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Alessandro Gandelli, Francesco Grimaccia, Marco Mussetta, Paola Pirinoli, Riccardo Enrico Zich

Genetical Swarm Optimization: an Evolutionary Algorithm for Antenna Design

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Original scientific paper

In this paper a new effective optimization algorithm called Genetical Swarm Optimization (GSO) is presented. This is an hybrid algorithm developed in order to combine in the most effective way the properties of two of the most popular evolutionary optimization approaches now in use for the optimization of electromagnetic structures, the Particle Swarm Optimization (PSO) and Genetic Algorithms (GA). This algorithm is essentially, as PSO and GA, a population-based heuristic search technique, which can be used to solve combinatorial optimization problems, modeled on the concepts of natural selection and evolution (GA) but also based on cultural and social rules derived from the analysis of the swarm intelligence and from the interaction among particles (PSO). Preliminary analyses are here presented with respect to the other optimization techniques dealing with a classical optimization problem. The optimized design of a printed reflectarray antenna is finally reported with numerical results.

Key words: evolutionary optimization, hybridization strategies, reflectarray antennas

1 INTRODUCTION

In recent years several global optimization algorithms have been developed for the optimization of every kind of electromagnetic problems. Global search methods present two competing goals, *exploration* and *exploitation*: exploration is important to ensure that every part of the solution domain is searched enough to provide a reliable estimate of the global optimum; exploitation, instead, is also important to concentrate the search effort around the best solutions found so far by searching their neighborhoods to reach better solutions [1].

Generally the solution domain of an electromagnetic optimization problem may present discontinuous and non differentiable regions, and so it is often necessary to introduce suitable approximations of the electromagnetic phenomena in order to conserve computational resources. Furthermore, when the number of variables increases to hundreds or thousands, the traditional algorithms show their limits.

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, and consequently their performances are evaluated in terms of speed of convergence. Furthermore, the problem of premature convergence of the best individuals of the population to a local optimum is a well known drawback frequently found in these techniques. To overcome these limits, in previous papers, the authors proposed a new kind of hybrid method consisting in a strong co-operation of GA and PSO [2, 3].

This technique, exploiting the distinctive attributes of the two algorithms, results in a general purpose tool that can represent a fast method for optimization of large domain objective functions. This feature makes it suitable for application on a wide range of electromagnetics problems.

In the following two sections the most important features of GA and PSO are presented, while in section 4 the GSO itself is illustrated. In section 5 preliminary studies on the performances of the GSO are presented with respect to the other traditional techniques. Section 6 shows other extensions of the proposed hybrid algorithm. Finally, section 7 reports the design of a planar reflectarray antenna, optimized with the proposed technique; numerical results of the obtained configuration are reported.

2 GENETIC ALGORITHM OPTIMIZATION

Genetic Algorithm (GA) is one of the most effective evolutionary algorithm developed until now [4, 5]; it simulates the natural evolution, in terms of survival of the fittest, adopting pseudo-biological operators such as selection, crossover, mutation, and many other additional operators introduced to get a faster convergence rate.

In GA, the set of parameters that characterizes a specific problem is called an individual or a chromosome and it is composed of a list of genes. Each gene contains the parameter itself or a suitable encoding of it. Each individual therefore represents a point in the search space, and hence a possible solution to the problem. The fitness function is therefore evaluated for each individual of the population, resulting in a score assigned to the individual. Based on this fitness score, a new population is generated iteratively with each successive population referred to as a generation.

Starting from a population of randomly generated individuals, the three basic GA operators (selection, crossover, and mutation) are applied in order to manipulate the genetic composition of this population. Selection is the process by which the most highly rated individuals in the current generation are chosen to be involved as parents in the creation of a new generation. The crossover operator produces two new individuals (i.e. candidate solutions) by recombining the information from two parents. Crossover operation occurs in two steps. In the first one, a given number of crossing sites, along with the parent individual, are selected uniformly at random. In the second step, two new individuals are formed by exchanging alternate pairs of selection between the selected sites. The random mutation of some gene values in an individual is the third GA operator.

