ADJOINT BASED EVOLUTIONARY

OPTIMIZATION OF ANTENNAS

ADJOINT BASED EVOLUTIONARY OPTIMIZATION OF ANTENNAS

By

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ABSTRACT

This thesis proposes a novel evolutionary approach in antenna design optimization. In this approach using the adjoint sensitivity, readily available in electromagnetic simulation software, a gradient-based optimization process is implemented. In this method coordinates of some control points are used as the optimization variables, and the antenna structure evolves through the optimization process to satisfy the appropriate constraints. This method has been illustrated by design of a number of microstrip antennas.

In the next step this method has been modified using constraints on angles between some hypothetical lines in the antenna structure to keep the antenna structure physical during the optimization process.

Also a new optimization problem has been defined to reduce the spacing between antenna elements in an antenna array for MIMO systems. The initial antenna structure to solve this problem is one of the antenna structures designed previously in this work. A 1 by 2 and a 1 by 3 antenna array for MIMO systems have been designed using this method and measurement of the fabricated antenna verifies the simulation results.

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would always look at them as great examples. They taught me to work hard in my studies. They encouraged me, with their motivational talks toward my goals, and I really appreciate them for that.

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CHAPTER 1

INTRODUCTION

Computer-aided design (CAD) and analysis started growing as an important subject of research, after emerging the technology of first generation computers in 1950s. CAD became a major branch of research in the area of engineering, microwave and millimeter-wave circuits and antennas. In the beginning, modeling and simulation of radio-frequency (RF) and microwave structures was approximate. Representation of complex electromagnetic (EM) environment in simulations was by using transmission lines and equivalent-circuit lumped elements. This method was fast for computational resources for that time and it would provide physical insight and it is still popular between electromagnetic computational communities. But by increasing the computational power of computers, various numerical methods emerged for full-wave electromagnetic simulations. Because of calculating complete field solution for the structure, these new methods have better accuracy compared to the old ones. As mentioned before these methods emerged with increasing the computational power of computers and it is an essential need for these methods. This is the main drawback for the full-wave electromagnetic solvers, which sometimes makes them very slow. Thus, it is challenging to use full-wave electromagnetic simulation in optimization procedures, which is usually referred as simulation-based optimization.

Design optimization in electromagnetics has been growing constantly with the permanent advancement in the electromagnetic simulation methods and software. But the optimization algorithms have not changed greatly. Evolutionary algorithms, which are mostly related to genetic algorithm and particle swarm algorithm, are popular between the optimization algorithms. This is because of they are easy to understand and user friendly [1]–[11]. Optimization have been a main part of design procedure of electromagnetic devices and they have been applied in designing many cases including antennas [12]–[19], antenna arrays [20]–[29], frequency selective surfaces [30]–[36], filters [37] and [38] and many others.

1.1. MOTIVATION

In antenna design, optimization is very important, because antenna characteristics such as input impedance, gain, sidelobe level etc., are known to be highly nonlinear function with respect to design variables. Also very often they have functional and slop discontinuities. So, in the design procedure of antenna structures usually a template is chosen as an initial geometry. Then, by changing all the parameters in the antenna structure, the optimized structure is obtained. But during this optimization process the initial template will not change. For instance, when we are trying to optimize a rectangular patch antenna and we just use its width and length as the optimization parameters, at the end of the optimization we still have a rectangular patch antenna, and the template is the same.

The optimized structure is supposed to meet all the required specifications, but this may not happen every time. At this stage of the design procedure usually using another template the same procedure would be repeated, until the right template is found. This problem might be because the optimizer is trapped in a local optimum or the template of the initial structure of the antenna is incapable of satisfying the requirements. Although the optimizer may find the best possible design, it might not satisfy the required specifications. In these cases, even with try all the possible values of the design parameters we cannot get the required structure. To overcome these problems many evolutionary population-based stochastic algorithms have been developed to find the global optimum. These kinds of algorithms usually start from an initial population, which, in each generation they evolve their structure to reach to the optimum design. Evolving the antenna structure might just be with changing some parameters or maybe by adding or removing some parts of the antenna [39].

In this thesis we try to develop a geometry evolutionary method for antenna design, exploiting adjoint sensitivities in the optimization algorithm. We apply our method in designing microstrip antennas in different frequency bands. Also using this method we design some antenna arrays for MIMO systems.

1.2. CONTRIBUTIONS

In this thesis we develop a geometry evolutionary method for antenna design. Here, using coordinates of control points in antenna structure as the optimization variables the antenna structure would evolve to the optimum design during the optimization process. Properly defining the optimization problem and formulating it we could use a gradient-based algorithm, to solve it. Using HFSS [40] as the electromagnetic simulator and MATLAB [41] as the optimizer the antenna optimization is done automatically. In each iteration of the optimization process the optimizer would change the coordinates of the control points as the optimization variables and then it would run the simulation and export the responses and their sensitivities. Using the responses and their sensitivities the optimizer would decide to change the optimization variables in the direction of the optimum design, and run the simulation again.

The author’s contribution in this thesis can be summarized as follows:

1. Formulating and defining the antenna design optimization problem using the coordinates of control points in the antenna structure.
2. Implementation and solving the antenna design optimization problem using a gradient-based algorithm, using HFSS as the electromagnetic simulator and MATLAB as the optimizer.
3. Applying this new method to design and fabricate three microstrip antennas and increasing their bandwidth with optimizing the antenna structure and validating it with measurements.

4. Formulating and defining an optimization problem to reduce the size of antenna arrays for MIMO systems by reducing the spacing between antenna elements.
5. Implementation and solving the optimization problem using a gradient-based algorithm using HFSS as the electromagnetic simulator and MATLAB as the optimizer.
6. Designing, fabrication, and measurement of a 1 by 2 and a 1 by 3 element antenna array for UWB MIMO systems, using this new method and validating the simulations.

1.3. OUTLINE OF THESIS

In chapter 2 there is a review on the previous methods in antenna design. We have reviewed many evolutionary population-based stochastic algorithms. They include computational intelligence, genetic algorithm, particle swarm optimization, ant colony optimization, simulated annealing, and invasive optimization method.

In chapter 3, a novel optimization method for antenna structure has been described. This method has been illustrated through three antennas examples and has enhanced their bandwidth. The simulation and measurement results have been presented in this chapter.

In chapter 4, constraints of the new optimization method has been modified. This modified method has been used to design a single element UWB microstrip monopole antenna. Then a new optimization problem is defined to reduce the spacing between elements of a MIMO antenna array. By solving this new optimization problem a 1 by 2 and a 1 by 3 UWB antenna array for MIMO systems have been designed. Also the simulation results have confirmed by measurements of the fabricated antennas.

Finally the thesis is concluded in chapter 5, which also includes future works and suggestions.

REFERENCES

[1] J. Kennedy and R. Eberhart, “Particle swarm optimization,” in Proc. 9th Int. Conf. on Neural Networks, Nov. 1995, vol. 4, pp. 1942–1948.

[2] R. Eberhart and J. Kennedy, “A new optimizer using particle swarm theory,” in IEEE Proc. 6h Int. Symp. on Micro Machine and Human Science, Oct. 1995, pp. 39–43.

[3] J. Robinson and Y. Rahmat-Samii, “Particle swarm optimization in electromagnetics,” IEEE Trans. Antennas Propag., vol. 52, pp. 397–407, Feb. 2004.

[4] D. Gies, “Particle swarm optimization: applications in electromagnetic design,” M. Eng. thesis, UCLA, Los Angeles, CA, 2004.

[5] J. Kennedy and R. Eberhart, Swarm Intelligence. New York: Morgan Kaufmann and Academic Press, 2001.

[6] J. H. Holland, “Genetic algorithms and the optimal allocation of trials,” SIAM J. Comput., vol. 2, no. 2, Jun. 1973.

[7] Y. Rahmat-Samii and E. Michielssen, Eds., Electromagnetic Optimization by Genetic Algorithms. New York: Wiley, 1999.

[8] R. L. Haupt and D. H. Werner, Genetic Algorithms in Electromagnetics. Hoboken, NJ: Wiley, 2007.

[9] D. S. Weile and E. Michielssen, “Genetic algorithm optimization applied to electromagnetics: A review,” IEEE Trans. Antennas Propag., vol. 45, pp. 343–353, Mar. 1997.

[10] R. Storn and K. Price, “Differential evolution—A simple and efficient heuristic for global optimization over continuous spaces,” J. Global Optim., vol. 11, no. 4, pp. 341–359, Dec. 1997.

[11] K. V. Price, R. M. Storn, and J. A. Lampinen, Differential Evolution: A Practical Approach to Global Optimization, in Natural Computing. Heidelberg: Springer-Verlag, 2005.

[12] N. Jin and Y. Rahmat-Samii, “Parallel particle swarm optimization and finite difference time-domain (PSO/FDTD) algorithm for multiband and wide-band patch antenna designs,” IEEE Trans. Antennas Propag., vol. 53, pp. 3459–3468, Nov. 2005.

[13] N. Jin and Y. Rahmat-Samii, “Advances in particle swarm optimization for antenna designs: Real-number, binary, single-objective and multiobjective implementations,” IEEE Trans. Antennas Propag., vol. 55, pp. 556–567, Mar. 2007.

[14] N. Jin and Y. Rahmat-Samii, “Particle swarm optimization for antenna designs in engineering electromagnetics,” J. Artif. Evol. Applicat., vol. 2008, no. 9, Jan. 2008.

[15] F. J. Villegas, T. Cwik, Y. Rahmat-Samii, and M. Manteghi, “A parallel electromagnetic genetic-algorithm optimization (EGO) application for patch antenna design,” IEEE Trans. Antennas Propag., vol. 52, pp. 2424–2435, Sep. 2004.

[16] D. H.Werner, P. L.Werner, and K. H. Church, “Genetically engineered multiband fractal antennas,” IEEE Electron. Lett., vol. 37, no. 19, pp. 1150–1151, Sep. 2001.

[17] B. Schlobohm, F. Arndt, and J. Kless, “Direct PO optimized dual-offset reflector antennas for small earth stations and for millimeter wave atmospheric sensors,” IEEE Trans. Microwave Theory Tech., vol. 40, pp. 1310–1317, Jun. 1992.

[18] A. Hoorfar and Y. Liu, “Antenna optimization using an evolutionary programming algorithm with a hybrid mutation operator,” in Proc. IEEE Int. Symp. on Antennas Propag., 2000, vol. 2, p. 1029.

[19] M. John and M. J. Ammann, “Antenna optimization with a computationally efficient multiobjective evolutionary algorithm,” IEEE Trans. Antennas Propag., vol. 57, pp. 260–263, Jan. 2009.

[20] D. S. Weile and E. Michielssen, “Integer coded Pareto genetic algorithm design of constrained antenna arrays,” IEEE Electron. Lett., vol. 32, no. 19, pp. 1744–1745, Sep. 1996.

[21] T. G. Spence and D. H. Werner, “Design of broadband planar arrays based on the optimization of aperiodic tilings,” IEEE Trans. Antennas Propag., vol. 56, pp. 76–86, Jan. 2008.

[22] R. L. Haupt, “Thinned arrays using genetic algorithms,” IEEE Trans. Antennas Propag., vol. 42, pp. 993–999, Jul. 1994.

[23] J. S. Petko and D. H. Werner, "The evolution of optimal linear polyfractal arrays using genetic algorithms," IEEE Trans. Antennas Propag., vol. 53, pp. 3604–3615, Nov. 2005.

[24] J. S. Petko and D. H. Werner, "An autopolyploidy-based genetic algorithm for enhanced evolution of linear polyfractal arrays," IEEE Trans. Antennas Propag., vol. 55, pp. 583–593, Mar. 2007.

[25] J. S. Petko and D. H. Werner, "The pareto optimization of ultrawideband polyfractal arrays," IEEE Trans. Antennas Propag., vol. 56, pp. 97–107, Jan. 2008.

[26] M. G. Bray, D. H.Werner, D.W. Boeringer, and D. W. Machuga, "Optimization of thinned aperiodic linear phased arrays using genetic algorithms to reduce grating lobes during scanning," IEEE Trans. Antennas Propag., vol. 50, pp. 1732–1742, Dec. 2002.

[27] M. D. Gregory and D. H. Werner, "Ultrawideband aperiodic antenna arrays based on optimized raised power series representations," IEEE Trans. Antennas Propag., vol. 58, Mar. 2010.

[28] D. W. Boeringer, D. H.Werner, and D. W. Machuga, "A simultaneous parameter adaptation scheme for genetic algorithms with application to phased array synthesis," IEEE Trans. Antennas Propag., vol. 53, pp. 356–371, Jan. 2005.

[29] D. W. Boeringer and D. H. Werner, "Efficiency-constrained particle swarm optimization of a modified Bernstein polynomial for conformal array excitation amplitude synthesis," IEEE Trans. Antennas Propag., vol. 53, pp. 2662–2673, Aug. 2005.

[30] J. A. Bossard, X. Liang, L. Li, S. Yun, D. H. Werner, B. Weiner, T. S. Mayer, P. F. Cristman, A. Diaz, and I. C. Khoo, "Tunable frequency selective surfaces and negative-zero-positive index metamaterials based on liquid crystals," IEEE Trans. Antennas Propag., vol. 56, pp. 1308–1320, May 2008.

[31] J. A. Bossard, D. H.Werner, T. S.Mayer, J. A. Smith, Y. U. Tang, R. P. Drupp, and L. Li, "The design and fabrication of planar multiband metallodielectric frequency selective surfaces and infrared applications," IEEE Trans. Antennas Propag., vol. 54, pp. 1265–1276, Apr. 2006.

[32] J. A. Bossard, D. H. Werner, T. S. Mayer, and R. P. Drupp, "A novel design methodology for reconfigurable frequency selective surfaces using genetic algorithms," IEEE Trans. Antennas Propag., vol. 53, pp. 1390–1400, Apr. 2005.

[33] M. A. Gingrich and D. H. Werner, "Synthesis of low/zero index of refraction metamaterials from frequency selective surfaces using genetic algorithms," IEEE Electron. Lett., vol. 41, no. 23, pp. 1266–1267, Nov. 2005.

[34] D. J. Kern, D. H. Werner, and M. Lisovich, "Metaferrites: Usign electromagnetic bandgap structures to synthesize metamaterial ferrites," IEEE Trans. Antennas Propag., vol. 53, pp. 1382–1389, Apr. 2005.

[35] D. J. Kern, D. H. Werner, A. Monorchio, L. Lanuzza, and M. J. Wilhelm, "The design synthesis of multiband artificial magnetic conductors using high impedance frequency selective surfaces," IEEE Trans. Antennas Propag., vol. 53, pp. 8–17, Jan. 2005.

[36] S. Genovesi, R. Mittra, A. Monorchio, and G. Manara, "Particle swarm optimization for the design of frequency selective surfaces," IEEE Antennas Wireless Propag. Lett., vol. 5, pp. 277–279, 2006.

[37] M.-I. Lai and S.-K. Jeng, "Compact microstrip dual-band bandpass filter design using genetic algorithm techniques," IEEE Trans. Microwave Theory Tech., vol. 54, pp. 160–168, Jan. 2006.

[38] S. K. Guodos and J. N. Sahalos, "Pareto optimal microwave filter design using multiobjective differential evolution," IEEE Trans. Antennas Propag., vol. 58, pp. 132–144, Jan. 2010.

[39] Y. Rahmat-Samii, "Modern antenna designs using nature inspired optimization techniques: Let darwin and the bees help designing your multi band MIMO antennas," *Proceedings of IEEE Radio and Wireless Symposium (RWS)*, pp. 463–466, Jan. 2007.

[40] "HFSS" ver. 13, ANSYS, Inc., Canonsburg, PA, 2010.

[41] "Matlab" ver. 7, The MathWorks Inc., Natick, MA. 2010.

CHAPTER 2

EVOLUTIONARY ALGORITHMS IN ANTENNA DESIGN

2.1. INTRODUCTION

Since the simulation tools in electromagnetics (EM) design optimization have had steady advancement over the last years, the optimization algorithms that are used have remained largely the same. Genetic algorithms (GAs) and particle swarm optimization (PSO)-related techniques dominate the mainstream of evolutionary strategies (ES), mostly due to widespread availability, understanding and user friendliness [1]–[11]. These optimization techniques have had great success and have been applied in a wide variety of electromagnetic device design problems including antennas [12]–[19], antenna arrays [20]–[29], frequency selective surfaces [30]–[36], filters [37] and [38] and many others.

Antenna problems are challenging design problems, since the antenna characteristics such as input impedance, gain, sidelobe level etc., are known to be extremely sensitive to design variables, which are dimensions of different elements, number of elements, position of elements, etc. This corresponds to a highly nonlinear function space with functional and slop discontinuities.

Population-based stochastic algorithms are widely used for optimizing such problems, as they usually explore multiple solutions simultaneously. This class of algorithms have been used in a wide range of engineering design problems, including the domain of electromagnetics [9].

