WCCI 2012 IEEE World Congress on Computational Intelligence
June, 10-15, 2012 - Brisbane, Australia IEEE CEC

Comparison of different optimization techniques in the design of electromagnetic devices

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***Abstract*— In recent years there has been an increasing attention to some novel evolutionary techniques, such as for example Ant Colony Optimization (ACO), Biogeography Based Optimization (BBO), Differential Evolution (DE), Population-Based Incremental Learning (PBIL) and Stud Genetic Algorithm (SGA). The design of a microwave filter, a planar array and an elliptical reflectarray are here addressed in order to compare their performances on benchmark EM optimization problems. Results show that some techniques (DE, BBO, SGA) are particularly effective in dealing with antenna optimization.**

I. Introduction

Numerical optimization techniques are widely applied to engineering design problems. Among these the design of antennas and micro to sub-millimetre wave components is a potential field of application [1]. Optimization problems with more than one objective function, often conflicting, are quite common dealing with practical engineering problems. In these cases there is no a single solution, but the real challenge is to find a good trade-off solution that represents the best compromise among the considered objectives. In recent years a considerable number of computational techniques have been proposed for the global optimization of complex and multi-objective functions. These procedures are commonly called Evolutionary Algorithms and the most known are Genetic Algorithms (GA) and Particle Swarm Optimization (PSO).

In this paper the authors considers in particular the less common techniques, namely Ant Colony Optimization (ACO) [2], Biogeography Based Optimization (BBO) [3], Differential Evolution (DE) [4], Population-Based Incremental Learning (PBIL) [5] and Stud Genetic Algorithm (SGA) [6]. The performances of these procedures are here analysed over three EM benchmark problem, the design of a band-pass microstrip filter, the optimization of a planar array and the design of a dual layer reflectarray.

II. Considered Optimization Techniques

The evolutionary optimization algorithms considered in this work are here described.

A. Ant Colony Optimization

ACO is a relatively novel optimization algorithm that has been recently introduced also in EM problem optimization [7]. This technique belongs to the family of population-based optimization algorithms and it is inspired by the foraging behavior of ants [2].

At first ants' movements are stochastic, but, as soon as the source of food is found, the shortest path between food and nest is marked with pheromone, deposited by ants in order to guide the other members of the colony. A famous example of application for this algorithm in the so called TSP (Traveling Salesman Problem), in which, given a set of cities, the shortest tour that allows to visit every city once and only once must be planned.

In ACO a population of artificial ants is considered, and each of them builds a solution for the given problem. A value of pheromone is associated to every solution component, so that in the following iteration every ant has a guide toward a good solution.

B. Biogeography-Based Optimization

BBO is a recently introduced evolutionary algorithm based on the science of biogeography. Biogeography is the study of the geographical distribution of biological organisms [3, 8].

BBO shares some features with other evolutionary optimization methods, thus it is applicable to many of the problems that could also be solved with GA and PSO, namely, high-dimension problems with multiple local optima. However, BBO also has some features that are unique among biology-based optimization methods. In fact, in BBO the problem possible solutions are identified as islands or habitats, and its operators are based on the concept of migration, to share information between the problem solutions. In particular, BBO introduces four new parameters:

- suitability index variable (SIV) represents a variable that characterize habitability in an island, i.e. in a solution,
- habitat suitability index (HSI), represents the goodness of the solution, similarly to the fitness score concept in GA,
- emigration rate (μ) indicates how likely a solution is to share its features with other solutions,
- immigration rate (λ) indicates how likely a solution is to accept features from other solutions;

A high performing solution has a high emigration rate and low immigration rate, while a low performing habitat has a low emigration rate and high immigration rate. In fact, the maximum possible immigration rate occurs when there are zero species in the habitat. As the island HSI increases, the number of species grows, the habitat becomes more crowded, and more species are able to leave the island to explore other possible habitats, thus increasing the emigration rate.

