# Null Steering and Multi-beams Design by Complex Weight of antennas Array with the use of APSO-GA

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***Abstract: -*** An efficient method based on the hybrid model with breeding and subpopulations, between genetic algorithm and a modified particle swarm optimizer for the linear antenna arrays pattern synthesis with prescribed nulls in the interference direction and multi-lobe beam forming by the complex weights of each array element is presented. In general, the pattern synthesis technique that generates a desired pattern is a greatly nonlinear optimization problem. The proposed method is based on the hybrid model algorithm and the linear antenna array synthesis was modeled as a multi-objective optimization problem. Multi-objective optimization is concerned with the maximization of a vector of objectives functions in the directions of desired signal that can be subject of a number of constraints. Several numerical results with the imposed single, multiple and broad nulls sectors are provided and compared with published results to illustrate the performance of the proposed method.

*Key-Words: -* Hybrid model, antenna array, interference suppression, multi- lobe beam forming.

## 1 Introduction

The antenna array pattern synthesis in order to steer nulls to the direction of interference while maintaining the main beam directed to the desired signal has received much attention [1–5]. It plays an important role in communication system, sonar, and radar applications to improve the performance (maximizing signal to interference ratio) and to cancel the jammer signal [6]. Interference suppression in antenna arrays can be achieved by steering nulls in the directions of undesired signals while keeping the main lobe in the direction of user activity by adjusting the excitation amplitude and phase. Recently, evolutionary algorithms such as particle swarm optimization (PSO) [7], simulated annealing (SA) [1], and genetic algorithms (GA) [3] have been studied for array synthesis including null constrains. The evolutionary algorithms can be considered as a powerful and interesting technique for solving large kinds of electromagnetic problems. Advantages of evolutionary computation are the capability to find a global optimum, without being trapped in local optima, and the possibility to face nonlinear and discontinuous problems, with a great number of variables. On the other hand, these algorithms have strong stochastic bases, thus they require a great number of iterations to get significant results. To solve the antenna array pattern synthesis problems, among a number of optimization procedures, the artificial intelligence techniques such as genetic, simulated annealing and tabu search algorithms owing to their simplicity, flexibility and accuracy have received much attention. Genetic algorithm (GA) is a search technique based on an abstract model of Darwinian evolution. Simulated annealing (SA) technique is essentially a local search, in which a move to an inferior solution is allowed with a probability, according to some Boltzmann-type distribution, that decreases as the process progresses. Tabu search (TS) algorithm has been developed to be an effective and efficient scheme for combinatorial optimization that combines a hill-climbing search strategy based on a set of elementary moves and a heuristics to avoid to stops at sub-optimal points and the occurrence of cycles. Recently, particle swarm optimization algorithm (PSO) is proposed for solving global numerical optimization problem. The search techniques mentioned above are the probabilistic search techniques that are simple and easily be implemented without any gradient calculation. This study uses an electromagnetic optimization technique, hybrid particle swarm optimizer with breeding and subpopulation [8]. The technique proposed in this paper is based on hybrid model algorithm to synthesis steered beams with zero in desired direction. The linear antenna array synthesis was modeled as a multi-objectives optimization problem. To verify the validity of the technique, several illustrative examples are simulated.

## 2 Mathematical Formulation

Consider a linear array composed by *2*N* equispaced isotropic antenna elements with interelement spacing *λ /2*. If the element excitations are conjugate-symmetrical about the center of the array, the perturbed array pattern can be written as:

$$F(\theta) = 2\sum_{k=1}^{N} a_k \cos\left(\frac{2\pi}{\lambda} d_k \sin(\theta) + \delta_k\right) \tag{1}$$

Where λ is the wavelength, $\theta$ denotes the angular direction, $a_k$ is the excitation amplitude, $\delta_k$ is the excitation phase and $d_k$ is the $x$ coordinate, normalised to wavelength, of the nth array element.

The radiation diagram of an antenna used in our applications is determined for substrate with the permittivity equal to 3.5, thickness equal to 0.159 *cm* and operating at 5 GHz.

The array factor in dB is given by:

$$P(\theta) = 20\log(F(\theta)_{normalised}) \tag{2}$$

The mathematical statement of the optimization process is:

$$Find\ \max f(v) \rightarrow v_{opt} \tag{3}$$

Where $f(v)$ is the objective function of parameter variables $v$.

The optimization problem can be modeled by minimization the value of difference between the perturbed and the desired patterns. Mathematically, the optimization problem can be written as:

$$f = Max - \int_0^{\pi} \left|F_d(\theta) - F(\theta)\right| d\theta \tag{4}$$

## 3 Hybrid Particle Swarm Optimizer with Breeding and Subpopulations

The hybrid model incorporates one major aspect of the standard GA into the PSO, the reproduction. In the following work, we will refer to the used reproduction and recombination of genes only as breeding. Breeding is one of the core elements that make the standard GA a powerful algorithm. Hence our hypothesis was that a PSO hybrid with breeding has the potential to reach a better solution than the standard PSO. In addition to breeding we introduce a hybrid with both breeding and subpopulations. Subpopulations have previously been introduced to standard GA models mainly to prevent premature convergence to suboptimal points [9]. Our motivation for this extension was that the PSO models, including the hybrid PSO with breeding, also reach suboptimal solutions. Breeding between particles in different subpopulations was also added as an interaction mechanism between subpopulations. The traditional PSO model, described by [10], consists of a number of particles moving around in the search space, each representing a possible solution to a numerical problem. Each particle has a position vector $X_i=(x_{i1},\ldots,x_{id},\ldots,x_{iD})$, a velocity vector $V_i=(v_{i1},\ldots,v_{id},\ldots,v_{iD})$, the position $P_i=(p_{i1},\ldots,p_{id},\ldots,p_{iD})$ and fitness of the best point encountered by the particle, and the index *(g)* of the best particle in the swarm. At each iteration the velocity of each particle is updated according to their best encountered position and the best position encountered by any particle, in the following way:

$$v_{id} = w \times v_{id} + c_1 \times rand\ () \times (p_{id} - x_{id}) + c_2 \times rand\ () \times (p_{gd} - x_{id}) \tag{5}$$

$w$ is the inertia weight described in [11] and $P_{gd}$ is the best position known for all particles. $C_1$ and $C_2$ are random values different for each particle and for each dimension. If the velocity is higher than a certain limit, called $V_{max}$, this limit will be used as the new velocity for this particle in this dimension, thus keeping the particles within the search space. The position of each particle is updated at each iteration. This is done by adding the velocity vector to the position vector;

$$x_{id} = x_{id} + v_{id} \tag{6}$$

The particles have no neighbourhood restrictions, meaning that each particle can affect all other particles. This neighbourhood is of type star (fully connected network), which has been shown to be a good neighbourhood type in [12]. Fig.1 shows the structure illustration of the hybrid model.

```
Begin
    Initialise
    While (not terminate-condition) do
      Begin
        Evaluate
        Calculate new velocity vectors
        Move
        Breed
      End
End
```

Fig.1 The structure of the hybrid model.

