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ON THE DESIGN AND RELIABILITY ANALYSIS OF ELECTROMAGNETIC ABSORBERS USING REAL-CODED GENETIC ALGORITHM AND MONTE CARLO SIMULATION

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Abstract—In this paper, we propose an approach for designing and quantitatively assessing the performance of the multilayered radar-absorbing structure. In our proposed approach, a five layered radar-absorbing materials design is optimized from the predefined materials database. But to determine the optimal choice of the material and thickness of each layer, a combined binary and real-coded genetic algorithm (GA) is used to handle the integer and real variables involved in such designs. Further, the proposed approach employs the Latin hypercube sampling with Monte Carlo Simulation to carry out the performance based reliability analysis of the design. Absorber synthesized results are compared with the published work using other algorithms. The outcomes of our approach show that the combined GA works quite well, and most prominently the reliability analysis provides the decision maker a means to select among the several design alternatives available before him.

1. INTRODUCTION

Electro-Magnetic Interference (EMI) of signals can have undesirable consequence ranging from device tracking to device performance in both civil and military applications. Besides, the current trends accentuate on the miniaturization of devices/device assemblies in one compact enclosure also causes serious concern related to interference of signals. Accordingly, the need for protective materials to avoid diminished product performance or product failures or to meet the requirements of emission limits set by governmental agencies worldwide

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has prompted the need for the design and manufacturing of high shielding/absorbing materials [1–5].

The shielding or its efficiency is measured in terms of shielding effectiveness (SE) and it is defined by IEEE standard [6] as the *ratio of the signal received (from transmitter) without the shield to the received signal inside the shield*. The shielding concepts are adopted in EMI applications, while absorption concepts are quite often utilized for radar-absorbing materials (RAMs) [7]. Designing a technical and economical competitive electromagnetic (EM) shield/absorber to meet the electromagnetic compatibility standards or shielding requirements are crucial as over-shielding increases the cost, weight and processing complexity of materials, whereas under-shielding could results in device/equipment failure [8].

In the area of absorbers, many researchers have been addressing the design of multilayered RAMs or EM absorbers for the requirements of stealth/hiding modern weapons for the last two decades. The design problem of these EM absorbers mainly lies in the minimization of reflection coefficient in the specific band of frequency and angle of incidence for any transverse electric (TE)/transverse magnetic (TM) polarization through the selection of the material type, the ordering, and the thickness of each layer from the predefined or recorded database. To tackle this absorber design problem, genetic algorithms (GAs) [9–12], particle swarm optimization (PSO) [13], self-adaptive differential evolution (SADE) [14], differential evolution (DE) with competitive control-parameter setting technique [15], central force optimization (CFO), gravitational search algorithm (GSA) [16] and winning particle optimization (WPO) [7], have been employed. Among these techniques, Asi and Dib [16] reported that the results of CFO are comparable to SADE and better than PSO and GSA. Further, the application of binary-coded GA for solving the design problem of continuous search space undergo various difficulties as pointed out by [17]: a) Switching to nearby solution needed alteration of many bits; b) Larger string length requires in order to achieve higher precision which increases the complexity for computation; c) Using single-point crossover the feasible children solution from the two feasible parent solution may not be created. Literature indicates that Binary-coded GA has shown its effectiveness to solve the problems of integer or discrete type of variables, however real-coded GA can solve the problems of continuous search space effectively. The efficiency of both type of algorithms are combined and enhanced simultaneously by introducing various operators by [17–21] to solve the problems of mixed integer variables.

The problem, what we observe, in the results obtained by the above techniques to solve the absorber design problem is that the absorber with low reflection coefficient results in increased total thickness, which in turn increases the cost and weight of the material. Besides, the evaluation of absorption in optimization problem with respect to a normal incident field may lead to under performance of the resulting optimized absorbing structure as, in practice, the direction (angle of incidence), polarization and frequency of EM radiation are not deterministic [22]. Since the absorber design problem involved two kinds of variable, viz., material number (integer) and thickness (real) a mixed GA (that can handle both binary and real valued variables) appears to be the more viable technique rather than employing only binary or real-coded GA. Further for the performance measurement of the optimized design the limit state or failure function of the absorber is evaluated using Monte Carlo Simulation (MCS) technique [23–25]. Since MCS is easy to apply, robust and its accuracy is not dependent on the problem dimension or complexity except it requires a large number of simulation runs to obtain a good estimate. To deal with this limitation, we employ the Latin hypercube sampling (LHS) technique, which converges with smaller sample size [26].