C. Differential Evolution

DE is a novel heuristic approach for optimizing nonlinear and non-differentiable continuous space functions [4]. Its application on EM and EMC problem has been recently assessed [9].

A population in DE consists vectors randomly initialized from a uniform distribution. Each vector represents a solution. The initial population evolves in each generation with the use of three operators: mutation, crossover and selection, as in GA. Depending on the form of these operators several DE variants or strategies exist in the literature.

DE requires few control variables, is robust, easy to use, and lends itself very well to parallel computation.

D. Population-Based Incremental Learning

PBIL is a type of evolutionary algorithm where the genotype of an entire population (probability vector) is evolved rather than individual members [5].

In PBIL, genes are represented as real values in the range [0,1], indicating the probability that any particular allele appears in that gene. After the generation of a new population from the probability vector, the fitness of each member is evaluated and ranked. Population genotype (probability vector) is the updated based on fittest individual. Mutation is usually used to help increase diversity and reintroduce information that may have been lost at an earlier stage.

E. Stud Genetic Algorithm

SGA is a relatively unknown variation of the well-known Genetic Algorithm, developed years ago by Khatib and Fleming [6].

The basic idea behind the SGA is to use the best individual in the population to mate with all others to produce the new offspring. No stochastic selection is used, but, after initializing a random population, the fittest individual (the Stud) is chosen for mating. Crossover is then performed between the Stud and the remaining elements.

III. MICROSTRIP FILTER DESIGN

The optimization techniques here considered have been applied to the design of a symmetric microstrip band-pass microwave filter, consisting in a cascade of $2N$-1 lines, each of which with electrical length equal to $\lambda_g/2$ at the central frequency (being λ_g the guided wavelength, given by $\lambda_g/$□$_{eff}$, where □$_{eff}$ is the effective permittivity, related to the relative permittivity of the substrate □$_r$ and λ_0 is the free-space wavelength), but different width, as shown in Figure 1. In the present case, the layout of the filter is printed on a single layer dielectric characterized by the relative dielectric constant of □$_r$ = 3.5 and thickness h = 1.58mm. The lines are disposed symmetrically with respect to the central one, as shown in [10].

A. Filter model

The filter can be easily modeled with its transmission line equivalent model, i.e. with a cascade of $2N$-1 transmission lines, having all the same electrical length ($\lambda_g/2$), but different characteristic impedance Z_i, since this latter quantity depends

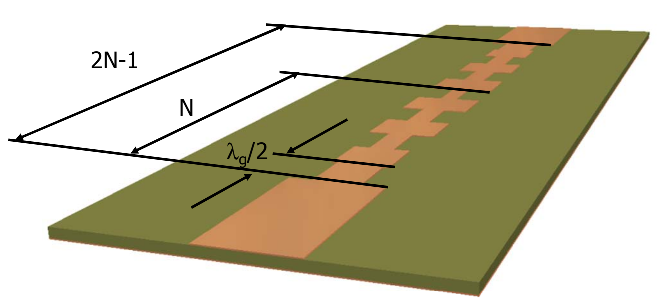

Fig. 1 The considered microstrip filter geometry.

on the line width w_i. The filter can be therefore seen as a sequence of two-port networks, each of which can be represented by its chain matrix [11], whose entries depend only on the characteristic impedance and on the electric length. The chain matrix of the entire structure is given by the product of $2N$-1 single chain matrices and the transmission coefficient (i.e. the transfer function) of the filter is expressed in terms of the entries of the chain matrix of the whole structure:

$$S_{21} = \frac{2\sqrt{Z_{out}/Z_{in}}}{A_{tot} + B_{tot}/Z_{in} + (Z_{out}/Z_{in})(C_{tot}Z_{in} + D_{tot})} \tag{6}$$

where Z_{out}, Z_{in} are the reference impedances at the output and input ports of the filter, respectively.

