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Smart Hybrid Genetic Algorithms in the bandwidth optimization of a PIFA Antenna

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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 a smart optimization technique using a hybridized Genetic Algorithms (GA) and comparison with more classical GA techniques. The hybridization involves primarily a clustering mechanism coupled with the intelligence of the Binary String Fitness Characterization (BSFC) technique. The optimization engine is applied to the design of a Planar Inverted-F Antenna (PIFA) in order to achieve an optimal bandwidth performance in the 2 GHz band. During the optimization process, the PIFA is modeled and evaluated using the finite-difference time domain (FDTD) method.**

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 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 GA optimization techniques have been analyzed to find a better convergence mechanism when applied to the modeling method.

The GA is a very powerful search and optimization tool which works differently compared to classical search and optimization methods. GA is nowadays being increasingly applied to various optimizing problems owing to its wide applicability, ease of use and global perspective.

The GA tool actually provides interesting insight into the design and optimization of antennas. As described in [3] GAs are able not only to optimize performance of existing antenna designs, but also to create new kinds of antennas with highly counterintuitive designs. Using a GA, it is possible to prescribe the desired performance of an antenna and allow the computer to find the parameters for the optimal design.

Previous researches [4] have demonstrated that GAs are being applied to many different antenna designs. GAs are very suitable in the engineering areas as antenna principles, which are a subset of electromagnetics and founded on Maxwell's equations, are complex to understand and grasp intuitively.

One of the studies which are more relevant to the context of this project have explored the design and optimization of PIFA antennas using FDTD and GA [5], with focus on standard GA technique.

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.

This paper presents a smart hybridized GA which has been applied to the FDTD modeling technique and the performance analysis has been extended and compared using other GA techniques.

II. Methodology

The methodology 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 and fine-tuned by varying some of the key parameters, such as the height of the radiating plates or the position of the feeding wire of the antenna. The optimal performance is achieved using the GA technique. As part of the optimization work, different GA techniques have been experimented to analyze the convergence behavior towards the best solution.

A. Implementation of the FDTD

FDTD starts by discretizing a three-dimensional space into rectangular cells, which are called Yee Lattice [6]. 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

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and Δz. Fig. 1 shows the positions of fields within a Yee cell.

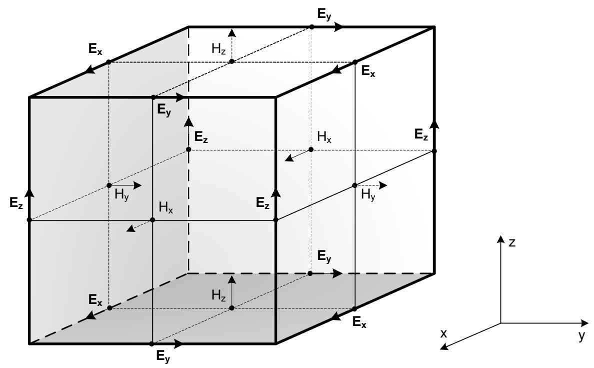

Fig. 1. An FDTD cell or Yee cell showing the positions of electric and magnetic field components.

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 [7], 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 $\beta = \dfrac{1}{\dfrac{\varepsilon'}{\Delta t} + \dfrac{\sigma_{eq}}{2}}$.

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.

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.

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

$$VSWR = \frac{1+|S_{11}|}{1-|S_{11}|}. \quad (2)$$

B. Implementation of the GA

The GA is the engine driving the optimization process and the FDTD modeling forms part of the fitness evaluation of the optimization. The GA begins its optimization 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. As this is a binary problem, the BSFC, when using the proposed CPS method, consist of ones representing correct outputs and zeros representing outputs which are incorrect. For the PIFA consisting of 5 different parameters, in this context, the BSFC length was taken as 32 bits.

