DESIGN OF MICROWAVE ABSORBERS USING IMPROVISED PARTICLE SWARM OPTIMIZATION ALGORITHM

A PROJECT REPORT

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BONAFIDE CERTIFICATE

This is to certify that the project report entitled

"**Design of Microwave Absorbers using Improvised Particle Swarm Optimization Algorithm".**

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in partial fulfillment of the requirements for the award of the **Degree of Bachelor of Technology** in **ELECTRONICS AND COMMUNICATION ENGINEERING** is a Bonafide record of the work carried out under our guidance and supervision at Amrita School of Engineering, Coimbatore.

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Dedicated to our parents and teachers for their continuous support and inspiration.

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ABSTRACT

Particle Swarm Optimization (PSO) algorithm has been applied in electromagnetics to design microwave absorbers. Generally, microwave absorbers are used for absorbing the electromagnetic radiation caused due to numerous electronic equipments and is being extensively used in stealth technology. The main aim of this work is to find and analyze the minimized maximum reflection coefficient over a range of frequency and angle of incidence for a fixed number of layers and polarization. An improvised PSO algorithm has been suggested by utilizing the pareto principle with an improvisation in social and cognitive parameters. The advantage of using this improvised algorithm is the intelligent search using velocity restriction factor to find the local optima. Based on the pareto principle a form of mutation technique is also used for better convergence. The choice of the social and the cognitive parameters depend on the function used and the type of convergence required. It has the flexibility to pick the neighborhood range for the search. The results have been compared and validated against popular PSO with conventional weights and it has been shown that, the introduced PSO performs much better on various benchmark functions such as Sphere function, Rastrigin function, Rosenbrock function etc. It has exhibited an improvement by giving an increase in accuracy and convergence for all the benchmark functions. The algorithm also succeeded in finding better values of reflection coefficient for the microwave absorber structures comparatively. The results have been compared and analyzed for various combinations of the microwave absorber structure and the thickness of each layer is also optimized for a predefined database. The same improvisation has been carried out for the optimization of solar cells and an increase in the efficiency of absorption power has been noted.

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LIST OF SYMBOLS

SYMBOL	DESCRIPTION	PAGE
n	Size of swarm	6
D	Dimension	7
f	Objective function	7
$itmax$	Maximum number of iterations	7
$c1$	Cognitive factor	7
$c2$	Social factor	7
w	Inertia weight	7
$pbest$	Personal best	7
$gbest$	Global best	7
v_i^D	Velocity of particle	8
x_i^D	Position of particle	8
$rand$	Random distribution	8
w_{max}	Maximum inertia weight	10
w_{min}	Minimum inertia weight	10
it	Number of iteration	10
Vr	Velocity restriction factor	10
k	Velocity restriction constant	10
x_i	Variable number	17
$fgbest$	Best solution	24
N	Number of layers	32
θ	Angle of incidence	33
d_N	Thickness	33
ε_i	Permittivity of ith layer	33
μ_i	Permeability of ith layer	33
K_i	Wave number	33
$R_{i,i+1}$	Reflection coefficient	33

$r_{i,i+1}$	Fresnel’s coefficient	33
ε_0	Permittivity of free space	33
μ_0	Permeability of free space	33
ω	Frequency of incident wave	34
F	Fitness function	34
φ	Weight of fitness function	34
f	Frequency	36
fm	Matching frequency	36
A	Maximum absorption	51
α	Absorption coefficient	51
AP	Absorption power	52
ε_l	Lattice permittivity	52
w_p	Plasma frequency	52
γ	Electric damping factor	52

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CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION ON OPTIMIZATION ALGORITHMS

Optimization algorithm is a mathematical process used to find the best solution amongst the available alternative solutions. Usually optimization algorithms are used for complex functions with multiple variables, in finding the point of minima or point of maxima. They came into origin around 1980 when artificial intelligence started to emerge, programming language was no longer in vogue and algorithms that react independently and adaptively became popular. There are various algorithms that are used to find the optimal minimum or maximum values of the function. Among the most used are Genetic algorithm, simulated annealing, particle swarm optimization [1].

Genetic Algorithm is an evolutionary algorithm. Evolutionary algorithms are those that are modeled based on the natural phenomenon of evolution, these have various techniques that simulate evolution to obtain the best possible solution for the mathematical function given. GA is based on Darwin's theory of evolution, where each particle's characteristics are considered as chromosomes, two such particles undergo a process of *crossover* and *mutation* and the resulting particle has characteristics from both particles. Thus over consequent generations better particles are obtained that move closer to the expected fitness value [1].

On the other hand, Particle swarm optimization (PSO) is computational algorithm based on social behavior of animals. Developed by Kennedy, Eberhart and Shi in 1995 [2-3], it simulates natural animal behavior most notably found in certain species of birds, fish and bees. These animals are collectively called a swarm; these can be birds in a flock or fish in a school. The individual animals are termed as particles, in a swarm and are made to move around the search space in a predefined pattern, which can be designed by the user or made random, depending on the user's interests or the requirements of the problem. This simulation is made as close as possible to that of the natural search of a bird for its food in a flock. The social and cognitive behavior of the flock are also modeled as a part of the equation for PSO, each particle in the swarm is at all times aware of its own optima, which is the best position the individual particle has travelled to and the group best, which is the best position any particle in that swarm has travelled to. Different particles, thus, explore in different velocities, from different positions, all of which are modeled to obtain results close to the natural order of swarming [3].

PSO has various advantages when compared to other algorithms. It is seen to be faster in both iterations and processing time. It offers freedom to the user to set the trade of between exploration and exploitation easily by iteratively varying parameters. Research in PSO over the recent year has progressed rapidly. It is widely being used in various fields and being improved to support new spheres. Problems in artificial intelligence, material design and various fields that require a quick optimization [4-6] utilize particle swarm optimization. Conventional PSO has a few drawbacks [2-3], it has a tendency to get stuck at a local minimum [7], and so research has been on trying to overcome the local optima problem, accelerating the convergence speed and increasing the accuracy [8-12]. PSO features various parameters to tweak and modify. A successful variant of this algorithm depends on how well the parameters have been manipulated and a clear understanding of the working of the algorithm itself. Literature has usually featured one or more parameters that are kept constant, while slightly varying a selected few brings better results. Consequently, a linearly decreasing pattern alone or a random pattern is used to govern the parameters, which can only give slightly better improvement over the available values. At times, a combination of PSO and some other algorithm, popularly known as hybrid algorithms, are employed which overcome a variety of PSO specific problems, but are relatively slow on convergence [13-15]. The improvised algorithm introduced in this work tries to overcome the above mentioned problems of low accuracy, slower convergence and local optima sedimentation by introducing various techniques obtained through many trials of machine learning. It also introduces a varying *inertial weight* based on the Pareto principle. The pareto principle can also be said as a natural phenomenon, where almost all real world application can be seen to follow the rules stated in the principle. Using the pareto principle, the PSO has been made to intelligently navigate the region, enabling it to converge to a better value with more precision.

The projected work has introduced three different techniques to achieve computational superiority and mathematical precision over the other algorithms.

- *Velocity Restriction*
- *Escape Probability mutation*
- *Improvised Inertial weight*

The first technique called the *velocity restriction* uses velocity, which is an important parameter that governs the convergence of the search space of each particle and maintains it in range of the optima. This technique is based on the Pareto principle (or the 80-20 rule) [19-20], it restricts the velocity iteratively in an exponential fashion. The second technique introduces a mutation based term which is termed the *escape probability*, which allows for a process of performing extensive exploration that focuses on finding other local optima easily. Mutation is an important technique that increases exploration capabilities, it is indispensable in case of multimodal functions. The third technique introduces an improved *inertial weight*. Inertial weight is another parameter that is closely related to velocity. It governs the next iterations dependency on the previous iteration's velocity [13]. Using the improved range provided, weight can be set so that it will progressively converge the search towards the minima over higher iterations. While convergence towards the minima is preferred in higher iterations, when used with the escape probability technique, the algorithm balances exploration and exploitation, so that wrongful convergence to a less than optimal solution is prevented.

The cognitive and social parameters which govern the *pbest* and *gbest* respectively are considered variable, this can be changed before every iteration depending on the designer's interest and this allows user to control over the neighbor of convergence, either towards the *pbest* or *gbest*. At each iteration, there is a condition for mutation that is based on the introduced *escape probability*, which is based on the number of times it moves out of the boundary. This provides the means to serve two purposes, of maintaining the position within the search space of interest and also frequently mutating the position of the particle. This idea is adopted from genetic algorithm, which is an evolutionary algorithm and thus has a higher ability to search randomly. The search when included with mutation has been shown to improve performance in many algorithms, paving the way for a more intelligent search of the neighborhood. The frequency of mutation is controlled by the *escape probability*, which is in turn controlled by the initial velocity that is set by the designer. A higher velocity is usually preferred to increase mutation count over each trial. With the application of the three techniques of *mutation*, *velocity restriction*, and the refined *inertial weight* the introduced algorithm has been made dynamic, adaptive and intelligent enough to work with various functions.

1.2 SUMMARY

In chapter 1, various evolutionary algorithms are studied and compared. In the following chapters, the above introduced algorithm has been applied to various applications and validated against previous literature. In chapter 2, the conventional particle swarm optimization has been elucidated. The purpose and requirements of the algorithm have been explained. The need for an improvisation has also been discussed. In chapter 3, for the proposed algorithm the required flow chart to form the algorithm has been explained. The algorithm has been tested against various benchmark functions to validate the efficiency of algorithm. The introduced algorithm has proved its ascendancy by giving better result for accuracy and convergence time. The next two chapters 4 and 5 deal with the applications considered to test the proposed algorithm. In chapter 4, the same algorithm has been applied to the field of electromagnetics. It is used to design microwave absorbers to obtain a minimum reflection coefficient. The algorithm has been validated and proves to give better accuracy for the design of microwave absorbers. In chapter 5, the proposed algorithm has been applied for optimization of solar cells. It is done to obtain a better efficiency for absorption power. The algorithm has proved to work better even in the case of solar cells application

CHAPTER 2

PARTICLE SWARM OPTIMIZATION

2.1 CONVENTIONAL PARTICLE SWARM OPTIMIZATION AND ITS VARIANTS

The PSO algorithm was first proposed for a swarm of particles of size *n* [2-3]. These particles went around the search space, recording its position and fitness values in search of the best optimum position using their swarm intelligence. The conventional PSO uses five basic principles namely [1],

- Proximity principle
- Diverse response principle
- Quality principle
- Adaptability principle
- Stability principle

At the start of first iteration for the algorithm, the number of variables *D* is specified, which denote the number of independent variables for the fitness function and the objective function itself, which is denoted as *f* and also specified. It is based on this function that the fitness values of each particle is calculated, compared. The other required parameters such as population size, swarm size, total number of iterations *itmax*, cognitive factor c_1, social factor c_2 and *inertial weight* ω are initialized. The topology, which denotes how the particles are positioned with respect to each other, can also be included, though for this work, no such topology is included. The *n* particles variables are positioned within the required boundary conditions. It is within this region that the PSO searches for the best optimum position. For the zeroth iteration, due to lack of values of position and velocity, a random allotment is done to the particles. This gives them a random position which is assigned as the *pbest* values for each particle, the best value among all the particles is assigned as the *gbest*. The initial velocity is set by the user. On these particles, during the first iteration, the algorithm is performed using Eq. (2.1) and Eq. (2.2) and the obtained values are the solutions for that iteration. *pbest* and *gbest* are the personal best of each particle and global best of the swarm respectively. In this given search space, the new position value is found by each of the particles during every iteration.

The position and velocity are calculated using the Eq. (2.1) and Eq. (2.2) given below.

$$v_i^D = w \times v_{i-1}^D + c1 \times rand1_i^D \times (pbest_i^D - x_i^D) + c2 \times rand2_i^D \times (gbest^D - x_i^D) \tag{2.1}$$

$$x_i^D = x_{i-1}^D + v_i^D \tag{2.2}$$

Where v_i^D is the velocity of the current iteration for each argument, ω is the *inertia weight*. $rand\_1_i^d$ and $rand\_2_i^d$ are two random distributions that range between 0 and 1. x_i^d is the position of each particle that will be updated from its previous value.

The new position value's fitness is compared and checked with its previous value. If the fitness value of the new value is found to be better than the previous value, the *pbest* value is updated else the previous value is retained. The best value among the *pbest* of all the particles is taken, if the value is better than the previous *gbest*, it is replaced as the updated *best* value, else the older value is retained. Inertia weight plays an important role in PSO, by significantly affecting the trade-off between exploration and exploitation in the PSO process [13]. Different variants of PSO can be modeled by changing each or all of the parameters such as the cognitive and social factor, different inertia weights, swarm size, network topologies in PSO etc. [16]. Hybridization and multi-objective are some of the variants using various techniques incorporated; these include a new process into the PSO, instead of just varying parameters that are already present. Hybridization, for instance, is a fusion of Genetic Algorithm and PSO, GA's mutation technique can be combined with PSO to prevent the algorithm from getting stuck at some local optima [1].