Genetic Algorithms are very efficient at exploring the entire search space, but are relatively poor in finding the precise local optimal solution in the region in which the algorithm converges. Many efforts on the enhancement of traditional GAs have been proposed [6, 7], by modifying the structure of the population or the role that an individual plays in it (distributed GA, cellular GA, and symbiotic GA) or by modifying the basic operations of traditional GA, or by adding new ones, such as elitism.

Hybrid genetic algorithms with local search methods have been introduced to improve the performance of GA in searching process, solving a wide variety of engineering design problems. They use local improvement procedures as a part of the evaluation of the individuals of the population: these procedures complement the global search strategy of the GA. Often they find better solutions than simple GA, searching more efficiently in the solution space.

The Genetic Algorithm developed for this application uses real encoded genes, since for high number of variables they show themselves faster than binary ones to converge towards the maximum value [8]. Several additional operators have been developed for GA in order to get a faster convergence rate.

3 PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization (PSO) is one of the more recently developed evolutionary technique, and it is based on a suitable model of social interaction between independent agents (particles) and it uses social knowledge in order to find the global maximum or minimum of a generic function [9]. While for the GA, as shown in section 2, the improvement in the population fitness is assured by pseudo-biological operators, such as selection, crossover and mutation, the main PSO operator is the velocity update that takes into account the best position explored during the iterations, resulting in a migration of the swarm towards the global optimum.

In the PSO the so called swarm intelligence (i.e. the experience accumulated during the evolution) is used to search the parameter space by controlling the trajectories of a set of particles according to a swarm-like set of rules [10, 11]. The position of each particle is used to compute the value of the function to be optimized. Consequently every position is a particular solution of the optimization problem. Individual particles traverse the problem hyper-space and are attracted by both the position of their best past performance and the position of the global best performance of the whole swarm. Particles are moved in the domain of the problem with variable speeds and every position they reach represents a particular configuration of the variables set, which is then evaluated in order to get a score.

As for GA, the starting point for PSO is the definition of a random population of particles. In the PSO technique each particle *i*-th is defined by its position vectors X_i in the space of the parameters to be optimized but, differently than GA, such a particle also has a random velocity V_i in the parameter space. At each iteration the particle moves according to its velocity and the cost function to be optimized $f(X)$ is evaluated for each particle in their current position. The value of the cost function is then compared with the best value obtained during the previous iterations. Besides, the best value ever obtained for each particle is stored and the corresponding position P_i is stored too. The velocity of the particle is then stochastically updated following the updating rules based on the attractions of the position P_i of its personal optimum and the position P_g, which is the global optimum.

Remembering that the global optimum is the best fitness value ever reached by all the swarm, equation (1) shows the well known standard PSO updating rule for particles' velocities:

$$V_{i+1} = \omega V_i + \phi_1 \eta_1 (P_i - X_i) + \phi_2 \eta_2 (P_g - X_i) \qquad (1)$$

where ω is a friction factor that tends to stop the particle and prevents oscillations around the optimal value, effectively speeding up convergence. ϕ_1 and ϕ_2 are constants, while η_1 and η_2 are random positive numbers with a uniform distribution between 0 and 1. The presence of random weights in the pull terms generated by the particle's best position P_i and the global swarm best position P_g causes wide oscillations and a random search in the entire parameter space. Such oscillations are precious whereas they broaden the search of each particle but they have some drawbacks since they can produce continuous oscillation around the optimal point. Such oscillation can be dampened, and so the convergence enhanced, via an effective use of the ω parameter.

4 GENETICAL SWARM OPTIMIZATION GENESIS

Some comparisons of the performances of GA and PSO are present in literature [12], underlining the reliability and convergence speed of both methods, but continuing in keeping them separate.

