A NEW HYBRID TECHNIQUE FOR THE OPTIMIZATION OF LARGE-DOMAIN ELECTROMAGNETIC PROBLEMS

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ABSTRACT – The paper presents a new hybrid evolutionary algorithm suitable for the optimization of large-domain electromagnetic problems. The hybrid technique, called Genetical Swarm Optimization (GSO), combines Genetic Algorithms (GA) and Particle Swarm Optimization (PSO). GSO algorithm is modeled on the concepts of Darwin's theory based on natural selection and evolution, and on cultural and social rules derived from the swarm intelligence. Numerical results are presented for both mathematical and electromagnetic optimization problems.

I. INTRODUCTION

In recent years several evolutionary algorithms have been developed for optimization of every kind of electromagnetic problems. The general goal of the optimization is to find a solution that represents the global maximum or minimum of a fitness function. Electromagnetic optimization problems generally involve a large number of parameters, that can be either continuous, discrete, or both, and often include constraints in allowable values. In addition, the solution domain of electromagnetic optimization problems often has non differentiable and discontinuous regions, and often utilizes approximations or models of the true electromagnetic phenomena to conserve computational resources.

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. Often global search methods are used together with other local search algorithm in order to improve efficiency and accuracy of the searching process [1].

The evolutionary computation algorithms (EA) are stochastic optimization methods, that emulate biologic processes or natural phenomena. The capability to find a global optimum, without being trapped in local optima, and the possibility to well face nonlinear and discontinuous problems, with great numbers of variables, are some advantages of these techniques. Besides these methods do not need to compute any derivatives in order to optimize the objective function and this fact allows to manage more complex fitness function.

Moreover, in contrast with traditional searching methods, EAs do not depend strongly on the starting point. Often a bad choice of the initial values can slow down the convergence of the entire process, or even drive the convergence towards a wrong solution, e.g. towards a local instead a global maximum or minimum. However, these algorithms have strong stochastic basis, therefore they need a lot of iterations to get a significant result, in particular when the optimization problem has a big number of unknowns.

Considering Genetic Algorithms and Particle Swarm Optimization algorithms, most of the times, PSO have faster convergence rate than GA early in the run, but they are often outperformed by GA for long simulation runs, or when the number of unknowns increase. This is due to the different types of search, adopted by the two algorithms.

The new hybrid technique here proposed, called Genetical Swarm Optimization, consists in a strong co-operation of GA and PSO, since it maintains the integration of the two techniques for the entire run of simulation. In each iteration, in fact, some of the individuals are substituted by new generated ones by means of GA, while the remaining part is the same of the previous generation but moved on the solution space by PSO. Doing so, the problem of premature convergence of the best individuals of the population to a local optimum, one of the most known drawbacks found in tests of hybrid global-local strategies, has been cancelled.

The effectiveness of the proposed procedure has been validated with different electromagnetics problems, showing a good behaviour in particular for the optimization of large-domain functions.

II. GA AND PSO

Genetic Algorithms [2],[3] simulate the natural evolution, in terms of survival of the fittest, adopting pseudo-biological operators such as selection, crossover and mutation. 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 by recombining the information from two parents. The random mutation of some gene values in an individual is the third GA operator.

One of the most recently developed evolutionary techniques is instead represented by the Particle Swarm Optimization [4]-[6], that is based on a model of social interaction between independent agents and uses social knowledge or swarm intelligence in order to find the global maximum or minimum of a function.

A brief introduction of PSO algorithm is given in this section. PSO uses social rules to search in the parameter space by controlling the trajectories of a set of indipendent particles. The position of each particle, representing a particular solution of the problem, is used to compute the value of the fitness function to be optimized. Each particle may change its position, and consequently may explore the solution space, simply varying its associated velocity.

The main PSO operator is, in fact, velocity update, that takes into account the best position, in terms of fitness value, reached by all the particles during their paths, G, and the best position that the agent itself has reached during its search, Pi, resulting in a migration of the entire swarm towards the global optimum.

At each iteration the particle moves around according to its velocity and position; the cost function to be optimized is evaluated for each particle in order to rank the current location. The velocity of the particle is then stochastically updated, according to the next formula:

$$V_i = \omega V_i + c_1 \varphi_1 (P_i - X_i) + c_2 \varphi_2 (G - X_i) \tag{1}$$

The term $\omega < 1$ is known as the "inertial weight" and it is a friction factor chosen between 0 and 1 in order to determine to what extent the particle remains along its original course unaffected by the pull of the other two terms; it is very important to prevent oscillations around the optimal value. The other two terms are known as self knowledge and social knowledge and they are balanced by the scaling factors $c_{1,2}$ that are constants and by $\varphi_{1,2}$ that are random, positive, numbers with a uniform distribution and a value that goes from 0 to 1.