The rest of this work is organized as follows: Section 2 describes the electromagnetic absorber model and objective problem formulation. Section 3, presents the solution methodology to solve design problem formulation using real-coded GA, and MCS technique for the reliability evaluation of EM absorber. Solutions of the example considered to illustrate the proposed approaches are presented in Section 4. Section 5 presents the summary and concluding remarks of this study.

2. ELECTROMAGNETIC ABSORBER MODEL AND COST FUNCTION FORMULATION

The EM absorber geometry under consideration is shown in Fig. 1. A plane wave is obliquely incident on multilayer planar media with n layers. Each layer is assumed to be homogeneous, isotropic and is characterized by its thickness d_k, dielectric constant ε_k, permeability μ_k, and conductivity σ_k.

For calculating the reflection coefficient ($\tilde{\Gamma}$), $(n+1)$th layer is represented by perfect electric conductor (PEC)/ground plane to serve as an ideal reflection medium. A generalized formulation to evaluate $\tilde{\Gamma}$ at the interface between layer k and $k+1$ by following the models

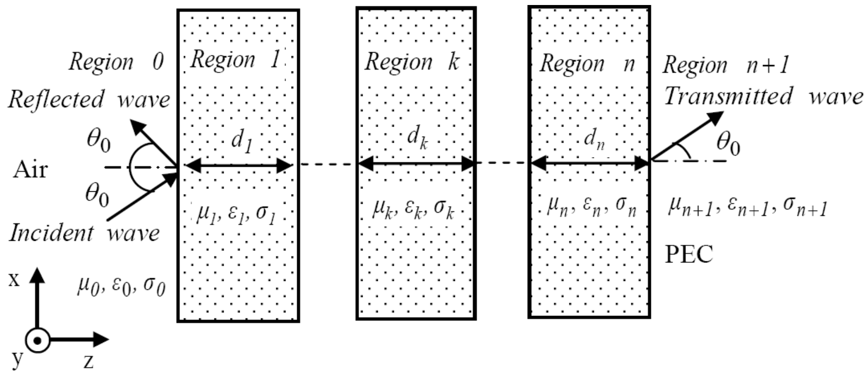

Figure 1. General structure of a multilayer EM absorber.

proposed by [15, 27] can be written as (1):

$$\tilde{\Gamma}_{k,k+1}^{TE/TM} = \frac{\Gamma_{k,k+1}^{TE/TM} + \tilde{\Gamma}_{k+1,\,k+2}^{TE/TM} e^{-j2k_{(k+1)z},\, d_{k+1}}}{1 + \Gamma_{k,k+1}^{TE/TM}\, \tilde{\Gamma}_{k+1,\,k+2}^{TE/TM} e^{-j2k_{(k+1)z},\, d_{k+1}}} \tag{1}$$

where for the TE polarization $\Gamma_{k,k+1} = \frac{\mu_{k+1}k_{kz} - \mu_k k_{(k+1)z}}{\mu_{k+1}k_{kz} + \mu_k k_{(k+1)z}}$, $\tilde{\Gamma}_{n,n+1} = -1$, and for TM polarization $\Gamma_{k,k+1} = \frac{\varepsilon_{k+1}k_{kz} - \varepsilon_k k_{(k+1)z}}{\varepsilon_{k+1}k_{kz} + \varepsilon_k k_{(k+1)z}}$, $\tilde{\Gamma}_{n,n+1} = +1$. The dielectric constant ε_k and wave number k_k, of the absorbing medium for the kth layer, for the sake of completeness, are given as (2)–(3):

$$\varepsilon_k = \varepsilon' - \left(\varepsilon'' + \frac{\sigma}{\omega}\right) = \varepsilon_k - j\varepsilon_k \tag{2}$$

where σ is the conductivity and ε', ε'' is the real and imaginary part of the kth layer permittivity.

$$k_k = \omega\sqrt{\mu_0\varepsilon_k}, \quad \omega = 2\pi f \tag{3}$$

where f is the frequency of incident EM waves in hertz (Hz). In the *Region 0*, the wavenumber is real quantity with the components $k_x = k\sin\theta_0$, $k_z = k\cos\theta_0$ with $k = \omega\sqrt{\mu_0\varepsilon}$ where θ_0 is the incidence angle of EM waves, and in the material medium, $k_{kx} = k_x$ and $k_{kz} = \sqrt{k_k^2 - k_{kx}^2}$. The total reflection coefficient of the EM absorbing structure is obtained by recursively evaluating (1) from $\tilde{\Gamma}_{n-1,n}$ to $\tilde{\Gamma}_{0,1}$.

