Using Simulation and the NSGA-II Evolutionary Multi-Objective Algorithm in the Design of a Compact Dual-band Equatorial Helix Antenna

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***Abstract*—The design of a Compact Dual-band Equatorial helix antenna is presented. These antennas are used for Telemetry, Tracking, and Control (TTC) of satellites from the terrain base station. A simulation-optimization process is presented, a simulation tool named MONURBS is linked with a well-known multi-objective algorithm (NSGA-II) in order to design and optimize the parameters of the antenna. The size of the antenna that fulfills radiation patterns needed for the communication are obtained using simulation together with a multi-objective algorithm. In this work, a comparison with previous designs and the antenna prototype are be presented showing that this approach can achive solutions expediting the process.**

***Keywords*: Simulation optimisation, NSGA-II, Antenna Design**

I. Introduction

In this work, we present an initial work applying simulation optimization, i.e., the application of simulation together a multi-objective algorithm, to optimize the design parameters of an antenna with very stringent constrains. In a previous work, Garcia et al [1] presented the design of a compact dual-band helical antenna for Telemetry, Tracking, and Control (TTC) applications in satellites. Here we replicate the work as a case study to expedite the process. The initial work was immersed in a ESA project 20995/NL/ST/na, "S-Band Toroidal Antenna", where the main contractor was RYMSA[1]. The most important requirements were stated as follows:

- Dual Band operation at 1.81 GHz and 2.55 GHz in the S Band (two frequencies).
- Right hand circular polarization (RHCP), the main electrical field that radiates the antenna.
- Peak maximum gain greater than 2 dBi for the RCHP polarization.
- Minimum gain of 0 dBi in the range coverage for the RHCP polarization.
- Cross-polar polarization level had to be smaller than -12 dB (difference between LHCP –Left Hand Circular Polarization– and RHCP), this is difficult to obtain.
- The above specifications in an equatorial radiation pattern had to be satisfied in the elevation angle with a range between 70 and 110 degrees.
- The weight of the prototype had to be as small as possible, therefore it was important to have small dimensions.

The above requirements are also shown graphically in Figures 1 and 2, where a mask has to be satisfied for radiation pattern in the desired directions for the main (RHCP) as well as for the cross-polar components (difference between $LHCP - RHCP$).

The radiation pattern depends on the geometrical parameters of the antenna, and therefore, it is important to define the geometrical model of the helix antenna. The model is defined by a cylinder that represents the base of the antenna and four strips attached to the topside of the cylinder. The opposite strips were short-circuited in the top of the antenna and as post was set internally to the four strips to be mechanically strong enough. Therefore, four parameters need to be optimized (see Figure 3): (i) number of turns of the helix, (ii) bottom radius, (iii) top radius and (iv) height.

Although the geometric model is quite simple, it has to be parametrized according to the previous requirements where there are several objectives that the optimization process has to deal with. In a previous work, the optimization process was carried out applying the *gradient descent* (GD) algorithm with a simulation tool called MONURBS to analyze and obtain the radiation pattern of the antenna. This GD method was used with a cost function that depended on the requirements previously described. However, it happened to be a very complex problem with large number of maximums and minimums that made the GD method not appropriate behaving like a random sampler in the search space, i.e., the valid ranges of the parameters. A huge number of simulations were needed to obtain a valid solution that satisfied all the requirements simultaneously. It was an extremely CPU intensive task that needed a very large time span (several months). As a consequence, we are now tackling this problem as a case study of applying multi-objective optimization techniques. As a result, we present here how applying the NSGA-II algorithm we were capable of obtaining a valid solution in a shorter time span