III. GSO

Some comparisons of the performances of GA and PSO are present in literature [7]-[9], underling the reliability and convergence speed of both methods, but continuing in keeping them separate. In particular PSO have faster convergence rate than GA early in the run, but often they are outperformed by GA for long simulation runs, when the last ones find 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 [8],[9], with good results, but with weak integration of the two strategies, because one algorithm is used mainly as the pre-optimizer for the initial population of the other one.

The new hybrid technique here proposed, called Genetical Swarm Optimization, consists in a strong co-operation of GA and PSO, since it maintains the integration of the two techniques for the entire run. In each iteration, in fact, the population is divided into two parts and it is evolved with the two techniques respectively. The two parts are then recombined in the updated population, that is again divided randomly into another two parts in the next iteration for another run of genetic or particle swarm operators. Fig.1 shows the flow chart of the developed algorithm.

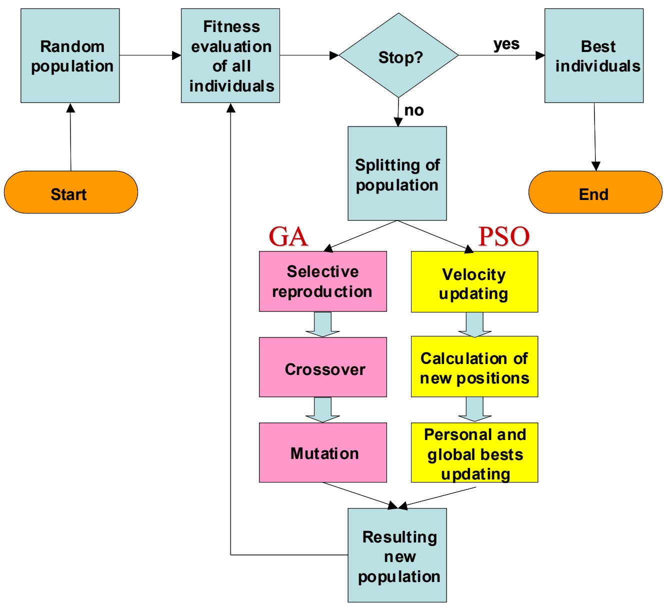

Fig.1   Flow-chart of the GSO algorithm.

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. This kind of updating results in a more natural evolution, where individuals not only improve thei scores for natural selection of the fitness, or for good-knowledge sharing, ut for both of them at the same time.

The driving parameter of the 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 updated according to PSO operators), HC=1 means pure GA, while 0<HC<1 means that the corresponding percentage of the population is developed by GA, the rest with PSO.

The authors compared the performances of the GSO algorithm, for different problems, also using a varying HC approach: in this case, the driving parameter is allowed to vary within the same run from 0.2 to 0.8 (GSO up) and from 0.8 to 0.2 (GSO down). Results of these approaches are shown in section IV.

IV. NUMERICAL RESULTS

In Fig.2-5 the performances of the GSO algorithm are reported. Two classical optimization problems have been considered: the first one is a typical N-dimensional sinc fitness function (Fig.2,3); the second is the synthesis of a linear array antenna of 40 elements controlled in amplitude (Fig.4,5).

In order to validate the effectiveness of the developed technique and to select the best value of the hybridization parameter different convergence rates, obtained with different HC values each time, have been analysed. This made it possible to compare GSO also with a pure PSO (obtained fixing HC=0) and a pure GA (obtained fixing HC=1).

Results shown in Fig.2 represent the fitness value reached by the optimizer in the same number of iteration for the sinc function optimization, with N=20. A maximum performance is shown around HC=0.2; this means that a 20% of population updated with GA, and the rest with PSO, is the best compromise for this new kind of hybrid evolutionary algorithm, for this considered problem. The effectiveness of this method is displayed in Fig.3, that reports the corresponding average fitness evolution over number of fitness evaluation (PFE: Performed Fitness Evaluation) for 5 cases: pure PSO, pure GA, GSO, GSO up, GSO down. In the same figure the blue line, representing the behaviour of a pure PSO technique, seems to stay at a zero value only for scale reasons; however the fact means that pure PSO does not work well if compared with the other 4 cases, but, as stated before, the presence of genetic operators in this technique, limited to a very small portion of the population, it is enough to dramatically increase its performances. Results for the array optimization problem are reported in Fig.4 (resulting far field radiation pattern) and Fig.5 (average fitness over number of fitness evaluation), showing that, in this case, the adoption of the pure PSO technique would be better than GA; anyway the best performance is obtained again with GSO, but with the HC value equal to 0.1, smaller than the previous one.

