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A Multiobjective Perspective for the Design of Frequency Selective Surfaces

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***Abstract*— The design of a frequency selective surface usually involves several aspects, as the geometry of the array element, the thickness of the substrate and the incidence angle, which must be adequately defined so that the multiple requirements for the specific task are fulfilled. In this work, we investigate the application of a multiobjective approach to the design of a microwave absorber in the X-band, considering the simultaneous optimization of the bandwidth and the attenuation in the chosen frequency band. The obtained results encourage the use of this approach, as the algorithm was capable of finding adequate trade-offs between the objectives.**

***Keywords*— Frequency selective surfaces, Band-stop filter, Multiobjective optimization, Meta-heuristics, NSGA-II.**

I. Introduction

In the field of applied electromagnetism, the study of frequency selective surfaces (FSSs) can be safely regarded as a most relevant topic, with more than 40 years of research. In simple terms, a FSS corresponds to a periodic structure containing planar array elements arranged on a dielectric substrate, which may either pass (transmit) or block, partially or completely, incoming electromagnetic waves at certain frequency bands. These structures have been explored in several applications, such as Radomes for aviation, invisible cloak and microwave absorbers in anechoic chambers [1], [2].

The exact frequency response of a FSS depends on several aspects, such as the geometry of the array element, the type and the thickness of the substrate, and the incidence angle of the plane wave [2], [3]. For a given application, these characteristics must be carefully defined having in view the requirements or the objectives to be attained. For example, in the context of an absorber surface, the attenuation, which is related to the transmission coefficient ($|S_{21}|$), should be maximized around the resonance frequency. Moreover, it is also desired to obtain a sufficiently large bandwidth for the task at hand, as well as an adequate high frequency interference.

The existence of multiple and potentially conflicting objectives poses an additional challenge to the design of a FSS. In this sense, the task of defining the characteristics of a FSS can be seen as a multiobjective optimization (MOO) problem, where there is no longer a single solution which simultaneously optimize all the objectives. Instead, there are multiple solutions, which compose the so-called Pareto set, offering distinct, albeit optimal, trade-offs among the objectives.

Even though there is a myriad of methods tailored to cope with MOO problems, evolutionary algorithms stand out in the literature due to their ability of approximating the Pareto front, i.e., of obtaining actual non-dominated solutions, and of finding a diversified set of these solutions, thus adequately covering the Pareto front [4], [5], [6]. An emblematic example of a successful MOO evolutionary algorithm is the NSGA-II (Non-dominated Sorting Genetic Algorithm II) [7].

Having these aspects in mind, in this work we investigate the application of a MOO algorithm, more specifically, the NSGA-II, to the problem of designing the parameters of a FSS. In particular, we consider a dual-layer square loop periodic element, which shall play the role of a microwave absorber for the X-band (8 GHz to 12 GHz). The chosen objectives to be optimized are related to the bandwidth and the average attenuation of -10 dB in the X-band.

The main motivation for this approach is that by adapting the parameters of the FSS with the aid of a robust search algorithm, we shall obtain a set of alternative configurations for the periodic element, each presenting a different optimal compromise between bandwidth and average attenuation.

From a manufacturing standpoint, the availability of such repertoire of alternative solutions is certainly beneficial, since it may be possible to select a posteriori the most adequate configuration not only in terms of the objectives, but also with respect to other aspects, like the involved cost and the feasibility of the physical implementation.

This paper is organized as follows: Section II describes general concepts related to FSS; additionally, in Subsection II-A, we specify the structure of the periodic element to be adjusted in this work, as well as the objectives involved in the optimization process. Section III covers the fundamental concepts related to multiobjective optimization and describes the NSGA-II algorithm. The simulation results achieved by NSGA-II in the FSS design are presented and analyzed in Section IV and, finally, Section V brings the general conclusions and perspectives for the continuity of this research.

II. Frequency Selective Surface

Frequency selective surfaces (FSSs) are resonant periodic structures using the micro-strip technology well-established in the literature. The numerous applications of FSSs have a major importance in the electromagnetic context and are

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commonly related to microwave and optical filters [1]. In recent years, these structures have been explored in different applications, such as Radome for aviation [8], wave polarizers [9], metamaterials invisible cloak [10], and absorbers [11].

