Pareto-optimal Design of Broadband Microwave Absorbers Using Genetic Algorithms.

E. Michielssen[†], *J. M. Sajer*[††] *and R. Mittra*[†]

[†]*Electromagnetic Communication Laboratory*
University of Illinois at Urbana-Champaign
Urbana, IL 61801
[††]*CEA-CESTA - le Barp, France*

1. Introduction

This paper illustrates the application of a multicriteria optimization technique to the synthesis of broadband microwave absorbtive coatings. In the past, a variety of techniques has been developed for the synthesis of multilayer absorbers, e.g., Salisbury [1], graded index, Jaumann [2], and Dallenbach screens. Recently, Pesque *et al.* have proposed an optimal control and a simulated annealing technique [3], and Michielssen *et al.* [4] described a synthesis procedure which utilizes the genetic algorithm. The latter technique seems to overcome some of the drawbacks of the simulated annealing algorithm proposed in [3], and easily lends itself to multicriteria optimization, as illustrated in the present paper. For many applications, the problem of designing a coating involves a trade-off between conflicting goals, namely those of minimizing the total coating thickness t while achieving maximum absorption. This paper proposes a continuation of the work presented in [4], by incorporating, within the genetic algorithm, a mechanism for investigating the trade-off between coating thickness and absorption, by using the concepts of Pareto-optimality.

2. Formulation

Given a predefined set of N_m available materials with frequency dependent permittivities $\varepsilon_i(f)$ and permeabilities $\mu_i(f)$ (i=1,..,N_m), the design of a multilayered coating (Fig. 1) requires the determination of the choice of a material for each layer and its thickness. To quantify the absorption characteristics of a coating, an objective function R is defined as the maximum of its reflection coefficient over a range of frequencies $\{f_1, f_2, .., f_{Nf}\}$ and incident angles $\{\theta_1, \theta_2, .., \theta_{N\theta}\}$ of interest. Given a restriction on the total coating thickness, the optimal choice for the design parameters leads to a coating which minimizes R , or, alternatively, to a coating with minimum total thickness for a desired R. The thickness t and reflectivity R of an arbitrarily constructed coating may be represented in a (t,R) graph as illustrated in Figure 2. The manifold of feasible designs is bounded by a trade-off curve which characterizes the Pareto-optimal designs. In the present context, a coating is referred to as Pareto-optimal, or non-dominated, provided that any perturbation of its design parameters results in a coating with an increased thickness and/or reflectivity R. The goal of the design method presented in this paper is to use the genetic algorithm to determine (i) the optimal trade-off curve for a given database of materials and objective function R, and, (ii) the design parameters of the coatings which characterize this curve.

Genetic algorithms [5] are iterative optimization procedures that start with a randomly selected population of potential solutions, and gradually evolve toward better solutions through the application of genetic operators. These genetic operators are derived from the processes of procreation observed in nature. Their repetitive application to a population of potential solutions results in an optimization process that resembles natural evolution. Genetic algorithms differ from other optimization techniques in several respects. First, genetic algorithms typically operate on a discretized and coded representation of the parameters which are to be optimized, rather than the parameters themselves. For the purpose of designing absorbing coatings from a given database of materials, a suitable bitwise representation of a coating, often referred to as a chromosome or a sequence, is obtained through discretization of its design parameters. Given the number of available materials, the maximum thickness of an individual layer, the required thickness resolution and the maximum number of layers N in a coating, a multilayer can be represented uniquely by a finite sequence of bits as illustrated in Figure 1. Second, the genetic operators which guide the population of potential solutions induce probabilistic, rather than deterministic transitions. The probabilistic nature of these operators greatly enhances the capabilities of the algorithm to search for a global rather than local objective function maximum. Third, genetic algorithms operate on a population of potential solutions, rather than a single solution candidate. Implementation of the advanced crowding operator in conjunction with schemes geared toward multicriteria optimization allows the algorithm to converge to a population of distinct Pareto-optimal solutions, rather than to a single optimal solution.

A flow chart of the genetic algorithm is shown in Figure 3. The three genetic operators governing the iterative search are often referred to as the selection, crossover and mutation operators. Through the repeated application of these operators, a randomly selected initial population of potential design sequences P_o is transformed into an equally large populations P_i in an iterative manner. Consecutive populations will increasingly contain better sequences and eventually converge to the optimal population P_{opt}, consisting of Pareto-optimal sequences. The selection operator implements the principle of the survival of the fittest. This operator generates new populations by statistically phasing out weak designs which do not fit the design objective. The cross-over operator generates new populations of designs by mating *parent* sequences generated by the selection operator and by combining their genetic information. The mutation operator modifies existing sequences by arbitrarily mutating their genetic content, and thereby safeguards the algorithm against premature convergence to a local extremum.