In each considered problem it is possible to see that, with a suitable HC value, GSO performs better then pure GA or pure PSO, reaching an higher fitness value (best position) in the same number of fitness evaluations. The other two cases, GSO up and GSO down, outperform GA and PSO and they behave well in both the optimization problems. Consequently, since the proper HC value seems to be strictly problem-dependant (i.e. the HC value used for the array optimisation would not be suitable for the sinc function optimisation) a varying ratio of GA and PSO generally produces better results and can be considered an acceptable trade-off between generality and convergence speed.

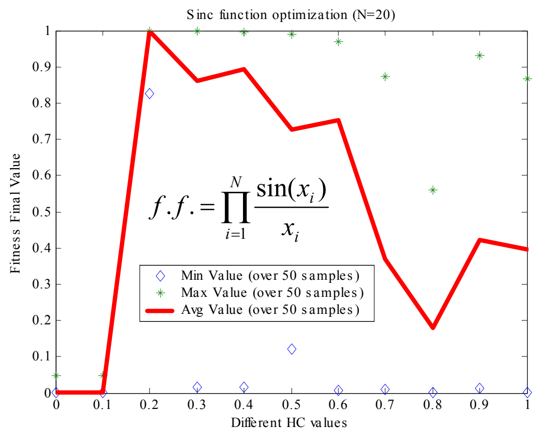

Fig.2. Fitness for different HC values (50 samples).

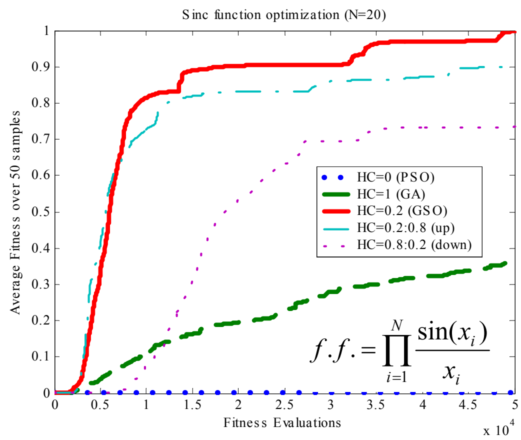

Fig.3. Average fitness over iterations (50 samples).

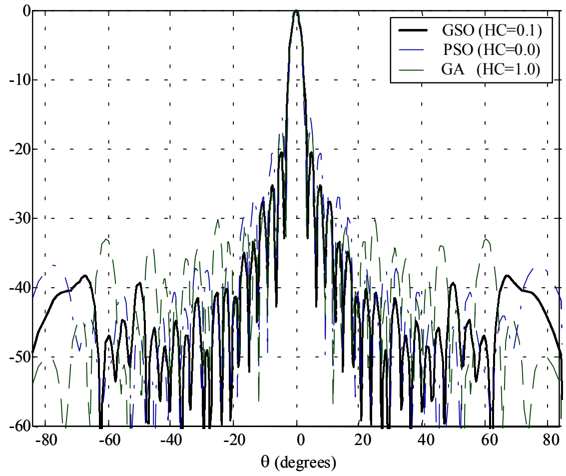

Fig.4. Resulting radiation pattern after 500 iterations.

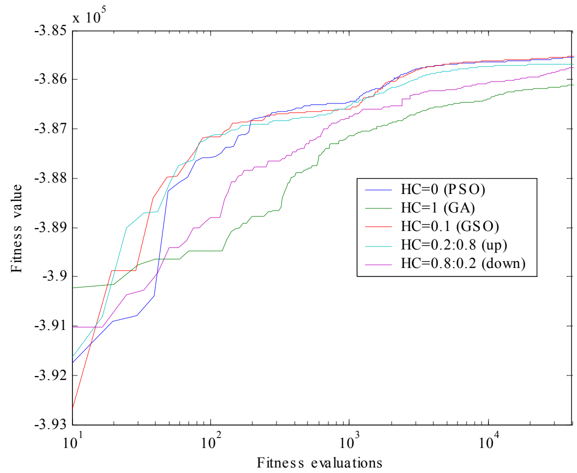

Fig.5. Fitness evolution over fitness evaluation (5 samples).

V. CONCLUSIONS

In this paper a new optimization method is proposed, in order to take the best characteristics of two previous well known evolutionary computation techniques: Genetic Algorithms and Particle Swarm Optimization. The Genetical Swarm Optimization algorithm emerges as a fast method for optimization of complex nonlinear objective functions and its generality makes it suitable for wide use in electromagnetic applications: in particular, due to the characteristic to perform a quick global search in the parameter space without getting trapped in local minima, it may be suitably adopted for solving optimum problems in the synthesis of linear and planar arrays or EBG materials, or in shielding structures design.

VI. REFERENCES

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