Optimization Techniques for Electromagnetic Design with Application to Loaded Antenna and Arrays

Simone Genovesi(1), Davide Bianchi(1), Agostino Monorchio(1), and Raj Mittra(2)
(1) Dipartimento di Ingegneria dell'Informazione, Università di Pisa
Via G. Caruso 16, Pisa 56122, Italy
(2) EMC lab, Department of Electrical Engineering, The Pennsylvania State University
Email: simone.genovesi (davide.bianchi, a.monorchio) @unipi.it, rajmittra@ieee.org

***Abstract* — Rapid development of new communication and radar systems, which require devices with improved capabilities and compliance with many requirements, poses a difficult challenge to the designers of these platforms. In many electromagnetic applications, where a large number of parameters need to be suitably tuned to achieve the desired functionality of a device, analytical solutions are not always available for complex real systems, so that the computational cost of a single analysis can be prohibitive; hence the design strategy has to be very effective and flexible. Optimization algorithms have often played an important role as reliable tools for electromagnetic designs. In this article, we review the main global optimization algorithms applied to electromagnetic (EM) problems, highlighting their most important features and distinctive characters. We also discuss some limits of their application, the evolution of recent paradigms and new research fronts. Finally, we demonstrate the effectiveness of a Genetic Algorithm optimization in improving the performance of a single loaded antenna, and that of an array of dipoles.**

***Index Terms*— Optimization, evolutionary algorithms, genetic algorithm, particle swarm, differential evolution, broadband antennas, scattering parameters, loaded antennas, matching network.**

I. Introduction

Modern communication, sensing and radar systems are characterized by an ever-increasing system complexity and multiple challenges on performance metrics that must be met, either by the system or by a single device [1]-[6]. In order to address the task of designing a new device or subsystem with a series of output requirements, we can adopt an approach, based on a parametric analysis, by considering the effects of modifying the most important parameters of an initial guess, which can be either an existing design or a new one that appears promising. However, even if the number of parameters exceeds just a few, this approach may require a large number of evaluations to determine the performance of the device for each configuration. More importantly, a comparison of the performance of each of these designs could not provide a sufficiently clear direction to follow and modify the initial guess in order to achieve the desired goal. A more efficient strategy is to provide the designer with a set of parameters which help tailor the design in such a way that it meets the desired specifications.

In this framework, the described problem can be cast as that of optimization. Broadly speaking, an optimization process consists of determining the optimal set of values of the variables which minimize or maximize a so-called "fitness" or "cost" function. This can be the case of the input parameters which completely describe the behavior of a device or a system and the search of their optimal values in order to meet certain required performance metrics. The function which evaluates the performances of the device is commonly referred to as the "fitness function" or "objective function", whereas the value assumed by this function for a particular input is called "fitness" or "cost". The landscape of optimization algorithms is truly vast and expansive, thanks to the improvements in existing approaches, or the proposal of new paradigms [7]-[12]. The most common approach to classifying the optimization techniques is to either categorize them into local and global ones, to label them as deterministic, stochastic or metaheuristic [13]-[18]. In addition to the ongoing improvements in the existing algorithms and the theoretical studies on numerous algorithms for computational optimization and artificial intelligence, increasing attention is being paid to the problem of global optimization schemes designed to solve real-world problems arising in various applications and the electromagnetic community has played a very active role in this area[19]-[22]. Global optimizers are useful tools that play an important role in the design workflow mostly because of their intrinsic ability to avoid getting trapped in local minima of the cost function but also because they circumvent the need for the derivatives of the fitness function. In addition, they are able to operate on discrete as well as continuous variables; they can be easily parallelized; they can handle multidimensional problems; and their final result is independent of the initial guess.

In this work, we will present a survey of the global optimization algorithms that are widely used for solving electromagnetic design problems by observing their most important features and focusing on the distinctive characters that render them unique. Finally we will draw some conclusions and present some observations, which would hopefully stimulate discussions and open up new research fronts.

To demonstrate the usefulness and reliability of optimization methods in electromagnetics, we will employ an optimization scheme based on a genetic algorithm and a fast solver to consider two test problems, namely the designs of a loaded antenna and a phased array.

II. Darwinian Optimizers

Observation of the nature and its dynamics has always been a great inspiration for the development of optimization algorithms. One of most remarkable case is represented by Darwin's theory of evolution, based on the concept of the survival of the fittest individual among the members of a population. The principles of natural selection and evolution have been adopted to realize optimization algorithms, and the number of research areas and real-world applications to which they have been successfully applied [23][24] is very large indeed. In the field of electromagnetism, particular attention has been devoted to Genetic Algorithms (GAs) and Differential Evolution (DE) schemes, although interesting results have also been obtained by using Microgenetic Algorithms (MGAs), Memetic Algorithms (MAs), Invasive Weed Optimization (IWO) and the Covariance Matrix Adaptation Evolutionary Strategy. The most important features of the above mentioned optimization strategies will be discussed in the following.

1) *Genetic Algorithm*

The first step performed in a GA algorithm is the encoding of each single parameters into a *gene*. The parameter can be a continuous variable or a discrete one and the corresponding value can be translated into a real or binary encoded gene [23],[25]. The gene represents the basic block of a chromosome which comprises all the parameters that completely describe the design variables. Therefore the chromosome represents a potential candidate for an optimal solution to the design problem under consideration. The flow chart of the basic GA optimizer s illustrated in Fig. 1. An initial population comprising of a set of chromosomes is created at the beginning of the evolutionary process. The performance of the parameters configuration encoded in each chromosome are evaluated by the cost function, which measures the goodness of each solution. For example, the encoded parameters are the substrate characteristics (thickness and permittivity) and the patch dimensions if we are looking for a resonant patch antenna. The fitness function represents the connection between the real physical problem and the optimization process. The cost function assigns a fitness value to each chromosome on the basis of the difference between the desired return loss and the one obtained by using the considered parameters. After the fitness evaluation of each individual, the GA enters its reproduction cycle. More in detail, the selection operator chooses the parents, who will participate in the generation of a new breed of solutions. This step is correlated with the fitness of each chromosome since the selection strategy operates by considering the goodness of each solution. There are numerous selection strategies, that are both stochastic and deterministic, but the proportionate selection and tournament selection are probably the ones that are used most widely [26]. In the former, also referred to as roulette-wheel selection, each chromosome has a probability of being selected based on its fitness value. For a maximization problem, the higher the fitness, the higher is the probability of being selected for reproduction. If we consider the *i-th* chromosome (C_i) and its fitness $f(C_i)$ then the probability of selection $p_{sel}(C_i)$ is

$$p_{sel}(C_i) = \frac{f(C_i)}{\sum_j f(C_j)}. \tag{1}$$

In this case chromosomes with high fitness values will have a better chance to contribute to the creation of the next generation with respect to chromosomes with lower fitness. However, even low fitness individuals have a non-zero probability of participating in some matings, and thus possibly transferring their genetic information to the genetic pool. The latter selection strategy chooses at random, a sub-population of N chromosomes which "fight" each other based on the "strength" of their fitness, and the winner becomes the selected individual. Once two parents have been selected, the generation of children can take place, via recombination with probability p_{Xover}, and mutation with probability p_{mut}. The recombination or crossover accepts two selected chromosomes as parents and produces two children. The simplest crossover is the single-point one which is illustrated in Fig. 2*(a)* for the case of binary-encoded chromosomes. Basically, a random position in each parent chromosome is selected in the cross-over process and the two portions of chromosomes are swapped between the two individuals. If the crossover does not occur, the two parents are included in the new generation without any change. The aim of the crossover is to evolve the genetic material of the parents' pool into new generation, which is relatively fitter than the previous one.

