

Optimal Design of Radar Absorbing Using A Novel Evolutionary Approach

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Abstract— The optimal design of thin, anti-reflection coatings as Radar Absorbing Materials (RAM) has long been a problem of considerable interest. Various methods of solving this problem has been attempted in the past. Here, an attempt has been made to design a new evolutionary method to solve the problem at hand. Also, it can be inferred from the that this good for the problems with a fixed domain. The efficiency of the method is verified by comparing other related schemes like Simple Genetic Algorithm (SGA) [1] and Differential Evolution (DE) [2] which have been earlier used in arriving at the optimal solutions for various problems.

I. INTRODUCTION

is an integral part of the military and security techniques that have been employed for a long time now. One of the important of stealth technology is to make a flying object like airplane etc. invisible to a radar by the enemies. The radar antenna measures the time taken for the reflection of radar signals to arrive, and with that information can tell how far away the object is. A stealth aircraft is up of completely flat surfaces, very sharp edges, and surfaces up of special materials/composites that absorb radar energy. Hence designing materials and their properties and dimensions for a stealth aircraft is a problem of significant technological importance.

II. MECHANISM OF STEALTH

In stealth technology, from reducing infrared and sound signatures, reflectance and radar absorbance play a huge role. When a radar signal hits a stealth plane, the signal reflects away at an. Since radar is the difficult form of detection to elude, avoiding detection is generally accomplished by reducing the radar cross (RCS) of the object to within the level of background noise thereby reducing the reflectance of the object. The most efficient way to reflect radar waves back to the transmitting radar is with two metal plates at right to one perpendicular to the incident radar wave. This occurs in the tail of a conventional aircraft, where the and

horizontal components of the tail are set at right. A different arrangement along with. Often, a stealth design has the tipped at an angle.

III. OBJECTIVE

to be light weight and have a low RCS, essentially a compromise between thickness (hence weight) and reflectivity. Pesque et al [3] proposed a designing absorbing coatings which is based control approach. In this thin absorbing are designed by cascading layers of different materials, maximizing the absorption properties of the over a frequency range, keeping its thickness or surface mass minimum. This had a major drawback of convergence to only a local minimum of the function, which was designed as the reflection over the frequency of interest.

The paper also analyzed the of using a optimization technique of simulated annealing [4] to overcome the problem of local minima. In this technique, a large of thin layers with thickness were stacked to obtain the final layer, their individual materials chosen from a predefined set of available RAM materials. To get a physically realizable solution, the of layers was to a fixed. This indirectly ceils the final thickness and hence the weight. Later on, better optimization techniques like Genetic Algorithms [5, 6] etc. have been employed for the same problem with better success.

IV. METHODS

To solve the problem, two well known biologically inspired algorithms besides a new evolutionary designed by us were employed. For the purpose of simplicity, this problem was modeled as a single objective problem. The other

of the [redacted] besides solving the problem of optimizing RAMs, was to test the efficiency of the basic optimization techniques without the addition of various heuristics. Hence, the testing was [redacted] to simple genetic algorithm and basic differential evolution in their original format. Our new approach is also built on similar lines using the differential evolution architecture and is [redacted] in its simplest form.

A. Genetic Algorithms

Genetic algorithms are biologically inspired algorithms devised by John Holland, his co-workers and students[7, 8]. They have been widely [redacted] problems with huge success. [redacted] selection, crossover and mutation for robust search of solutions in the given search space. It is significant to note that there has been attempts to employ GA for solving some other problems related to stealth [9]. The basic algorithm of GA has been very well described in the available literature hence, we present a condensed idea about the algorithm. The algorithm starts off with some initial guess solutions termed as a population. This population is allowed to [redacted] genetically using the genetic operations like selection, crossover and mutation of the solutions to give rise to the new offsprings i.e. better solutions are produced in the [redacted] generation. The iteration is [redacted] with the new population again, until a fixed [redacted] of generations is completed or the termination criteria is achieved.

B. Differential [redacted]

Differential [redacted] is an evolutionary approach which was [redacted] by Storn and Price[2]. This is a very simple approach and has been proved to be a robust optimizer for various non-linear and non-differentiable problems. It uses the concept of perturbations to search for [redacted] solutions in the domain space. The algorithm of differential evolution [redacted] a search procedure similar to GA. The [redacted] of offspring solutions in the above [redacted] algorithm is simplified by one of the suggested perturbation schemes[2]. The simplest [redacted] scheme is [redacted] in the following [redacted]. The robustness of the schemes can be improved by introducing the best solution or increasing the [redacted] of members in the perturbations as [redacted] elsewhere[2].

