Linear Antenna Array Optimization by Using Evolutionary Algorithms

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Abstract

In this paper, the Invasive Weeds optimization(IWO) is exploited to produce the array radiation pattern that is nearest to the desired objective which exhibits sidelobe level (SLL) suppression and/or null placement. The inter-element position of even element Linear Arrays Array (LAA) is optimized and relocated whilst maintaining uniform excitation over the array aperture and the phase of the antenna . IWO method is utilized here as an adaptive beam former that makes a uniform linear antenna array steer the main lobe towards the Direction of Arrival (DoA) of a desired signal, form nulls towards the respective DoA of several interference signals and achieve low side lobe level (SLL). The IWO algorithm can be successfully used to locate the optimum element positions based on symmetric. The results obtained showed that the IWO algorithm is capable of finding the optimal solution in most cases with superior performance over conventional and particle swarm optimization (PSO) methods.

Keywords: Invasive Weeds optimization (IWO) , Particle Swarm Optimization (PSO), Linear Antenna Arrays (LAA), Side Lobe Level (SLL).

الخلاصة

في هذا البحث تم استعمال خوارزمية العشبة الضارة Invasive Weeds optimization (IWO) لغرض الحصول على نمط الإشعاع الذي هو أقرب إلى الهدف المطلوب و الذي يلغي الحزم الجانبية الغير مرغوب فيها sidelobe (SLL) مع تقليل عرض الحزمة الرئيسية. تم تحسين مواقع العناصر الداخلية في الهوائي الخطي Linear Arrays Array (LAA) مع الحفاظ على الشدة المنتظمة و الطور للهوائي و قد استخدمت خوارزمية IWO بنجاح في تحديد المواقع الدقيقة للعناصر الداخلية للهوائي. وتستخدم IWO بتوجيه وتقليل عرض الحزمة الرئيسية mainlob (ML) للمجموعة الموحدة للهوائي الخطي نحو اتجاه الوصول Direction of Arrival(DoA) من الإشارة المطلوبة مع انخفاض مستوى الحزمة الجانبية (SLL). وأظهرت النتائج أن خوارزمية العشبة الضارة IWO قادرة على إيجاد الحل الأمثل في معظم الحالات مع أداء متفوق على التحسين على حساب الطرائق التقليدية وخوارزمية الحشد الجزئي particle swarm optimization (PSO).

الكلمات الدالة: خوارزمية العشبة الضارة, وخوارزمية الحشد الجزئي, الهوائي الخطي, الحزمة الجانبية.

1. Introduction

The antenna arrays are now the milestone for modern communication systems. Numerous studies on antenna arrays have been widely applied in phase array radar, satellite communications and other fields. The array pattern of an antenna array should possess high power gain, lower sidelobe levels, controllable beamwidth. They play a major role in the design of smart antenna arrays. The antenna arrays can be steered electronically toward the desired destination without the involvement of any mechanical parts using smart antenna algorithms [Deng J.H. et al., 2011, Jabbar A.N., 2011]. Antenna design problems and applications always involve optimization processes that must be solved efficiently and effectively. T o solve an antenna problem, an engineer must envisage a proper view of the problem in the hand. So, the design is the struggle of the designer for finding a solution which best suits the sketched view. In support of this need, there have been various optimization techniques proposed by antenna designers. Researchers around the world are investigating the possibility of building the optimum array. This array should have no side-lobe levels (SLLs). There are many approaches to achieve an optimized array. The ways to improve array response might concentrate on increasing the directivity (thinning the beam width angle) or decreasing the SLL or pushing the SLLs away from the main-lobe (ML) [Singh H., Jha R.M. 2012] .