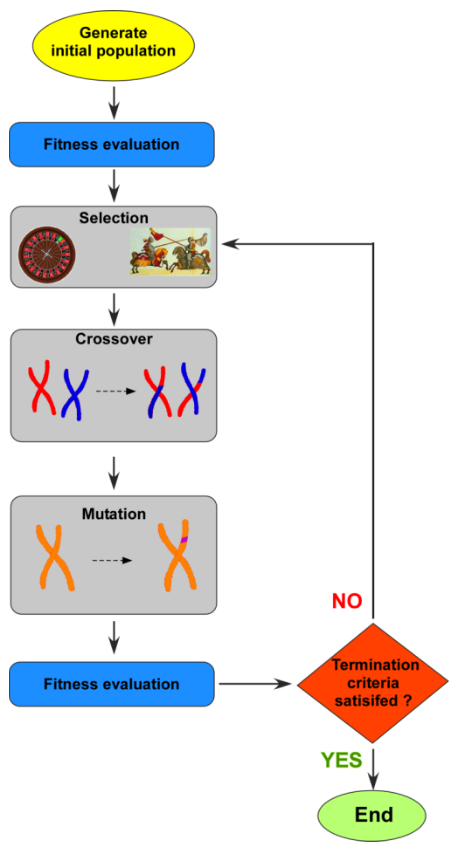

Fig. 1 – Flowchart of the basic genetic algorithm optimizer

On the other hand, the mutation operator explores portions of the solution space that are not included in the current genetic pool. In case of mutation a single chromosome is altered in a random position as illustrated in Fig. 2*(b)* for a binary GA implementation. Once the reproduction cycle is terminated, the performance characteristics of the new generation are evaluated. The optimization process is terminated if one of the GA designs satisfies the desired specifications; otherwise, the reproduction cycle iterates until the maximum number of generation is reached.

Modifications of this basic GA implementation are numerous, but one of the most relevant is represented by elitism [27]. In the simplest form of elitism, the best individual of the parental generation is included in the one of the children, provided that the best individual of the offspring generation is worse than the best chromosome of the preceding generation. This operation avoids the loss of genetic information expressed in the best individual of the pool, and thus helps the convergence to an optimal solution. Genetic Algorithms have been applied to a very wide spectrum of design problems [28]-[33], including antenna arrays [34]-[40], Frequency Selective Surfaces (FSSs) [41]-[43]; and metamaterials [44]-[46].

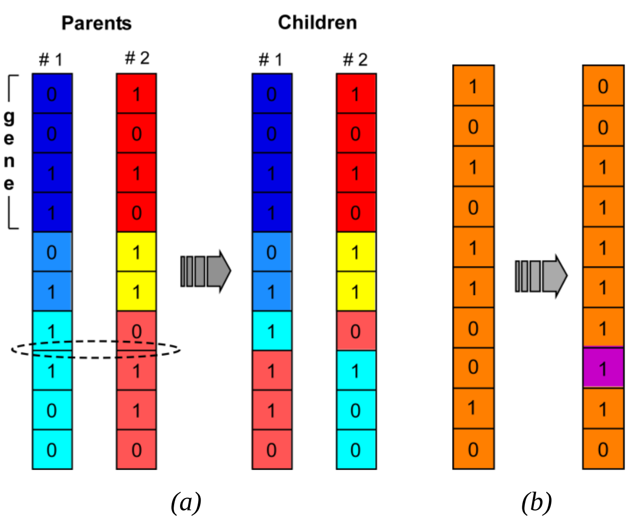

Fig. 2 - Example of single-point crossover and mutation operator applied to binary-encoded chromosomes. The structure of the chromosome as a set of genes is also highlighted.

2) *Differential Evolution*

The Differential Evolution (DE) paradigm has been proposed by Storn and Price [7] and is a population-based algorithm inspired by the natural laws governing the evolution of individuals as postulated by Darwin. The main difference between DE and GA is the use of the same evolutionary operators but in different ways. In particular, in DE the selection step is implemented following the crossover and mutation application and involves both the parents as well as children, thus providing an automatic inclusion of the best individual without any elitism strategy. In its simplest implementation, the DE begins by randomically generating a population of N vectors, each one comprising all the D parameters useful to completely describe the device or the system under optimization. The first step in this procedure is the process of mutation (Fig. 3). This operator produces a new vector of parameters (the *mutant vector*) by adding the weighted difference between two other population vectors (*vector#2* and *vector#3*) to a vector (*vector#1*). Next, the crossover step is implemented by mixing the parameters of the mutated vector with the ones of the *target vector*, to generate the *trial vector*. Finally, the selection operator compares the trial and target vectors and promotes the fittest one to the following generation. In order to build a new generation, each vector in the population has to serve as the target vector at least once. The mutant vector at generation G, $m_{i,G}$ (with $i = 1,2,\ldots,N$) is generated according to:

$$m_{i,G} = x_{v1,G-1} + F\left(x_{v2,G-1} - x_{v3,G-1}\right) \tag{2}$$

where $v1$, $v2$ and $v3$ are different vectors randomly selected from the overall population, and F is a real and constant factor which controls the differential variation of the difference between the vector#2 and vector#3.

The crossover contributes to the diversification of the genetic material and produces the trial vector $u_{i,G}$ from the mutant vector $m_{i,G}$ and the target vector $x_{i,G-1}$ following the rule

$$u_{i,G}(j) = \begin{cases} m_{i,G}(j) \; if \; \left(rand(j) \le CR\right) \; or \; j = rnbr(i) \\ x_{i,G-1}(j) \; if \; \left(rand(j) > CR\right) \; and \; j \ne rnbr(i) \end{cases} \tag{3}$$

where j=1,2,...D, $rand(j)$ is a random number within [0,1], CR is the crossover constant varying in the same interval [0,1] and $rnbr(i)$ is a randomly selected index within [1,2,…,D]. Numerous improvements of the described conventional Differential Evolution algorithm have been proposed [47]-[49] with successful results. The DE paradigm has been applied to numerous electromagnetic problems such as inverse scattering [50], antenna and array design [51]-[53].

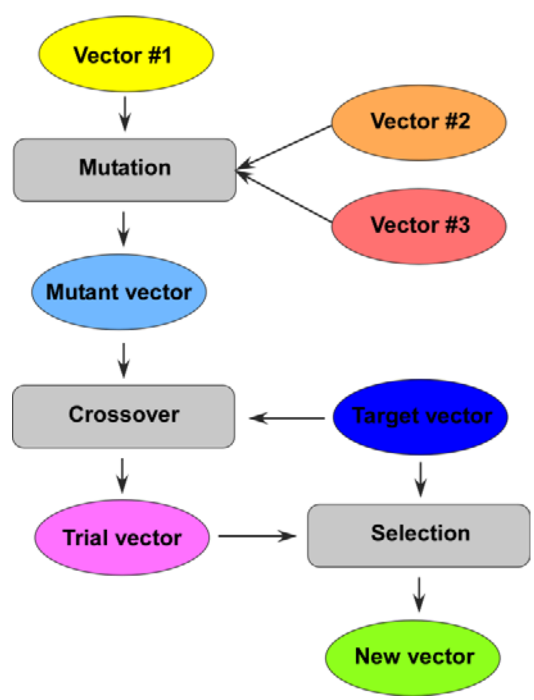

Fig. 3 – Flowchart of the basic employed in differential evolution for the generation of new individuals.