In a general way, the elements of a FSS are designed with a conductor material using lines or slots arranged according to a predefined pattern or in an aperture complementary geometry over a substrate [12]. With respect to the structure type, the FSSs are usually divided in capacitive and inductive elements. If the structure is arranged as conductor elements, it is considered as capacitive and acts as a band-stop filter; on the other hand, if the structure is composed of slots in a metal surface, it is inductive, with a behavior similar to a band-pass filter [13]. When the FSS elements have resonant characteristics, the inductive FSS presents total transmission around the resonant frequency, while total reflection is observed in the case of capacitive FSSs [1]. The FSS resonant frequency depends on the inductive/capacitive character created by the thickness and shape of the structure lines, the permittivity of the substrate material and the dimensions of the array element. Additionally, the behavior of the FSS is also influenced by the frequency, the incidence angle and the polarization of incident wave.

Simple FSS geometries can be designed by means of an approximation via equivalent circuit, which is composed of resistors, inductors and capacitors. This method was used by Marcuvitz [14] to represent waveguides as an equivalent circuit. The analytical methods for the FSS calculation and the design of simple geometric structures, such as square loop and Jerusalem cross, are described in detail in [3].

The FSS specifications have several considerations, as the definition of the geometrical shape of the periodic element, the type and the thickness of substrate material, and the resonant frequency. All these aspects need to be adequately managed in order to satisfy the application constraints.

Among the various FSS applications, this work focuses on the microwave absorber application. This class of device is used to reduce the electromagnetic energy incident in a certain material. In practical applications, the absorbers can be attached to resonant cavities, along with antenna Radome, in order to mitigate interference problems and signal coupling.

In this scenario, the effective configuration of the FSS has to be determined taking into account several requirements, such as bandwidth, operation frequency, angle of incidence and $|S_{21}|$ level. Therefore, the FSS design is, in fact, an optimization problem with multiple performance criteria, which need to be concomitantly optimized.

In Section II-A, we present the basic structure of the periodic element considered in this work, as well as the set of adjustable parameters and the objective functions related to the underlying MOO problem.

A. Design and Configuration

We considered a double-layer FSS whose periodic element is the square loop depicted in Fig. 1, similarly to the work of [15]. The capacitive FSS was chosen since we intend to build a band-stop filter with a significant $|S_{21}|$ in the X-band (8 GHz – 12 GHz). The choice of the FSS stop-band as the X-band was motivated by the possibility of future prototyping and the availability of equipment capable of analyzing the characteristics of the prototype up to this band. For similar reasons, a commonly used substrate named FR4 was adopted, with a thickness of 0.762 mm for each layer, a dielectric constant of 4.4 and a dielectric loss tangent of 0.02.

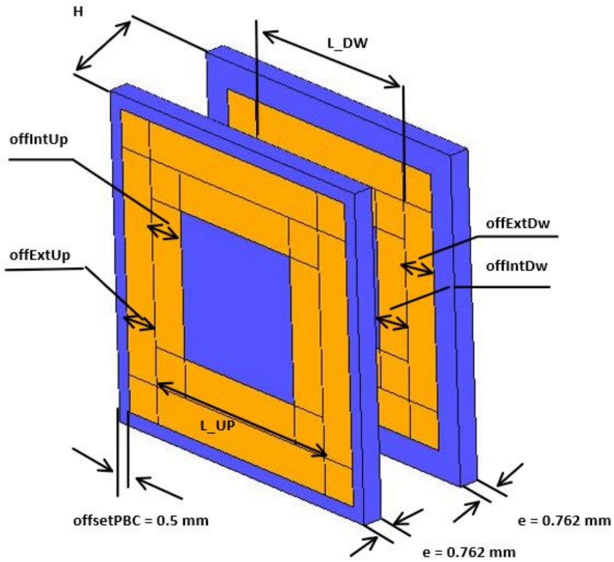

Fig. 1. Unit cell optimization model. Orange indicates conductor area.

The behavior of a band-stop filter is achieved by incorporating a square loop on each side of the FR4 and by separating them by a distance H, so that each square loop is responsible for a resonant frequency, as discussed in [3], and the distance between the layers of FR4 is responsible for the electromagnetic coupling.

The adjustable parameters of the periodic element are highlighted in Fig. 1: H – distance between the layers; L_{UP} – average perimeter of the up square loop divided by four; L_{DW} – average perimeter of the down square loop divided by four; $offIntUp$ – internal distance from L_{UP}; $offExtUp$ – external distance from L_{UP}; $offIntDw$ – internal distance from L_{DW}; $offExtDw$ – external distance from L_{DW}. For each of these parameters, we established a minimum and a maximum value in order to ensure that the frequency response of the FSS is approximately concentrated around the X-band.

