SNO Based Optimization for Shaped Beam Reflectarray Antennas

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Alessandro Niccolai [1], Riccardo Zich [1], Michele Beccaria[2], Paola Pirinoli[2]
[1]Dipartimento di Energia, Politecnico di Milano
Via La Masa 34, 20156 Milano, Italy
[2]Department of Electronics and Telecommunications Politecnico di Torino
Corso Duca degli Abruzzi 24, 10129 Torino, Italy
alessandro.niccolai@polimi.it, riccardo.zich@polimi.it,
michele.beccaria@polito.it, paola.pirinoli@polito.it

***Abstract*—The design of a shaped beam reflectarray is a challenging issues. The problem can be hardly addressed by deterministic techniques or standard optimization due to the elevated number of design variables and its non-convex nature while can be much easily solved adopting Evolutionary Optimization Algorithms. In particular, in this paper a recently introduced evolutionary approach, named Social Network Optimization (SNO) has been applied to the design of a reduced size shaped beam reflectarray: the obtained numerical results are promising and prove the effectiveness of the adopted method.**

***Index Terms*—Shaped beam, reflectarray, Social Network Optimization.**

I. Introduction

Evolutionary Algorithms (EAs) are effective and flexible techniques able to optimize multi-modal and non-convex cost functions like those modelling in general many engineering problems, and more specifically antenna ones: the Genetic Algorithm (GA), has been widely applied to antenna optimization [1], as well as the Particle Swarm optimization (PSO) [2]- [3]- [4]. Even if both of them produced satisfactory results, the increasing size of the problems and their complexity demand for new algorithms with higher efficiency.

A promising recently-developed algorithm is the Social Network Optimization [5], [6], that mimics the behaviour af the people when interacting right through a social network. It has been tested on several problems, from the optimization of a linear permanent magnet generator [7] to the design of pencil-beam Reflectrray (RA) antennas [8].

The optimization of a reflectarrays represents a good benchmark for the testing of an optimization technique. In fact, the surface of a RA is generally discretized with hundreds or thousands of re-radiating elements, each of one characterized by one or more geometrical parameters, that are use to control and properly adjust the phase of the incident field in order to obtain the desired radiation pattern: as a consequence, the associate mathematical problem present a very high number of degrees of freedom, that could be difficult to manage even by an evolutionary approach. As a consequence, the algorithm has to work hard to converge, in a reasonable number of iterations an without being trapped in local minima. Moreover, slow convergence means that the cost function modelling the problem has to be computed thousands of times, with a strong increase of the computational cost. For all these reasons, it is evident that an efficient optimization algorithm is necessary for the design of a reflectarray antenna.

SNO has been already applied successfully to the design of pencil-beam RAs [8]. Here, it is used for the optimization of a shaped beam reflectarray: the results on a reduced size configuration prove the effectiveness of the proposed method.

The paper is structured as it follows: the descriptions of the algorithm is reported in Sect. II; in Sect. III the problem to optimize, the adopted procedure, base on the use of the SNO, and some numerical results are shown. Finally, in Sect. IV some conclusions are drawn.

II. Social Network Optimization

Social Network Optimization is a population-based algorithm that takes its inspiration from the process of information sharing of social networks [9].

The algorithm population represents the members of a social network: they are characterized by the situation that they face, posted on the social as *status*, and by their character. Their interaction with other individuals is driven by their personal interests and by their reputation [7]. The status of an individual represents a candidate solution of the optimization problem, while his reputation is the cost or fitness value associated to the candidate solution. All the other variables and mechanisms are internal to the algorithm and force the population to explore, at each iteration, the problem domain of definition, in order to converge to the final optimal solution.

The Social Network is the virtual space in which the individuals interact and exchange information. This modifies the character of the people that will then face different situations [6]. The social network has its storage capability and it collects and keeps track of the best solution posted. The individuals belong to two different kind groups: groups of friends, collecting people with similar status, and groups of peers, set up by persons with similar character. In each group, every individual selects an influencer in the light of the ranking of the reputations. Having selected the influencers, each individual choses its desired option (*desideratum*) mixing

```
First population creation
while not termination criterion do
    Creation of the global ranking
    Update of stored solutions
    for all the population do
        Creation of friend and peer groups
        Selection of the two influencers
        Generation of the desired option
        Calculation of the new character
        Calculation of the new status
        Cost evaluation
    end for
end while
```

Fig. 1. Pseudo-code of Social Network Optimization

the statuses of the influencers accordingly to his personal interest.

