Design of Lightweight, Broad-Band Microwave Absorbers Using Genetic Algorithms

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***Abstract*— In this paper, a novel procedure for synthesizing multilayered radar absorbing coatings is presented. Given a predefined set of N_m available materials with frequency-dependent permittivities $\epsilon_i(f)$ and permeabilities $\mu_i(f)\,(i = 1,\cdots,N_m)$, the proposed technique simultaneously determines the optimal material choice for each layer and its thickness. This optimal choice results in a screen which maximally absorbs TM and TE incident plane waves for a prescribed range of frequencies $\{f_1, f_2, \cdots, f_{Nf}\}$ and incident angles $\{\theta_1, \theta_2, \cdots, \theta_{N\theta}\}$. The synthesis technique presented herein is based on a genetic algorithm. The present technique automatically places an upper bound on the total thickness of the coating, as well as the number of layers contained in the coating, which greatly simplifies manufacturing. In addition, the thickness or surface mass of the coating can be minimized simultaneously with the reflection coefficient. The algorithm was successfully applied to the synthesis of wide-band absorbing coatings in the frequency ranges of 0.2–2 GHz and 2–8 GHz.**

I. Introduction

THIS paper focuses on the design of wide-band, multilayered radar absorbing (RAM) coatings. In view of the application of these coatings in the area of low observability, the coatings not only need to exhibit a low reflection coefficient over a wide frequency range, but also need to be lightweight and thin. The primary goal of the research reported in this paper is the development of a simple technique for designing such coatings, and for investigating the tradeoff between a coating thickness (or weight) and reflectivity.

In the past, several techniques (e.g., Salisbury, graded index, Jaumann, and Dallenbach screens [1]–[3]) were proposed for designing absorbing coatings. In these techniques, the screens are usually designed using approximate closed-form expressions, or relatively simple optimization schemes [4]–[5]. Recently, Pesque *et al.* [6] proposed a technique for designing absorbing coatings which is based on an optimal control approach. In this method, thin absorbing coatings are designed by cascading layers of different materials, which are chosen from a predefined set of available materials, such that the absorption properties of the coating are maximized over a specified frequency range, while its thickness or surface mass is minimized. Although this optimal-control-based algorithm was shown to be very powerful, the authors acknowledge its major drawback of convergence to only a local minimum of the cost function, which was defined as the maximum reflection coefficient over the frequency band of interest. The possibility of existence of better absorbing, or equally absorbing but thinner coatings, can therefore not be excluded. To overcome this drawback, the authors also present a design technique which is based on the combinatorial optimization technique of simulated annealing (SA) [7]. In this technique, the coating is subdivided into a large number of thin layers with fixed thicknesses, each of which is assigned a material chosen from a predefined set of available materials. The optimal solution is found through iterative random perturbations of the material choices for each layer, and evaluations based on the well-known Metropolis criterion [8]. Although convergence to a global minimum can never be guaranteed, this technique usually leads to less reflective and thinner coatings when compared to the optimal control approach. However, the coatings synthesized using this particular implementation of the simulated annealing technique typically contain far more and consequently thinner layers than those obtained using the optimal control method. This leads to manufacturing problems due to the fragile nature of the typically available materials.

In this paper, a combinatorial optimization technique is presented for designing absorbing coatings which is based on a genetic algorithm. This algorithm offers several advantages over the existing optimal control and SA techniques. First, in contrast to the optimal control method [6], the present technique provides a mechanism for global search. In contrast to the SA-based technique presented in [6], the current technique succeeds in designing high-performance coatings consisting of only few layers, and therefore almost always leads to physically realizable structures. Second, the execution of the algorithm typically results in a number of "high-performance" designs rather than a single solution as offered by other techniques. A specific design can be selected from this set of solution candidates based on criteria which were not explicitly incorporated in the objective function, such as ease of manufacturing or production cost. A third advantage of the present technique, which is shared with other combinatorial optimization techniques, lies in its simplicity and ease of implementation when compared to gradient-based search procedures.

II. Formulation

Fig. 1 depicts the multilayered coating backed by a perfectly conducting ground plane. Assume the availability of a database containing a set of N_m different materials with frequency-

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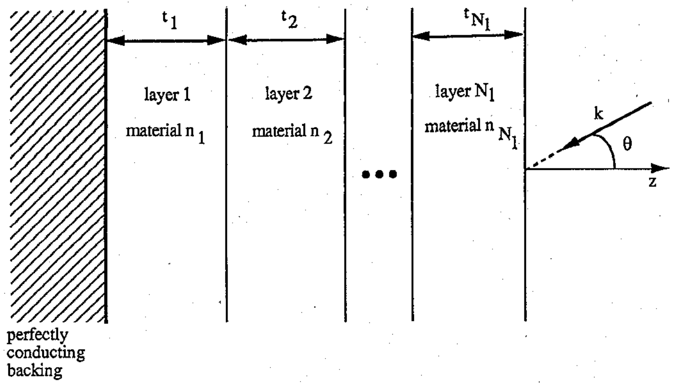

