Comparison of Evolutionary Optimization Algorithms for FM-TV Broadcasting Antenna Array Null Filling

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***Abstract* — Broadcasting antenna array null filling is a very challenging problem for antenna design optimization. This paper compares five antenna design optimization algorithms (Differential Evolution, Particle Swarm, Taguchi, Invasive Weed, Adaptive Invasive Weed) as solutions to the antenna array null filling problem. The algorithms compared are evolutionary algorithms which use mechanisms inspired by biological evolution, such as reproduction, mutation, recombination, and selection. The focus of the comparison is given to the algorithm with the best results, nevertheless, it becomes obvious that the algorithm which produces the best fitness (Invasive Weed Optimization) requires very substantial computational resources due to its random search nature.**

***Keywords*— antenna array, null filling, evolutionary optimization algorithms, Particle Swarm, PSO, Differential evolution, Invasive Weed Optimization, IWO.**

I. INTRODUCTION

Research on antennas has become very challenging, especially in the area of broadcasting [1-2]. A lot of techniques have been proposed for the design of base station antenna arrays in order to satisfy requirements, which are essential for broadcasting applications [3-4]. These requirements usually considered by a broadcasting antenna array are given below: (a) due to the large distance between the transmitting base station and the service area, the antenna array needs to produce a very narrow main lobe which, in conjunction with the need for reduction of the spatial spread of radiated power, results in the requirement of maximum gain. (b) Provided that the broadcasting base station is usually located at higher places relative to the service area, the main lobe is required to be tilted from the horizontal plane. Due to the large distance from the service area, the tilting angle is usually small (between 2 and 4 degrees). (c), in order to have satisfactory reception of transmitted signal inside an angular sector under the main lobe, the directional gain is not permitted to fall below a certain value in relation to the maximum gain value, which results in filling of radiation pattern nulls inside the above-mentioned angular sector. The level of null filling depends on the service type (e.g., FM radio, TV DVB-T) and the value of signal-to-noise ratio (SNR), (iv) In order to reduce the power reflection along the feeding lines and thus increase the efficiency of the whole feeding network, the impedance matching condition is required for every array element, which means that the standing wave ratio (SWR) of every element must be close to unity.

It is obvious that the design of such an antenna array is a multi-objective problem, since the above requirements must be simultaneously satisfied. Therefore, an optimization method is necessary to solve this kind of problem, [5-7]. Such an efficient method recently proposed is the Invasive Weed Optimization (IWO) method [5-12]. The IWO is an evolutionary method inspired from the invasive nature of weeds. Due to its fast convergence and performance, the IWO has been chosen to solve many problems in the area of electromagnetics. The optimization methods under study have been applied to optimize linear arrays according to the above-specified requirements. In all the cases studied here, a uniform-amplitude excitation distribution is considered to be applied on the array elements, since excitations of equal amplitudes are easily implemented in practice. In the two studied cases, linear arrays of 8 and 16 isotropic sources, respectively, are optimised for maximum gain, main lobe tilting and null filling, while the impedance matching condition is not required due to the use of isotropic sources. The radiation characteristics of each array need to be calculated for every evaluation of the fitness function, which is going to be minimized by the optimization methods. The optimization results exhibit the relative effectiveness of the proposed methods. More specifically, the IWO method has initially been proposed by Mehrabian and Lucas [5]. The IWO algorithm simulates the colonizing behavior of weeds in nature. Initially, a population of weeds is dispersed at random positions inside an N-dimensional search space, where N is the number of parameters to be optimized by the IWO algorithm for the given problem. These positions are produced by a uniform random number generator. The optimization algorithm is an iterative process and consists of three basic steps repeatedly applied on each iteration.

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In artificial intelligence, an evolutionary algorithm (EA) is a generic population-based metaheuristic optimization algorithm. An EA uses mechanisms inspired by biological evolution, such as reproduction, mutation, recombination, and selection. Candidate solutions to the optimization problem play the role of individuals in a population, and the fitness function determines the environment within which the solutions "live". Evolution of the population then takes place after the repeated application of the above operators. Artificial evolution (AE) describes a process involving individual evolutionary algorithms. EAs are individual components that participate in an EA.