Although, genetic algorithm (GA) and particle swarm optimization (PSO) are perhaps the most popular population-based stochastic optimization methods, there are a number of other techniques that have evolved recently, all of which can be classified as methods based on computational intelligence (CI). These methods that are based on computational intelligence either mimic biological systems (GAs, evolutionary algorithms, and artificial immune systems), physical processes (simulated annealing, magnetic hysteresis) or individual and collective behaviour (as in ants and swarms) [39].

In the rest of this chapter we go through some of the aforementioned methods with more details, to have a better understanding of them and to know their advantages and disadvantages.

2.2. COMPUTATIONAL INTELLIGENCE

Computational intelligence algorithm is based on learning originated from the experimental results that are reported by Shi and Eberhart [57] from their work on particle swarm optimization (PSO). They observed that the PSO performance was not sensitive to the initial number of particles in swarm, and showed a fast convergence potential.

The Computational intelligence algorithm has a leader-follower information exchange mechanism. Through this mechanism, individuals learn from the better performers. A criterion is needed in order to divide the individuals into a set of leaders and a set of followers. However, it is easy to assign fitness function to the individuals for unconstrained problems but it is not easy to do the same for constrained problems as there are no clear means to compare infeasible solutions. Common methods for comparison use different techniques to assign fitness values to infeasible individuals such as summation of constraint violations, summation of scaled constraint violations, maximum amount of constraint violation, scaled and weighted combinations of the above or adaptive weights and scaling factors. Such techniques of fitness assignment are computationally inexpensive, but they need additional inputs for scaling and aggregation.

In general, a multiobjective constrained minimization problem can be written as:

$$\begin{array}{ll} \text{Minimize } \boldsymbol{F} = \left[f_1(\boldsymbol{p}) \quad f_2(\boldsymbol{p}) \quad \cdots \quad f_k(\boldsymbol{p}) \right] & \\ \text{subject to } g_i(\boldsymbol{p}) \geq a_i, \quad i=1,2,\ldots,q & , \\ \qquad h_j(\boldsymbol{p}) = b_j, \quad j=1,2,\ldots,r & \end{array} \tag{2.1}$$

where there are k objectives, r equality and q inequality constraints, and $\boldsymbol{p} = [p_1, \ldots, p_n]^T$ is the vector of n optimization parameters. Each equality constraint is substituted by a pair of inequality constraints such as $h_j(\boldsymbol{p}) \leq b_j + \delta$

and $h_j(\boldsymbol{p}) \geq b_j - \delta$ to handle the equality constraints. Thus, *r* equality constraints would be substituted with 2*r* inequality constraints. The number of inequality constraints of the new problem is $s = q + 2r$. For any individual, there is a constraint satisfaction vector, $\mathbf{c} = [c_1 \; c_2 \; \ldots \; c_s]^T$, where $c_i \geq 0$ indicates the *i*th constraint is not satisfied and it is violated and it is equal to the value of violation as:

$$c_i = \begin{cases} 0 & \text{if } i\text{th constraint satisfied}, \; i = 1, 2, \ldots, s \\ a_i - g_i(\boldsymbol{p}) & \text{if } i\text{th constraint violated}, \; i = 1, 2, \ldots, q \\ b_i - \delta - h_i(\boldsymbol{p}) & \text{if } i\text{th constraint violated}, \; i = q+1, q+2, \ldots, q+r \\ -b_i - \delta + h_i(\boldsymbol{p}) & \text{if } i\text{th constraint violated}, \; i = q+r+1, q+r+2, \ldots, s \end{cases}$$

The constraint matrix for *M* individuals is thus given by:

$$\text{Constraint} = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1s} \\ c_{21} & c_{22} & \cdots & c_{2s} \\ \vdots & \vdots & \ddots & \vdots \\ c_{M1} & c_{M2} & \cdots & c_{Ms} \end{bmatrix}, \tag{2.2}$$

The objective matrix for *M* individuals is in this form

$$\text{Objective} = \begin{bmatrix} f_{11} & f_{12} & \cdots & f_{1k} \\ f_{21} & f_{22} & \cdots & f_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ f_{M1} & f_{M2} & \cdots & f_{Mk} \end{bmatrix}, \tag{2.3}$$

In a population we say individual $\boldsymbol{p}^1 = [p_1^1, \ldots, p_n^1]^T$ dominates $\boldsymbol{p}^2 = [p_1^2, \ldots, p_n^2]^T$ when $\boldsymbol{F}(\boldsymbol{p}^1)$ is partially less than $\boldsymbol{F}(\boldsymbol{p}^2)$, *i.e.* $f_i(a^1) \leq f_i(a^2); \forall i = 1, \ldots, k$ and $\exists i \in \{1, \ldots, k\}$ with $f_i(a^1) < f_i(a^2)$. If an individual do not dominate any of other individuals we call that individual non-dominated. Individuals are usually sorted using this definitions, in this method using the constraint matrix and the objective matrix in non-dominated sorting, the individuals are ranked. A linear expression is used for fitness evaluation, and the fitness of the *i*th individual is calculated using the rank of individuals:

$$\text{fitness}_i = 1 + \text{MaxRank} - \text{Rank}(i), \tag{2.4}$$

The Computational intelligence algorithm is based on the following rules:

- The algorithm tries to move the set of solutions toward feasibility before trying to improve objective function value of an infeasible individual.
- A feasible solution is favoured compared to an infeasible solution.
- Between feasible solutions, those with better fitness value are preferred.
- Between infeasible solutions we choose using a non-dominated rank based on the constraint matrix.

Ray in [58] suggested to use non-dominated rank of an individual to compare infeasible solutions. Also Srinivas and Deb in [59] have introduced a non-dominated sorting genetic algorithm (NSGA) to sort the individuals based on the constraint matrix. However, the process of non-dominated ranking based on a constraint matrix is computationally demanding, eliminates the need for scaling and weighting factors, which are needed to derive a single scalar measure of fitness.

This algorithm has three main sections which are leader identification, leader selection, and information acquisition. These three parts have been explained more in the following.

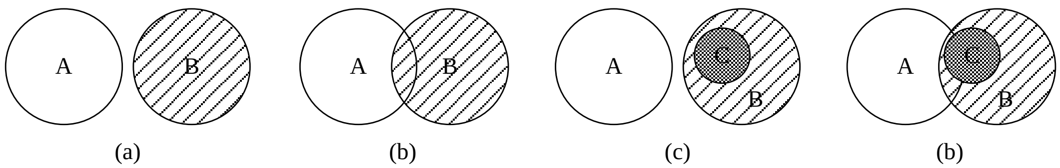


Figure 2.1. Schematic interpretation of leaders. (a) Leaders are constraint rank = 1, (b) leaders are {A} $\cap$ {B}, (c) leaders are all feasible solutions {C}, and (d) leaders are {A} $\cap$ {C}. [39]

A. Leader Identification

To identify the leaders we use a non-dominated sorting process based on the constraint matrix and the objective matrix. This process is both relative and adaptive because it changes depending on the overall performance of the individuals. Based on different scenarios, there would be different interpretation of leaders, which are shown in Figure 2.1. If the set of individuals were in the form as presented in Figure 2.1(a), the set of leaders is the one with constraint rank equal to 1. If it was in the form of Figure 2.1(b), the leaders are those that have constraint rank equal to 1 and also have an objective rank less than the average objective rank of the individuals at the same time. The leaders are the feasible individuals when there is any feasible solution, as in Figure 2.1(c), or the intersection of the set of feasible individuals and the set of good objective performers, as in Figure 2.1(d). Because of handling constraints and objectives separately, using non-dominated ranks and the use of two fitness measures, there is no need for scaling and aggregation. It is important to identify the *good* leaders, because it would mean subsequent exploration around their neighborhoods.

B. Leader Selection

In every step, the set of individuals are divided into a set of leaders and a set of followers. By not moving the leaders and keeping them in their original position we can ensures elitism. After selecting a leader for each follower and getting information from it the leader they move to a new location. Using a Roulette wheel mechanism, the leaders are selected. The better performing leaders have a greater chance to share information with the followers. In contrast to PSO where a particle has only access to some information, in this leader selection process, every follower has information about all the leaders to make a better choice.

C. Information Acquisition

The third key element in this algorithm is that a follower gets information from its leader and moves correspondingly. The information acquisition mechanism is similar to the crossover operation in genetic algorithm. The information acquisition operator explores neighbourhoods of the leader. During the process we can observe a bigger separation between the individuals results in a better exploration of the solution space, while a small separation between them results in a more focused neighbourhood search around the leader.

2.3. GENETIC ALGORITHM

The basic building blocks of genetic algorithms are genes. A gene is a parameter with a binary encoding. A chromosome in a genetic algorithm is a set of genes. We can assign a relative value to each chromosome which is associated with the cost function. The algorithm begins with a large set of random chromosomes. Values of the cost functions are evaluated for each chromosome. The chromosomes are sorted from the best-fit to the worst-fit, according to their associated cost functions. Then, worst-fit chromosomes are discarded, which leaves a superior subset of the original list. Chromosomes that survive become parents, and then by swapping some of the parents' genetic material, new offspring would be produced. The parents reproduce enough to compensate the number of discarded chromosomes. Thus, the total number of chromosomes remains constant during the optimization process. Mutations are a set of procedures which cause small random changes in chromosomes. Cost functions should be evaluated for the offspring and the mutated chromosomes, and the process is repeated. The algorithm stops after the maximum number of iterations is reached, or when a preselected acceptable solution is obtained.

Figure 2.2 is a simple flow chart of a genetic algorithm. The algorithm starts by defining a chromosome as an array of binary coded parameter values to be optimized. If the chromosome has N parameters in the algorithm, which means there are N parameters in the optimization problem, and they are given by $p_1, p_2, p_3, \ldots, p_N$, then the chromosome is written as

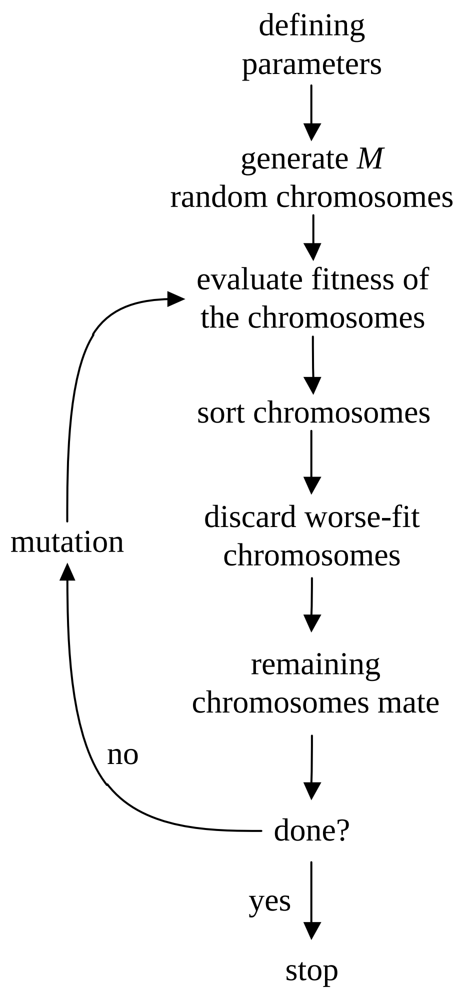


Figure 2.2. A flowchart of a genetic algorithm [40]

$$\text{chromosome} = [p_1 p_2 p_3 \cdots p_N], \tag{2.1}$$

Each chromosome is associated with a cost function value, found by evaluating a function, *F*, at $p_1, p_2, p_3, \ldots, p_N$. The cost function is represented by

$$\text{cost} = F(p_1, p_2, p_3, \ldots, p_N), \tag{2.2}$$

Each parameter (p_i) can be discrete or continuous. If the parameter is continuous, either some limits are needed on the parameters, or they should be restricted to a small set of possible values. One way to limit the parameters is to encode them in a binary sequence, and by choosing the number of bits which we allocate to each parameter we can control the accuracy of that parameter in the final solution. This encoding can be done using

$$q_i = \sum_{k=1}^{L} \frac{b[k]}{2^{k-1}} Q, \tag{2.3}$$

where

q_i = quantized version of p_i

L = number of quantization level for q_i

b = array containing the binary sequence representation q_i

Q = the largest quantization level

= half the largest-position value of q_i

The binary-encoded parameters (q_i) does not have to mathematically related to p_i using equation 2.3)). Instead, they may just represent some values. For instance, if p_i have four values of resistivity, then q_i can have two bits and each binary code can represent one of the values.

Here, only genetic algorithms implementation with the binary encoded parameters and not the parameters themselves is described. In order to evaluate the cost function, the chromosome must first be decoded. An example of a binary encoded chromosome that has N parameters, each encoded with O=10 bits, is

$$\text{chromosome}=\left[\underbrace{1101011110}_{q_1}\underbrace{1110111010}_{q_2}\ldots\underbrace{1011001111}_{q_N}\right], \qquad (2.4)$$

Substituting this binary representation into equation 2.3)) yields an array of quantized versions of the parameters. This chromosome has a total of $O\times N$ bits.

After planning a protocol to encode and decode the parameters, a set of random chromosomes is generated. Each chromosome has an associated cost function value, which is calculated from the cost function in equation 2.2)). For example if there is a random set of $M=8$ chromosomes, with their associated cost function values. In the next step in the algorithm, the chromosomes from best to worst are sorted according to their cost (assuming a low cost is good). Now, the worst chromosomes are discarded. Sometimes, the top x are kept (where x is even), and the bottom $M-x$ are discarded. Another possibility is to have a threshold for the cost to meet a specified level.

The next step, after sorting and discarding the chromosomes, is choosing mates for the remaining $M/2$ chromosomes. Any two chromosomes can mate. Some possible approaches are to pair the chromosomes from top to bottom of the list, pair them randomly, or pair the first one with $M/2$, second one with $M/2-1$, etc. [40]. After mating, new offsprings are formed from the pair-swapping parts of chromosomes. As an example, if two chromosomes are selected for mating, a random point is selected for crossover. The binary digits from parent chromosomes are swapped to the different sides of the crossover point, to form the offspring. In this case the random crossover point is between bits 5th and 6th digits, the new chromosomes are formed from

$$\left.\begin{array}{ll}\text{parent \#1} & \overline{\overline{10101}}\,\underline{00101} \\ \text{parent \#2} & \overline{11001}\,\underline{\underline{10011}}\end{array}\right\} \Rightarrow \left\{\begin{array}{ll}\text{offspring \#1} & \overline{\overline{10101}}\,\underline{\underline{10011}} \\ \text{offspring \#2} & \overline{11001}\,\underline{00101}\end{array}\right.$$

After discarding of $M/2$ chromosomes, pair and mate, the rest of the $M/2$ parents are left. By producing $M/2$ offspring in total again there are M chromosomes, which is the same number of chromosomes at the start.

At this step, random mutations modify some of the bits in the list of chromosomes, by changing a “0” to a “1” or vice versa. Some bits are randomly selected for mutation from the $M \times O \times N$, total number of bits in all the chromosomes. By increasing the number of mutations, the region of parameter space that the algorithm is searching widens. This would result in more freedom, which is important, since the algorithm focus on a particular region of parameter space. Typically, on the order of 1% of the bits mutate per iteration [40].

After the mutations, the cost function would be evaluated for the offspring and mutated chromosomes, and the process is repeated. The number of generations in this algorithm depends on whether an acceptable and optimum solution is reached, or the number of iterations is exceeded a preselected number. Ideally, at the end all of the chromosomes and associated costs should become almost similar, except for those that are mutated.

In [41] the algorithm has been modified with adding a search to find local optimums around each chromosome. This technique has been used to achieve the

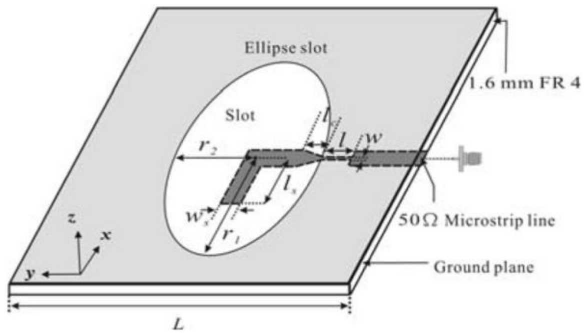


Figure 2.3. Geometry of the proposed wide slot CP antenna [41].

optimal impedance and axial ratio bandwidth. The antenna structure that has been optimized is shown in Figure 2.3, which is a slot circularly polarized (CP) slot antenna.

The parameters of optimization are r_1, r_2, l_s, w_s, l_c, l, and w. Also the fitness function has been defined as summation of a linear combination of S_{11} and axial ratio of the antenna structure for all the frequency points. Final values for the optimization parameters are 45.2, 28.5, 45, 4.1, 20.1, 13, and 0.9 mm respectively. The optimum antenna structure has achieved 50.8% for the 10 dB input impedance bandwidth with center frequency of 2480 MHz and 45.8% for the 3 dB axial ratio bandwidth with center frequency of 2400 MHz.

2.4. PARTICLE SWARM OPTIMIZATION

The particle swarm optimization (PSO) has been used in optimizing different multidimensional problems in a variety of fields [42]. Recently, this technique has been successfully applied to antenna design, and results were presented [43]. Also, this new stochastic evolutionary technique, based on the intelligent behaviour of swarms, has been shown in a few cases to perform better than other methods of optimization like genetic algorithms (GA) [44]. The best way to explain PSO is through an analogy similar to that used to develop it by Kennedy and Eberhart in 1995 [1].