The goal of the multilayer EM absorbing structure design lies into minimizing the reflection coefficient by optimizing the material choice, thickness and location under the defined electromagnetic and physical parameters such as, frequency, polarization, EM incidence angle and thickness. The materials for different layers are chosen from the predefined database whose constitute parameters may vary randomly with the frequency.

The objective or cost function of absorber design is expressed as the minimization of the objective function F written as (4):

$$F(m_1, d_1, m_2, d_2, \ldots, m_k, d_k) = \min\left\{\max\left(20\log_{10}\left|1\Big/\tilde{\Gamma}_{0,1}^{TE/TM}(f,\theta)\right|\right)\right\} \tag{4}$$

Subject to

$$\begin{aligned} & d_1 + \ldots + d_k \le D \quad \text{or} \quad d_1 + \ldots + d_k = D \\ & f \in f_L \text{ to } f_U, \quad \theta \in \theta_L \text{ to } \theta_U \\ & d_{1L}, \ldots, d_{kL} \le d_1, \ldots, d_k \le d_{1U}, \ldots, d_{kU} \\ & m_{1L}, \ldots, m_{kL} \le m_1, \ldots, m_k \le m_{1U}, \ldots, m_{kU} \end{aligned}$$

where $\max(20\log_{10}|1/\tilde{\Gamma}_{0,1}^{TE/TM}(f,\theta)|)$ is the maximum reflection coefficient (in dB) over the desired set of frequency, angle of incidence and polarization, and m_k and d_k represent the materials choice from the predefined database for the kth layer and its thickness (in millimeter) from the lower (L) and upper (U) bound, respectively. D is the total maximum thickness (in millimeter) preset for the absorber and can be expressed as the inequality or equality constraint based on the requirement of RAMs design.

3. SOLUTION APPROACH

3.1. Computational Steps Using Combined Real and Binary Coded GA

The steps of the implemented GA for the EM absorber design are enumerated here below:

1. Generate initial population (solution vectors (N)) within the specified domain of the individual physical or electromagnetic parameters of each layer prescribed by bit strings for integer valued variables and real values for real valued variables, respectively.

2. Compute objective function and check constraints for each solution vector for any violation then calculate the fitness function proposed by Deb [19]:

$$F(\vec{x}) = f(x) = \begin{cases} f(\vec{x}), & \text{if } g_j(\vec{x}) \ge 0 \quad \forall j = 1, 2, \ldots, m, \\ f_{\max} + \sum\limits_{j=1}^{m} \langle g_j(\vec{x}) \rangle, & \text{otherwise.} \end{cases}$$

where, $f_{\max}$ is objective function value of the worst feasible solution in population, $F(\vec{x})$ the fitness function, $g_j(\vec{x})$ for $j = 1, 2, \ldots, m$ the number of constraints, and $\langle g_j(\vec{x})\rangle$ (bracket penalty operator) $= g_j(\vec{x})$, when $g_j(\vec{x})$ is negative, and zero, otherwise. For the minimization problem the fitness function can be taken as:

$$F'(\vec{x}) = 1/(1 + F(\vec{x}))$$

3. Apply the tournament selection operator (T_n) for selecting the good strings to form the mating pool.

In this selection technique, the tournaments are played between the random sets of competitors equal to the size of tournament specified. As a result the string corresponding to the better solution will be the winner of the tournament. In this way the strings with the worst solution will be eliminated after all the tournaments played in order to get the population of winners equal to N.

4. Perform crossover on random pairs of parents strings selected from the mating pool with the probability of mutation (p_m).

If the string to be crossed is of integer variables coded in binary numbers then use binary crossover operator, otherwise, apply the simulated binary crossover operator [17] to real variables.

Two children solution c_1 and c_2 from the two real valued parents p_1 and p_2 are calculated as follows:

Generate a random number u between 0 and 1, and then find the ordinate $\bar{\beta}$ from the polynomial probability distribution function as follows:

$$\bar{\beta} = \begin{cases} (2u)^{1/(\eta_c+1)}, & \text{if } u \le 0.5 \\ \left(\frac{1}{2(1-u)}\right)^{1/(\eta_c+1)} & \text{otherwise,} \end{cases}$$

where η_c is the distribution index and can be taken any nonnegative value. A small value of η_c allows the children solution to be created far away from the parent solutions and vice versa. For solving these optimization problems we have used $\eta_c = 1$. The children solutions are calculated as:

$$c_1 = 0.5\left((p_1 + p_2) - \bar{\beta}\,|p_2 - p_1|\right)$$

$$c_2 = 0.5\left((p_1 + p_2) + \bar{\beta}\,|p_2 - p_1|\right)$$

For calculating the c_1 and c_2 within the given constraints of variables (p_L and p_U), $\bar{\beta}$ needs to be changed as:

$$\bar{\beta} = \begin{cases} (\alpha u)^{1/(\eta_c+1)}, & \text{if } u \le 1/\alpha \\ \left(\frac{1}{2-\alpha u}\right)^{1/(\eta_c+1)} & \text{otherwise,} \end{cases}$$

where $\alpha = 2 - \beta^{-(\eta_c+1)}$ and $\beta = 1 + \frac{2}{c_2 - c_1}\min\left[(p_1 - p_L), (p_U - p_2)\right]$.

