# Optimization of the Return Loss of Differentially Fed Microstrip Patch Antenna Using ANN and Firefly Algorithm

**Rupinder Kaur · Munish Rattan**

**Abstract** The microstrip patch antenna that have more than two feed points or lines is known as differential fed microstrip patch antenna. In this paper, firefly algorithm (FA) and artificial neural network (ANN) has been applied to a 'Flower' shaped differentially fed microstrip patch antenna for optimizing the return loss. This new optimization method is much faster than conventional optimization methods. FA is the new nature-inspired algorithm which is based on the flashing behavior of fireflies in the summer sky in the hot and humid regions. To validate the ability of FA, the results obtained from FA are compared with that obtained using genetic algorithm (GA) and ANN, and it has been observed that FA performs better as compared to GA.

**Keywords** Microstrip patch antenna · Firefly algorithm · Genetic algorithm · Neural networks · Objective function · Optimization · Return loss

## 1 Introduction

Microstrip antennas have many distinct and pleasing properties such as low profile, light weight, compact and conformable in structure, easy to fabricate and to be integrated with different solid-state devices [1]. Therefore, microstrip patch antennas have been widely used in radio systems for different applications. The Radio systems often used microstrip patch antenna for the operation that are usually single ended signals. But now days, radio systems have begun to be designed for differential signal operation, because the differential signal operation is more suitable for high-level integration or single-chip solution of radio systems. Radio systems that used differential signal operation usually requires differential antennas to

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get rid of heavy off-chip and loss on chip balun to improve the transmitter power efficiency and reduce the noise effect due to balun. The microstrip patch antenna that has two or more feeds is known as differential fed microstrip patch antenna (DFMA). There are different types of feeding techniques for microstrip patch antenna such as microstrip feed line, co-axial probe feed, proximity coupled and aperture coupled feed. In order to design any differentially feed microstrip patch antenna mostly co-axial and microstrip feed lines are used. These DFMA's are having different applications such as in [2], it is presented that a differentially-driven microstrip antenna has been merged with a push-pull power amplifier in Gallium Arsenide semiconductor technology, in [3] differentially-driven microstrip antenna has been integrated with a push-pull power amplifier in complementary metal oxide semiconductor technology and in [4] differentially-driven microstrip antenna has been integrated with an oscillator including a buffer amplifier in Silicon Germanium semiconductor technology. The differential receiving microstrip antenna acts also as an input balun that offers a new ability to design small, robust and cost-effective smart antenna arrays.

Recently, many nature inspired optimization techniques such as genetic algorithm (GA), bacterial foraging optimization (BFO), particle swarm optimization (PSO), ant colony optimization (ACO) etc. have been applied to different engineering problems. In this paper, firefly algorithm (FA) has been used for the optimization of return losses of 'Flower' shaped differentially fed microstrip patch antenna. Return Loss is a parameter defined as the loss of a signal power resulting from the reflection caused by the discontinuity in a transmission line. Return loss with a negative sign is known as reflection coefficient. It is also defined as the ratio of the reflected power to the incident power. For any antenna to work efficiently, the value of return loss should be more negative than $-10$ dB. FA is an optimization algorithm influenced by the behavior and motion of fireflies. FA is found to have superior performance in many cases [5]. In order to achieve this, a trained neural network is used as a fitness function which is developed using MATLAB and simulations have been carried out. In the design process of antenna, trained neural network (NN) is used for estimating return loss. In optimization process, a proper objective function is defined and minimized with FA in order to obtain optimum return losses. Neural networks (NN) are extremely helpful in the problems where the relationship between inputs and outputs are not easily modeled. The optimization of return loss of a 'Flower' shaped DFMA has also been obtained using GA and artificial neural networks for comparative evaluation.

After a brief introduction, rest of the paper is organized as follows: Sect. 2 discusses about the DFMA geometry followed by a detailed discussion on firefly algorithm in Sect. 3. Section 4 discusses the steps involved in application of FA and ANN on DFMA. Section 5 consists of the simulation results obtained after applying FA to get the optimized value of return loss and the comparison between FA and GA results. The work has been concluded in Sect. 6.