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 [8] 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) [8] has been used for the crossover operation. This method aims to minimize the population variance throughout the iteration process. In the CPS process, the fitness value can be seen as the probability of two individuals mating and the mathematical formula of this probability can be expressed as

$$p_c(f_1, f_2) = \frac{\sum \mathrm{XO}R(f_1, f_2)}{\sum \mathrm{XO}R(f_1, f_2) + \mathrm{NO}R(f_1, f_2)}, \quad (3)$$

where f_m is the binary fitness string of individual m and Σ represents the summation of each bit in the binary string.

The objective is to maintain the search period of the optimization 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) Smart Hybrid GA

The analysis and work done in the fitness evaluation area [8], [9] 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 other techniques experimented.

Therefore, in order to optimize the process and to bring more intelligence to the computation, 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 [10]. Fig. 2 illustrates the conventional GA and the clustered GA.

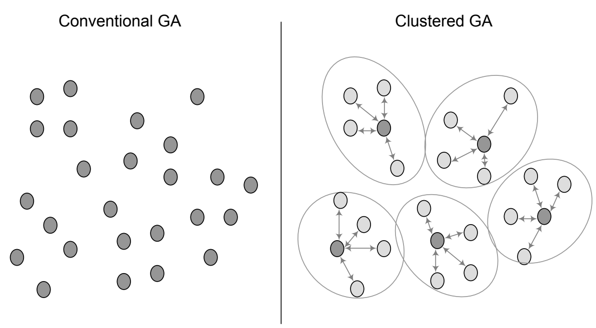

Fig. 2. Conventional GA vs. Clustered GA.

Clustering is a simple method of grouping the population into several small groups, called as clusters [11]. 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. Computation of the distance is generally done using equation

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

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.

In this project, the initial setup has been adjusted to fit the PIFA optimization context. A large enough population size of 100 individuals was initialized. The number of bits, representing the problem variables, has been increased so as to have more relevant and significant outcome. Finally to cater for the hybridized approach, the number of individuals in the cluster has been setup to 5.

The run parameters are described in the table 1.

TABLE I
INITIAL SETUP AND PARAMETERS

Parameter	Setup Value
Number of generation	150
Population size	100
Number of problem variables	50
Number of individual in a cluster	5
Genetic operators	Crossover, Mutation
Selection operator	CPS
Operator probabilities	0.9, 0.1

The high level process experimented is illustrated in Fig. 3.

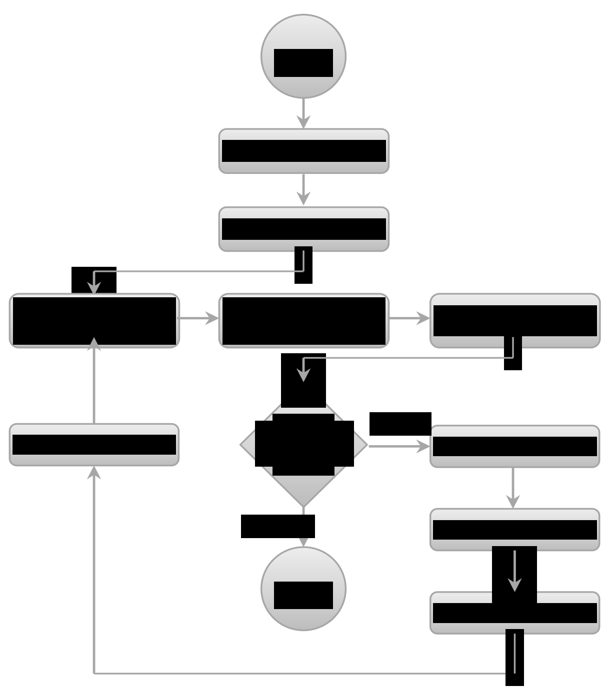

Fig. 3. High level workflow of the Smart Hybrid GA.

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. Fig. 4 shows the electromagnetic propagation simulated from the FDTD.