The evolution of the population is described by the two following equations:

$$\vec{c}_i(t+1) = \alpha \cdot \vec{c}_i(t) + \beta \cdot (\vec{d}_i - \vec{s}_i(t)) \quad (1)$$

$$\vec{s}_i(t+1) = \vec{s}_i(t) + \vec{c}_i(t+1) \quad (2)$$

where $\vec{c}_i(t)$ and $\vec{c}_i(t+1)$ are the actual and the future characters of the i-th individual, $\vec{s}_i(t)$ and $\vec{d}_i$ are his actual status and desideratum; α and β are two user-defined parameters. It can be noticed that at each iteration the status of an individual depends on the status at the previous iteration and by his current character; at its turn, this last is expressed in terms of the previous status and character and of the desideratum.

Figure 1 reports the pseudo-code of SNO.

III. Shaped beam reflectarray optimization

The SNO is here applied to the design of a reflectarray with a cosine squared radiation pattern in the E-plane. In order to test the applicability of the SNO to this kind of problem, a reduced size configuration is considered. The reflectarray consists in 24 × 24 re-radiating square patch elements printed on a layer of Diclad 527, with $\epsilon_r = 2.57$, losses $\tan\delta = 0.0022$ and thickness of 0.8 mm. To avoid grating lobes, the unit-cell size has been chosen equal to $\lambda_0/2$ and therefore the total size of the RA surface is equal to $12\lambda_0$, where λ is the wavelength at the design frequency f_0. The phase of the reflected field is controlled varying the side d of the square patches: in Fig. 2, the variation of the amplitude (top) and phase (bottom) of the reflection coefficient with d is plotted. The amplitude is almost everywhere equal to 0 dB, it just decreases a little in correspondence of the patch resonant size, while the phase varies smoothly and cover a range of almost 300°. These curves have been obtained considering the unit-cell embedded in a infinitely periodic lattice and performing the analysis of the resulting structure with CST-Microwave Studio.

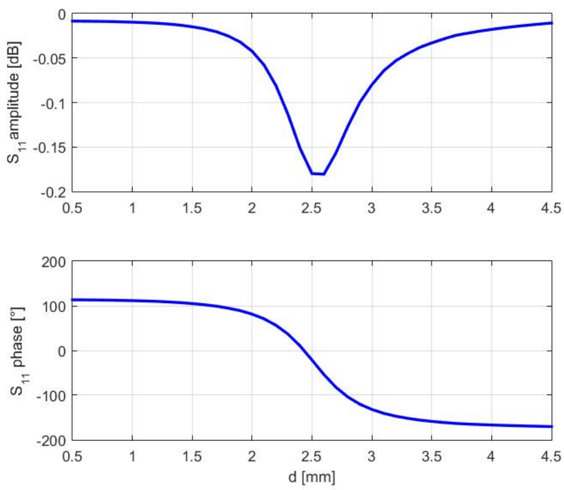

Fig. 2. Variation of the reflection coefficient with the side d of the RA unit-cell square patch. Top: amplitude. Bottom: phase.

The adopted feed is a Potter horn, center-fed, with a focal distance $f/D = 1$ that allows to obtain a tapering of -10 dB at the edges of the reflectarray.

The design variables of this optimization problem are obviously its degrees of freedom, i.e. the size d of the RA patches. They are 576 overall, but taking advantage of the symmetry with respect to a vertical plane the final adjustment of the RA patches have to show, the effective number of optimization variables reduces to 288.

The objective of the optimization process, i.e. to obtain a cosine squared shaped beam in the E-plane, has been implemented by means of two masks. The upper mask serves to constrain the SLL, and the width of the main beam. In the angular region corresponding to the shaped beam, a lower mask is added, with the same behaviour of the upper one and with the aim to limit the acceptable ripple, here equal to 2.5 dB.