## 2 'Flower' Shaped Differentially Fed Microstrip Patch Antenna Geometry

In recent years, increasing competition in the wireless communication market has generated the need for fully integrated radio frequency (RF) front-end solutions, for which differential signals are preferable [6]. Because most conventional antennas are single-port devices, a balun is usually used to connect the single-fed antenna and integrated circuits [6]. However the balun is the reason for the loss of signal due to which fully integrated solutions are not obtained. Thus due to balun the efficiency problem rises. When the antenna is excited with a differential signal; the balun is no longer necessary. Thus these differentially fed microstrip
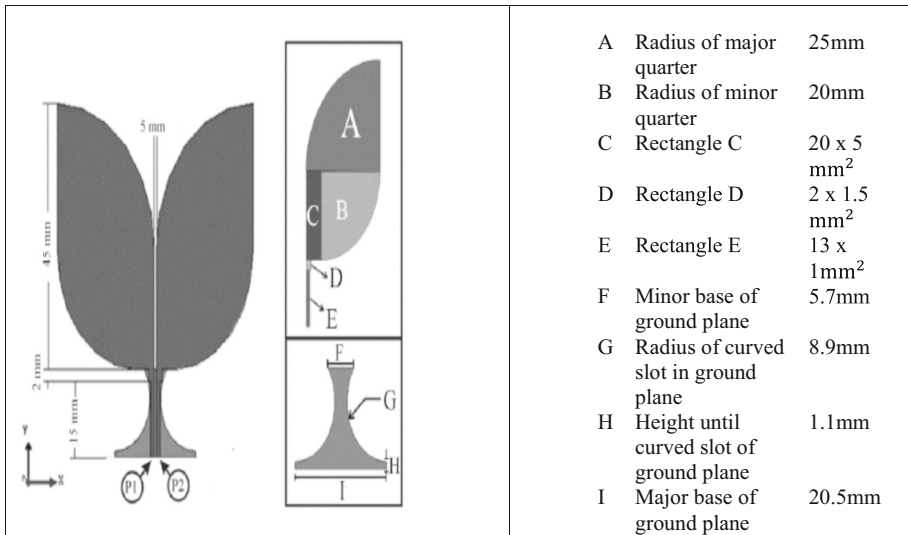
| | | | |
|---|---|---|---|
| A | Radius of major quarter | 25mm |
| B | Radius of minor quarter | 20mm |
| C | Rectangle C | 20 x 5 mm$^2$ |
| D | Rectangle D | 2 x 1.5 mm$^2$ |
| E | Rectangle E | 13 x 1mm$^2$ |
| F | Minor base of ground plane | 5.7mm |
| G | Radius of curved slot in ground plane | 8.9mm |
| H | Height until curved slot of ground plane | 1.1mm |
| I | Major base of ground plane | 20.5mm |

**Fig. 1**  Dimensions for DFMA geometry [6]

patch antennas may help to get rid from the highly heavy balun, due to which these DFMA's are in demand.

### 2.1 Basic Parameters and Antenna Dimensions

In the design of a differentially fed microstrip patch antenna, there are two feed lines required. In our design, microstrip feeding technique is used. In this type of feed technique, a conducting strip is connected directly to the edge of the Microstrip Patch. The conducting strip is smaller in width as compared to the patch and this kind of feed arrangement has the advantage that the feed can be etched on the same substrate to provide a planar structure. The purpose of the inset cut in the patch is to match the impedance of the feed line to the patch without the need for any additional matching element. This is achieved by properly controlling the inset position. The Flower shaped DFMA geometry is designed using IE3D tool box of Zeland program manager 14.0. The basic parameters used for the design of antenna are:

- Height of substrate $= 0.813$ mm
- Dielectric constant $= 3.55$
- Length of patch $= 62$ mm
- Width of patch $= 55$ mm.

In the design of 'Flower' shaped differentially fed microstrip patch antenna, two quarters of circles with different radius are used to build the aperture as shown in Fig. 1 i.e. A and B. The rectangle labeled as C is used to fill the space due to the difference of radius. On the other hand, to obtain differential current between ports P1 and P2, the width and separation of microstrip coupled lines (rectangle E) were calculated to be 50Ω for odd-mode propagation [6]. The optimization of lines required a rectangle D on each line. The ground plane was modified to a curved profile with 8.9 mm of radius on each side (letter G) [6]. All these dimensions of the flower shaped DFMA are shown in Fig. 1.