Fig. 1. Multilayered RAM coating under investigation.

dependent permittivities $\epsilon_i(f)$ and permeabilities $\mu_i(f)\,(i = 1, \cdots, N_m)$. The design goal is to determine a coating consisting of N_l layers, such that the coating exhibits a low reflection at a prescribed set of frequencies $f_i\,(i = 1, \cdots, N_f)$ and incident angles $\theta_i\,(i = 1, \cdots, N_\theta)$, for both the TE and TM polarizations. The design process therefore encompasses the determination of the optimal choice of the material for each layer and its thickness. In the context of the present problem, an objective or fitness function F which attains a maximum for the optimal coating is given by

$$\begin{aligned} &F(n_1, t_1, n_2, t_2, \cdots, n_{N_l}, t_{N_l}) \\ &\quad = \min_{i,j}[1 - |R^{\mathrm{TE/TM}}(\theta_i, f_j)|] \end{aligned} \tag{1}$$

where n_i and t_i represent the material choice for layer i and its thickness, respectively. The reflection coefficients R^{TE} and R^{TM} for the multilayered structure are calculated using a recursive procedure [9] as

$$R_i^{\mathrm{TE/TM}} = \frac{\tilde{R}_i^{\mathrm{TE/TM}} + R_{i-1}^{\mathrm{TE/TM}} e^{-2jk_{z,i-1}t_{i-1}}}{1 + \tilde{R}_i^{\mathrm{TE/TM}} R_{i-1}^{\mathrm{TE/TM}} e^{-2jk_{z,i-1}t_{i-1}}} \qquad ox(2)$$

where

$$\begin{aligned} \tilde{R}_i^{\mathrm{TE}} &= \frac{\mu_{i-1}k_{z,i} - \mu_i k_{z,i-1}}{\mu_{i-1}k_{z,i} + \mu_i k_{z,i-1}} && i > 0 \\ &= -1 && i = 0 \\ \tilde{R}_i^{\mathrm{TM}} &= \frac{\epsilon_{i-1}k_{z,i} - \epsilon_i k_{z,i-1}}{\epsilon_{i-1}k_{z,i} + \epsilon_i k_{z,i-1}} && i > 0 \\ &= -1 && i = 0 \end{aligned} \tag{3}$$

and $k_{z,i}$ is the wavenumber along z in layer i.

For certain applications, the coating should not only absorb incident plane waves over a wide range of frequencies and incident angles, but should also be as light as possible. This objective is achieved by including a penalty term in the fitness function as

$$\begin{aligned} &F(n_1, t_1, n_2, t_2, \cdots, n_{N_l}, t_{N_l}) \\ &\quad = \min_{i,j}[1 - |R_{N_l}^{\mathrm{TE/TM}}(\theta_i, f_j)|] \\ &\qquad + \gamma \left[N_l m_{\max} T_{\max} - \sum_{k-1,N_l} m(n_k) t_k \right] \end{aligned} \tag{4}$$

where $\gamma > 0$ is a coefficient which weighs the relative importance of the reflection and thickness requirements. $T_{\max}$ is the preset maximum thickness of a single layer of the coating. $m(n_i)$ is the surface mass per unit thickness of the material chosen for layer i, and $m_{\max} = \max(m(i), i = 1, N_m)$. If the overall thickness instead of the surface mass of the coating needs to be minimized, the same objective function can be used with all surface masses $m(i)$ set to unity.

The optimal choice of material for each layer and the thickness of each layer is determined simultaneously by an optimization technique based on a genetic algorithm. Genetic algorithms [10]–[13] 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. Real coded genetic algorithms which directly operate on the parameters which are to be optimized have been developed [14]–[15], but are not suited for the present problem. Second, the genetic operators which guide the population of potential solutions induce probabilistic rather than deterministic transitions. The three genetic operators governing the iterative search are often referred to as the selection, crossover, and mutation operators. The probabilistic nature of all three operators greatly enhances the capabilities of the algorithm to search for a global rather than local fitness function maximum. Other optimization techniques, e.g., SA (Davis [13]), share the same feature. Third, as mentioned above, genetic algorithms operate on a population of potential solutions rather than a single solution candidate. Implementation of the advanced crowding operator allows the algorithm to converge to a population of distinct near-optimal solutions rather than a single optimal solution. Descriptions of the selection, crossover, and mutation operators, as well as the crowding mechanism, are given later.

