Multiobjective Synthesis of Electromagnetic Devices using Nondominated Sorting Genetic Algorithms

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1. Introduction

Though the basic laws of electromagnetics have been well understood since the time of Maxwell and Hertz, the design of devices based on these laws remains a very complicated procedure. Before the recent advent of stochastic optimization techniques such as Simulated Annealing (SA) [1] and Genetic Algorithms (GAs) [2], electromagnetic design procedures either relied on deterministic gradient type searches which are susceptible to getting trapped in local optima, or on human intuition and guesswork. Given an objective function which somehow measures the overall quality of a problem solution, many studies (e.g.[3-7]) have shown stochastic techniques to be very successful in locating optimal or near-optimal designs in electromagnetic problems.

However, most problems in engineering are multifaceted and thus not well treated by such an unwavering charge at a single goal abstracted into an objective function. Instead, tradeoffs must be found which ensure that the device meets all of many possibly interfering design goals. Though this is often accomplished by algebraically combining the multitude of goals into a single goal, such a process involves an enormous amount of experimentation to find an objective function which produces the necessary combination of features. This work therefore proposes a method for finding the set of all optimal tradeoffs (as defined by the concept of *Pareto optimality* defined below) between conflicting goals inherent in a given design problem. The method, applicable to a plethora of electromagnetic design problems, is demonstrated by application to the design of broadband multilayered microwave absorbers to minimize thickness and reflectance, and to thinned antenna arrays and arrays with digital phase shifters to minimize maximum sidelobe level and beamwidth.

2. Formulation

In seeking all optimal tradeoffs in a given design, we define "optimal" inexclusively—any design is considered optimal if there is no achievable design within the problem constraints which is better with respect to all goals. In general, imagine a design problem with a vector $\mathbf{f} = (f^1, \cdots, f^G)$ of G objectives, each of which we wish to minimize, and two candidate designs with objective function vectors $\mathbf{f}_1$ and $\mathbf{f}_2$ respectively. Design 1 is said to *dominate* design 2 (or $\mathbf{f}_2$ is said to be *inferior* to $\mathbf{f}_1$) if for all $i \in \{1, 2, \ldots, G\}$ $f_1^i \le f_2^i$, and there exists at least one i such that $f_1^i < f_2^i$. A design is said to be *nondominated* if there exists no feasible design in the entire solution space which dominates it. The Pareto front is the set of all such nondominated designs (Fig 1a) [2, 8]. In the case of broadband

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microwave absorbers, the designs must have low thickness t and low reflectance R to be practical. Thus, for a given data base of materials and number of layers of absorbing material, the Pareto front consists of those designs which are thinnest for a given reflectivity.

In this study, a modified GA is used to construct the entire Pareto front. Unlike usual gradient based optimization techniques, GAs operate on an entire population of designs at a single time. Each design is encoded into a *chromosome* which represents of all of the salient features of a design (for example, the thicknesses and materials in a multilayer microwave absorber). Three operators then produce new populations (of the same size) in turn. The *selection* operator implements survival of the fittest by differentially allotting space in the next population based on objective function value; good chromosomes get many representatives and bad ones may get none. The improved population is then manipulated by the *crossover* operator which creates from each pair of parents (with a given fixed probability) two "offspring" chromosomes which are genetic hybrids of their parents. Finally, each chromosome is *mutated* with a given probability, randomly altering the design it represents. This processes is then iterated producing *generations* of improved populations of designs.

The above described standard GA is used for single objective optimization, and would converge as illustrated in Fig. 1b for a linear combination $R+\alpha t$ of objectives instead of the behavior shown in 1c which represents true Pareto optimization with the population converging to different points on the front. For Pareto optimization, this standard GA is modified into the Nondominated Sorting GA (NSGA) [8] by changing the action of its selection operator in two ways. First, the population is ranked according to its relative nondominance. Nondominated designs are give a rank of one, the designs that would be nondominated if the rank one designs were removed are given a rank of two, and so on. Objective function values are then based on rank. Unfortuantely, nondomination ranking cannot ensure that the entire front is found since it does not force the GA to find different points on the front. Thus, the NSGA also relies on sharing, a technique based on the competition of organisms for limited resources in the environment, to promote diversity. Since similar organisms share resources in the environment, nature will favor creatures that are novel. Thus the NSGA will reduce the objective function values by a *niche count* [2], roughly proportional to the population density around a given design.