In this type of feed technique, the conducting strips are connected directly to the edge of the microstrip patch as shown in Fig. 2. The conducting strips are smaller in width as

**Fig. 2** Flower shaped DFMA designed in IE3D software
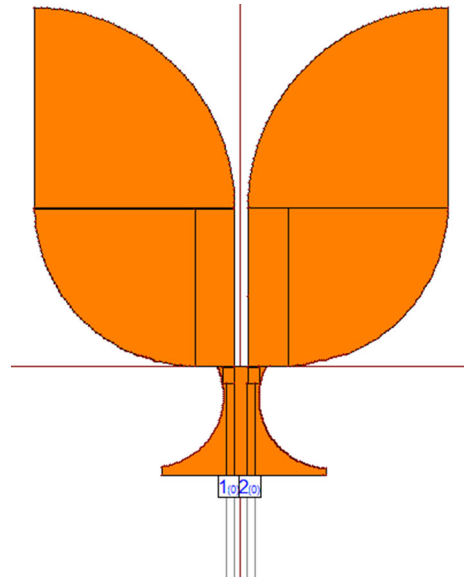


compared to the patch and this kind of feed arrangement has the advantage that the feed can be etched on the same substrate to provide a planar structure. The purpose of the inset cut in the patch is to match the impedance of the feed line to the patch without the need for any additional matching element. This is achieved by properly controlling the inset position and the lengths of the strips. Hence this is an easy feeding scheme, since it provides ease of fabrication and simplicity in modeling as well as impedance matching. The feed radiation also leads to undesired cross polarized radiation. Due to impedance matching, the loss of a signal power resulting from the reflection caused by the discontinuity in a transmission line does not occur. This causes minimization of the return loss.

Figure 2 shows the geometry of flower shaped DFMA designed using IE3D software. After performing simulation using IE3D, next step is to using ANN and FA. Before using ANN we have to prepare a data set using IE3D for the training of neural networks. The data set have 100 samples of two inputs i.e. E1 and E2, and one output i.e. return loss. Where E1 and E2 represent the lengths of microstrip feed lines. The trained artificial neural network has been used as an objective function for the firefly algorithm (FA).

## 3 Firefly Algorithm

Firefly algorithm is proposed by Dr. Xin-She Yang at Cambridge University in 2007 for solving continuous constrained optimization problems [5], and this algorithm is based on the swarm behavior such as fish, insects, or bird schooling in nature [7]. The firefly algorithm (FA) is a metaheuristic, nature-inspired, optimization algorithm which stands on the flashing behavior of fireflies, or lighting bugs, in the summer sky in the tropical temperature zones [8]. The fireflies use bioluminescence with various flashing patterns in order to perform communication with each other and to search the mates [9]. The firefly algorithm has many similarities with other algorithms such as the PSO, Artificial Bee Colony optimization (ABC), and Bacterial Foraging (BFA), based on the so-called swarm intelligence. FA has

much simpler concept and easy to implement. Firefly algorithm is a relatively new member of swarm intelligence family [5].

The firefly algorithm is based on the flashing characteristics of fireflies. For simplicity, we can idealize these flashing characteristics as the following three rules [10]

- All fireflies are unisex so that one firefly is attracted to other fireflies regardless of their sex.
- Attractiveness is proportional to their brightness, thus for any two flashing fireflies, the less brighter one will move towards the brighter one. The attractiveness is proportional to the brightness and they both decrease as their distance increases. If no one is brighter than a particular firefly, it moves randomly.
- The brightness or light intensity of a firefly is affected or determined by the landscape of the objective function to be optimized.

For a maximization problem, the brightness can simply be proportional to the objective function. Other forms of brightness can be defined in a similar way to the fitness function in GAs or the bacterial foraging algorithm (BFA) [11].

In the FA, there are two essential issues: the change of light intensity and formulation of the attractiveness. Generally, we can always assume that the attractiveness of a firefly is obtained by its brightness or light intensity. Further the light intensity is associated with the encoded objective function. In the simplest case for maximum optimization problems, the brightness (B) of a firefly at a particular location (x) can be taken as $B(x) \propto f(x)$. However, the attractiveness $\beta$ should be seen in the eyes of the judged by the other fireflies. Thus, it should vary with the distance $d_{ij}$ between firefly i and firefly j. As light intensity reduces with the distance from its source and another thing is that light is also absorbed in the media or space, so we should allow the attractiveness to vary with the degree of absorption.

In the simplest form, the light intensity B(d) varies with the distance d monotonically and exponentially. That is

$$B = B_o e^{-\gamma d} \qquad (1)$$

where $B_o$ is the original light intensity and $\gamma$ is the light absorption coefficient. As a firefly's attractiveness is proportional to the light intensity seen by adjacent fireflies, we can now define the attractiveness $\beta$ of a firefly by

$$\beta = \beta_o e^{-\gamma d^2} \qquad (2)$$

where $\beta_o$ is the attractiveness at d=0. Schematically, the firefly algorithm (FA) can be summarized as the pseudo code as shown in Fig. 3.