Many approaches were put to test to achieve this goal. These approaches are either statistical approaches, evolutionary , or modified algorithms . The physical locations of the elements are left intact. This means that the tuning frequencies are not altered. In this research [Li N., Appl., 2011, Wang X.K., Jiao, Y.C., Tan, Y-Y. 2012]. The desired radiation pattern of the antenna array can be realized by determining the physical layout of the antenna array and by choosing suitable complex excitation of the amplitude and phase of the currents that are applied on the array elements. Thus, evolutional optimization algorithm such as genetic algorithm (GA), simulated annealing (SA), and particle swarm optimization (PSO), and Invasive Weed Optimization (IWO) have been introduced in antenna designs. [Rattan M., Patterh M. S., and Sohi B. S. 2008].

Currently, IWO algorithm is applied in many practical problems especially in electromagnetics. It has been used to obtain excitation coefficients of reconfigurable antenna arrays [Mallahzadeh A. R., 2008]; optimize the amplitude, phase, spacing and position of the elements in 37-element hexagon array and suppress the SLL of linear array [Bevelacqua P. J. and Balanis C. A., 2007].

2. Linear Antenna Array Synthesis

A one-dimensional symmetric LAA is assumed which is placed along the x-axis as depicted in Fig. 1. It has even number of elements up to **N**. The array factor is.

$$AF(\emptyset) = 2\sum_{n=1}^{N} I_n \cos[kd_n \cos(\emptyset) + \beta_n] \qquad (1)$$

where k, I_n, β_n, Ø , and d_n are the wave number $\beta= 2\pi/\lambda$, excitation amplitude, phase, observation angle, and location of the nth element from the reference node at the origin, respectively. Assuming uniform excitation of amplitude, $\mathbf{I_n} = 1$ and phase $\boldsymbol{\beta_n} = 0$, the array factor can be written as [Yang, F. et al, 2007].

$$AF(\emptyset) = 2\sum_{n=1}^{N} \cos[kd_n \cos(\emptyset)]$$

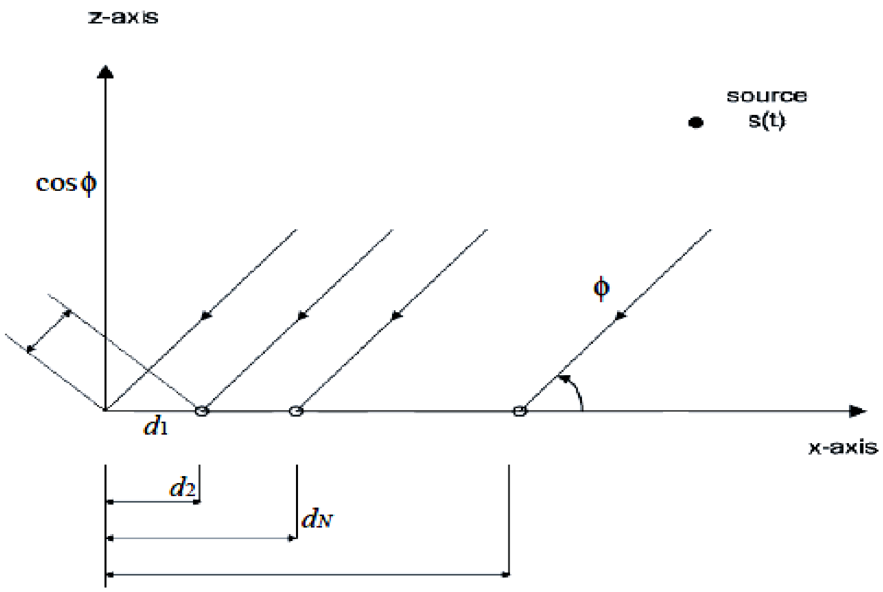

Figure 1: 2N linear array geometry.

3. Invasive Weed Optimization Method

To simulate the colonizing behavior of weeds some basic properties of the process is considered below [Mehrabian A.R. and Lucas C. 2006, Akbarzadeh A. and Sadeghi M., June 2011]

1-First of all, the N parameters (variables) that need to be optimized should be selected. Then, for each of these variables in the N-dimensional solution space, a maximum and minimum value should be assigned (defining the solution space).