The cost function consists in the integral of the squared error of the radiation patter when exceeding one of the two masks:

$$c = \sum_\theta \sum_\phi (\Delta_{up}^2(\theta,\phi) + \Delta_{dw}^2(\theta,\phi)) \quad (3)$$

where Δ_{up} and Δ_{dw} are the two error functions, defined as:

$$\Delta_{up}(\theta,\phi) = \begin{cases} E(\theta,\phi) - M_{up}(\theta,\phi) & E(\theta,\phi) > M_{up}(\theta,\phi) \\ 0 & E(\theta,\phi) \le M_{up}(\theta,\phi) \end{cases} \quad (4)$$

$$\Delta_{dw}(\theta,\phi) = \begin{cases} M_{dw}(\theta,\phi) - E(\theta,\phi) & E(\theta,\phi) < M_{dw}(\theta,\phi) \\ 0 & E(\theta,\phi) \ge M_{dw}(\theta,\phi) \end{cases} \quad (5)$$

being $E(\theta,\phi)$ the radiated field, and M_{up} M_{dw} the upper and the lower masks, respectively.

Due to the large number of design variables, the optimization process requires 50,000 cost function evaluations. 16 independent trials have been done and the obtained convergence curves are shown in Figure 3, where each coloured line represents the evolution of one trial and the black thicker

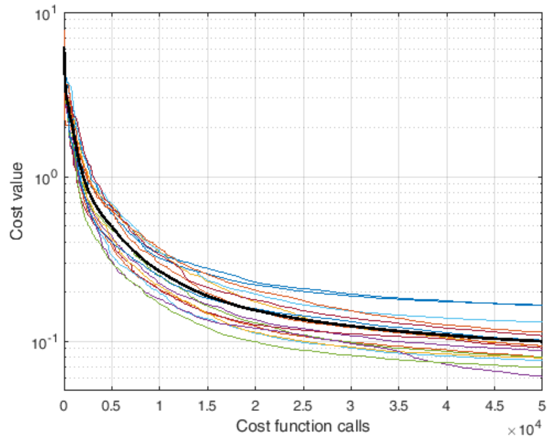

Fig. 3. Convergence curves of the optimization process. The black bolt line is the average convergence. The cost is represented in a logarithmic scale.

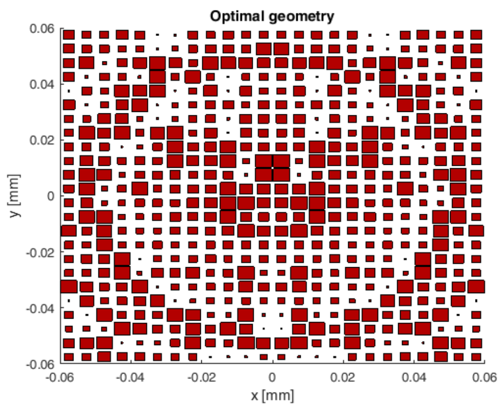

Fig. 4. Optimal RA geometry found by SNO.

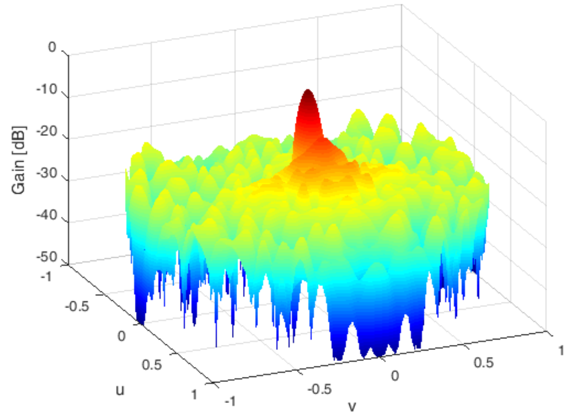

Fig. 5. 3D radiation pattern of the optimal solution.