The distance between any two fireflies i and j at $x_i$ and $x_j$ can be defined by the Cartesian distance

$$d_{ij} = \|x_i - x_j\| \qquad (3)$$

The movement of a firefly i is attracted to another more attractive (brighter) firefly j is determined by

$$X_i = x_i + \beta_o e^{-\gamma d_{ij}^2}(X_j - X_i) + \alpha \varepsilon_i \qquad (4)$$

where the second term in Eq. 4 is due to the attraction, while the third term is randomization with the vector of random variables $\varepsilon_i$ being drawn from a Gaussian distribution.

For most of the cases in our implementation, we can take $\beta_o = 1$, $\alpha = [0, 1]$, and $\gamma = 1$.

Generally, the parameter characterizes i.e. the variation of the attractiveness, and its value is mostly important in determining the speed of the convergence and how the FA algorithm

Objective function is f(x), x = $(x_1 \ldots x_y)^T$

Initialize the population of fireflies $x_i$ (i = 1, 2, ..., n)

light absorption coefficient γ is defined

while (t < Max Generation)

for i = 1 : n all n fireflies

for j = 1 : i all n fireflies

Light intensity $B_i$ at $x_i$ is determined by f($x_i$)

if ($B_j$ >$B_i$ )

Move firefly i towards j in all y dimensions

end if

Attractiveness varies with distance d via exp [−γd]

Evaluate the new solutions and update light intensity

end for j

end for i

Rank the fireflies and find the current best

end while

**Fig. 3** Pseudo code for the firefly algorithm

behaves. In theory, γ ε[0, ∞], but in practice, $\gamma = O(1)$ is determined by the characteristic or mean length of the system to be optimized.

In one extreme when $\gamma \to 0$, the attractiveness is constant β = $β_o$. It means that the light intensity does not decrease in an idealized sky [10]. Thus, a flashing firefly can be seen anywhere in the domain. Thus, a single (usually global) optimum can easily be obtained.

In the current optimization problem, light intensity corresponds to fitness function, which is return loss in our case. It is defined as

$$f(x_i) = -S_{11}(i)$$

where $S_{11}$ is the return loss of ith firefly position and each firefly position is corresponds to one antenna geometry. The attractiveness of firefly is an indication of difference in fitness of best firefly and firefly under consideration.

## 4 Applications of FA and ANN on DFMA

The design steps involved have been enlisted below:

*Step 1: Preparing data base training of neural network* To prepare the data base, first a flower shaped base geometry is designed and its return loss is noted. Then 100 different geometries with different feed lengths have been redesigned and simulated and their corresponding return loss values are noted in the form of a table. This table has been used for neural network training.

**Table 1** Values of feed lengths provided by FA

| | |
|---|---|
| Microstrip feed length E1 | 19.657 mm |
| Microstrip feed length E2 | 13.254 mm |

*Step 2: Train the neural network* A feed forward neural network has been designed. It has been trained using the data provided by the table obtained in step 1. This trained neural network will be used as a fitness function in the next step.

*Step 3: Application of Firefly Algorithm* In this step, FA has been applied to the optimization problem. FA needs a fitness function, which is provided by neural network in our case. Various random firefly positions are generated corresponding to different antenna geometries and the fitness value is returned by neural network to the FA for each case. After some fixed number of iterations, the algorithm converges to an optimum fitness value and correspondingly we get the optimal design parameters of antenna.

*Step 4*: The optimal geometries obtained has been designed in IE3D and its actual return loss value is obtained after simulation.

*Step 5*: The results obtained by FA-ANN and actual simulation result given by IE3D has been compared and it has been observed that there is good match between IE3D results and Matlab simulation results.

## 5 Simulation Results and Comparisons

The Firefly algorithm discussed above has been implemented using MATLAB and applied in order to get optimized value of the return loss for the DFMA. Then we have to perform simulations for comparison purpose to ensure that FA is better as compare to GA.

### 5.1 Simulation Results of DFMA Using Values of Feed Lengths Provided by ANN and FA

The configuration of flower shaped DFMA is firstly designed and then simulated using IE3D software. By using training data set obtained from IE3D we have to train artificial neural networks. Process of capturing the unknown information hidden in data is called training of neural networks. The ANN has been trained using 100 samples. The back propagation model has been used with 40 neurons having three layers i.e. input layer, output layer and hidden layer. A trained ANN is taken as objective function in FA for optimization. They learn input–output relationships from given collection of representative examples. After performing the training of neural networks, apply the optimization tool FA to get optimized value of return loss. The parameters used in FA are given as follows:

- Number of generations $= 50$
- Number of fireflies $= 20$
- Randomization parameter, $\alpha = 0.25$
- The attractiveness, $\beta = 0.2$
- The light absorption coefficient, $\gamma = 1$

FA provides optimum value of return loss i.e. $-45$ dB. The microstrip feed lengths provide by FA tool are given below in Table 1.