Due to the different search method adopted by the two algorithms, the typical selection-crossover-mutation approach versus the velocity update one, both the algorithms have shown a good performance for some particular applications but not for other ones. For example we noticed in our simulations that sometimes GA outperformed PSO, but occasionally the opposite happened showing the typical application driven characteristic of any single technique. In particular PSO seems to have faster convergence rate than GA early in the run, but often it is outperformed by GA for long simulation runs, when the last one finds a better solution.

Anyway, the population-based representation of the parameters that characterizes a particular solution is the same for both the algorithms; therefore it is possible to implement an hybrid technique in order to utilize the qualities and uniqueness of the two algorithms. Some attempts have been done in this direction, with good results, but with a weak integration of the two strategies. Precisely, most of the times one technique is used mainly as a pre-optimizer for the initial population of the other technique. In [13], for example, the authors test two different combinations of GA and PSO, using the results of one algorithm as a starting point for the other (in both the orders) to optimize a profiled corrugated horn antenna. Another hybridization strategy is proposed in [14], where the upper-half of the best-performing individuals in a population is regarded as elite and, before using GA operators, it is first enhanced by means of PSO, instead of being reproduced directly to the next generation.

The hybrid technique here proposed, called Genetical Swarm Optimization (GSO), consists in a strong cooperation of GA and PSO, since it maintains the integration of the two techniques for the entire run. In fact, this kind of updating technique yields a particular evolutionary process where individuals not only improve their score for natural selection of the fitness or for good-knowledge sharing, but for both of them at the same time.

In each iteration the population is divided into two parts and they are evolved with the two techniques respectively. They are then recombined in the updated population, that is again divided randomly into two parts in the next iteration for another run of genetic or particle swarm operators. Figure 1 shows the idea that stands behind the algorithm and the way to mixing the two main techniques.

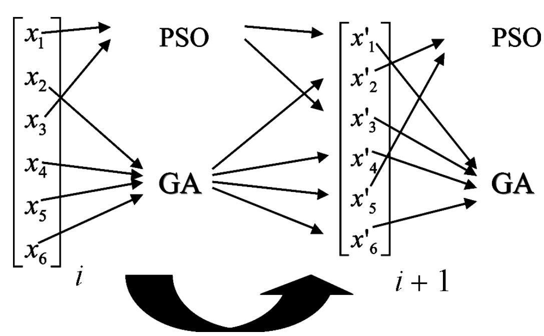

Fig. 1 Splitting of the population in subgroups during the iterations

The population update concept can be easily understood thinking that a part of the individuals is substituted by new generated ones by means of GA, while the remaining are the same of the previous generation but moved on the solution space by PSO.

The driving parameter of GSO algorithm is the Hybridization Coefficient (HC); it expresses the percentage of population that in each iteration is evolved with GA: so $HC = 0$ means the procedure is a pure PSO (the whole population is processed according to PSO operators), $HC = 1$ means pure GA (the whole population is optimized according to GA operators), while $0 < HC < 1$ means that the corresponding percentage of the population is developed by GA, while the rest with PSO technique.

5 PRELIMINARY ANALYSES

With the aim to validate the effectiveness of the developed technique, we used different values of *HC* in order to discover the best hybridization parameter and to compare GSO with pure PSO and GA, simply by setting $HC=0$ or $HC=1$.

A first comparison of the different performances has been made on a classical optimization problem, i.e. finding the maximum of a *N*-dimensional sinc function given by the equation:

$$f(X)=\prod_{i=1}^{N}\frac{\sin(x_i-x_{0,i})}{(x_i-x_{0,i})} \tag{2}$$

where *N* is the dimension of the domain, $x_i \in (0,1)$ and $x_{0,i}=0.3\forall i$. To analyze the efficiency of the different approaches when the solution space dimension increases, the authors chose three different cases of growing complexity, thus considering $N=5$,10 and 20.