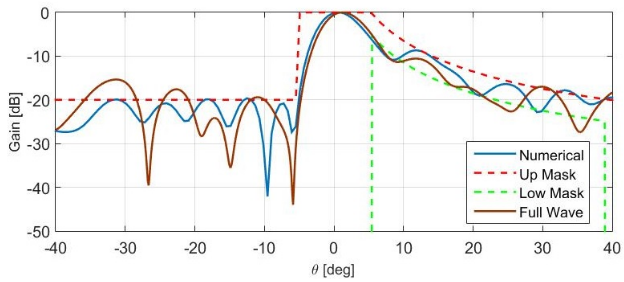

Fig. 6. Radiation pattern in the E-plane.

line is the average convergence. It is worth to notice that the optimization process shows a very high initial speed and then it slows down. Moreover, the curves are quite close each other and this prove the good reliability of the algorithm.

The optimal geometry found by SNO is shown in Figure 4.

A 3D view of the optimized antenna radiation pattern is shown in Figs 5, while in 6 the cut in the E-plane is plotted, together with the upper and the lower masks; moreover, the radiation pattern computed with a full-wave analysis of the designed configuration, carried on with CST-Microwave Studio, has been also added. During the optimization process the radiating features of the RA are computed with a reduced computational cost approach (i.e. the Aperture field Method, [10]) and therefore the obtained results have to be confirmed through a more accurate analysis. The comparison between the radiation patterns computed with the two methods are in good agreement: the curve obtained with the full-wave approach satisfies the mask almost everywhere, and this confirms the goodness of the optimization procedure, taking also into account that it has not taken into account aspects as the feed blockage, not negligible in a configuration like the considered one.

IV. Conclusions

In this paper, the feasibility of the SNO for a shaped beam Reflectarray Antenna optimization is proved, through the numerical analysis of a reduced size configuration radiating a cosine squared pattern in E-plane. In view of the obtained good results, the method will be further validated by its application to larger structures with off-set feed, and by the experimental characterization of a prototype.

References

[1] Rahmat-Samii and E. Michielssen, "Electromagnetic optimization by genetic algorithms," *Microwave Journal*, vol. 42, no. 11, pp. 232-232, 1999.

[2] J. Robinson and Y. Rahmat-Samii, "Particle Swarm Optimization in Electromagnetics," *IEEE Trans. on Antennas and Propag.*, vol. 2, pp. 297-407, 2004.

[3] D. Boeringer and D. Werner, "Particle Swarm Optimization versus Genetic Algorithms for Phased Array Synthesis," *IEEE Trans. on Antennas and Propag.*, vol. 3, pp. 771-779, 2004.

[4] D. Olcan, R. Golubovic and B. Kolundzija, "On the Efficiency of Particle Swarm Optimizer when Applied to Antenna Optimization", *IEEE Int. Antennas and Propag. Symposium*, pp. 3297-3300, 2006

[5] M. Ruello, A. Niccolai, F. Grimaccia, M. Mussetta and R. E. Zich, "Black-hole PSO and SNO for electromagnetic optimization", *Evolutionary Computation (CEC), 2014 IEEE Congress on*, pp. 1912-1916, 2014

[6] A. Niccolai, F. Grimaccia, M. Mussetta, P. Pirinoli, V. H. Bui and R. E. Zich, "Social network optimization for microwave circuits design," *Progress In Electromagnetics Research C*, vol. 58, pp. 51-60, EMW Publishing, 2015.

[7] F. Grimaccia, G. Gruosso, M. Mussetta, P. Pirinoli, V. H. Bui and R. E. Zich, "Design of Tubular Permanent Magnet Generators for Vehicle Energy Harvesting by means of Social Network Optimization," *IEEE Transactions on Industrial Electronics*, IEEE, 2017.

[8] A. Niccolai, F. Grimaccia, M. Mussetta and R. E. Zich, ”Reflectarray optimization by means of SNO and PSO”, *IEEE Int. Antennas and Propag. Symposium*, IEEE, pp. 781-782, 2016

[9] R. Albi, F. Grimaccia, M. Mussetta, A. Niccolai, and R. E. Zich, ”A new algorithm for antenna optimization in aerospace applications: The sounding rocket test case”, *Electromagnetics in Advanced Applications (ICEAA), 2013 International Conference on*, IEEE, pp. 1537-1540, 2013

[10] J. Huang, J. A. Encinar, *Reflectarray Antennas,* John Wiley & Sons, 2007.