Even if this model does not take into account the interactions between the different lines, it represents a good compromise between the accuracy in modeling the filter and the low computational cost that is a very important aspect when optimization tools as the PSO are used, since they required the evaluation of the cost function thousands of times.

The performances of the filter depend on the number of lines used for its realization (the greater is N, the larger is the bandwidth, but also the longer the filter is), and on the values of the characteristic impedance of the equivalent transmission lines. Here P is fixed and the filter widths w_i are optimized, to meet these design constraints:

- the bandwidth has to be equal or greater than a fixed value;
- minimization of the in-band ripple;
- maximization of the out of band rejection.

B. Numerical Results

To confirm the capabilities of ACO, BBO, DE, IPBL and SGA in dealing with EM problems, and to compare their features with those of other more consolidated evolutionary algorithms, they are here applied to the design of a microstrip band-pass filter, consisting in a sequence of different width, $\lambda_g/2$ sections of line, as described in Section II.

The cost function takes into account the bandwidth, the absolute value of the transmission coefficient $|S_{21}|$ in the rejection band and the ripple in the pass band.

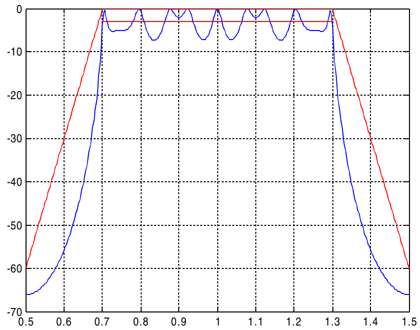

Fig. 2 Best filter response obtained after optimization with ACO

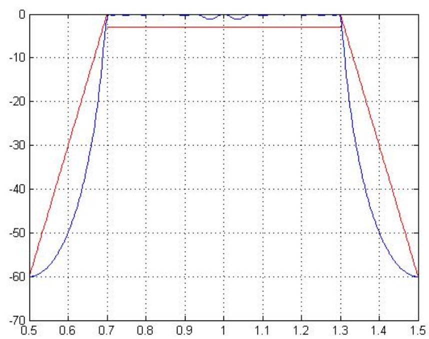

Fig. 3 Best filter response obtained after optimization with BBO

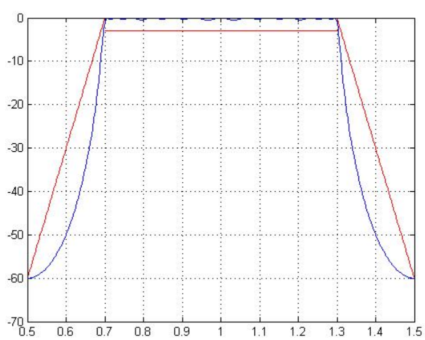

Fig. 4 Best filter response obtained after optimization with DE

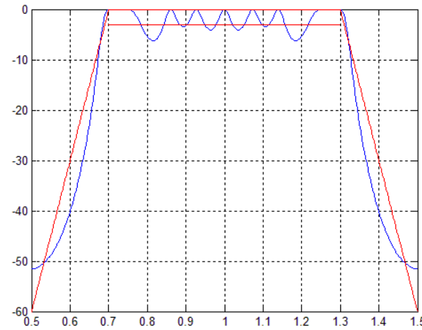

Fig. 5 Best filter response obtained after optimization with PBIL

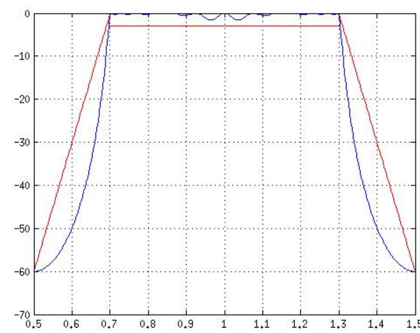

Fig. 6 Best filter response obtained after optimization with SGA

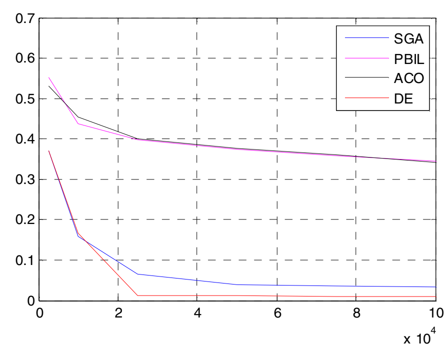

Fig. 7 Comparison of performances for different algorithms: convergence of cost function value s during iteration.