[1] http://www.tryo.es/

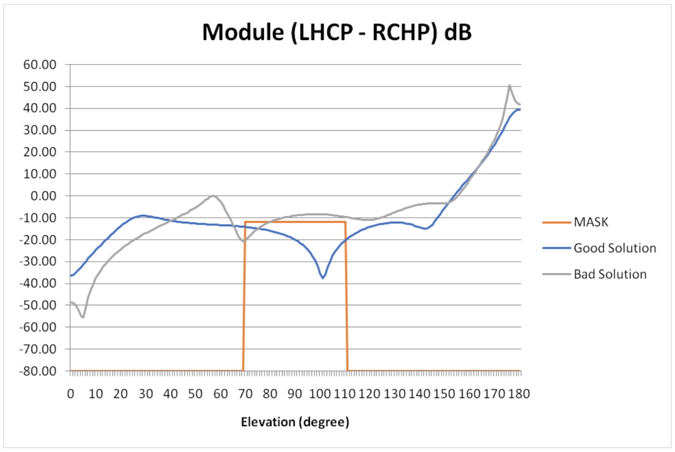

Fig. 1. Cross-polar Objective

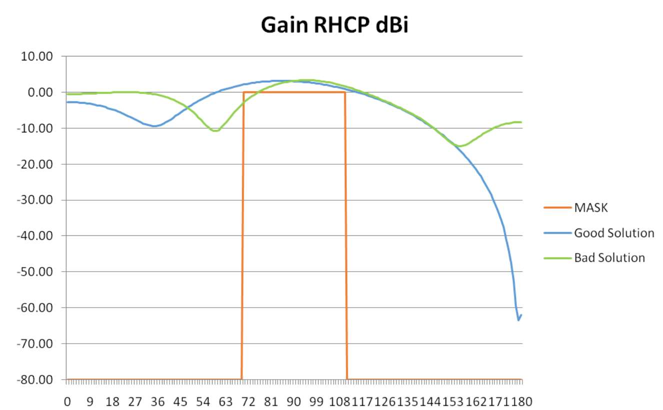

Fig. 2. Gain Objective

using less CPU time.

As a multi-objective algorithm, we have selected a well known algorithm, the Non-dominated Sorting Genetic Algorithm (NSGA-II) [2] as the most referenced algorithm in the multi-objective literature.

This paper is organized as follows. A definition of the experimental work with a brief overview of the computing simulation tool used to obtain the radiation pattern will is presented in Section II. Section III covers the background on meta-heuristics and multi-objective optimization as well as how it is integrated with an antenna simulation tool. Next, results are presented in Section IV and finally conclusions and future work are discussed in Section V.

II. Experimental Work

In order to obtain the radiation patterns of the antenna shown in Figure 3, it is necessary to use a simulation computer program that given the four geometrical parameters of the antenna (i) builds the geometrical model, (ii) prepares the model to be simulated and (iii) simulates the antenna to obtain the radiation patterns to be processed by the multi-

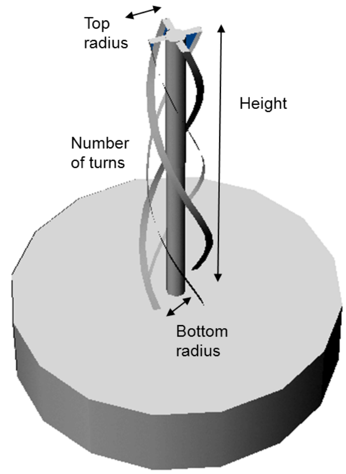

Fig. 3. Antenna and parameters to optimize

objective parameters. Figure 4 shows the block diagram of the electromagnetic simulation stage.

The geometrical model is built using a software that given the previously stated parameters can create a geometrical file in AutoCAD DXF (Drawing Interchange Format) with the surfaces that define the antenna. This file must be previously processed to be simulated with a mesher that discretize the antenna parameters as input to the simulator that calculates the radiation pattern using a simulation software called MONURBS [3]. This simulation software is being developed by the Electromagnetic Computing Group at the University of Alcala, and it is included in as part of an electromagnetic suite, newFASANT[2]. This suite can be used in many applications like electromagnetic field analysis of any complex 3D structures such as reflectors, horns, microstrip passive devices, periodical structures, antenna on board, etc. Also, the RCS of complex platforms with arbitrary materials and the compatibility between different devices mounted on the same platform. The MONURBS code is based on the Moment Method Technique (MoM) that is a full-wave solution. When the object to be analyzed is large, this technique is both CPU and memory consuming and cannot be applied if the resources of the machine are not high. To overcome this, several techniques have been implemented to speed up the simulation whilst using less memory: (i) Fast Multipole Multilevel Method (MLFLMM) [4], [1] and (ii) the Characteristics Basis Function Method (CBFM) [5], [6]. Also, the Message Passing Interface (MPI) and OpenMP paradigms have also been implemented to solve the problem using less CPU time with multiprocessor machines.