The breeding is done by first determining which of the particles that should breed. This is done by iterating through all the particles and with probability $p_b$ (breeding probability = 0.6), mark a given particle for breeding. Note that the fitness is not used when selecting particles for breeding. From the pool of marked particles we now select two random particles for breeding. This is done until the pool of marked particles is empty. The parent particles are replaced by their offspring particles, thereby keeping the population size fixed. The position of the offspring is found for each dimension by arithmetic crossover on the position of the parents:

$$Child_1(x_i) = p_i * parent_1(x_i) + (1 - p_i) * parent_2(x_i) \quad (7)$$

$$Child_2(x_i) = p_i * parent_2(x_i) + (1 - p_i) * parent_1(x_i) \quad (8)$$

Where $p_i$ is a uniformly distributed random value between 0 and 1. The velocity vectors of the offspring are calculated as the sum of the velocity vectors of the parents normalized to the original length of each parent velocity vector.

$$Child_1(\vec{v}) = \frac{parent_1(\vec{v}) + parent_2(\vec{v})}{\left|parent_1(\vec{v}) + parent_2(\vec{v})\right|}\left|parent_1\right| \quad (9)$$

$$Child_2(\vec{v}) = \frac{parent_1(\vec{v}) + parent_2(\vec{v})}{\left|parent_1(\vec{v}) + parent_2(\vec{v})\right|}\left|parent_2\right| \quad (10)$$

The arithmetic crossover of positions in the search space is one of the most commonly used crossover methods with standard real valued GA, placing the offspring within the hypercube spanned by the parent particles. The main motivation behind the crossover is that offspring particles benefit from both parents. In theory this allows good examination of the search space between particles. Having two particles on different suboptimal peaks breed could result in an escape from a local optimum, and thus aid in achieving a better one. We used the same idea for the crossover of the velocity vector. Adding the velocity vectors of the parents results in the velocity vector of the offspring. Thus each parent affects the direction of each offspring velocity vector equally. In order to control that the offspring velocity was not getting too fast or too slow, the offspring velocity vector is normalized to the length of the velocity vector of one of the parent particles. The starting position of a new offspring particle is used as the initial value for this particle's best found optimum ($\vec{p}_i$). The motivation for introducing subpopulations is to restrict the gene flow (keeping the diversity) and thereby attempt to evade suboptimal convergence. The subpopulation hybrid PSO model is an extension of the just described breeding hybrid PSO model. In this new model the particles are divided into a number of subpopulations. The purpose of the subpopulations is that each subpopulation has its own unique best known optimum. The velocity vector of a particle is updated as before except that the best known position ($\vec{p}_g$ in the formula) now refers to the best known position within the subpopulation that the particle belongs to. In terms of the neighbourhood topology suggested by Kennedy in [10], each subpopulation has its own star neighbourhood. The only interaction between subpopulations is if parents from different subpopulations breed. Breeding is now possible both within a subpopulation but also between different subpopulations. An extra parameter called probability of same subpopulation breeding $p_{sb}$ determines whether a given particle selected for breeding is to breed within the same subpopulation (probability $p_{sb}$ = 0.6), or with a particle from another subpopulation (probability 1-$p_{sb}$). Replacing each parent with an offspring particle ensures a constant subpopulation size.

# 4 Numerical Results

To demonstrate the validity of the proposed method that synthesizes the array pattern with suppress single, multiple, and broad-band interference signal with the imposed directions and maximum tolerance of SLL using complex current excitations, several computer simulation examples using an equispaced linear array with one half wave interelement spaced 16 isotropic elements were performed. The simulation is run on *hp Elitebook i5* computer with 4 GB of RAM. The algorithm of hybrid model is implemented using Matlab.

The results of steering beam in the direction of the desired signal and creating single suppressed wide band interferences are presented in Figs 2, 5 and 8.

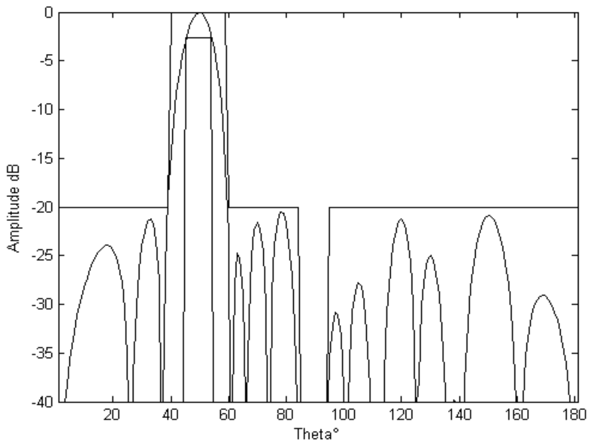



Fig.2 Pattern synthesis with a wide single null imposed at 0° and steering lobe at −40°.

The total numbers of function evaluations is 200 iterations for this kind of excitation with 3 sub-swarms of 40 particles each one.