The goal of a bee swarm in a field is to find the location with the highest population of flowers. The bees start in random locations with random velocities and random directions looking for flowers without knowing anything about the field a priori. Each bee can only remember where it found the most number of flowers, and somehow knows the location where the other bees found the most number of flowers. Torn between returning to the location where it had personally found the most flowers, or toward the direction of the location where the other bees found the most number of flowers, reported by others. The bee accelerates in both directions changing its direction to fly somewhere between the two locations depending on whether nostalgia or social influence dominates in each iteration. Also, a bee might find a place with a higher density of flowers than it had found before. Then, it would be drawn to the location where is the best place found by other bees as well as this new location, because it would replace with the previous one. In addition to that, occasionally, one bee may find a place with more concentration of flowers than had been found by other bees in the whole swarm. Then all the other bees would be drawn toward that new location in addition to their own personal discovery. This way the bees fly over the locations of greatest concentration of flowers in the field, and then go back toward them. They are always comparing the territory, which they fly over, with previously discovered locations with highest density, hoping to find a better location, which might have the absolute highest concentration of flowers. This would eventually lead them to the place in the field with the highest density of flowers. Soon, all the bees only fly around this place. Unable to find any location with higher density of flowers, so they are constantly drawn back to the same point.

2.3.1. PSO Language

In this section the language used to discuss the PSO is explained, which follows the analogy of particles in a swarm. Some of the key words are particle or agent, Location or position, *pbest*, and *gbest*. More detailed descriptions of them are given below.

1) *Particle or Agent:* Every individual in the swarm (bees in the analogy above) is called as a particle or agent. All of the particles in the swarm act individually under the same rules. These rules are moving toward the best personal and best global location while checking the value of its current location.

2) *Position:* In the analogy above position is location of bees in the field, which is presented by coordinates on the *x-y* plane. However, in general we can extend this idea to any *N*-dimensional problem. The *N*-dimensional space is the solution space, and any point in this space represents a solution to the problem being optimized. In the analogy above a physical location on the *x-y* plane is a solution, but this could just as easily represent number of elements and their position in an antenna array. In general these can be any optmizable parameters.

Defining the optimization problem with a set of parameters that could represent a position in the solution space is an important step in using the PSO.

4) *pbest:* In the aforementioned analogy each bee records the position where it personally discovered the most concentration of flowers. This position has the best fitness value, which is personally discovered by a bee is called the personal best or *pbest*. Each bee has its own *pbest* depending on the path it has flown. At each point through its flying, the bee compares the fitness value of its current point to *pbest*. If the current point has a better fitness value, *pbest* is changed to the current point.

5) *gbest:* Each bee also knows the highest density of flowers discovered by the other bees in the whole swarm. This position with the highest fitness discovered is called as the global best or *gbest*. There is one *gbest* for the whole swarm, to which all the bees are drawn. Every bee at each point through its flight path compares the fitness of their current point to the *gbest*. If the fitness of their current point has better fitness, *gbest* is changed to the bee's current position.

2.3.2. Development of the PSO Algorithm

After understanding the language and terms used in PSO, in this section algorithm development is described in 5 steps.

1) *Define the Solution Space:*

The first step is to choose the parameters which need to be optimized and determine their range, to search for the optimal solution. This means specifying a minimum and maximum value of each parameter in an *N*-dimensional optimization problem.

2) *Define a Fitness Function:*

In this step, we define the link between the PSO algorithm and the physical world. It is critical that a properly chosen function accurately represents the goodness of the solution in a single number. The fitness function should be dependent on all the characteristics we want to optimize. The fitness function and the solution space must be defined for each optimization problem separately. However, the rest of the algorithm is independent of the physical system being optimized.

3) *Initialize Random Swarm Location and Velocities:*

To begin the algorithm, we assign each particle a random location and a velocity that is random both in its direction and magnitude. Since in the beginning the initial position is the only location discovered by the particles, each particle's *pbest* would be this position. Then the first *gbest* is the best position between these initial positions.

4) *Systematically Fly the Particles through the Solution Space:*

Then particles must be moved in the solution space like the bees in a swarm. The algorithm moves the particles by a small amount, one by one, for the entire swarm. The following steps take place for each particle separately.

a) *Evaluate the Particle's Fitness, Compare to gbest, pbest:* Using the fitness function we can evaluate the coordinates of the particle in solution space and assign a fitness value to the current location. If the fitness value is greater than the value of *pbest* for that particle, or the global *gbest*, then the corresponding position to *pbest* or *gbest* would be substituted with the current location.

b) *Update the Particle's Velocity:* Handling the particles' velocity is the most important element of the optimization algorithm. Velocity of the particle updates using the relative locations of *pbest* and *gbest*. It is drawn to them according to the following equation:

$$\boldsymbol{V}_{i+1,j}=w\times\boldsymbol{V}_{i,j}+c_1\text{rand}(\ )\times\left(pbest\text{-}\boldsymbol{P}_{i,j}\right)+c_2\text{rand}(\ )\times\left(gbest\text{-}\boldsymbol{P}_{i,j}\right), \qquad (2.5)$$

where $\boldsymbol{P}_{i,j}$ is the vector of *j*th particle's coordinate in the *i*th iteration and $\boldsymbol{V}_{i,j}$ is the vector of velocity of the *j*th particle in the *i*th iteration where these vectors are 1 by N in an *N*-dimensional optimization. From this equation we can say the new velocity is the scaled old velocity biased in the direction of *gbest* and *pbest* for that particular dimension. c_1 and c_2 are scaling factors which are used to determine the "pull" of *pbest* and *gbest*. These are respectively called the cognitive and social rates. c_1 determines how fast the particle is going toward the memory of his best location, and c_2 determines how fast the particle is going toward the rest of the swarm. By increasing c_1 each particle is encouraged more to explore the solution space toward its own *pbest* and by increasing c_2 each particle is encouraged more to explore the global optimum.

The rand( ) function generates a number between 0.0 and 1.0. Generally the two rand( ) functions in 2.5)) call the function separately. *w* is the "inertial weight," which is between 0.0 and 1.0, determines how much the particle remains along its original path. This is also another way to balance exploration and exploitation. The movement of the particle can be followed based on 2.5)). The particle accelerates in the direction of *gbest* and *pbest* until they pass them. This "overflying" of the local and global optima is that many believe is one secret to the PSOs success [46].

c) *Move the Particle:*

After velocity has been calculated, the next step is to change the particles position to their new position. The velocity is usually for one time step, which is assumed equal to one. The new coordinate is calculated for each of the dimensions using:

$$\boldsymbol{P}_{i+1,j} = \boldsymbol{P}_{i,j} + \Delta t \times \boldsymbol{V}_{i,j}, \tag{2.6}$$

Then the particles' location is changed to the location calculated by 2.6)). The complex nature of this algorithm, which includes several independent agents, makes it suitable for implementation on parallel processors.

5) *Repeat:* This process should be repeated from step 4) for all the particles. In this way the particles change their positions and then they are evaluated again. It is like snapshots of live swarm every second, which at those moments all the particles with their positions, and *pbest*, and *gbest* are updated before moving the particles for another second. This would be repeated until the

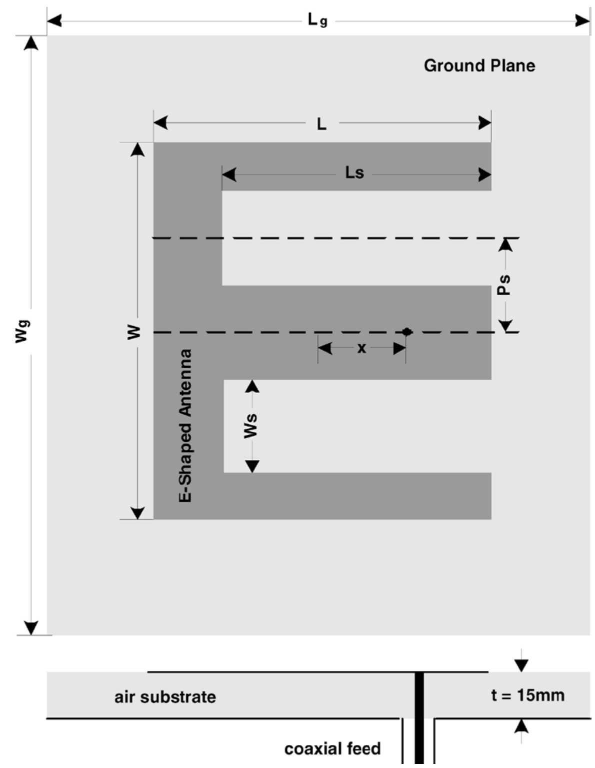


Figure 2.4. Configuration of an E-shaped patch antenna. There are six geometrical parameters to be optimized [47].

termination criteria are satisfied. There are several kinds of termination criteria. The most popular criterion is a maximum iteration number. With this criterion the PSO stops when the loop starting with Step 4) has been repeated a predefined number of times. The next type of stopping criterion is reaching a predefined value for the fitness. With this option at any iteration if a solution is found that is greater than or equal to the satisfactory fitness value, the PSO is stopped. This criterion is used when there is a specific engineering target to achieve, and finding the “best” solution is not necessary. A final criterion is about to achieve a minimum standard deviation (STD). This criterion compares the STD of the particles in the swarm to a predefined STD. If the current STD is less than the predefined STD, it means all the particles are converged around the *gbest*. Then, the algorithm stops with the assumption that it has stagnated around the optimum solution. It is important to mention that all the aforementioned criteria can be used in any combination with each other.

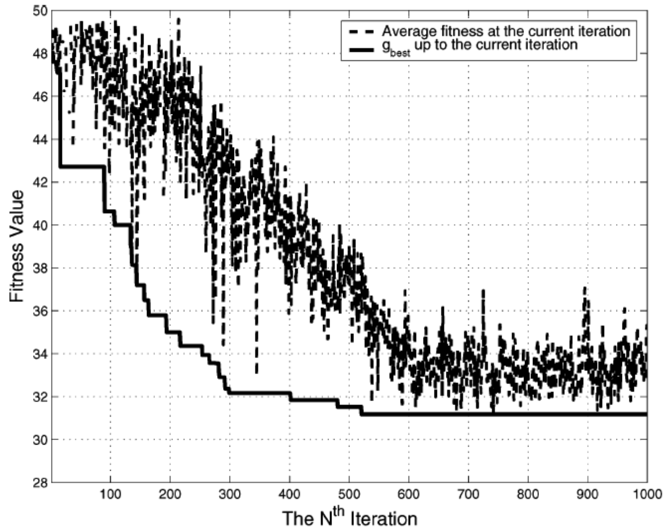
In [47] using a FDTD antenna simulator and PSO as the optimization method, two E-shaped antenna has been designed. For one of the antennas the optimization has been done to reduce the return loss of the antenna structure in two frequencies of 1.8 and 2.4 GHz. For the other antenna the optimization has been done to be able to cover the entire frequency range from 1.8 to 2.4 GHz. The antenna structure and the geometrical parameters that have been used in the optimization process are shown in Figure 2.4. The optimization parameters are L, W, L_s, W_s, P_s, and x, which are respectively in the range of (30, 96), (30, 96), (0, 96), (0, 48), (0, 48), and (-48,48) mm, because we want to keep the E-shape structure and also because the substrate dimension is fixed at 100 mm by 120 mm. Also other constraints should be applied to maintain the E-shape of the antenna:

$$L_s < L, \tag{2.7}$$

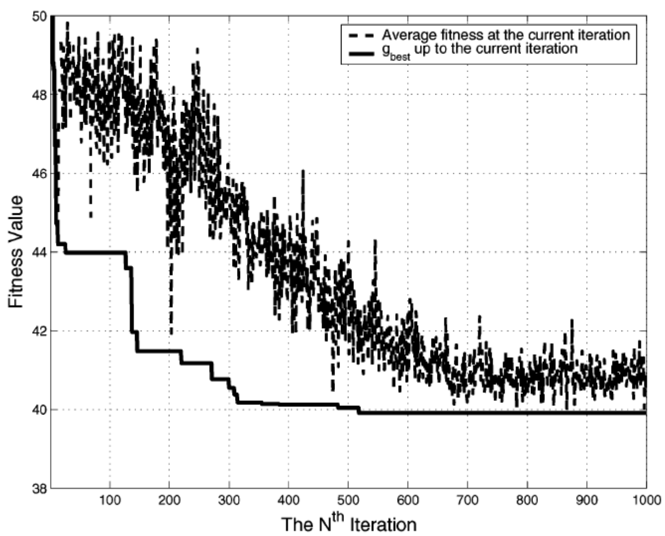
$$P_s > \frac{W_s}{2}, \tag{2.8}$$

$$P_s + \frac{W_s}{2} < \frac{W}{2}, \tag{2.9}$$

$$|x| < \frac{L}{2}. \tag{2.10}$$



(a)



(b)

Figure 2.5. Convergence results for E-shaped antenna designs. (a) The optimization of antenna I (dual-frequency antenna). (b) The optimization of antenna II (wide-band antenna) [47].

The fitness functions for optimization of the two antenna designs are different. For the first antenna (antenna I) in order to reduce the *S*-parameter the fitness function has been defined as

$$F=50+max\left(S_{11,1.8\,GHz},S_{11,2.4\,GHz}\right). \qquad (2.11)$$


(a)

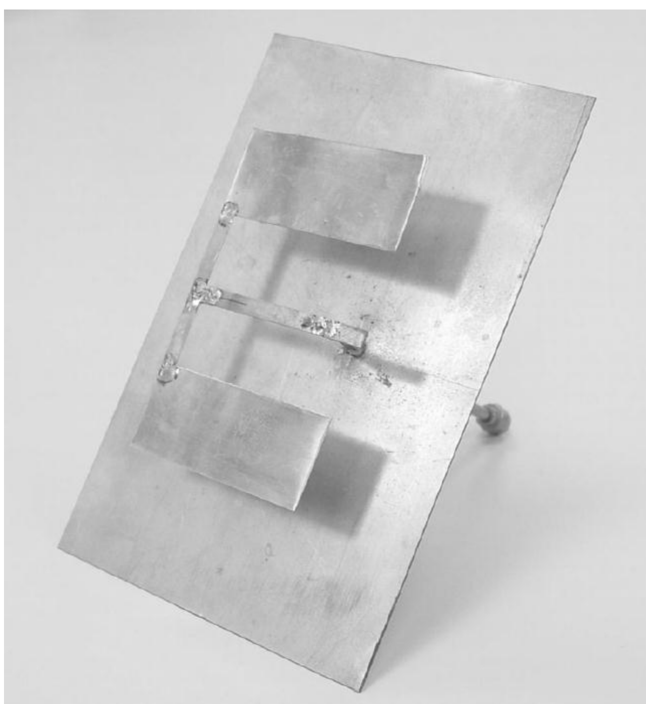

(b)

Figure 2.6. Fabricated antenna structures. (a) Antenna I (dual-frequency antenna). (b) Antenna II (wide-band antenna). [47]

But for the second antenna in order to reduce the *S*-parameter over the frequency range of 1.8 to 2.4 GHz, the fitness function has been defined as

$$F=50+max\left(S_{11,\ from\ 1.8\ GHz\ to\ 2.4\ GHz}\right). \tag{2.12}$$

For these two antenna designs optimizations a 10-particle swarm, and the maximum number of iteration of 1000 are used. In Figure 2.5 the convergence results of the two optimization processes. In the first optimization 3150 FDTD simulations are done among 6974 encountered positions, but in the second 4606 FDTD simulations are done among 6766 encountered positions.

For the first antenna the final values of the optimization parameters are 54, 46, 47, 20, 12, and 14. For the second antenna these values are 52, 82, 48, 20, 12, and 13, which are assigned to L, W, L_s, W_s, P_s, and x respectively. Also the fabricated antenna structures are shown in Figure 2.6.

2.5. ANT COLONY OPTIMIZATION

The ant colony optimization (ACO) is a global optimization method. It is based on the behaviour of ant colonies in finding food and it is a “short path” based algorithm. When the ants are searching around to find food, they release pheromone on the ground. The other ants select their paths based on level of pheromone on the ground. So, the higher the pheromone level, the more food can be found using this path. Furthermore, the pheromone on the ground can be used to remember the path to the food; also it’s good for new ants that are added to the trail to get more food from that place. The pheromone also evaporates to the air slowly during time. This fact decreases the chance of a trail toward a source of food, to be chosen by the ants when its food is finished.