The parameter $offsetPBC$, which corresponds to the distance between the upper copper trail and the periodic boundary condition, remained fixed, as well as the thickness of the substrate (e).

As mentioned in Section I, we propose to use a MOO algorithm to design the geometry of the periodic element. Let $\mathbf{x} = [\mathbf{H}, \mathbf{L_{DW}}, \mathbf{L_{UP}}, \mathbf{offIntDw}, \mathbf{offExtUp}, \mathbf{offIntDw}, \mathbf{offIntUp}]$ be the parameter vector describing a candidate structure for the FSS, which contains the values for the seven aforementioned adjustable parameters. In this work, we aim at obtaining the optimal solutions considering two objectives: (1) maximum bandwidth and (2) maximum average attenuation in the stop-band. The former objective was mathematically represented by the evaluation function $f_1(\mathbf{x}) = \frac{1}{\text{bandwidth}}$, which must be minimized. The bandwidth is determined as the size of the band located between the cutoff frequencies in the frequency response of the FSS, which correspond to the frequencies at which the magnitude is -10 dB. The latter objective is associated with the evaluation function $f_2(\mathbf{x})$, which must also be minimized and corresponds to the average value of the magnitude of the frequency response below -10 dB. Therefore, our goal is to minimize both functions in order to find the Pareto Front, which means obtaining alternative structures with large bandwidth and with a good average attenuation.

III. Multiobjective Optimization

A multiobjective optimization (MOO) problem is characterized by the existence of several evaluation criteria for each candidate solution, which must be simultaneously optimized. As a rule, the objectives are conflicting, which means that the goal in this task is to retrieve a set of optimum trade-offs among the objectives.

A fundamental concept in MOO is known as dominance [5], [6]. A solution $\mathbf{x}_1 \in \Omega$, where Ω denotes the search space, dominates a solution $\mathbf{x}_2$ (denoted as $\mathbf{x}_1 \preceq \mathbf{x}_2$) if, and only if, $\mathbf{x}_1$ is better than or equal to $\mathbf{x}_2$ considering all the objectives, and there is at least one objective for which $\mathbf{x}_1$ is strictly better than $\mathbf{x}_2$. In this case, $\mathbf{x}_1$ represents a better compromise between the objectives when compared with $\mathbf{x}_2$.

Therefore, the challenge in MOO problems consists in obtaining the set of all non-dominated solutions in the search space, which corresponds to the Pareto set [5], [6].

Another peculiarity of MOO problems is the necessity of dealing with two different spaces during the search: (*i*) the search space Ω itself, where all candidate solutions $\mathbf{x}$ lie, and (*ii*) the objective space $\mathcal{F}$. Each solution in Ω can be mapped to a point in the objective space $\mathcal{F}$ by computing the value of each objective function $f_i(\cdot), i = 1, \ldots, M$ for $\mathbf{x} \in \Omega$.

Having this aspect in mind, the search process in MOO can be also visualized in the objective space, where we want to find the region containing all the non-dominate solutions, i.e., the region in $\mathcal{F}$ associated with the Pareto set, which is the so-called Pareto front [5], [6].

Any strategy designed to solve a MOO problem aims at obtaining a diverse set of non-dominated solutions that are adequately spread along the Pareto front, in order to attain a rich set of trade-offs between the objectives. This perspective is particularly interesting when the decision about which solution will be effectively implemented is taken a posteriori, i.e., after the search process is concluded.

In this context, meta-heuristics emerge as promising alternatives, since they are less sensitive to the shape of the Pareto front (e.g., convex or non-convex), and can be readily applied to different problems requiring a minimum amount of a priori information. Additionally, since these methods typically work with a population of candidate solutions, they are capable of finding multiple solutions in the Pareto front in a single execution [5], [6].

In particular, evolutionary algorithms occupy a prominent position in the MOO literature. Among the well-established methods, it is safe to affirm that the NSGA-II (Nondominated Sorting Genetic Algorithm II) is one of the most famous and most explored methods, especially when the number of objectives is not large, achieving excellent results in several applications [4], [5], [7].