Figures 2-6 shows the frequency response of the filter with *N*=9 elements optimized with ACO, BBO, DE, PBIL, SGA, respectively.

The convergence curves reported in Figure 7 show that some techniques, in particular DE, BBO and SGA are particular effective in dealing with this kind of complex optimization, mainly due to their ability to face complex discontinuous problems.

Planar Array Optimization

In order to evaluate and compare the capability of ACO, BBO, DE, IPBL and SGA in dealing with EM problems with traditional EAs, these techniques are here applied to the design of a planar array with 12x12 elements, as described in [12]. Optimization parameters are the phase values of the excitation of each element, as shown in Figure 8. The cost function takes into account a specific threshold for the side-lobe level. Results reported in Figures 9-13 show that some techniques, in particular DE, BBO, and SGA are particular effective in dealing with this kind of complex optimization, mainly due to their ability to face complex discontinuous problems.

IV. Reflectarray Optimization

The use of planar reflectarray antennas in satellite communications is increasing, since they overcome some disadvantages of conventional reflector antennas and phased arrays [13]. The main point in the design of such antennas is to adopt suitable elements for the planar reflector, as shown in

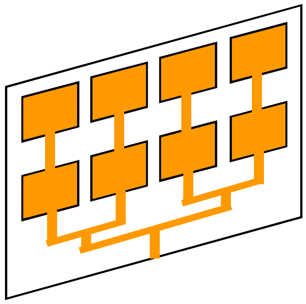

Fig. 8 Sample planar array geometry.

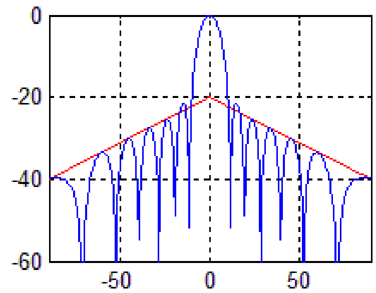

Fig. 9 Best result obtained after optimization with ACO.

