Evolutionary Technique Based CAD Model for Microstrip Antenna Synthesis

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***Abstract*—Electromagnetic optimization problems are generaly non-convex and continuous, which requires high computational resources. Evolutionary based methods are very much suitable for these type of problems.This paper presents evolutionary based CAD model for microstrip antenna synthesis. Two different CAD models based on GA (Genetic Algorithm) and DE (Differential Evolution) is proposed here for synthesizing a Rectangular Microstrip Antenna. Comparision between the two CAD models is discussed int htis paper. Transmission Line Model (TLM) analysis is considered for the design of the CAD model.The input to the proposed model is desired frequency, and the output is the design parameters of the patch and feed.**

I. Introduction

Microstrip antenna, because of its advantages like smaller size, lower cost, low weight, better performance, ease of fabrication, etc., is now a major research area for the microwave engineers. Development of new patch shapes and integrating the metamaterial concept to microstrip antennas, which have made remarkable miniaturization and more efficient antennas, has made a tremendous impact the research area. However, the difficulty lies with design and analysis of the antennas with unconventional design structures as it needs costly EM simulation tools. Soft computing techniques [1], [2] has been evolved as an alternative to the difficulties. In the recent years, soft computing technique has gained a momentum in application to electromagnetic device and systems.

II. Background Study

In this work we have shown the soft computing technique, GA (Genetic Algorithm) and Differential Evolution (DE), to develop a CAD model for Rectangular Microstrip Antenna (RMPA) synthesis. GA and DE, as an optimization tool, is being widely applied across the disciplines and has solved many engineering problems which include antenna optimization. A new approach to develop a CAD model using the optimization tool is carried out in this paper.The workflow is divided into two sections. First, we have shown the implementation of DE and then GA.

Microstrip antenna theory is well established and documented in [3]. Figure 1 shows a basic structure of a rectangular microstrip antenna with microstrip feeding technique. While designing an antenna, the design parameters or the antenna dimensions are calculated from the complex microwave equations at a particular frequency. For designing an RMPA, four primary design parameters are needed to calculated such as

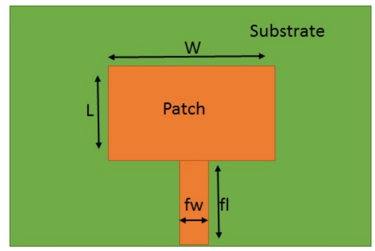

Fig. 1. Microstrip Antenna

patch width W, patch length L, feed width fw and the feed length fl. Along with this the substrate properties, such as the dielectric property and height of the substrate also plays a significant role in antenna design and performance. However, these parameters are to be kept constant as per the availability in the market. In this work, we have demonstrated the calculation of the four primary design parameters at the desired frequency using evolutionary CAD models. The Schematic diagram of the model is shown in figure 2.

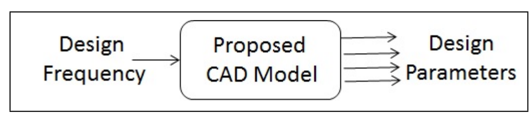

Fig. 2. CAD Model

III. Antenna Synthesis with Genetic Algorithm

Fig 3 is a schematic diagram of genetic algorithm workflow. The algorithm, based on Darwin's theory of "survival of the fittest," is being widely applied across fields of engineering [4]–[7]. GA has got popularity as an optimization, but here we have used it as an estimation tool. We estimate the design parameters of an RMPA. We minimize the following Cost Function to obtain the solution set from GA or the design parameters.

$$F_t = |S_d - S_o|_{\min} \tag{1}$$

where S_d is the Reflection coefficient at desired frequency whose value should be less than -10dB, so that the matching between the antenna and the feed will be such that, maximum power can transferred.S_o is the Reflection coefficient obtained from the solution set generated from GA. To claculate the refelection coefficient and formation of the objective function

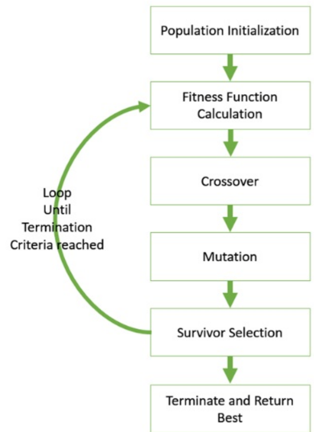

Fig. 3. Genetic Algorithm

is achieved from the equations available for MPA [3]. Equation 2 to equation 6 shows the basic design equations for MPA.

$$W = \frac{c}{2f_r}\sqrt{\frac{2}{\varepsilon_r + 1}} \tag{2}$$

$$\varepsilon_{eff} = \frac{\varepsilon_r + 1}{2} + \frac{\varepsilon_r - 1}{2}\left(\frac{1}{\sqrt{1 + \frac{12h}{W}}}\right) \tag{3}$$

$$L = L_{eff} - 2\Delta L \tag{4}$$

$$L_{eff} = \frac{c}{2f_r\sqrt{(\varepsilon_{eff})}} \tag{5}$$

$$\frac{\Delta L}{h} = 0.412\frac{(\varepsilon_{eff} + 0.3)\left(\frac{W}{h} + 0.264\right)}{(\varepsilon_{eff} - 0.258)\left(\frac{W}{h} + 0.8\right)} \tag{6}$$