Antenna arrays play an important role in detecting and processing signals arriving from different directions. The goal in antenna array geometry synthesis is to determine the physical layout of the array that produces a radiation pattern that is closest to the desired pattern. The shape of the desired pattern can vary widely depending on the application.

Before starting to use an EA, setting up the problem is required, which means making sure than an EA is the optimal solution to the problem. Secondly, the parameters that need optimization must be decided. The parameter which needs to be maximized is the fitness of the population and it is used to generate the next population after being evaluated.

Some basic optimization concepts for electromagnetic applications will be evaluated for this project and these are the following: 1. Differential Evolution (DE), 2. Particle Swarm Optimization (PSO), 3. Invasive Weed Optimization (IWO), 4. Taguchi's Optimization Method, 5. Adaptive IWO (ADIWO).

The main steps of an EA are explained and shown on the flowchart below for a better understanding.

1. Initialization of Population: Initially a random population size is generated. Size differs depending on the problem, so that the entire range of possible solutions is allowed.

2. Evaluation of Fitness: Each individual of the population has a fitness value which is evaluated to decide which individuals have the best fitness.

3. Selection of Population with the Best Fitness: After the fitness evaluation the individuals with the best fitness values are chosen and are used for the next population.

4. Termination: Steps 2 and 3 are repeated until the best fitness is found and the process is terminated.

II. EVOLUTIONARY ALGORITHMS

A. *Differential Evolution*

The general problem that an optimization algorithm is concerned with, is to determine the vector variable x so as to optimise:

$$f(x); x = \{x_1, x_2, ..., x_D\} \quad (1)$$

Where, D is the dimensionality of the function. The variable domains are defined by their lower and upper bounds: $x_{j,low}, x_{j,upp}; j \in \{1,...,D\}$.

The population of the original DE algorithm contains NP D-dimensional vectors:

$$x_{i,G} = \{x_{i,1,G}, x_{i,2,G}, ..., x_{i,D,G}\}, i = 1,2,..., NP \quad (2)$$

Where, G is the generation

During one generation for each vector, DE employs mutation and crossover operations to produce a trial vector:

$$u_{i,G} = \{u_{i,1,G}, u_{i,2,G}, ..., u_{i,D,G}\}, i = 1,2,..., NP \quad (3)$$

Then, a selection operation is used to choose vectors for the next generation (G+1). The initial population is selected uniform randomly between the lower $(x_{j,low})$ and upper $(x_{j,upp})$ bounds defined for each variable x_j. These bounds are specified by the user according to the nature of the problem. After initialization, DE performs several vector transforms (with the above mentioned operations), in a process called evolution.

B. *Particle Swarm*

In PSO terminology, [13-14], every individual in the swarm is called “particle” or “agent”. The number S of the particles that compose the swarm is called “population size”. A population size between 10 and 50 is optimal for many problems. All the particles act in the same way like bees do, they move in the search space and update their velocity according to the best positions already found by themselves and by their neighbors, trying to find an even better position. Each particle is treated as point in an N-dimensional space. The position of the i-th particle $(i = 1,....S)$ is represented as $x_i = (x_{i1}, x_{i2}, ..., x_{iN})$, where $x_{in} (n = 1,..., N)$ are the position coordinates. Each coordinate x_{in} may be limited in the respective (n-th) dimension between an upper boundary U_n and a lower boundary L_n, so that $L_n \le x_n \le U_n (n = 1,..., N)$. The difference $R_n = U_n - L_n$ between the two boundaries is called “dynamic range” of the n-th dimension. The performance of each particle is measured according to a predefined mathematical function F called “fitness function”, which is related to the problem to be solved. The value of the fitness function depends on the position coordinates, i.e, $F = F(x_i) = F(x_{i1}, x_{i2}, ..., x_{iN})$. Actually, the particle position is considered to be improved as the value of the fitness function is increased/or decreased (maximization or minimization problem). The best previous position (best position) of the i-th particle is recorded and represented as $p_i = (p_{i1}, p_{i2}, ..., p_{iN})$.