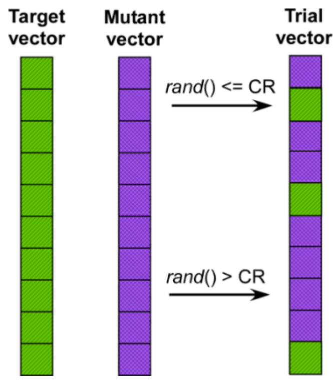

Fig. 4 – Illustration of the crossover process in Differential Evolution.

3) *Microgenetic Algorithm and Memetic Algorithm*

Microgenetic Algorithms (MGAs) and Memetic Algorithms (MAs) represent other interesting optimization strategies. In MGA, small-size populations evolve to locate promising areas in the search space. Since the population dimension is smaller than that of the GA, the MGA migrates into the near-optimal regions with fewer iterations. It is evident that a small population cannot provide the necessary diversity in the genetic pool; therefore, the population has to be restarted after some generations to explore the available search space, keeping only one or more of the best individuals, and thus avoiding the interim convergence into a local minimum, which is undesirable. In MGA the population evolves by employing the recombination of the two chromosomes for the generation of an offspring but the mutation is absent. This mutation inhibition is related to the frequent restart of the population which guarantees a suitable exploration of the search space. MGAs have been successfully applied to the design of antennas [31],[55], Frequency Selective Surfaces (FSSs) and absorbers [56],[57].

The Memetic Algorithm is based on the concept of meme [58] and mimics the process of transmission of ideas. In this framework, every idea is a potential optimal solution, in the same manner that a chromosome is a candidate solution in the GA. The operators employed in the MA evolutionary process are the same as those in the GA, namely crossover, mutation and selection. However, the distinctive feature of the MA that separates it from the GA involves a local optimization procedure, which is applied to each idea of the overall set in order to reach the closest point of a minimum. This procedure is applied at the very beginning of the process and at the end of each iteration; thus it leads to a population which is associated with only the local minima. The evolution of the ideas is guaranteed by the aforementioned GA operators, which force the exploration of the solution domain. Interesting examples of the application of MA to electromagnetic problems can be found in [59],[60].

4) *Invasive Weed Optimization*

Another example of competitive evolutionary algorithm is represented by the Invasive Weed Optimization (IWO). This stochastic evolutionary algorithm is inspired by the infestation of the weed in nature, and was introduced in [82]. By following the natural metaphor, the weed invades a crop field, exploits the available resources and produces new weeds. Each weed generates its own seed independently, without any relation with the other infestations. However, the number of weeds produced by each flowering depends on the fitness value of each single parasitic plant. The level of infestation grows until the maximum number of weeds is reached and then a competitive mechanism is activated to favor a better adaptation of the weed and, hence, an improved solution. Practically speaking, the crop field is the solution space and the seed includes the complete set of the optimization variables. This seed grows up and becomes a plant of the colony. The process that brings from a seed to a plant is the fitness evaluation. After the ranking of all the plants, the number of seeds produced by each one of them is decided on the basis of the fitness value. The better is the plant fitness the more seeds will be generated by that plant. The produced seeds are scattered all over the search space by using normally distributed random numbers with mean equal to the location of the flowering plant and a varying standard deviation. We should point out that IWO does not involve any mating and that the independent reproduction of a plant allows us to work with a different number of variables during the evolutionary process. This optimization paradigm has been proposed to the electromagnetic community in [83] and it has been applied [84]-[87] mainly to antenna design problems.

5) *Covariance Matrix Adaptation Evolution Strategy*

This relatively new paradigm belongs to the family of Evolutionary Strategy (ES) and it was proposed by Hansen and Ostermeier in [88].

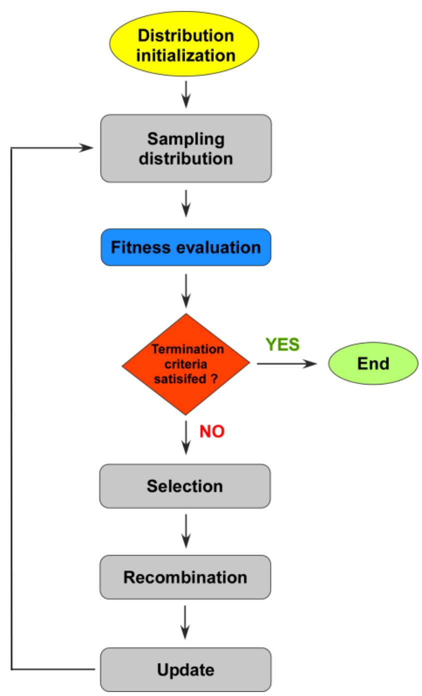

Fig. 5 – Flow chart of the Covariance Matrix Adaptation Evolution Strategy.

The Covariance Matrix Adaptation Evolution Strategy (CMA-ES) makes use of both recombination and mutation operators and, in common with all Darwinian-like algorithms, it imposes the "survival of the fittest" criterion. Although the CMA-ES algorithm regulates the population behavior inside the search space with the same GA operators, the algorithm constantly moves and reshapes the multivariate Gaussian distribution which models the population of potential solutions. Therefore the CMA-ES is essentially a moving and adaptive distribution which explores the parameter space. The intrinsic nature of this algorithm also permits the orientation of the axes of the search distribution (an ellipse for two parameters, an ellipsoid for three and an hyper-ellipsoid for larger number of parameters). Sometimes the axes are aligned with the original parameters, other times they may be not; hence the algorithm reveals the parameters or a combination of them which determine the most effective design variations. An overview of the CMA-ES flow chart is provided in Fig. 5.

More in detail, the generic *i*-th population member, x_i, in the *N*-dimensional search space is defined by using the multivariate Gaussian distribution

$$x_i = \mathcal{N}\left(\langle x\rangle, \sigma^2 \mathrm{C}\right) \tag{4}$$

where $\mathcal{N}$ represents a Gaussian distribution with mean $<x>$ and standard deviation $\sigma^2 C$. C is the covariance matrix and it can be broken into its eigenvectors and eigenvalues as

$$C = BD^2B^T \tag{5}$$

where D is a diagonal-only matrix thus allowing the numerical sampling in the form

$$x_i \cong \langle x\rangle + \sigma \mathrm{BD}\mathcal{N}(0,\mathrm{I}) \,. \tag{6}$$

At the beginning (Fig. 5) the distribution is initialized by choosing the number of individuals in the population, λ, the initial value of the mean and standard deviation of the distribution and other specific self-adaptive parameters described in detail in [88]. The distribution expressed by (6) is sampled at λ points and the cost function is evaluated for each one. Then, if an optimal solution has not been reached already, the individuals are ranked and the μ best ones are selected. The new distribution mean is determined in the recombination step on the basis of selected μ members. The update of the covariance matrix and the other distribution parameters are performed before the new sampling. The CMA-ES has been recently applied to electromagnetic design problems in [89] and it has found application in antenna design [90],[91] and biomedicine [92].

III. Cooperative Optimizers

It is apparent that the previously mentioned Darwinian algorithms are characterized by the harsh competition among all the individuals of the population and that, although with several possible algorithm diversifications, only the stronger chromosomes drive the evolution. On the contrary, there are other population-based algorithms that are based on the cooperation among the set of candidate solutions which exploit all the benefit provided by the exchange of information for pursuing the common search of the optimal solution. Among the most representative cases we can mention the Particle Swarm Optimization (PSO) and the Ant Colony Optimization (ACO).