Here it is assumed that $p_1 < p_2$, moreover the above equation can be modified for $p_1 > p_2$.

5. Apply the mutation operation to the selected variable from the real and bit from the binary population with mutation probability of p_m.

For the real valued variable use mutation incorporating the polynomial probability distribution [18] and for the binary string apply the mutation by flipping the bit from the string. To calculate the mutation for the real constraint variables, a perturbance factor $\bar{\delta}$ is computed as:

$$\bar{\delta} = \begin{cases} \left[2u + (1-2u)(1-\delta)^{\eta_m+1}\right]^{1/(\eta_m+1)} - 1 & \text{if } u \leq 0.5; \\ 1 - \left[2(1-u) + 2(u-0.5)(1-\delta)^{\eta_m+1}\right]^{1/(\eta_m+1)} & \text{otherwise,} \end{cases}$$

where, u is the random number between 0 and 1, η_m the distribution index and can take any nonnegative value, and $\delta = \min[(p - p_L), (p_U - p)]/(p_U - p_L)$. The maximum permissible perturbance in the parent value p is $\Delta_{\max} = p_U - p_L$. Thereafter, the mutated child solution is calculates as follows:

$$c = p + \bar{\delta}\Delta_{\max}.$$

6. Substitute the previous population generated with the newly produced after selection, crossover and mutation phase.

7. Check the stopping criteria based on defined number of generation (G), *if* the specified criteria met stop the algorithm, *else* repeat from step 2.

3.2. Reliability Assessment Using Monte Carlo Simulation Technique

As per stress-strength interference theory in reliability [28], a stress is any load (e.g., electrical, mechanical, thermal, chemical, etc.) that acts on the system and failure occurs once the stress exceeds the strength. As the strength is viewed as the maximum stress that the system can withstand without failure, the reliability is not dependent on time and known as static reliability. The factors that vary in random fashion and affect the absorption of the structure are angle of incidence, polarization and frequency of the incoming EM waves, and thus preventing it to deliver the required performance. The reliability analysis using MCS incorporates the individual distribution of the variables affecting the design performance [29]. If the performance of the design is to be evaluated for certain defined (or desired) value such as A, shown in Fig. 2, then the multilayer absorbing structure reliability is defined as the probability that the performance of the design is greater than A, i.e., $R = P[\mathit{Performance} > A]$.

For the reliability analysis of the optimized multilayer design, basic random variables are expressed in vector form as, $X =$

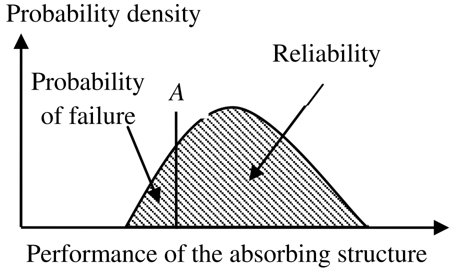

Figure 2. Probability density of the EM absorber performance.

$[X_1, X_2, \ldots, X_n]^T$, where each variable follows a particular probability density function (*pdf*). The estimated probability of failure $\tilde{p}_f$ (5) is calculated by the multi-dimensional integration over the failure region for which performance or limit state function, denoted by $g(X)$, takes value less than zero.

$$\tilde{p}_f = P\left[g(X) \leq 0\right] = \int\limits_{g(X)\leq 0} f_X(x_1, x_2, \ldots, x_n) dx_1 dx_2 \ldots dx_n \qquad (5)$$

where $f_X(x_1, x_2, \ldots, x_n) dx_1 dx_2 \ldots dx_n$ is the joint *pdf* of the input random variables $X_1, X_2, \ldots, X_n$ and x_i the instantiation of X_i. It is to be noted that even for known *pdfs* of random variables, Equation (5) may not be in a close form and is difficult to solve, necessitating the use of numerical techniques. In order to avoid such calculation and efficiently approximating the $\tilde{p}_f$, methods such as, first-order reliability method (FORM), second-order reliability method (SORM) and Monte Carlo simulation (MCS) can be applied. MCS technique involves random sampling where each variable is sampled several times from their respective and representative (or estimated) *pdf* to obtain the probability distribution of output response. Using MCS, the estimated probability of failure (5) can be determined by (6)