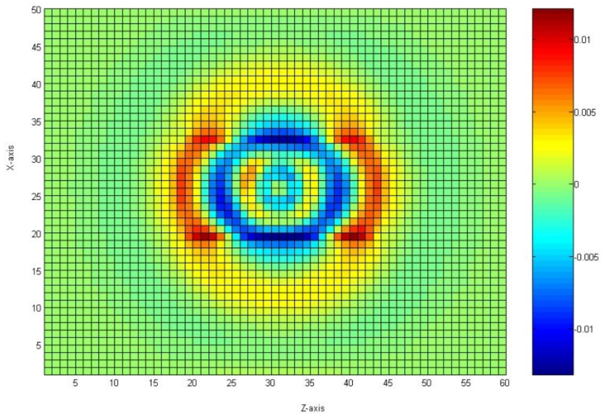

Fig. 4. Electromagnetic propagation from PIFA using FDTD.

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. 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. 5, is plotted to show how the bandwidth is obtained.

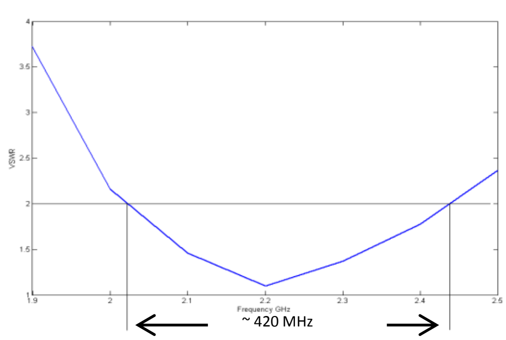

Fig. 5. Graph of VSWR v/s frequency.

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 much longer.

The Binary Coded GA has proved to be a very good optimizing tool and if used properly, it may serve to solve various problems of search and optimization. Classical optimizing methods usually take much longer time to find the optimal solution as compared to the Binary GA method. Fig. 6 shows one of the convergence trend of the BCGA during the simulation.

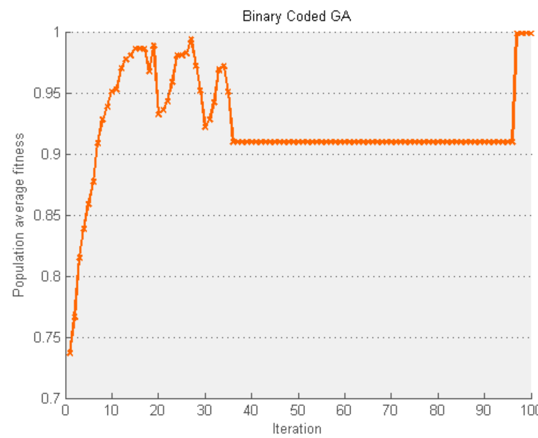

Fig. 6. BCGA Convergence.

The Real Coded GA has been chosen as the alternative for Binary Coded GA. One of the most important features of the RCGA is its capacity to exploit local continuities. Owing to the use of real parameters in RCGA, large domains for the variables can be used as opposed to BCGA implementations where increasing the domain would decrease the precision. In our work, the convergence towards the optimal solution was seen to happen more quickly. However, owing to large computational space and real valued parameters, the RCGA took significantly more time for the optimisation and simulation. Fig. 7 shows one of the convergence trends of the RCGA, which is noticeably smoother than the BCGA.

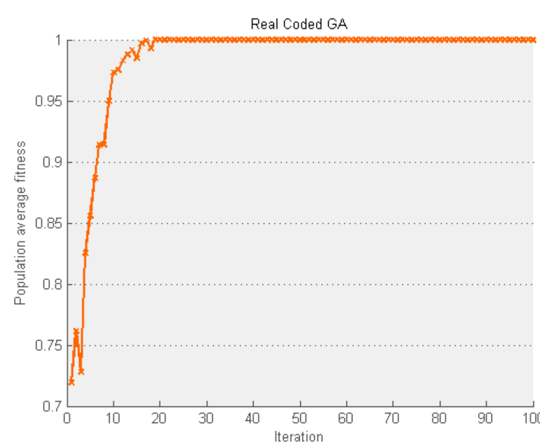

Fig. 7. RCGA Convergence.