1) Particle Swarm Optimization

The PSO algorithm has been originally proposed by Kennedy and Eberhart [61] and it has gleaned the idea from the social behavior of animals, such as birds or insects which are grouped in a flock or a swarm, respectively. All the basic units of the group, called particles (or agents) are trial solutions for the problem to be optimized and are free to fly through the multidimensional parameter-space searching for the optimal solution. The search-space represents the global set of potential results, where each dimension of this space corresponds to a parameter of the problem to be solved. A distinctive feature of the PSO algorithm is that each member of the swarm exploits the solution space by taking into account both the experience of the single particle and that of the entire swarm. It is also useful to highlight that the search direction is intrinsically multiple for the PSO since each agent has its own search trajectory whereas in the case of GA, the genetic pool seldom deviates from the path traced by the best chromosome. The position of the generic agent k at a certain instant i is expressed by the vector X as follows:

$$X^k(i) = \left(x_1^k(i), x_2^k(i), \ldots, x_N^k(i)\right) \tag{7}$$

where each $x_n(i)$ component represents a parameter of the N-dimensional physical problem. In the conventional PSO algorithm, each particle is randomly located at a certain position at the beginning of the process and traverses the multidimensional space with a random velocity, both in direction and magnitude, which are limited by the dynamic range of that dimension. The particle is free to fly inside the defined N-dimensional space, within the constraints imposed by the N boundary conditions, which delimit the extent of the search space between a minimum ($x_{n,min}$) and maximum ($x_{n,MAX}$) and, hence, the values of the parameters during the optimization process. At the generic time step $i+1$, the velocity of the simple particle k along each direction is updated following the rule

$$\begin{aligned} v_n^k(i+1) = w \cdot v_n^k(i) + c_1 \cdot rand() \cdot \left(p_{best,n}^k(i) - x_n^k(i)\right) \\ + c_2 \cdot rand() \cdot \left(g_{best,n}(i) - x_n^k(i)\right) \end{aligned} \tag{8}$$

which implies that, the new velocity is the sum of three components at each iteration step. The first one is the actual velocity, scaled by the factor w which models the inertia of the particle, while the two following terms express the attraction due to $p_{best,n}^k$ and $g_{best,n}$ found at the time step i. The former term is the best position along the direction n, found by the agent during its own wandering up to the i-th time step. The value of c_1 encourages the independent search for the best, regardless of the experience of the swarm. Contrarily, the latter term is the best position along the direction n, discovered by the entire swarm at time step i, and c_2 controls the exploitation of the actual best. The random generator *rand()* produces the appropriate chaotic component of a real swarm. The position of each particle is then updated according to the equation

$$x_n^k(i+1) = x_n^k(i) + v_n^k(i) \cdot \Delta t \tag{9}$$

where Δt is the time step. Suitable boundary conditions change the state or the velocity of the particle when it hits the designated borders. A representation of the PSO search strategy is illustrated in Fig. 6. Particle Swarm has been applied to a great variety of applications including antenna and array design as well as metamaterial synthesis [62]-[75].

2) *Ant Colony Optimization*

Ant Colony Optimization (ACO) was introduced in the late 90's by Dorigo and his colleagues [77] and since then it has been further developed [78]. It is a population-based approach which mimics the behavior of real antes. The key point of this approach is represented by the way the single agents exchange the information about the more promising trails that connect the nodes in the solution space. This preferred paths are referred to as *pheromone trails* since the real ants release this substance on the ground in different quantities, depending on their path. The pheromone trails offers a reference to the ant that pass by on this trace that can also reinforce it by adding its own pheromone. This mechanism establishes a positive feedback among the members of the colony since the probability with which an ant chooses to follow a certain path increases with the level of pheromone on it and, hence, with the number of ants that previously run across the same path. This cooperative behavior produces a faster growth of the pheromone on shorter paths which highlight the direction toward possible optimal locations. To prevent an unlimited accumulation of pheromone an *evaporation factor* is included in the updating of the trail intensity as well a *tabu list* is associate to each ant in order to prevent an immediate visit to an already known place. Ant Colony Optimization has been successfully applied to inverse problems [79], [80] and to antenna design [81].

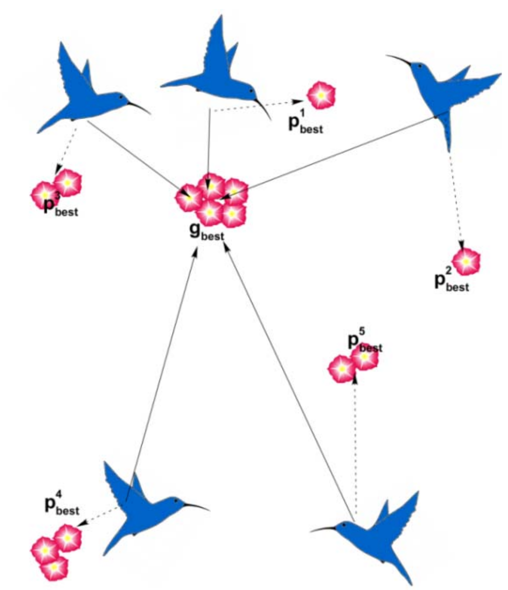

Fig. 6 – Each bird of the flock is attracted both by the area with the highest concentration of flowers that was found so far by the entire swarm (g_{best}) and by the location it has individually found during its wandering (p_{best}).

IV. Other Optimization Paradigms

In addition to the methods described above, we would like to mention other optimization paradigms that may be further exploited by the electromagnetic community. One of the first proposed nature-inspired stochastic algorithm is the Simulated Annealing (SA). This optimizator searches for the optimal solution within the parameter domain by modeling the physical mechanism of the cooling process of a solid object [93]. The cost function determines the energy state of the object which has to be minimized. Every time the performances of a new set of parameter are evaluated, there is a chance that the new set replaces the old one depending on a probability P which is given by the Boltzman distribution

$$P(E) = e^{-E/kT} \tag{10}$$

where E is the change in energy with respect to the previous configuration, T is the system temperature and k is the Boltzman's constant. If the new energy state is lower than the old one, the new set of parameters replaces the old one; otherwise, the new configuration is not automatically discarded but it is accepted with probability P in order to avoid the stagnation in a local minima. After a predetermined number of iterations the temperature T decreases following the so-called *annealing scheme* and other iterations of the SA algorithm are performed until a termination condition based on the number of iterations or on system temperature is satisfied. The SA has been successfully applied to microwave imaging [94] and to array design [95],[96].

Other optimization methods mimicking natural phenomena that have been applied to EM problems are the Central Force Optimization (CFO) [97]; the Wind-Driven Optimization (WDO) [98]; and, the Artificial Immune System (AIS) strategy [99]-[101]. It is also worthwhile to cite Artificial Neural Networks (ANNs) [102], Fuzzy logic [103] and Tabu Search (TS) [104] methods, which have proven to be useful tools, especially in antenna design and inverse scattering problems [105]-[114].

Noticeably, hybridization between a local and a global algorithm or among different evolutionary paradigms is a possible option that can be followed with a view to combining the best features of each single strategy [115],[118].

Finally, we would like to briefly mention algorithms addressing multi-objective problems. When dealing with a multi-objective design we have to face a problem different from a single-objective one where a global minimum or maximum represents the best solution. In the case of multiple cost functions a solution that fully satisfies all the requirements may not exist. Moreover, even a slight change in a design parameter representing an improvement for one objective can cause, at the same time, deterioration to another one.

The use of a single objective defined by a weighted sum of the objectives in order to solve a multi objective problem is a topic which has received a great deal of attention [119]-[121]. However, as it has been demonstrated in [120] and [121], this method is not efficient when applied on some non-convex solution domains, since it is inherently unable to describe complex preference information but it is dependent on the preferences of the designer that decide the weights.