The change of x_i is:

$$\Delta x_i = u_i \Delta\tau \quad (4)$$

Δt is the time interval, $\upsilon_i = (v_{i1}, v_{i2}, \ldots, v_{iN})$ is the velocity of the i-th particle, and $\upsilon_{in} (n = 1, \ldots, N)$ are the velocity coordinates.

Calculation of velocity:

Considering that $\Delta t = 1$, the position change becomes $\Delta x_i = \upsilon_i$. Thus, the new position of the i-th particle after a time step is given by:

$$x_i(t+1) = x_i(t) + \upsilon_i(t+1) \quad (5)$$

Particle swarms have been studied in two types of neighborhood, called “gbest” and “lbest”. In the gbest neighborhood, every particle is attracted to the best position found by any particle of the swarm which is called “gbest position”.

In the lbest neighborhood, each (i-th) individual is affected by the best performance of its Ki immediate neighbors which is called “lbest position”. The equation of velocity for gbest model is:

$$\begin{aligned} u_i(t+1) &= w*u_i(t) + c_1 rand(t)* \\ &[p_i(t) - x_i(t)] + c_2 rand(t)*[g(t) - x_i(t)] \end{aligned} \quad (6)$$

Where, w = inertia weight (0.0 - 0.1), c1 and c2 are cognitive coefficient, and social coefficient respectively, and rand(t) is a function that generates random numbers from a uniform distribution between 0.0 and 1.0. The equation of velocity for lbest model is:

$$\begin{aligned} u_i(t+1) &= w*u_i(t) + c_1 rand(t)* \\ &[p_i(t) - x_i(t)] + c_2 rand(t)*[l_i(t) - x_i(t)] \end{aligned} \quad (7)$$

C. *Taguchi*

The development of Taguchi’s method is based on orthogonal arrays (OAs) that have a profound background in statistics. Orthogonal arrays were introduced in the 1940s and have been widely used in designing experiments. They provide an efficient and systematic way to determine control parameters so that the optimal result can be found with only a few experimental runs. This section briefly reviews the fundamental concepts of OAs, such as their definition, important properties, and constructions. The procedure of Taguchi algorithm consists of five stages. These stages are the following:

1. Problem Initialization: The optimization procedure starts with the problem initialization, which includes the selection of a proper OA and the design of a suitable fitness function. The selection of an OA (E, P, L, t) mainly depends on the number of optimization parameters. Where E is the number of Experiments, P is the number of Parameters, L is the number of Levels, and t is the strength.

2. Input Parameters Designation: The input parameters need to be selected to conduct the experiments. When the OA is used, the corresponding numerical values for the levels of each input parameter should be determined. For each i_th iteration and each p_th parameter, the level difference 〚LD〛_pi is calculated by the following formula:

$$LD_{pi} = rr^{i-1} LD_{p1},\ p = 1, \ldots, P \quad (8)$$

Where, $LD_{p1} = \dfrac{(max_p - min_p A)}{(L+1)},\ p = 1, \ldots, P$ (9)

is the initial level difference and rr is the reduced rate. Also, max_p and min_p are respectively the upper and the lower bound of the p_th parameter.

3. Experiments Conduction and Response Table Building: The fitness function fit_{ei} for each experiment (e) can be calculated and the fitness value is converted to the signal-to-noise (S/N) ratio (η) in Taguchi’s method using the following formula:

$$\eta = -20 \log \log(Fitness) \quad (10)$$

A small fitness value results in a large S/N ratio. After conducting all experiments in the first iteration, the fitness values and corresponding S/N ratios are obtained and listed. The average fitness values in dB are then extracted for each parameter and each level to build the response table by applying the expression:

$$\bar{\eta}_{lpi} = \left(L/E\right) \sum_{e, OA(e,p)=l} \eta_{ei},\ p = 1, \ldots, P\ \&\ l = 1, \ldots, L \quad (11)$$

4. Optimal Level Values Identification: Finding the largest S/N ratio in each column of response table can identify the optimal level for that parameter. When the optimal levels are identified, a confirmation experiment is performed using the combination of the optimal levels identified in the response table. This confirmation test is not repetitious because the OA-based experiment is a fractional factorial experiment. The fitness value obtained from the optimal combination is regarded as the fitness value of the current iteration.