The implementation of this natural behaviour in an optimization algorithm would be well suited for discrete and continuous problems. Firstly we need to define two functions for pheromone concentration and fitness evaluation and also choose some parameters, such as number of ants, α_1, α_2 (which would be defined later), etc., and then:

Initialize $I_1, I_2, \ldots, I_n$

For each iteration

    For each ant

        For each adjoining node

            Calculate pheromone function and desirability

        End for

    Choose one node

    If food is found

        Mode 0: Come back home

    Else-if ant is at home

        Mode 1: Searching food

    End if

    Update pheromone

    End for

End for

Solution is I_1, I_2, …, I_n with best result [46]

We have *N* parameters, which corresponds to an *N*-dimensional space of solutions. Every ant has a vector solution with values of the parameters. The solution space is described with nodes. The ants move between nodes through the *N*-dimensional space of solutions by using the fitness value and the pheromone concentration level. To choose between the neighbouring nodes, the ants make a probabilistic decision among all of them. The value of the vector of solutions in a neighbouring node is calculated by changing the state of only one element of the vector. So, every ant has *N* neighbouring nodes, and it needs to choose to move toward one of them, in a probabilistic manner. One of the most popular forms for combining the two values of fitness function and pheromone level, to calculate the probability of choosing nodes in ant's path is [48]:

$$p_{i,j}(t) = \frac{\left[\gamma_j(t)\right]^{\alpha_1} . \left[F_j\right]^{\alpha_2}}{\sum_{k \in S_i} \left[\gamma_k(t)\right]^{\alpha_1} . \left[F_k\right]^{\alpha_2}}, \tag{2.13}$$

where $p_{i,j}$ is the probability of choosing node *j* at iteration *t* from node *i*, F_j is the fitness value of node *j*, $\gamma_j(t)$ is the pheromone level of node *j* at iteration *t*, α_2 is the parameter used for controlling the importance of pheromone while α_2 does the same for the fitness value. S_i is the set of nodes *k* available at decision point *i*.

We can implement the function γ_j in different ways. This function indicates the pheromone level of nodes which changes during time. This includes

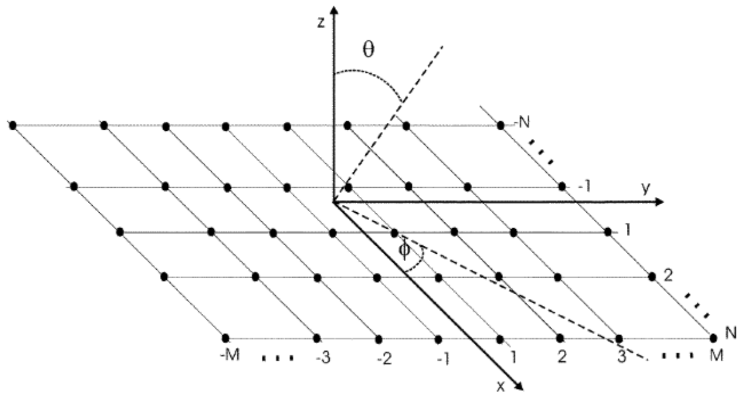


Figure 2.7. A 2N by 2M element symmetric planar array in XY plane.

the evaporation during time and the level increase when ants visit that node. A possible approach is [49]:

$$\gamma_j(t+1) = \gamma_j(t) + \Delta\gamma_j(t) - \delta(t), \tag{2.14}$$

where $\Delta\gamma_j(t)$ is the value which is added on node j because of visit of another ant, and $\delta(t)$ is the pheromone persistence, which is defined by:

$$\delta(t) = \begin{cases} \rho, & if \ \mathrm{mod}\left(\dfrac{t}{\tau}\right) = 0 \\ 0, & if \ \mathrm{mod}\left(\dfrac{t}{\tau}\right) \neq 0 \end{cases}, \tag{2.15}$$

where τ is the period time which the pheromone evaporates completely, and ρ is the coefficient of pheromone evaporation by the time period.

In this section only a brief description of the general concepts that constitute ACO-based algorithms has been presented. Further information can be found in [49].

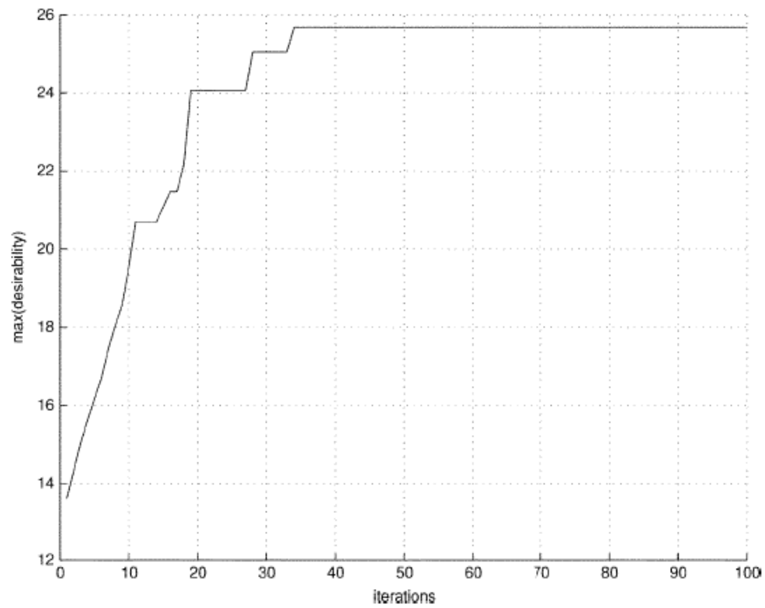


Figure 2.8. Maximum desirability versus the number of iterations.

In [46] a 20 by 10 planar array antenna (Figure 2.7) has been optimized to have side-lobe level (SLL) less than -24 dB both planes ($\phi = 0°$ and $\phi = 90°$). Antenna elements in this example are isotropic. In this example number of ants is 10 and stopping criterion is to reach maximum 100 iterations. Other parameters of the have been selected experimentally and they are $\rho = 1$, $\tau = 20$, $\Delta\gamma_j(t) = 1$, $\alpha_1 = 5$, and $\alpha_1 = 30$. The fitness function in this example has been defined as

$$F_j = min\left(\left|SLL_{\phi=0°}(dB)\right|,\ \left|SLL_{\phi=90°}(dB)\right|\right). \tag{2.16}$$

In Figure 2.8 convergence of the maximum desirability to the maximum has been shown, which shows a relatively fast convergence at iteration 40th.

2.6. SIMULATED ANNEALING

Originally, simulated annealing aims to simulate the behaviour of the molecules of a substance during a slow temperature reduction that would result in the formation of crystals, which are the state with minimum energy [50], [51]. This technique has been used to solve other types of problems which are based on the analogy between the state of each variable *y* that affects a fitness function and the state of each molecule in a substance. The fitness function, here called the energy function $F(\boldsymbol{p})$, where $\boldsymbol{p}$ is the vector of state variables. In this algorithm at each iteration the current state configuration $\boldsymbol{p}_i$, is induced with a small random perturbation (where *i* is the iteration number). If $\boldsymbol{p}^*$, the new configuration results into decreasing in the energy function, then it would definitely be accepted as the new current state ($\boldsymbol{p}_{i+1} = \boldsymbol{p}^*$). Instead, if $\boldsymbol{p}^*$ results into increasing the energy function, it might be accepted with a probability dependent on the system temperature, according to the Boltzmann distribution. This probability is higher with the higher system temperature. So, the probability that $\boldsymbol{p}^*$ might be accepted as the new current state, $P\{\boldsymbol{p}_{i+1} = \boldsymbol{p}^*\}$, can be written as:

$$P\{\boldsymbol{p}_{i+1} = \boldsymbol{p}^*\} = \begin{cases} exp\left\{\dfrac{-\left[F(\boldsymbol{p}^*) - F(\boldsymbol{p}_i)\right]}{kT}\right\}, & \text{if } F(\boldsymbol{p}^*) > F(\boldsymbol{p}_i) \\ 1, & \text{otherwise} \end{cases}, \quad (2.17)$$

where *T* is the system temperature and *k* is the Boltzmann constant. The system temperature, *T*, is decreasing in time with increasing the number of iterations, and

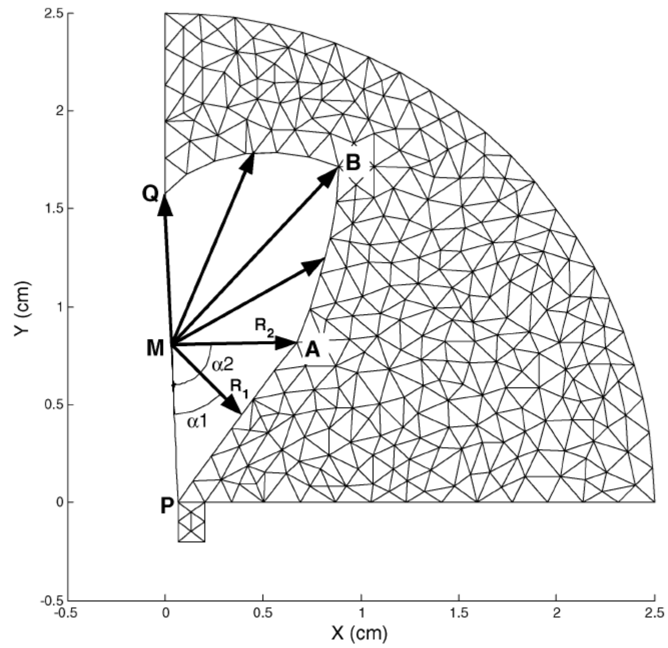


Figure 2.9. Position vector of Control points the antenna model [54].

it is following a logarithmic relationship with the number of iterations [50] [51], until the configuration freezes in a certain final state. Because of its probabilistic nature, this method has a notable advantage over classic methods of local descent, although it is computationally more expensive. By repeating the process with different initial points, we can increase the chance of finding the global optimum at the end of the process, even though it cannot be guaranteed.

In [52] and [53], SA was used to find the optimum positions of the antenna elements in an array for different applications. In [52], they addressed the problem of applying linear arrays to an interferometric imaging technique, which is generally used in radio astronomy. His main objective was to improve the angular resolution of radio telescopes. Also, Hayward in [53] tried to find the best positions for the antenna elements in order to maximize gain of the array in

Figure 2.10. Prototype photograph with the whole ground plane [54].

passive applications of conventional beamforming and matched-field beamforming in a two-dimensional isotropic noise field.

In [54] using $L+\max\left\{\left|S_{11}\right|_{dB}\right\}$ as the energy function a monopole antenna has been designed to cover 2 to 11 GHz. In the energy function L is a positive number to make the energy function to have a positive value during the optimization. In each iteration the S-parameter has been calculated for 19 equally spaced frequency points over the frequency band. The finite element electromagnetic simulator in this work has been HFSS. The optimization variables are the length of the position vector of the 6 control points which has been shown in Figure 2.9. So there are 6 variables to be optimized, and the angles of the position vectors are fixed. This optimization has been done in 6107 iterations and the optimized design has been shown in Figure 2.10.

2.7. Invasive Weed Optimization

After introducing Genetic algorithm, particle swarm, and ant colony, in this section another numerical stochastic method is introduced. These methods are all inspired from natural process, and they have been used in order to solve an antenna optimization problem. Invasive weed optimization method has been inspired from colonized weeds. This algorithm has been used in dynamic and control system theory for the first time [55].

To understand the colonizing behaviour of weeds, here are some basic properties of the process [55], [56]:

1) A finite number of seeds are being distributed over the solution space.

2) All the seeds grow to a flowering plant and produce more seeds depending on their fitness value.

3) The new seeds are randomly spread out in the solution space and grow to new plants.

4) This process is repeated until the number of plants is equal to the predefined maximum number of plants. Now only the plants with best fitness value can survive and reproduce, and others are being destroyed. This reproduction and elimination continues and the fitness value of the weeds improves in each iteration until maximum number of iterations is reached. The process can be explained in details as follows:

A) Initialize a population

Initial number of seeds is distributed in the *N*-dimensional solution space with random positions.

B) Reproduction

Only some of the plants are allowed to produce seeds, and that's decided by the plants fitness value and the colony's lowest and highest fitness values. Also the number of seeds that each plant produces depends on its fitness value. It increases linearly from the minimum possible seed production to its maximum level.

C) Spatial dispersal

The produced seeds are randomly spread over the *N*-dimensional solution space by a zero mean normal distribution, but with a varying variance. This ensures that the new seeds will be randomly distributed but also they stay near the parent plant. The standard deviation, σ, of the normal distribution will be reduced from a predefined initial value, σ_{initial}, to a final value, σ_{final}, in every step (generation). For this reduction, a nonlinear variation has shown good performance, which is given in:

$$\sigma_{iter} = \frac{\left(iter_{\max} - iter\right)^n}{iter_{\max}^n}\left(\sigma_{initial} - \sigma_{final}\right) + \sigma_{final} \tag{2.18}$$

where $iter_{\max}$ is the predefined maximum number of iterations, σ_{iter} is the standard deviation at the present iteration and *n* is the nonlinear modulation index.

D) Competitive exclusion

If a plant produces no seeds then it would be extinct. Otherwise, It would reproduce to the maximum number of plants. So, there should be a competition between plants for limiting the number of plants in a colony.

After some iterations, the number of plants in a colony will reach its maximum level by fast reproduction, however, it is expected that the plants with higher fitness value have been reproduced more. A mechanism for eliminating the plants with poor fitness in each generation activates by reaching the maximum number of plants in the colony ($P_{\max}$). By activation of the elimination mechanism weeds produce seeds according to the mechanism mentioned in the step B. Then, they are spread over the solution space according to step C. After distributing all the seeds in the solution space, they together with the parent form a colony of weeds. And then, the weeds with lower fitness value are eliminated to have the maximum allowable number of weeds in a colony. In this way, the parents and the new weeds are compared together and the ones with better fitness value survive and they are allowed to reproduce again. The elimination mechanism for population control is applied in the next generations until the stopping criteria are satisfied.

2.8. CONCLUSION

In this chapter we covered some of the most popular global optimization methods in electromagnetics and antenna design. All these methods have a lot of different parameters which need to be set carefully, and finally the user ends up repeating the whole optimization process over and over with different values for the aforementioned parameters in the optimization process to find the best optimum solution for the problem. So, using these optimization methods is basically to optimize the values of the optimization method for the specific problem that we want to optimize.

Also none of the popular global optimization methods use the information in the gradients of the objective function. For example using this information we can optimize the problem in very lower number of iterations and function evaluations. One of the best ways to calculate gradients of the objective function in electromagnetics and antenna problems is to use adjoint sensitivities available in the commercial electromagnetic software. Using the adjoint sensitivities available in the electromagnetic simulation software we can use a gradient-based optimization method to optimize our problem, which is the antenna structure. In the next chapters we are going to present a new evolutionary optimization method to optimize shape of the antenna structure.

REFERENCES

[1] J. Kennedy and R. Eberhart, "Particle swarm optimization," in Proc. 9th Int. Conf. on Neural Networks, Nov. 1995, vol. 4, pp. 1942–1948.

[2] R. Eberhart and J. Kennedy, "A new optimizer using particle swarm theory," in IEEE Proc. 6h Int. Symp. on Micro Machine and Human Science, Oct. 1995, pp. 39–43.

[3] J. Robinson and Y. Rahmat-Samii, "Particle swarm optimization in electromagnetics," IEEE Trans. Antennas Propag., vol. 52, pp. 397–407, Feb. 2004.

[4] D. Gies, "Particle swarm optimization: applications in electromagnetic design," M. Eng. thesis, UCLA, Los Angeles, CA, 2004.

[5] J. Kennedy and R. Eberhart, Swarm Intelligence. New York: Morgan Kaufmann and Academic Press, 2001.

[6] J. H. Holland, "Genetic algorithms and the optimal allocation of trials," SIAM J. Comput., vol. 2, no. 2, Jun. 1973.

[7] Y. Rahmat-Samii and E. Michielssen, Eds., Electromagnetic Optimization by Genetic Algorithms. New York: Wiley, 1999.

[8] R. L. Haupt and D. H. Werner, Genetic Algorithms in Electromagnetics. Hoboken, NJ: Wiley, 2007.

[9] D. S. Weile and E. Michielssen, "Genetic algorithm optimization applied to electromagnetics: A review," IEEE Trans. Antennas Propag., vol. 45, pp. 343–353, Mar. 1997.

[10] R. Storn and K. Price, “Differential evolution—A simple and efficient heuristic for global optimization over continuous spaces,” J. Global Optim., vol. 11, no. 4, pp. 341–359, Dec. 1997.

[11] K. V. Price, R. M. Storn, and J. A. Lampinen, Differential Evolution: A Practical Approach to Global Optimization, in Natural Computing. Heidelberg: Springer-Verlag, 2005.

[12] N. Jin and Y. Rahmat-Samii, “Parallel particle swarm optimization and finite difference time-domain (PSO/FDTD) algorithm for multiband and wide-band patch antenna designs,” IEEE Trans. Antennas Propag., vol. 53, pp. 3459–3468, Nov. 2005.

[13] N. Jin and Y. Rahmat-Samii, “Advances in particle swarm optimization for antenna designs: Real-number, binary, single-objective and multiobjective implementations,” IEEE Trans. Antennas Propag., vol. 55, pp. 556–567, Mar. 2007.

[14] N. Jin and Y. Rahmat-Samii, “Particle swarm optimization for antenna designs in engineering electromagnetics,” J. Artif. Evol. Applicat., vol. 2008, no. 9, Jan. 2008.