The GA is started with a initial solution set $X = \left\{X_i^1, X_i^2, X_i^3, ...X_i^D\right\}$,i $= 1, 2, 3$...........NP, where NP is the number of population and D is the number of parameters. The population generated has a boundary condition as $X_{\max} = \left\{X_{\max}^1, X_{\max}^2, X_{\max}^3, ..., X_{\max}^D\right\}$ $and\ X_{\min} = \left\{X_{\min}^1, X_{\min}^2, X_{\min}^3, ...X_{\min}^D\right\}$

For this work we have set NP=20 and D=4, as we have four design variables. The following are the variables used for generating the intial population.

$$\left\{\begin{array}{l} X_i^1 = w = width\,of\,the\,patch \\ X_i^2 = l = \ length\,of\,the\,patch \\ X_i^3 = fl = microstrip\,feed\,length \\ X_i^4 = fw = microstrip\,feed\,width \end{array}\right\} \tag{7}$$

After initialization, fitness for each individual solution is calculated using eqn 1. Then we moved forward to the evolution process i.e.; crossover is performed. Parent chromosomes are selected on their fitness basis, i.e., two individuals with the best fitness are chosen, and the binary encoding is done to perform the crossover. The single point crossover was conducted on the parent set. Further mutation is performed to obtain child chromosomes, in which a randomly chosen bit is flipped. After mutation process is over fitness is evaluated for both parent and child chromosomes. The fittest chromosomes were added to the population set, and the rest are discarded. However, we noticed that some problems were associated with this process because of which convergence could not be achieved. During mutation process, there is a possibility that an MSB of the binarily coded chromosomes will flip and it will result a big change in the solution set. This problem was solved with gray coding, instead of binary coding. When the mutation problem was solved with gray coding, still the problem resist while converting the solution set to binary, as floating point numbers were difficult to handle. Therefore instead of any kind of coding, we opted direct coding. In direct coding we were able to get the solution, but the algorithm was inconsistent. The inconsistency was there because of the parent selection process. Some the parents becomes so dominant that, other chromosomes do not get a chance to participate in further generations, resulting in non-convergence of the algorithm. So, instead of choosing the fittest chromosome, we used tournament method of parent selection, where each chromosome get a fares chance to go to the next generation, and the diversity is maintained. Other parent selection methods were also applied, but the combination of direct coding with tournament selection yield a better result. The obtained Results are discussed in later in this paper and compared with the results of DE-CAD model results.

IV. Antenna Synthesis with Differential Evolution

Storn and Price [8] proposed an optimization algorithm based on population-based stochastic search technique, which was widely accepted by researchers across the discipline [9]–[11] The schematic algorithm flow of DE is shown in figure 4. Unlike GA, in DE, after initialization, mutation operation is performed in the first stage followed by crossover and selection. In the 1st stage of the algorithm design parameters and the solution range is given. And the end of the algorithm, i.e. at selection step, the solution set is evaluated for the objective function and the best solution set selected. The total number of iterations is dependent upon the termination criteria. There two major factors, scaling factor (F) and crossover rate (CR), which controls the convergence of the algorithm [12].

Similar to GA based CAD model, design parameters such as W, L, fw and fl are the output of the proposed CAD model whereas the design frequency is the input.

The objective function is formulated such as, at the given design frequency the return loss will be less than or equal to -10dB and the impedance will be 50ohm. Cost function for DE-CAD model is same as that of GA-CAD model, as shown in eqn 1. In the first step of the algrithm , the initial

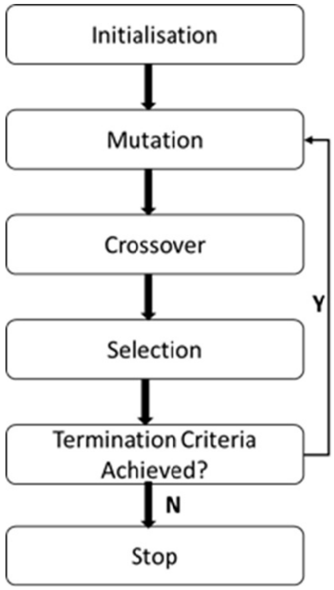

Fig. 4. Differential Evolution

population is generated with the variables as shown in eqn 7. From the different availble mutation strategies we have adopted DE/rand/1 method, and a mutant vector is generated as $V_i = \{v_i^1, v_i^2, v_i^3, ...v_i^D\}$, where D is the dimension of the solution set. A new set of population is generated using eqn 8, where F is the scaling factor and r_1, r_2 and r_3 are random generated variables.

$$V_i = X_{r_1^i} + F.(X_{r_2^i} - X_{r_3^i}) \tag{8}$$

After mutation is over crossover is performed on each pair of X_i and its corresponding V_i, which generates a trial vector as $U_i = \{u_i^1, u_i^2, u_i^3, ...u_i^D\}$. We have done the binomial crossover, expressed in eqn 9

$$U_i^j = \left\{ \begin{array}{ll} v_i^1 & if\ ((rand_j[0,1) \leq CR\ or\ (j = jrand) \\ x_i^j & Otherwise \end{array} \right\} \tag{9}$$