5. Optimization Range Reduction: If the results of the current iteration do not meet the termination criteria, which are discussed in the following subsection, the process is repeated in the next iteration, otherwise, the procedure is terminated.

D. *Invasive Weed & Adaptive Invasive Weed*

The Invasive Weed Optimization (IWO) is an optimization algorithm that is also proposed for Electromagnetic applications. The IWO is a numerical optimization algorithm inspired from weed colonization and it was first introduced by Mehrabian and Lucas in 2006, [5]. This optimizer can in certain instances outperform other algorithms like the particle swarm optimization (PSO) and is able to handle new electromagnetic optimization problems. The colonization behavior of weeds follows the steps bellow:

1. First, there is a set of variables that are in need of optimizing. Once these variables are selected the minimum and maximum values for these variables are set.
2. Once the variables are set, the seeds are randomly positioned in an N-dimensional problem space. Each seed position is considered to be a solution. These positions will contain a value for each variable previously set. That means N values for N variables.

3. Subsequently, each seed will grow into a plant. The fitness function returns a fitness value that represents how good the solution will be for each individual seed. Once each seed is assigned a fitness value, it is called a plant.
4. In order for a plant to produce new seeds, and how many seeds, it must meet certain fitness values. Based on the fitness value rank every plant has, it produces a number of seeds between a minimum and maximum possible number. The closer to the set variables a plant is, the more seeds it is allowed to produce.
5. The seeds created in the previous step are spread over the search space. Every new seed is distributed using random numbers for the values of its location but with the numbers whose average value equal to the parent plants location as well as varying standard deviations. The standard deviation (SD) at the present time step can be expressed by:

$$\sigma = \frac{(I_{MAX} - I)^n}{(I_{MAX})^n}(\sigma_{in} - \sigma_{fi}) + \sigma_{fi} \tag{12}$$

Where, I is the number of iterations and I_{MAX} the maximum number of iterations. σ_{in} and σ_{fi} are defined as the initial and final standard deviations respectively and n is the nonlinear modulation index.
6. Once all seeds have found a position over the search area they become plants and take fitness values and rank along with their parents. In order to keep the maximum number of plants in the colony, plants that are not fit are discarded.
7. The plants that survive produce in turn new seeds and the process is repeated until the maximum number of iterations is reached or the desired fitness achieved.

In the Adaptive IWO (ADIWO), the standard deviation σ of the dispersion of the seeds produced by a weed is a linear function of the fitness value f of this weed. Considering that the goal is the minimization of the fitness function, σ can be estimated according to the following expression:

$$\sigma = \frac{\sigma_{MAX} - \sigma_{min}}{f_{MAX} - f_{min}} f + \frac{\sigma_{min} f_{MAX} - \sigma_{MAX} f_{min}}{f_{MAX} - f_{min}} \tag{13}$$

Where, σ_{MAX} and σ_{min} are the standard deviation limits defined in the same way as in the original IWO algorithm, while f_{MAX} and f_{min} represent respectively the maximum and minimum fitness values at a certain iteration. The ADIWO algorithm has the same structure as the original IWO algorithm. The only difference lies in the calculation of σ which is performed by using (13). It is easy to realize that the best weed ($f = f_{min}$) disperses its seeds with the minimum σ ($\sigma = \sigma_{min}$), while the worst weed ($f = f_{MAX}$) disperses its seeds with the maximum σ ($\sigma = \sigma_{MAX}$). Therefore, the weeds have different behavior depending on their fitness values. As the fitness value gets closer to f_{min}, the exploration ability of the weed is reduced and thus the weed can only fine-tune its near-optimal position. On the contrary, as f gets closer to f_{MAX}, the exploration ability of the weed increases and thus the weed is capable of exploring the search space to find better positions. In this way, the exploration ability of the weed colony is maintained until the end of the optimization process. Moreover, the adaptive seed dispersion makes the ADIWO converge faster than the original IWO although it is less accurate.