The coded representation of the coating consists of a sequence of bits which contains information on the material choice for each layer and its thickness. Given a database containing $N_m = 2^{N_{mb}}$ different materials, the material choice for layer j is represented by a sequence M_j of N_{mb} bits, as

$$M_j = m_j^1 m_j^2 \cdots m_j^{N_{mb}}. \tag{5}$$

If the total number of available materials N_m is not an integer power of two, N_{mb} is chosen such that $2^{N_{mb}-1} < N_m < 2^{N_{mb}}$, and multiple "codings" are assigned to the same material. Numerical results have shown that this will not deteriorate the quality of the final design. The thickness of a layer j, which is a continuous variable, is discretized and represented by a finite sequence of N_{tb} bits as

$$T_j = t_j^1 t_j^2 \cdots t_j^{N_{tb}} \tag{6}$$

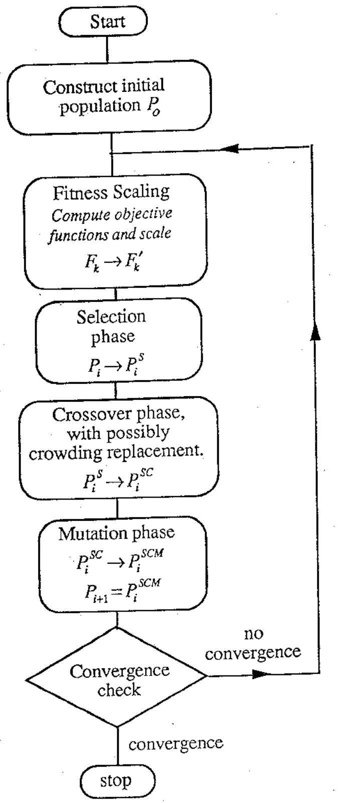

Fig. 2. Flowchart of genetic algorithm. The convergence of the algorithm is checked for by tracking the performance of the best sequence in the population, as well as the average performance of all sequences. If no improvements in both quantities occur for a large number of cycles, e.g., N_{pop} cycles, the algorithm is assumed to have converged.

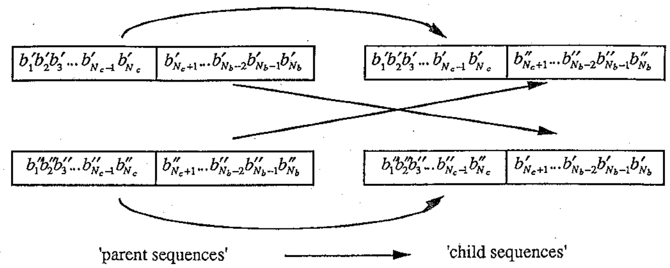

Fig. 3. Illustration of the crossover operation. Two arbitrarily selected "parent" sequences are crossed over by selecting an arbitrary "crossover site" $N_c\,(0 < N_c < N_b)$, and by constructing two "child" sequences by combining the group of bits appearing to the left of the crossover site of the first parent with those appearing to the right of the crossover site of the second parent, and vice versa.

from which the actual layer thickness is computed as

$$T_j = \sum_{i=1,N_{tb}} T_e t_j^i 2^{(i-1)}. \tag{7}$$

T_e represents the desired thickness resolution. The number of bits representing the layer thickness N_{tb} should be chosen in accordance with the resolution T_e such that the maximum thickness for each layer $T_{\max} = T_e(2^{N_{tb}} - 1)$ provides an adequate upper bound for the expected thickness of an individual layer.

From (6) and (7), the material choice for layer j and its thickness are uniquely represented by a sequence L_j as

$$L_j = M_j T_j. \tag{8}$$

The entire coating is represented by the composite sequence G, referred to as a chromosome in the context of genetic algorithms, as

$$G = L_1 L_2 \cdots L_{N_{l-1}} L_{N_l}. \tag{9}$$

The genetic algorithm, a flowchart of which is shown in Fig. 2, starts with a large population P_o containing N_{pop} such sequences G_1–$G_{N_{\text{pop}}}$ in which each sequence consists of a randomly selected string of $N_l(N_{mb} + N_{tb})$ bits. The genetic algorithm then proceeds by iteratively generating a new population P_{i+1}, which is derived from the previous population P_i through the application of the selection, crossover, and mutation operators. During the selection operation, a new population P_i^S of size N_{pop} is derived from the existing population P_i using a procedure which is often referred to as weighted roulette wheel selection. In this process, N_{pop} sequences are selected from P_i, and placed into P_i^S through N_{pop} independent spins of a roulette wheel on which each sequence in P_i is assigned a slice with an area which is proportional to its objective function value. The probability p_k for sequence k to be selected during a particular spin is therefore given by

$$p_k = \frac{F_k}{\sum_{i=1,N_{\text{pop}}} F_i} \qquad (k = 1, \cdots, N_{\text{pop}}) \tag{10}$$

where F_k represents the fitness function value for sequence k. Alternate selection schemes are detailed in [11], [16]. The selection process ensures the new population P_i^S to contain, on the average, more sequences with high fitness values.

