Human-vs Machine Design of Antennas: Evolution Behavior in Genetic Shape Optimization

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Human- vs Machine Design of Antennas: evolution behavior in Genetic Shape optimization

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***Abstract*—Random-based global optimization algorithms have found extensive application in the domain of antenna shape design, especially when conventional solutions relying on human expertise are lacking. In this research contribution, we investigate the performance of random-based global optimization in scenarios where the design problem could otherwise be tackled through conventional human-guided design methods and parameter adjustments driven by simulations. The present case study involves shape optimization of a 2D pixelated domain, performed via binary coding and a Genetic Algorithm (GA). The reference geometry is a square resonant patch-type antenna with optimized probe feeding position. The initial domain is a pin-centered rectangle larger than the patch itself, so that the optimizer is eventually free to indirectly find the best pin position corresponding to the best design of the patch.**

***Index Terms*—Optimization, Electromagnetics, Antennas, Genetic Algorithm.**

I. Introduction

Automated antenna design encompasses a wide spectrum of instances and approaches, ranging from highly structured array synthesis to the more conventional "parameter sweep" methods offered in commercial simulation suites. It can always be conceptualized as an optimization problem, and there are situations where it's advantageous to formulate and implement it as such.

The complexity of the design instance increases with its comprehensiveness, making it more algorithmically challenging. In this context, we specifically focus on the complete design of the antenna metal layout, involving shape optimization, with examples such as [1] and [2]. This problem, like many others of practical significance, is characterized by its non-convex and non-linear nature. Consequently, it necessitates the use of global optimization algorithms, which are predominantly random-based, such as the Genetic Algorithm (GA) [4].

A central concern is the attainment of the global optimum. If the algorithm fails to converge, it suggests that the specified constraints may be excessively stringent and require relaxation.

A more straightforward yet significant simplification would be to establish a level of confidence in the obtained results.

Interestingly, random-based global optimization is typically applied in design scenarios where it's not feasible to create a simplified problem model leading to design formulas or to deal with a small number of free parameters amenable to exhaustive search and simulation (i.e., "parameter sweep"). This approach is particularly logical in such cases.

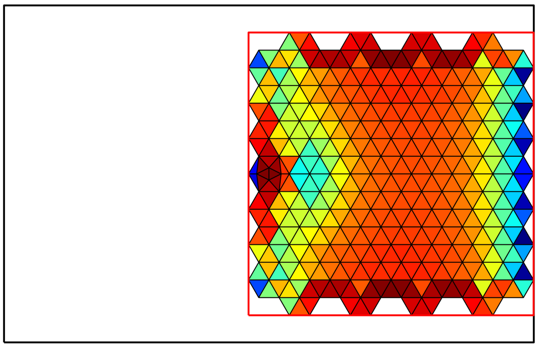

Fig. 1. Reference: square patch with optimized probe position; the rectangle overlay indicates the optimization domain used henceforth in machine design.

The aim of this contribution diverges from the norm. We intend to address a design problem for which human expertise is available and is routinely tackled using parametric simulations. We will approach the same design instance as a "machine" design, employing a random-based global algorithm like GA to perform full shape optimization.

This endeavor will enable us to draw observations regarding machine-driven design and, hopefully, provide insights for future applications.

Preliminary results have been presented in the conference paper [3].

II. Study Case

In this contribution we tackle the shape optimization of 2D patch antenna probe-fed in free space. The design of typical structures is covered in most textbooks, and one often completes the design by doing a thorough search for the position of the feeding probe. The results of the latter are shown in Fig. 1. As reference solution we use a square patch built with the same hexagonal pixels of the following analysis to allow a closer degree of comparison with the machine design, which is explained below. Accordingly the serrated edges have no other specific function.

The design has been done either at single and multi-frequency to make evident the difference in the behaviour of the optimization process increasing the computational complexity of the fitness function

III. Machine Design

The "machine" design has been tackled through a GA algorithm coupled with Method of Moments (MoM) solver for which the (tested) implementation is described in [1], [2].

The patch's surface is divided into pixels, where metal pixels can either be retained or left empty, using a binary encoding method that is highly compatible with the genetic algorithm (GA). This approach allows to assemble the impedance matrix Z only once at the beginning of the optimization process and then remove time by time only the rows and columns correspondent to the pixels left void i.e. the zeros of the chromosomes arrays. In order to avoid ambiguous fabrication due to elements touching only through vertexes, such in the case of quadrangular pixels, we used hexagonal pixels as in [2] which ensure the connectivity of the optimized structure only across the edges. The surface of the antenna is located at a height $h = \lambda/15$ from a ground plane modeled as infinite. The feeding mechanism has been simplified through a voltage gap model applied to a 2D strip of dimensions $d_y = \lambda/50$ and $h = \lambda/15$. The rectangular domain of optimization (overlay in Fig. 1) has been chosen so that the probe feeding position, initially in the center, can be indirectly optimized while optimizing the metal distribution and can result in a range corresponding to that used in human design without having to move the pin junction. In this way the optimizer converges both towards the best structure and the best relative probe positioning at the same time. Its dimensions are respectively $L_x \times L_y = 0.85\lambda \times 0.55\lambda$.