III. Multi-Objective Evolutionary Algorithms and Simulation-Based Optimization

Meta-heuristics are a family of approximate optimization techniques for solving the computational problem. There

[2] `http://www.fasant.com/`

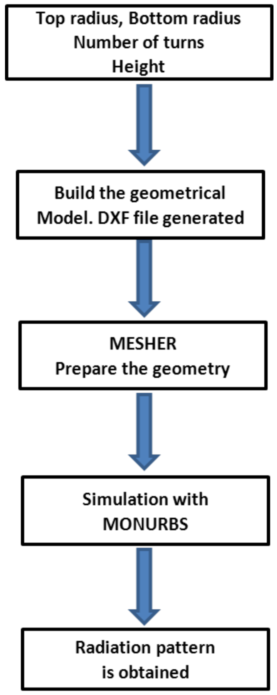

Fig. 4. Electromagnetic simulation stage block diagram

are multiple meta-heuristic techniques available, and Multi-objective Optimisation problems (MOOP) are those that involve multiple and conflicting objective functions. In general, threre are multiple valid solutions that are defined using the *Pareto front*.

Evolutionary algorithms (EAs) are particularly desirable to solve Multi-Objective Optimisation problems (MOOPs), primarily because of their population-based nature. This enables them to capture the dominance relations in the population as a way to guide the search towards the *Pareto-optimal front*. The set of non-dominated solutions, also known as *Pareto-optimal*, constitute the *Pareto front*, i.e., a set of solutions for which no objective can be improved without worsening at least one of the other objectives.

EAs usually contain several parameters that need to be tuned for each particular application at the same time considering: (i) non-conflicting objectives, i.e., achieve a single optimal solution satisfies all objectives simultaneously; (ii) competing objectives, i.e., cannot be optimized simultaneously. In addition, since the EAs are stochastic optimization techniques, different runs tend to produce different results. Therefore, multiple runs of the same algorithm on a given problem are needed to statistically describe their performance on that problem. For a more detailed discussion of the application of EAs in multi-objective optimization, the reader is referred to Coello et al [7] and Deb et al [2]. Multi-objective EAs need to fulfill two primary roles:

1) Guiding the search towards the Pareto-optimal set to accomplish optimal or near-optimized solutions.
2) Maintaining a diverse population to achieve a well distributed non-dominated front, thereby fully exploring the solution space.

A. The Non-dominated Sorting Genetic Algorithm-II

In this work, we used the most popular and still state of the art multi-objective algorithm, the Non-dominated Sorting Genetic Algorithm-II (NSGA-II) developed by Deb et al [2] as an extension of an earlier proposal by Srinivas and Deb [8].

The population individuals (solutions) are evaluated (i.e. they are assigned fitness values) in relation to how close they are to the *Pareto front* and a *crowding* measure. The NSGA-II algorithm also considers the sparsity (density) of the individuals belonging to the same rank using a crowding measure (the Manhattan distance among individuals), with the idea of promoting diversity within the ranks (the larger the sparsity, the better). In addition, the NSGA-II includes elitism in order to maintain the best solutions from the *Pareto front* found.

The rank of each individual is based on the level of non-domination. Therefore, each solution has two attributes: (i) non-domination rank and (ii) crowding distance. In other words, between two solutions with differing non-domination ranks, the solution with the lower rank is preferred. Otherwise, if both solutions belong to the same front, then the solution that is located in a less crowded region is preferred. The Algorithm 1 shows the jMetal evolutionary algorithm pseudocode (with the addition of lines 3 and 6 that are the calls to the simulator as explained in the next Section).

In this work, we used the implementation provided in the jMetal[3] framework [9]for multi-objective optimization with metaheuristics together with a simulation software of antenna radiation, MONURBS, as previously described.

B. Linking jMetal with the MONURBS simulation tool

As jMetal is being developed in Java, the communication is also handled using the Java^{TM} runtime API to simulate the antenna radiation using the antenna parameters generated by the multi-objective algorithm. Therefore, to perform the data exchange between jMetal and MONURBS, it was necessary to modify the structure of the evolutionary algorithm implemented in jMetal adding a *pre-evaluation* step just before evaluating the population. The calls are carried out in lines 3 and 6 in the NSGA Algorithm 1 to the *AntennaSimulation(E)* method (see Algorithm 2) to illustrate the communication between jMetal and MONURBS.