[15] F. J. Villegas, T. Cwik, Y. Rahmat-Samii, and M. Manteghi, “A parallel electromagnetic genetic-algorithm optimization (EGO) application for patch antenna design,” IEEE Trans. Antennas Propag., vol. 52, pp. 2424–2435, Sep. 2004.

[16] D. H.Werner, P. L.Werner, and K. H. Church, “Genetically engineered multiband fractal antennas,” IEEE Electron. Lett., vol. 37, no. 19, pp. 1150–1151, Sep. 2001.

[17] B. Schlobohm, F. Arndt, and J. Kless, “Direct PO optimized dual-offset reflector antennas for small earth stations and for millimeter wave atmospheric sensors,” IEEE Trans. Microwave Theory Tech., vol. 40, pp. 1310–1317, Jun. 1992.

[18] A. Hoorfar and Y. Liu, “Antenna optimization using an evolutionary programming algorithm with a hybrid mutation operator,” in Proc. IEEE Int. Symp. on Antennas Propag., 2000, vol. 2, p. 1029.

[19] M. John and M. J. Ammann, “Antenna optimization with a computationally efficient multiobjective evolutionary algorithm,” IEEE Trans. Antennas Propag., vol. 57, pp. 260–263, Jan. 2009.

[20] D. S. Weile and E. Michielssen, “Integer coded Pareto genetic algorithm design of constrained antenna arrays,” IEEE Electron. Lett., vol. 32, no. 19, pp. 1744–1745, Sep. 1996.

[21] T. G. Spence and D. H. Werner, “Design of broadband planar arrays based on the optimization of aperiodic tilings,” IEEE Trans. Antennas Propag., vol. 56, pp. 76–86, Jan. 2008.

[22] R. L. Haupt, “Thinned arrays using genetic algorithms,” IEEE Trans. Antennas Propag., vol. 42, pp. 993–999, Jul. 1994.

[23] J. S. Petko and D. H. Werner, “The evolution of optimal linear polyfractal arrays using genetic algorithms,” IEEE Trans. Antennas Propag., vol. 53, pp. 3604–3615, Nov. 2005.

[24] J. S. Petko and D. H. Werner, “An autopolyploidy-based genetic algorithm for enhanced evolution of linear polyfractal arrays,” IEEE Trans. Antennas Propag., vol. 55, pp. 583–593, Mar. 2007.

[25] J. S. Petko and D. H. Werner, “The pareto optimization of ultrawideband polyfractal arrays,” IEEE Trans. Antennas Propag., vol. 56, pp. 97–107, Jan. 2008.

[26] M. G. Bray, D. H.Werner, D.W. Boeringer, and D. W. Machuga, “Optimization of thinned aperiodic linear phased arrays using genetic algorithms to reduce grating lobes during scanning,” IEEE Trans. Antennas Propag., vol. 50, pp. 1732–1742, Dec. 2002.

[27] M. D. Gregory and D. H. Werner, “Ultrawideband aperiodic antenna arrays based on optimized raised power series representations,” IEEE Trans. Antennas Propag., vol. 58, Mar. 2010.

[28] D. W. Boeringer, D. H.Werner, and D. W. Machuga, “A simultaneous parameter adaptation scheme for genetic algorithms with application to phased array synthesis,” IEEE Trans. Antennas Propag., vol. 53, pp. 356–371, Jan. 2005.

[29] D. W. Boeringer and D. H. Werner, “Efficiency-constrained particle swarm optimization of a modified Bernstein polynomial for conformal array excitation amplitude synthesis," IEEE Trans. Antennas Propag., vol. 53, pp. 2662–2673, Aug. 2005.

[30] J. A. Bossard, X. Liang, L. Li, S. Yun, D. H. Werner, B. Weiner, T. S. Mayer, P. F. Cristman, A. Diaz, and I. C. Khoo, "Tunable frequency selective surfaces and negative-zero-positive index metamaterials based on liquid crystals," IEEE Trans. Antennas Propag., vol. 56, pp. 1308–1320, May 2008.

[31] J. A. Bossard, D. H.Werner, T. S.Mayer, J. A. Smith, Y. U. Tang, R. P. Drupp, and L. Li, "The design and fabrication of planar multiband metallodielectric frequency selective surfaces and infrared applications," IEEE Trans. Antennas Propag., vol. 54, pp. 1265–1276, Apr. 2006.

[32] J. A. Bossard, D. H. Werner, T. S. Mayer, and R. P. Drupp, "A novel design methodology for reconfigurable frequency selective surfaces using genetic algorithms," IEEE Trans. Antennas Propag., vol. 53, pp. 1390–1400, Apr. 2005.

[33] M. A. Gingrich and D. H. Werner, "Synthesis of low/zero index of refraction metamaterials from frequency selective surfaces using genetic algorithms," IEEE Electron. Lett., vol. 41, no. 23, pp. 1266–1267, Nov. 2005.

[34] D. J. Kern, D. H. Werner, and M. Lisovich, "Metaferrites: Usign electromagnetic bandgap structures to synthesize metamaterial ferrites," IEEE Trans. Antennas Propag., vol. 53, pp. 1382–1389, Apr. 2005.

[35] D. J. Kern, D. H. Werner, A. Monorchio, L. Lanuzza, and M. J. Wilhelm, "The design synthesis of multiband artificial magnetic conductors using high impedance frequency selective surfaces," IEEE Trans. Antennas Propag., vol. 53, pp. 8–17, Jan. 2005.

[36] S. Genovesi, R. Mittra, A. Monorchio, and G. Manara, "Particle swarm optimization for the design of frequency selective surfaces," IEEE Antennas Wireless Propag. Lett., vol. 5, pp. 277–279, 2006.

[37] M.-I. Lai and S.-K. Jeng, "Compact microstrip dual-band bandpass filter design using genetic algorithm techniques," IEEE Trans. Microwave Theory Tech., vol. 54, pp. 160–168, Jan. 2006.

[38] S. K. Guodos and J. N. Sahalos, "Pareto optimal microwave filter design using multiobjective differential evolution," IEEE Trans. Antennas Propag., vol. 58, pp. 132–144, Jan. 2010.

[39] N. V. Venkatarayalu and T. Ray, "Optimum design of yagi–uda antennas using computational intelligence," IEEE Trans. Antennas Propag., vol. 52, no. 7, pp. 1811–1818, July 2004.

[40] R. L. Haupt, "An introduction to genetic algorithms for electromagnetics", IEEE Antenna and Propag. Magazine, vol. 37, no. 2, pp. 7–15, April 1995.

[41] L. Y. Tseng, and T. Y. Han, "An Evolutionary Design Method Using Genetic Local Search Algorithm to Obtain Broad/Dual-Band Characteristics for Circular Polarization Slot Antennas" IEEE Trans. Antennas Propag., vol. 58, no. 5, pp. 1811–1818, May 2010.

[42] R. C. Eberhart and Y. Shi, “Evolving artificial neural networks,” in Proc. 1998 Int. Conf. Neural Networks and Brain, Beijing, P.R.C., 1998.

[43] J. Robinson, S. Sinton, and Y. Rahmat-Samii, “Particle swarm, genetic algorithm, and their hybrids: optimization of a profiled corrugated horn antenna,” in Proc. IEEE Int. Symp. Antennas Propagation, vol. 1, San Antonio, TX, 2002, pp. 314–317.

[44] J. Kennedy and W. M. Spears, “Matching algorithms to problems: an experimental test of the particle swarm and some genetic algorithms on multi modal problem generator,” in Proc. IEEE Int. Conf. Evolutionary Computation, 1998.

[45] J. Kennedy and R. Eberhart, “A discrete binary version of the particle swarm algorithm,” in Proc. 1997 Conf. Systems, Man, Cybernetics, Piscataway, NJ, 1997.

[46] Ó. Quevedo-Teruel and E. Rajo-Iglesias, “Ant colony optimization in thinned array synthesis with minimum sidelobe level,” IEEE Trans. and Wireless Propag. Letters, vol. 5, no. 1, pp. 349–352, Dec. 2006.

[47] N. Jin and Y. Rahmat-Samii, “Parallel particle swarm optimization and finite-difference time-domain (PSO/FDTD) algorithm for multiband and wide-band patch antenna designs” IEEE Trans. Antennas Propag., vol. 53, no. 11, pp. 3459–3468, Nov. 2005.

[48] M. Dorigo, V. Maniezzo, and A. Colorni, "Ant system: Optimization by a colony of cooperating agents," IEEE Trans. Syst., Man, Cybern. B, Cybern., vol. 26, no. 1, pp. 29–41, Feb. 1996.

[49] M. Dorigo and T. Stutzle, Ant Colony Optimization. Cambridge, MA: MIT Press, 2004.

[50] S. Kirkpatrick, C. D. Gellatt, Jr., and M. P. Vecchi, "Optimization by simulated annealing," Sci., vol. 220, no. 4598, pp. 671480, 1983.

[51] W. A. Kuperman, M. D. Collins, J. S. Perkins, and N. R. Davis, "Optimal time-domain beamforming with simulated annealing including application of a priori information," J. Acoust. Soc. Amer., vol. 88, pp. 1802-1810, Oct. 1990.

[52] C. S. Ruf, "Numerical annealing of low-redundancy linear arrays," IEEE Trans. Antennas Propagat., vol. 41, pp. 85-90, Jan. 1993.

[53] T. J. Hayward, "Optimization of the hydrophone placement for acoustic arrays using simulated annealing," J. Acoust. Soc. Amer., vol. 95, pp. 201-212, Jan. 1994.

[54] J. Martínez-Fernández, J. M. Gil, and J. Zapata, "Ultrawideband Optimized Profile Monopole Antenna by Means of Simulated Annealing Algorithm and the Finite Element Method," IEEE Trans. Antennas Propag., vol. 55, no. 6, pp. 1826–1832, June 2007.

[55] A. R. Mehrabian and C. Lucas, “A novel numerical optimization algorithm inspired from weed colonization,” Ecological Informatics, vol. 1, no. 4, pp. 355-366, Dec. 2006.

[56] B. Dadalipour, A. R. Mallahzadeh, and Z. Davoodi-Rad, “Application of the invasive weed optimization technique for antenna configurations,” in Proc. 2008 Loughborough Antennas and Propag. Conf., UK, March 2008.

[57] Y. Shi and R. C. Eberhart, “Empirical study of particle swarm optimization,” in Proc. Congr. Evolutionary Computation. Piscataway, NJ, 1999, pp. 1945–1950.

[58] T. Ray, K. Tai, and K. C. Seow, “An evolutionary algorithm for constrained optimization,” in Proc. Genetic and Evolutionary Computation Conf.. San Matteo, CA, 2000, pp. 771–777.

[59] N. Srinivas and K. Deb, “Multiobjective optimization using non-dominated sorting in genetic algorithms,” Evolutionary Comput., vol. 2, no. 3, pp. 221–248, 1994.

[60] T. Ray and P. Saini, “Engineering design optimization using a swarm with an intelligent information sharing among individuals,” Eng. Optimization, vol. 33, no. 6, pp. 735–748, 2002.

CHAPTER 3

ANTENNA DESIGN EXPLOITING ADJOINT SENSITIVITY-BASED GEOMETRY EVOLUTION

3.1. INTRODUCTION

The design of antennas usually starts with a structure with some initial geometry. This geometry represents a known design template. The parameters of this template are usually changed to meet the design specifications without changing the template itself. For example, a rectangular patch antenna is a template whose optimizable parameters are the length and width of the patch. The changes in the initial design are usually carried out through an optimization algorithm (optimizer). The optimizer drives the electromagnetic (EM) simulator to change different template parameters towards an optimal solution.

The optimization process may not reach a satisfactory design for a number of reasons. The optimizer may get trapped into a local minimum. The optimizer may reach the best possible solution but the selected template is not able to satisfy the given design constraints. Global optimization approaches may help find the global solution at the cost of a dramatic increase in the number of required EM simulations. These algorithms have been explained in the previous chapter. All of them utilize nature-inspired mechanisms to locate the global optimal design. They, however, may not be able to locate a good design if the utilized template is not able to satisfy the design specifications.

Other evolutionary approaches aim at changing the antenna structure through different mechanisms. These include adding or removing square metallization on the antenna surface [6], changing the antenna profile through global optimization [1], or using MEMs switches to change the antenna structure [7]. These approaches do not make use of response sensitivities which may be costly.

Recently, there has been significant development in the theory of adjoint sensitivities using EM solvers. It was shown that using at most one EM simulation, the sensitivities of a given objective function with respect to all parameters is obtained regardless of the number of parameters. This approach was developed for the Finite Element Method (FEM) [8], the transmission line method (TLM) [9], the FDTD method [10], the Method of Moments (MoM) [11], and the Beam Propagation method (BPM) [12]. In [13], it was shown for the first time that no adjoint simulation is needed to estimate the wideband adjoint sensitivities of the *S*-parameters. This approach is denoted as Self-Adjoint Sensitivity Analysis (SASA). Adjoint sensitivities have been utilized in [14] and [15] for solving optimization problems. SASA approaches have recently become available in a number of commercial solvers including HFSS [16] and CST [17].

In this chapter, we present a framework for novel adjoint sensitivity-based evolutionary method antenna design. Our approach makes use of the recent developments in the theory of adjoint sensitivities. The design parameters are chosen as the coordinates of the vertices of a number of control points of the structure. Using the readily available sensitivity information, the structure evolves into arbitrary shapes through the change in the position of the control vertices. The number of the vertices indicates the allowed degrees of freedom of the structure. Feasibility conditions may be applied to limit the possibility of creating non-physical structures that violate geometrical constraints.

This chapter is organized as follows; In the next section, we state the antenna design problem as an optimization problem. Then, we briefly review the available self-adjoint sensitivity analysis approaches both in the time and frequency domains. After that in the next section our approach is presented. Afterward a number of examples illustrate our antenna design approach. Finally, conclusions are given in the last Section.

3.2. THE OPTIMIZATION PROBLEM

The problem addressed here is to determine the optimal parameter values of a given antenna structure. This design problem can be cast in the form of a general multi objective optimization problem which was mentioned in the previous chapter and it was simplified to the following mathematical form:

$$\begin{aligned} &\min_{\boldsymbol{p}} \boldsymbol{F}(\boldsymbol{p}) \\ \textit{subject to:}\quad &\boldsymbol{g}(\boldsymbol{p}) \le \mathbf{0} \end{aligned} \tag{3.1}$$

where $\boldsymbol{F}(\boldsymbol{p})$ is the objective function, which is to be minimized, and $\boldsymbol{p}$ is the vector of the optimization variables. The vector function $\boldsymbol{g}$ represents the linear and nonlinear constraints on the optimizable parameters $\boldsymbol{p}$. These constraints can be used to impose feasibility or other constraints on the optimal design. In a typical antenna problem, the objective function $\boldsymbol{F}$ is dependent on the S-parameters at a number of frequencies. Other responses such as the radiation pattern in certain directions may also be included. Here, we focus only on the case where $\boldsymbol{F}$ is a function of the S-parameters.

3.3. ADJOINT SENSITIVITIES

Adjoint sensitivity analysis aims at efficiently estimating the sensitivities of a given objective function with respect to all designable parameters. In the time domain, this function has the general form:

$$F = \int_{\Omega}\int_0^{T_m} \psi(\boldsymbol{p},\boldsymbol{V})\,dt\,d\Omega, \tag{3.2}$$

where Ω is the observation domain. ψ is the integral kernel and $\boldsymbol{V}$ is the vector of temporal time domain field quantities. They represent, for example, voltage impulses in the TLM method and electric and magnetic fields components in the FDTD technique. The *S*-parameter calculations can be cast in the form 3.2)).

For the TLM and FDTD techniques, the EM simulation can be cast in the form [10]:

$$\boldsymbol{M}\ddot{\boldsymbol{V}} + \boldsymbol{N}\dot{\boldsymbol{V}} + \boldsymbol{K}\boldsymbol{V} = \boldsymbol{Q},\ \boldsymbol{V}(0) = \boldsymbol{0},\ \dot{\boldsymbol{V}}(0) = \boldsymbol{0}, \tag{3.3}$$

where $\boldsymbol{M}$, $\boldsymbol{N}$, and $\boldsymbol{K}$ are system matrices that are functions of the material properties and utilized discretization. $\boldsymbol{Q}$ is the vector of temporal excitations.

The classical approach for estimating the sensitivities of the objective function 3.2)) with respect to all n parameters utilizes finite difference approximations. These approximations repeatedly simulated the structure for perturbed parameter values. For example, the derivatives obtained using Central Finite Differences (CFD) using:

$$\frac{\partial F}{\partial p_j} \approx \frac{F(p_j + \Delta p_j) - F(p_j - \Delta p_j)}{2\Delta p_j},\ j=1,\ 2,\ldots,\ n, \tag{3.4}$$

The cost of evaluating finite differences for problems with large number of parameters or with intensive simulation times can be prohibitive.

