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A Comparison Between two Different Techniques for Beam-scanning Reflectarray Antennas Design

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***Abstract*—The possibility of introducing beam-scanning capabilities in reflectarray (RA) antennas is becoming more and more important and several solutions have been proposed. Among them, a possible approach consists in using a passive RA and acting on the feed to achieve the beam-scanning. However, the fulfillment of the desired high gain constraints over the entire scanning range is still a challenging issue. Here, two different design techniques are considered and compared: a more conventional one, i.e. the bifocal design technique, and a more innovative approach, based on the use of an efficient evolutionary algorithm, the Social Network Optimization technique. The obtained results show the effectiveness of this last method, enabling the design of a RA with scanning capability over a wide angular range, outperforming the bifocal configuration.**

I. Introduction

High gain antennas, and in particular Reflectarray Antennas (RAs), became more and more important in the last years, because of the requirements imposed by several applications. Among other features, many of them ask for the capability of the antenna to perform the steering of the beam over a desired angular region. The straightforward solution is that of using a phased array [1], or, if a RA would be used, to introduce in each unit cell active elements as varactors, pin-diodes or MEMS [2]–[4]. Even if the resulting antenna has very good performance, its complexity and cost is generally quite high, and therefore in some cases it could be unaffordable. To overcome this problem, a possible RA-based alternative could be that of using a passive planar reflector, as in pencil beam configurations, and performing the beam-scanning with different feed arrangements: for each of them the entire antenna is supposed to radiate a pattern with a maximum in a different direction in the desired scanning range [5]. However, the problem of defining the correct phase distribution providing high and constant gain for all the different scanning angles is complex, highly nonlinear, and hard to manage since many different concurring objective functions have to be simultaneously fulfilled [6], having a too small number of degrees of freedom (equal to the product between the number of the RA unit cells ant their free geometrical parameters) at disposal: the consequence is a degradation of the radiation patterns, showing a decrease of the maximum gain and an increase of the Side Lobe level (SLL).

In view of these considerations, and with the aim of improving the performance of a passive beam-scanning RA, here two promising approaches are analyzed and compared: a sub-optimal deterministic method and a suitable evolutionary optimization based technique. The first one is a most assessed approach, based on the idea to design the RA as it was a bifocal lens: the results available in literature [7] confirm its capability to provide an antenna whose radiation patterns are almost the same over the considered scanning coverage, but at the cost of a reduction of the maximum gain. The optimization technique here proposed is based on the use of an Evolutionary Algorithm (EA), since this class of approaches is extremely effective dealing with complex nonlinear problems. Among the EAs, Social Network Optimization (SNO) has been here chosen due to its promising results when applied to a similarly complex class of problems [8]. In order to properly compare the results, the two approaches have been tested on the design of a 24×24 RA: as it is shown in Sect. III, the configuration optimized with the SNO outperforms the bifocal RA, for what concerns both the gain value and the SLL.

II. Analysed system and designing techniques

In this section, the system under analysis is described and then the two designing techniques are detailed.

A. System description

The considered RA consists in 24×24 unit cells with size $\lambda/2$ at 30 GHz, in order to avoid grating lobes. The re-radiating elements are square patched, printed on a Diclad® 527 layer, characterized by $\epsilon_r = 2.55$ and thickness of 0.8 mm. The phase of the reflected field is controlled varying the side W of the patches: in case of normal incidence, a maximum phase variation of 300° is achieved [8]. The reflective surface is illuminated by a rectangular horn, whose radiation pattern can be approximated with the function $cos(\theta)^q$ being $q = 7.7$. The focal distance f/D is 0.8, in order to have a -10 dB of taper at the edges of the RA. The beam steering is obtained moving the feed along a circular arc. The position of the feed is assumed to be specular to the direction of maximum radiation of the RA, that can varies over the scanning range, i.e. between $-40°$ and $+40°$ in the E-plane.

B. Bifocal design technique

According to what is available in literature, the procedure for the design of a bifocal RA can be summarized as in the following:

- the feed is assumed to be in an offset position, with the main beam that forms a certain angle θ_1 with the *z-axis*, orthogonal to the RA plane, and the required phase distribution ϕ_1 is computed;
- then, the feed is rotated along a circular arc, to form an angle θ_2 with the *z-axis* and another phase distribution ϕ_2 is computed;
- each element of the RA is finally designed, to compensate the mean value ϕ_{BFM} between ϕ_1 and ϕ_2.

Here, the design of the RA has been done with $\phi_1 = +40°$ and $\phi_2 = -40°$.

C. Social Network Optimization-based design technique

In this section, only the main features of the Social Network Optimization and of the adopted optimization environment are summarized; a more accurate description, including also the results of the comparison with other EAs, is reported in [11].

SNO is a population-based EA that simulates how the information spreads out, grows and develops in online social networks [9]. This algorithm has been widely used for antenna design and it proved its effectiveness on different engineering optimization problems, even compared with other more commonly used EAs [10], and for this reason has been here adopted.