The results reported in Figures 2–4 shows the fitness behavior related to different *HC* values for the function (2), for different problem dimensions. In addition the same figures show that the best *HC* value is 0.2 for the *N*-dimensional sinc function and it does not depend on the dimension of the problem. Furthermore, the obtained best *HC* value (0.2) means that, for a big-sized problem, the basic PSO can be strongly improved by adding a small percentage of genetic operators on the population.

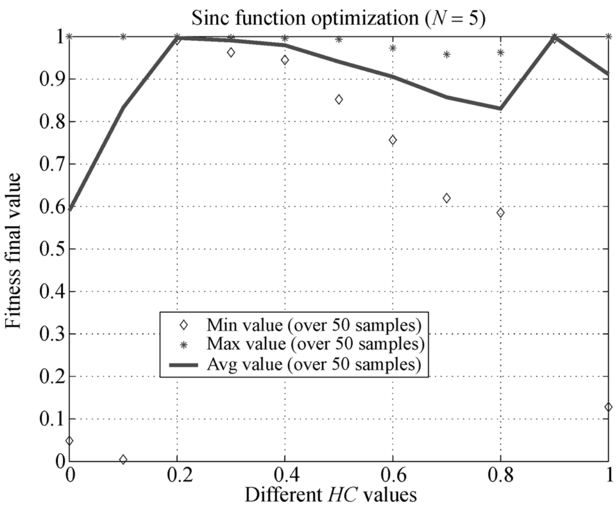

Fig. 2 Final fitness for different HC values (5-D sinc function optimization, average over 50 samples)

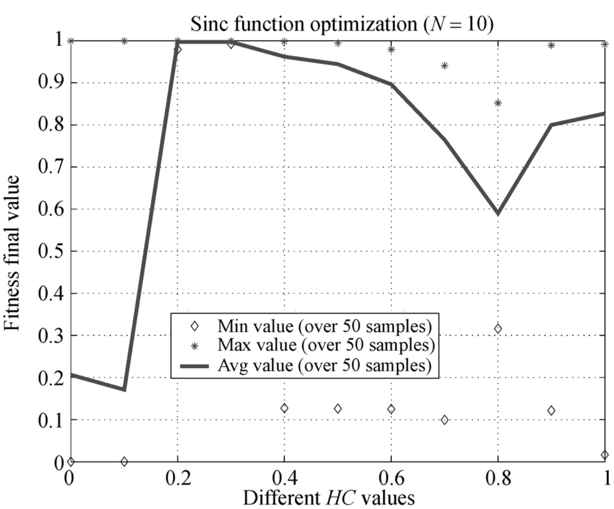

Fig. 3 Final fitness for different HC values (10-D sinc function optimization, average over 50 samples)

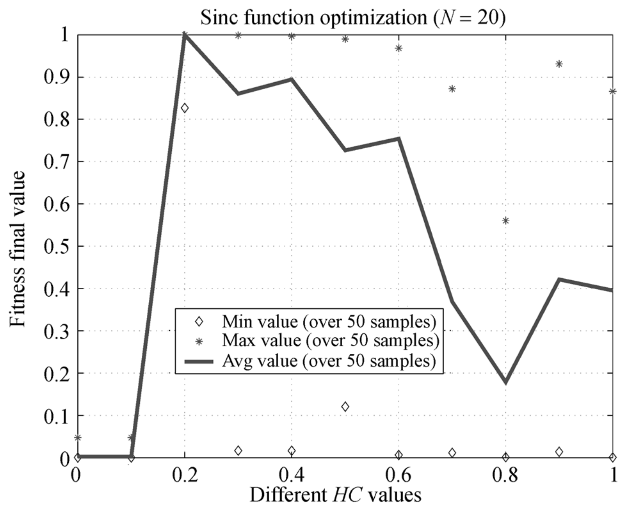

Fig. 4 Final fitness for different HC values (20-D sinc function optimization, average over 50 samples)