C. Controlled Differential [redacted]

The novel evolutionary approach that we are introducing is termed as Controlled Differential [redacted] (CDE). The approach tries to combine the advantages of both GA and DE for this problem. It tries to use as little system parameters as [redacted] and takes less [redacted] time like DE, besides [redacted]

$$\text{DE: New}[i] = \text{base}[i] + F * (\text{mem1}[i] - \text{mem2}[i])$$

$$\text{CDE: New}[i] = \text{base}[i] + /- [0,1] * (\text{base}[i] - \text{limit}[i])$$

Here, i th variable is considered. 'New' is the probable offspring, 'base' can be a [redacted] member/best member/current member selected from the population of solutions and mem1 and mem2 are two [redacted] members other than the current member. The [redacted] divides the range of each variable into two parts and then the search is directed towards the ends. It is quite obvious that this [redacted] shall be [redacted] efficient for searching a vast domain space in a shorter time but at the same time confining to the domain limits. This procedure has been largely inspired by the standard divide and rule algorithm using for searching.

V. FORMULATION

It was assumed that the layers are built upon a perfectly [redacted] plane surface along (fig. 1) with the set N of all available absorbing materials with frequency range dependant permittivities $\epsilon_i(f)$ and permeabilities $\mu_i(f)$, where $\{i=1 \text{ to } N\}$

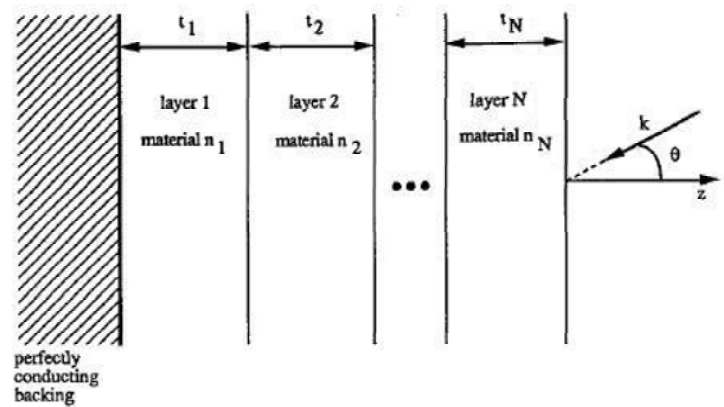


Fig. 1. Multilayer model of coating layers

$N\}$ [10]. Here we have adopted a standard set of 16 materials as the set of N in this six layer case, as earlier attempts have been [redacted] for 4 or 5 layers by many authors. A table of the details regarding the permittivity and permeability of the absorbing materials [redacted] is also given in Table 1.

A detailed formulation of the function has been [redacted] by Michielssen et al [10]. The objective now is to design a [redacted] of 6 layers such that it exhibits low reflection at prescribed frequencies f_i ($i=1 \text{ to } N$) and incident [redacted] θ_i ($i=1 \text{ to } N$) for both electric (T_E) and magnetic (T_M) polarizations. The fitness function which attains the [redacted] for the optimal [redacted] was given by:

$$F(n_1, t_1, \dots, n_N, t_N) = \min_{i,j} [1 - |R_i^{TE/TM}(\theta_i, f_i)|]$$

where, n_i , t_i , $R_i^{TE/TM}$, θ_i , f_i represent the material code, thickness of the layer, reflection coefficient, angle of incidence and frequency of incident radiation for the i^{th} layer considered for [redacted]

Table 1. Relative Permittivities and Permeabilities of the 16 materials in the database

Lossless Dielectric Materials($\mu_r = 1.0 + j0$)		
S. No.	ϵ_r	
1.	10.0+j0	
2.	50.0+j0	
Lossy Magnetic Materials($\epsilon_r = 15.0 + j0$)		
$\mu = \mu_r - j\mu_i$ $\mu_r(f) = \frac{\mu_r(1GHz)}{f^\alpha}$ $\mu_i(f) = \frac{\mu_i(1GHz)}{f^\beta}$		
S. No.	$\mu_r(1GHz), \alpha$	$\mu_i(1GHz), \beta$
3.	5.0, 0.974	10.0, 0.961
4.	3.0, 1.000	15.0, 0.957
5.	7.0, 1.000	12.0, 1.000
Lossy Dielectric Materials($\mu_r = 1.0 + j0$)		
$\epsilon = \epsilon_r - j\epsilon_i$ $\epsilon_r(f) = \frac{\epsilon_r(1GHz)}{f^\alpha}$ $\epsilon_i(f) = \frac{\epsilon_i(1GHz)}{f^\beta}$		
S. No.	$\epsilon_r(1GHz), \alpha$	$\epsilon_i(1GHz), \beta$
3.	5.0, 0.861	8.0, 0.569
4.	8.0, 0.778	10.0, 0.682
5.	10.0, 0.778	6.0, 0.861
Relaxation-type Magnetic Materials		
$\mu = \mu_r - j\mu_i$ $\mu_r = \frac{\mu_{rm}f_m^2}{f^2+f_m^2}$ $\mu_i = \frac{\mu_{rm}f_m^2 f}{f^2+f_m^2}$		
where f and f_m are in GHz		
S. No.	μ_{rm}	f_m
9.	35.0	0.8
10.	35.0	0.5
11.	30.0	1.0
12.	18.0	0.5
13.	20.0	1.5
14.	30.0	2.5
15.	30.0	2.0
16.	25.0	3.5