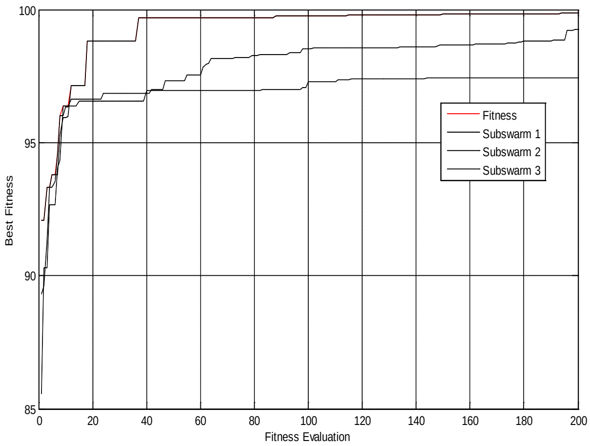
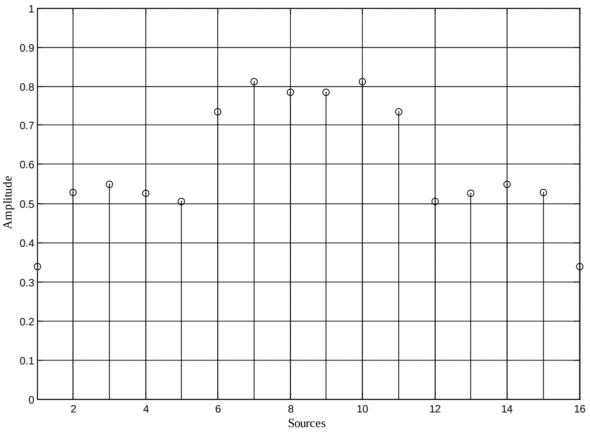



Fig.3 Convergence of the algorithm versus the number of iterations.

The hybrid model APSO-AG synthesis results of amplitudes phases are traced in Fig.4 and are given in Table 1.



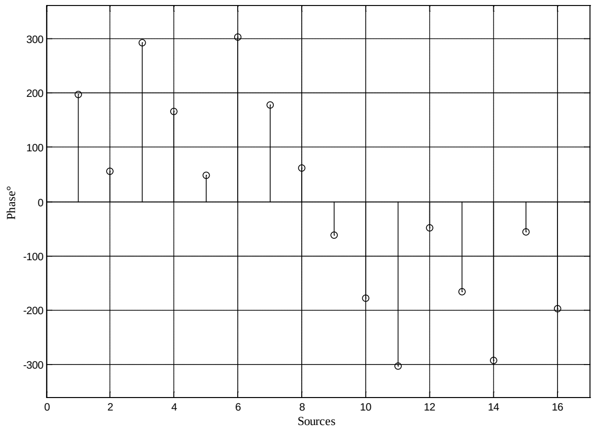




Fig.4 The element excitation required to achieve the desired pattern.

The array pattern synthesis is shown in Fig.5. From this figure we can see that the maximum sidelobe level is lower than -20 dB.

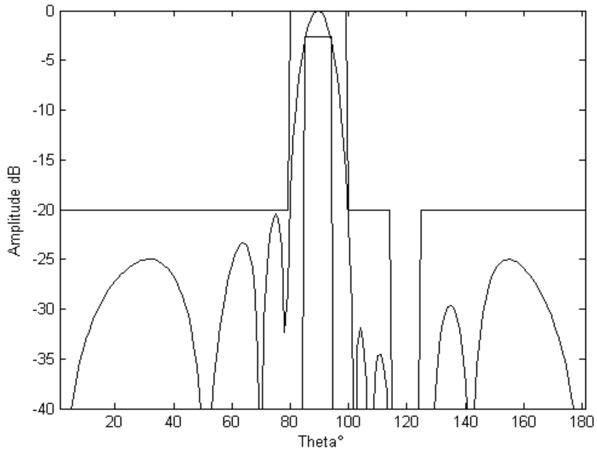



Fig.5 Pattern synthesis with a wide single null imposed at 30° and steering lobe at 0°.

For the design specification of amplitude-phase synthesis APSO-AG is run for 200 generations.

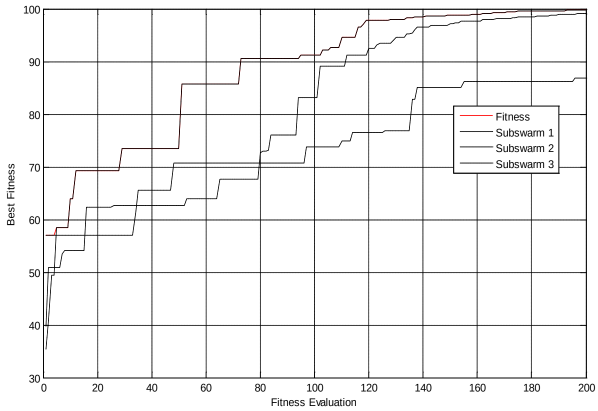



Fig.6 Convergence of the algorithm versus the number of iterations.

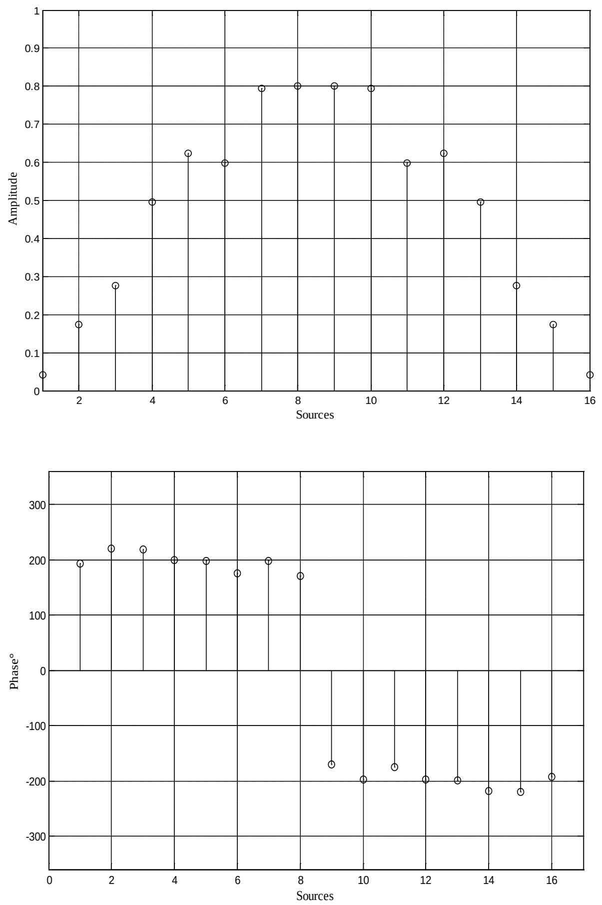



Fig.7 The element excitation required to achieve the desired pattern.