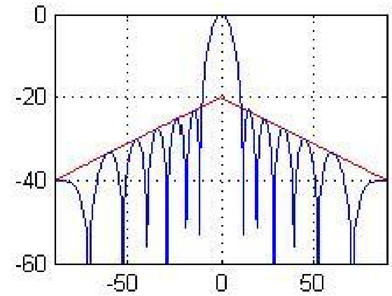

Fig. 10 Best result obtained after optimization with BBO

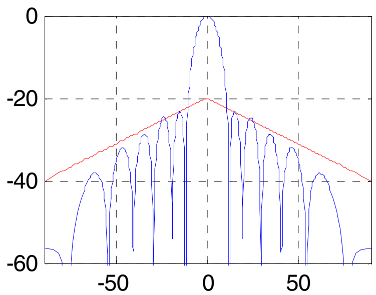

Fig. 11 Best result obtained after optimization with DE

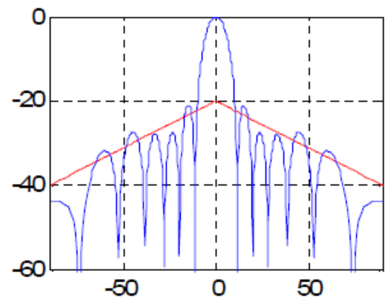

Fig. 12 Best result obtained after optimization with PBIL

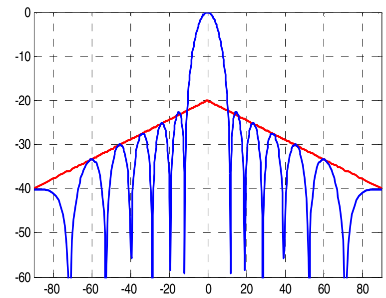

Fig. 13 Best result obtained after optimization with SGA

Figure 14, in order to compensate the different path length of the field illuminating onto different points of the reflector plane itself, which results in a phase difference of the contributions to the reflected field coming from those different points. Therefore the design of such a reflectarray can be achieved using a numerical optimization technique.

A. Design procedure

The design of a double layer elliptical reflectarray of 329 elements, as presented in [1], is here used as a benchmark test for the considered optimization algorithms: it adopts square patches as array elements; for each element, the upper-layer patch is smaller than the lower one; the dimension of the unit cell is 0.6λ, but the actual patch position may slightly shift according to the optimization. Thus the design parameters are the width of the patches on both layers and the shift of each element from the regular lattice distribution. Considering all the symmetries involved in the analysed structure, the total number of free parameters is 193.

In the considered design the central frequency is 10 GHz. A tapered slotline antenna (TSA) is employed as a linear polarization feed, located at focus, realizing a f/D ratio of 0.65.

TABLE I. DIRECTIVITY AND APERTURE EFFICIENCY

Method	*ACO*	*BBO*	*DE*	*PBIL*	*SGA*
Direct. (dB)	26,9	30,5	30,5	27,7	30,4
Apert. Eff.	0,311	0,709	0,708	0,374	0,695

The feed radiation pattern is shaped in order to provide a uniform illumination corresponding to a maximum aperture efficiency.

B. Numerical Results

To confirm the capabilities of ACO, BBO, DE, PBIL and SGA in dealing with EM problems, and to compare their features with those of other more consolidated evolutionary algorithms, they are here applied to the design of an elliptical reflectarray with 329 elements. The cost function takes into account a specific threshold for the sidelobe level.

Figures 15-19 show the best radiation pattern obtained with different techniques after 10000 function evaluations and several independent trials; the corresponding directivity and aperture efficiency are also reported in Table I.

The reported results show that some techniques, namely DE, BBO, and SGA are particular effective in dealing with this kind of complex optimization, mainly due to their ability to face complex discontinuous problems.

ACKNOWLEDGMENT

This work is part of the ASPRI educational program of Politecnico di Milano; the students who collaborated to this project are: Riccardo Albi, Giada Agoletti, Jacopo Banchetti, Matteo Bertarini, Lorenzo Combi, Andrea Carbonara, Pietro D'Antuono, Tommaso Guffanti, Tommaso Guggiari, Federico Lo Presti, Alberto Oregio Catelan, Paolo Scaramuzzino, Alessandro Serboli, Oleg Testoni, Tommaso Zanelli, Enrico Zucchelli.

The here considered optimization algorithms were taken from [14].

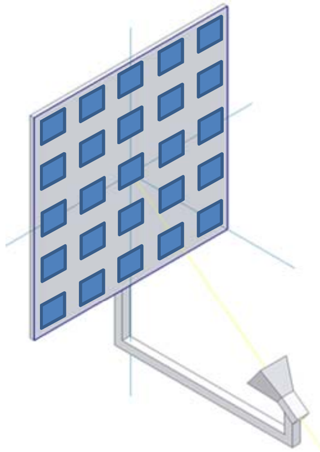

Fig. 14 Sample off-set reflectarray geometry.