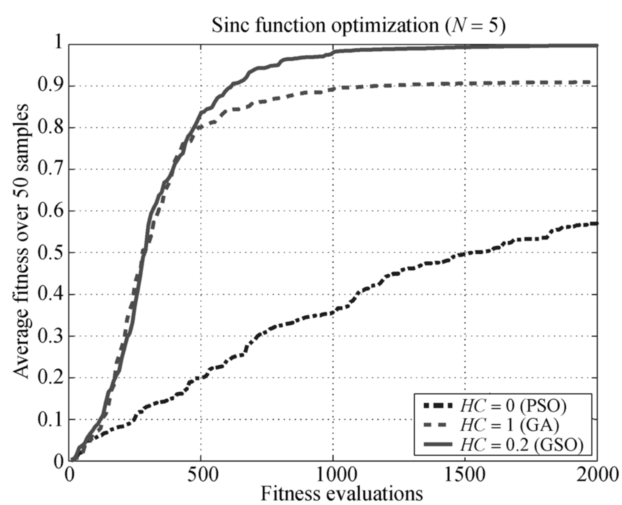

Fig. 5 GSO, PSO and GA fitness evolution for 5-D sinc function optimization (average over 50 samples)

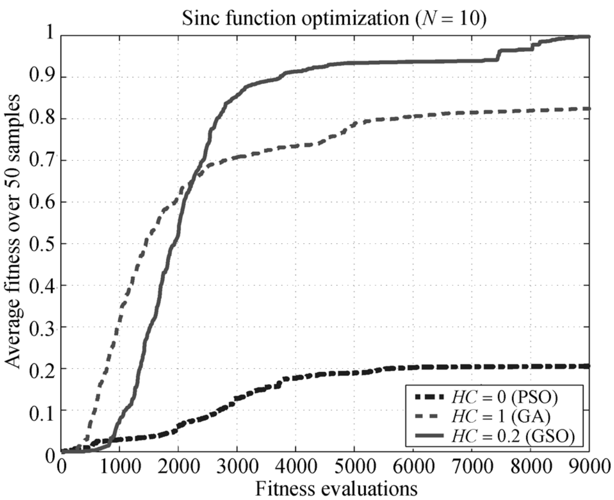

Fig. 6. GSO, PSO and GA fitness evolution for 10-D sinc function optimization (average over 50 samples)

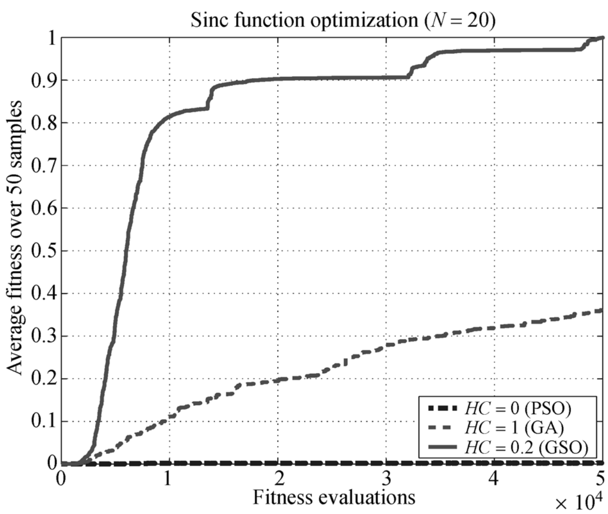

Fig. 7. GSO, PSO and GA fitness evolution for 20-D sinc function optimization (average over 50 samples)

Moreover, while for a small number of unknown GSO performance is similar to GA and PSO ones (Figure 5), if the size of the problem increases (Figures 6, 7), GSO behavior improves and outperforms GA and PSO during iterations.

It is important to notice that the evaluation of the fitness function is the most relevant time consuming task, while the computational overhead of the optimizer operators, different for the considered techniques, is negligible. This is particularly true in electromagnetic optimization. Therefore the larger the population, the longer is the single iteration, since several evaluations of the fitness function must be performed to complete the step. For this reason, the different techniques have been compared in terms of performed fitness evaluations rather than iterations, in order to fairly compare the different algorithms regardless of the number of individuals in the population.