In this work, we employed NSGA-II to perform the optimization of the parameters of the periodic element in a FSS. Even though there are more recent MOO methods, including NSGA-III [16], a more sophisticated version of NSGA-II designed to cope with many-objective optimization, we decided to begin our research by investigating the potential benefits of a MOO-based design strategy for FSS considering a classical, yet powerful, algorithm.

A. NSGA-II

The evolutionary method known as NSGA-II is an elitist genetic algorithm specially-tailored for MOO, which presents two main features: (*i*) a sorting mechanism of solutions based on the level of non-dominance; and (*ii*) a selection criterion based on a crowding distance for preserving diversity in the objective space. Algorithm 1 presents the pseudocode of NSGA-II. For more details about the implementation of each step, we refer the reader to the work in [7].

At each iteration i, standard recombination and mutation operators are used to create an offspring population $\mathcal{Q}_i$ from current population $\mathcal{P}_i$ (Lines 5 and 6). Next, the candidate solutions in the combined population $\mathcal{P}_i \cup \mathcal{Q}_i$ are evaluated considering the objective functions of the problem (Line 7), and, then, are ranked according to a non-dominance criterion (Line 8).

More specifically, the algorithm separates the solutions in subsets (or fronts) $\mathcal{S}_k$, putting in the same subset individuals that present the same level of non-dominance. The first front, $\mathcal{S}_1$, contains the non-dominated solutions within the current repertoire $\mathcal{P}_i \cup \mathcal{Q}_i$. Therefore, $\mathcal{S}_1$ corresponds to the subset of the best solutions found, which potentially includes Pareto-optimal solutions.

The second front, $\mathcal{S}_2$, contains the individuals that are dominated by at least one solution from $\mathcal{S}_1$, but are mutually non-dominated. In the general case, the individuals in front $\mathcal{S}_k$ are dominated by at least one solution from the previous fronts $\mathcal{S}_l, l < k$, and are mutually non-dominated.

After the solutions are ranked, the algorithm progressively tries to insert individuals in the next population $\mathcal{P}_{i+1}$, starting from the best front $\mathcal{S}_1$ (Lines 9 to 16). If the number of individuals in the current front is larger than the number of available spots in $\mathcal{P}_{i+1}$, then a selection procedure is applied, giving preference to the solutions that occupy less crowded regions in the objective space. Otherwise, the entire front can be included in $\mathcal{P}_{i+1}$.

In order to select a subset of solutions from the same front, a measure called crowding distance (CD) is computed. For each solution $\mathbf{x}_i$, CD_i corresponds to the volume of the hypercube delimited by the solutions adjacent to $\mathbf{x}_i$ in the objective space. Hence, larger values of crowding distance indicate that the individual lies in a less crowded region of the objective space. Therefore, in order to increase diversity and, hopefully, achieve a good coverage of the Pareto front, solutions presenting large values of crowding distance are preferred.

Algorithm 1 NSGA-II

Function $[\mathcal{P}]$ = NSGA-II(N,p_m,p_c,T)
$i \Leftarrow 0$; $\mathcal{P}_i \Leftarrow$ initialize(N)
while $i < T$ **do**
  $\mathcal{Q}_i \Leftarrow$ crossover($\mathcal{P}_i, p_c$)
  $\mathcal{P}_i$,$\mathcal{Q}_i \Leftarrow$ mutation($\mathcal{O}_i, \mathcal{Q}_i, p_m$)
  $\mathbf{F}_{\mathcal{P}}, \mathbf{F}_{\mathcal{Q}} \Leftarrow$ evaluation($\mathcal{P}_i$,$\mathcal{Q}_i$)
  $\mathcal{S} \Leftarrow$ non-dominated-sorting($\mathcal{P}_i$,$\mathcal{Q}_i$,$\mathbf{F}_{\mathcal{P}}$, $\mathbf{F}_{\mathcal{Q}}$)
  $\mathcal{P}_{i+1} = \emptyset$; $k = 1$
  while $|\mathcal{P}_{i+1}| + |\mathcal{S}_k| \leq N$ **do**
    $\mathcal{P}_{i+1} \Leftarrow \mathcal{P}_{i+1} \cup \mathcal{S}_k$; $k \Leftarrow k + 1$
  end while
  $\mathcal{S}_k^* \Leftarrow$ select-crowding-distance($\mathcal{S}_k$,$N - |\mathcal{P}_{i+1}|$)
  $\mathcal{P}_{i+1} \Leftarrow \mathcal{P}_{i+1} \cup \mathcal{S}_k^*$; $i \Leftarrow i + 1$
end while

The user-defined parameters of NSGA-II are: the number of individuals in the population (N); the probabilities of mutation and crossover (p_m and p_c, respectively) and the maximum number of iterations (T).