The GA by clustering, on the other hand, has shown to converge efficiently to the optimal solution. The computational cost is much lower than RCGA and consequently, the population size could be increased without considerably affecting the performance of the optimisation. Fig. 8 shows one of the convergence trend of the Clustering GA during the simulation. The convergence seems to be longer than the RCGA but performance is much better because of the FDTD evaluation of only the representatives of each cluster.

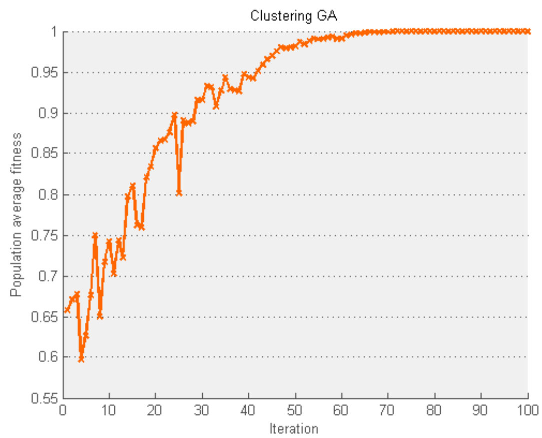

Fig. 8. Clustered GA.

The BSFC/CPS method was experimented on the PIFA problem in an attempt to further enhance the GA optimisation process. From the outcome of the simulation, it is observed that the convergence gain is obvious in terms of average fitness and the number of runs ending in optimal (zero error) solution is increased. As this is a binary problem, the BSFC, accompanied by the CPS method, consisted of ones representing correct outputs and zeros representing outputs which are incorrect. For the PIFA consisting of five different parameters, the BSFC length was taken as 32 bits. Fig. 9 shows one of the convergence trends of the BSFC GA during the simulation.

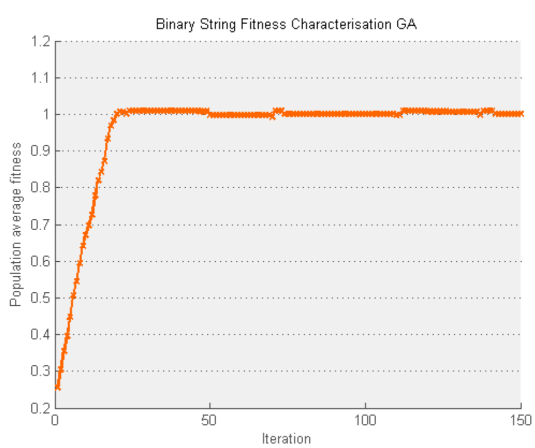

Fig. 9. BSFC GA Convergence.

The BSFC/CPS driven GA is seen to outperform the standard crossover methods in terms of convergence.

The hybridised GA consists primarily of the clustering mechanism along with the BSFC methodology applied to the optimisation process. Since the BSFC alone was observed to consume considerable amount of computational cost, some further intelligence by clustering mechanism has been applied to the optimisation process to reduce the surplus of computational calculation. Fig. 10 shows one of the convergence trends of the smart hybridised GA during the simulation.

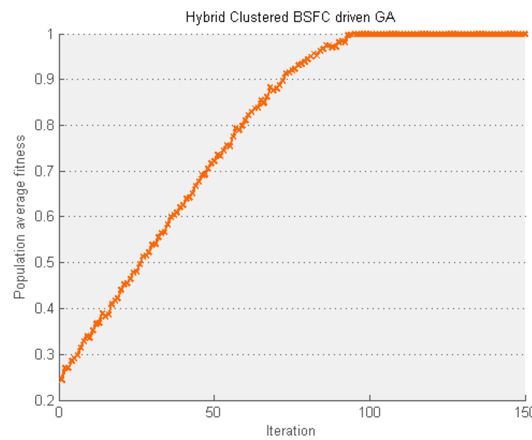

Fig. 10. Smart Hybridized GA Convergence.

The results are interesting as although the number of iterations to reach the optimal has increased, the computational cost is significantly lower.

In order to demonstrate the efficiency of the smart hybrid GA, a comparison analysis has been made on the recently proven converging mechanism, the Heuristic Particle Swarm Ant Colony Optimiser (HPSACO). Fig. 11 shows one of the convergence trends of the HPSACO when applied to the PIFA problem.