For achieving a proper optimization performance, it is important to properly design the entire optimization environment, that in the present case is sketched in Figure 1. The idea is that of optimizing the radiation patterns, evaluating the error with respect to a predefined 3D mask, for several scanning angles inside the considered coverage. Since it is symmetrical with respect to the direction orthogonal to the RA surface, the distribution of the phase, and consequently of the patches, needed to have maximum radiation in the positive or negative part of the scanning range is also symmetrical with respect to a horizontal plane. Therefore, the optimization has been carried out just considering the positive sub-range, reduced to [10°,40°] to avoid the blockage from the feed. Inside this interval, the four radiation patterns having maximum radiation for $\theta_{max} = 10°, 20°, 30°, 40°$ have been then considered to write the cost function. In addition to the terms that take into account the error between these radiation patterns and the corresponding masks other ones have been added, to control that the directions of maximum radiation were actually the desired ones. To make less expensive the evaluation of the cost function still guaranteeing a good accuracy, the radiation patterns are computed with the Aperture Field Method (AFM) [12].

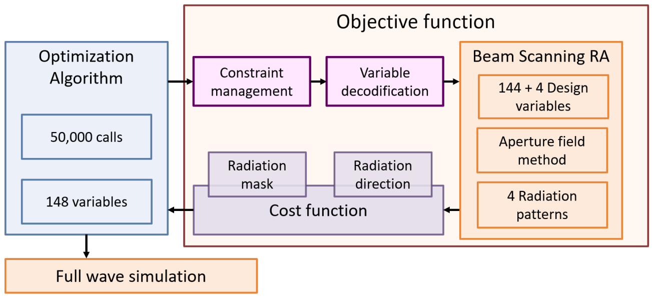

Fig. 1. Optimization environment for Social Network Optimization design.

There are two types of design variables: the size of the patches and the beam deviation factors (BDFs). The number of the first one is equal to $N^2 = 576$; however, due to the double symmetry of the patch distribution, it reduces to $N^2/4 = 144$. The BDF is instead defined as the ratio between θ_{max} and the incident angle θ_{inc} (see Fig. 2). Ideally, BDF = 1, but in a real life situation it has a lower value. The number of beam deviation factors depends on the number of directions of maximum radiation considered during the optimization process, that in the present application is equal to four. The total number of optimization variables is therefore equal to 148. Since they have different domain of definition, they are normalized in such a way to vary in the range $[0, 1]$. These normalized variables are furthermore constrained by an impenetrable wall boundary condition.

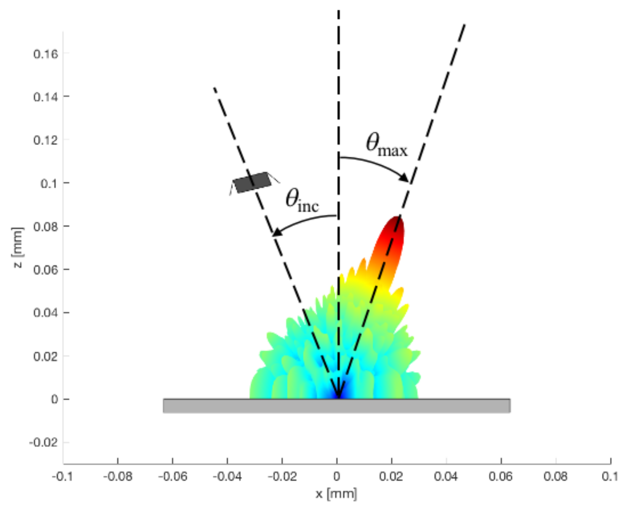

Fig. 2. Angles concurring to the definition of the BDF.

III. Results and Discussion

The SNO performance is firstly assessed through the comparison with other EAs. Fig. 3 shows the average convergence curves of five different Evolutionary Algorithms: Genetic Algorithm (GA) [13], Particle Swarm Optimization (PSO) [14], Stud-GA (SGA) [15], M_QC_{10}-Biogeography-Based Optimization (M_QC_{10}-BBO) [16], and SNO. In order to make a fair comparison between these algorithms, the termination criterion has been set for all of them to 50,000 objective function calls: in this way, the optimization time of the different algorithms is the same. In fact, the self-time of the optimization algorithm is below the 2% of the total time required. For overcoming the intrinsic stochasticity of the algorithms, 50 independent trials have been performed, and the curves in Fig. 3 show the average convergence over these trials.