IV. Analysis of Results

In this section, we present the results obtained with NSGA-II when applied to the design of the dual-layer periodic element described in Section II-A.

The simulations were carried out using Matlab® and FEKO®, considering an AMD FX(tm) 8350 Eight-Core Processor, with 4.00 GHz, 32 GB of memory and a 64-bits operational system. The parameters of NSGA-II were defined according to preliminary experiments and assumed the following values: $N = 15$, $T = 21$, $p_m = 0.6$ and $p_c = 1.0$.

It is important to remark that besides implementing the MOO algorithm, we also had to establish a communication mechanism between Matlab® and FEKO® in order to run the electromagnetic simulation in the latter software each time a candidate solution of NSGA-II needed to be evaluated. The entire simulation took over than seven days to be completed, even using a relatively small number of individuals and iterations, which constitutes a very time-consuming process.

Fig. 2 exhibits the population $\mathcal{P}_i$ in the objective space maintained by NSGA-II at different iterations i of the search process. It is possible to observe that the algorithm tends to move the individuals towards the regions of small values of $f_1(\cdot)$ and/or of $f_2(\cdot)$, discovering more adequate trade-offs between the objectives.

In fact, if we consider all the solutions displayed in Fig. 2, it is possible to identify six non-dominated individuals in the final population. In order to facilitate the visualization, we show in Fig. 3 the non-dominated solutions obtained by NSGA-II. Interestingly, some of these non-dominated solutions were discovered by NSGA-II in an early stage of the search process, which means that the sorting mechanism accompanied with the selection procedure adopted in NSGA-II succeeded in preserving the non-dominated solutions found during the search process.

The non-dominated solutions highlighted in Fig. 3 represent a potential Pareto front for our problem, since we cannot guarantee whether they are, indeed, Pareto-optimal solutions.

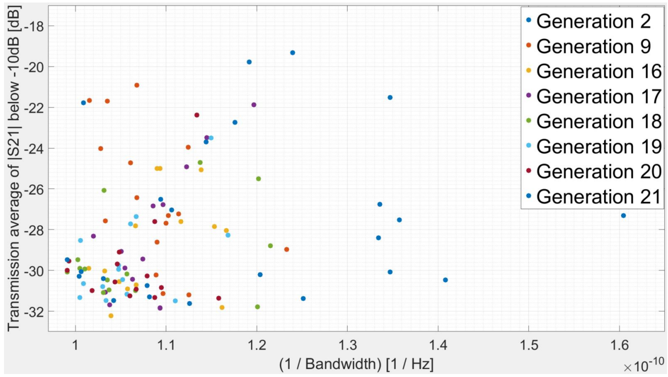

Fig. 2. Distribution of the population evolved by NSGA-II in the objective space, considering different iterations of the search process.

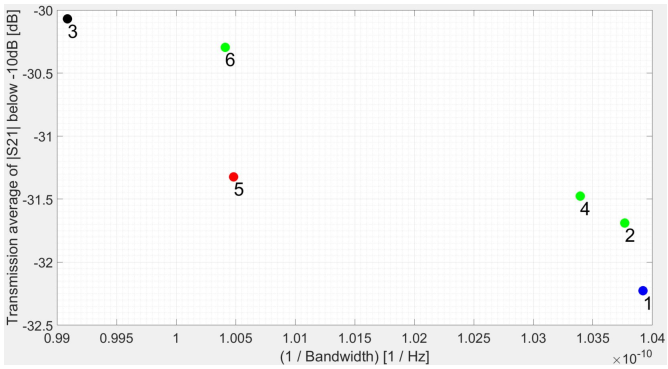

Fig. 3. The non-dominated solutions found by NSGA-II, representing a potential Pareto front for the problem.

Nonetheless, each of them offers a different trade-off between bandwidth and average transmission of $|S_{21}|$ below -10 dB, being pertinent alternatives for the implementation of the periodic element of the FSS.

Para, Tab. I presents the values of the bandwidth (and its inverse) along with the average transmission of $|S_{21}|$ below -10 dB associated with the non-dominated solutions found by NSGA-II.

TABLE I
Performance achieved by non-dominated solutions.