Adjoint Variable Methods (AVMs) offer an alternative approach for sensitivity analysis. The sensitivities of the objective function $\boldsymbol{F}$ with respect to all design parameters are obtained by carrying out the time domain adjoint simulation:

$$\boldsymbol{M}^T\ddot{\boldsymbol{\lambda}} - \boldsymbol{N}^T\dot{\boldsymbol{\lambda}} + \boldsymbol{K}^T\boldsymbol{\lambda} = \frac{\partial\psi}{\partial\boldsymbol{V}},\ \boldsymbol{\lambda}(T_m) = 0,\ \dot{\boldsymbol{\lambda}}(T_m) = 0 \tag{3.5}$$

Through the original field $\boldsymbol{V}$ and the adjoint field $\boldsymbol{\lambda}$, the sensitivities of the objective function are evaluated by:

$$\frac{\partial F}{\partial p_i} = -\int_{\Omega}\int_0^{T_m} \boldsymbol{\lambda}^T \boldsymbol{\eta}_i \, dt d\Omega, \tag{3.6}$$

where the vector $\boldsymbol{\eta}$ is a function of the vector $\boldsymbol{V}$. The subscript "i" in 3.6)) indicates that $\boldsymbol{\eta}$ is different for different parameter. For the S-parameters, the adjoint simulation 3.5)) can be eliminated as the vector $\boldsymbol{\lambda}$ is deducible from the vector $\boldsymbol{V}$ through a simple transformation [13]. A similar approach is implemented in the time domain solver CST [16].

In the frequency domain, it is usually required to estimate the sensitivities of a complex objective function of the form $\boldsymbol{F}(\boldsymbol{p},\boldsymbol{I})$ where $\boldsymbol{I}$ is the vector of frequency domain state variables. These variables represent surface currents as in the Method of Moments (MoM) or spatial frequency domain fields as in the Finite Element Method (FEM). It is obtained by solving the structure's system of linear equations:

$$\boldsymbol{Z}\boldsymbol{I} = \boldsymbol{Q}, \tag{3.7}$$

Frequency domain AVM analysis requires evaluating the adjoint vector $\boldsymbol{I}$ through the adjoint system [11]:

$$\boldsymbol{Z}^T\hat{\boldsymbol{I}} = \left(\partial\tilde{F} / \partial\boldsymbol{I}\right)^T, \tag{3.8}$$

Knowing the original and adjoint fields $\boldsymbol{I}$ and $\hat{\boldsymbol{I}}$, the sensitivities of the objective function with respect to the *j*th parameter are thus given by [12]

$$\partial\tilde{\boldsymbol{F}} / \partial p_j = \hat{\boldsymbol{I}}^T((\partial\boldsymbol{Q} / \partial p_j) - (\partial(\boldsymbol{Z}\bar{\boldsymbol{I}}) / \partial p_j)) \tag{3.9}$$

where $\bar{\boldsymbol{I}}$ is the solution of 3.7)) at the current set of parameters. If the objective function represents an *S*-parameter, the adjoint simulation 3.8)) is not needed. The vector $\hat{\boldsymbol{I}}$ is deducible from the original field $\boldsymbol{I}$. A similar self-adjoint approach is implemented in the commercial EM solver HFSS.

3.4. OUR APPROACH

The typical approach used in traditional antenna design approaches utilizes geometry templates whose parameters can be optimized without changing the template itself. For example, the length and width of a rectangular patch antenna are optimized to meet the design specifications. The final design would still be a rectangular patch antenna. It follows that the design template is preserved while changing only its parameters.

In this work, we adopt a different approach. The optimized parameters $\boldsymbol{p}$ are selected as the coordinates of a number of control points of the structure. For a 2D planar structure with N evolvable points, the vector of design parameters is given by $\boldsymbol{p}=[x_1\ \ y_1\ \ x_2\ \ y_2\ \ldots\ x_N\ \ y_N]^T$. By changing these parameters, we allow the structure to evolve into a completely different template that is more likely to satisfy our design constraints.

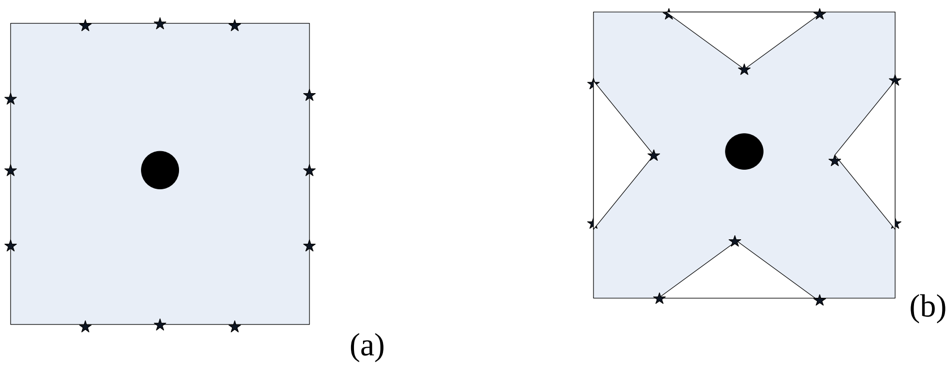


Figure 3.1. The top view of the coaxial-fed rectangular patch antenna before (a) and after (b) control vertices were allowed to evolve using adjoint sensitivity information.

For example, consider the coaxial-fed patch antenna shown in Figure 3.1(a). The points to be selected as control parameters are shown with a star. The choice of these points may be done based on initial sensitivity analysis phase that determines which points affect the response more. Following our approach, this initial design structure may evolve into the structure shown in Figure 3.1(b) which may better satisfy the design constraints.

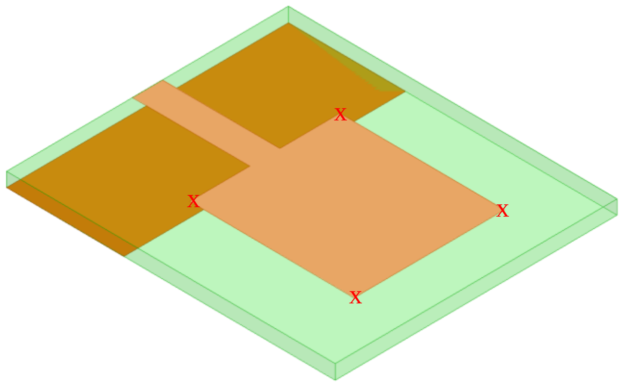
We utilize in our approach a gradient-based optimization technique. Such a technique requires not only the function value of the response but also its gradient with respect to the different parameters. The gradient of the objective function $\partial \boldsymbol{F}/\partial \boldsymbol{p}$ is required at every optimization iteration. If the function $\boldsymbol{F}(\boldsymbol{p})$ is non-differentiable as in the case of the classical minimax function [19], the Jacobian of its sub functions is estimated through adjoint sensitivities and utilized in the optimization process. In general, our design approach evaluates, if applicable, the Jacobian matrix:

$$\boldsymbol{J} = \begin{bmatrix} \left(\partial F / \partial \boldsymbol{p}\right)^T \\ \left(\partial \boldsymbol{g} / \partial \boldsymbol{p}\right)^T \end{bmatrix}, \tag{3.10}$$

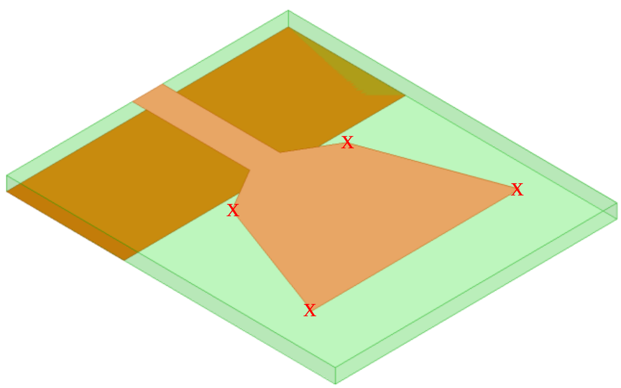
The number of parameters may be large if we allow for a significant number of evolvable vertices. In such a case, the cost of evaluating the gradient may be extensive using traditional finite difference approaches.

We instead utilize the self-adjoint sensitivity approach of the S-parameters [13] which offers an efficient approach for gradient estimation. Using no extra EM simulations, the gradient of the response with respect to all parameters is estimated over the frequency band of interest. This approach has been recently adopted by a number of commercial EM solvers, e.g., HFSS and CST. We utilize in our approach the self-adjoint sensitivities available in HFSS. Our Matlab [20] optimization code drives HFSS and utilizes the values of the S-parameters and their sensitivities supplied by HFSS to solve the optimization problem 3.1)). Any suitable gradient-based optimization algorithm can thus be applied.

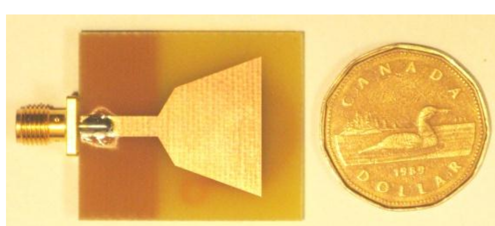
Because our approach utilizes the coordinates of the control vertices as optimization parameters, it is possible that during the optimization iterations a non physical structure may be created. This may happen in the cases that have a relatively large number of control points. In such structure, for example, two edges may cross one another which are not permissible in a planar structure. This kind of problems can be solved using different starting initial design. Feasibility conditions on the structure also may be added as nonlinear constraints in 3.1)).



(a)



(b)



(c)

Figure 3.2. The starting (a) and final (b) geometry and top view (c) of the fabricated design of the monopole antenna structure.

This guarantees that no such a structure is created during the optimization iterations.

It should also be noted that our approach obtains a local minimum of the objective function. Starting with different initial geometries, the antenna structure will likely evolve to final geometries with different values of the objective function. We thus aim at obtaining only one feasible solution which satisfies the give design specifications.

3.5. EXAMPLES

In this section we illustrate our approach through a number of examples. All these examples were carried out using the commercial EM solver HFSS. The optimization functions in MATLAB drive HFSS. The geometry is evolved based on the *S*-parameter information and their adjoint sensitivities available from HFSS.

3.5.1. A Monopole Microstrip Antenna

In this example, we apply our approach to a single microstrip monopole. Our target is to convert this monopole into an UWB antenna by optimizing the coordinates of a number of selected coordinates. This single layer structure includes a microstrip patch, a microstrip feedline, and a ground plan. The structure is shown in Figure 3.2(a). The initial design is narrow band with dimensions as reported in previous papers [20]-[22].

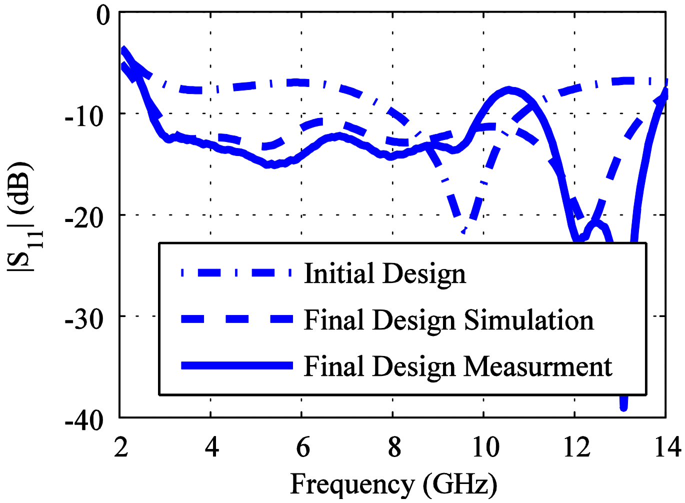
We use the x and y coordinates of four vertices of rectangular microstrip patch of the starting structure as the variables of the optimization problem. These vertices are marked with an "x" in Figure 3.2(a). The vector of optimization variables has thus eight components $\boldsymbol{p}$ =[x_1 y_1 x_2 y_2 x_3 y_3 x_4 y_4].

The optimization problem to be solved is given by:

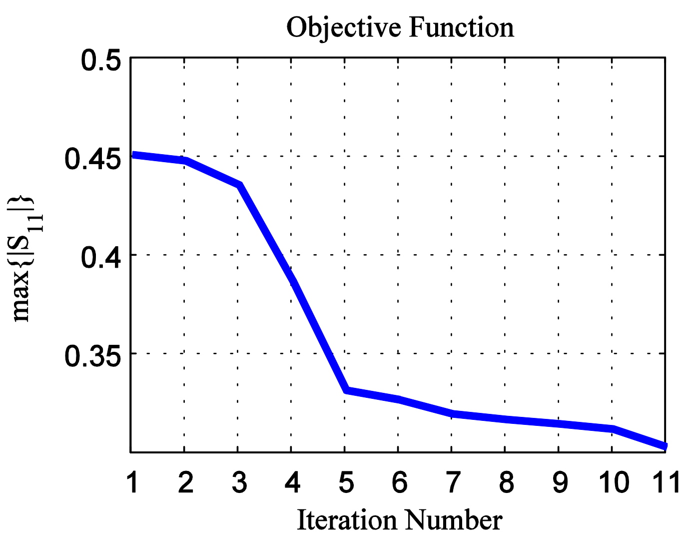
$$\begin{gathered} \min_{\boldsymbol{p}} \max_{j} \left(F_j\right) \\ \textit{subject to} \quad \boldsymbol{p}_{lb} \le \boldsymbol{p} \le \boldsymbol{p}_{ub} \end{gathered} \tag{3.11}$$

The vector of $\boldsymbol{F}_j$, j=1, 2, …, 9 are the values of $|S_{11}|$ over frequencies in the range 3-11 GHz, which covers the UWB frequency range. The simulation of the structure has been done in 9 frequency points which are linearly distributed over the frequency band [3.0-11.0] GHz. The objective function to be minimized is the maximum of $\{|S_{11}|\}$ over the specified frequency range. $\boldsymbol{p}_{lb}$ and $\boldsymbol{p}_{ub}$ are, respectively, the lower and upper bounds of optimization variables. These bounds are enforced on the optimization problem to have a physically realizable structure as the solution of the optimization process. The substrate of the antenna is a 30 mm×35 mm×1.5 mm FR4. It has a relative permittivity of 4.4. The length of the feed line is equal to the length of the ground plan and is equal to 12.5 mm.

The EM simulator HFSS supplies the values all $\boldsymbol{F}_j$ and their gradient with respect to all the optimization variables p using its built-in adjoint sensitivities. We utilize the MATLAB function fminimax in solving 3.1)). After 11 iterations the design specifications of the UWB antenna are satisfied. The starting point for the optimization process is shown in the second column of Table 3.1. Notice that the negative sign appears because the variables are coordinates of the vertices and some are negative with respect to the selected axis. The utilized upper and lower



(a)



(b)

Figure 3.3. (a) the value of the return loss in dB at the initial and final designs and (b) the value of the objective function value at each iteration for the microstrip monopole antenna.

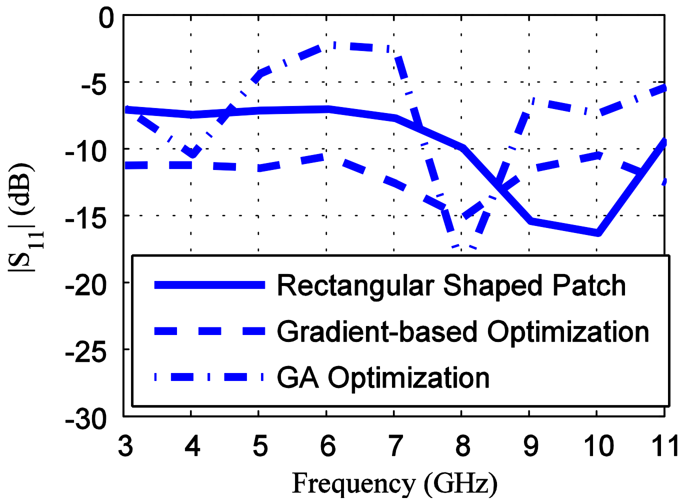
bands are given by $\boldsymbol{p}_{ub}$ =[15 35 15 35 15 35 15 35] mm and $\boldsymbol{p}_{lb}$ =[-15 12.5 -15 12.5 -15 12.5 -15 12.5] mm. The final solution of the optimization problem is shown in the third column of Table 3.1. The optimized antenna structure and top

Table 3.1. Initial and final parameters for the monopole example

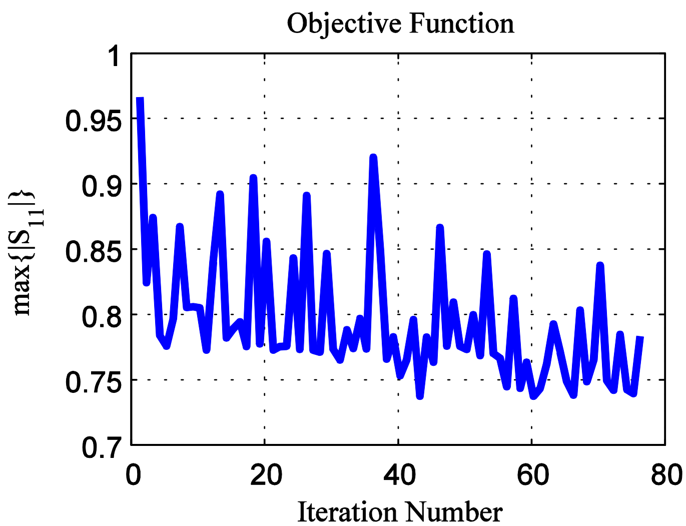
point	initial design (mm)	final design (mm)
(x_1, y_1)	(8.0, 12.5)	(7.1482, 14.3440)
(x_2, y_2)	(8.0, 30.0)	(8.2614, 30.4482)
(x_3, y_3)	(-8.0, 30.0)	(-8.2490, 30.4451)
(x_4, y_4)	(-8.0, 12.5)	(-7.1072, 14.3276)

view of the fabricated design are shown respectively in Figure 3.2(b) and Figure 3.2(c). The values of $|S_{11}|$ in dB at the initial and final designs are shown in Figure 3.3(a). Figure 3.3(b) shows the decrease of the objective function (max $\{|S_{11}|\}$) in the optimization process.