2- A finite number of seeds are being randomly dispread over the defined solution space. In other words, each seed takes a random position in the N-dimensional problem space. Each seed's position is an initial solution, containing N values for the N variables, of the optimization problem (initialize population).

3- Each initial seed grows to a flowering plant. That is, the fitness function, defined to represent the goodness of the solution, returns a fitness value for each seed. After assigning the fitness value to the corresponding seed, it is called a plant (Evaluate the fitness of each individual).

4- Before the flowering plants produce new seeds, they are ranked based on their assigned fitness values. Then, each flowering plant is allowed to produce seeds depending on its ranking in the colony. In other words, the number of seeds each plant produces depends on its fitness value or ranking and increases from the minimum possible seeds production, S_{min} , to its maximum, S_{max}. Those seeds that solve the problem better correspond to the plants which are more adapted to the colony and consequently produce more seeds. This step adds an important property to the algorithm by allowing all of the plants to participate in the reproduction contest (Rank the population and reproduce new seeds).

5- The produced seeds in this step are being dispread over the search space by normally distributed random numbers with mean equal to the location of the producing plants and varying standard deviations. The standard deviation (SD) at the present time step can be expressed by Eq. 2 [Halder U., Das S., Maity D., etal ,2011]

$$\sigma_{iter} = \frac{(iter_{max} - iter)^n}{iter_{max}^n}\left(\sigma_{initial} + \sigma_{final}\right) + \sigma_{final} \quad (2)$$

where $iter_{max}$ is the maximum number of iterations, $\boldsymbol{\sigma}_{iter}$ is the SD at the present step and n is the nonlinear modulation index.

6- After that all seeds have found their positions over the search area, the new seeds grow to the flowering plants and then, they are ranked together with their parents. Plants with lower ranking in the colony are eliminated to reach the maximum number of plants in the colony, . It is obvious that the number of fitness evaluations, the population size, is more than the maximum number of plants in the colony (competitive exclusion).

7- Survived plants can produce new seeds based on their ranking in the colony. The process is repeated at step 3 till either the maximum number of iteration is reached or the fitness criterion is met (repeat).

3.1. Competitive Exclusion

If a plant leaves no offspring then it would go extinct, otherwise they would take over the world. Thus, there is a need for some kind of competition between plants for limiting the maximum number of plants in a colony. After passing some iterations, the number of plants in a colony will reach its maximum level by fast reproduction, however, it is expected that the fitter plants have been reproduced more than the undesirable plants. By reaching the maximum number of plants in the colony (P_{max}), a mechanism for eliminating the plants with poor fitness in the generation activates. The elimination mechanism works as follows: when the maximum number of weeds in a colony is reached, each weed is allowed to produce seeds according to the mechanism mentioned in the section 3 item 3. The produced seeds are then allowed to spread over the search area according to section 3 item 4. When all seeds have found their position in the search area, they are ranked together with their parents (as a colony of weeds). Next, the weeds with lower fitness are eliminated to reach the maximum allowable population in a colony. In this way, the plants and offsprings are ranked together and the ones with better fitness survive and are allowed to replicate. The population control mechanism is also applied to their offspring up to the end of a given run, realizing competitive exclusion. Consider a set of population or swarm of matrix X, with elements that are referred as plants or agents. Each plant represents possible solution in defined population size, maxplant. For an N-dimensional problem, the position of the i-th plants (i = 1,..., maxplant) is represented as:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1N} \\ x_{21} & x_{22} & \cdots & x_{2N} \\ & \vdots & & \\ x_{i1} & x_{i2} & \cdots & x_{iN} \end{bmatrix}$$

i.e., the position coordinates of the elements. x_{i1} is limited between search space , The i-th plant in the solution space is determined by fitness function value which depends on the plant value. Every time the value of the fitness function i.e., F is minimized, the plant values is improved by new generations of seeds, each plant will generate number of seeds which are limited between two boundaries, $seed_{max}$ and $seed_{min}$. These seeds spread over the search space according to Eq. 2 and will generate new plants during in search space to fine new generation [Mallahzadeh A. R.,2008].