3. Numerical Results

To illustrate the technique, several design problems were considered. Figure 2 shows the actual behavior of the NSGA when applied to reducing the normal reflectance over a given frequency band and thickness of broadband microwave absorbers with five layers for operation from 0.2-2 GHz built from a database of 16 materials [7]. Each of the 8000 points in the figure represents a design the GA has found, and the dense edge of the mass is the front. Because of the large population, most of the front is found by generation 10.

Figure 3 shows the Pareto front achieved by the application of the NSGA to a the design of absorbers from 2-8 GHz with five layers and the same database as above, as well as the frequency response of two representative designs from the Pareto front. A population size of 8000 is again used, and the resulting front shown is after 150 generations.

Additional design examples demonstrating the application of the technique to microwave absorbers designed for several angles of incidence, and to one and two dimensional antenna arrays with digital phase shifters, and thinned antenna arrays will be provided in the presentation.

References

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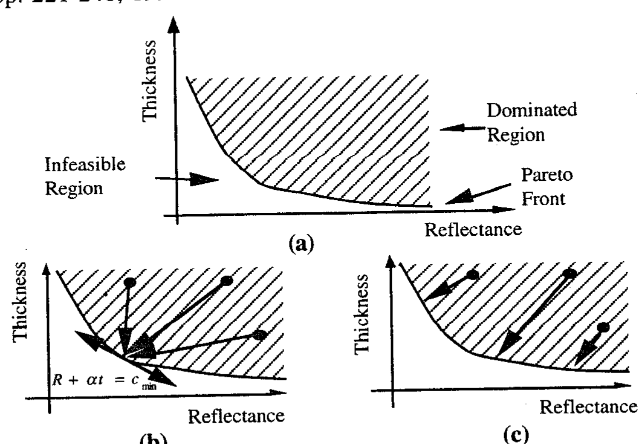

Figure 1: **(a)** Definition of the Pareto front; **(b)** Single objective optimization; **(c)** Desired multiobjective performance

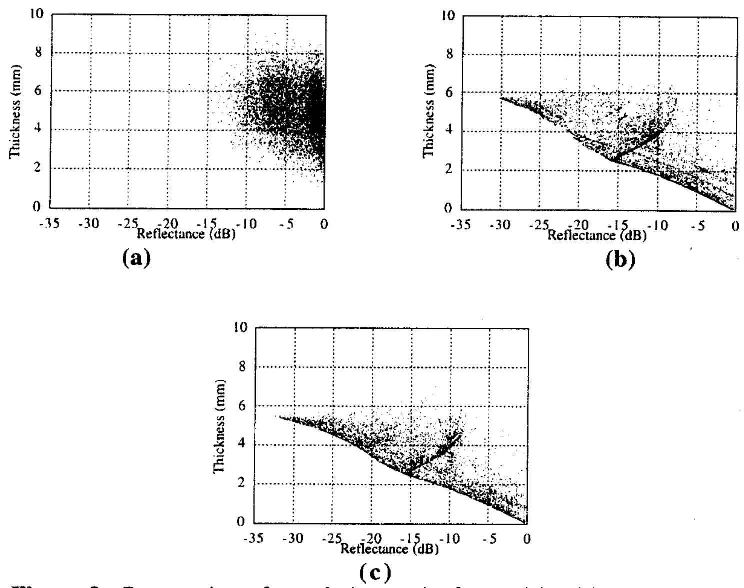

Figure 2: Progression of population to the front. **(a)** Initial Population; **(b)** Generation 10; **(c)** Generation 150

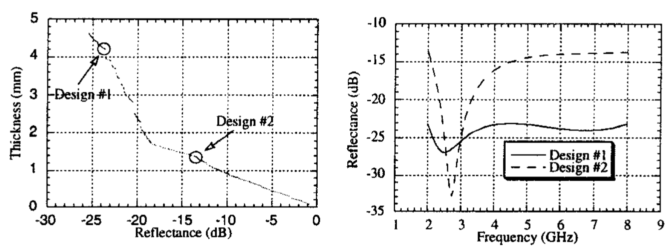

Figure 3: A Pareto curve for the materials database in [7] between 2-8 GHz. The frequency response of two designs is inset.