The Fig.8 shows the normalized absolute power pattern in dB, the maximum side lobe level reach - 20 dB with a wide and deep single null imposed at 0° and steering lobe at 35°, we note that there is a very good agreement between desired and obtained results. The convergence of the algorithm is shown in Fig.9.

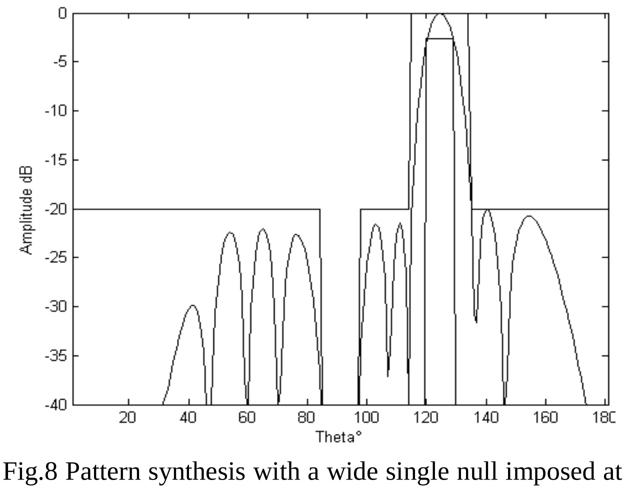



Fig.8 Pattern synthesis with a wide single null imposed at 0° and steering lobe at 35°.

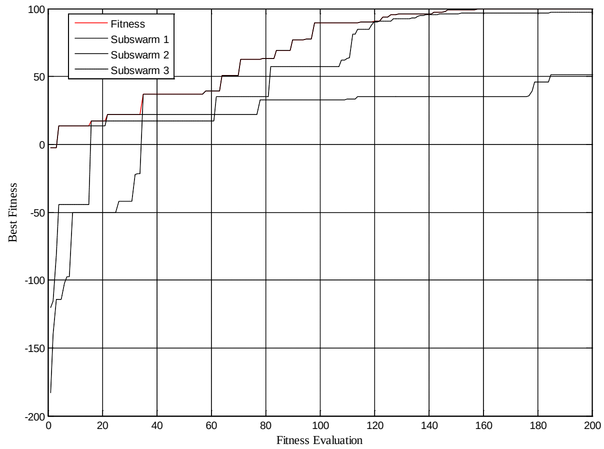



Fig.9 Convergence of the algorithm versus the number ofiterations.

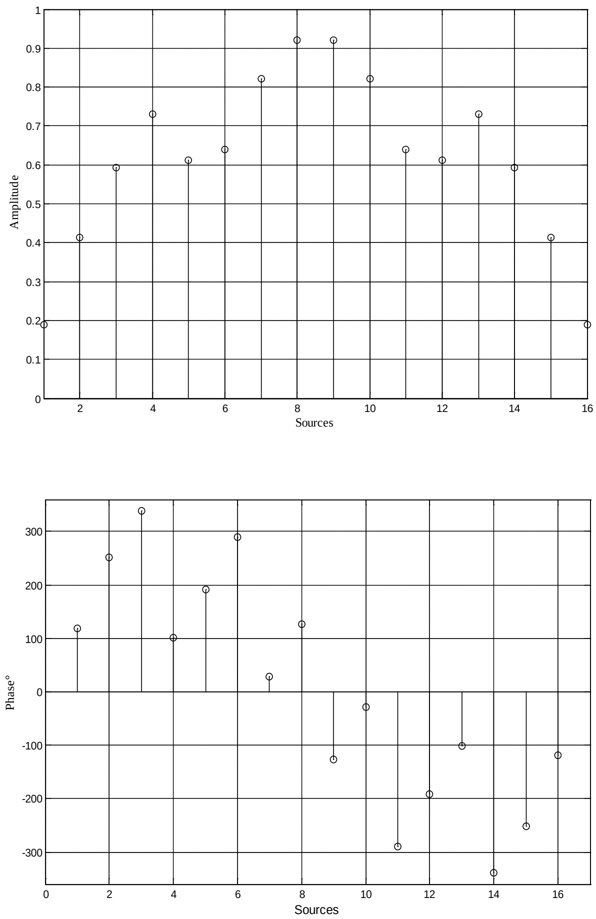



Fig.10 The element excitation required to achieve the desired pattern.

The best results obtained by the hybrid model are shown in Fig.10, and the values are presented in Table1.

The proposed method can create the multiple mainbeams in the directions of the different users.

Figs.11 and 14 have shown the result of a simulation with 16 isotropic elements, cancelling interferers with -60°, and two nulls at -60°and wide null at 0°, respectively. And two steering lobes at -20° and 40°.

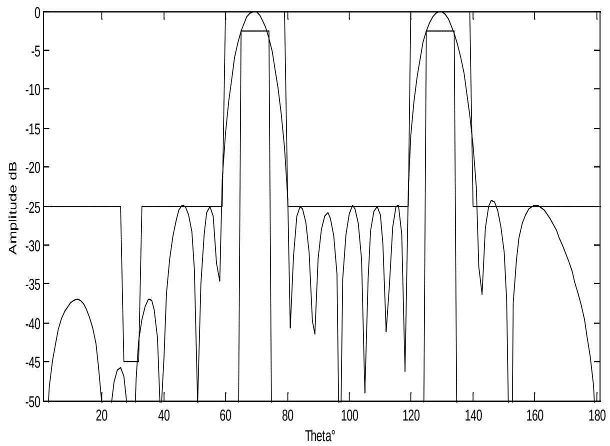



Fig.11 The radiation pattern with a sector interference nulling around −60° and two steering lobes at −20° and 40°.

After 400 iterations, the fitness value reach to it maximum and the optimization process ended due to meeting the design goal. The convergence curve of fitness is presented in Fig.12.