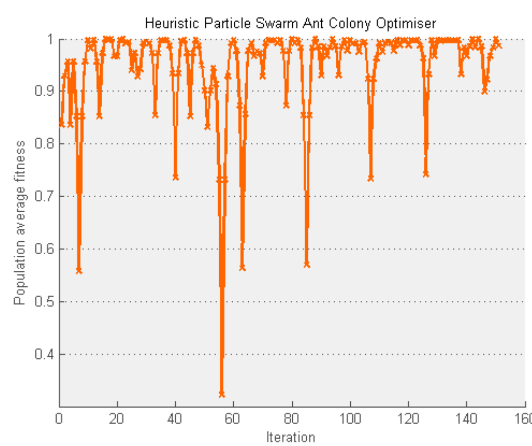

Fig. 11. HPSACO Convergence.

The smart hybridised GA is observed to have visible tendency to converge to the optimal solution whereas the

HPSACO has an erratic behaviour although the optimal solution was achieved at several points.

Fig. 11 shows the comparison of the simulation time using the different algorithms.

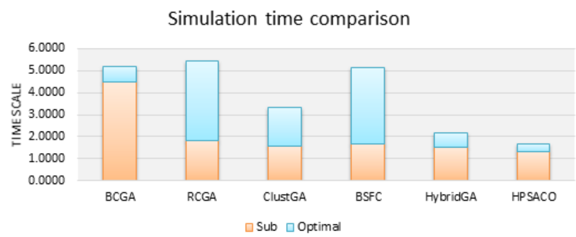

Fig. 11. Simulation time comparison.

The results highlight the efficiency of the smart hybrid GA as compared to the other techniques explored. This hybridisation could be applied in multi-objective computation, such as enhancing the performance optimisation done in [12] using multi-objective GA. Similarly, in the problem presented as a multi-objective optimisation in [13], the hybridised GA could be a good enrichment in the optimisation context.

Owing to its combinatorial optimisation, the GA has been used extensively in this project using binary mode as well as continuous mode for the optimisation of the PIFA. The GA has proved to be a very robust algorithm with respect to its parameters, namely the population size and operators – selection, crossover and mutation.

The bandwidth obtained is approximately 420 MHz. This is the optimal solution generated by the optimisation GA. The values of the parameters used for achieving this particular bandwidth are: $f_x = 3$ cells (6mm), $f_z = 3$ cells (6mm) and $h = 4$ cells (8mm).

The convergence could have been better if the population size of the GA was bigger and if the number of values used for the parameters were larger. However, this might have caused the simulation to last much longer. Subsequently, a proper trade-off between convergence and computational cost was considered and the number of values taken for the parameters were optimised and the population size adjusted accordingly so that the simulation could efficiently output pertinent results.

One of the major drawbacks observed in the GA is the local optima. In Binary-Coded GA or Real-Coded GA, a difficulty regarding the boundaries of the decision variables may often arise and the optimisation may converge wrongly or take very long to converge to the optimal solution. GA therefore may get stuck on a local optimum solution, which is only the sub-optimal solution of the more global problem. Similar issues on convergence or slowness of convergence have been faced during the PIFA optimisation process while adjusting the parameters. It has then been observed that the operators play a crucial role in tackling these issues. The operators (crossover or mutation) can change an individual in a population in such a way that it may provide the required escape from the suboptimal zone. In this way the operators act as one of the main drives towards the optimal solution.

IV. Conclusion

The GA has demonstrated to be a much convenient tool for complex engineering problems, particularly those which can be described in chromosome encoding. Its application in the PIFA design optimisation has resulted in interesting results. One of the particularities observed in GA is that the problem can be solved using multiple solutions, even though the problems are multi-dimensional, non-differential, non-continuous or non-parametrical.

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 smart hybrid mechanism through clustering, involving both BCGA and RCGA, has been applied. Consequently, this has led to an increase in 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 simulated time comparison highlight the efficiency of the smart hybrid GA as compared to the other techniques explored.

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