Hybrid BSCF Genetic Algorithms in the optimisation of a PIFA Antenna

AMEERUDDEN Mohammad Riyad, RUGHOOPUTH Harry C. S
Department of Electronics and Communication Engineering
University of Mauritius
Réduit, Mauritius
ameerudden_riyad@infosys.com

Abstract **- With the exponential development of mobile communications and the miniaturization of radio frequency transceivers, the need for small and low profile antennas at mobile frequencies is constantly growing. Therefore, new antennas should be developed to provide both larger bandwidth and small dimensions.**

This paper presents an intelligent optimisation technique using a hybridized Genetic Algorithms (GA) coupled with the intelligence of the Binary String Fitness Characterization (BSFC) technique. The aim of this project is to design and optimize the bandwidth of a Planar Inverted-F Antenna (PIFA) in order to achieve a larger bandwidth in the 2 GHz band. The optimization technique used is based on the Binary Coded GA (BCGA) and Real-Coded GA (RCGA). The optimisation process has been enhanced by using a Clustering Algorithm to minimize the computational cost. During the optimization process, the different PIFA models are evaluated using the finite-difference time domain (FDTD) method.

Index Terms – BCGA, BSFC, Genetic Algorithms; Hybrid GA, PIFA, RCGA

I. Introduction

The Planar Inverted-F Antenna (PIFA) is the most widely used antenna owing to its low profile, simple structure and ease of fabrication, and primarily its high efficiency and wideband characteristic. Recently, PIFAs have been drawn much attention in antenna design and manufacturing as published in [1] and [2] papers. High gain of antennas, which is an important characteristic in terms of their performance, may only be attained through proper design and structure. However, there are many parameters, such as the sizes of the radiating elements, position of feeding wires, etc. that challenge engineers and manufacturers to design smaller antennas. The objective of this work is to maximize the bandwidth of a PIFA antenna while keeping its overall size small. While doing so, the optimization techniques have been analyzed to find a better convergence mechanism when applied to the modeling method.

A. Modelling methods

To analyze electromagnetic propagation in space, there exist different kind of three-dimensional full-wave methods and among these, three methods have become the most popular: the Finite Element Method (FEM), the Transmission Line Matrix (TLM) and the Finite Difference Time Domain (FDTD) method.

The application of these methods requires the use of powerful computers and delivers good approximation of electric and magnetic field propagation. To evaluate the performance of the antenna and observe the three-dimensional propagation of the electric and magnetic fields, the FDTD method was used.

B. Optimisation techniques

Owing to nonlinearities and complex interactions among problem variables, a search space may have more than one optimal solution. When solving problems, there is no escape if traditional methods get attracted to any of these locally optimal solutions.

Evolutionary algorithms, on the other hand, are based on the principles of biological evolution as explained [3]. Genetic algorithms (GA) are a class of evolutionary algorithm which provides optimization capabilities to a wide range of problems. Some of the issues that affect the traditional tools also affect GAs, but GAs have proved to be far more robust at handling complex and non-linear problems. The GA can providentially alleviate the difficulties of the sub-optimal solution. In this work, several GA techniques have been experimented and their behaviors have been analyzed in an attempt to find out the best optimization mechanism.

II. Methodology

The method used in this project involves the modeling of the PIFA using the FDTD method through which the bandwidth of the antenna is evaluated. The bandwidth is adjusted by varying some of the key parameters of the antenna in the optimization process so as to converge to the optimal performance. As part of the analysis work, different GA techniques have been experimented to analyze the convergence behavior towards the best solution.

A. Implementation of FDTD

FDTD starts by discretizing a three-dimensional space into rectangular cells, which are called Yee Lattice [4]. The Yee lattice is specially designed to solve vector electromagnetic field problems on a rectilinear grid. The grid is assumed to be uniformly spaced, with each cell having edge lengths Δx, Δy and Δz. Fig. 1 shows the positions of fields within a Yee cell.

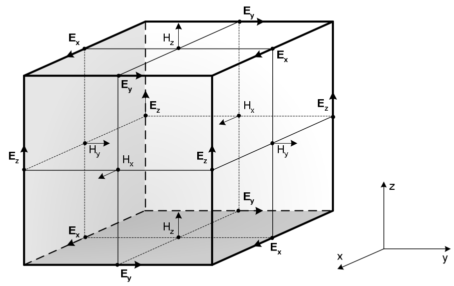

FIGURE 1. An FDTD cell or Yee cell showing the positions of electric and magnetic field components

Every E component is surrounded by four circulating H components. Likewise, every H component is surrounded by four circulating E components. In this way, the curl operations in Maxwell's equations can be performed efficiently.