$$\tilde{p}_f = \frac{1}{B} \sum_{i=1}^{B} I(X) = \frac{B_f}{B} \qquad (6)$$

where $I(X) = 1$ if $g(X) \leq 0$ and 0, otherwise, B is the total number of simulation cycles and B_f is the total number of cases where failure has occurred. In order to estimate $\tilde{p}_f$ within certain confidence bound with allowable error, an adequate number of simulation cycles are required. The percentage error in the estimated probability of failure with 95% confidence interval, i.e., the difference between the exact probability

p_f^T (if sampled infinite times) and simulation result is given by (7):

$$error\% = \sqrt{\left(1 - p_f^T\right) / \left(B \times p_f^T\right)} \times 200 \quad (7)$$

Based on the error calculation (7) it can be estimated that with the 1% of error for the required probability of failure of 0.01, the numbers of MCS required would be around four million. Therefore, with the four million simulation cycles the probability of failure estimated using MCS will fall into the range 0.01 ± 0.0001 with 95% confidence. In order to achieve more precise estimates with the same/lesser number of simulations as compared to random sampling (RS) an alternative sampling technique called Latin Hypercube Sampling (LHS) is implemented. This sampling approach divides each variable $X_1, X_2, \ldots, X_n$ into m intervals with equal probability and selects one value from each interval randomly according to the probability density in the interval. The m values thus obtained from each interval are paired in random manner to form total m pairs and then these samples are used to evaluate the output response probabilistically.

4. EXAMPLES

Two examples are given for illustrating the effectiveness of the proposed approaches. The illustrative designs use the fictitious materials database provided by Michielssen et al. [9] and has also extensively been used by many researchers [13–16] to show the efficacy of various algorithms. Although their properties are fictitious yet they are representative of wide class of materials available for absorber designs. The database is being reproduced in Table 1 for the sake of completeness.

The number of materials in the database is limited to 16; however, database can be extended for any number of materials (experimentally achieved/fictitious) such as the materials database used by the researchers in reference [7, 12, 30].

The algorithm is run for 20 independent trials each with a population size, $N = 300$ and number of iterations, $G = 150$. The other parameters are set to, $p_c = 0.95$, $p_m = 0.03$, $T_n = 4$, respectively. Here we present the best three out of 20 results from our algorithm and a comparison in terms of best, worst, mean, standard deviation with the designs obtained by the researchers [15, 16] utilizing other optimization algorithms such as PSO, GSA, DE and CFO. The reliability, i.e., $R = 1 - \tilde{p}_f$ of the optimized absorbing structure designs is evaluated using MCS as described in *Section 3.2*. The limit state or

Table 1. Predefined database of 16 materials.

Lossless Dielectric Materials ($\mu' = 1$, $\mu'' = 0$)				
No.				ε'
1				10
2				50
Lossy Magnetic Materials ($\varepsilon' = 15$, $\varepsilon'' = 0$) $\mu = \mu' - j\mu''$, $\mu'(f) = \frac{\mu'(1\,\text{GHz})}{f^a}$, $\mu''(f) = \frac{\mu''(1\,\text{GHz})}{f^b}$				
No.	μ' (1 GHz)	a	μ'' (1 GHz)	b
3	5	0.974	10	0.961
4	3	1.000	15	0.957
5	7	1.000	12	1.000
Lossy Dielectric Materials ($\mu' = 1$, $\mu'' = 0$) $\varepsilon = \varepsilon' - j\varepsilon''$, $\varepsilon'(f) = \frac{\varepsilon'(1\,\text{GHz})}{f^a}$, $\varepsilon''(f) = \frac{\varepsilon''(1\,\text{GHz})}{f^b}$				
No.	ε' (1 GHz)	a	ε'' (1 GHz)	b
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 ($\varepsilon' = 15$, $\varepsilon'' = 0$) $\mu = \mu' - j\mu''$, $\mu'(f) = \frac{\mu_m f_m^2}{f^2 + f_m^2}$, $\mu''(f) = \frac{\mu_m f_m f}{f^2 + f_m^2}$ f and f_m in GHz				
		μ_m		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

performance function for evaluating the $\tilde{p}_f$ is defined by (8):

$$g(X) = -15 - 20\log_{10}\left|1\Big/\tilde{\Gamma}_{0,1}(X)\right| \tag{8}$$

where $\tilde{\Gamma}_{0,1}(X)$ is the reflection coefficient as a function of the independent uniformly distributed random variables, i.e., angle of incidence, frequency and polarization. Two different operating conditions (OC) are considered for evaluating the reliability of optimized designs: OC1) angle of incidence (0–50°), frequency (2–

8 GHz), TM polarization, and OC2) angle of incidence (0–50°), frequency (2–8 GHz), both (TE and TM) polarization. Monte Carlo was performed using the LHS of angle of incidence, frequency and RS of the polarization.

