Optimization of beam scanning Reflectarray using MQC10-BBO and SNO Algorithms

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Optimization of beam scanning Reflectarray using $M_Q C_{10}$-BBO and SNO Algorithms

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***Abstract*—In this paper, some numerical results about the optimization of a reflectarray with scanning capabilities are presented. Two different, innovative algorithms are compared, the $M_Q C_{10}$-Biogeography Based Optimization ($M_Q C_{10}$-BBO) and the Social Network Optimization (SNO): both are applied to the design of a planar Reflectarray with scanning capabilities, and the obtained results, validated by a full-wave analysis, prove that the two methods allow to have good features over a scanning angle of ±40°.**

***Index Terms*—optimization, Reflectarray, scanning-beam**

I. Introduction

Reflectarrays (RAs) are nowadays a well-established technology for the realization of high-gain, fixed beam antennas [1]. More recently, they have been also used for obtaining scanning-beam antennas; to do it, the most straightforward solution is that of introducing one or more active element, as p.i.n. diodes or MEMS, in each unit-cell: the resulting performances are good, but at the cost of a significant increasing of the antenna complexity. Another solution is that of adopting a passive reflectarray and to change the direction of maximum radiation acting on the direction of arrival of the incident field, i.e. moving the feed or using a feed array [2]. In this way, the antenna complexity is reduced, but also its performances are poorer: in fact, the phase delay introduced by each unit-cell depends also from the angle of incidence, and therefore if this last one changes, the unit-cell behaves in a different way and a defocusing effect occurs.

In order to solve this drawback, several solutions have been proposed, as the use of a larger RA [3], partially illuminated in correspondence of each position of the feed, or the design of a bifocal RA [4]. Here, another solution is proposed, based on the use of a global, evolutionary algorithm to optimize the phase distribution on the RA surface so that the radiation patterns in the different directions do not degrade too much. In particular, two different algorithms are considered and compared, the $M_Q C_{10}$-BBO, a modified version of the Biogeography Based Optimization (BBO) introduced in [5], and the Social Network Optimization (SNO). Both have already been applied successefully to different problems [6]–[12], most of which involving the design of antenna systems [7], [9]–[11] and therefore they seem suitable for the optimization of a scanning-beam RA, characterized by many control parameters (the geometrical quantities of the unit-cells discretizing the reflectarray surface) and by a generally computational expensive cost function.

In this paper, some results on their application to the optimized design of a reduced size reflectarray are shown; they prove the effectiveness of both the algorithms, that provide two configurations with good radiating features over a scanning range of ±40°.

II. Optimization methods

Due to the high non-linearities of the problem, Evolutionary Optimization Algorithms (EAs) have been selected as suitable tools for designing the system. In particular, two EAs have been considered: the $M_m C_n$ Biogeography Based Optimization and Social Network Optimization.

The optimization process with EAs follows the scheme shown in Figure 1. The central element is a population that is composed by a set of candidate solutions, each one defined as the vector of optimization variables.

The optimization variables are mapped in the design variables of the problem (*i.e.* a set of physical parameters that can affect the system behaviour). Simulating the system, some performance parameters can be calculated and, then, mapped back to the optimizer as cost values.

The population is evolved during iterations accordingly to the specific algorithm operators.

In the following, a brief description of the adopted algorithms is provided.

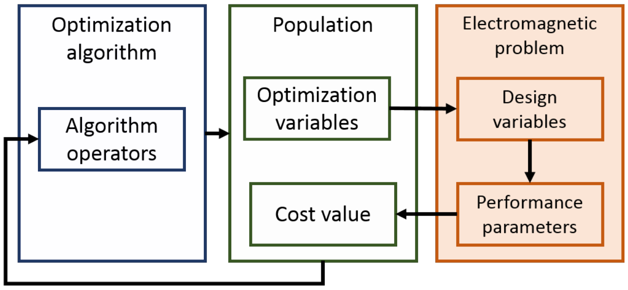

Fig. 1. Working principles in EAs.

A. Modified Biogeography Based Optimization

Biogeography Based Optimization is an Evolutionary Optimization algorithm that is inspired by species migration mechanisms [5]. During the testing of the algorithm, it has been noticed that in many cases the convergence stagnates into local minima, and therefore several modified versions have been introduced, with improved features.