Arrays must be used to represent the discrete space into a high-level programming language. One-dimensional space is represented by a 1D array, similarly 2D and 3D discrete spaces are represented by 2D and 3D arrays respectively. As explained in [5], the electric and magnetic equations are expressed in Array Space as

$$H_x^{n+\frac{1}{2}}(i,j,k) = H_x^{n-\frac{1}{2}}(i,j,k) - \frac{\Delta t}{\mu}\left[\frac{E_z^n(i,j+1,k) - E_z^n(i,j,k)}{\Delta y}\right] + \frac{\Delta t}{\mu}\left[\frac{E_y^n(i,j,k+1) - E_y^n(i,j,k)}{\Delta z}\right] \quad (1)$$

where $\alpha = \dfrac{\dfrac{\varepsilon'}{\Delta t} - \dfrac{\sigma_{eq}}{2}}{\dfrac{\varepsilon'}{\Delta t} + \dfrac{\sigma_{eq}}{2}}$ and $\beta = \dfrac{1}{\dfrac{\varepsilon'}{\Delta t} + \dfrac{\sigma_{eq}}{2}}$.

1) FDTD onto PIFA

After having discretized the computational space and time, the FDTD has to be applied to the PIFA in order to simulate the propagating E-fields and H-fields. The structure of the PIFA varies according to the different context in which it is used. This work deals only with the basic geometry of a PIFA which normally consists of a ground plate, a radiating plate and a feeding wire. To excite the PIFA with a wide range of frequencies, a Gaussian pulse implemented as soft source has been used as the excitation source. The source is represented by the feeding wire of the PIFA.

2) Absorbing Boundary Condition

Various absorbing boundary conditions have been used for truncating the FDTD mesh in this project, and among those, the Higdon boundary condition, the Dispersive boundary condition and the Mur's second-order boundary condition provide minimal reflection. However the Higdon boundary and Dispersive boundary do not provide significant attenuation over the frequency range of interest. Thus, because of its effectiveness, the Mur's second order boundary condition has been used in all the numerical results presented in this work.

3) Source

In order to excite the PIFA structure, ideally the field distribution of the dominant mode in the plane of excitation would be used. However, this distribution is not accurately specified for an arbitrary geometry. Instead, a y-directed electric field can be used to excite the antenna. A Gaussian pulse implemented as soft source is used as the excitation source and this is given by the equation

$$E(t) = \cos(\omega_o t)\, e^{-\frac{t^2}{2\tau^2}} \quad (2)$$

where ω is 2π f and f is the frequency of the pulse, t is the time step and τ controls the width of the pulse.

4) Performance Evaluation

The Voltage Standing Wave Ratio (VSWR) is the key to obtaining the bandwidth of the PIFA and thus, the key to achieve the objective of this project. In order to obtain the VSWR, the input impedance of the PIFA has first to be determined. The generalized input or line impedance can be simply calculated using the line voltage and current at a fixed point on the transmission line. These are obtained by Fourier transforming the time-dependent voltages and currents. Using the input impedance calculated, the S11 parameter can be obtained and consequently the VSWR is calculated as

$$VSWR = \frac{1 + |S_{11}|}{1 - |S_{11}|} \quad (3)$$

$$\alpha + \beta = \chi. \qquad (1) \qquad (1)$$

B. Implementation of the GA

The GA is the engine driving the optimisation process and the FDTD modelling forms part of the fitness evaluation of the optimisation. The GA begins its optimisation with an initial random population, evaluates the fitness of each solution and selects the best ones for convergence towards the optimal solution, which will result to the best bandwidth performance, therefore the optimal antenna design. Following the previous work done in this area where different techniques were studied, this work presents further experimentation which involves the BSFC. In this work, the GA has been enhanced using a novel hybrid technique combining both BCGA and RCGA.

1) BSFC

In GA, selecting parents based on their fitness value, whether using absolute values, tournaments or a ranking system, is by far one of the most important conditions to satisfy in order to have a population evolving in the right direction. However, as demonstrated in [6] considering an individual in terms of a single value can be often limiting. In a typical GA problem, an individual may be very good at certain aspects of the problem and very poor at others. Consequently, considering only a consolidated overall fitness value for an individual may ignore the individual's detailed task-wise performance. In this regards, this technique has been applied in this project and the population strengths and weaknesses has been considered for the fitness evaluation.

As part of this process, an efficient pairwise parent selection process, the Comparative Partner Selection (CPS) [6] has been used for the crossover operation. This method aims to minimise the population variance throughout the iteration process. The objective is to maintain the search period of the optimisation process, while individuals that do not satisfy all training cases equally (i.e., having a BSFC consisting of ones) do not dominate the population. Unlike other proposed methods to maintain diversity as evolution proceeds, the process experimented in this work is an effective mechanism for problem decomposition. The idea is to maintain a population that is capable of solving all training cases equally and has a good overall fitness value. The probability of crossover is devised in such a way that two similar individuals in terms of BSFC is less likely to happen than the crossover of two individuals with considerable difference in weaknesses.