MCS-LHS Versus MCS-RS: Before estimating the $\tilde{p}_f$, a comparison of sampling strategy, i.e., LHS and RS was performed as shown in Fig. 3 for the five layered optimized material parameters reported in Table 2.

LHS and RS were generated by assuming the uniform distributions of angle of incidence (0–50°) and frequency (2–8 GHz), respectively. Polarization, i.e., TE and TM, are generated randomly using uniform distribution and used with the LHS or RS of incidence angle and frequency. MCS was performed ten times with each sample size employed in MCS-LHS (RS), and mean probability of failure and sample variance was calculated, respectively (depicted in Fig. 3(a)). For comparison purpose, we took, $R = 0.915967$ (estimated with ten million MCS-LHS cycles) equal to the true probability of failure. Examining the mean R, it can be seen that with both sampling technique, mean R approaches the assumed true probability of failure with one million simulations. However, MCS-LHS is found to be better than MCS-RS with every samples size as it provided lesser sample variance as compared to MCS-RS (Fig. 3(b)).

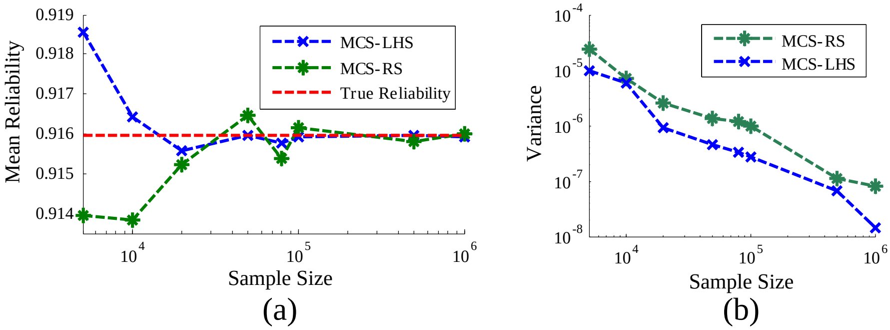

Figure 3. (a) Mean reliability and (b) sample variance as a function of sample size in MCS.

Table 2. Five layered absorbing structure parameters.

Layer	1	2	3	4	5
M. No.	16	6	6	5	15
Thickness	0.4126	0.9546	1.9309	0.2014	1.2746

Table 3. Optimized design parameters (of three structures, HT1, HT2, HT3) for the five layer absorber.

	HT1		HT2		HT3	
Layer	M. No.	d (mm)	M. No.	d (mm)	M. No.	d (mm)
1	16	0.4126	16	0.4529	16	0.4622
2	6	0.9546	6	1.8722	6	1.6796
3	6	1.9309	5	0.8886	1	0.5273
4	5	0.2014	15	0.1678	13	0.4725
5	15	1.2746	13	1.0379	11	1.1804
6	Ground plane		Ground plane		Ground plane	
D (mm)	4.7741		4.4194		4.3220	
Max. reflection coefficient (dB)	−25.6701		−24.3142		−23.4394	
Reliability for OC1	0.9601		0.9702		0.982	
Reliability for OC2	0.916		0.9031		0.8939	

***Example 1*:** A five layer absorbing structure is optimized using the objective function (4) at normal incidence, i.e., $\theta = 0$ and 2–8 GHz frequency range of EM waves, under the following constraints and variable ranges:

$$F(m_1, d_1, m_2, d_2, \ldots, m_k, d_k) = \min \left\{ \max \left(20 \log_{10} \left| 1 \Big/ \tilde{\Gamma}_{0,1}^{TE/TM}(f, \theta) \right| \right) \right\}$$

Subject to

$$d_1 + d_2 + d_3 + d_4 + d_5 \leq 5$$
$$0 \leq d_1, d_2, d_3, d_4, d_5 \leq 2$$
$$1 \leq m_1, m_2, m_3, m_4, m_5 \leq 16$$

Table 3 shows the design parameters of three different designs of absorbing structures (HT1, HT2, and HT3) obtained out of 20 solutions, while Table 4 shows the reported results in literature by using CFO, DE, GSA, and PSO algorithms. Reliability of each design is calculated for the OC1, OC2 and shown in the last two rows of the Table 3 and Table 4. It can be seen that the design HT1 gives maximum reflection coefficient compared to HT2, however, HT2 offers lesser total thickness. On comparing the results of HT2 with results in Table 4, HT2 results are better than PSO, GSA in terms of total thickness and maximum reflection coefficient, and DE, CFO in terms of total thickness and reliability for OC1.