In this type of resonant antennas, sidelobes are generally not a significant concern. Therefore, important performance indicators that have to be considered are the gain at the broadside direction, denoted as G, and the input reflection coefficient Γ_{in} with respect to a 50Ω reference impedance, and they are both expressed through the realized gain

$$G_R = (1 - |\Gamma_{in}|^2)G \quad (1)$$

Furthermore, to incorporate the geometry into the fitness function while avoiding multi-objective optimization, the aperture efficiency naturally emerged as the primary quality metric. Subsequently, we employed the concept of a "total" effective area, determined with respect to the realized gain, along with the "occupied area" A_{geom}, defined as the rectangle that encompasses the entire metalization. This approach culminated in the calculation of the "total" aperture effectiveness

$$A_{eff}^{tot} = \frac{\lambda^2}{4\pi} G_R, \quad \nu^{tot} = \frac{A_{eff}^{tot}}{A_{geom}} \quad (2)$$

The latter follows directly as the objective (fitness) function to be maximized.

IV. Conclusion

These results show a sub-optimality of the square patch: the optimized structures for both single Fig. 4 and multi-frequency Fig. 5 lays inside the perimeter of the square patch. Despite it, the optimizer continues to enhance the value of the fitness function removing additional pixels.

It is important to notice that they show a "bi-phasic" behavior: in a first phase the optimizer only produces what we called "dendritic" structures Fig. 2, full of branches and disconnected sub-graphs, until a jump of the value of the fitness function over the one of reference solution . Across this jump, the radiating geometry is shrank inside the domain of the square patch and after it, a second phase is characterized by the further optimization of the performances beyond the reference one Fig. 4 and Fig. Fig. 5.

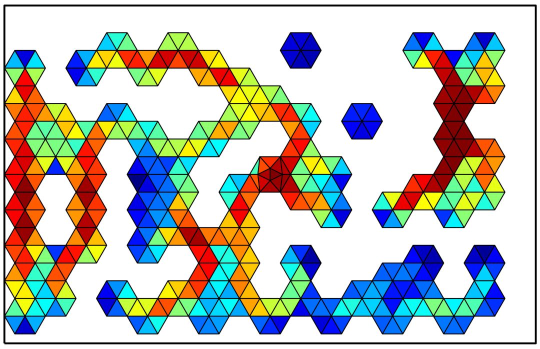

Fig. 2. dendritic solution with aperture efficiency lower than 0.80. Single frequency optimization at 10GHz

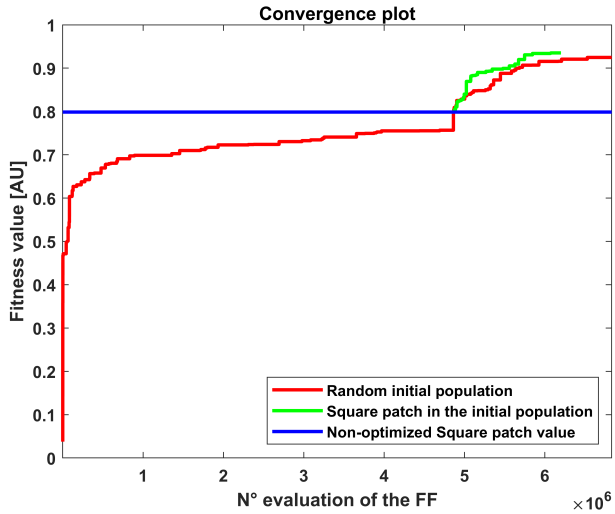

Fig. 3. Convergence rate of single frequency optimization

Acknowledgment

This work was supported by the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 955476.

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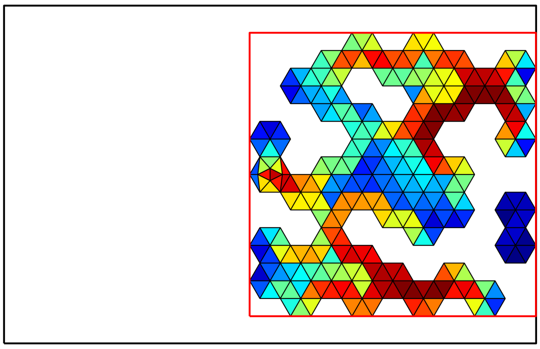

Fig. 4. Solution with aperture efficiency greater than 0.80 starting from a random initial population. Single frequency optimization at 10GHz

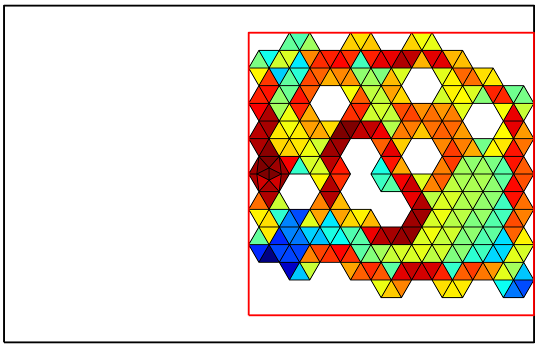

Fig. 5. Solution with aperture efficiency greater than 0.80 starting from the square patch individual in the initial population. Multi-frequency optimization at 10GHz $\pm$ 5%

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