III. RESULTS

The evolutionary optimisation algorithms were applied to two cases of linear array optimisation. A uniform-amplitude excitation distribution is considered in every case. The two cases considered concern a theoretical aspect of linear array design and therefore the arrays are considered to be composed respectively of 8 (case 1) and 16 (case 2) isotropic sources. In these cases, the optimization is performed for maximum array gain G_p, $\Delta\theta_{des} = 2^\circ$ (downward main lobe tilting), and $g_{des} = -20\text{dB}$ (null-filling) inside a sector from 90° to 120°, which are achieved by minimizing the fitness function. Since G_p is required to be maximised without reaching any desired value, two reference values of directional gain are calculated in order to be used for comparison with G_p. These values are: (i) the maximum directional gain G_{bp} of a broadside linear array (i.e., array without main lobe tilting, $\Delta\theta_{des} = 0^\circ$) composed respectively of 8 (for case 1) and 16 (for case 2) isotropic sources with equal inter-element distances d and equal excitation phases, and without the requirement for null-filling, and (ii) the maximum directional gain G_{tp} of a linear array composed respectively of 8 (for case 1) and 16 (for case 2) isotropic sources with equal inter-element distances d and equal excitation phase differences between adjacent sources given by the expression

$$\Delta\phi = \frac{2\pi}{\lambda} d \sin(\Delta\theta_{des}) \tag{14}$$

where $\Delta\theta_{des} = 2^\circ$, and finally without the requirement for null-filling. In all the cases, the IWO algorithm is applied with $ns_{\min} = 0$, $ns_{\max} = 5$, $\sigma_{\min} = 0$, $\sigma_{\max} = 0.5$ and $\mu = 2.5$. In cases 1, where N=8, 14 parameters need to be optimised. A population of 82 weeds is used. Also, the algorithm terminates after 5,000 iterations. In cases 2, where N=16, 30 parameters must be optimized. The IWO algorithm again is using a population of 82 weeds. Due to the large number of optimisation parameters in case 2 (30 parameters), 10,000 iterations are used to complete the execution of the algorithm.

All of the optimization algorithms were applied for two different scenarios. One scenario is an antenna array with eight elements and another is with sixteen elements. The chosen total number of iterations of each case was selected so that the algorithms will be able to pick the best possible final population for each case. Each case was run 20 times for every algorithm, which is enough for an average fitness evaluation of every algorithm, except for the Taguchi algorithm which automatically selects the total number of iterations.

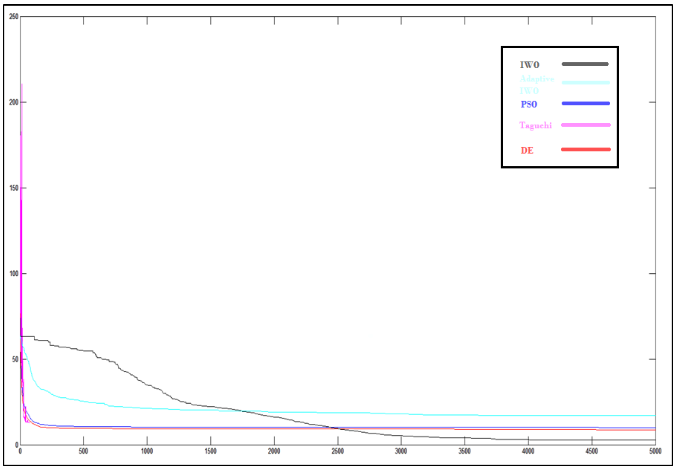

Fig. 1. Convergence (Fitness/Iterations) diagram of all the algorithms for the antenna array with 8 elements (Differential Evolution, PSO, Taguchi, IWO, Adaptive IWO).