The statistical comparison of the algorithms is shown in Table 5. It is interesting to observe that although the proposed approach appears

Table 4. Optimized design parameters from CFO, DE, GSA and PSO for *Example 1*.

	CFO		DE		GSA		PSO	
Layer	*M*. No.	*d* (mm)	M. No.	*d* (mm)	M. No.	*d* (mm)	M. No.	*d* (mm)
1	16	0.377	16	0.384	16	0.418	14	0.455
2	6	1.572	6	0.433	6	1.593	6	1.995
3	6	0.991	6	1.143	8	0.485	8	0.322
4	6	0.377	6	1.446	13	1.366	5	0.986
5	15	1.425	15	1.454	4	0.986	11	1.128
6	Ground plane		Ground plane		Ground plane		Ground plane	
D (mm)	4.744		4.860		4.850		4.888	
Max. reflection coefficient (dB)	−25.698		−25.485		−21.955		−23.889	
OC1	0.9639		0.9597		0.9851		0.9815	
OC2	0.918		0.9191		0.8912		0.8932	

Table 5. Comparison with PSO, GSA, DE, CFO and proposed approach after 20 trials for *Example 1*.

	Optimized reflection coefficient			
Algorithm	Best	Worst	Mean	Standard deviation
PSO	−23.889	−19.838	−22.495	1.133
GSA	−21.955	−10.222	−15.552	2.802
DE	−25.485	−22.760	−24.001	0.784
CFO	−25.698	−21.848	−23.154	0.988
Proposed approach	−25.6701	−23.4394	−24.1689	0.4013

to have failed to yield a design with maximum reflection coefficient as obtained by CFO, yet its efficiency can be seen in smallest mean and standard deviation of 20 runs.

A schematic performances *pdf* of the HT3 and GSA structure designs' for OC1 are plotted in Fig. 4 by using the *Kernel density estimate* for the continuous *pdf* approximation [31]. These designs are clearly distinguished by the area representing the probability of failure, i.e., $g(X) \leq 0$. Designers have to choose the design with the best reliability in order to obtain safe and reliable absorbing structure that can give the required performance in the given operating environment. Reliability statistic provides useful information when the designer has

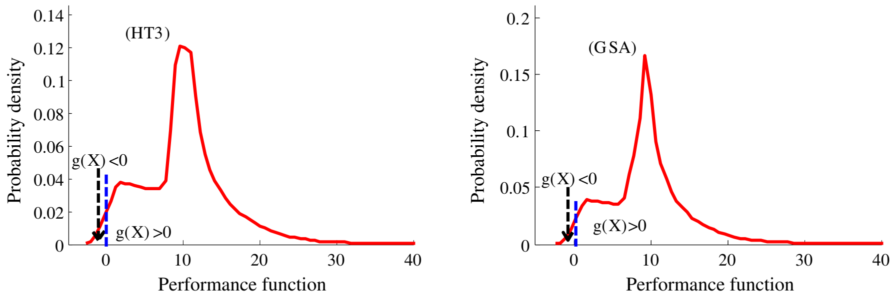

Figure 4. Probability density of the HT3 and GSA designs.

Table 6. Optimized design parameters (of three structures, LT1, LT2, LT3) for the five layer absorber.

	LT1		LT2		LT3	
Layer	M. No.	d (mm)	M. No.	d (mm)	M. No.	d (mm)
1	16	0.5758	16	0.5656	16	0.5735
2	8	0.2333	7	0.8115	2	0.5600
3	7	0.6269	2	0.4113	13	0.7050
4	2	0.4516	11	0.1182	15	0.0957
5	15	0.6611	15	0.6126	5	0.1699
6	Ground plane		Ground plane		Ground plane	
D (mm)	2.5487		2.5192		2.1041	
Max. reflection coefficient (dB)	−20.7035		−20.6728		−18.6981	
Reliability for OC1	0.9737		0.9810		0.9961	
Reliability for OC2	0.8781		0.8717		0.8364	

to decide among the designs presented in Table 3 and Table 4. GSA results have higher reliability for OC1 among the designs presented. However, on comparing GSA results with HT3, it can be seen that HT3 is 528 μm thinner and provides better reflection coefficient than GSA. Alternatively, under OC2 operating condition DE design results have higher reliability. Therefore, the reliability statistic attached with the respective design can give an overall idea of design selection and necessity for further optimization with different margin of safety.