2.2 SUMMARY

Chapter 2 discusses on particle swarm optimization. Various disadvantages of particle swarm optimization are discussed and give way to think for the need for formulating the new proposed algorithm**.**

CHAPTER 3

IMPROVISED PSO

3.1 IMPROVISATION ON PSO

The improvised PSO has new techniques like *mutation*, *velocity restriction* and improvised ranges for factors, which makes it different from conventional PSO. Yet it is still similar to the conventional PSO. It has a restricted search in different range of weights, and *velocity restriction* which is based on the Pareto principle. The Pareto principle states that the cause for the 80 percent of the outcome is 20 percent of the income or vice versa. The *inertial weight* is calculated using Eq. (3.1). Applying the Pareto principle, *inertial weight* is varied from values between 0.8 to 0, to cover 80 percent of the area, which is a higher neighborhood of exploration and to find the 20 percent of the local optima once the convergence has started towards a satisfactory optima. The inertial weight is given by,

$$w_i = wmax - \frac{wmax - wmin}{itmax} \times it \tag{3.1}$$

Where w_i is the weight of each iteration, *wmax* and *wmin* are around 0.8 and 0 respectively. Values used in the trials are 0.7 and 0.1 respectively. *itmax* denotes the maximum number of iterations and *it* denotes the current iteration. Another technique called *velocity restriction*, which is calculated using the Eq. (3.1.b), that modifies the previous velocity's effect on the current position, is given below

$$Vr = e^{-\frac{it}{k \times itmax}} \tag{3.2}$$

Where V_r is the *velocity restriction* factor. *k* is a constant, whose value is taken as 4 for an optimum range. For every iteration, Eq. (3.2) should be multiplied along with the maximum velocity, this value should be recorded and during the next iteration, this deducted value is further reduced. This is done to restrict the search boundary. It decreases exponentially. Based on the requirements, the speed can be modified by changing the value of *k* by the user. The *escape probability* determines the exploration process, for which frequent mutations are performed. This *escape probability,* which stabilizes the swarm search, is calculated using an algorithm that also prevents the particle from moving out of the boundary.

3.1.1 MUTATION

Mutation is a technique that is taken from genetic algorithm. Mutation is very helpful in increasing exploration capabilities of an algorithm. How it achieves such an advantage is by randomizing the position of a particular particle to some other position within the search space. Mutation is usually determined by a function that flags positive when a certain requirement is satisfied. Commonly used criteria for mutation is satisfying a particular probability by a randomly generated number during each iteration. If the criteria is satisfied, then the particle for which this probability flag function was performed gets its position altered either randomly or as decided by the designer. This is done for every particle, for every iteration. By randomly placing a particle in some other part of the search space, new optima can be discovered either in the new position itself or during its transit towards the *gbest*. Higher number of mutation maybe increase the possibility of discovering better optima, but also decreases the speed slightly. Achieving the right tradeoff between speed and exploration is necessary [1].

3.1.2 VELOCITY RESTRICTION

Velocity restriction is a technique that is introduced to converge the search pattern of the particles. This factor reduces the boundary for the search space by reducing the maximum velocity at the end of each iteration. This is done exponentially, as governed by Eq. (3.2). The equation is varied according to the pareto principle, where the velocity is reduced by 80% of its previous value during each iteration. This is based on the trials from learning where it is seen that once convergence has begun and the particles have started to home in on some particular optima, some better optima is usually found within 80 percent of its current search area. This when done iteratively over consequent iterations has a tendency to greatly improve accuracy of the solution. This technique is mainly for exploitation of the current optimal solution and exploration is made minimal. To counteract the loss of exploration mutation can be introduced.

3.1.3 ESCAPE PROBABILITY

As any mutation technique requires a criterion to be fulfilled for the mutation function to be performed, a technique of mutation based on *escape probability* is chosen. A particle may move out of the defined boundary, which is bound to happen in algorithms due to increased initial velocity, this cannot be reduced as initial velocity determines the speed with which the particle seeks the optimal solution. During such cases the particle has to be brought back into the search region. This can be done in a variety of ways, commonly used are a modulus technique or a random generation technique. This technique is unique as in, while it incorporates random placement of the particles, the position for placing the particle is randomly taken from the intersection of the total search space and a region around the *gbest.* This region around the gbest is the region within the boundary given by,

$$\textit{Gbest boundary} = (\text{gbest} + v_{max}, \text{gbest} - v_{max}) \quad (3.3)$$

Where v_{max} is the maximum value of velocity amongst all the particles. So the space to place the mutated particle is given by

$$\textit{Mutation Space} = \text{Search space} \cap \textit{gbest boundary} \quad (3.4)$$

This is done to achieve extensive exploration, mutation into the region of search space that is already being explored by the other particles makes the process redundant. Eq. (3.3) ensures that mutation only occurs in area that is outside the *gbest boundary.* Finally, this mutation is performed when the particle escapes the boundary, when the position of any particle is outside the search boundary, its position is reset according to Eq. (3.4).

3.1.4 IMPROVISED INERTIA WEIGHTS

Inertial weight determines the effect of the previous velocity on the current velocity, increased velocity means higher speed of movement for the particles, and lower velocity means less [13]. To increase accuracy, the algorithm should search within the region near the current *gbest*. Over higher iterations, the algorithm focuses mainly on exploitation of the best value available, and exploration reduces. To aid the exploitation of the best value, inertial weight should be reduced iteratively. The introduced range for $wmax$ and $wmin$ varies from 0.8 to 0. Using Eq. (3.1), it can be seen that at the beginning of the PSO, the inertial weight was 0.8 and at the end of the iterations, it is 0. Instead of 0, $wmin$ can also be set as 0.1, this ensures a minimal effect of the previous velocity, while also increases speed of convergence.

3.2 PSEUDOCODE FOR IMPROVISED PSO

Step A: Initialize all the required parameters (such as the dimensions, population size, swarm size, total number of iterations *itmax*, cognitive and social factors, *inertial weights)*, and specify the objective function.

Step B: Calculate the *inertial weight* for each iteration using Eq. (3.1), within the range 0.8 - 0.0.

Step C: Calculate the *velocity restriction* parameter for each of the iterations using Eq. (3.2)

Step D: Define the boundary conditions in which the particles search for the best optimum position.

Step E: Initialize random values for position and velocity of each particle as *pbest* and *gbest*.

Step F: Find the next *gbest* and *pbest* values.

Step G: Find the new Position of the particle

Step H: Find the new velocity of each particle using *velocity restriction* technique using Eq. (2.1) and Eq. (3.2).

Step I: Update the position of each particle using Eq. (2.2) and the new velocity.

Step J: Restrict each particle to the defined boundary using the mutation technique, utilizing *escape probability*.

Step K: Compare and check the new position value with the previous value.   If the value obtained is better than the previous value, go to *Step M*, else go to *Step N*.

Step L: Update the previous values of *pbest* and *gbest* with the new best value obtained.

Step M: Go to *Step O*.

Step N: Retain the previous values of *pbest* and *gbest*.

Step O: If i<=*itmax*, i++, go to step *G* else go to *Step P*.

Step P: Indicate the optimum value of *pbest* and *gbest*.

Below is a Flowchart detailing the working of the improvised PSO.

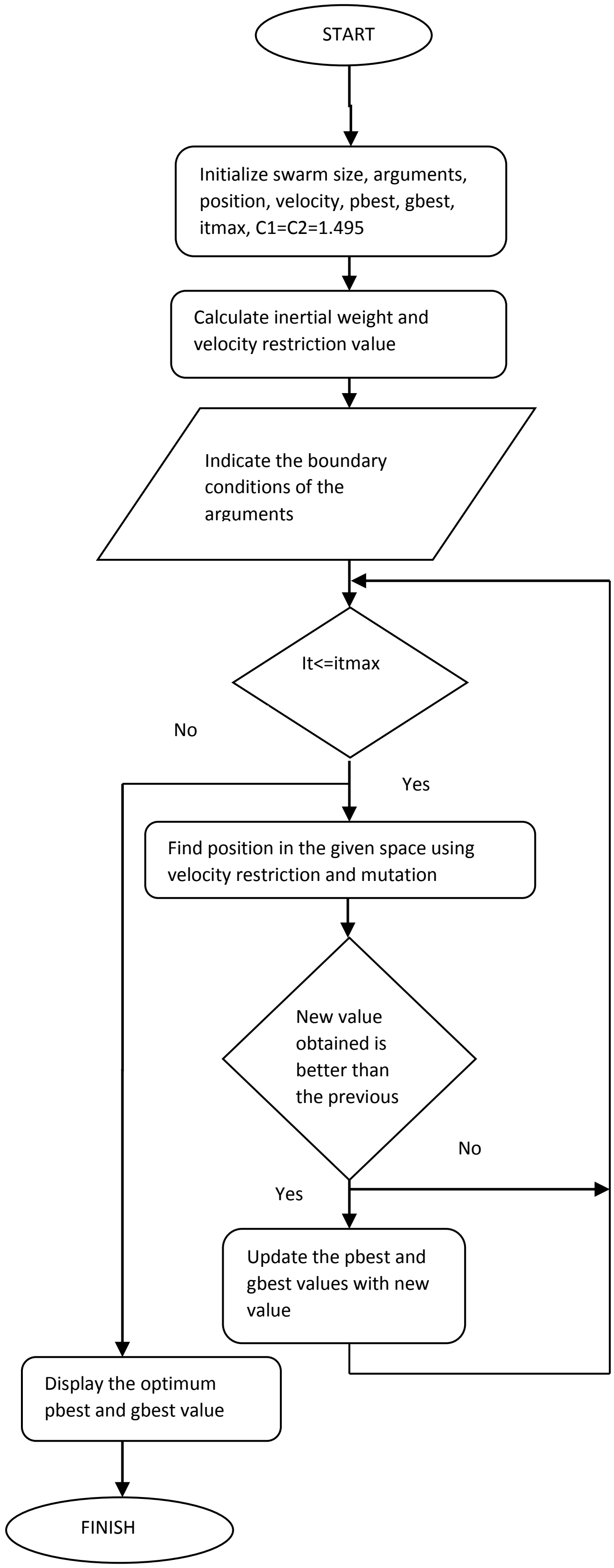


Fig 3.1: *Flow chart on improvised PSO*

3.3 ALGORITHMIC VALIDATION

The test functions also known as benchmark functions have an aim of giving a generic idea about the various situations that the improvised PSO has to face when different kinds of problems are stated. The various benchmark functions are used to validate the improvised Particle Swarm Optimization (PSO) functions and the obtained results have been tabulated and are improved comparatively [13-15]. The code is simulated in Matlab®. System specification of PC is core I3 4005u, 1.7 GHz and 4 GB RAM. The various benchmark functions used are

(a)Sphere function, which is continuous, unimodal and has D local minima.
(b)Rastrigin function, which is multimodal and has several local minima.
(c)Rosenbrock function, also known as valley or banana function is unimodal.
(d)Michalewicz function, referred as valleys and ridges, which is multimodal and has D local minima and are usually.
(e)Shubert function, which has many local and global minima.

The obtained results are run for 220 iterations and over 30 independent trials with a total of 100 particles. The search has been done over a search space of [-5.12,5.12] for Eq. (3.5), Eq. (3.6), Eq. (3.7) and Eq. (3.9) functions and [$-\pi$, π] for Eq. (3.8), as given in [21]. The 2D plot between mean function value of all particles and number of iterations of Sphere, Rastrigin, Rosenbrock, Michalewicz and Shubert functions respectively including equations and 3D plots are given as follows.

3.3.1 BENCHMARK FUNCTIONS

(a) *Sphere Function:*

$$f = \sum_{i=1}^{D} {x_i}^2 \tag{3.5}$$

(b) *Rastrigin Function:*

$$f = \sum_{i=1}^{D} {x_i}^2 - 10\cos(2\pi i) + 10 \tag{3.6}$$

(c) *Rosenbrock Function:*

$$f = \sum_{i=1}^{D-1} [100(x_{i+1} - x_i)^2 + (x_i - 1)^2 \tag{3.7}$$

(d) *Michalewicz Function:*

$$f = -\sum_{i=1}^{D} \sin(x_i) \times (\sin\left(\frac{i{x_i}^2}{\pi}\right))^{20} \tag{3.8}$$