6 THE GSO ALGORITHM CLASS

The *HC* approach opens a wide spectrum of possible merging strategies between GA and PSO, since the *HC* itself can be varied during the optimization run. In fact, the number of individuals evolved by a particular procedure, in each iteration, can change according to predefined variation rules of the *HC* parameter, in order to exploit a better convergence. This feature essentially extends the GSO concept to stand as a class of hybrid evolutionary algorithms.

For istance, a step variation of *HC* between 0 and 1 (or vice versa) occurring after half the run, realizes an hybridization approach similar to the one used in [13], where the population is initially evolved by PSO, then the resulting individuals, after about 50 % iterations, are evolved by GA (and vice versa).

Several variation rules for *HC* have been here considered, in order to explore different hybridization strategies for the GSO algorithm and to compare new approaches with others already present in literature. The set of hybridization rules considered by the authors has been reported in Table 1 and in Figure 8. In the following, a variable *HC* parame-

Table 1 **Rules of variation for the HC parameter during iterations**

Rule name	$HC(k)$
PSO	$HC(k) = 0 \ \forall k$
GA	$HC(k) = 1 \ \forall k$
Static hybridization	$HC(k) = HC \ \forall k$
Fluctuating	$HC(k) = \frac{1 + (-1)^k}{2}$
Step function down	$HC(k) = 1 - U\left(k - \frac{K}{2}\right)$
Step function up	$HC(k) = U\left(k - \frac{K}{2}\right)$
Linear decrease	$HC(k) = 1 - \frac{k-1}{K-1}$
Linear increase	$HC(k) = \frac{k-1}{K-1}$

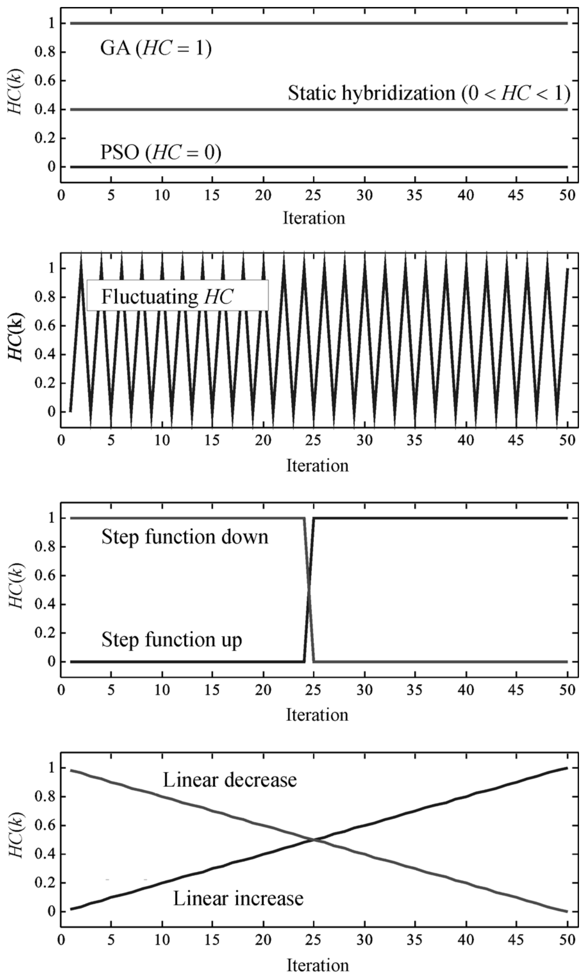

Fig. 8 Rules of variation for the HC parameter during iterations

ter will be referred as $HC(k)$, where $k = 1...K$ is the current iteration and K is the total number of iterations.