The IWO is employed to optimize the optimum element position in order to improve the radiation pattern of the LAA, with maxplant = 60. The objective of the algorithm is to find the optimum values G, that corresponds to the minimum value of the fitness function, F_{min}. The fitness function identifies how good the value vector of each plant satisfies the requirements of the optimization problem. The fitness function is computed by Eq. 3:

$$F = \sum_{s=i}^{s=j} |AF(\phi_s)|^2 + \sum_{n} |AF(\phi_n)|^2 \qquad (3)$$

where s is the region where the SLL is suppressed and n is the angle where the nulls are placed. As the fitness function decreases, the radiation pattern improves with related plant's value $\mathbf{x_{iN}}$ .Therefore, when the fitness function discovers its optimized minimum value, the IWO algorithm will terminate successfully.

4. Particle Swarm optimization

PSO was originally created by Kennedy et al. during their observation of wild life communities. Thereafter, they discovered the optimization capability of this algorithm. The PSO is based on the observation of how the bird flocks or fish schools or any similar communities behave during their mass migration from one area to another. These particles tend to organize themselves in tight formation to follow the leader which has the best fitness. Every particle should maintain a distance from its neighbor particle to avoid collision, unlike the IWO that allows the particles to coincide on the same spot. Each particle is a candidate for a solution. Once one of the particles discovers a solution, the rest of the particles follow it. During the process the other particles are sweeping the area for better solutions to take the lead. To formulate the algorithm, first start by generating the particle population randomly using a uniform probability density and then Eq.4.1and 4.2 are used for updating both of the velocity and the position of each particle [Kennedy J. Eberhart R. 1995].

$$v_i((i))(t) = w * v_i((i-1)) + c_1 1 r_1 1 (p_i besti(t) - p_i i(t-1) + c_2 2 r_2 2 (g_i besti - p_i i(t-1) \quad (4.1)$$

$$p_i = p_i(t-1) + v_i(t) \quad (4.2)$$

Where w is inertia weight, c_1 and c_2 are acceleration constants and r is a random number, the range [0,1]. For equation (4.1), the first part represents the inertia of pervious velocity; the second part is the "cognition" part, which represents the private thinking by itself; the third part is the "social" part, which represents the cooperation among the particles. $pbest_i$ is the personal best position recorded by particle i, while g_{besti} is the global best position obtained by any particle in the population.

However, for the highly connected networks, the faster convergence comes at the price of susceptibility to local minima, mainly due to the fact that the extent of coverage in the search space is less than for less connected social networks. For sparsely connected networks with a large amount of clustering in neighborhoods, it can also happen that the search space is not covered sufficiently to obtain the best possible solutions. Each cluster contains individuals in a tight neighborhood covering only a part of the search space. Within these network structures there usually exist a few clusters, with a low connectivity between clusters. Consequently information on only a limited part of the search space is shared with a slow flow of information between clusters [Tanji, Y., Matsushita H., Sekiya,H., September 2011].

5. Results and Discussion

A 2N-element LAA with different numbers of elements and desired radiation pattern have been considered to assess the effectiveness of the IWO in the optimization. The LAA is assumed to be symmetric about the x-axis with uniform interelement spacing of $\lambda_0 = \lambda/2$. Initially, the initial plants, X is randomly generated in the range of 0 to 1.5 to produce more diverse possible solutions. Some boundary conditions are also defined to D_n which is allowed to vary from $0.8\lambda_0$ to $1.5\lambda_0$. The applied parameters are:

IWO parameters

n_ini = 10; % number of initial plants
itmax = 10; % max number of iterations
No. of run = 1; % numbers of runs
plant_max_no= 60; % max no. of plants
seedmax= 5; % max number of seeds