On the other hand, for this class of problems an ideal set of solutions, commonly referred to as Pareto Front (PF), can be distinguished over which no other solution of the population dominates [122]. Multi-objective evolutionary algorithms (MOEAs) are suitable strategies to search for the simultaneous optimization of conflicting design objectives. The algorithm chosen as a benchmark is the Non-dominated Sorting Genetic Algorithm II (NSGA-II) [123], which has proven to outperform two other recent MOEAs such as the Pareto-Archived Evolution Strategy (PAES) [124] and the Strength-Pareto Evolutionary Algorithm (SPEA) [125]. MOEAs have been recently adopted in the electromagnetic community to design antennas [126],[127], arrays [128]-[131] and metamaterials [131]-[133]. A further level of challenge can be represented by a multi-objective optimization where some additional constraints have been explicitly imposed to the decision variables, thus reducing the available search space [134], [135].

V. Tuning Menu, Free Lunch and Computational Cost

As is well known to everyone who has used an optimization algorithm to solve a design problem, one of the most important tasks is to set the population dimension and all the other parameters that are necessary for the considered paradigm. For example, we have to specify the mutation and crossover probabilities for the GA and the cognitive and social rates for the PSO. Some optimizers, such as the CMA-ES, try to adapt their behavior in order to minimize the collateral effects of a non ideal setup. There are clearly suggested values for the aforementioned quantities that may come from empirical parametric examinations or theoretical studies [19], [136]-[139] but this problem is far from being completely resolved [140]. The tuning of the parameters may also depend on the specific design problem, which is clearly connected to the shape of the solution domain.

At this point, it seems obvious to ask if there is a sort of “super optimizer” which requires no tuning, a champion which is always able to beat all other optimizers in the field of convergence speed and reliability. A very important contribution on this exciting topic was provided by Wolpert and Macready in [141] where they introduced the no-free-lunch theorem. This theorem states that there is no single optimization method that can outperform all others on all the possible problems. For example, this means that one of the aforementioned algorithms will be very efficient in solving a class of problem (say antenna design) but on another class (travel salesman problem) it will take longer than another one. From a slightly different point of view, Radcliffe [142] has affirmed that without any problem-specific knowledge, an optimization algorithm cannot surpass the performance of a simple enumeration. Therefore, the more problem-specific information are employed in the algorithm structure and tuning, the better the performance will be. However, since we are not looking for an all-possible problem solver but we are exploiting optimization methods in the EM field, we are continuously motivated to refine these tools to perform better than all others in a particular application niche.

A subject related to the previous discussion is the estimate of the convergence rate of an optimization algorithm. We may say that the convergence rate in a measure that enable us to quantify how many times the cost function needs to be calculated before reaching the optimal solution. The electromagnetic simulations that are connected to the fitness evaluation are computationally intense; hence the convergence is strictly related to the time necessary to individuate the desired design. Since many optimization algorithms can be easily parallelized, one possible solution to reduce the waiting time can be to exploit all the available hardware [143]-[147]. Although this has no effect on convergence, we have reduced the time by employing more computational resources. However, the required time for even a single EM simulation can be sometime on the order of hours; therefore, even the evaluation of very few generations of a small population can take days even when using parallel algorithm implementations. Recently, some researchers have focused their attention on enhancing the efficiency of the algorithm by employing surrogate models. The surrogate can be seen as a coarse model of the real object under design. After a proper phase of training, which requires a few cost function evaluations, the surrogate model is used in the optimization process to provide reliable predictions of the behavior of the real model, without requiring long computational times. Some interesting examples of this approach can be found in [148]-[153].

VI. Fast Antenna Optimization

As already mentioned, the optimized design of modern antennas or arrays requires a significant effort in terms of computational resources, since the tuning of all the antenna parameters can seldom be carried out by using analytical methods, particularly if the device is installed in a complex scenario, and requires the use of full-wave solvers. Moreover, it may be necessary to include a matching network for the antennas in order to satisfy the requirements on bandwidth, gain or beam-scanning [30][31]. The bottleneck of a cumbersome numerical evaluation of the antenna or array performances can be tackled by resorting to the synergic use of a procedure for the fast evaluation of the input parameter of the cost function and the exploitation of an effective optimization algorithm. In the following, we describe a fast procedure for the analysis of loaded antennas and then present two test cases, namely a dipole antenna and an array of dipoles, both located on a finite ground plane, to illustrate the reliability and efficiency of the optimization algorithms.

1) Scattering Matrix for Fast Analysis and Genetic Algorithm Optimization

Let us consider the $N \times N$ scattering matrix $\overline{\overline{S}}$ of an N-port microwave device. If we terminate m of its ports on loads with a known reflectance ρ, we can define the scattering matrix $\overline{\overline{S}}'$ for the obtained microwave device that has now $(N-m)$ available ports by using the following relations

$$\begin{bmatrix}\bar{b}'\\ \bar{b}''\end{bmatrix}=\begin{bmatrix}\bar{\bar{S}}_{11} & \bar{\bar{S}}_{12}\\ \bar{\bar{S}}_{21} & S_{22}\end{bmatrix}\begin{bmatrix}\bar{a}'\\ \bar{a}''\end{bmatrix},$$

$$\bar{\bar{\rho}}=\begin{bmatrix}\rho_{N-m+1} & 0 & 0 & 0 & 0\\ 0 & \rho_{N-m+2} & 0 & 0 & 0\\ 0 & 0 & \dots & 0 & 0\\ 0 & 0 & 0 & \rho_{N-1} & 0\\ 0 & 0 & 0 & 0 & \rho_N\end{bmatrix}, \quad (11)$$

$$\bar{b}'=\left(\bar{\bar{S}}_{11}+\bar{\bar{S}}_{12}\bar{\bar{\rho}}\left(\bar{\bar{I}}-\bar{\bar{S}}_{22}\bar{\bar{\rho}}\right)^{-1}\bar{\bar{S}}_{21}\right)\bar{a}'=\bar{\bar{S}}'\bar{a}';$$

where a_i and b_i represents the incident and the reflected power levels at the i-th port of the network. The columns and rows of the original matrix are rearranged to define a block ($\bar{\bar{S}}_{11}$) involving only the unloaded ports (single primed vectors) and a block ($\bar{\bar{S}}_{22}$), which refer to the loaded ones (double primed vectors). Therefore, once the scattering matrix of the initial microwave device has been evaluated by using a full-wave solver, the performances characteristics in terms of bandwidth, gain and efficiency of the loaded antenna can be calculated quickly [154],[155].

Let us consider the loaded dipole illustrated in Fig. 7. In order to provide an antenna design capable of satisfying the desired specifications we need to select the configuration of the loads and their values as well as the impedance transformer ratio n. Let us assume that the antenna dimensions are fixed, as are the set of all available locations of the loads in order to ease the fabrication process. The set of available loads is comprised of series as well as parallel RLC circuits, including open and short circuits. Also, we symmetrically distribute the $2N$ loads Z_i (i=1,2,…,N) along the two arms of the dipole. It is worthwhile to point out that, in contrast to Z or Y matrices, the use of the scattering matrix makes it possible for us to include short and open circuits in the fast antenna analysis without introducing any undefined term in the scattering matrix of the final microwave device.

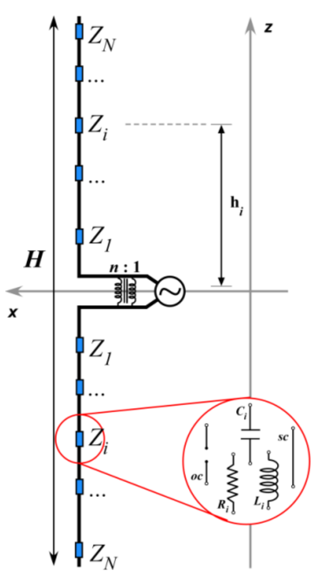

Fig. 7 – Arbitrary loaded dipole antenna with symmetrical Z_i circuits (series RLC, parallel RLC circuits, open and short circuits).