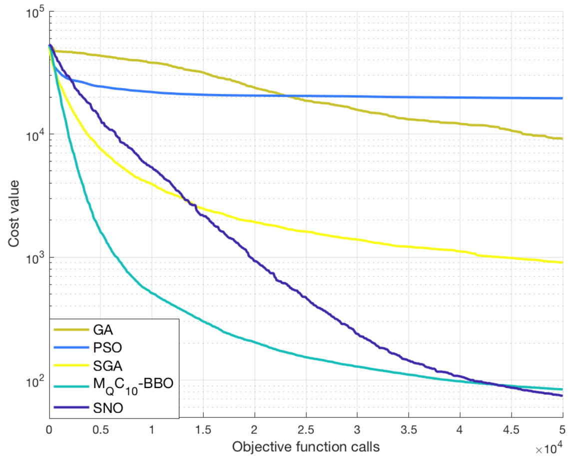

Fig. 3. Average convergence curves of different Evolutionary Algorithms.

From Figure 3 it is possible to see the effectiveness of SNO in optimizing the beam scanning reflectarray: it outperforms all the traditional algorithms and the SGA, while it has performance with that of the M_QC_{10}-BBO.

For what concerns the comparison between the reflectarray designed with SNO and the bifocal one, it has been carried on using the full-wave approach implemented in CST Microwave Studio® for their simulation and the evaluation of their radiation patterns for the values of θ_{max} considered during the optimization process.

As an example, in Fig. 4 the comparison between the normalized radiation patterns with pointing direction characterized by $\theta_{max} = 30°$ in both the E-plane and H-plane, are shown. The bifocal RA has a radiation pattern with a larger main beam and higher SLLs. Finally, in Fig. 5 the variation of the gain with the scanning angle is plotted: the one relative to the bifocal configuration has a maximum in correspondence of $\theta_{max} = 30°$, while that of the optimized RA decreases with the increasing of the scanning angle, but it has a variation not larger than 1 dB till $\theta_{max} = 35°$ and it is always larger than the gain of the bifocal solution.

These results prove that the SNO outperforms the bifocal approach for the design of a beam-scanning RA. Because of the accuracy of the method adopted for the antennas simulation, it is expected a good agreement between the results it provides and those coming from an experimental characterization of prototypes.

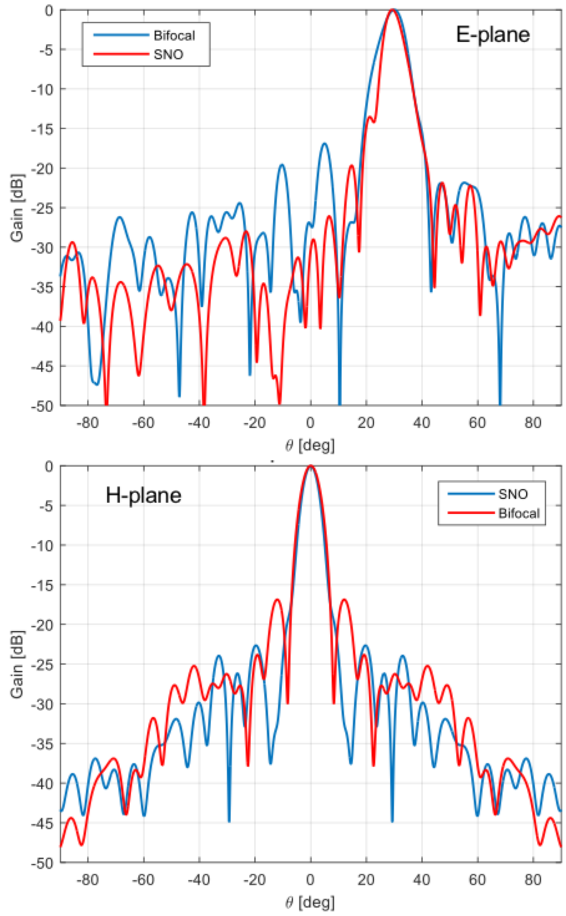

Fig. 4. Comparison between the computed radiation patterns in the E-plane (top) and in the H-plane (bottom), evaluated with the bifocal and the SNO method.

IV. Conclusions

In this paper the design of a beam-scanning passive reflectarray antenna has been faced with two different methodologies: the bifocal design and exploiting the Social Network Optimization. At the conference time results on the experimental characterization of the two antenna prototypes and on the SNO-based design of larger beam-scanning RAs will be presented.

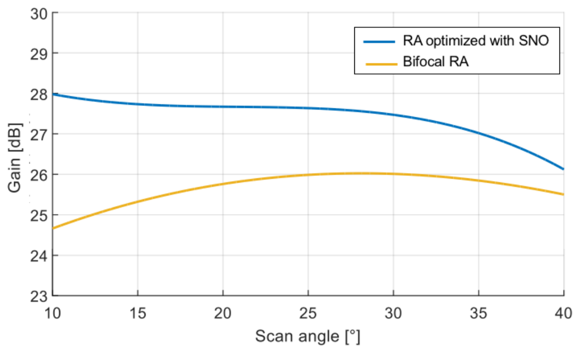

Fig. 5. Variation of the gain with the scanning angles for both the RA optimized with SNO and the bifocal one.

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