The crossover operation is carried out on the population P_i^S to generate the population P_i^{SC}. In this process, abstraction is made of the fact that each sequence consists of a number of substrings L_j which themselves consist of material bits "m" and thickness bits "t," and each sequence is viewed simply as a sequence of individual bits "b" (which can be either "m" or "t"). The crossover operation is carried out as follows. First, two sequences ("parents"), are picked arbitrarily from P_i^S. Then, two new sequences ("children") are created as shown in Fig. 3 with probability P_{cross}. The new sequences form the population P_i^{SC}. If no crossing is carried out, the "parent" sequences are simply copied into the "child" sequences. Typically, p_{cross} is chosen in the range $0.8 < p_{\text{cross}} < 1$. This crossover process is repeated until the number of sequences in P_i^{SC} equals N_{pop}. The purpose of the crossover operation is to combine building blocks of highly fit sequences, and form new sequences with better fitness values.

The mutation operator constructs a population P_i^{SCM} from P_i^{SC} by copying sequences from P_i^{SC} after randomly flipping bit values from 1 to 0 or vice versa with a probability of p_{mut}. Typically, the mutation probability p_{mut} remains very small, on the order of 0.0001–0.005. A high p_{mut} will lead to the destruction of the valuable information stored in the highly fit sequences. The population P_i^{SCM}, obtained after the mutation phase, serves as the starting point for the next iteration cycle, i.e., $P_{i+1} = P_i^{SCM}$. The mutation phase is only of secondary importance compared to the selection and crossover phases. However, mutation helps maintain diversity in the population by forcing search in new regions of the decision space, and therefore leads to alternative sequences.

Through the repeated applications of reproduction, crossover, and mutation operators, the initial population P_o is transformed into a new population P_i in an iterative manner. The new populations will increasingly contain better sequences, and eventually converge to the optimal population P_{opt} consisting of optimal sequences G_{opt}. The genetic algorithm as described above may converge to a local optimum due to several phenomena. First, when the initial population consists of mostly unfit sequences along with a few highly fit sequences, the few fit sequences start to dominate early on in the process and prevent any improvements due to premature convergence. Second, when the population consists of many highly fit sequences, with very little difference between them, the algorithm may fail to distinguish the best sequence out of the population, which leads to poor and slow convergence. These drawbacks are alleviated by implementing a scheme called "fitness scaling" [11] where the fitness values of an entire population are scaled before the selection phase in each iteration. The scaling is carried out by

$$F_k' = AF_k + B \qquad (k = 1, \cdots, N_{\text{pop}}) \tag{11}$$

where F_k' is the scaled fitness vaue which is used in (10) during the selection phase. The coefficients A and B are chosen such that the maximum and average F' differ by at least 20% and no more than 100%. Further details of this scaling rule ar given in [11].

The above-described algorithm ensures convergence to a population of near-optimal or optimal sequences that are highly identical. However, distinct sequences which are characterized by nearly identical fitness values may exist. Some of these alternative sequences may be preferred over others based on criteria which were not explicitly incorporated in the objective function. Therefore, it would be preferable to converge to a population which contains a number of clearly distinct, but highly fit sequences. This can be achieved by employing a mechanism called crowding replacement, as proposed by DeJong [17], [12]. He argues that, in nature, a large subpopulation of near-identical individuals competes for near-identical resources. This limits the growth of that subpopulation, which in turn gives rise to the possibility of a multitude of coexisting distinct subpopulations. The crowding replacement technique simulates this principle as follows. Initially, the population P_i^{SC} is simply taken as P_i. Each sequence that is constructed through the selection and crossover process is compared to a subpopulation of P_i^{SC}. The sequence within this subpopulation which most resembles the newly created sequence on a bit-by-bit basis is then selected to "die," and is replaced by the new sequence. The subpopulation to which the newly created sequence is compared typically contains only two–three randomly selected members (the "crowding factor"). Other mechanisms for effectively achieving the same goal, namely, multimodal function optimization and the crowding mechanism, are described in detail in [11].