We begin the optimization process by calculating the scattering matrix of the antenna using a full-wave solver and store the $(2N+1)$x$(2N+1)$ matrix as shown in Fig. 8. The evolutionary algorithm employed for the optimization scheme is the Genetic Algorithm, which encodes each chromosome of the population by using the values and the types of the N different Z_i loads (i = 1,2,..,N). Next, each loaded antenna, which is described entirely by the genes of the chromosome, is analyzed by using the fast method previously described and the cost function is evaluated. The algorithm is terminated if the desired performance is achieved by the optimized design otherwise, the current population is replaced by the offspring obtained by using the standard GA operators (selection crossover and mutation) and the process is continued until either all the criteria have been met or a predefined number of iteration has been reached. To derive these results we have employed a binary-GA with a population of 40 chromosomes, a one-point crossover (rate = 0.85), a roulette-wheel selection, and an adaptive mutation rate (max rate = 0.2) to prevent the fitness function from stagnating.

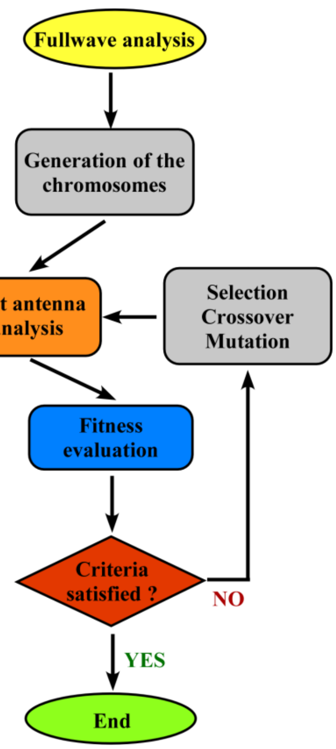

Fig. 8 – Flow chart of the proposed optimization procedure. The full wave solver is employed only once at the beginning of the process.

2) *Loaded Dipole on Finite Ground Plane*

For the first example, we consider a dipole antenna of length H = 60 cm, placed at distance d_{ground} = 22.5 cm from a finite metallic plate whose dimensions are L_{ground} = 6 m and W_{ground} = 10.5 m (see Fig. 9).

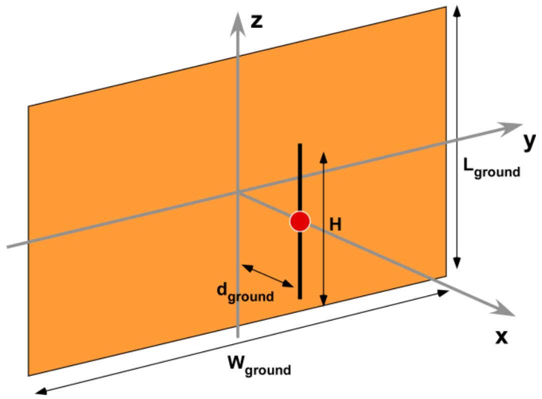

Fig. 9 – Test case #1: dipole antenna placed parallel to a finite ground plane.

The aim of the optimized design of the loaded antenna is to achieve a bandwidth which is larger than the unloaded antenna, while it exhibits a realized gain greater than 0 dBi in the boresight directions. The length of the loaded antenna is the same as that of the original (unloaded) one. The number of loads is equal to eight (four in each dipole arm) and their positions are given by $z_i = i$ H/10 in the upper arm (with i = 1,2,3,4) and specular in the lower one. The fitness function to be minimized is given by:

$$fitness = \frac{1}{N_f}\left(\sum_{i=1}^{N_f} c_1^i K_{VWSR}\left(i\right) + c_2^i K_{Gain}\left(i\right)\right) \tag{12}$$

where N_f is the total number of samples within the considered frequency range and $c_{1,2}^i$ are the weight coefficients which provide a tailored tune of the performances in different parts of the operating bandwidth. The two terms $K_{VSWR}(i)$ and $K_{Gain}(i)$ refer to the antenna bandwidth and antenna gain at the i-th frequency point, respectively, and they are defined as follows:

$$K_{VSWR}\left(i\right) = \begin{cases} 0, \quad if \quad VSWR\left(i\right) \le VSWR_{ref} \\ \dfrac{VSWR\left(i\right) - VSWR_{ref}}{VSWR\left(i\right)}, otherwise \end{cases}, \tag{13}$$

$$K_{Gain}^i = \begin{cases} 0, \quad if \quad Gain\left(i\right) \ge Gain_{ref} \\ \dfrac{Gain_{ref} - Gain\left(i\right)}{Gain_{ref}}, otherwise \end{cases},$$

where the $VWSR_{ref}$ is set equal to 3.0 and $Gain_{ref}$ is 3 dBi. Based on 100 optimization runs, each one comprising 300 generations, we have found that the convergence on the solution meeting the imposed specifications is reached during the first 100 generations in almost 90% of the cases. The results of the GA optimization process are illustrated in Fig. 10 and Fig. 11. Note that, the antenna bandwidth increases from 30 MHz to more than 100 MHz and the realized gain is always greater than 3 dB. The selected loads are listed in Table I, and the optimum transformer ratio n is equal to 1.5.

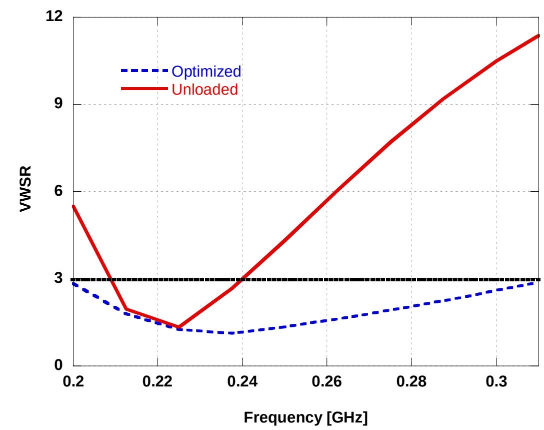

Fig. 10 – Comparison between the original unloaded dipole and the optimized loaded one.

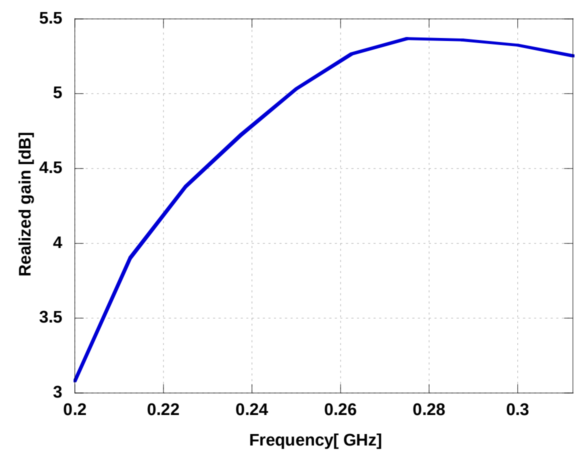

Fig. 11 – Realized gain of the optimized loaded antenna.

Table I - Optimized configuration of loads in the upper arm (specular in the lower other one).