2) Hybrid BSFC with Clustering

The analysis and work done in the fitness evaluation area [6], [7] has highlighted the benefits of the BSFC. However, when applied to the current problem, it has been observed that the performance varies, and in most of the cases the process of converging to the optimal solution takes longer, as compared to the previous techniques experimented.

Therefore, in order to optimise the process and computation time in this work, the Clustering algorithm has been applied along with the BSFC concept. The clustering GA helps to reduce the cost of evaluation and accelerate the convergence [8]. Fig. 2 illustrates the conventional GA and the clustered GA.

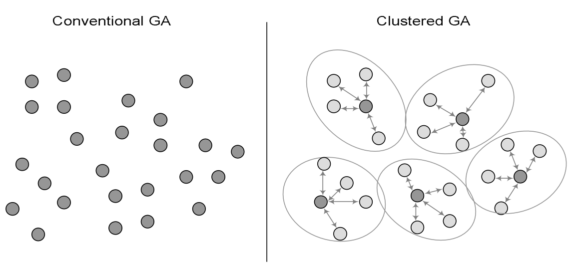

FIGURE 2. Conventional GA vs. Clustered GA

As illustrated in Fig. 3, clustering is a simple method of grouping the population into several small groups, called as clusters [9]. The algorithm evaluates only one representative for each cluster. The fitness of other individuals is estimated from the representatives' fitness. Using this method, large population can be maintained with reasonably less evaluation cost. One of the important factors to take into consideration for clustering is the similarity measure. This is commonly achieved using distance measures such as Euclidean distance, City block distance and Minkowski distance [10]. Computation of the distance is generally done using equation

$$d_y = d(X_i, X_j) = m\sqrt{\sum_{k=1}^{p} \left| x_{ik} - x_{jk} \right|^m} \quad (4)$$

where m=1, m=2 and m ≥ 3 for City block distance, Euclidean distance and Minkowski distance respectively. In order to adapt to the project situation, a combination of binary-coded and real-coded has been used. The BCGA has been used for the BSFC and evaluation process whereas the RCGA has been used for better clustering.

III. Experimental Results

A succession of tests was carried out throughout the work to check whether the implementation of the FDTD was appropriate to evaluate the performance of the PIFA. These tests were carried out using different boundary conditions, different excitation pulses and different computational space size. The PIFA was excited using a Gaussian waveform of frequency ranging from 1.9 GHz to 2.5 GHz. The feeding point, that is, the source location was varied by adjusting the parameters fx and fz. The height of the radiating plate from the ground plate was also varied by changing the value of another parameter 'h'. The variation of the height was quite small (approximately 2mm) since the idea of the project is to maximize the bandwidth of the PIFA while keeping the overall dimensions constant. Fig. 3 shows the electromagnetic propagation simulated from the FDTD. The bandwidth is defined by the range of frequencies where the VSWR is less than 2, which represents the 2GHz range. A graph of VSWR against frequencies, as shown in Fig. 4, is plotted to show how the bandwidth is obtained.

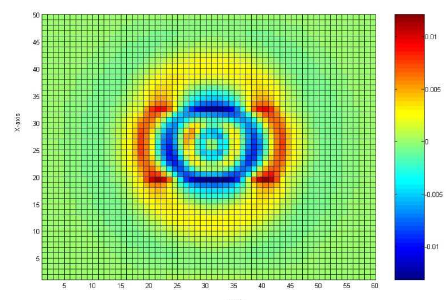

FIGURE 3. Electromagnetic propagation from PIFA using FDTD

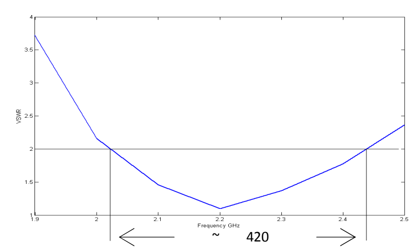

FIGURE 4. Graph of VSWR v/s frequency

The bandwidth obtained from the simulation is approximately 420 MHz. This is the optimal solution generated by the GA. The ground and radiating plates' dimensions were set to 50x26mm and 22x14mm respectively. The values of the parameters used for achieving this particular bandwidth are fx = 3 cells (6mm), fz = 3 cells (6mm) and h = 4 cells (8mm). The results could be enhanced if the population size of the GA was bigger and if the number of discrete values used for the parameters were larger. However, as mentioned previously, this would cause the simulation to last longer.

As for the GA process, the figures 5 and 6 illustrate the results obtained from the different techniques which were experimented. It is observed that convergence using the clustered BSFC is smooth and less costly, in terms of performance, but happens over more iteration, owing to the fact that the fitness is estimated through clustering and evaluated using BSFC.