In this paper the the M_QC_{10} modification of the algorithm is considered [7], that differs from the original algorithm for two different variation.

The first one regards the migration model: in fact, instead of the linear one, that results ia a high pressure ratio of the algorithm and in an early convergence, a quadratic model is implemented. The second modification is the introduction of the cataclysm: when a local minimum is reached and the convergence is stopped, a cataclysm destroys the most of the species and new ones are introduced.

These two modifications, codified in the algorithm name through M_Q, that gives the information about the type of migration model adopted, and C_{10}, informing about the presence of the cataclysm and the minimum number of iterations between two following events, have been demonstrated to be very effective in antenna optimization [7], [10].

B. Social Network Optimization

Social Network Optimization (SNO) takes its inspiration by the idea diffusion process in Online Social Networks.

The algorithm is based on two interacting data structure: the population, composed by *users*, and the Social Network, composed by *posts* written by the users.

The starting element of the algorithm are the user's *opinions*, *i.e.* a vector that has the same size of the optimization variables. These opinion are codified in a post *status* by means of a process, the linguistic transposition, that introduces some differences between the opinions and the status.

The status variables represent the optimization variables that are send to the problem simulator that calculate the performances of the system in that configuration. These are mapped back to the algorithm in the *visibility* value of the post.

In SNO, users interact accordingly two different networks: the friends and the trusted. Friendship is a strong connection and it evolves accordingly to the common number of friends among users. Trust network is a weaker connection and it evolves on the basis of the previous reputation value and of the visibility values: when a user publish a post with high visibility, his reputation increases.

At every iterations, the two networks are evolved and, inside each one, users selects some influencing ideas. These ideas are combined in a crossover-based way to create a new idea ($\mathbf{a}(t)$) that modifies the user's opinions ($\mathbf{o}(t)$) accordingly to the complex contagion model:

$$\mathbf{o}(t+1) = \mathbf{o}(t) + \alpha[\mathbf{o}(t) - \mathbf{o}(t-1)] + \beta[\mathbf{a}(t) - \mathbf{o}(t)] \qquad (1)$$

At this point new users' opinions are created and the process can be repeated iteratively until the termination criterion is satisfied. Figure 2 shows the flow chart of SNO.

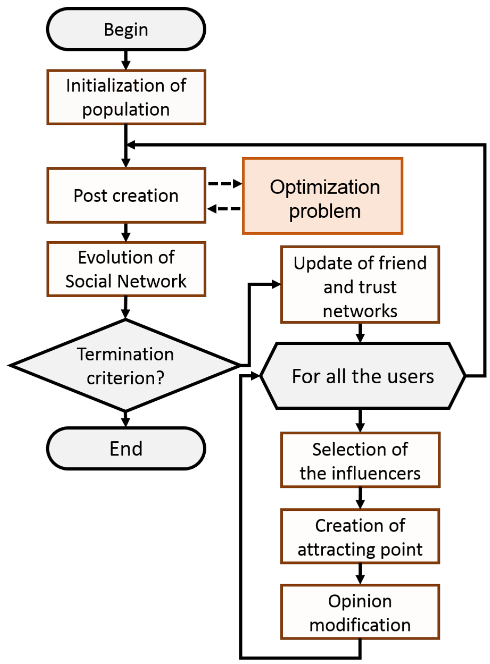

Fig. 2. Social Network Optimization Flow Chart.

Social Network Optimization has been applied successfully to antenna optimization [9], [11] and to other engineering design problems [8], [12].

III. Reflectarray Design

A. Antenna description

The SNO and the M_QC_{10}-BBO have been applied to the design of a RA with size $D = 12\lambda$ at the design frequency of 30 GHz, discretized with 24×24 unit-cells. The feed has a focal distance from the aperture of 0.9D in order to maintain a -10 dB of taper at the edges. The re-radiating elements are simple square patches printed on a Diclad 527 substrate with $\epsilon_r = 2.55$ with negligible losses and a thickness of 0.8 mm. The objective of the optimizers is to obtain radiation pattern below a properly designed mask for each of the considered direction of maximum radiation in the angular range $\pm 40°$. The beam-scanning is obtained rotating the feed along a circular arc, forming an angle equal to the one of the optimization objective, that is the direction of maximum radiation.