(e) *Shubert Function:*

$$f = \prod_{i=1}^{D} \ (\sum_{j=1}^{s} jcos((j+1) \times x_i + j)) \tag{3.9}$$

3.4 BENCHMARK FUNCTIONS PLOT

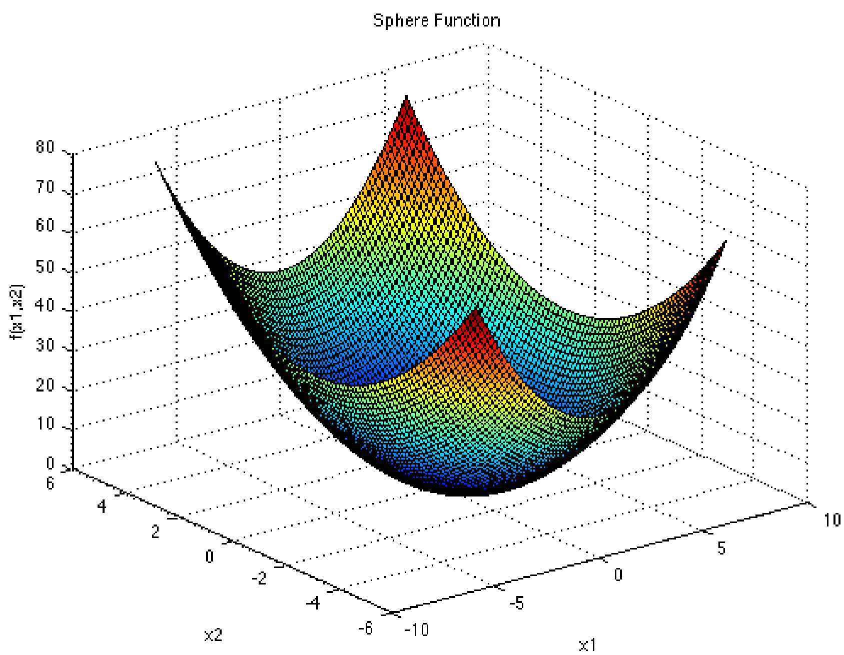


Fig 3.2: Sphere function

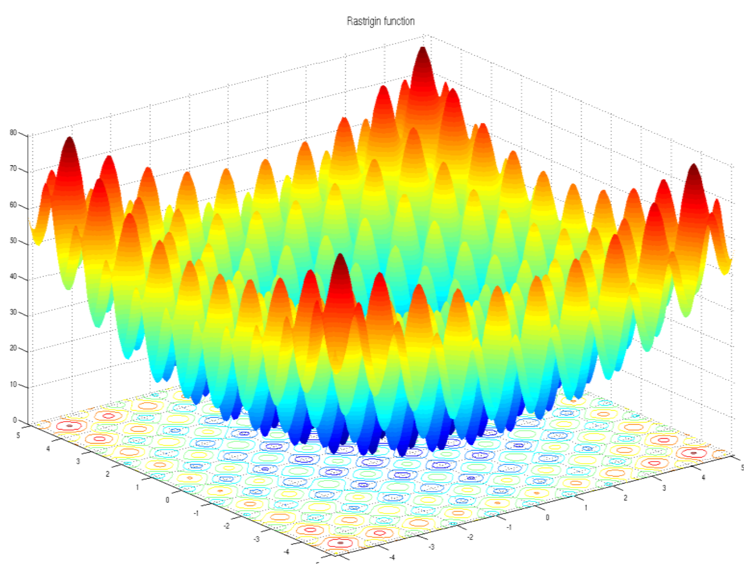


Fig 3.3: Rastrigin function

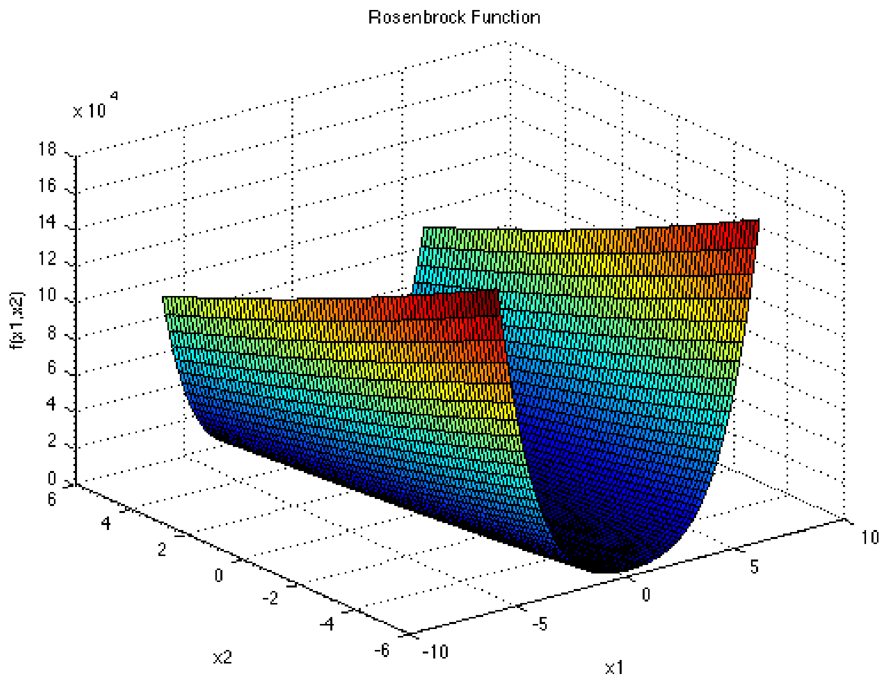


Fig 3.4: Rosenbrock function

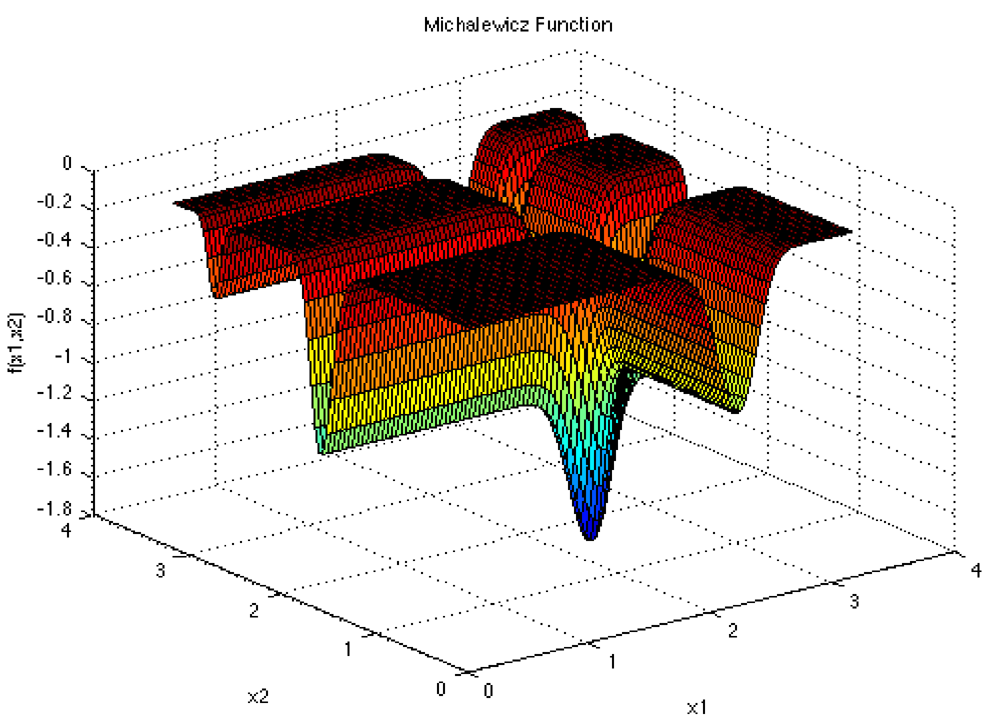


Fig 3.5: Michalewicz function

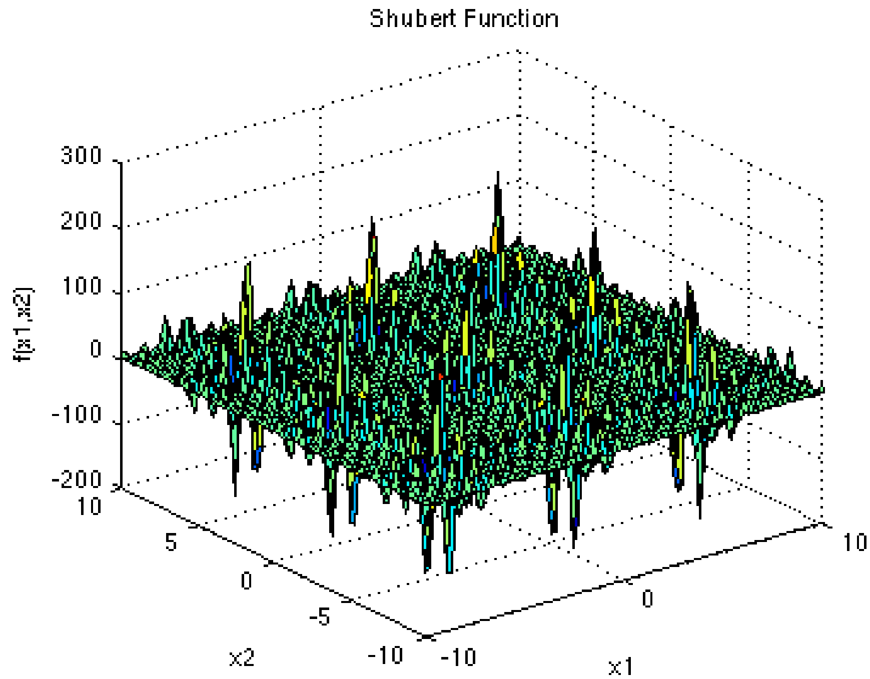


Fig 3.6: Shubert function

3.5 CONVERGENCE PLOTS

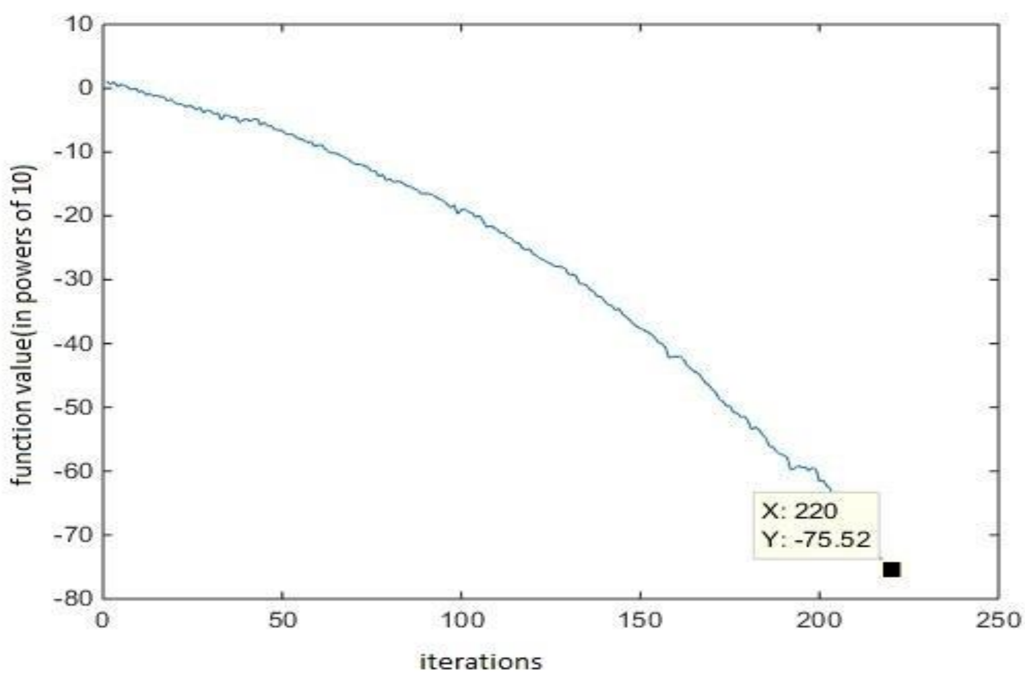


Fig 3.7: Function value vs. iterations of Sphere function

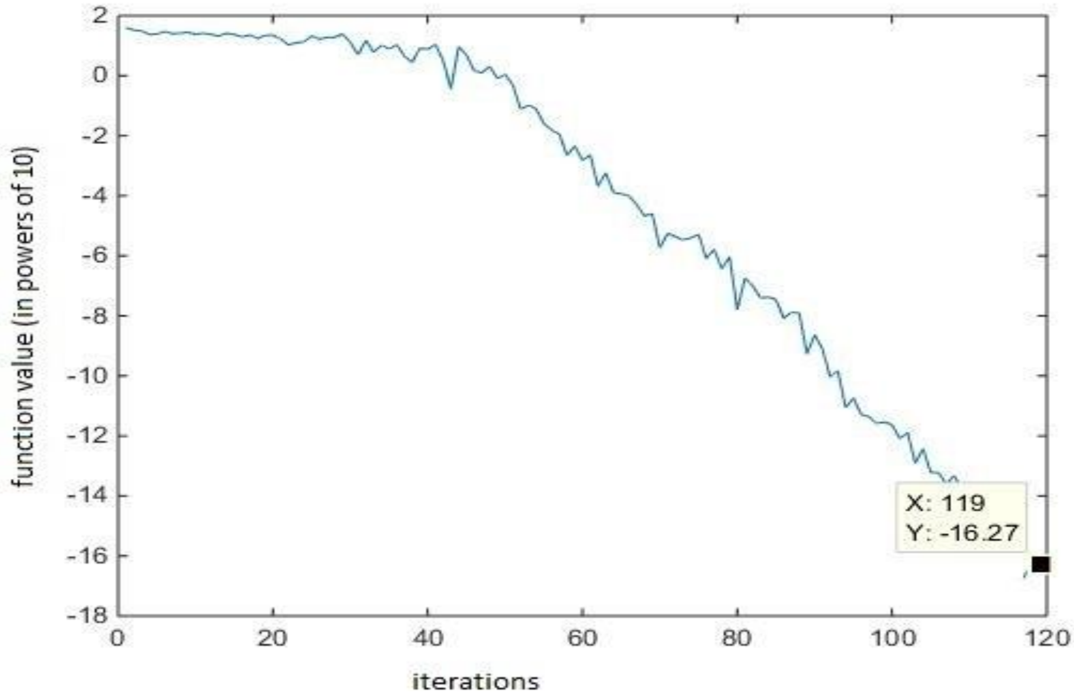


Fig 3.8: Function value vs iterations of Rastrigin function

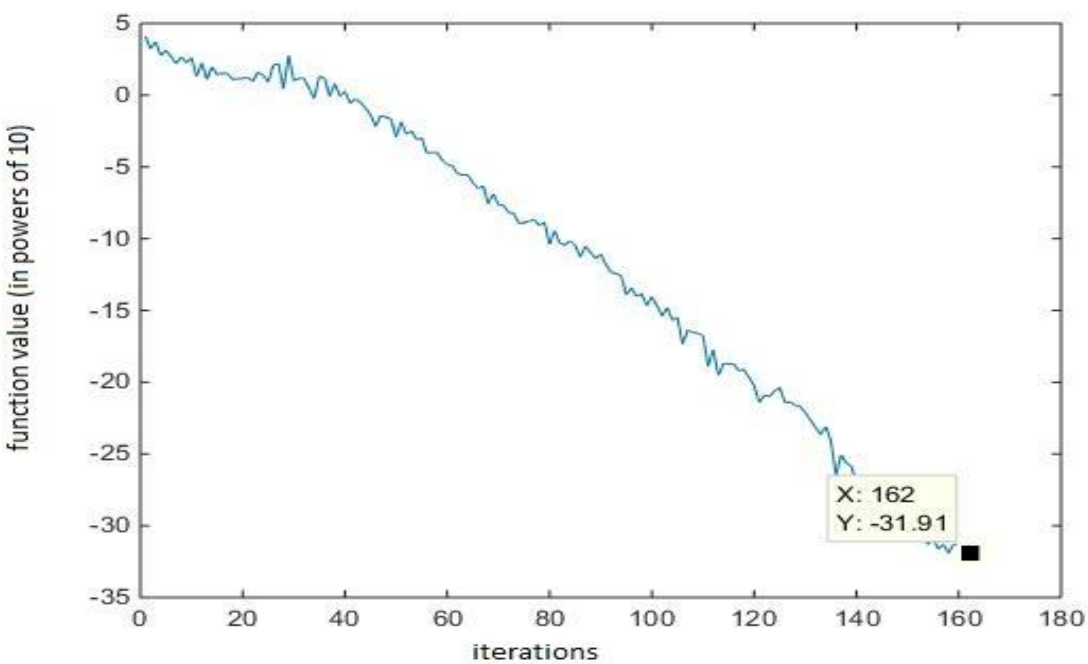


Fig 3.9: Function value vs iterations of Rosenbrock function

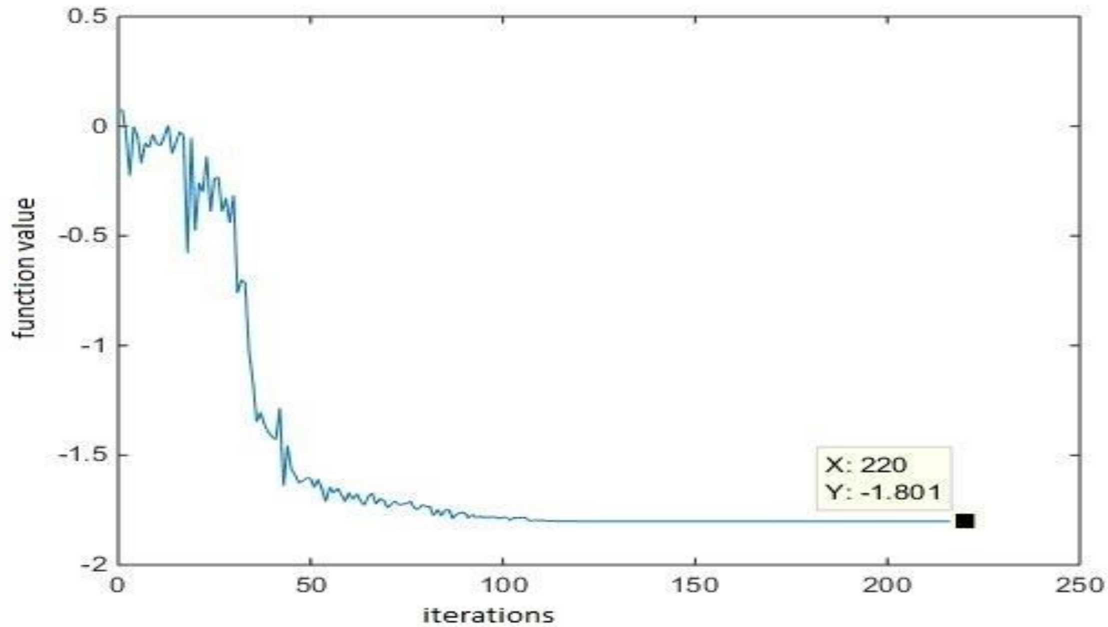


Fig 3.10: Function value vs iterations of Michalewicz function

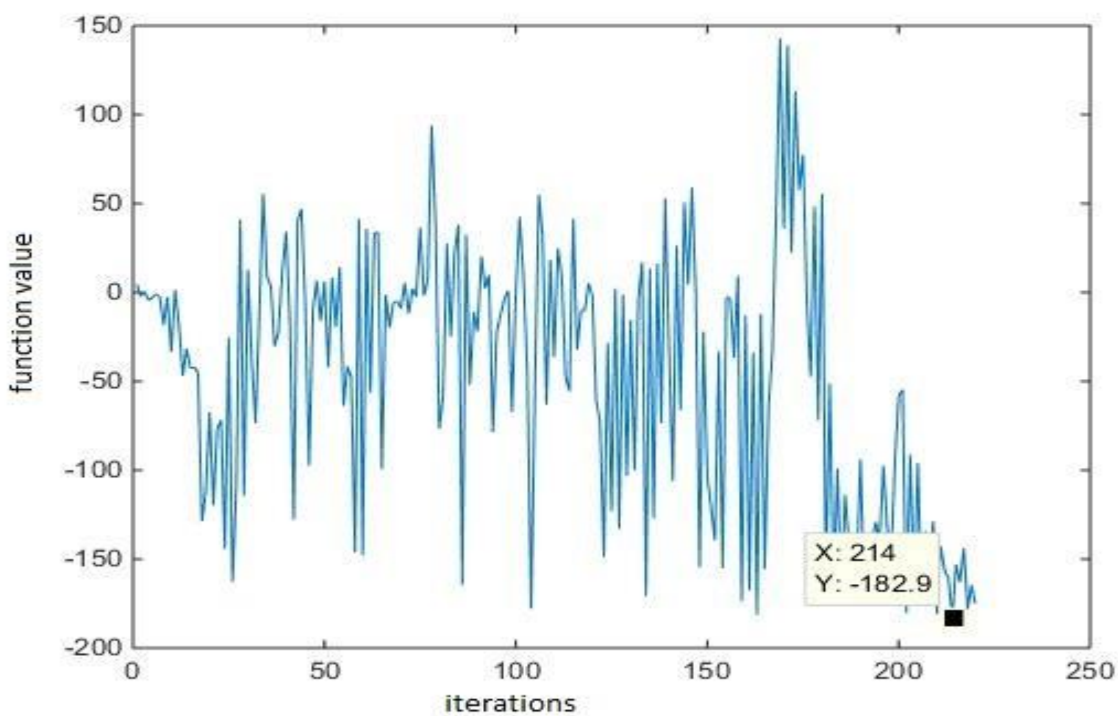


Fig 3.11: Function value vs iterations of shubert function

3.6 RESULTS ON CONVERGENCE

Table 3.1: Iterations at which Benchmark functions converge.

Function	***Iterations at which the gbest values are obtained***			
	Mean	***Std.Dev.***	***Fastest***	***Slowest***
Sphere	220	220	220	220
Rastigin	88.03333	6.895692	78	109
Shubert	26.2	2.265179	23	31
Michelawicz	30.03333	3.090400	26	40
Rosenbrock	136.5333	5.309285	128	148

Table 3.2: Results Obtained for the algorithm on various benchmark functions.

Benchmark Functions		*Mean*	*Std.Dev.*	*Best Fit*	*Worst Fit*	*Expected value [21]*
Sphere	X_1	-1.45E-37	8.87989E-37	6.87E-37	-4.79E-36	0
	X_2	-5.60E-37	3.49677E-36	2.30E-36	-1.89E-35	0
	Fgbest	1.29E-71	6.54056E-71	1.23E-82	3.58E-70	0
Rastrigin	X_1	-1.63E-09	2.37965E-09	-3.75E-09	3.51E-09	0
	X_2	-4.79E-10	2.03184E-09	-3.73E-09	2.89E-09	0
	Fgbest	0	0	0	0	0
Shubert	X_1	-0.67279	1.533821	-1.42662	4.858057	Several Minima
	X_2	-0.29594	2.076847	-1.42523	4.858044	Several Minima
	Fgbest	-186.725	0.007744	186.7304	-186.705	-186.7309
Michalewickz	X_1	2.202906	5.87319E-10	2.202906	2.202906	2.20
	X_2	1.570796	2.11439E-09	1.570796	1.570796	1.57
	Fgbest	-1.8013	6.77522E-16	-1.8013	-1.8013	-1.8013
Rosenbrock	X_1	1	0	1	1	1
	X_2	1	0	1	1	1
	Fgbest	0	0	0	0	0

In Table 3.2 , X_1 denotes the position in the first dimension. X_2 denotes the position in the second dimension and fgbest is the fitness value, that is dependant on X_1 and X_2 as described by Eq. (2.1). Table 3.2 shows the values of X_1, X_2 and fgbest using the equations Eq. (3.5), Eq. (3.6), Eq. (3.7), Eq. (3.8) and Eq. (3.9) for various benchmark functions.

Table 3.3: Performance comparison amongst literature and proposed algorithm on Benchmark Functions.

Function Name		[14]	[15]	[18]	Obtained Results
Mean	Sphere	2.46E-11	1.44E-23	3.80E-27	**1.29E-71**
	Rastrigin	NA	0.01	0.01	**0**
	Michalewicz	-1.87688	-1.89473	-1.8966	**-1.8013**
	Shubert	-186.704	**-186.728**	-186.717	-186.725
Standard Deviation	Sphere	1.35E-10	7.86E-23	2.08E-26	**6.54056E-71**
	Rastrigin	0.181654	0.252429	0.252429	**0**
	Michalewicz	0.093425	0.090563	0.086769	**6.77522E-16**
	Shubert	0.141864	0.011918	0.076175	**0.007744**

3.7 ALGORITHMIC PERFORMANCE ANALYSIS

In this chapter, the benchmark functions, for Eq. (3.5), Eq. (3.6), Eq. (3.7) the y-axis for the 2D plot is indexed in powers of 10, as the expected values from mathematical calculation [21] is close to zero. For Eq. (3.8), Eq. (3.9) the y-axis is in real values. Table 3.1 shows the iteration at which the minimum value is obtained for each benchmark function. Combining the 2D plots and Table 3.1, various inferences can be made. In Table 3.1 for the Shubert function, which is multimodal, a large number of spikes can be seen, which denote various particles exploring other parts of the search space for potential global minima until the 220 iterations end, whereas the minima has been reached at around the 26th iteration Table 3.1. Thus the ability of the algorithm to explore exhaustively even after getting settled at the minima is demonstrated. Minima are due to the mutation factor introduced using escape probability. For the sphere function , which has a single minima , the algorithm tries to attain the best possible value, from Table 3.2 , it can be seen that the algorithm is precise up to 10^{-71} on an average , In such functions , the algorithm chooses exploitation over exploration which leads to much better values as proven in Table 3.3.