For this example we tried using genetic algorithm to solve the same optimization problem 3.11)). We used again one of MATLAB functions for the genetic optimization algorithm. In Figure 3.4(a) we can see the values of $|S_{11}|$ in dB for the optimized antenna structure using genetic algorithm, the rectangular shaped antenna, and the optimized antenna structure using the gradient-based optimization method using fminimax. Also in Figure 3.4(b) we can see the values of the objective function (max $\{|S_{11}|\}$) during the optimization process by the genetic algorithm.



(a)



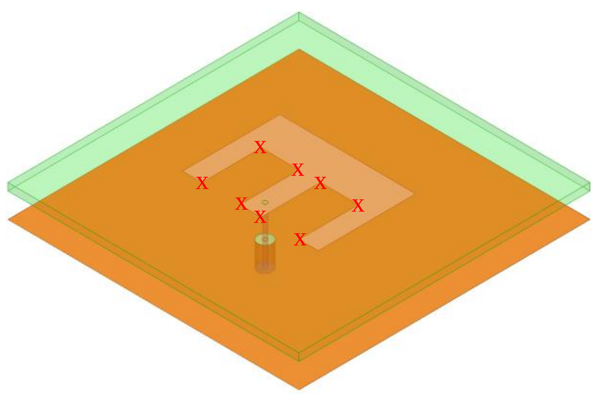
(b)

Figure 3.4. (a) the value of the return loss in dB for the rectangular shaped antenna, gradient-based optimization, and the genetic algorithm optimization and (b) the value of the objective function value at each iteration for the microstrip monopole antenna using genetic algorithm.

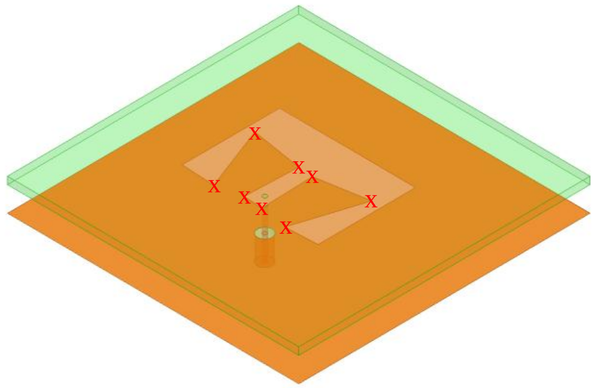
3.5.2. An E-shaped antenna

In this example, we apply our approach to the design of an E-shaped probe-fed microstrip antenna for wireless communication applications [23], [24]. The antenna structure consists of a ground plane, an air gap, and an FR4 substrate with a thickness of 1.5 mm. The dimensions of the substrate are 60 mm × 60 mm ×1.5 mm. The thickness of the air gap is 5.0 mm. The starting structure of the optimization process is shown in Figure 3.5(a).

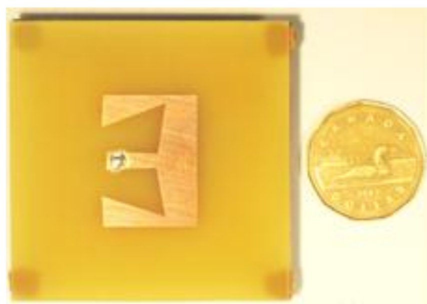
We choose the x and y coordinates of eight vertices as optimization variables. These vertices are marked with a red "x" as shown in Figure 3.5(a). The vector of optimization variables is thus $\boldsymbol{p}=[x_1\ y_1\ x_2\ y_2\ x_3\ y_3\ x_4\ y_4\ x_5\ y_5\ x_6\ y_6\ x_7\ y_7\ x_8\ y_8]^T$. The optimization problem to be solved is identical to 3.11)). The



(a)



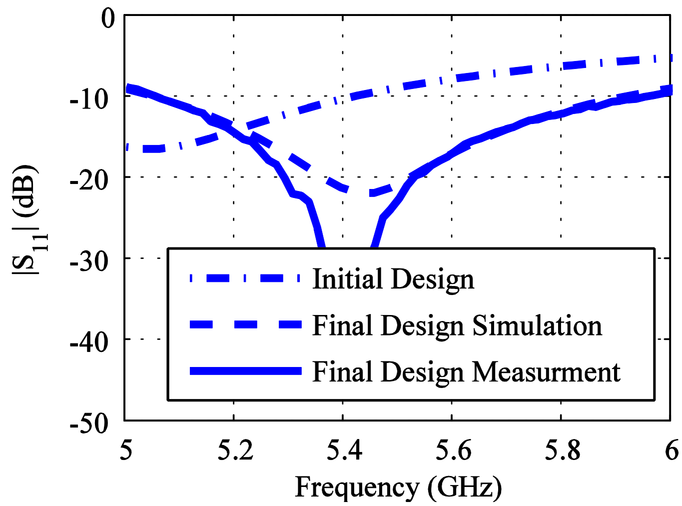
(b)



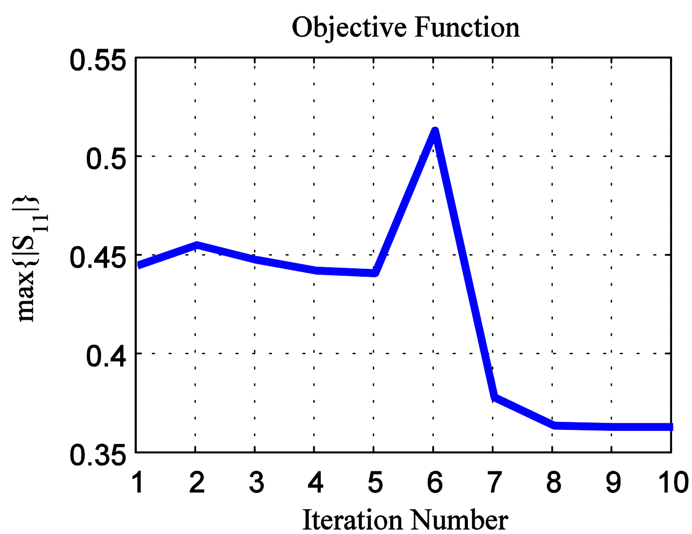
(c)

Figure 3.5. The starting (a) and final (b) geometry and top view (c) of the fabricated design of the the E-shaped antenna.

vector of $\boldsymbol{F}_j$ contains the values of $|S_{11}|$ at 10 frequencies evenly covering the band 5-6 GHz. The frequencies are linearly spaced in the frequency band.



(a)



(b)

Figure 3.6. (a) the value of the return loss in dB at the initial and final designs and (b) the value of the objective function value at each iteration for the E-shaped antenna.

The optimization process is done in the same way as the previous example, by using the MATLAB function fminimax. The starting point for the optimization process is given in the second column of Table 3.2. The upper bound

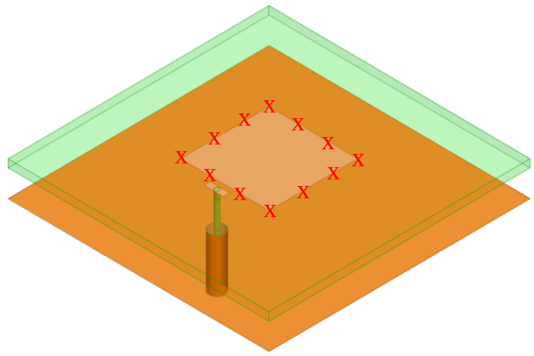
Table 3.2. Initial and final parameters for the E-shaped antenna

point	initial design (mm)	final design (mm)
(x_1, y_1)	(-10, -8.7)	(10.3290, -7.2383)
(x_2, y_2)	(-7, -8.7)	(-3.2655, -12.2912)
(x_3, y_3)	(-7, -2.2)	(-1.5994, -1.5775)
(x_4, y_4)	(10, -2.2)	(9.1761, -2.0847)
(x_5, y_5)	(10, 2.2)	(9.3920, 1.7680)
(x_6, y_6)	(-7, 2.2)	(-1.2730, 1.4774)
(x_7, y_7)	(-7, 8.7)	(-3.1724, 11.8225)
(x_8, y_8)	(10, 8.7)	(10.3455, 7.4790)

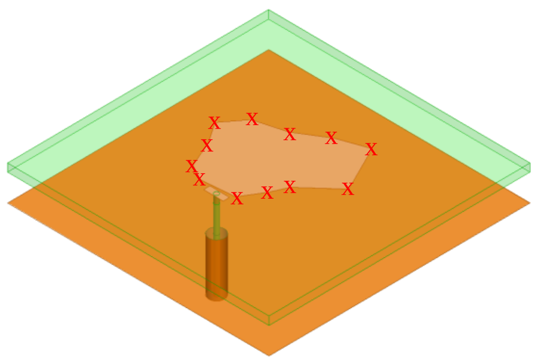
for all the variables is 30 and the lower bound is -30. These bounds limit the structure to the 60 mm × 60 mm substrate. The final solution of the optimization problem is given in the third column of Table 3.2. The optimized antenna structure and top view of the fabricated design are shown respectively in Figure 3.5(b) and Figure 3.5(c). The change of the objective function at each iteration is shown in Figure 3.6(a). The response of the structure at the final structure is shown in Figure 3.6(b).

3.5.3. A Capacitively-Fed Microstrip Antenna

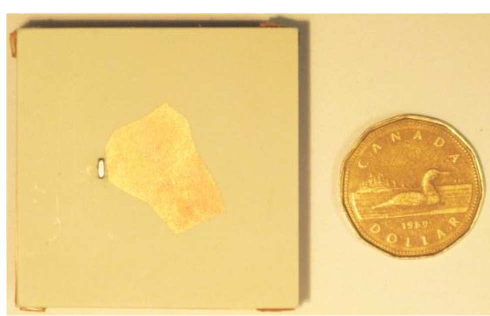
We also apply our approach to improve the bandwidth of a capacitively probe-fed microstrip antenna. The maximum bandwidth achieved of this structure in pervious works is 52% [25], [26]. The antenna structure has two microstrip patches. A main patch, which is to be optimized, and a 3.7 mm × 1.2 mm patch



(a)

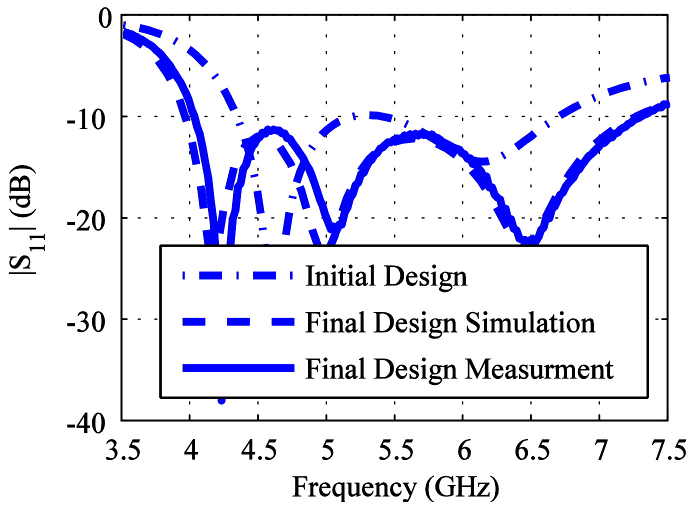


(b)

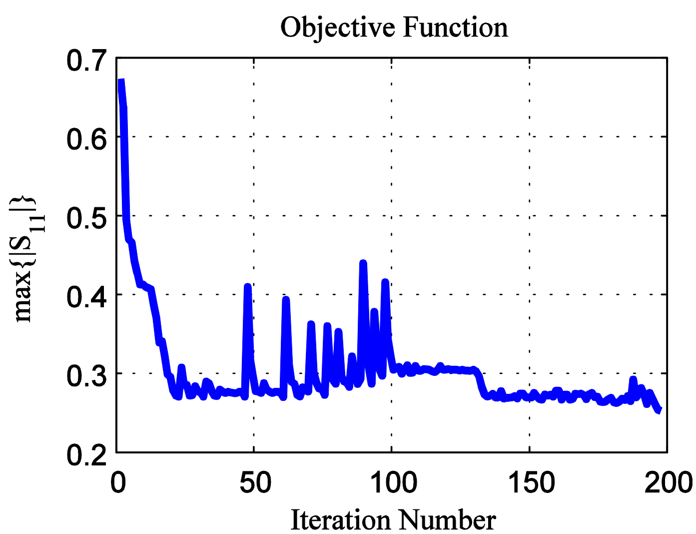


(c)

Figure 3.7. The starting (a) and final (b) geometry and top view (c) of the fabricated design of the the capacitively-fed antenna.

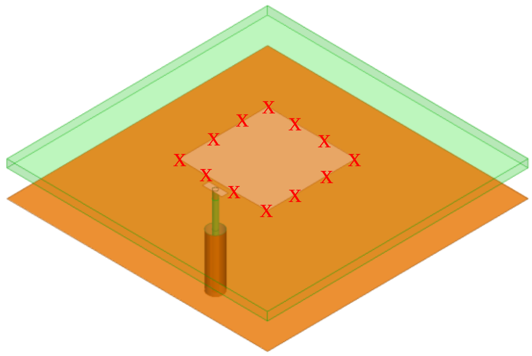


(a)

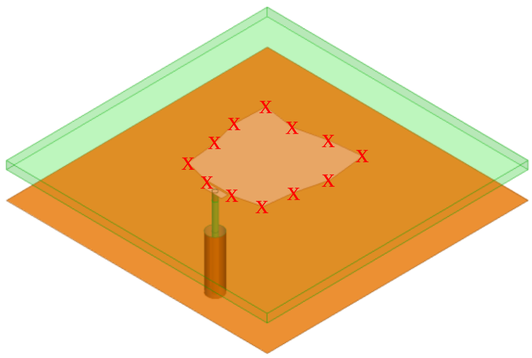


(b)

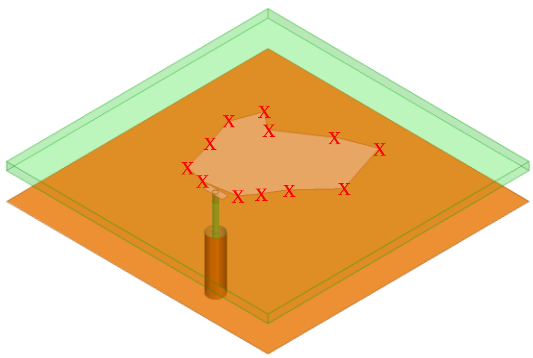
Figure 3.8. (a) the value of the return loss in dB at the initial and final designs and (b) the value of the objective function value at each iteration for the capacitively-fed antenna.



(a)



(b)



(c)

Figure 3.9. The antenna structure in iteration 3 (a), 12 (b), and 18 (c) of the optimization process which corresponds to objective function equal 0.5 (a), 0.4 (b), and 0.3 (c)

Table 3.3. Initial and final parameters for the capacitive-fed antenna

point	initial design (mm)	final design (mm)
(x_1, y_1)	(-8.5, -8.5)	(-5.3633, -8.7011)
(x_2, y_2)	(-2.8333, -8.5)	(-1.4687, -11.7488)
(x_3, y_3)	(2.8333, -8.5)	(2.4818, -9.0689)
(x_4, y_4)	(8.5, -8.5)	(7.6311, -6.8408)
(x_5, y_5)	(8.5, -2.8333)	(9.2986, -3.8876)
(x_6, y_6)	(8.5, 2.8333)	(8.7158, 2.3469)
(x_7, y_7)	(8.5, 8.5)	(4.7774, 4.7886)
(x_8, y_8)	(2.8333, 8.5)	(1.8947, 6.0772)
(x_9, y_9)	(-2.8333, 8.5)	(-3.3988, 11.9247)
(x_{10}, y_{10})	(-8.5, 8.5)	(-12.2114, 7.5617)
(x_{11}, y_{11})	(-8.5, 2.8333)	(-10.2569, 2.2686)
(x_{12}, y_{12})	(-8.5, -2.8333)	(-6.9423, -3.1556)

which is fed by a coaxial cable. They are placed on top of a 50 mm × 50 mm ×1.52 mm substrate. The substrate is a Rogers RO3003 with a relative permittivity of 3. Also, a 5.0 mm air gap is used between the substrate and the ground plan. The initial structure of the optimization process is shown in Figure 3.7(a).