Position	Load	Value
z = 1/10 H	Short	---
z = 1/5 H	parallel RLC	R = 50Ω; L = 21.4 nH; C = 19.6 pF
z =3/10 H	C	C = 13.4 pF
z =2/5 H	R	R = 9 Ω;

3) Array of Dipoles on a Finite Ground Plane

In this second example the addressed scenario is shown in Fig. 12 where an array of eleven equally-spaced dipoles (d_{ground} = 22.5 cm, d = 45 cm) are placed parallel to the same finite ground plane as in the previous example. We are interested in observing the array behavior in terms of active reflection coefficient and realized gain along the main beam direction when the main beam is scanned in the horizontal plane.

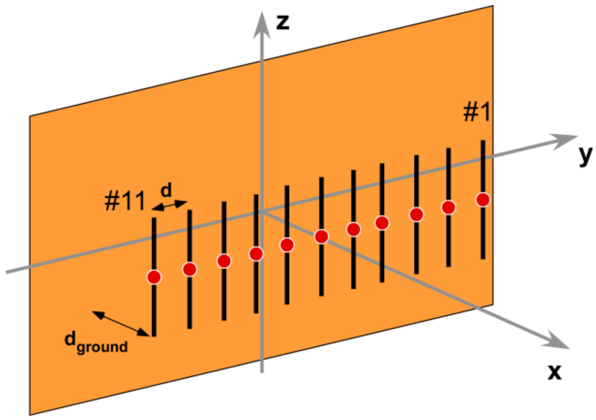

Fig. 12 – Test case #2: array of eleven equally-spaced dipole antennas placed parallel to a finite ground plane.

Let us consider four different scan angles, $\phi_1 = 0$ deg, $\phi_2 = 10°$, $\phi_3 = 20°$ and $\phi_4 = 30°$. Without any loading of the dipole antennas the active reflection coefficient of each radiator [156] is represented in Fig. 13 and Fig. 14 where for the sake of brevity only the results for$\phi_1 = 0$ deg and $\phi_4 = 30°$ are reported. It is apparent that the requirement on the acceptable VSWR is not satisfied especially around 0.22-0.224 GHz and that scan blindness occurs at certain scan angles for which the realized gain drops significantly with respect to broadside when scanning at $\phi = 10°$ and $20°$.

Table II - Optimized configuration of loads in the upper arm of each dipole (specular in the lower other one).

Position	Load	Value
z = H/10	Short	---
z =1/5 H	Short	---
z =3/10 H	Short	---
z =2/5 H	parallel RLC	R = 50Ω; L = 46.6 nH; C = 16.1 pF

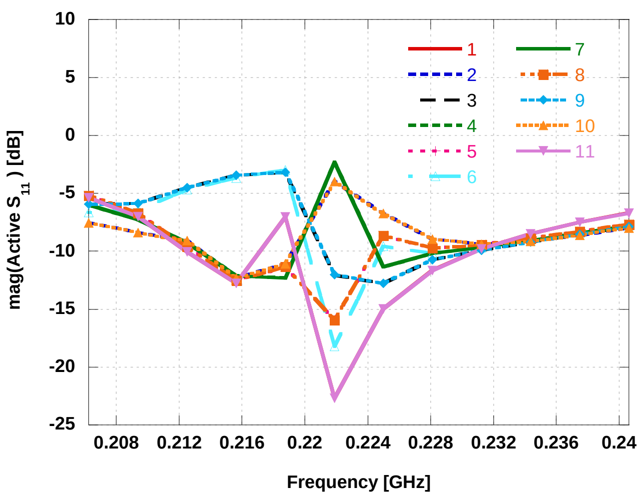

Fig. 13 – Active reflection coefficient for $\phi_1 = 0$ deg.

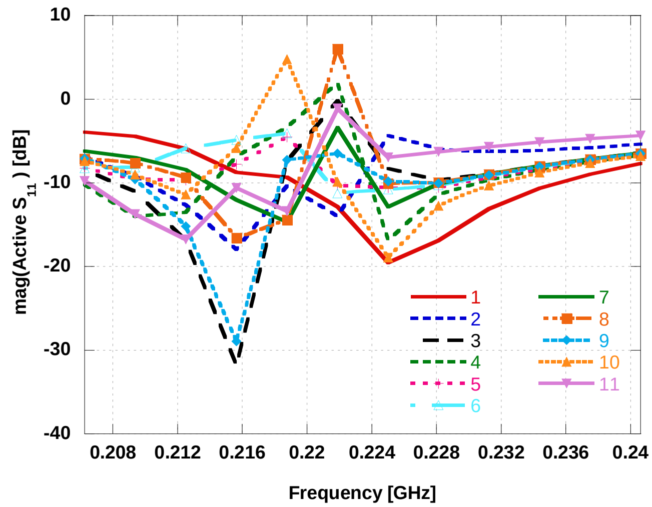

Fig. 14 – Active reflection coefficient for $\phi_4 = 30$ deg.

In this case, the GA is applied to find an optimum configuration of the loads (identical for all radiators) which enables all the elements to radiate with the imposed limit on the VSWR for all of the four scan angles in our specifications. For this case, the cost function to be minimized is expressed as

$$fitness = \frac{1}{N_f N_{steer}} \sum_{i_f=1}^{N_f} \sum_{i_{steer}=1}^{N_{steer}} \left(\frac{1}{N_{elem}} \sum_{i_{elem}=1}^{N_{elem}} f_1(i_f, i_{steer}, i_{elem}) + f_2(i_f, i_{steer}) \right), \quad (14)$$

$$f_1(i_f, i_{steer}, i_{elem}) = c_1^i K_{VSWR}(i_f, i_{steer}, i_{elem}),$$

$$f_2(i_f, i_{steer}) = c_2^i K_{GAIN}(i_f, i_{steer}),$$

where N_f is the total number of samples within the considered frequency range; N_{steer} is the total number of considered scan angles; N_{elem} is the number of element; and $c_{1,2}^i$ are the weight coefficients. The two terms $K_{VSWR}(i_f, i_{steer}, i_{elem})$ and $K_{Gain}(i_f$ $i_{steer},)$ are the same parameters as defined in (13). On the basis of 100 optimization runs, each one comprising 500 generations, we have found that the convergence of a solution satisfying the imposed specifications is reached during the first 300 generations in almost 90% of the cases. The selected loads are listed in Table II, and the optimal transformer ratio n was founded to be equal to 1.1. It is apparent from Fig. 15 and Fig. 16 that the optimized configuration of the dipoles satisfies the imposed requirement on the VSWR. A comparison of the realized gains for the four different scan directions is illustrated in

Fig. 17 and Fig. 18, and they clearly demonstrate that the optimized design is superior to that of the unloaded array in terms of performance.

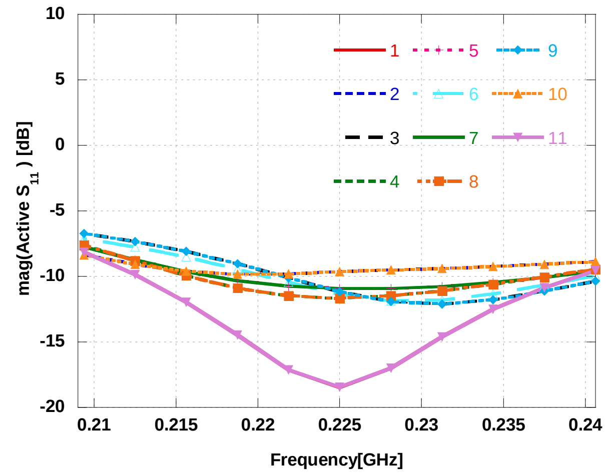

Fig. 15 – Optimized active reflection coefficient for ϕ_1 = 0 deg.