In Table 3.2, the best fit column denotes the best value obtained, this value is the global minimum that has been obtained through the algorithm over the trials .The mean and standard deviation denote the algorithms variation from the bestfit value. It has been shown that, the algorithm performs with minimal variance for most of the benchmark functions when the fgbest value is concerned. Incase of X_1 and X_2, the average and the standar deviation are close to the expected values, except in case of Eq. (3.9), the shubert function, as the function exhibits the same mimimum value at multiple points in the given search space. This discrepancy is expected out of such a function and can be verified matematically [21] . Table 3.3 shows the fgbest values using the introduced algorithm i.e the fitness value and it is compared with [14], [15], [18]. The proposed algorithm exhibits much better values in unimodal functions like Sphere Function, and almost precise values in multimodal functions like the Rastrigin, Rosenbrock, Michalewicz, etc.

Table 3.3 compares the mean and standard deviation obtained from the benchmark functions such as Spherical, Rastrigin, Michalewicz and Shubert. Rosenbrock function is neglected due to lack of information. Amongst the compared values, the best value is highlighted. On comparision of the mean values with [14] and [18], which is 2.46E-11 and 3.80E-27 respectively, it is observed that for the proposed algorithm the mean value is 1.29E-71 which is an increase in the accuracy for sphere function. For Rastrigin function and Michelawicz function, the expected value has been obtained. For Shubert function, [15] exhibits the best value, and the algorithm in this work is only second to it with an error of 0.0016 % . In Table 3.2 it has also been shown that the expected result for rosenbrock function has been obtained.

3.8 SUMMARY

So far in chapter 3 the need for the proposed algorithm has been discussed. The parametric requirements and problem formulation has been explained. Various benchmark functions are used to validate and has proved to produce better results for accuracy and convergence time for the number of iterations considered. The results have been analyzed based on their convergence rate with other literature sources.

CHAPTER 4

DESIGN OF MICROWAVE ABSORBERS

4.1 INTRODUCTION TO MICROWAVE ABSORBERS

Plasma stealth technology or low observable technology is a technique used in missiles, aircrafts, satellites, ships and submarines, which makes them less perceptible to radar, infrared, sonar or any other methods of detection. The detection range of the target is also reduced making it possible for the target to approach the radar before being detected. It is also called multi spectral camouflage as it is trying to hide from these parts of electromagnetic spectrum [22]. This stealth technology is mainly used to hide from the enemy forces. A stealth vehicle is a vehicle designed to have a particular spectral signature. Based on the threats projected, the degree to which a vehicle is stealth is chosen. It is the interaction between ionized gas (plasma) and electromagnetic radiation that tries to reduce the Radar cross section. Radar cross section (RCS) is the ability of a target to reflect radar signals back to the radar receiver. The RCS is a comparison of the strength of the target's reflected signal to the reflected signal from a sphere of cross sectional area. The RCS of a target is determined by three parameters cross section that is projected, reflectivity and directivity. RCS (f) can be given as

$$f = Cross\ section \times Directivity \times Reflectivity$$

Where reflectivity is the power radiated back by the target to the receiver [22]. Hence the RCS factor should be reduced as much as possible. Reduced RCS from literature have proved to increase the surviving ability of the target. The main factor that affects the RCS is the material which it is made of. Hence radar absorbent materials are used to absorb all the incident Radio frequency radiation caused. Also due to a lot of computerization and surplus amount of electronic equipments used inside a stealth vehicle, it makes the vehicle vulnerable to passive detection. Plasma is used to control the electromagnetic radiation reflected from the target and is possible at a particular frequency where the plasma conductivity allows for strong interaction with the radio wave coming towards the target .Three processes can occur based on the relation between the plasma frequency and frequency of the radio wave that are reflection or absorption.