TABLE I
RELATIVE PERMITTIVITIES AND PERMEABILITIES OF THE 16 MATERIALS IN THE DATABASE

Lossless Dielectric Materials (μ_r=1.+j0.)		
#	ε_r	
1	10+j0.	
2	50+j0.	
Lossy Magnetic Materials (ε_r=15.+j0.) $\mu=\mu_r - j\mu_i$ $\mu_r(f)=\frac{\mu_r(1GHz)}{f^\alpha}$ $\mu_i(f)=\frac{\mu_i(1GHz)}{f^\beta}$		
#	$\mu_r(1GHz),\alpha$	$\mu_i(1GHz),\beta$
3	5.,0.974	10., 0.961
4	3., 1.000	15., 0.957
5	7., 1.000	12., 1.000
Lossy Dielectric Materials (μ_r=1.+j0.) $\varepsilon=\varepsilon_r - j\varepsilon_i$ $\varepsilon_r(f)=\frac{\varepsilon_r(1GHz)}{f^\alpha}$ $\varepsilon_i(f)=\frac{\varepsilon_i(1GHz)}{f^\beta}$		
#	$\varepsilon_r(1GHz),\alpha$	$\varepsilon_i(1GHz),\beta$
6	5., 0.861	8., 0.569
7	8., 0.778	10.,0.682
8	10., 0.778	6., 0.861
Relaxation-type Magnetic Materials $\mu=\mu_r - j\mu_i$ $\mu_r=\frac{\mu_{rm} f_m^2}{f^2+f_m^2}$ $\mu_i=\frac{\mu_{rm} f_m f}{f^2+f_m^2}$ (f and fm in GHz)		
#	μ_{rm}	f_m
9	35.	0.8
10	35.	0.5
11	30.	1.0
12	18.	0.5
13	20.	1.5
14	30.	2.5
15	30.	2.0
16	25.	3.5

III. NUMERICAL RESULTS

This section presents several numerical results to illustrate the usefulness of the above technique. For the purpose of illustration, a small database containing 16 different materials was compiled. The number of materials was limited to 16 only for clarity of presentation. Databases with many more materials can be handled by the new technique at a relatively small additional computational cost since it was experimentally observed that, within the limits of the present study, the required number of sequences in a population N_{pop} varies linearly with the bit length of the sequences, which itself only increases as $\log_2 N_m$. The relative permittivities and permeabilities of the 16 materials are summarized in Table I. Although these material characteristics are fictitious, they are representative of a wide class of available RAM. The materials in the database fall into three categories.

1) Lossless dielectrics with frequency-independent permittivity (materials 1–2).

2) Lossy magnetics (materials 3–5) and lossy dielectrics (materials 6–8). These materials are specified through their

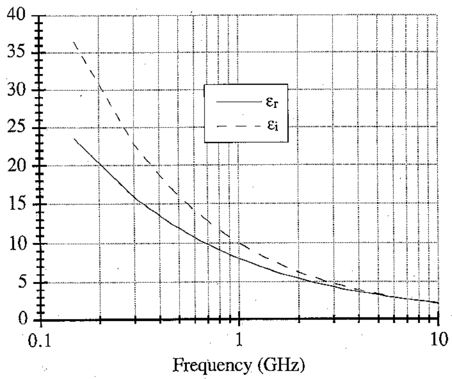

Fig. 4. Real and imaginary parts of the relative permittivity of material 7 versus frequency.

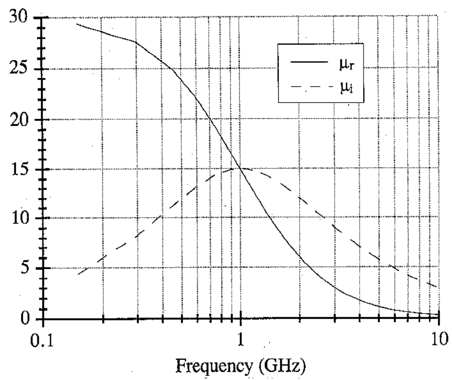

Fig. 5. Real and imaginary parts of the relative permeability of material 11 versus frequency.

TABLE II

Design Parameters for Four Structures, Labeled LF1, LF2, LF3, and LF4, Obtained by Optimizing the Objective Function of (4) for 0.2 GHz $< f <$ 2 GHz with $\gamma = 0, 0.5, 1.0$, and 2.0, Respectively. The Characteristics of Each Layer are Denoted as n_i/t_i, where n_i is the Material Choice for Layer i (See Table I) and t_i is its Thickness (Expressed in Millimeters).