7 REFLECTARRAY DESIGN OPTIMIZATION

As a further test application, the described optimization process has been applied to the design of an elliptical microstrip reflectarray (see Figure 9), composed of 309 patches printed on a substrate with height $h = 1.6$ mm and dielectric constant $\epsilon_r = 2.17$, at the resonance frequency $f = 18$ GHz. The distance between elements that avoids the presence of grating lobes is 15 mm and so the total height of the panel is about 31 cm. The feed is in offset position and the radiation pattern of the incident field in the design procedure is approximated with a cosine-on-pedestal function.

In order to effectively reduce the computational load of the fitness function, a convenient simplified representation of the single element pattern, as well as of the total re-radiated field have been adopted.

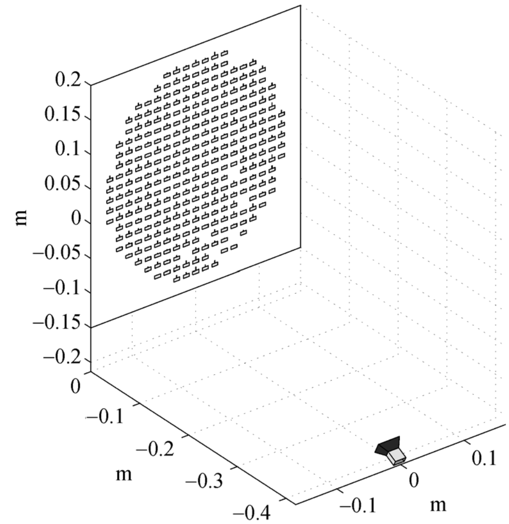

Fig. 9 The planar reflectarray antenna designed with GSO

Therefore in the considered model each radiator is described with its equivalent circuit and, to obtain the total re-radiated field, all the single contributions are summed. The neglecting of the mutual coupling is actually an acceptable approximation, since in the final configuration all the elements of the array have a significantly different size, i.e. they have a different resonance frequency; therefore the mutual coupling can be assumed negligible. For what concerns the possible techniques to compensate the different phase shift of the incident field on the different elements, it has been shown in previous works [15] that among the different combination analyzed, one of the most efficient is combining the presence of a stub with the variation of the patch size.

The optimization of the whole reflectarray has been carried out using the previously presented hybrid technique, whose target was the maximization of the re-radiated field in the desired direction, with the simultaneous minimization of the side lobe levels. Once the total size of the array and the spacing between the patches is fixed, a proper number of elements is located in the aperture. From that point the algorithm proceeds in varying the width of the patches and the lengths of the stubs (these are actually the two geometrical features to optimize), up to the satisfaction of the required fitness optimum.

In Figure 10 the fitness values of the solutions proposed by different GSO configurations are compared: for clarity, this plot reports just the results corresponding to the best performing values of HC, in order to understand how the proposed variation rules can affect the speed of convergence and reliability.

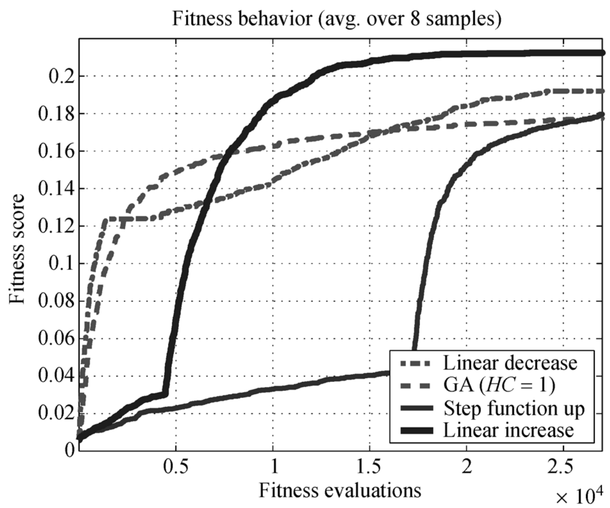

Fig. 10 Fitness score behavior for the reflectarray antenna optimization

The resulting far field radiation pattern after the optimization process are displayed in Figure 11. The optimization has been carried out taking into account the contribution of the ground plane to the reflected field (as described in [16]), thus forcing the optimizer to find the best configuration with this additional constrain. Therefore the radiation patterns shown in Figure 11 have a different side lobes level in the E and H planes due to the ground plane effect.