PSO parameters

xmax = 4; % maximum of initialization space
xmin =0; % minimum of initialization space
wf = 0.00000001; % final value of standard deviation
wini= 1; % initial value of standard deviation
n = 3; % nonlinear modulation index
seedmin= 0; % min number of seeds

n = 50; % Size of the swarm " no of birds "
iteration =10; % Maximum number of "birds steps"
No. of run = 5; % numbers of runs
c2 =1.2; % PSO parameter C1
c1 = 0.12; % PSO parameter C2
w =1; % PSO momentum or inertia

Case 1. A 64--element LAA is designed for null placement at 80° and 100°. Fig. 2 shows that deep nulls of -95 dB. The element positions for both conventional, PSO and IWO methods are given in Fig. 3. The radiation pattern is presented in Fig. 2. It is clearly seen that the IWO algorithm provides improvement to the SLL suppression. Almost all sidelobes have been minimized particularly the first SLL with smaller beamwidth is obtained.

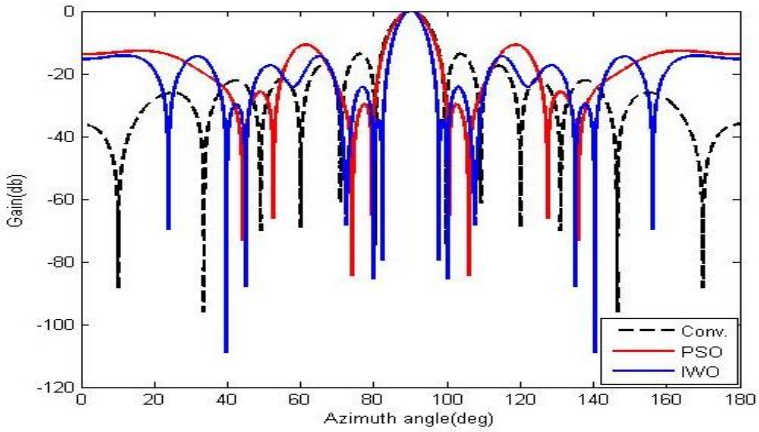

Figure 2: Radiation patterns of 64-element LAA by using IWO, PSO and conventional methods. SLL suppression at (0^o, 85^o) and (95^o, 180^o). The null placements are at 80^o and 100^o.

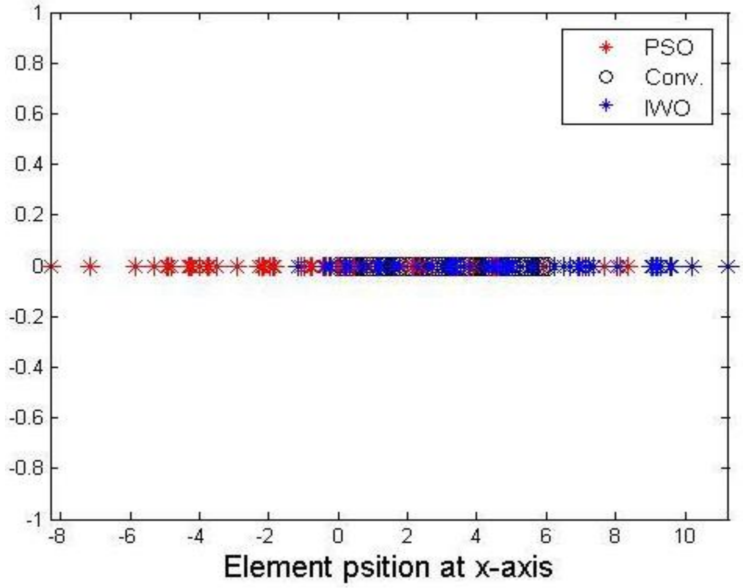

Figure 3: Element position of the 64-element LAA using IWO, PSO and conventional methods. Numbers are normalized wrt ¸ λ0¸λ/2

Case 2. A 128-element LAA is designed for null placement at 80^o and 100^o. Fig. 4 shows that deep nulls of -75 dB, it can be inferred that smaller beamwidth is obtained by using IWO. In addition, Almost all sidelobes have been minimized particularly the first SLL and far sidelobes in spite of increasing the number of elements compared with conventional and PSO methods. The element positions for conventional, PSO and IWO methods are given in Fig 5.