1. When the frequency is higher than the plasma frequency, the incoming radio wave is absorbed and converted into thermal energy.
2. The frequency is lower than the plasma frequency, the incoming wave is reflected.
3. The two frequencies are equal, resonance will occur.

Hence the design should be done in such a way the frequency of plasma is lesser than that of the frequency of incoming radio wave [23]. There are also other methods to reduce reflection. The electromagnetic wave passing through the plasma can be reflected by the metal. Then the incoming wave and reflected wave are approximately equal in power and they form two phasors. They cancel each other out when the two phasors are of opposite phase. Most military applications use microwave frequencies, which have a higher frequency range than plasma frequency. Hence microwave absorbers have been extensively used to reduce these above mentioned factors and they are mounted on surfaces of the target to reduce the RCS factor.

Absorbers are materials that inhibit electromagnetic radiation's transmission or reflection. Normally dielectrics combined with metal are used for the design of microwave absorbers. Some other applications for these absorbers include spatial light modulators, emitters, sensors, wireless communication, and thermophotovoltaics [24]. There are two types of absorbers: broadband absorbers and resonant absorbers. Broadband absorbers are frequency independent and can therefore are used across a broad spectrum. The resonant absorbers, because of the desired resonance of the material are dependent upon a particular frequency at a particular wavelength. Some types of resonant absorbers are Jaumann absorber, Salisbury screen, Dallenbach layer and circuit analog absorbers. Research on designs of broadband absorbers for the above applications has found immense amount of interest recently [25-28]. The design of absorbers depends upon factors such as angle of incidence, range of frequency, permittivity, permeability, polarization, thickness and the arrangement of these materials. Literature shows that researchers have tried to optimize these parameters earlier using various evolutionary algorithms such as Genetic algorithm (GA) [29-30], Simulated annealing (SA) [31], Self adaptive differential evolutionary algorithm (SADEA) [32], Central force optimization (CFO) [36] and Particle swarm optimization (PSO) [34]. The above algorithms have shown improvement in the design of these absorbers in their thicknesses and material arrangement, however because of the complexity of the design, the optimization of reflection coefficient and thickness can be improved even more reducing the overhead cost. GA is comparatively difficult because of its complexity and extensive time for computational **[**33**].** In Simulated annealing method, it has a high tendency to get trapped in local minima and also takes a larger time to converge [33]. Literature shows that Particle swarm optimization (PSO) outperforms GA and simulated annealing [33]. Hence an improvised Particle swarm optimization is used in this project to design a microwave absorber that gives a minimum overall reflection coefficient over a range of frequency and angle of incidence for a practically achievable thickness. When the overall maximum reflection coefficient is minimized, the overall absorption is maximized.

4.2 OVERVIEW ON DESIGN OF MICROWAVE ABSORBERS

In previous literature, Chew's recursive formula has been used for designing of microwave absorber for multiple layers [34]. This formula calculates the reflection coefficient. This is a recursive formula and calculates with the preceding term acting as a function to the next term. The recursive computation is done for TM and TE polarizations and for wide angle of incidence. TE and TM polarizations correspond to the electric and magnetic fields respectively [35]. The range of frequency, angle of incidence and number of layers are already determined. Whereas, the thickness and materials to be used for each layer has to be determined. Reported literature has calculated the reflection coefficient for various numbers of layers [36]. But due to the current demand for thinner absorbers the optimization done so far can be further optimized. For the calculation of reflection coefficient, an absorber, with five layers is considered in the microwave frequency range. The thickness and material arrangement for the layers are optimized over a range of frequency and angle of incidence for both TM and TE polarizations. Since most of the military and civil applications lie in the bands S, C, X and Ku the design is optimized for these particular frequency bands. Optimization done with recursive computation alone is not so efficient [34]. Hence improvised particle swarm optimization has been used to achieve a better result for reflection coefficient.

The work has been divided into two parts and is expanded in section 4.5. It concentrates on finding the best microwave absorber design and its corresponding angle of incidence and frequency. Second part in section 4.6, analyses on how the frequency and angle of incidence affects the reflection coefficient for varying number of layers. Ultimately, the best microwave absorber with the least reflection coefficient for a particular frequency range has been designed.

4.3 PHYSICAL MODEL OF MICROWAVE ABSORBER

An *N* planar layered microwave absorber on a substrate of a Perfect Electric Conductor (PEC) as layer *N+1* is illustrated below in the Fig 4.1 [34].

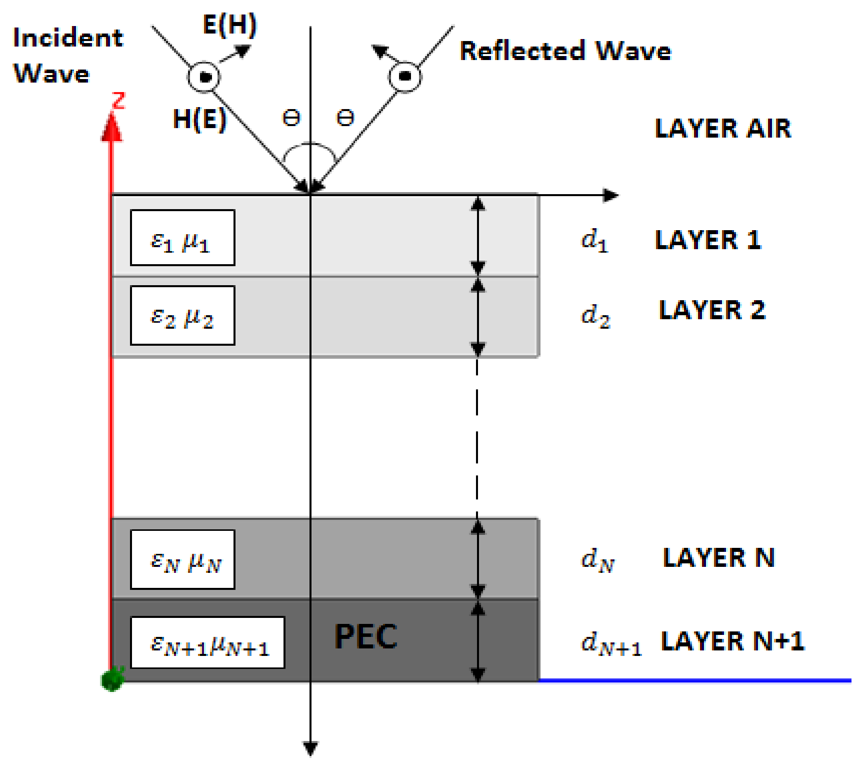


Fig 4.1: Physical arrangement of materials for microwave absorber design

As in Fig 4.1 an electromagnetic wave is obliquely incident on layer 1 (first layer) of the multilayer structure from air (the free space region) with an angle of incidence θ. The incident wave travels through all the *N* layers of the absorber each having a thickness d_N and majority of the energy is being absorbed by each layer which is completely reflected by the PEC layer. The reflected energy from PEC is then again absorbed by the *N* layers above it, ultimately acting like an absorber.

The unknown parameters required here are the thickness of each layer and the arrangement of each material. Hence the Chew's recursive formula is used. In the formulae the reverse computation is carried out. The reflection coefficient between any two layers *N* and *N+1* can be calculated using Eq. (4.1). Fresnel's coefficient for TE polarizations and TM polarization is given in equation Eq. (4.2) and equation Eq. (4.3) respectively. In the given equation Eq. (4.4), the complex permittivity and permeability are denoted as ε_i and μ_i for the *i*th layer, respectively and K_i denotes the wave number and is defined as

$$R_{i,i+1} = \frac{r_{i,i+1} + R_{i+1,i+2}\exp(-2jk_{i+1}d_{i+1})}{1 + r_{i,i+1}\ R_{i+1,i+2}\exp(-2jk_{i+1}d_{i+1})} \qquad (4.1) \quad \text{where } i=1, 2 \ldots N$$

$$r_{i,i+1} = \frac{\mu_{i+1}k_i - \mu_i k_{i+1}}{\mu_{i+1}k_i + \mu_i k_{i+1}} \qquad i < N \qquad (4.2)$$

$$r_{i,i+1} = \frac{\varepsilon_{i+1}k_i - \varepsilon_i k_{i+1}}{\varepsilon_{i+1}k_i + \varepsilon_i k_{i+1}} \qquad i < N \qquad (4.3)$$

$$K_i = w\sqrt{\mu_i\varepsilon_i - \mu_0\varepsilon_0 sin^2(\theta)} \qquad (4.4)$$

Here ε_0 and μ_0 is the permittivity and permeability of free space and *w* is the frequency of the incident wave.

$\varepsilon_0 = 8.854 \times 10^{-12} F/m$

$\mu_0 = 4\pi \times 10^{-7}\, H/m$

The reflection coefficient between the penultimate and the last layer *N* and *N+1* is set to *+1* for TM polarization and *-1* for TE polarization respectively [34]. For angle of incidence 0° (normal incidence), the reflection coefficient holds the same result for both TE and TM polarization [35]. Since the last interface reflection coefficient *R (N, N+1)* is calculated, the reflection coefficients of the subsequent layers can be calculated. Hence the reflection coefficient is calculated starting from the last layer and the further moving on to the first layer. Finally the required reflection coefficient *R (0, 1)* is obtained by recursive computation.

4.4 FITNESS FUNCTION FORMULATION

The fitness function for finding the minimum reflection coefficient is formulated as given in Eq. (4.4.a)

$$F = \varphi_1 \times 20log_{10}\left(\max\left(\left|R_{0,1}\right|\right)\right) + \varphi_2 \times \sum_{i=1}^{N} d_i \qquad (4.5)$$

The above fitness function *F* is minimized for calculating the overall weighted sum of the total maximum reflection coefficient of the microwave absorber over a range of frequency and given angle of incidence for TM and TE polarizations. The fitness value contains two factors to be minimized, the thickness of each individual layer and the reflection coefficient of the first layer. Improvised particle swarm optimization along with Chew's recursive formula has been used. The fitness function is designed to focusing on obtaining the minimum reflection coefficient and the thickness is optimized to give this minimum reflection coefficient. Here φ_1 and φ_2 are the weighted coefficients considered to calculate the total fitness value [35]. These weights are used to normalize the fitness function giving importance to both the factors. For this, a predefined set of materials as in Table 4.1 [34] is considered. This database is widely used in literature and is a substitute for the various range of microwave absorbers available and these 16 materials are categorized as: lossless dielectric materials [a], lossy magnetic [b] and dielectric materials [c], and relaxation-type magnetic materials [d] [34]. While designing for each layer the corresponding material and its properties must be calculated separately. The values for ε and μ for each material, must be calculated using Table 4.1. The ε and μ values given in the Table 4.1 are the relative permittivity and permeability. Hence they should be multiplied with permittivity and permeability of free space to get the permittivity and permeability values.

$$\varepsilon = \varepsilon_r \times \varepsilon_0$$

$$\mu = \mu_r \times \mu_0$$

Here ε_r is the relative permittivity and μ_r is the relative permeability.

Table 4.1: Predefined database from [34] for design of microwave absorber

a. Lossless Dielectric Material

No.	$\boldsymbol{\varepsilon'}$	$\boldsymbol{\varepsilon''}$	$\boldsymbol{\mu'}$	$\boldsymbol{\mu''}$
1	10	0	1	0
2	50	0	1	0

b. Lossy Magnetic Material

$\mu = \mu' - j\mu''$ $\quad$ $\mu'(f) = \frac{\mu'(1\ GHz)}{f^a}$ $\quad$ $\mu''(f) = \frac{\mu''(1\ GHz)}{f^b}$

No.	$\boldsymbol{\varepsilon'}$	$\boldsymbol{A}$	$\boldsymbol{\varepsilon''}$	$\boldsymbol{b}$	$\boldsymbol{\mu'(1GHz)}$	$\boldsymbol{\mu''(1GHz)}$
3	15	0.974	0	0.961	5	10
4	15	1.000	0	0.957	3	15
5	15	1.000	0	1.000	7	12

c. Lossy Dielectricic Material

$\varepsilon = \varepsilon' - j\varepsilon''$ $\quad$ $\varepsilon'(f) = \frac{\varepsilon'(1\ GHz)}{f^a}$ $\quad$ $\varepsilon''(f) = \frac{\varepsilon''(1\ GHz)}{f^b}$

No.	$\boldsymbol{\varepsilon'\ (1GHz)}$	$\boldsymbol{\varepsilon''(1GHz)}$	$\boldsymbol{\mu'}$	$\boldsymbol{a}$	$\boldsymbol{\mu''}$	$\boldsymbol{b}$
6	5	8	1	0.861	0	0.569
7	8	10	1	0.778	0	0.682
8	10	6	1	0.778	0	0.861

d. Relaxation- Type Magnetic Material

$\mu = \mu' - j\mu''$ $\quad$ $\mu'(f) = \frac{\mu_m f_m^2}{f^2 + f_m^2}$ $\quad$ $\mu''(f) = \frac{\mu_m f_m f}{f^2 + f_m^2}$

***f and f**m* *in* GHz where *f* is the frequency considered for design and *fm* is the matching frequency**

No.	$\boldsymbol{\varepsilon'}$	$\boldsymbol{\varepsilon''}$	$\boldsymbol{\mu_m}$	$\boldsymbol{f_m}$
9	15	0	35	0.8
10	15	0	35	0.5
11	15	0	30	1.0
12	15	0	18	0.5
13	15	0	20	1.5
14	15	0	30	2.5
15	15	0	30	2.0
16	15	0	25	3.5

4.5 DESIGN REQUIREMENTS FOR MICROWAVE ABSORBERS

The improvised Particle Swarm Optimization is applied on the design of microwave absorbers for various combinations of 16 materials available for 5 layers for a range of frequency and angle of incidence. Matlab® is used for coding using a PC with core I5 4005u, 1.7 GHz and 4 GB RAM. The number of particles in swarm is considered as 30 and 10 dimensions are considered which are the 5 layers and their corresponding thicknesses. The search boundary is restricted by setting the maximum layer thickness to 1.5mm. For each design presented, 700 iterations are carried out for every 20 independent trials. For each design the frequency range considered is from 2 to 18GHz based on the application with an increment of 0.1 GHz. The angle of incidences considered are from 0° to $75^{\circ}$for a set size of 15°.The mean and standard deviation of the 20 trials is taken into consideration and the best is chosen for the microwave absorber design. Here φ_1 *and* φ_2 is considered as 1 and 1000 respectively, for comparison. The weight can be chosen according to the set of parameters that will have more effect on the fitness function.