Where $j = 1, 2, 3, ...D$, CR is the crossover rate with aspecified parameter value as $[0, 1)$ and j_{rand} =Randomly generated integer within the range $[1, D]$. Selection is the final step in the algorithm in which best parameter set is selected by comparing the newly generated solution set from crossover with the initial population. The parameter set with better fitness value is included in the population and the rest are discarded. the selection procedure can be written mathematically as eqn 10.$f(U_i)$ and $f(X_i)$ are calculated from the cost function shown in eqn 1

$$X_i^j = \left\{ \begin{array}{ll} U_i^1 & if\ f(U_i^1) \leq f(X_i^1) \\ X_i^j & Otherwise \end{array} \right\} \tag{10}$$

The process is repeated till the stopping criteria is fulfilled. The Values for scaling factor(F) and cross over rate(CR) are chosen within the range of $0.4 < F < 1$ and $0.3 < CR < 0.9$. However, there is no literature available how to chose the scaling factor(F) and cross over rate(CR), hence we started with values 0.4 and 0.3 for scaling factor and crossover rate respectively and modified the values by observing the convergence of the algorithm. We found that 0.5 and 0.7 are the optimal values of F and CR for our work.

V. Results and Discussions

We have compared the results obtained from both the CAD models (GA and DE). Table I shows the results obtained from DE based CAD model. Population size was taken 40. The mutation strategy for DE is taken as $DE/best/1$. FR4 substrate is considered in this work with $1.59mm$ of thickness and with a dielectric constant of 4.3. We have compared the performance of the CAD models at three different frequencies.

TABLE I
Design Parameters obtained from DE-CAD model

Design Freq. (GHz)	Return loss (dB)	Impedance (ohm)	Patch Width (mm)	Patch Length (mm)	Feed Length (mm)	Feed width (mm)
3	-30	47.46	41.3	11.3	44.5	2.8
3.5	-15.05	40.99	36.5	30.1	36.1	4.9
4	-39.7	47.7	27.5	27.2	41.3	2.1

In table II the results for GA-CAD model is shown. Population size for GA-CAD model is 40. Direct coding method is adopted for this model. Tournament parent selection with single point crossover is performed. Total number of generation was taken 500.

TABLE II
Design Parameters obtained from GA-CAD model

Design Freq. (GHz)	Return loss (dB)	Impedance (ohm)	Patch Width (mm)	Patch Length (mm)	Feed Length (mm)	Feed width (mm)
3	-17.9	82.35	27	11.1	44.7	3.4
3.5	-14.6	87	39.9	29.9	42.6	4.3
4	-26.5	34.7	39.92	26.7	34.5	5.8

It is observed that for both the models the return loss at designed frequency is below 10dB and the impedance is nearly 50ohm for DE-CAD model whereas fpr GA-CAD model impedance matching is not good, which states that the designed antenna from DE-CAD model is in good matching with the feeding probes. Fig 5 and fig 6 shows the output for three design frequencies, for DE-CAD nad GA-CAD model respectively.

VI. Conclusion

The developed CAD models based on DE nad GA is an efficient and fast computing method for RMPA synthesis. As we know TLM analysis is a approximated model, the accuracy can be improved with surrogate model approach. However DE-CAD model was found more accurate and robust. The impedance matching in GA-CAD model was not good Further similar CAD models can be developed for other antennas also.

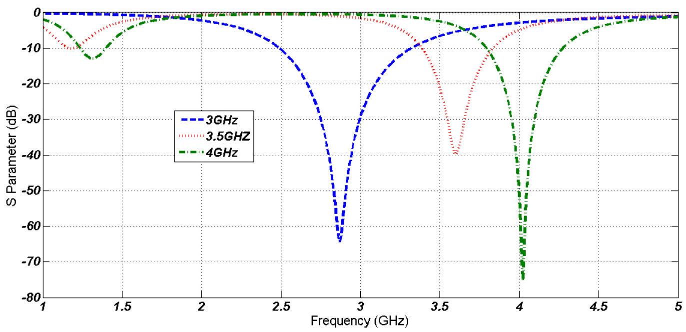

Fig. 5. DE-CAD Model Output

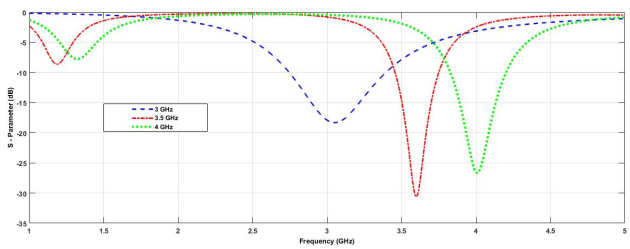

Fig. 6. GA-CAD Model Output

This models can also be integrated with the surrogate based models to synthesise slotted patch antennas, for which direct formla is not available.

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