.25λ Distribution	
	Voltage	Phase (degrees)	Amplitude	Phase (degrees)	Amplitude	Phase (degrees)
1 & 20	0.0007	-50.6250	0.0580	-140.625	0.0692	-180.000
2 & 19	0.1220	-28.1250	0.1322	180.0000	0.1740	174.3750
3 & 18	0.2498	-45.0000	0.2843	-174.375	0.3317	-174.375
4 & 17	0.3675	-78.7500	0.4096	135.0000	0.3884	140.6250
5 & 16	0.3206	-151.875	0.3860	67.5000	0.4583	78.7500

6 & 15	0.7274	-168.750	0.6969	50.6250	0.8557	50.6250
7 & 14	0.8189	157.500	0.9622	22.5000	0.9994	33.7500
8 & 13	0.8188	146.2500	0.7685	5.6250	0.8383	22.5000
9 & 12	0.6822	95.6250	0.7921	-39.3750	0.8501	-33.7500
10 & 11	0.8846	61.8750	0.8534	-78.7500	0.9997	-67.5000

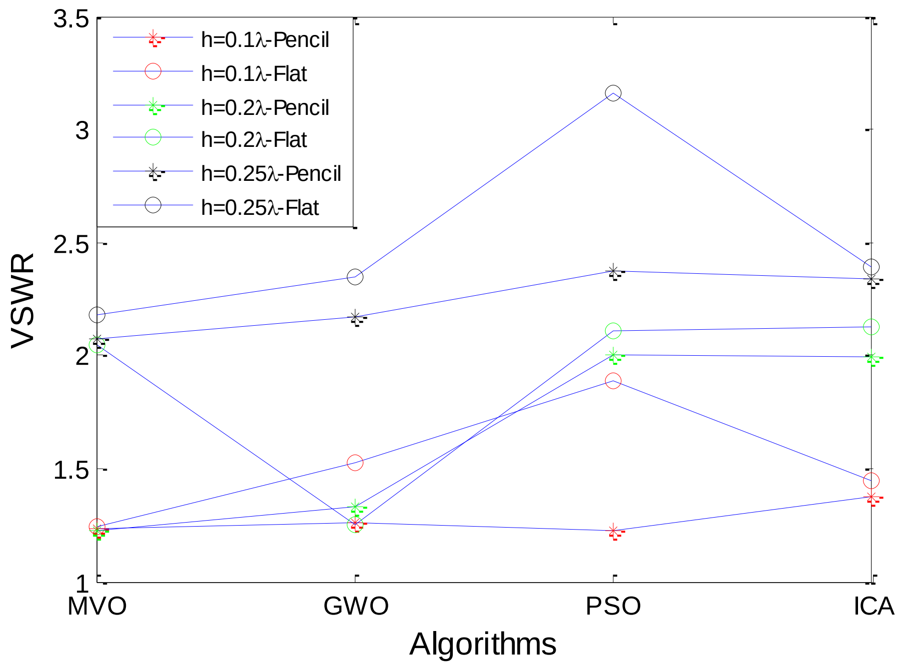

Figure 5. VSWR values versus algorithms

Table 5. Fitness values and Computation time details

Distance *h*	**Fitness values**			
	MVO	**GWO**	**PSO**	**ICA**
0.1	0.0058	0.1078	2.0711	0.8678
0.2	1.0868	1.5703	1.3754	1.9395
0.25	1.4596	1.8518	8.3029	8.6239
Distance *h*	**Computational time in seconds**			
0.1	18001	18507	21730	22726
0.2	18432	19421	19020	19529
0.25	18389	17777	18380	19053