3. Numerical Results.

Using a database containing 16 different materials (the database for the material parameters is not reproduced here because of space limitations, but may be found in [4]), including lossless and lossy dielectrics, lossy magnetics and materials with a relaxation type characteristic, a set of Pareto-optimal designs is generated for operation in the frequency range of 2-8 GHz. The initial population consists of 1000 design candidates which consist of a maximum of 5 layers. The algorithm converges, after approximately 100 iterations, towards a set of Pareto-optimal designs, the (t,R) trade-off curve of which is shown in Figure 4. In the process of generating the trade-off curve, the algorithm naturally generates and stores the design parameters of its respective coatings. To verify the Pareto-optimality of these coatings, their design parameters are randomly perturbed. For all cases tested, the (t,R) characteristics of these perturbed coatings lie above the optimal (t,R) curve, and hence the perturbed designs are not Pareto-optimal. This trade-off curve entirely describes the absorbtion characteristics of the database for a given frequency range, and a specified maximum for the number of layers in the coating.

References

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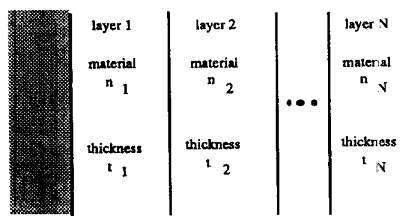

$$n_i \leftrightarrow M_i = \{b_1^{M_i}, b_2^{M_i}, \ldots, b_{nmat}^{M_i}\} \ (b_j^{M_i} = 0,1 \mid j = 1,..,n_{ma}, i = 1,..,N)$$

$$t_i \leftrightarrow T_i = \{b_1^{T_i}, b_2^{T_i}, \ldots, b_{nmat}^{T_i}\} \ (b_j^{T_i} = 0,1 \mid j = 1,..,n_{th}, i = 1,..,N)$$

$$absorber \leftrightarrow \{(M_1, T_1), \ldots, (M_i, T_i), \ldots, (M_N, T_N)\}$$

Figure 1 : Structure under investigation and coding procedure.

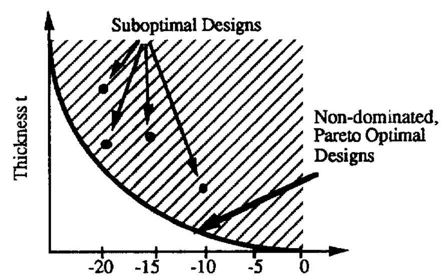

Figure 2 : Non-dominated, Pareto-optimal designs and inferior designs in t-R space.

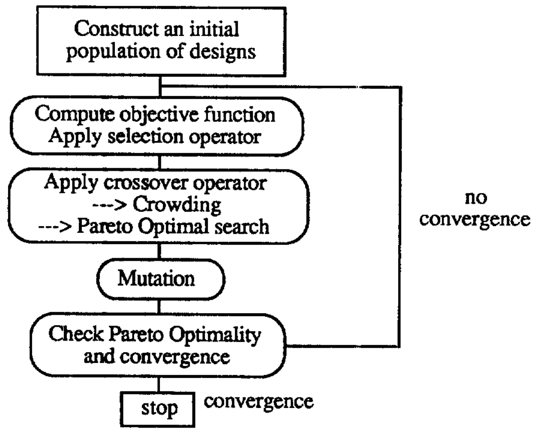

Figure 3 : Flow chart of the Genetic Algorithm.

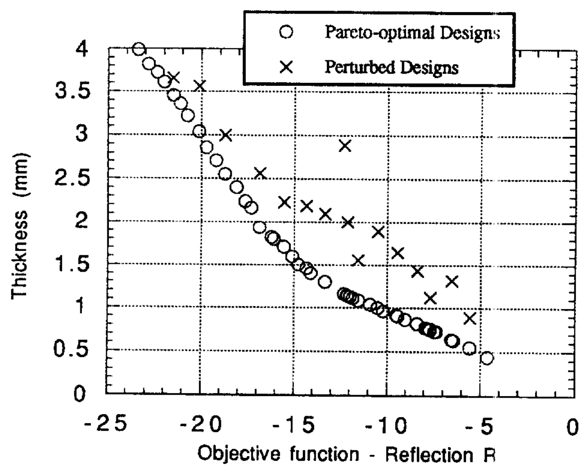

Figure 4 : Optimal design curve obtained using GA.