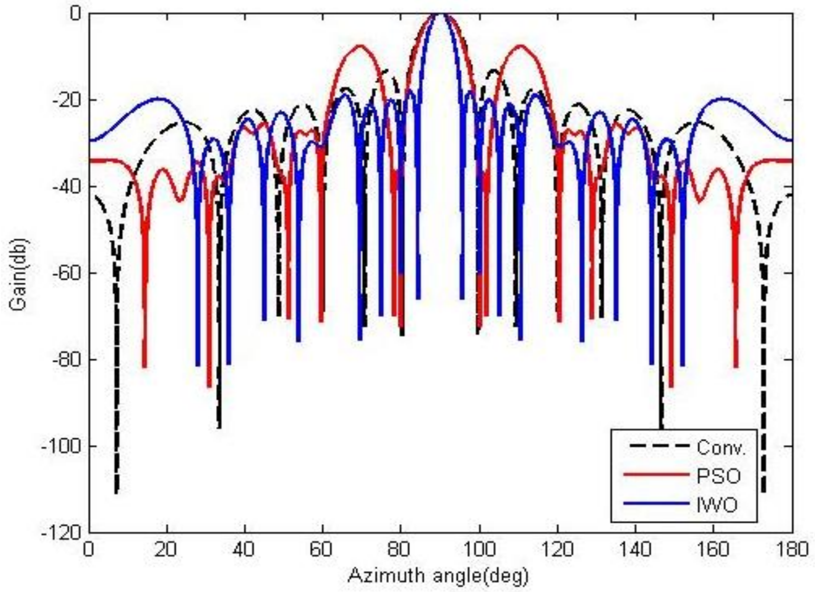

Figure 4: Radiation patterns of 128-element LAA by using, IWO, PSO and conventional methods. SLL suppression at (0^o, 85^o) and (95^o, 180^o). The null placements are at 80^o and 100^o.

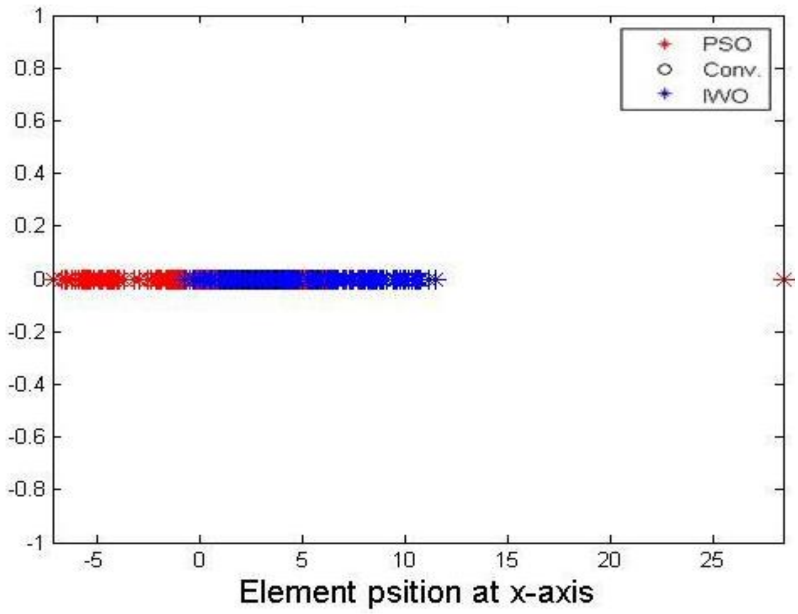

Figure 5: Element position of the 128-element LAA using IWO, PSO and conventional methods. Numbers are normalized wrt ¸ λ0¸λ/2.