IV. Results

In this section, we show solutions found by both (i) using MONURBS (as standalone tool using its built-in *Gradient Descent* optimizer) and (ii) combining MONURBS and jMetal. The configuration of the problem ranges:

- Number of turns: [0.2, 3]
- Bottom radius: [0.01, 0.067]
- Top radius: [0.01, 0.067]

[3]https://github.com/jMetal/

Algorithm 1 NSGA-II Algorithm [2]

$P \leftarrow$ **makeInitalRandomPopulation**()
antennaSimulation(P) ▷ Call the simulator
$t \leftarrow 0$
while $t \leq max\_generations$ **do**
  $Q \leftarrow$ **makeNewPopulation**(P)
  antennaSimulation(Q) ▷ Call the simulator
  $R \leftarrow P \cup Q$ ▷ Combine parents and offsprings
  $\mathcal{F} \leftarrow$ **fastNonDominatedSort**(R) ▷ Compute *Ranks*
  $P \leftarrow \emptyset \wedge i \leftarrow 1$
  while $|P| + |\mathcal{F}_i| \leq N$ **do**
    $P \leftarrow P \cup F_i$ ▷ Add ith rank to population
    $i \leftarrow i + 1$
  end while
  if $|P| \neq N$ **then**
    crowdingDistance($\mathcal{F}_i$) ▷ Calculate crowding
    $P \leftarrow P \cup$ **bestCrowdingSolutions**($\mathcal{F}_i, |P| - N$)
  end if
  $t \leftarrow t + 1$
end while
$\mathcal{F} \leftarrow$ **fastNonDominatedSort**(R)
return $\mathcal{F}_1$ ▷ Return the best *Pareto rank*

Algorithm 2 antennaSimulation(P)

for each element E in population P **do**
  if E does not violates problem constraints **then**
    Invoke MONURBS process with E parameters
    Wait until MONURBS process finalizes
    Parse MONURBS return
    Update E evaluation values
  end if
end for
return Population evaluation information

- Height: [0.01, 0.5]

Also, the configuration of NSGA-II was as follows:

- Population size: 50
- Maximum number of algorithm iterations: 5,000
- Crossover operator: Simulated binary crossover
  - Crossover probability: 90%
  - Crossover distribution index: 20
- Mutation operator: Polynomial mutation
  - Mutation distribution index: 20
  - Mutation probability: 25%

The results are shown in Table I. The first row shows the result obtained with the MONURBS *Gradient Descent* in order to compare such results with the ones obtained by the NSGA-II algorithm in the next rows. Figures 5 to 8 also show the results graphically. It can be observed that all solutions met the constraints defined for this problem. It can also be observed that all solutions found for his problem are very close to each other. Although this allow us to define a small range and flexibility in the range of variables, all solutions found were practically equivalent. In a future work, we will need to apply

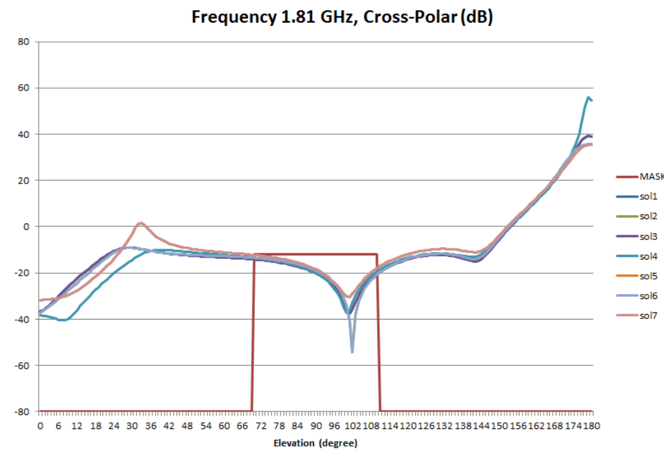

Fig. 5. Results for cross-polar objectives for frequency 1.81 Ghz

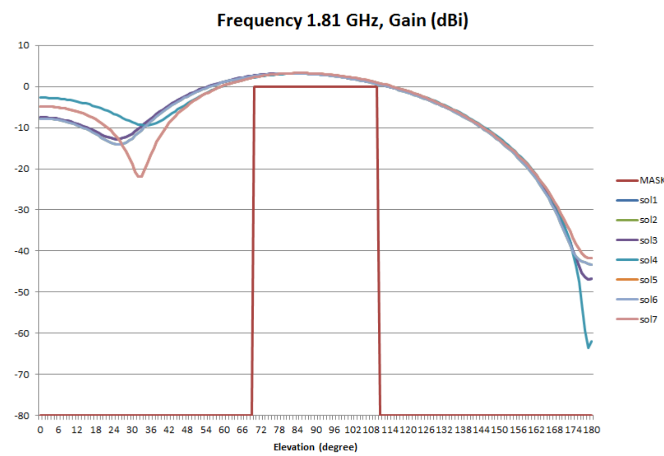

Fig. 6. Results for the gain objective for frequency 1.81 Ghz

other multi-objective algorithms and techniques to explore if there are other parameters that are significantly different.