Pareto Front Individuals	Bandwidth (GHz)	$f_1(\cdot)$ $(\frac{1}{Hz})$	$f_2(\cdot)$ (dB)
1	9.6228	$1.0392e^{-10}$	-32.2272
2	9.6368	$1.0377e^{-10}$	-31.6898
3	10.0920	$9.9088e^{-11}$	-30.0712
4	9.6718	$1.0339e^{-10}$	-31.4765
5	9.9519	$1.0048e^{-10}$	-31.3235
6	9.9589	$1.0041e^{-10}$	-30.2953

It is possible to notice in Tab. I that the bandwidth achieved by the obtained solutions is quite large. Moreover, all the solutions attained an adequate level of average transmission. In other words, with a single execution of NSGA-II, we were able to obtain six candidate solutions, each leading to a different specification for the double-layer periodic element, which achieved desirable performances for both objectives. The possibility of obtaining a set of diverse solutions, each representing a different trade-off between the involved objectives, is precisely the main advantage of exploring a multiobjective optimization approach for this problem.

In Fig. 4, we show the frequency responses associated with three solutions selected from the non-dominated set. In particular, the chosen solutions correspond to individuals 1, 3 and 5 from Fig. 3, which are indicated by blue, black and red circles, respectively. Individuals 1 and 3 are the extreme solutions at the potential Pareto front: while individual 3 has the largest bandwidth, individual 1 has the best average transmission below -10 dB. On the other hand, individual 5 achieved an intermediate level of bandwidth and average transmission.

Moreover, the obtained results reveal a good $|S_{21}|$ in the X-band for all individuals on Fig. 4. Also, it is important to point out that the relative bandwidths of 87.84%, 88.20% and 88.17% to individual 1, 3 and 5, respectively, are obtained with a simple design and approximately 5.8 mm thickness structure on average, which represents a thickness per lambda max of 0.1246 for individual 1, 0.1234 for individual 3 and 0.1241 for individual 5.

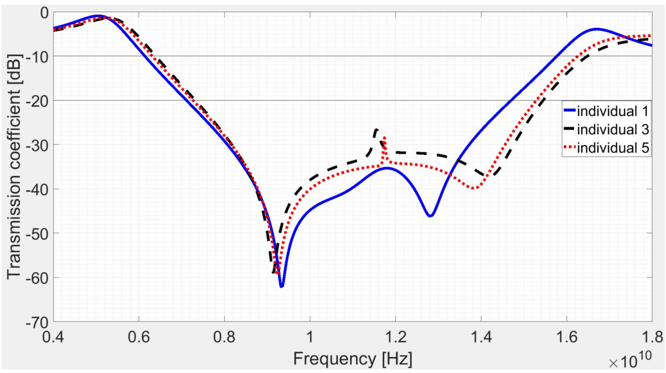

Fig. 4. Transmission coefficient ($|S_{21}|$) associated with three individuals from the potential Pareto Front.

V. Conclusion

In this work, we employed a multiobjective approach to the design of the periodic element of a FSS acting as a microwave absorber in the X-band. In particular, we explored the NSGA-II algorithm to adapt the parameters of a dual-layer square loop FSS in order to simultaneously optimize the bandwidth and the attenuation in the stop-band.

The obtained results revealed that NSGA-II was capable of finding some alternative non-dominated solutions belonging to a potential Pareto front, each of them offering a different trade-off between the desired objectives. It is interesting to remark that the $|S_{21}|$ of -10 dB on X-band was successfully achieved for all solutions in the potential Pareto Front. Moreover, we also found structures with average transmission inferior to -30 dB, which means a very good absorber. At the same time, all the non-dominated solutions found by NSGA-II can be considered as ultrawideband filters.

Therefore, the NSGA-II proved to be an effective strategy for dealing with the multiple objectives related to the frequency response of the FSS, discovering alternative configurations of a basic geometry with adequate bandwidth and attenuation, without using different kind of materials (only FR4), or more complex geometries.

Evidently, there are several aspects that need to be further developed in future researches. It is certainly relevant to seek for strategies to reduce the computational cost of the optimization process, which is mainly due to the intensive electromagnetic simulation involved in each evaluation. Additionally, this study has to be extended in several directions, by considering more complex structures, or even additional objective functions, as well as other scenarios considering different polarizations and incidence angles for the FSS. Finally, a more thorough comparative analysis including other MOO algorithms needs to be performed.

VI. Acknowledgment

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