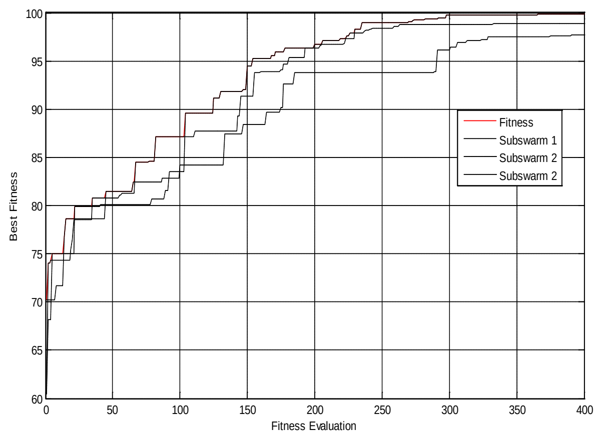



Fig.12 Convergence of the algorithm versus the number ofiterations.

The element excitations required to achieve the desired pattern are traced in Fig.13 and shown in Table 2.

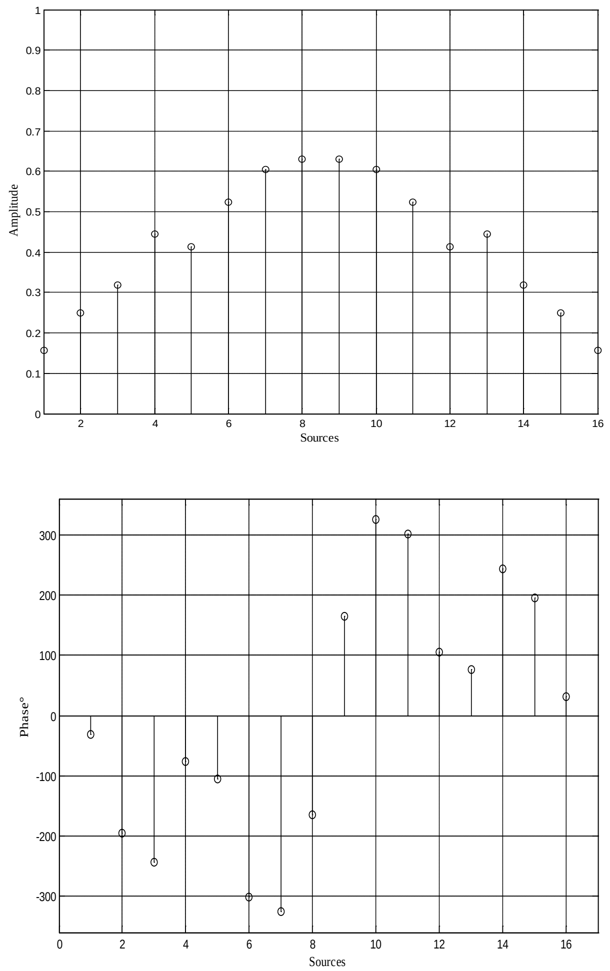



Fig.13 The element excitation required to achieve the desired pattern.

We show the comparison of the far-field patterns among the hybrid model simulation results, and the sequential quadratic programming (SQP) algorithm simulated results in [13]. An improvement of about 10 dB in the side lobe level is obtained.

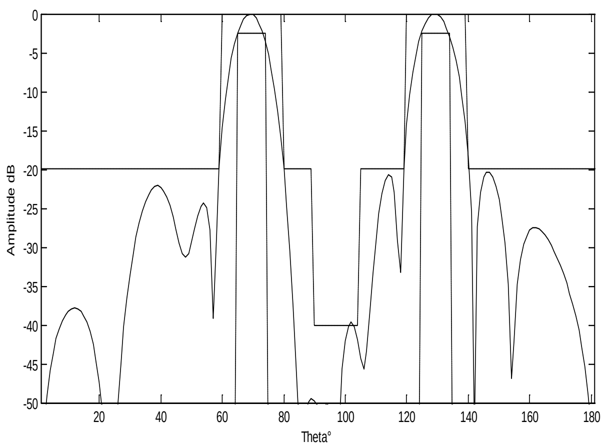



Fig.14 The radiation pattern with a wide sectors interference nulling around 0° and two steering lobes at −20° and 40°.

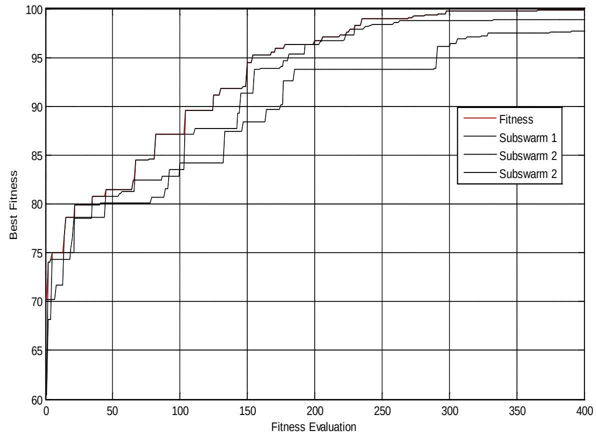



Fig.15 Convergence of the algorithm versus the number of iterations.

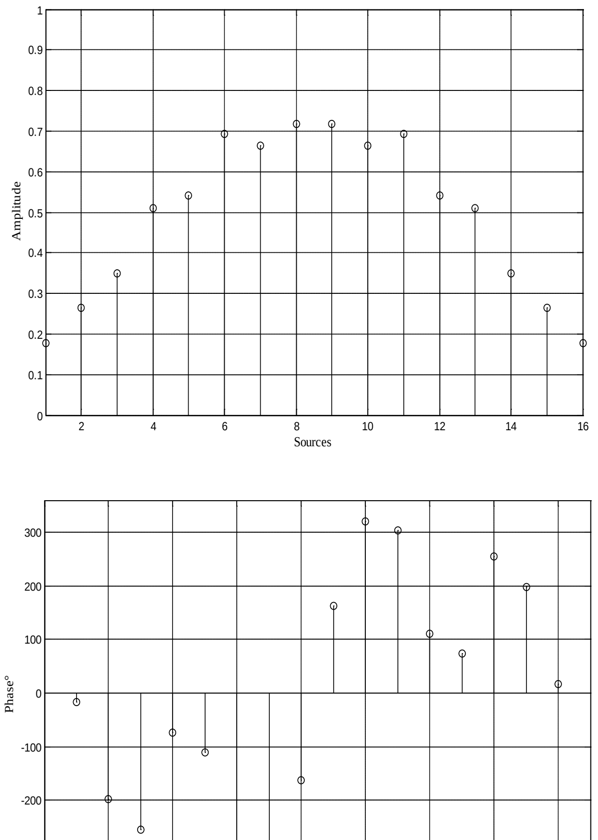



Fig.16 The element excitation required to achieve the desired pattern.

we introduce the cases of an array with 16 equispaced isotropic elements with λ/2 interelement spacing, which is supposed to generate three beams steered towards the three angles $\theta_1$= -30°, $\theta_2$ = 0° and $\theta_3$=30° with interference nulling at -15° and 15° respectively.