Table 4.2: Database of the parameters considered for microwave absorber design.

Design No.	1	2	3	4	5	6	7	8	9	10	11
Polarization	TE/TM	TM	TE	TM	TM	TM	TM	TE	TE	TE	TE
Angle of incidence	0°	15°	15°	30°	45°	60°	75°	30°	45°	60°	75°

4.6 ANALYSIS REQUIREMENTS FOR MICROWAVE ABSORBERS

The microwave absorbers are frequency independent materials. Hence they are designed for a range of frequency. This relation of frequency with reflection coefficient is established in Fresnel's equation. Hence an analyis on the effect of frequency on absorber design is conducted for various microwave absorbers from the best obtained results. As per the literature above suggested a microwave absorber for TM polarization and for an angle of 45° is designed using three different number of layers over three ranges of frequency S and C band (2-8GHz), X band (8-12GHz) and Ku band (12-18GHz). Various experiments on N=2 layers absorbers have been designed in earlier literature [37]. The increase in the number of layers have shown improvement in obtaining the minimum reflection coefficient. Hence this analysis will help to choose microwave absorbers according to specific frequency band for the required application. Also based on the thickness specification the absorber can be choosen. The number of layers are considered excluding the PEC layer and it is considered as *N+1th* layer which acts as the substrate for every design. This experiment is carried out using improvised particle swarm optimization for a changing dimension which is the number of layers.

Table 4.3: Database of the parameters considered for analysis of microwave absorbers

Design No	Frequency Range(GHz)	Number of layers	Polarization and Angle of incidence
12	2-8	4	TM 45°
13	8-12		
14	12-18		
15	2-8	5	
16	8-12		
17	12-18		
18	2-8	6	
19	8-12		
20	12-18		

4.6.1 ALGORITHM SPECIFIC REQUIREMENTS

The *c1* and *c2* parameters are considered as in Eq. (4.6) and Eq. (4.7)

$$c1(i) = (c1_{max} - c1_{\min}) \times \left(\frac{it}{itmax}\right) + c1_{min}$$

where $c1_{min} = 2.5$ and $c1_{max} = 0.5$ (4.6)

$$c2(i) = (c2_{max} - c2_{\min}) \times \left(\frac{it}{itmax}\right) + c2_{min}$$

where $c2_{min} = 0.5$ and $c2_{max} = 2.5$ (4.7)

The velocity restriction factor *Vr* is considered as 16.

4.6.2 FLOWCHART FOR MICROWAVE ABSORBER DESIGN

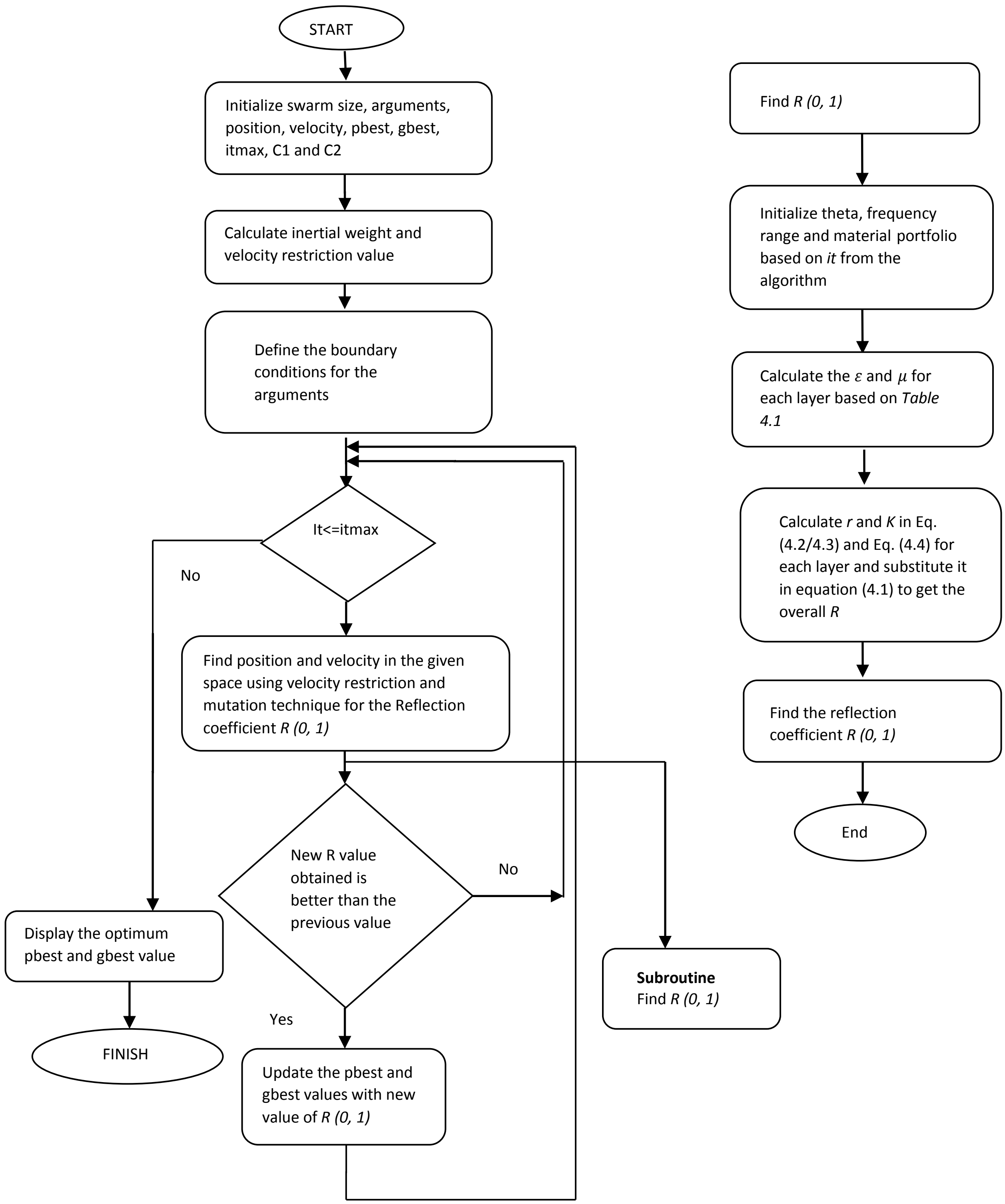


Fig 4.2: Flow chart for Improvised PSO for microwave absorber design.

4.7 RESULTS AND DISCUSSION

Table 4.4: Gbest comparitive results for 20 trials

Design No.	Ref [35]				Proposed Algorithm			
	Gbest	Worst	Mean	Standard deviation	Gbest	Worst	Mean	Standard deviation
4	−15.89	−4.02	−14.45	0.81	-16.03	-13.72	-15.18	0.71
5	−22.68	−4.01	−20.05	1.09	-23.33	-19.25	-21.28	1.18
6	−25.11	−6.61	−24.85	2.32	-23.29	-20.54	-21.93	0.34
7	−22.24	−1.67	−20.23	0.85	-22.42	-18.68	-20.87	1.46
8	−10.47	−1.72	−10.05	0.27	-11.78	-9.21	-10.27	0.78
9	−8.81	−0.93	−8.23	0.36	-8.82	-6.07	-7.68	0.76
10	−5.20	0.08	−4.78	0.23	-5.25	-4.51	-4.92	0.28
11	−1.53	0.92	−1.31	0.08	-1.60	-0.20	-0.66	0.37

From Table 4.4 it is observed that the Gbest, Worst, Mean and Standard deviation and is compared with [35] to show the ascendancy of the proposed algorithm. The values above are calculated for 700 iterations for 20 independent trials. From Table 4.4 it is evident that the proposed algorithm gives us a better result for all designs (excluding design no.6). The gbest is that of the fitness function that contains reflection coefficient as well as thickness. Hence to obtain the reflection coefficient for each design the added thickness must be removed. The Design nos. 1, 2 and 3 are designed for normal incidence and for 15° for five layers which is not done in [35].

Table 4.5: Parametric requirement for microwave absorber designs 1-3

Design No.	Layer	Material no.	Thickness (mm)	Reflection Coefficient (dB)	Total Thickness (mm)
Design 1	1	16	0.24332	-16.102	3.2109
	2	8	0.33948		
	3	7	0.81477		
	4	6	0.76302		
	5	15	1.05037		
Design 2	1	16	0.25814	-16.594	3.27005
	2	8	0.89143		
	3	8	0.72297		
	4	11	0.82739		
	5	10	0.57012		
Design 3	1	16	0.27428	-15.309	3.19418
	2	7	0.63671		
	3	6	1.13055		
	4	13	0.46773		
	5	15	0.68491		

Table 4.6: Parametric requirement for microwave absorber designs 4-6

Design No.	Layer	Material nos.	Thickness (mm)	Proposed Algorithm		Ref [35]	
				RC (dB)	Total Thickness (mm)	RC(dB)	*Total Thickness (mm)
Design 4	1	16	0.22407	-20.010	3.9754	-19.306	3.4144
	2	6	1.43077				
	3	13	0.49299				
	4	5	1.22021				
	5	10	0.60731				
Design 5	1	16	0.12205	-27.316	4.2397	-26.519	3.8420
	2	6	1.49978				
	3	14	0.38438				
	4	4	0.95693				
	5	4	1.27658				
Design 6	1	7	0.97532	-27.353	4.0666	−29.149	4.0354
	2	9	0.32104				
	3	8	0.62741				
	4	7	0.94466				
	5	4	1.19824				

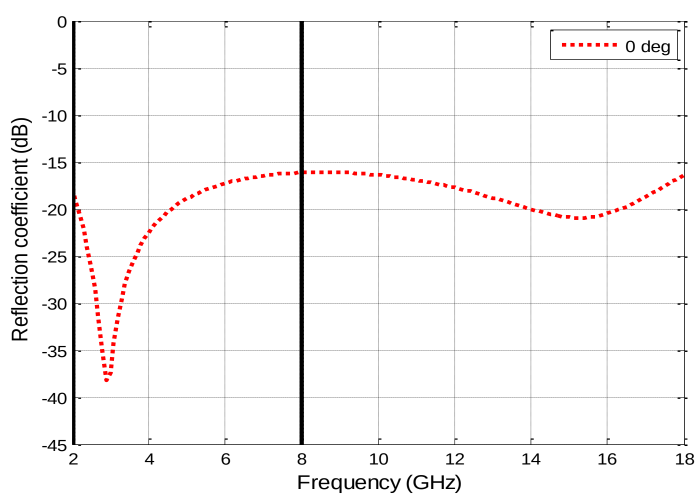
Table 4.7: Parametric requirement for microwave absorber designs 7-11

Design No.	Layer	Material nos.	Thickness (mm)	Proposed Algorithm		Ref [35]	
				RC (dB)	Total Thickness (mm)	**RC(dB)**	*Total Thickness (mm)
Design 7	1	7	0.43144	-25.558	3.1433	−25.379	3.1351
	2	12	0.61446				
	3	2	1.49954				
	4	12	0.30706				
	5	4	0.29077				
Design 8	1	16	0.22809	-15.519	3.7355	−15.393	3.6694
	2	8	0.63982				
	3	6	1.47215				
	4	14	0.42288				
	5	9	0.97265				
Design 9	1	16	0.25436	-12.521	3.714	−12.244	3.4387
	2	6	1.36323				
	3	6	1.02108				
	4	16	0.52167				
	5	15	0.55552				
Design 10	1	16	0.25129	-8.6658	3.6176	−8.5332	3.3370
	2	8	0.89135				
	3	8	0.38858				
	4	6	1.27394				
	5	14	0.81252				
Design 11	1	16	0.26655	-4.3047	3.2855	−3.2196	1.6837
	2	8	1.02714				
	3	6	0.65834				
	4	6	0.54992				
	5	14	0.78356				

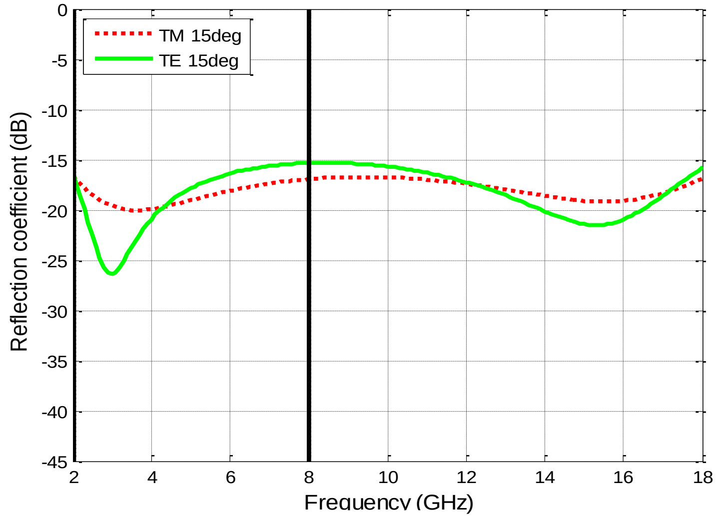
*The aggregate for thickness in [35] do not tally.