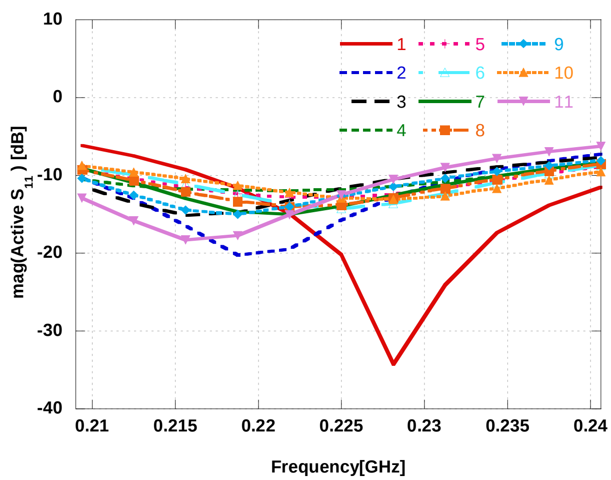

Fig. 16 – Optimized active reflection coefficient for ϕ_4 = 30 deg.

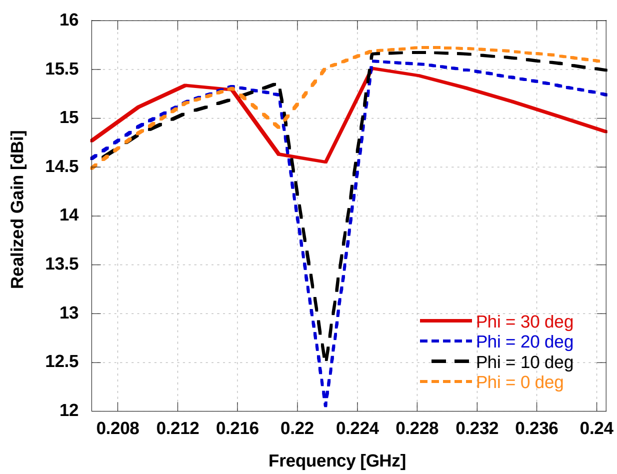

Fig. 17 – Realized gains of the original array for the four different directions.

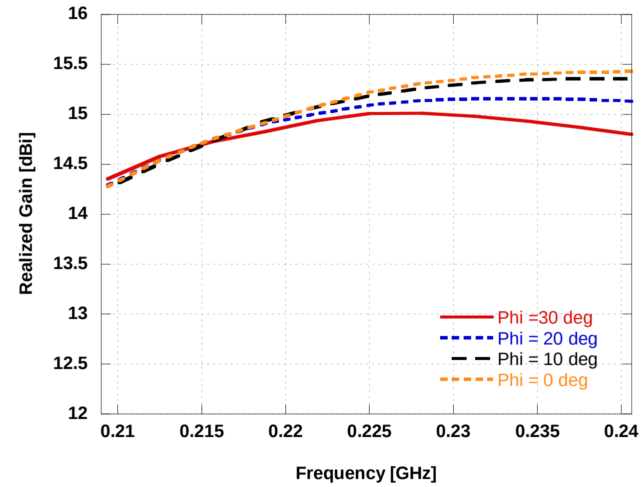

Fig. 18 – Realized gains of the optimized array for the four different directions.

VII. CONCLUSION

In this paper, we have reviewed a number of global optimization algorithms applied to EM problems. We have described the most distinctive features of optimization algorithms inspired by the competitive nature of Darwin's theory of evolution, and have pointed out the cooperative strategies exploited by particle swarms and other nature-inspired evolutionary algorithms. We have also presented some strategies that can be used to improve the rate of convergence and to reduce the computational cost. Finally, we have briefly described a fast procedure for evaluating the response of a loaded antenna starting from the scattering matrix of the unloaded radiator, to speed up the cost function evaluation. The reliability and efficiency of this approach have been tested by using the GA optimization algorithm to improve the performance of a single loaded antenna, as well as that of an array of loaded dipoles. The proposed algorithm can be also successfully applied for more complex antenna arrangements, even on conformal surfaces, and may be exploited for investigating the antenna performance on large platforms with a great reduction of computational time with respect to a brute-force approach.

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Simone Genovesi (S’99-M’07) received the Laurea degree in telecommunication engineering and the Ph.D. degree in information engineering from the University of Pisa, Pisa, Italy, in 2003 and 2007, respectively. Since 2003 he has been collaborating with the Electromagnetic Communication Laboratory, Pennsylvania State University (Penn State), University Park. From 2004 to 2006 he has been a research associate at the ISTI institute of the National Research Council of Italy (ISTI-CNR) in Pisa. In 2010 he affiliated with the National Laboratory Radar and Surveillance (RaSS). He is currently an Assistant Professor at the Microwave and Radiation Laboratory, University of Pisa. His research is focused on metamaterials, RFID, antenna optimization and evolutionary algorithms.

Davide Bianchi was born in Livorno, Tuscany, IT, in 1983. He received the B.S. and M.S. degrees in Telecommunication engineering from The University of Pisa, IT, in 2006 and 2008, respectively. After being the recipient of a grant issued by the italian Ministry of Education and Science (MIUR), in 2013 he receiveid the Ph.D. degree in remote sensing engineering at the Pisa University Department of Information Engineering. Since 2009 Mr. Bianchi has been affiliated with the National Inter-University Consortium for Telecommunications (CNIT) which presented him with a research grant in the field of antenna theory and design for HF-Skywave radar applications. In 2010 he was presented with a 2009-2010 FSE (European Social Fund) Graduate Student Award and he was a visiting student in the Pennsylvania State University (Penn State) at the Computational Electromagnetics and Antennas Research Lab (CEARL), University Park. In 2012 he affiliated with the National Laboratory Radar and Surveillance (RaSS) and he is currently a Postdoctoral Research Fellow for the Microwave and Radiation Lab (MRL) at the University of Pisa. His main research topics include computational electromagnetics and evolutionary strategies with applications to ultrawideband and phased array design as well as conformal antenna optimization and miniaturization. Other interests include parallel and high performance computer programming.

Agostino Monorchio (S’89–M’96–SM’04–F’12) received the Laurea degree in electronics engineering and the Ph.D. degree in methods and technologies for environmental monitoring from the University of Pisa, Pisa, Italy, in 1991 and 1994, respectively. During 1995, he joined the Radio Astronomy Group, Arcetri Astrophysical Observatory, Florence, Italy, as a Postdoctoral Research Fellow, in the area of antennas and microwave systems. He has been collaborating with the Electromagnetic Communication Laboratory, Pennsylvania State University (Penn State), University Park, and he is an Affiliate of the Computational Electromagnetics and Antennas Research Laboratory. He has been a Visiting Scientist at the University of Granada, Spain, and at the Communication University of China in Beijing. In 2010 he affiliated with the Pisa Section of INFN, the National Institute of Nuclear Physics. He is currently an Associate Professor in the School of Engineering, University of Pisa, and Adjunct Professor at the Italian Naval Academy of Livorno. He is also an Adjunct Professor in the Department of Electrical

Engineering, Penn State. He is on the Teaching Board of the Ph.D. course in “Remote Sensing” and on the council of the Ph.D. School of Engineering “Leonardo da Vinci” at the University of Pisa.
He has been a reviewer for many scientific journals and he has been supervising numerous research projects related to applied electromagnetic, commissioned and supported by national companies and public institutions.
Prof. Monorchio is active in a number of areas including computational electromagnetics, microwave metamaterials, antennas and radio propagation for wireless networks, active antennas and electromagnetic compatibility.
Dr. Monorchio has served as Associate Editor of the IEEE ANTENNAS AND WIRELESS PROPAGATION LETTERS. He received a Summa Foundation Fellowship and a NATO Senior Fellowship.