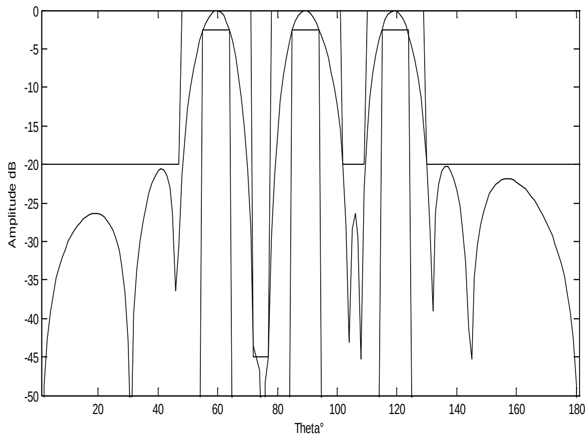



Fig.17 The radiation pattern with interference nulling at -15° and tree steering lobes at −30°, 0 and 30°.

The corresponding number of iterations is 1000 iterations as shown in Fig.18.

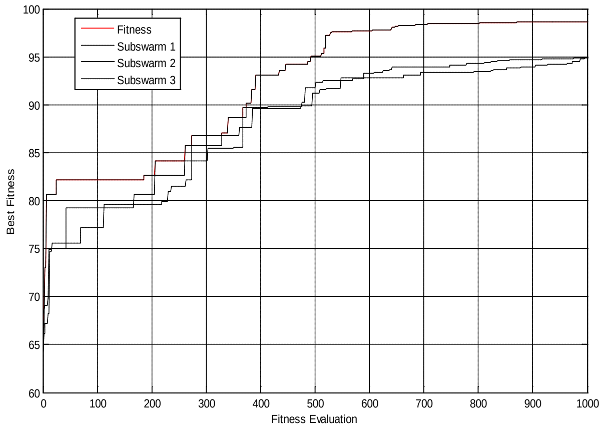
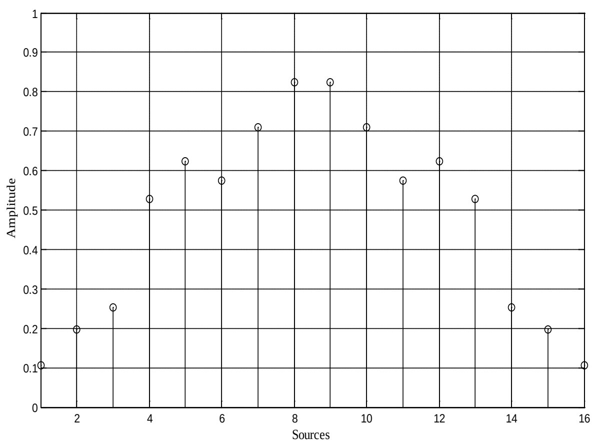



Fig.18 Convergence of the algorithm versus the number ofiterations.



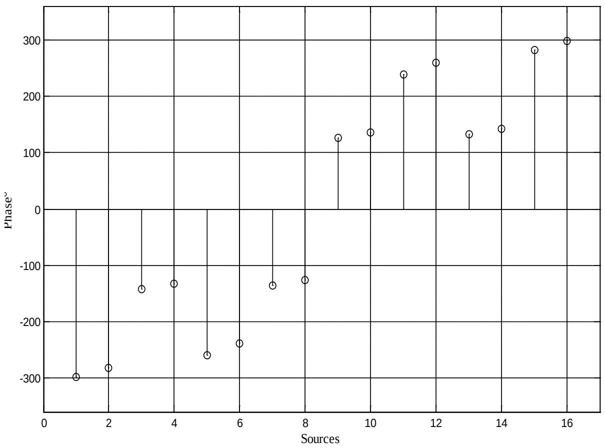



Fig.19 The element excitation required to achieve the desired pattern.

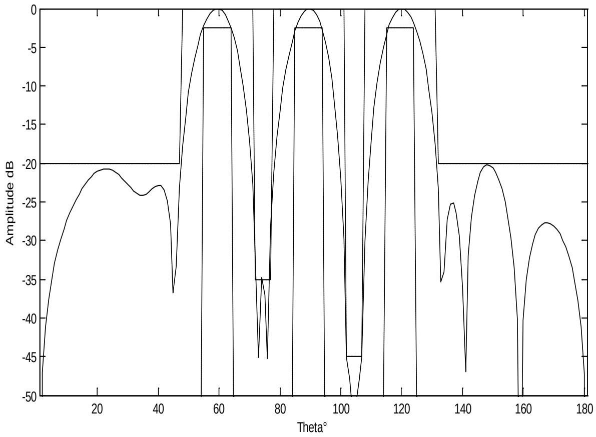



Fig.20 The radiation pattern with interference nulling at 15° and tree steering lobes at −30°, 0 and 30°.

The best fitness value returned versus the number of calls to the fitness evaluator was achieved after 2000.

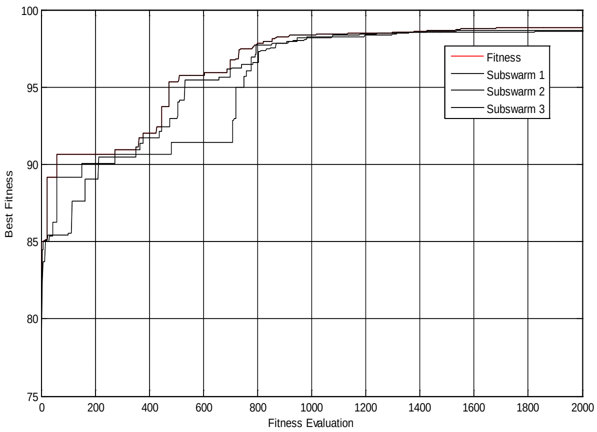



Fig.21 Convergence of the algorithm versus the number of iterations.