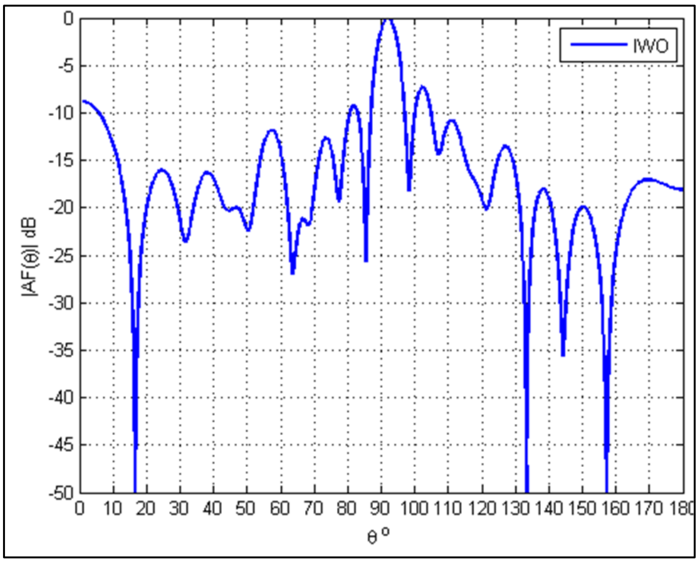

Fig. 2. Radiation Pattern of IWO optimized antenna array with 8 elements.

The target of the simulations was to maximize gain of the derived antenna (optimization variables are: dipole element distances, positions and phases) and the gain not to drop below -20dB from the peak value between the 92º and 120º azimuth angle. The fitness values per iteration for both the antenna array with eight and sixteen elements of all the algorithms are shown and a final comparison can be obtained concerning the behavior of each algorithm. The graphs depict the average convergence of the algorithms in 20 executions. In both scenarios all of the algorithms produced a radiation pattern which satisfies an antenna design with broadcasting capabilities for UHF-VHF frequencies (relative gain is higher than -20dB between 92º and 120º, no deep null). The important observation is that the best fitness is produced by the IWO algorithm. Although, the rest of the algorithms produce initial populations with better fitness values, IWO optimizes the fitness value per iteration at a slower rate compared to the rest of the algorithms, thus it needs a more computation time. These facts indicate the possibility of upgrades with a possible combination of algorithms.

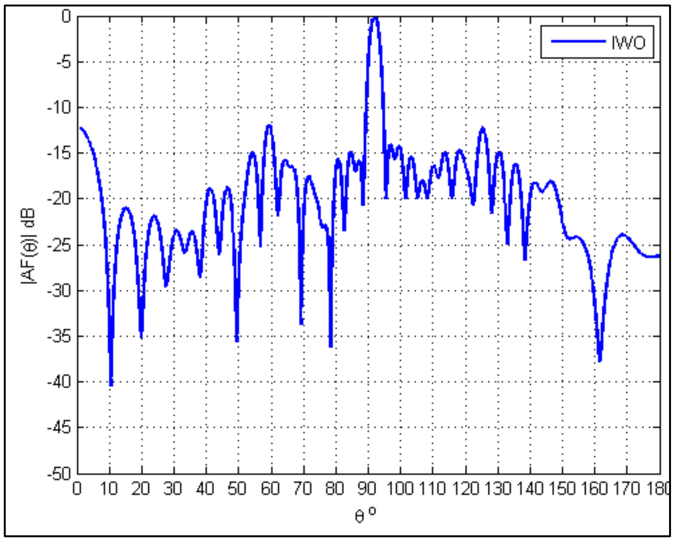

Fig. 3. Radiation Pattern of IWO optimized antenna array with 16 elements.

IV. Conclusions

Several evolutionary optimization algorithms are used in the design of an optimized broadcasting antenna array with null-filling. It is established that IWO produces the best results since it gives the lowest fitness value in comparison with the other examined algorithms. Another very important factor is the time of completion needed for every algorithm, and it is seen that improved and accelerated versions of the algorithms are required.

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