Table 1 summarizes the simulation results for the above antennas for the PSO and IWO.

Table 1 Antenna arrays simulation results

Array Configuration						
128 Element			64 Element			
IWO	PSO	Conv.	IWO	PSO	Conv.	
2	6	6	4	6	6	†ML Beamwidth (deg)
-28	-10	-20	-38	-30	-28	‡SLL

†ML: MainLobe
‡SideLobe Level

6. Conclusion

The IWO algorithm has been shown to successfully improve the radiation pattern of the LAA as desired. All the design requirements of the radiation pattern simulation for the LAA is presented and highly satisfied. The developed IWO algorithm has successfully optimized the position of the array elements to demonstrate a radiation pattern with either suppressed SLL, null placement, or both.

The PSO showed bad results with huge numbers of elements compared with the IWO for all of the arrays under investigation. The PSO succeeded in finding an optimum array with SLLs at the expense of ML complete deformation. The final results of the PSO show a high concentration (swarming particles) that led to the deterioration in performance. On the other hand, the IWO gave very realistic results. In all the array configurations, the IWO succeeded in finding a set of weights that minimize the SLL and minimize the ML in all the same.

7. References

Akbarzadeh A. and Sadeghi M., June 2011" **Parameter Study in Plastic Injection Molding Processusing Statistical Methods and IWO Algorithm**" International Journal of Modeling and Optimization, Vol. 1, No. 2.

Bevelacqua P. J. and Balanis C. A., 2007 " **Minimum sidelobe levels for linear arrays, antennas and propagation**," IEEE Transactions on Antennas and Propagation, Vol. 55, No. 12.

Deng J.H, et al., 2011, "**Low complexity hybrid smart antenna with directional elements over frequency-selective fading channel**", in 13th Int. Conf. Advanced Communication Technology (ICACT), , 110–114.

Halder U., Das S., Maity, D. etal **,2011** " **Self Adaptive Cluster Based and Weed Inspired Differential Evolution Algorithm For Real World Optimization**", **IEEE.**

Jabbar A.N., 2011 "**adaptive blind beamforming algorithm for smart antenna arrays**", A novel ultra-fast ultra-simple Prog. Electromagn.329–348.

Kennedy J., Eberhart, R., 1995 "**Particle swarm optimization**", in Proc. IEEE Int. Conf. on Neural Networks IV, , 1942–1948.

Li N., Appl., 2011, "**The application of sparse antenna array synthesis based onimproved mind evolutionary algorithm**", International Journal. Intell. Syst. P: 40–46.

Mallahzadeh A. R.,2008 " **Application of the Invasive Weed Optimization Technique For Antenna**" Configurations Progress In Electromagnetics Research, PIER 79, 137–150,

Mehrabian A. R. and Lucas C. 2006, "**A novel numerical optimization algorithm inspired from weed colonization**," Ecological Informatics, Vol.1.

Rattan M., Patterh M. S., and Sohi B. S. 2008 " **Design of a linear array of half wave parallel dipoles using particle swarm optimization**", Progress In Electromagnetics Research M, Vol. 2,.

Singh H., Jha R.M. 2012, " **Trends in adaptive array processing**", International Journal Antennas Propag. 1–20.

Tanji Y., Matsushita H., Sekiya H. September 2011. "**Acceleration of PSO for designing class E amplifier**", in Int. Symp. Nonlinear Theory and its Applications, Kobe, Japan, 4–7, 491–494.

Wang X.K., Jiao, Y. C., Tan, Y. Y. 2012, "**Gradual thinning synthesis for linear array based on iterative Fourier techniques**, ". Prog. Electromagn. , 299–320.

Yang F. et al, 2007, "**Technique in Electromagnetics Linear Antenna Array Synthesis Using Taguchi's Method**", IEEE Transactions On Antennas And Propagation, Vol. 55, No. 3.