evaluated using a recursive

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

where if $i > 0$,

$$\tilde{R}_i^{TE} = \frac{\mu_{i-1}k_{z,i} - \mu_i k_{z,i-1}}{\mu_{i-1}k_{z,i} + \mu_i k_{z,i-1}}$$

$$\tilde{R}_i^{TM} = \frac{\epsilon_{i-1}k_{z,i} - \epsilon_i k_{z,i-1}}{\epsilon_{i-1}k_{z,i} + \epsilon_i k_{z,i-1}}$$

if $i=0$, $\tilde{R}_i^{TE} = -1$ and $\tilde{R}_i^{TM} = -1$

$k_{z,i}$ is the wave along z axis in layer i .

But for most applications, the coating should not only exhibit excellent absorbent properties over a wide range of frequencies and incident angles, but also contribute as less weight as possible to the structure on which the coating is being made. Here comes the importance of a penalty term in the fitness function. The penalty function will ensure that there

is an adequate compromise between the two opposing criteria that we are dealing with in this problem.

$$F(n_1, t_1, \dots, n_N, t_N) = \frac{1}{1 + |R^{TE/TM}(\theta_i, f_i)|} + \gamma [NT_{max} - \sum_{k=1}^N t_k]$$

where γ is a coefficient which weighs the relative importance of the reflection and thickness requirements. T_{max} is the preset maximum thickness of any single layer. The values of γ were selected to be 0, 0.5, 1.0, 2.0 and the problem was analyzed. The values of T_{max} were taken as 2 mm. The optimization was carried out for two ranges of frequencies namely 0.2-2 GHz and 2-8 GHz. The maximum reflectance point with minimum thickness was obtained for each value of γ was obtained for each of the three algorithms and their pareto front was compared.

VI. RESULTS AND DISCUSSION

The problem was solved by the three different algorithms on a machine with 256 MB RAM. The CPU time calculated using the standard C functions and tabulated for the purpose of comparison of the three procedures. The results are tabulated below:

Results for frequency range = 2-8 GHz

Table 2. Results for GA

γ	Reflectance	Thickness	Time Taken
0.0	-23.231148 db	10.946763 mm	337171 μ s
0.5	-23.231148 db	12.000000 mm	600265 μ s
1.0	-24.457256 db	11.462634 mm	439312 μ s
2.0	-34.862094 db	11.415737 mm	225109 μ s

Table 3. Results for DE

γ	Reflectance	Thickness	Time Taken
0.0	-71.686861 db	7.933856 mm	662031 μ s
0.5	-64.336197 db	3.759083 mm	2603563 μ s
1.0	-55.573034 db	3.011388 mm	4882062 μ s
2.0	-52.617550 db	3.011388 mm	2414218 μ s

Table 4. Results for CDE

γ	Reflectance	Thickness	Time Taken
0.0	-90.268691 db	1.034642 mm	35406 μ s
0.5	-64.546140 db	1.675644 mm	225343 μ s
1.0	-79.487315 db	2.449362 mm	290828 μ s
2.0	-80.691132 db	4.052368 mm	14156 μ s

Results for frequency range = 0.2-2 GHz

Table 5. Results for GA

γ	Reflectance	Thickness	Time Taken
0.0	-18.005909 db	11.937470 mm	537171 μ s
0.5	-19.886591 db	11.964827 mm	564234 μ s
1.0	-21.478785 db	11.017109 mm	472328 μ s
2.0	-19.500778 db	0.0548510 mm	633203 μ s

Table 6. Results for DE

γ	Reflectance	Thickness	Time Taken
0.0	-61.080127 db	4.689347 mm	283468 μ s
0.5	-58.834151 db	2.611252 mm	1907750 μ s
1.0	-53.801141 db	1.596287 mm	1038485 μ s
2.0	-57.568369 db	1.601839 mm	1909594 μ s

Table 7. Results for CDE

γ	Reflectance	Thickness	Time Taken
0.0	-68.841520 db	2.537389 mm	357437 μ s
0.5	-73.869734 db	3.942393 mm	42656 μ s
1.0	-79.487315 db	2.449362 mm	290828 μ s
2.0	-62.761168 db	4.107350 mm	158046 μ s

The results show a very clear trend that Differential Evolution has performed better than Genetic Algorithms both in terms of reflectance and the CPU time. Similarly, Controlled Differential Evolution has produced better solutions than Differential Evolution in more than one count. Hence, it is clear that the heuristics that we tried to implement has produced better results. The most significant aspect of these results are the fact that the usage of Differential Evolution and our own new Controlled Differential Evolution for this problem. This has led to a very low reflectance of around -90 db. Earlier reports [3], [10], [11] have reported a minimum reflectance of around -40 db. Hence, the reflectance, the thickness has been minimized considerably. To get a clear idea about the performance of different algorithms we present the pareto fronts of the results for both the frequency ranges.