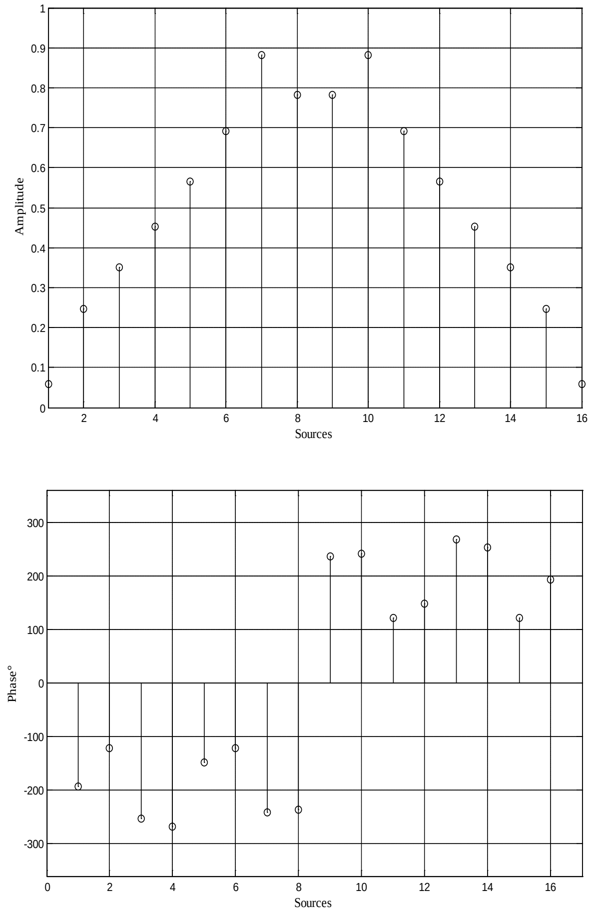



Fig.22 The element excitation required to achieve the desired pattern.

With the same array as the last section, and the same type of synthesis, we present synthesis results of multibeam array as indicated in the Fig.23, it shows the radiation pattern with four steering lobes at 30°,0°, 14° and 38°, null at -30°.

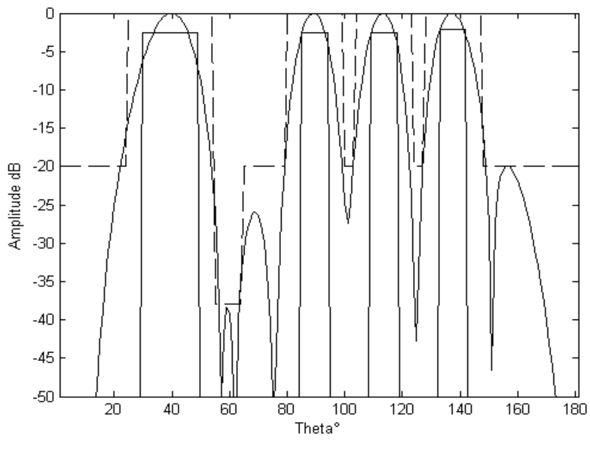



Fig.23 The radiation pattern with four steering lobes at -30°,0°,14° and 38°, and null around -30°.

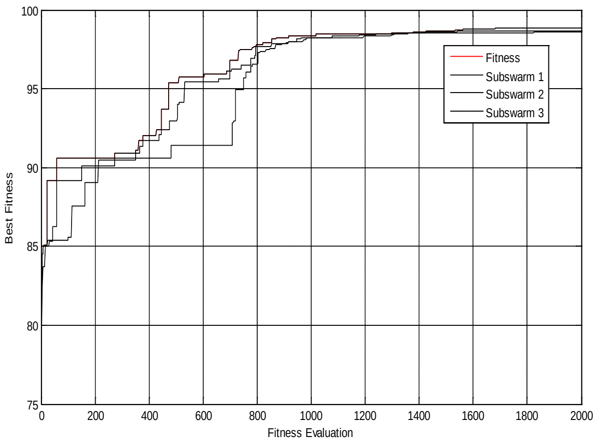



Fig.24 Convergence of the algorithm versus the number of iterations.

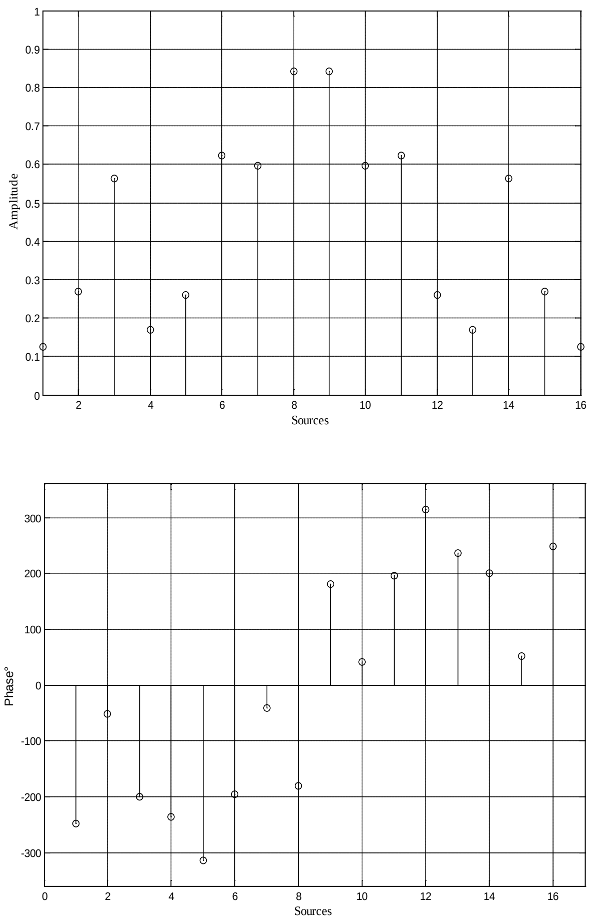



Fig.25 The element excitation required to achieve the desired pattern.