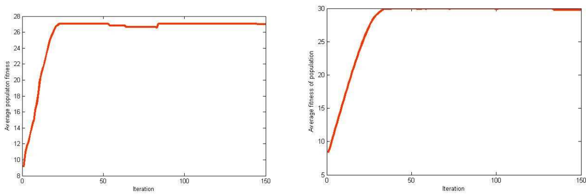

FIGURE 5. Convergence trend without and with BSFC

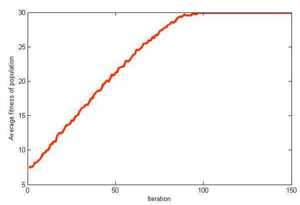

FIGURE 6. Convergence trend with Clustered BSFC

IV. CONCLUSION

A. *FDTD Outcome*

The results show that at different positions of the feeding wire of the PIFA, different waveforms are generated and therefore different values of the input impedance and of the VSWR are obtained. The frequency of the Gaussian source was chosen at random for each of the source locations. The simulated results also show how the E-fields in between the radiating plate and the ground plate are highly concentrated and how they attenuate and fade out as they propagate in the surroundings.

The FDTD technique was found to be a very powerful tool for the analysis of electromagnetic propagation. However, the FDTD method is limited by the amount of computational memory storage required, which depends on the complexity of the problem structure. The total storage requirement for a given computation can be determined by considering that each three-dimensional FDTD cell requires six real number storage places for the six field components, and an additional large storage for the number of iterations.

One of the area of improvement identified is to optimize the processing logic and calculation logic which are currently used. Optimisation can be done in the codes itself, whereby loops and conditional statements can be re-written to make the computational complexity less. The Space and results precision can also be altered such that reasonable output can be achieved by decreasing the computational space.

B. *GA Outcome*

While the BCGA and RCGA have shown to be very good optimization methods, it has been observed that both may get stuck to sub optimal solution. The BSFC/CPS method was experimented with 150 runs for our PIFA problem and the convergence gain is visible in terms of average fitness and the number of runs ending in optimal (zero error) solutions is increased.

However, even though, the BSFC/CPS driven GA outperforms the others methods in terms of convergence, an increase in computational cost has been observed. In this regards, the clustering mechanism, has been applied. Consequently, this has led to an increase the number of iterations to reach the optimal solution but the computational cost is much lower. As such, a proper trade-off between convergence and performance could be observed.

The future work in this area will focus on improving crossover and mutation operators in RCGA and experimenting the combination of different operators for a self-adaptive behaviour. One of the approaches in improving the crossover operator would be to use Laplace distribution.

ACKNOWLEDGMENT

I would like to thank the Tertiary Education Commission (TEC) of Mauritius for sponsoring my post graduate research work at the University of Mauritius. I am also grateful to my wife, Shehzanah, whose understanding and ability to put things back in perspective at critical times have been very helpful.

REFERENCES

[1] Lehu Wen, Yingzeng Yin, Yan Wang, Jingxiu Huang, Xueshi Ren, Shaoli Zuo, "A novel PIFA antenna for broadband circular polarization", Microwave and Optical Technology Letters - Wiley Online Library, Nov 2010.

[2] Quevedo-Teruel O., Pucci E. and Rajo-Iglesias E., "Compact Loaded PIFA for Multifrequency Applications", Antennas and Propagation, IEEE Transactions, Vol. 58 Issue 3, March 2010.

[3] Whitlet D., Mathias K., Rana S., and Dzubera J., "Evaluating evolutionary algorithms", Artifical Intelligence, 1996.

[4] Yee K. S., "Numerical solution of initial boundary value problems involving Maxwell's equations in isotropic media", IEEE Trans. Antennas Propagat., vol. AP-14, pp. 302-307, May 1966.

[5] Gedney and Maloney, "Finite Difference Time Domain modeling and applications", FDTD Short Course, Mar. 1997.

[6] Peter Day and Asoke K. Nandi, "Binary String Fitness Characterization and Comparative Partner Selection in Genetic Programming", IEEE Trans. Evol. Comput., 2008.

[7] R. I. (Bob) McKay, "Fitness sharing in genetic programming," in Proc. Genetic and Evol. Comput. Conf. (GECCO-2000), D. Whitley, D. Goldberg, E. Cantu-Paz, L. Spector, I. Parmee, and H.-G. Beyer, Eds., Las Vegas, NV, Jul. 10–12, 2000, pp. 435–442.

[8] Seront, G. and Bersini, H., "A new GA-local search hybrid for continuous optimization based on multi level single linkage clustering," Proc. of GECCO-2000, pp.90~95, 2000.

[9] Gose, E., Johnsonbaugh, R. and Jost, S., "Pattern Recognition and Image Analysis", Prentice Hall PTR, 1996.

[10] Kandel, A., Fuzzy Techniques in Pattern Recognition, A Wiley-Interscience Publication, 1982.