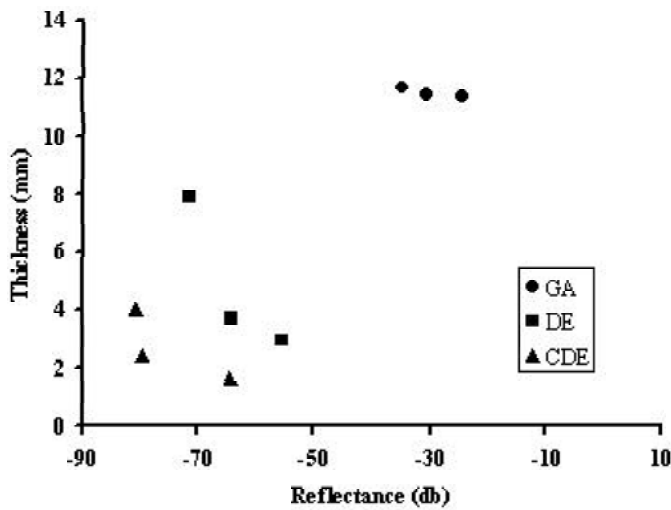


Fig. 2. Pareto front for frequency 2-8 GHz

It is very clear from fig. 2 and fig. 3, that the Differential Evolution has been successful in unearthing better solutions compared to the Genetic Algorithms, which has been the common technique employed for optimizing RAMs. Also, Controlled Differential Evolution has performed better than Differential Evolution in terms of both the solutions and the

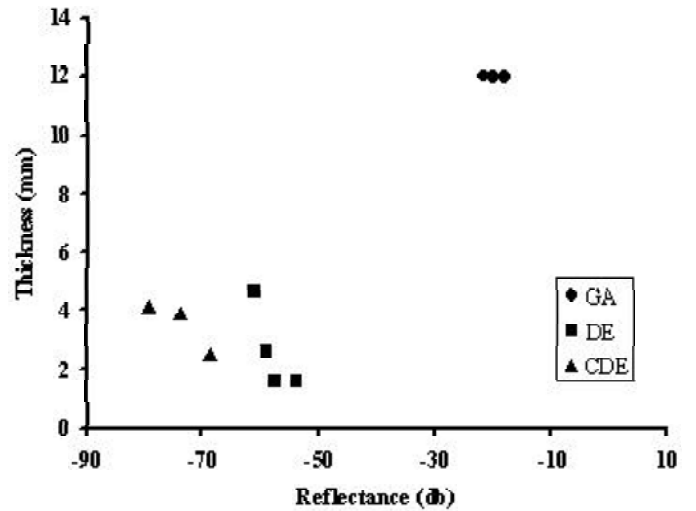


Fig. 3. Pareto front for frequency 0.2-2 GHz

CPU time taken. A closer look at the results can suggest that in some cases Controlled Differential Evolution has produced better results in a shorter time i.e. even by one or two orders of magnitude. This is a very significant step forward as such algorithms can be employed for problems which are very complex in nature with limited domain of search.

While comparing the results of the original DE and CDE, we can see that in the case of the frequency range 2-8 GHz, CDE has produced a far superior Pareto front but in the case of the frequency range 0.2-2 GHz, CDE seems to have got the Pareto front in the upper half of the Pareto front where as DE has got some of the points in the lower half. Two of the solutions obtained through DE are inferior to the solutions obtained through CDE but the other two seem to be the extension of the front produced by CDE. So, in general the effectiveness of CDE in unearthing the best Pareto optimal solution is very clear.

VII. CONCLUSION

This work gains significant importance as it has given an insight on the effectiveness of Differential Evolution for the optimization of RAMs. Hence, a new evolutionary procedure built on the DE framework has been suggested. This seems to be better suited for the problems with a well defined search space than other algorithms like Genetic Algorithms or Differential Evolution. Also, the results obtained for the optimization of RAM materials are considerably better than the reports. Thus we conclude that CDE is among the most useful optimization procedures for the optimization of RAMs. Further analysis by implementing more constraints and variables in the problem can give better insight to the problem at our hand. Testing of CDE by converting the same problem or a different one to a multiobjective optimization problem can lead to interesting results.

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