V. Conclusions and Future Work

In this paper, we presented a simulation optimization approach to the design of helical antennas. Here we used a well known multi-objective algorithm and still state of the art algorithm, NSGA-II, that was capable of improving the time and effort needed to find valid solutions (antenna shape and dimensions) when compared with finding solutions using the gradient descent as a searching technique together a simulator tool. The use of multi-objective algorithm reduced the time-cost of algorithm execution when compared with a precious approach using the gradien descent. Also, the simulation-optimization approach allow us to obtain multiple correct solutions that provide some flexibility and can help to choose the final design of the antenna. Having more solutions, with different dimensions but all optimal from the radiation point of view, offers more possibilities for the manufacturing not

TABLE I
SOLUTIONS FOUND BY USING JMETAL AND MONURBS

Algorithm	Turns	Bottom radius (cm)	Top radius (cm)	Height (cm)
Gradient Descent	0.831	1.945	1.022	13.8
NSGA-II 1:	0.786665455	2.45821492	1.373155458	10.007858
NSGA-II 2:	0.786665455	2.33895369	1.373155458	10.1971342
NSGA-II 3:	0.786665455	2.45821492	1.373155366	10.007675
NSGA-II 4:	0.7907970555	2.45791823	1.450520708	10.007858
NSGA-II 5:	0.7765074908	1.92872455	1.407211304	11.449133
NSGA-II 6:	0.786665455	2.33895355	1.373155366	10.1971342
NSGA-II 7:	0.7765074910	1.92872635	1.407211304	11.449401

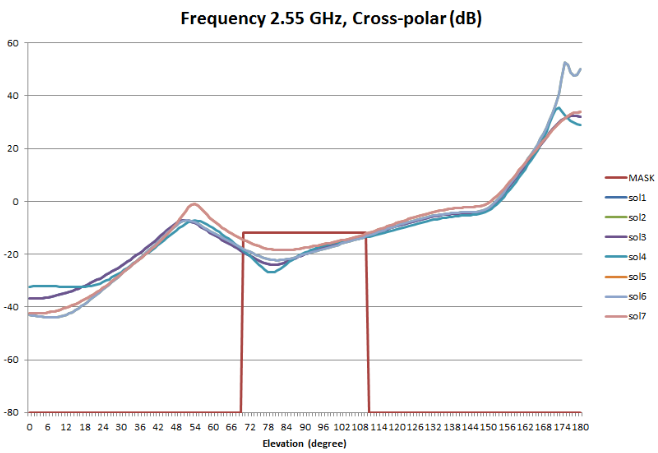

Fig. 7. Results for cross-polar objectives for frequency 2.55 Ghz

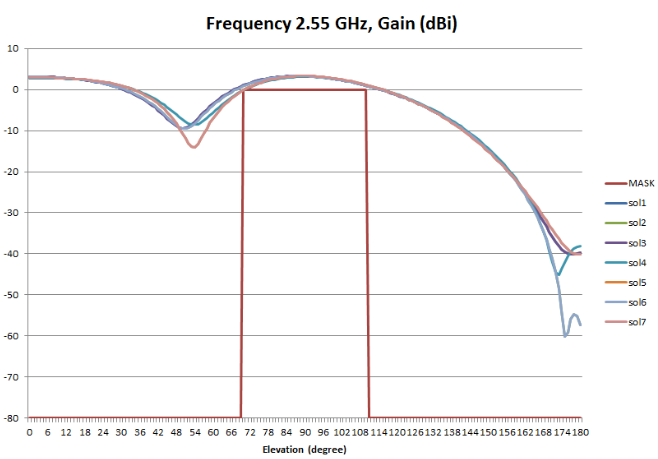

Fig. 8. Results for the gain objective for frequency 2.55 Ghz

only for the antenna but the rest of elements that are coupled closely to it.

Future works include the use other multi-objective algorithms capable of handling the constrains to compare and adapt them to the difficulty of this problem. We will also explore many-objective algorithms as we are handling four objectives in this work.

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