***Example 2*:** This design is similar to previous design of absorption except, the total thickness of the structure is set to less than or equal to 2.57 mm. The best solutions obtained are shown in Table 6, labeled as LT1, LT2, and LT3, respectively, whereas Table 7 shows the optimized design parameters reported in literature by using CFO, DE, GSA, and PSO algorithms.

It is amply evident again that the designs' parameters obtained (LT1, LT2) using the proposed algorithm is better than PSO, GSA for achieving maximum reflection coefficient in the desired frequency band, and comparable to DE, CFO for offering lesser total thickness. The proposed algorithms' capability to reach towards optimum is also compared statistically with the PSO, GSA, DE, and CFO algorithms in Table 8. It can be seen that the proposed algorithm has better mean and standard deviation values. The performance based reliability of the designs in the Table 6 and Table 7 reveal that PSO design has higher

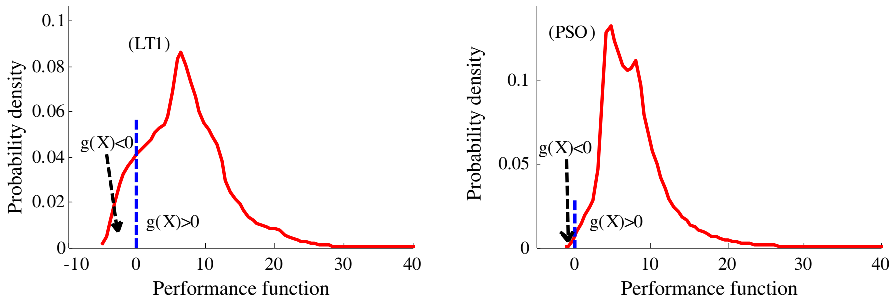

Figure 5. Probability density of the LT1 and PSO designs.

Table 7. Optimized design parameters from CFO, DE, GSA and PSO for *Example 2*.

	CFO		DE		GSA		PSO	
Layer	M. No.	d (mm)	M. No.	d (mm)	M. No.	d (mm)	M. No.	d (mm)
1	16	0.561	16	0.562	16	0.575	16	0.397
2	7	0.850	7	0.897	1	0.574	14	0.201
3	2	0.393	2	0.408	2	0.345	2	0.658
4	13	0.158	15	0.592	9	0.355	13	0.524
5	15	0.605	15	0.111	9	0.699	11	0.353
6	Ground plane		Ground plane		Ground plane		Ground plane	
D (mm)	2.569		2.57		2.550		2.134	
Max. reflection coefficient (dB)	−20.825		−20.910		−18.292		−18.373	
OC1	0.9813		0.9794		0.9909		0.9980	
OC2	0.8715		0.8731		0.8469		0.8343	

Table 8. Comparison with PSO, GSA, DE, CFO and proposed approach after 20 trials for *Example 2*.

	Optimized reflection coefficient			
Algorithm	Best	Worst	Mean	Standard deviation
PSO	−18.373	−11.775	−14.205	1.653
GSA	−18.292	−6.082	−12.778	2.697
DE	−20.910	−17.687	−19.204	0.725
CFO	−20.825	−15.388	−19.115	1.226
Proposed approach	−20.7035	−18.6981	−19.4485	0.6972

reliability for OC1 than LT3 design; however, LT3 offers slightly lesser total thickness than design by PSO. On the other hand LT1 design provides higher reliability for OC2 operating condition. Performance *pdf* of the LT1 (for OC2) and PSO (for OC1) designs are plotted schematically using *kernel density estimate* in the Fig. 5.

5. CONCLUSION

This paper dealt with the optimal design of multilayered design of absorbing structure by using combined binary and real-coded GA. The proposed approaches incorporated a novel procedure (MCS-LHS) for evaluating the performance based reliability of the designs under specified load and operating EM conditions. The performance based reliability of the designs by using the MCS-LHS gives designer a different angle to look into the design from quantitative performance perspective apart from the maximum reflection coefficient as well as thickness.

Further, a combined binary and real-coded GA has been applied to obtain an optimal design of two five layered absorber structures under the same ranges of variables except thickness. The resultant designs have been compared with the designs reported in the literature by using algorithms such as CFO, DE, GSA, and PSO. The statistical comparison has shown that the proposed approach is much robust and outperforms the CFO, DE, GSA, and PSO algorithms.

The proposed approach analyzed the effect of external factors on an optimal design. However, there are several other factors which can further influence the performance of the designed absorber. Such factors may come up from the uncertainties arising from the manufacturing process and behavior of the materials with respect to temperature. Such factors of uncertainty can also be considered suitably in the proposed algorithm.

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