RC denotes the reflection coefficient. The minimum reflection coefficient and the thickness for each 5 layered design is obtained from Table 4.5 to Table 4.7 . Comparing to literature values in [35] the designs 4 to 11 (excluding design 6) give an improvement of more than 0.2dB. The thickness is optimized to obtain the best minimum reflection coefficient. The best result obtained after optimization is with design 5 for TM polarization and angle of incidence 45°. The reflection coefficient obtained for design 5 in this work is 0.8dB more than that obtained in literature [35] which is -27.316dB. The best results obtained for each microwave absorber designed are shown in Fig 4.3. From the reflection coefficient versus frequency graphs it can be observed that for a particular frequency, TM and TE polarized waves have a diverse characteristics and vary based on the polarization and angle of incidence. Each design gives a different reflection coefficient and corresponding thickness. Even the materials chosen after optimization vary based on each design. The same combination of materials may not produce good results when the angle of incidence, polarization or frequency range is changed.

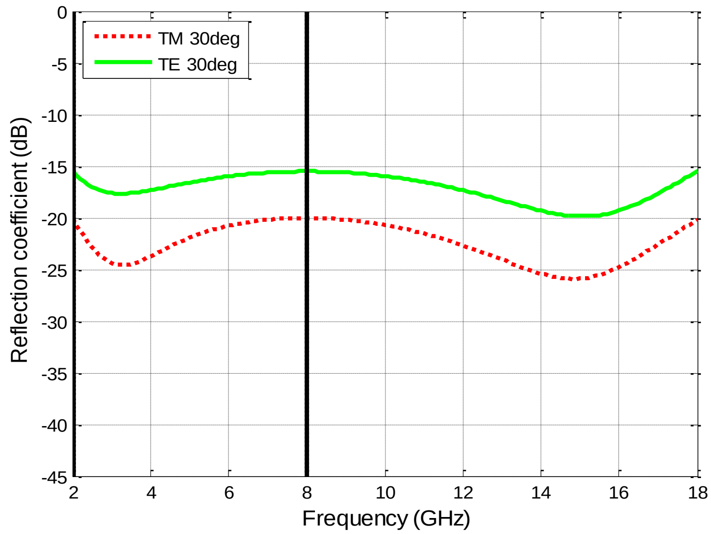
4.7.1 FREQUENCY RESPONSE FOR REFLECTION COEFFICIENT



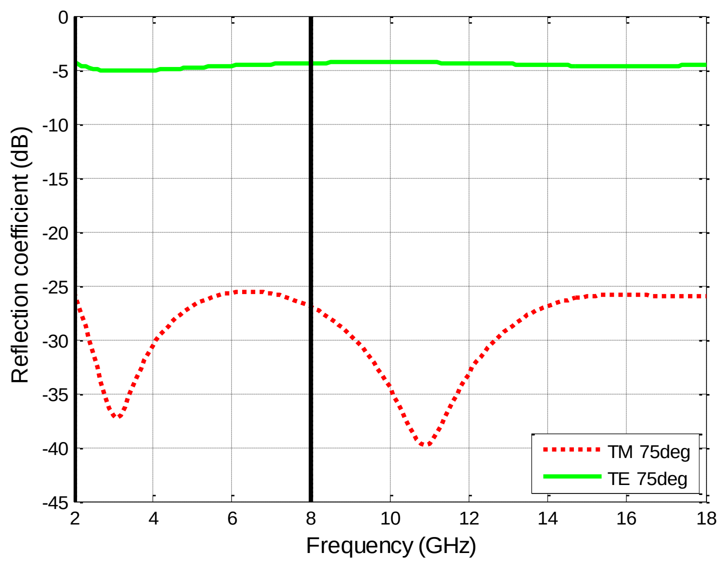
[A]


TM 15deg
TE 15deg
Reflection coefficient (dB)
Frequency (GHz)

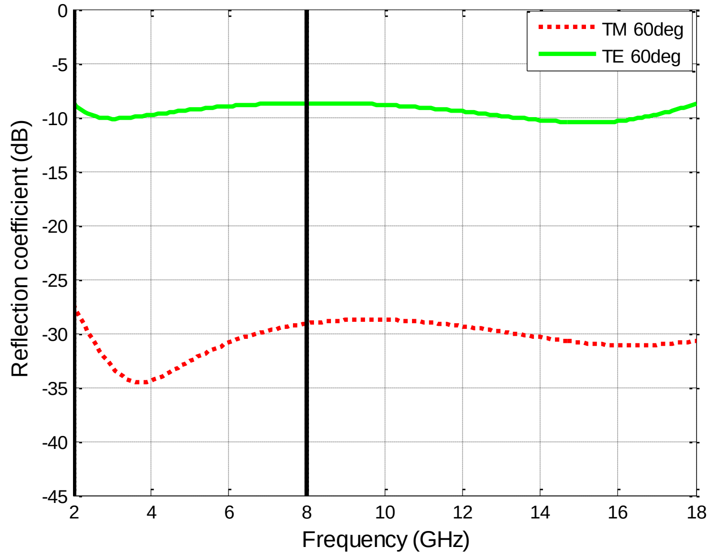
[B]


TM 30deg
TE 30deg
Reflection coefficient (dB)
Frequency (GHz)

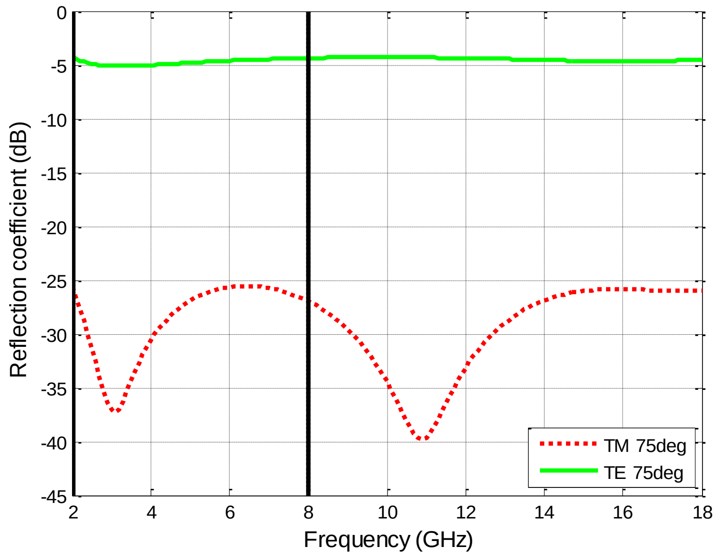
[C]


TM 75deg
TE 75deg
Reflection coefficient (dB)
Frequency (GHz)

[D]



[E]



[F]

Fig 4.3*:* [A] Reflection coefficient vs frequency for angle of incidence 0°.
[B] Reflection coefficient vs frequency for TE and TM polarization for angle of incidence 15°.
[C] Reflection coefficient vs frequency for TE and TM polarization for angle of incidence 30°.
[D] Reflection coefficient vs frequency for TE and TM polarization for angle of incidence 45°.
[E] Reflection coefficient vs frequency for TE and TM polarization for angle of incidence 60°.
[F] Reflection coefficient vs frequency for TE and TM polarization for angle of incidence 75°.

4.8 RESULT ANALYSIS

Table 4.8: Result for microwave absorbers for 4 number of layers for TM polarization

Design No.	Layer	Material nos.	Thickness (mm)	Reflection Coefficient (dB)	Total Thickness (mm)
Design 12 (2-8GHz) 45°	1	16	0.27099	-26.674	3.49093
	2	7	1.16000		
	3	3	1.10388		
	4	9	0.95932		
Design 13 (8-12GHz) 45°	1	8	0.78582	-27.594	1.77374
	2	16	0.19500		
	3	7	0.49050		
	4	15	0.30273		
Design 14 (12-18GHz) 45°	1	16	0.09727	-35.056	2.10040
	2	6	1.13070		
	3	14	0.29367		
	4	4	0.57876		

Table 4.9: Result for microwave absorbers for 5 number of layers for TM polarization

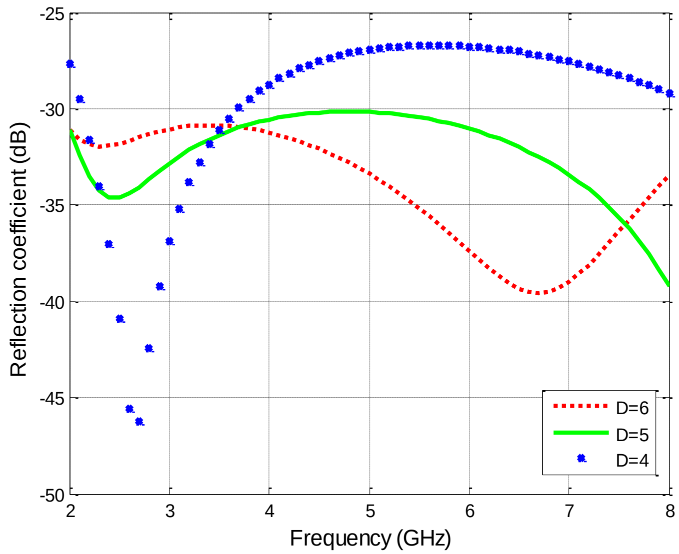
Design No.	Layer	Material nos.	Thickness (mm)	Reflection Coefficient (dB)	Total Thickness(mm)
Design 15 (2-8GHz) 45°	1	16	0.26315	-30.152	4.02701
	2	7	0.96001		
	3	8	1.15852		
	4	10	0.60756		
	5	9	1.03777		
Design 16 (8-12GHz) 45°	1	14	0.19051	-33.339	2.79410
	2	6	0.93641		
	3	6	0.61459		
	4	9	0.68933		
	5	10	0.36343		
Design 17 (12-18GHz) 45°	1	16	0.14724	-29.535	2.15088
	2	6	0.41555		
	3	6	0.07906		
	4	7	0.73426		
	5	11	0.77476		

Table 4.10: Result for microwave absorbers for 6 number of layers for TM polarization

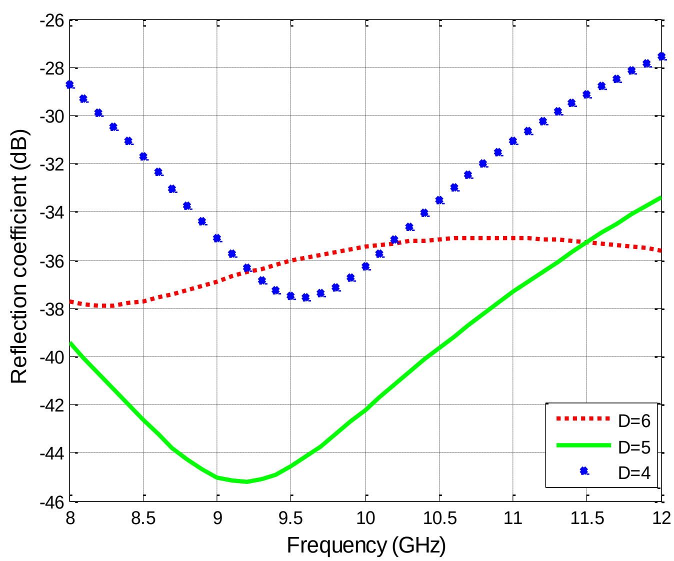
Design No.	Layer	Material nos.	Thickness (mm)	Reflection Coefficient (dB)	Total Thickness(mm)
Design 18 (2-8GHz) 45°	1	16	0.29309	-30.848	4.41163
	2	6	1.06000		
	3	7	0.38876		
	4	10	0.89880		
	5	10	0.80850		
	6	10	0.96300		
Design 19 (8-12GHz) 45°	1	14	0.08386	- 35.081	3.21183
	2	8	0.74699		
	3	7	0.90371		
	4	7	0.53770		
	5	8	0.47761		
	6	16	0.46124		
Design 20 (12-18GHz) 45°	1	7	0.18526	-28.353	2.95384
	2	16	0.15701		
	3	6	1.01808		
	4	8	0.49187		
	5	8	0.25507		
	6	11	0.84655		

From the data available in Table 4.8, Table 4.9 and Table 4.10, a direct relation to thickness, frequency band and number of layers can be inferred. As the thickness increases, the reflection coefficient should also increase. Hence the need for optimization comes in. After optimization, for the frequency band 2-8GHz design 18 has shown the best result for absorber design with a reflection coefficient higher than the other two designs 12 and 15 respectively, in the same band. Similarly, for the frequency band 8-12GHz design 19 has proved to be the best comparing to design 13 and design 16. Hence in the frequency bands S, C and X microwave absorbers with 6 layers (N=6) is advisable for minimum reflection coefficient. In the case of the frequency band 12-18GHz design 14 proves to be the better comparing to design 17 and design 20. Hence for X band microwave absorbers with 4 layers (N=4) is advisable for obtaining minimum reflection coefficient. Also based on the application if it is thickness specific, the above database will prove to be useful for selecting the parameters required for the microwave absorber design. Based on the application and the requirement of the range of frequency the required number of layers can be selected. Fig 4.4 [a], [b] and [c] are plotted for specified range of frequency vs reflection coefficient for TM polarization for an angle of incidence 45°.