The best results obtained by the hybrid model are listen in table 3.

# 5 Conclusion

A method for antenna array pattern synthesis based on the hybrid model algorithm has been presented. The problem can be modeled as a multicriteria optimization, where the optimization objectives are the maximum of the signal at the direction of wanted sources subject to the constraints of minimization of the signal at the direction of unwanted sources. The numerical results show that the complex excitation control using the hybrid model algorithm is efficient for prescribed single, multiple and broad nulls, and control the null depth and maximum of sidelobe level.

Table 1. Amplitude and phase distributions

| N° | Fig.2 | | Fig.5 | | Fig.8 | |
|---|---|---|---|---|---|---|
| | Amplitude | Phase° | Amplitude | Phase° | Amplitude | Phase° |
| **1** | 0.3395 | 197.4527 | 0.0415 | 193.5967 | 0.1886 | 118.9861 |
| **2** | 0.5283 | 55.0612 | 0.1741 | 220.7091 | 0.4125 | 252.0613 |
| **3** | 0.5497 | 292.0538 | 0.2767 | 217.7984 | 0.5932 | 337.9592 |
| **4** | 0.5268 | 166.3927 | 0.4947 | 198.4783 | 0.7315 | 101.6828 |
| **5** | 0.5050 | 48.7243 | 0.6246 | 198.3637 | 0.6131 | 190.6975 |
| **6** | 0.7350 | 302.8540 | 0.5982 | 175.5256 | 0.6393 | 290.0599 |
| **7** | 0.8115 | 177.3132 | 0.7941 | 198.0944 | 0.8223 | 27.9489 |
| **8** | 0.7835 | 61.4841 | 0.8008 | 170.3346 | 0.9206 | 126.6695 |
| **9** | 0.7835 | -61.4841 | 0.8008 | -170.334 | 0.9206 | -126.669 |
| **10** | 0.8115 | -177.313 | 0.7941 | -198.094 | 0.8223 | -27.9489 |
| **11** | 0.7350 | -302.854 | 0.5982 | -175.525 | 0.6393 | -290.059 |
| **12** | 0.5050 | -48.7243 | 0.6246 | -198.363 | 0.6131 | -190.697 |
| **13** | 0.5268 | -166.392 | 0.4947 | -198.478 | 0.7315 | -101.682 |
| **14** | 0.5497 | -292.053 | 0.2767 | -217.798 | 0.5932 | -337.959 |
| **15** | 0.5283 | -55.0612 | 0.1741 | -220.709 | 0.4125 | -252.061 |
| **16** | 0.3395 | -197.452 | 0.0415 | -193.596 | 0.1886 | -118.986 |

Table 2. Amplitude and phase distributions

| N° | Fig.11 | | Fig.14 | | Fig.17 | |
|---|---|---|---|---|---|---|
| | Amplitude | Phase° | Amplitude | Phase° | Amplitude | Phase° |
| **1** | 0.1566 | 31.1001 | 0.1768 | 16.919 | 0.1064 | 297.416 |
| **2** | 0.2501 | 195.178 | 0.2641 | 198.839 | 0.1972 | 281.666 |
| **3** | 0.3189 | 243.358 | 0.3503 | 254.525 | 0.2533 | 142.448 |
| **4** | 0.4457 | 75.8367 | 0.51 | 73.7454 | 0.5272 | 132.88 |
| **5** | 0.4134 | 104.696 | 0.542 | 110.162 | 0.6225 | 259.24 |
| **6** | 0.523 | 301.885 | 0.6921 | 303.822 | 0.5755 | 238.075 |
| **7** | 0.6037 | 326.041 | 0.6645 | 320.747 | 0.7106 | 135.155 |
| **8** | 0.6307 | 165.246 | 0.7186 | 163.344 | 0.823 | 126.549 |
| **9** | 0.6307 | -165.24 | 0.7186 | -163.34 | 0.823 | -126.54 |
| **10** | 0.6037 | -326.04 | 0.6645 | -320.74 | 0.7106 | -135.15 |
| **11** | 0.523 | -301.88 | 0.6921 | -303.82 | 0.5755 | -238.07 |
| **12** | 0.4134 | -104.69 | 0.542 | -110.16 | 0.6225 | -259.24 |
| **13** | 0.4457 | -75.836 | 0.51 | -73.745 | 0.5272 | -132.88 |
| **14** | 0.3189 | -243.35 | 0.3503 | -254.52 | 0.2533 | -142.44 |
| **15** | 0.2501 | -195.17 | 0.2641 | -198.83 | 0.1972 | -281.66 |
| **16** | 0.1566 | -31.100 | 0.1768 | -16.919 | 0.1064 | -297.41 |

Table 3. Amplitude and phase distributions

| N° | Fig.20 | | Fig.23 | |
|---|---|---|---|---|
| | Amplitude | Phase° | Amplitude | Phase° |
| **1** | 0.0592 | 192.8 | 0.1244 | 248.509 |
| **2** | 0.2465 | 120.762 | 0.2678 | 52.064 |
| **3** | 0.3496 | 252.09 | 0.5634 | 200.122 |
| **4** | 0.4516 | 267.748 | 0.169 | 236.001 |
| **5** | 0.5649 | 147.559 | 0.2592 | 314.439 |
| **6** | 0.6924 | 122.12 | 0.6237 | 195.034 |
| **7** | 0.882 | 241.679 | 0.5956 | 41.367 |
| **8** | 0.7826 | 235.972 | 0.841 | 181.117 |
| **9** | 0.7826 | -235.972 | 0.841 | -181.117 |
| **10** | 0.882 | -241.679 | 0.5956 | -41.367 |
| **11** | 0.6924 | -122.12 | 0.6237 | -195.034 |
| **12** | 0.5649 | -147.559 | 0.2592 | -314.439 |
| **13** | 0.4516 | -267.748 | 0.169 | -236.001 |
| **14** | 0.3496 | -252.09 | 0.5634 | -200.122 |
| **15** | 0.2465 | -120.762 | 0.2678 | -52.064 |
| **16** | 0.0592 | -192.8 | 0.1244 | -248.509 |

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