B. Optimization results

The optimization has been carried on calculating the radiation patter with the aperture field method [1] in four different cases, each characterized by a different direction of maximum radiation inside the selected angular range. The radiation pattern has been calculated on discrete grid with 41 samples on θ and 35 in ϕ. For each radiation pattern, the mask has been defined imposing the main beam width, the maximum SSL close to the beam and at $\theta = \pm\pi/2$.

The adopted optimization variables are all the size of the patches and the beam deviation factor for each scanning angle. Due to the symmetry of the system, the total number of design variables is 148.

The problem is intrinsically multiobjective. In fact, for each scan angle two objectives can be identified: the direction of the main beam and the integral of the radiation pattern exceeding the mask. Here, the several objectives have been implemented in a single cost function, inside of which each of them is multiplied by a suitable weight factor.

The termination criterion has been set to 50,000 objective function calls: this guarantees a fair comparison because it is a good indicator of the computational time required by both the algorithms. For each algorithm, 24 independent trials have been performed.

Figure 3 shows a comparison between the algorithms in terms of average convergence and the best trial. SNO is characterized by a fast convergence at the beginning, while the modified BBO is slower but, at the end, its average value becomes better than the SNO one. On the other hand, the best trial of SNO is always outperforming the best of the modified BBO.

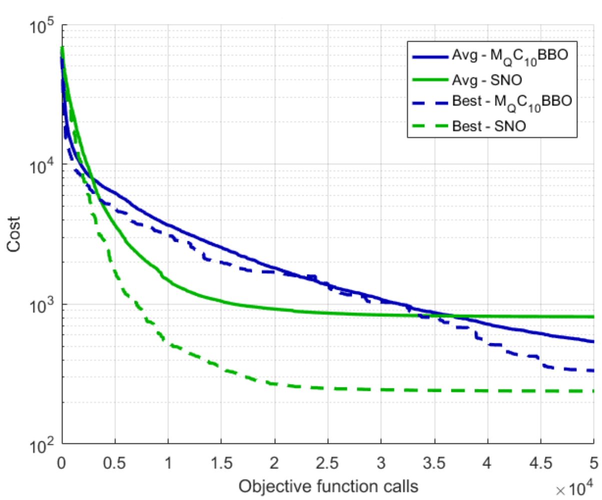

Fig. 3. Curves of convergence of the M_QC_{10}-BBO and of the SNO. Solid lines: average value over 24 separate trials; dotted line: best trial.

After the optimization process, a full-wave simulation with the software CST Microwave Studio of the two resulting antennas have been performed, for all the scanning angles. In Fig. 4 the gain versus the scanning angles, for both the two algorithms, is plotted. As it can be seen, the gain of both the configurations designed with the two algorithms is quite stable over the entire angular range. In particular the SNO shows a loss of the gain of only 1.2 dB from 10°to 40°.

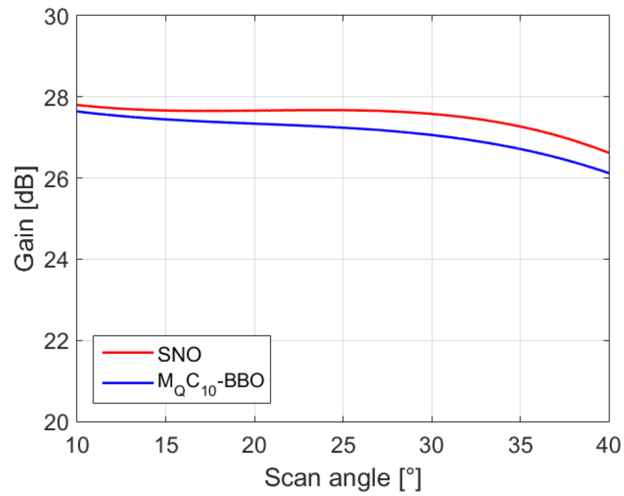

Fig. 4. Variation of the gain with the direction of maximum radiation obtained by the full-wave simulation of the two RAs designed with the two optimization algorithms.

IV. Conclusion

In conclusion, it is possible to state that two innovative evolutionary algorithms are successfully applied to the optimization of a beam scanning Reflectarray Antenna. The full-wave results prove the effectiveness of the design process, obtaining a high gain with a very good stability in the overall angular region. In order to validate these numerical results, the future work comprises the manufacturing of prototypes and the related measurements.

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