Using these dimensions of microstrip feed lines, we design the DFMA using IE3D and after simulation we obtain the value of return loss $-45$ dB that is match with the results of FA. The return loss obtained after simulation using FA is shown in Fig. 4.
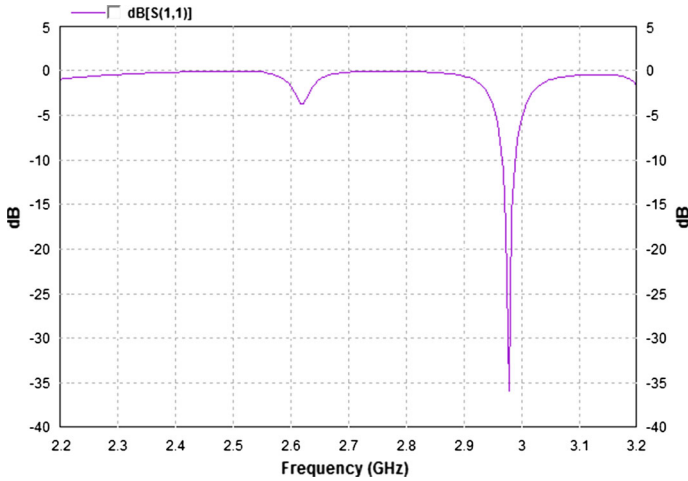
**Fig. 4** Return loss obtained using GA

**Table 2** Values of feed lengths provided by GA

| | |
|---|---|
| Microstrip feed length E1 | 13.333 mm |
| Microstrip feed length E2 | 15.001 mm |

**Table 3** Return Loss obtained using FA and GA

| | |
|---|---|
| Return loss obtained using FA | −45 dB |
| Return loss obtained using GA | −35 dB |

## 5.2 Simulation Results of DFMA Using Values of Microstrip Feed Lines Provided by ANN and GA

In this section, after the simulation of DFMA using IE3D we have to use GA tool in order to get the optimized value of return loss. GAs are an increasingly popular method of optimization being applied to many fields including electromagnetic motivated by Darwin's theories of evolution and the concept of "survival of the fittest". It provides optimum value of return loss i.e. −34.29 dB. The feed lengths provide by GA tool are given below in Table 2.

By using these dimensions of microstrip feed lines, we have designed the DFMA using IE3D software and after simulation we obtain the value of return loss is −35 dB matches with the results provided by GA. Table 3 shows below the results obtained by FA and GA which can also be compared with each other. The return loss obtained after simulation using GA is shown in Fig. 5. On comparing we found that firefly algorithm provides better result that is minimum return loss as compare to GA.

## 6 Conclusion

In this paper, firefly algorithm is employed in order to obtain optimized value of return loss for a differentially fed microstrip patch antenna. Simulation results and the comparative study of FA with GA prove that the optimized return loss obtained by this firefly algorithm is smaller
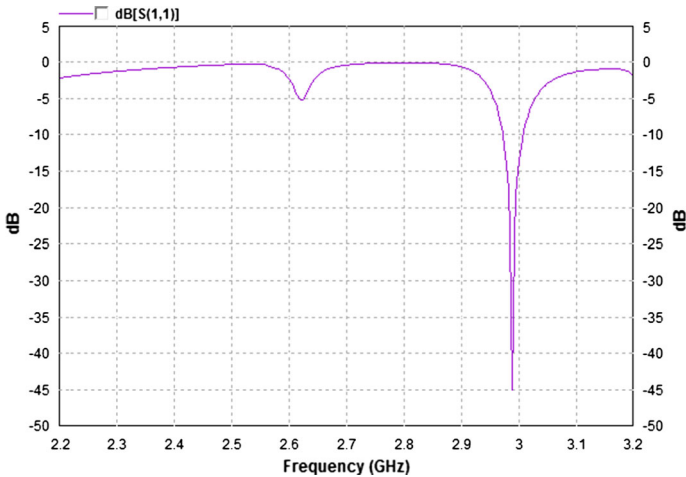
**Fig. 5** Return loss obtained using FA

(better) than that obtained for conventional GA system. The results obtained also depict that the values of the objectives that were aimed at are improved and are more satisfactory when using FA. Further, the firefly algorithm is very simple to implement, less complex and easy to understand. In last, we can conclude that FA is a better option over GA for the optimization of the return loss for a microstrip patch antennas.

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