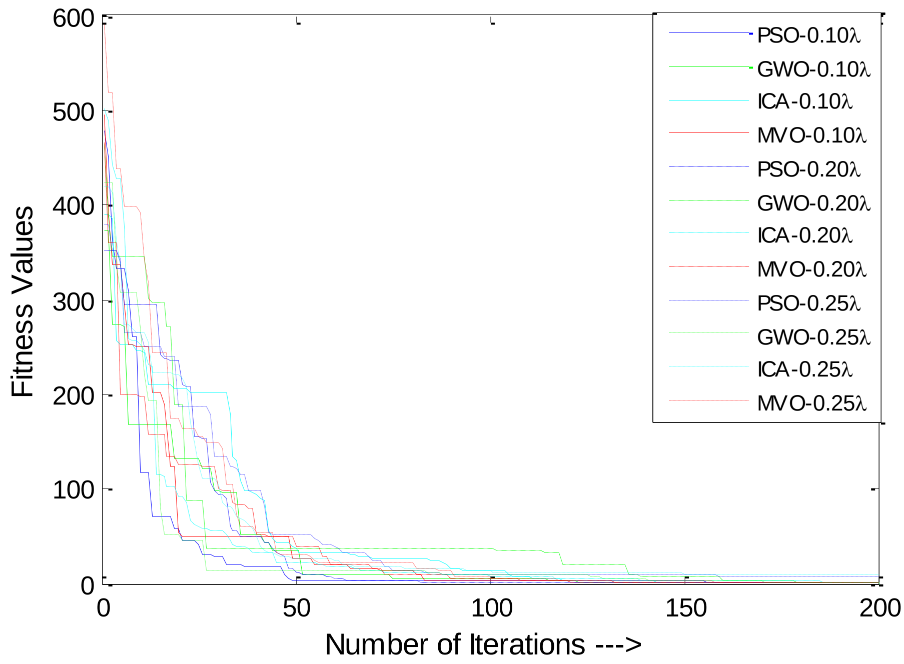

Figure 6. Fitness values versus Number of Iterations

Table 6. Parameter values for the linear array for various inter-element distances.

Patterns	Parameters	Desired values	Obtained values		
			MVO d=0.5λ	MVO d=0.6λ	MVO d=0.4λ
Pencil beam	SLL in dB	-22	-22.0934	-21.664	-22.3405
	VSWR	1.3	1.2359	1.1981	1.3182
Flat-top beam	SLL in dB	-22	-23.1407	-21.1033	-16.743
	VSWR	1.3	1.2444	1.2067	1.4087
	Ripple in dB (75° < ϕ <105°)	0.5	0.57652	-4.7205	0.59074

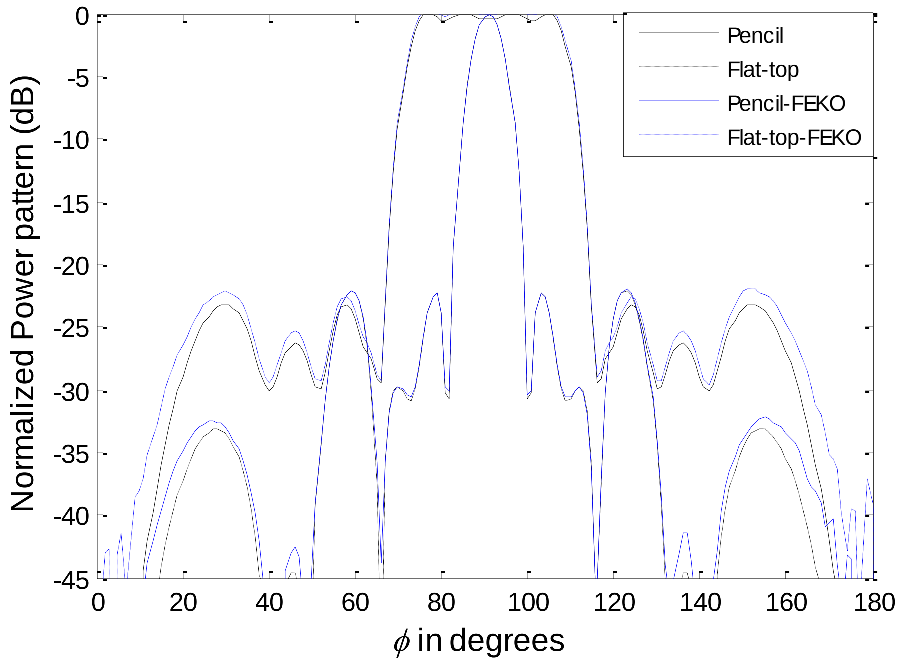

Figure 7. Normalized Power in dB vs ϕ in degrees for the linear array placed at a distance of 0.10λ from the ground plane using MATLAB simulated outputs and FEKO generated outputs.