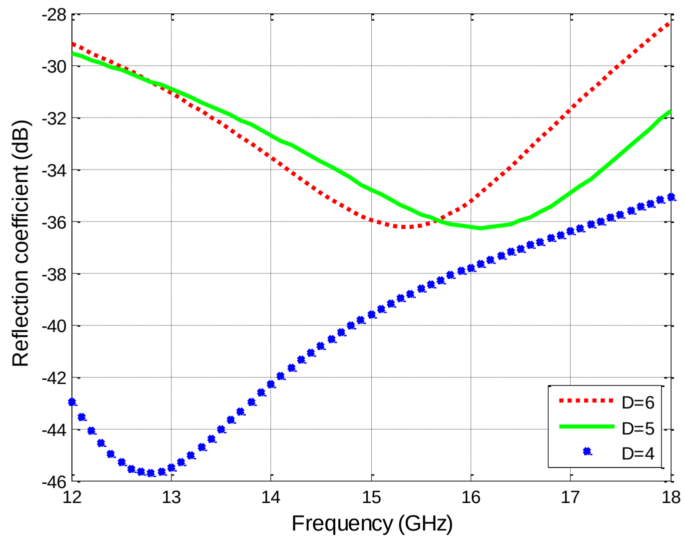
4.8.1 ANALYSIS OF FREQUENCY RESPONSE



[a]



[b]



[c]

Fig 4.4: [a] Reflection coefficient vs frequency for 2-8GHz, TM polarization for angle of incidence 45°.
[b] Reflection coefficient vs frequency for 8-12GHz, TM polarization for angle of incidence 45°.
[c] Reflection coefficient vs frequency for 12-18GHz, TM polarization for angle of incidence 45°.

4.9 SUMMARY

In this chapter the proposed algorithm has been applied on a specific application field i.e., microwave absorber design. The physical modeling and parametric requirements for absorbers are specified. The minimum reflection is found for various angles of incidence and over a range of frequency. The obtained result has been validated with literature and proved to give a better accuracy, an increase in 0.3dB and more. A set of designs for 1-11 has been optimized for obtaining the minimum reflection coefficient. The frequency response for each microwave absorber design is analyzed over a varying number of layers to elucidate the correlation and significance.

CHAPTER 5

OPTIMIZATION OF SOLAR CELLS

5.1 OVERVIEW ON DESIGN OF SOLAR CELLS

Solar cells or photovoltaic cells are electrical devices that convert the light energy into electricity by the photovoltaic effect. Solar cells are the integral part of photovoltaic modules, known as solar panels. The main attribute for the operation of photovoltaic cell is the absorption of light. To increase the absorption of light we have to use materials that are specific to light absorption such as crystalline silicon (solar grade silicon), monocrystalline silicon solar cells, epitaxial silicon, and polycrystalline silicon. Monocrystalline silicon solar cells are the most efficient. The reported efficient solar cell was with 46 percent efficiency [38]. Hence this work concentrates on increasing the absorption capacity of solar cells. The absorption of solar cells is given by Eq. (5.1)

$$A = \alpha d \tag{5.1}$$

Here A is the maximum absorption, α is the absorption coefficient and d is the total thickness of the solar cell [39]. By increasing the absorption we can reduce the cost by making the cells thinner. The efficiency must be enhanced to maximum extent possible to decrease the reflection factor of solar cells. The extent to which the reflection coefficient can be decreased is the main challenge of this work. Many solar cells are designed to absorb a wavelength in the range of 0.25 to 3.0 micron. For this, literature has used left handed materials (LHM) [39]. LHM is metamaterial. Metamaterials are materials that are arranged or manufactured in a way required for the application and they are generally not found in nature. The geometrical arrangement of several multiple elements such as plastics or metals forms the metamaterial. The shape, size, geometry and arrangement give the metamaterial intelligence allowing them to manipulate electromagnetic waves. They have the capability to block, absorb, enhance or even bend waves. LHM are materials having negative refractive index i.e., permittivity and permeability is negative. A multilayered structure packed in vacuum has been designed.

5.2 PHYSICAL MODELING OF SOLAR CELLS

The design considered is illustrated in the Fig 5.1.

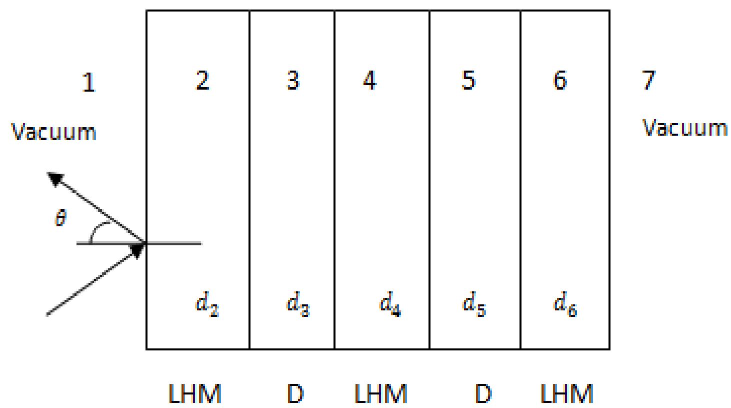


Fig 5.1: Physical arrangement of materials for solar cells [39]

The layers 2, 4 and 6 are the left handed material layers and layers 3 and 5 are the dielectrics packed in between the LHM. Layer 1 and 7 are considered as vacuum with semi-infinite thickness. The thicknesses of the other layers are taken as d_N where N=2, 3... 6. The reflection coefficient is calculated using Chew's recursive formula as given in Eq. 4.1. Here from the recursive formula the reflection coefficient is obtained, from that the absorption power can be calculated as given in Eq. (5.2)

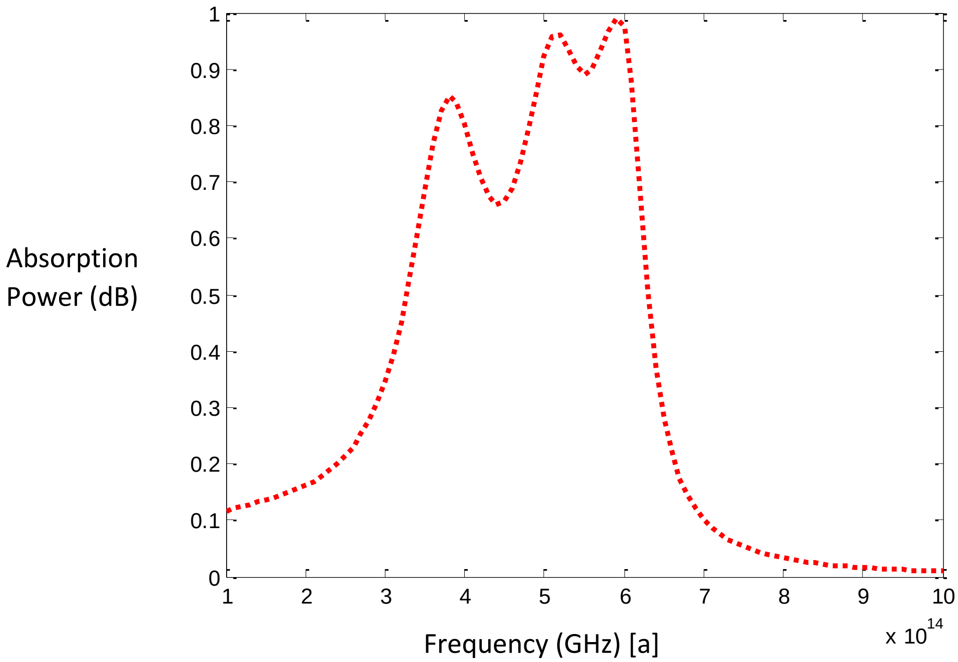
$$AP = 1 - |R|^2 \tag{5.2}$$

AP is the absorption power in dB and R is the reflection coefficient in dB. The permittivity for LHM is calculated using the Drude medium model given in Eq. (5.3)

$$\varepsilon(w) = \varepsilon_l - \frac{w_p}{w^2 + iw\gamma} \tag{5.3}$$

Here $\varepsilon(w)$ is the permittivity of the left handed material that is dependent on the frequency, $\varepsilon_l = 9.1$ is the permittivity of the lattice, $w_p = 1.2 \times 10^{16} Hz$ is the phase plasma frequency and $\gamma = 1.2 \times 10^{14} Hz$ is the electric damping factor. The relative permeability for LHM is negative, that is $\mu_r = -1$. The dielectric layers 3 and 5 is silicon dioxide SiO_2 with refractive index n=1.455 and permeability of free space μ_0.

5.3 FREQUENCY RESPONSE AND ANALYSIS FOR ABSORPTION POWER



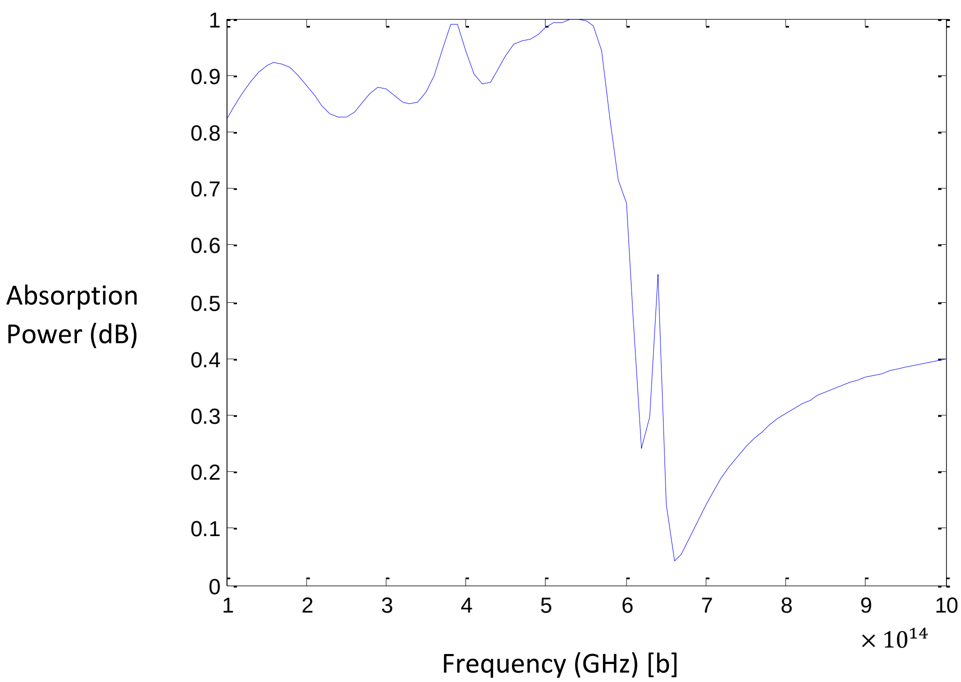


Fig 5.2: [a] Absorption power vs. frequency plot from [39]

[b] Absorption power vs. frequency plot for the proposed algorithm.

Considering the design for solar cells in [39] the absorption power vs. frequency was plotted for $\mu_r = -1$. For the frequency range 1×10^{14} to 6.3×10^{14} the permittivity is negative and for the range 6.4×10^{14} to 10×10^{14} the permittivity is positive. The varying permittivity has an effect on the absorption power. The absorption power increase and is high in the range 1×10^{14} to 6.3×10^{14} and reduces in the range 6.3×10^{14} to 10×10^{14}. Hence after optimization with the proposed particle swarm optimization, from the above fig 5.2 [b] it is visible that the absorption power is increased to a very high value. Approximately more than 25 % increase is observed. But the thickness is comparatively increased to obtain this increase.

Table 5.1: Thickness specification for design of solar cells

Materials	**Proposed Algorithm**
	Thickness (nm)
LHM	2.65159
DIELECTRIC	273.14580
LHM	289.10669
DIELECTRIC	261.77625
LHM	84.59717
TOTAL	**911.27750**

5.4 SUMMARY

In this chapter, the proposed algorithm has been applied to optimize solar cells. This work is carried out due to the growing demand for optimized solar cells. Here the absorption power increase has been given prominence. The absorption power after the application of PSO has proved to give a better efficiency of almost 25% for the design mentioned above.

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

6.1 CONCLUSION

The PSO variant introduced in the work has three modifications, namely, a new range of linearly varying inertia weight to work with most real time and natural order functions that follow the exponential rule, a *mutation* technique to control particles that move too fast and increase exploration capability, and a *velocity restriction* factor that converges the search space exponentially over the given range. The algorithm has been proven to work well for both unimodal and multimodal functions. It can especially tackle multimodal functions better due to the inclusion of the pareto effect in various phases of the algorithm. The algorithm seems to be promising for any number of dimensions with any function and is expected to produce a better solution. This improvised PSO has been applied for the optimal design of broadband microwave absorbers. For a given range of frequency and angle of incidence, number of layers and their corresponding thickness are the factors that can be varied in order to get a desired response. The algorithm produced the best design for microwave absorber for TM polarization and angle of incidence 45° in the frequency range 2-18GHz. Hence the obtained microwave absorber can be used for the design of stealth applications. The same technique has been applied to optimize design of solar cells and has proved to increase the efficiency by 25% with the proposed algorithm. Hence in future the cost of materials required to design the solar cells can be reduced. In future, the proposed algorithm can be used for any number of dimensions and makes it useful in many fields of application. The detection of aircrafts becomes even more difficult strengthening the military. The cost of solar cells can be decreased to a great extent if more modifications can be done on the algorithm. The structural modification of the solar cells can be done using the optimization algorithm. The solar cells can be realized for various angle of incidence and frequencies. It has witnessed a faster growth and enhanced interest due to its social impact towards practical implementation and feasibility.

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