Design	HF1	HF2	HF3	HF4
γ	0.	0.5	1.0	2.0
layer 1	2 / 1.155	13 / 0.975	14 / 0.009	9 / 0.078
layer 2	11 / 0.885	2 / 0.465	15 / 0.051	9 / 0.411
layer 3	5 / 1.272	5 / 0.261	15 / 0.477	9 / 0.435
layer 4	6 / 1.446	8 / 0.432	2 / 0.636	15 / 0.039
layer 5	16 / 0.486	16 / 0.537	16 / 0.588	14 / 0.273
total thickness	5.244	2.670	1.761	1.236
maximum reflection (2-8 GHz)	-23.5 at 0º -16 at 40º	-19.8	-17	-13

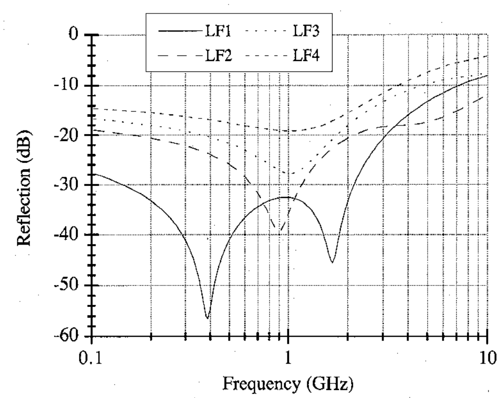

Fig. 6. Reflection coefficient at normal incidence for the four structures (LF1, LF2, LF3, and LF4) described in Table II.

permeability/permittivity at 1 GHz and the decay coefficients α and β as defined in Table I. The magnetic materials have a permittivity of $15 + j0$, whereas the dielectric materials have a permeability of $1 + j0$.

3) Lossy magnetics with a relaxation type characteristic (materials 9–16). These materials are specified through their real permeability at dc, μ_{rm}, and the frequency f_m at which the imaginary part peaks. The permittivity always equals $15 + j0$.

As an example, the permittivities and permeabilities of materials 7 and 11 are plotted in Figs. 4 and 5, respectively. Only the simultaneous minimization of the reflection coefficient and the thickness is considered here, i.e., $m(i) = 1 (i = 1, 16)$.

First, the design of coatings in the frequency band 0.2–2 GHz is considered. In this example, the reflection coefficient is minimized only for normal incidence. For all results discussed in this section, the objective function (4) is computed by sampling the reflection coefficient at ten frequency points, distributed uniformly over the frequency range of interest. The number of layers in the coating is fixed at five, and the thickness of each of the layers is modeled using 12 b. Given the size of the database, each coating is represented by a string of 80 b. The maximum thickness of each individual layer was fixed at 2 mm and the total number of sequences in the population at 100. The design parameters for four different structures (LF1, LF2, LF3, and LF4), obtained by differently weighing the relative importance of the minimum thickness requirement in the objective function ($\gamma = 0, 0.5, 1.0, 2.0$) are given in Table II. The corresponding reflection coefficients are plotted in Fig. 6. As γ is increased, the optimal design becomes thinner (the thickness decreases from 5.51 to 2.47 mm), but as expected, also more reflective (the minimum reflection coefficient increases from -33 to -14 dB). Using an identical database and coating representations, the design of absorbers in the frequency ranges of 2–8 GHz and 0.5–8 GHz is investigated. The design parameters of the resulting coatings (labeled HF1, HF2, HF3, and HF4 for 2–8 GHz, BB1 and BB2 for 0.5–8 GHz) are given in Tables III and IV, and the corresponding reflection coefficients are shown in Figs. 7 and 8. Again, the tradeoff between reflectivity and coating thickness, represented by γ, is clearly observed. The quality of all designs and the nature of the corresponding objective function maxima were verified by executing the algorithm several times, using different population sizes N_{pop}, string lengths N_{tb}, and seed numbers for the random number generators. Given appropriate values for the A and B scaling coefficients in (11) (resulting in a difference between the maximum and average objective function values of approximately 30%), the algorithm always converged to designs with performances, very similar to those of the designs presented herein.

TABLE III
DESIGN PARAMETERS FOR FOUR STRUCTURES, LABELED HF1, HF2, HF3, AND HF4, OBTAINED BY OPTIMIZING THE OBJECTIVE FUNCTION OF (4) FOR 2 GHz $< f <$ 8 GHz WITH $\gamma = 0, 0.5, 1.0$, AND 2.0, RESPECTIVELY. THE CHARACTERISTICS OF EACH LAYER ARE DENOTED AS n_i/t_i, WHERE n_i IS THE MATERIAL CHOICE FOR LAYER i (SEE TABLE I) AND t_i IS ITS THICKNESS (EXPRESSED IN MILLIMETERS).