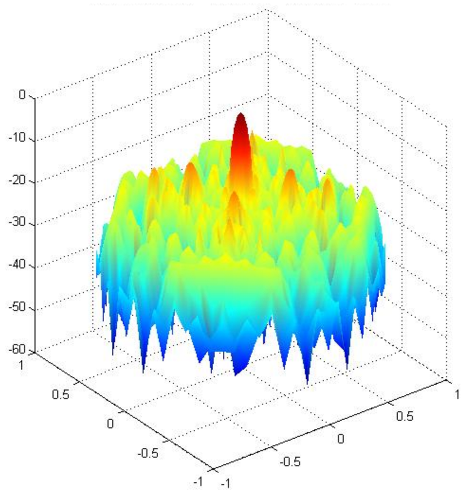

Fig. 15 Best result obtained after optimization with ACO.

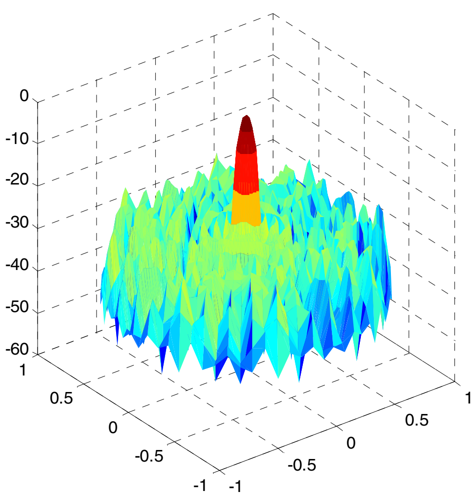

Fig. 16 Best result obtained after optimization with BBO

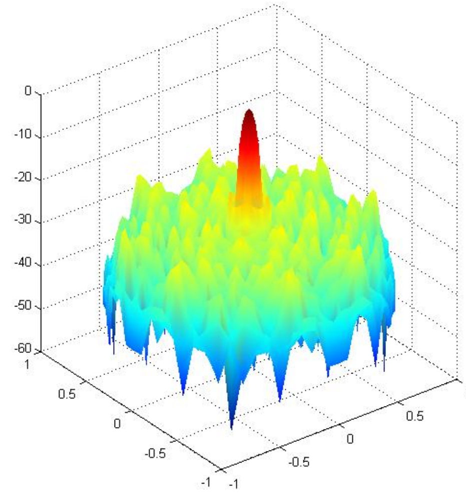

Fig. 17 Best result obtained after optimization with DE

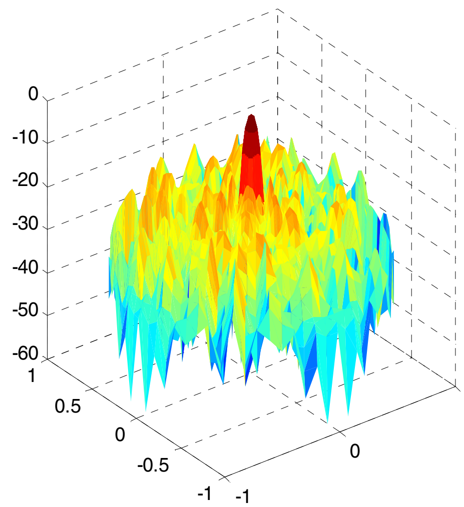

Fig. 18 Best result obtained after optimization with PBIL

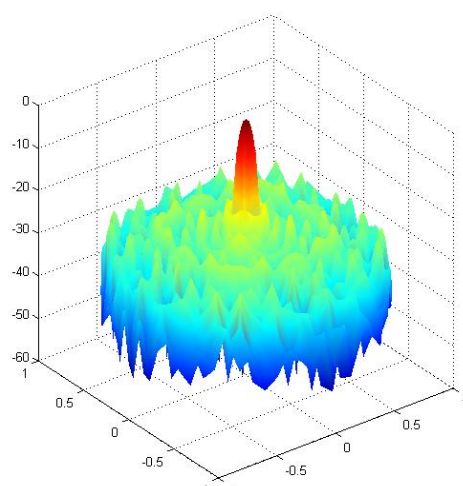

Fig. 19 Best result obtained after optimization with SGA

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