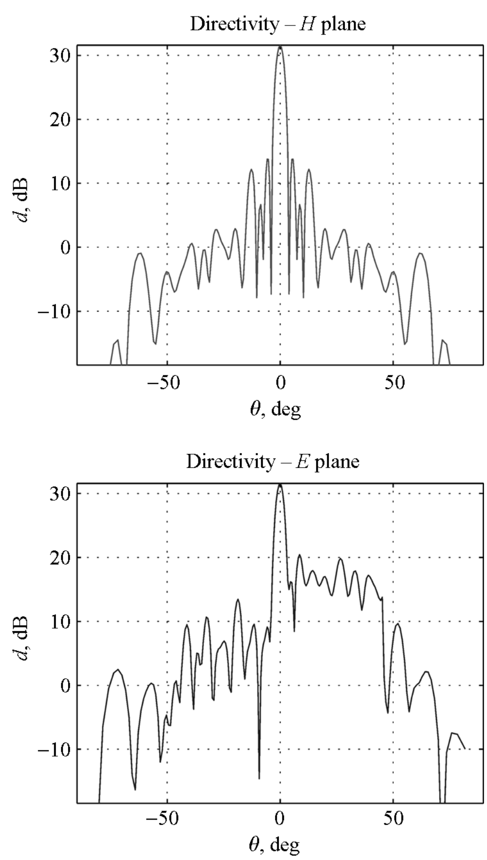

Fig. 11 Radiation pattern of the optimized configuration in the H and E planes

8 CONCLUSIONS

A novel class of hybrid evolutionary algorithms has been presented. The proposed technique integrates the main features of GA and PSO into the optimization process, in order to take advantage of the peculiarities of these two methods.

Preliminary studies of the performances over different optimization tasks have been conducted to understand the convergence behavior, showing that GSO is very effective in exploring the problem hyperspace, especially for the optimization of large domain objective functions.

The proposed technique has been applied to the design of a planar reflectarray antenna, in order to optimize the geometrical features of its elements. The reported results show that the GSO class of procedures is reliable and effective: this feature makes it suitable for a wider application in electromagnetics.

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Genetska optimizacija roja: evolucijski algoritam za dizajn antena. U radu je predstavljen novi efektivni optimizacijski algoritam nazvan genetska optimizacija roja (GSO). To je hibridni algoritam s ciljem da efektivno kombinira svojstva dva najpopularnija evolucijska optimizacijska algoritma, optimizacija roja čestica (PSO) i genetski algoritam (GA), u svrhu optimiziranja elektromagnetskih struktura. Novi algoritam je u principu i PSO i GA, populacijski zasnovana heuristična tehnika pretraživanja, koji može biti korišten za rješavanje kombinatornih optimizacijskih problema modeliranih na osnovi koncepta prirodne selekcije i evolucije (GA) kao i na osnovi kulturnih i socijalnih pravila proizašlih iz analize inteligencije počela i iz međudjelovanja čestica (PSO). Rezultati preliminarne analize prikazani su u radu i uspoređeni s ostalim optimizacijskim tehnikama na klasičnim optimizacijskim problemima.

Ključne riječi: evolucijski optimizacijski algoritmi, hibridne metode strategije, reflektorski antenski nizovi

AUTHORS' ADDRESSES

Alessandro Gandelli
Francesco Grimaccia
Marco Mussetta
Riccardo Enrico Zich

Politecnico di Milano, Dipartimento di Elettrotecnica
Piazza Leonardo da Vinci, 32 – 20133 Milano, Italy
E-mail: riccardo.zich@etec.polimi.it

Paola Pirinoli

Politecnico di Torino, Dipartimento di Elettronica
Corso Duca degli Abruzzi 24 – 10129 Torino, Italy
E-mail: paola.pirinoli@polito.it

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