Design	LF1	LF2	LF3	LF4
γ	0.	0.5	1.0	2.0
layer 1	4 / 1.380	4 / 0.234	4 / 0.114	4 / 0.276
layer 2	4 / 0.984	4 / 0.306	4 / 0.984	4 / 0.156
layer 3	4 / 1.182	4 / 1.440	4 / 0.918	4 / 0.126
layer 4	8 / 1.002	4 / 1.092	4 / 0.738	4 / 1.284
layer 5	14 / 0.966	16 / 0.516	14 / 0.180	4 / 0.636
total thickness	5.512	3.588	2.934	2.478
maximum reflection (0.2-2 GHz)	-33	-21	-18	-14

TABLE IV
DESIGN PARAMETERS FOR FIVE STRUCTURES, LABELED BB1, BB2, TMH, CHF1, AND CHF2, OBTAINED BY OPTIMIZING THE OBJECTIVE FUNCTION OF (4) UNDER VARIOUS CONDITIONS. THE CHARACTERISTICS OF EACH LAYER ARE DENOTED AS n_i/t_i, WHERE n_i IS THE MATERIAL CHOICE FOR LAYER i (SEE TABLE I) AND t_i IS ITS THICKNESS (EXPRESSED IN MILLIMETERS). THE "MAXIMUM REFLECTION COEFFICIENT" REFERS TO THE FREQUENCY RANGES OF 0.5–8 GHz FOR DESIGNS BB1 AND BB2 AND 2–8 GHz FOR THE OTHERS.

Design	BB1	BB2	TMH	CHF1	CHF2
γ	0.	0.3	0.	1.	1.
layer 1	5 / 0.594	4 / 0.960	6 / 0.348	11 / 0.027	9 / 1.050
layer 2	4 / 0.036	4 / 1.008	13 / 0.423	14 / 0.081	2 / 0.324
layer 3	5 / 3.072	2 / 0.258	10 / 1.740	15 / 0.438	1 / 0.378
layer 4	6 / 2.076	5 / 0.612	6 / 2.202	2 / 0.627	16 / 0.537
layer 5	14/ 0.462	16 / 0.468	14 / 0.399	16 / 0.591	5 / 0.003
total thickness	6.24	3.306	5.112	1.764	2.292
maximum reflection	-21	-17	-20 at 0° -20 at 40°	-17	-17

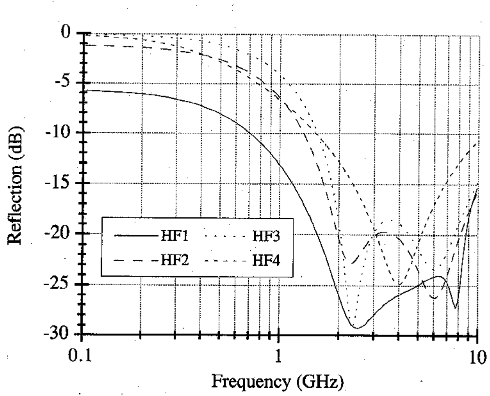

Fig. 7. Reflection coefficient at normal incidence for the four structures (HF1, HF2,HF3, and HF4) described in Table III.

Next, the design of coatings which exhibit low reflectivity for normal and oblique incidence is investigated. Due to the high refractive indexes of the materials, the coatings designed by minimizing the reflection at normal incidence are also near optimal for oblique incidence, especially when both

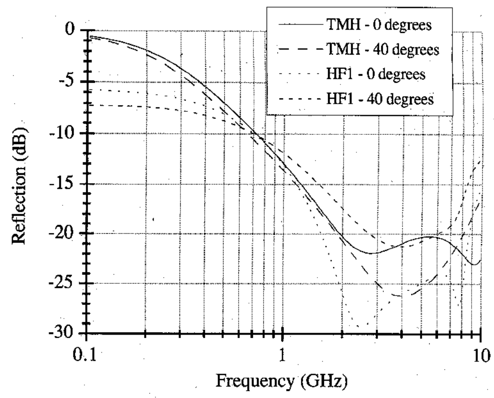

Fig. 8. Reflection coefficient at normal incidence for designs BB1 and BB2 described in Table IV.

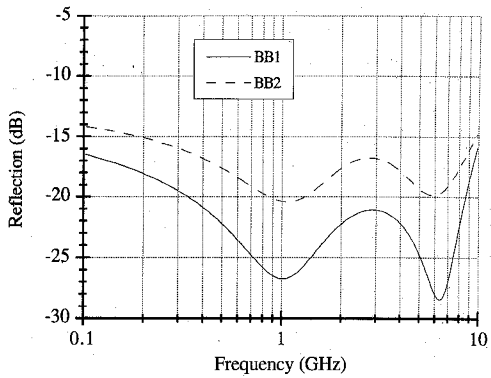

Fig. 9. Reflection coefficient at normal incidence and oblique incidence ($\theta = 40°$ for the TMH Structure described in Table IV.

the TM and TE polarizations are considered simultaneously as expressed by (4). If both polarizations are investigated separately, i.e., if the coating is optimized for one incident polarization only, considerable improvement can be realized. This is illustrated in Fig. 9, which compares the reflection coefficients of a coating which was designed to yield a low reflection under TM incidence simultaneously for $\theta = 0°$ and $\theta = 40°$, with that of a coating (labeled TMH) which was optimized for $\theta = 0°$ only. The design parameters of the coating is given in Table IV. Similar results can be obtained for the TE polarization.

The results presented in Figs. 6–7 and Tables II–III correspond to coatings obtained without crowding replacement. As outlined above, the crowding replacement mechanism provides the algorithm with the capability of sustaining several subpopulations containing distinct near-optimal sequences, rather than a population which consists entirely of highly identical sequences. To illustrate the effect of crowding replacement, the problem of minimizing the reflection coefficient in the frequency band of 2–8 GHz under normal incidence is considered. Fig. 10 shows the reflection coefficient of two distinct, but competitive coatings (labeled CHF1 and CHF2) which were present in a mature population obtained with crowding replacement. The design parameters of the coatings are presented in Table IV. These results illustrate the usefulness of the

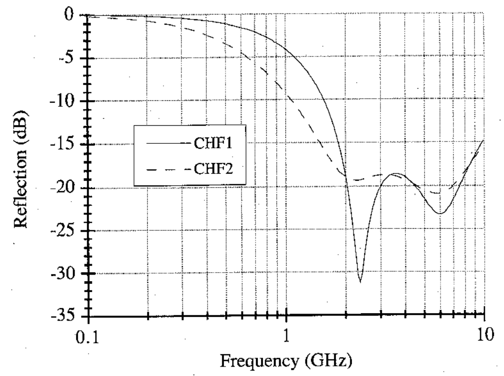

Fig. 10. Reflection coefficient at normal incidence for the CHF1 and CHF2 structures described in Table IV.

crowding mechanism in obtaining several "high-performance" designs with a single program execution.

The design technique presented in this paper is certainly more computer intensive than gradient-based design methods. However, since genetic algorithms are implicitly parallel, their full potential can only be achieved through implementation on parallel machines On a DEC-5000 workstation, all designs presented in this paper were completed in approximately 10 min of CPU time which, given the population size and sequence length specified above, allows for approximately 500 iteration cycles.

IV. Conclusions

In this paper, a novel procedure for synthesizing multilayered radar absorbing coatings was presented. Given a database describing the frequency dependence of the permittivities and permeabilities of the available materials, the proposed technique simultaneously determines the material choice for each layer and its thickness. The resulting coatings contain no more than a predefined number of layers, which greatly enhances the design of a reproducible coating compared to the simulated annealing approach of Pesque *et al.* [6]. Although a maximum thickness of the total coating is automatically imposed through the selection of the incremental thickness T_e and the finite-length binary representation of T_j, the thickness of the layer can simultaneously be minimized by including a penalty in the objective function. The algorithm was successfully applied to the synthesis of wide-band absorbing coatings in the frequency ranges of 0.2–2 GHz, 0.5–8 GHz, and 2–8 GHz. The usefulness of the technique in investigating the tradeoff between coating thickness and reflectivity, as well as its capabilities in obtaining several designs during a single program execution, was illustrated.

The advantages of the technique presented in this paper are threefold. First, the search algorithm is probabilistic in nature. This significantly improves the capabilities of the method in searching for a global rather than local function maximum when compared to gradient-based search procedures. Second, the implementation of the present technique is simple and easy. The technique is transparent with respect to the size of the material database, as well as the nature of the materials contained in it. Another aspect of the versatility of the present technique, not fully investigated in this paper, lies in the ease with which the objective function F can be manipulated to design coatings according to different criteria, e.g., cost. Third, the present method compared to other techniques typically yields several design choices rather than a single one. This feature becomes very useful when certain intangible design criteria need to be considered.

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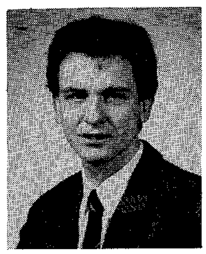

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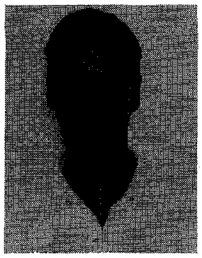

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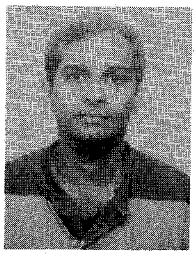

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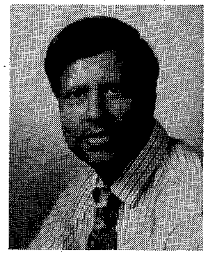

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