In this example, we increase the optimizable degrees of freedom. The coordinates of 12 vertices are chosen as optimization variables. These vertices are marked with red dots in Figure 3.7(a). The vector of optimization variables is

$\boldsymbol{p}=[x_1\ y_1\ x_2\ y_2\ x_3\ y_3\ x_4\ y_4\ x_5\ y_5\ x_6\ y_6\ x_7\ y_7\ x_8\ y_8\ x_9\ y_9\ x_{10}\ y_{10}\ x_{11}\ y_{11}\ x_{12}\ y_{12}]^T$. The optimization problem has the same form as 3.11)). The vector $\boldsymbol{F}_j$ has 20 frequency components evenly spread over the bandwidth 4-7 GHz. The frequencies are linearly spaced in the frequency band. Each component of $\boldsymbol{F}_j$ corresponds to the value of $|S_{11}|$ at one frequency. The optimal structure and the top view of the fabricated design are shown respectively in Figure 3.7(b) and Figure 3.7(c). The initial and final responses are shown in Figure 3.8(a). The starting point for the optimization process is given in the second column of Table 3.3. The upper bound for all the variables is 25 and the lower bound is -25, because all vertices must be within the 50 mm × 50 mm substrate. The final solution of the optimization problem is given in the third column of Table 3.3.

The values of the maximum of $|S_{11}|$ over all frequencies at different iterations of the optimization process are shown in Figure 3.8(b). Figure 3.9(a), (b) and (c) show the antenna structure for iterations 3, 12, and 18 which correspond to objective functions values 0.5, 0.4, and 0.3, respectively. We allowed for 200 optimization iterations. This number of iterations is expected given the relatively large number of design parameters. The bandwidth of the final structure is 58% which is more than the optimized result reported in [25] and [26]. It should be noted that we optimize only for the antenna bandwidth. Other antenna factors such as the gain and radiation pattern have not been considered. The development of self-adjoint approaches for these factors are still an open area of research.

3.6. CONCLUSION

A new evolutionary method is presented for the design of antenna structures. Our approach exploits the readily available adjoint sensitivities in evolving antenna structures. The coordinates of a number of control vertices allow the structure to evolve to satisfy the design specifications. Our approach was illustrated through a number of examples. It can be easily integrated with commercial softwares that estimate self-adjoint adjoint sensitivities as a by-product of the electromagnetic simulation.

REFERENCES

[1] J. Martinez-Fernandez, J.M. Gil, J. Zapata, "Ultrawideband optimized profile monopole antenna by means of simulated annealing algorithm and the finite element method," *IEEE Trans. Antennas Propag.*, vol. 55, no. 6 , pp. 1826–1832, June 2007.

[2] Lin-Yu Tseng, and Tuan-Yung Han, "An evolutionary design method using genetic local search algorithm to obtain broad/dual-band characteristics for circular polarization slot antennas," *IEEE Trans. Antennas Propag.*, vol. 58, no. 5, pp. 1449–1456, May 2010.

[3] J. Robinson and Y. Rahmat-Samii, "Particle swarm optimization in electromagnetics," *IEEE Trans. Antennas Propag.*, vol. 52, no. 2, pp. 397–407, Feb. 2004.

[4] J. Aelterman, R. Goossens, F. Declercq, and H. Rogier, "Ant colony optimisation-based radiation pattern manipulation algorithm for Electronically Steerable Array Radiator Antennas," *IET Sci. Meas. Technol.*, vol. 3, no. 4, pp. 302–311, July 2009.

[5] A. R. Mallahzadeh, H. Oraizi, and Z. Davoodi-Rad, "Application of the invasive weed optimization technique for antenna configurations," *Journal of Progress In Electromagnetic Research (PIER)*, vol. 79, pp. 137–150, 2008.

[6] Y. Rahmat-Samii, "Modern antenna designs using nature inspired optimization techniques: Let darwin and the bees help designing your multi band MIMO antennas," *Proceedings of IEEE Radio and Wireless Symposium (RWS)*, pp. 463–466, Jan. 2007.

[7] C. Zhang, S. Yang, H. K. Pan, A.E. Fathy, S. El-Ghazaly, V. K. Nair, "A reconfigurable multiband patch antenna for wireless applications using MEMS switches," *Microwave and Optical Technology Letters*, vol. 51, no. 8, pp. 1892–1896, Aug. 2009

[8] H. Akel, J. P. Webb, "Design sensitivities for scattering-matrix calculation with tetrahedral edge elements," *IEEE Transactions on Magnetics*, vol. 36, no. 4, pp. 1043–1046, July 2000.

[9] M. H. Bakr and N.K. Nikolova, "An adjoint variable method for time domain TLM with wideband Johns matrix boundaries," *IEEE Trans. Microwave Theory Tech.*, vol. 52, no. 2, pp. 678–685, Feb. 2004.

[10] N. K. Nikolova, H. W. Tam, and M. H. Bakr, "Sensitivity analysis with the FDTD method on structured grids," *IEEE Trans. Microwave Theory Tech.*, vol. 52, no. 4, pp. 1207–1216, April 2004.

[11] E. A. Soliman, M. H. Bakr, and N. K. Nikolova, "An adjoint variable method for sensitivity calculations of multiport devices," *IEEE Trans. Microwave Theory Tech.*, vol. 52, no. 2, pp. 589–599, Feb. 2004.

[12] M. A. Swillam, M. H. Bakr, and X. Li , "Efficient adjoint sensitivity analysis exploiting the FD-BPM," *IEEE/OSA Journal of Lightwave Technology*, vol. 25, no. 7, pp. 1861–1869, July 2007.

[13] M. H. Bakr, N. K. Nikolova, and P. A. W. Basl, “Self-adjoint S-parameter sensitivities for lossless homogeneous TLM problems,” *International Journal of Numerical Modelling: Electronic Networks, Devices and Fields*, vol. 18, no. 6, pp. 441–455, Nov. 2005.

[14] G. Kiziltas, D. Psychoudakis, J. L. Volakis, N. Kikuchi, ”Topology design optimization of dielectric substrates for bandwidth improvement of a patch antenna,” *IEEE Trans. Antennas and Prop.*, vol. 51, no. 10, pp. 2732–2743, Oct. 2003.

[15] N. Uchida, S. Nishiwaki, K. Izui, M. Yoshimura, T. Nomura, and K. Sato ”Simultaneous shape and topology optimization for the design of patch antennas,” Proceedings of Antennas and Prop. (EuCAP), pp. 103–107, March 2009.

[16] “HFSS” ver. 13, ANSYS, Inc., Canonsburg, PA, 2010.

[17] “CST” ver. 2010.00, CST, Inc., Framingham, MA, 2010.

[18] M. H. Bakr, M. Ghassemi, and N. Sangary, “Bandwidth enhancement of narrow band antennas exploiting adjoint-based geometry evolution,” *Proceedings of IEEE International Symposium on Antennas and Propagation*, pp. 2909–2911, July 2011.

[19] J. W. Bandler, W. Kellermann, and K. Madsen, “A superlinearly convergent minimax algorithm for microwave circuit design,” *Proceedings of IEEE Trans. Microwave Theory Tech.*, vol. 33, no. 12, pp. 1519–1530, June 1985.

[20] "Matlab" ver. 7, The MathWorks Inc., Natick, MA. 2010.

[21] L. Wang, W. Wu, X.- W.Shi, F. Wei, and Q. Huang, "Design of novel monopole UWB antenna with a notched ground," *Progress In Electromagnetics Research (PIER) C*, vol. 5, pp. 13–20, 2008.

[22] N. P. Agrawall, G. Kumar, and K. P. Ray, "Wide-band planar monopole antennas", *IEEE Trans. Antennas Propag.*, vol. 46, no. 2, pp. 294–295, Feb. 1998.

[23] L. Zhang, Z. Cui, Yong-Chang Jiao, and Fu-Shun Zhang, "Broadband patch antenna design using differential evolution algorithm," *Microwave and Optical Technology Letters*, vol. 51, no. 7, pp. 1692–1695, July 2009.

[24] A. Khidre, K. F. Lee, F. Yang, and A. Elsherbeni, "Wideband circularly polarized E-shaped patch antenna for wireless applications," *IEEE Antennas and Propagation Magazine*, vol. 52, no.5, pp. 219–229, Oct. 2010.

[25] G. Mayhew-Ridgers, J. W. Odendaal, and J. Joubert, "Single-layer capacitive feed for wideband probe-fed microstrip antenna elements," *IEEE Trans. Antennas Propag.*, vol. 51, no. 6, pp. 1405–1407, June 2003.

[26] V. G. Kasabegoudar and K. J. Vinoy, "Coplanar capacitively coupled probe fed microstrip antennas for wideband applications," *IEEE Trans. Antennas Propag.*, vol. 58, no. 10, pp. 3131–3138, Oct. 2010.

CHAPTER 4

MIMO ANTENNA DESIGN USING GEOMETRY EVOLUTION GRADIENT-BASED OPTIMIZATION

4.1. INTRODUCTION

To improve the channel capacity of communication systems, utilizing MIMO systems is regarded a promising solution. Using multiple antennas in the transmitter and receiver in a MIMO system, we can make the best use of the radiated power. UWB technology has been widely used due to the capability of high data rate in short range communications [1]. UWB systems are limited to short range communications because of the limitation in power according to federal communication committee (FCC) [2].

In MIMO antenna design, several approaches were presented to reduce the coupling between antenna elements. For instance, suspended inductive lines before the antenna elements were used to reduce the coupling between two mobile phone PIFAs [3]. In [4], a tree-like parasitic structure was added between the two antenna elements to reduce coupling in a 2 by 1 UWB antenna array for MIMO systems. In [4], using two quarter wavelength slits on the ground plane, a narrowband transmission zero is created in the coupling path between elements of a PIFA array of a handheld device. Other techniques include increasing the spacing between the antenna elements or placing the antenna elements rotated by 90 degrees relative to each other to minimize the coupling between them, see for example [6].

In this thesis, we present a novel approach to minimizing the distance between elements of a MIMO antenna array while also minimizing the coupling. In this method, we first design a single element antenna using a modified adjoint-based geometry evolution optimization [7] with appropriate constraints. In the second stage, using an evolutionary approach, the elements of the geometry of the elements in the antenna array are allowed to evolve to allow for reducing the spacing between them while simultaneously reducing the coupling. This method is first applied to the design single element UWB microstrip monopole. We then design 1-by-2 and a 1-by-3 UWB MIMO systems. We use HFSS [14]as the EM solver. It efficiently supplies both the *S*-parameters and their gradients with respect to all the optimization parameters over the frequency band of interest. Matlab [16]is used as the gradient-based optimizer. The Matlab optimization code derives HFSS and uses the exported values of *S*-parameters, and their gradient, to find the local minimum.

In the following sections of this chapter, the new approach in antenna design is clarified and then the optimization problems are defined and solved using a modified adjoint-based geometry evolution optimization. We explain both the design of the single-antenna element and the minimization of the distance between antenna elements. Finally our method is illustrated through the design a single element UWB microstrip monopole, a 1-by-2 MIMO system, and a 1-by-3 MIMO system with UWB microstrip monopoles.

4.2. MIMO SYSTEMS

Since the early works in [18] and [19], MIMO technique have seen wide application in the field of wireless communications. The new approach of using multiple antennas in the transmitter and receiver of a wireless systems to improve the channel capacity has been known to be effective in rich multipath environments [20]. Using this technique in a communication system channel capacity can exceed the upper bound given by Shannon for a single-input single-output (SISO) system.

Several important factors determine the performance of a MIMO system. Spatial multiplexing of the MIMO elements increases the channel capacity. Sufficient spacing between antenna elements, correct number of elements, and appropriate array geometry create enough spatial diversity for spatial multiplexing. As an extension of spatial diversity, polarization diversity may be used to reduce the coupling between antenna elements. Also, angel or pattern diversity can be useful for spatial multiplexing. When patterns of different antenna elements have different beams, they can receive and transmit signals in different directions and different path. This results in a rich multipath environment. Spatial, polarization, and pattern diversity are thus the three techniques used in the MIMO antenna design [20].

The situation is more sophisticated in designing MIMO antennas for handset applications. Generally in a MIMO system, elements of the antenna array need to be decoupled [20]. In handheld devices, however, there is also limitations in size [21]. In addition to diversity techniques, multi probe [22], [23], and multimode [24] excitation have also been applied in this area. These techniques can be very useful in designing MIMO antennas with small size for hand held devices.

4.3. OUR APPROACH

A. Introduction

In traditional antenna design typically one stage is the optimization of the parameters of the antenna structure to find the best design for the specific application and the corresponding characteristics. At this stage usually some typical parameters of the antenna structure are selected for the optimization process. For example, in a rectangular microstrip patch, width and length of the rectangular patch are two parameters that are usually optimized. Optimizing these parameters, in some cases, may not result in a design that satisfies the design specifications. The reason is that template of the design did not change and this template may not be capable of satisfying the specifications. For instance, in the aforementioned example, after optimizing width and length of the rectangular microstrip patch the template of the antenna structure is not changed and the microstrip patch is still rectangular shape.

Our new approach utilizes a different approach. The optimization parameters are the coordinates of a number of control points of the antenna structure. By changing these control points, the antenna geometry would change significantly. For a 2D planar structure, the vector of optimization parameters is given by $\boldsymbol{p}=[x_1\ \ y_1\ \ x_2\ \ y_2\ \ \ldots\ \ x_N\ \ y_N]^T$, where N is the number of control points. By choosing their coordinates as the optimization parameters, there are more degrees of freedom in the optimization process. It is more likely that the antenna structure would satisfy the design specifications. The number of optimization parameters may be large which may make the computational cost heavy. Adjoint sensitivity techniques offer an efficient approach for gradient-based optimization. They make optimization using coordinates of the control points feasible. Using a self-adjoint sensitivity analysis approach for calculating gradients of S-parameters [8]-[13], we can estimate the gradient of *S*-parameters with respect to all the optimization parameters, regardless of their number, in one simulation. This approach recently has been adopted in some of the commercial EM solvers, e.g., HFSS, and CST [15].

B. Single Stage Optimization Problem

Our approach for designing a MIMO system has two stages. The first one is for designing a single element antenna. The second one is for minimizing the spacing between antenna elements in the MIMO antenna array.

In the first stage we want to minimize the |S11| of the single element in the frequency band of interest. The objective function of the optimization problem is the maximum value of |S11| in the specified frequency band. Because in our approach the coordinates of the control vertices can freely move, non physical structures can occur during the optimization iterations. Some constraints are imposed on the optimization parameters to avoid non physical structures. The optimization problem may be cast in the form:

$$\begin{gathered} \min_{\boldsymbol{p}} \ \max_{j} \ \left(F_j\right) \\ \textit{subject to} \quad \boldsymbol{p}_{lb} \le \boldsymbol{p} \le \boldsymbol{p}_{ub}, \\ a_i \ge 0 \end{gathered} \tag{2.1}$$

where the values F_j, j=1, 2, …, N are the values of $|S_{11}|$ on N frequency points, which are uniformly distributed over the specified frequency band. $\boldsymbol{p}$ is the vector of optimization parameters, which are the coordinates of M control points, and it is given by $\boldsymbol{p}=[x_1 \ \ y_1 \ \ x_2 \ \ y_2 \ \ \ldots \ \ x_M \ \ y_M]^T$. $\boldsymbol{p}_{lb}$ and $\boldsymbol{p}_{ub}$ are vectors of upper limits and lower limits of the optimization parameters, which are defined by the dimensions of the antenna structure. They define the free space that the control point can move. The values a_i, $i=1, 2, \ldots, M-1$ are the angles between hypothetical lines from the origin to the control points (see Figure 4.1). By construing these angles to be always positive during the optimization process we can ensure that the

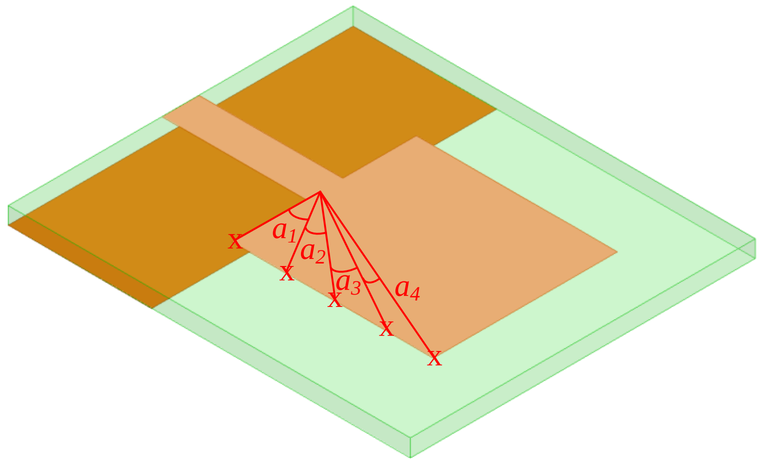


Figure 4.1. The starting geometry of the UWB single element antenna structure.

aforementioned nonphysical structure would not happen, and the vertices would not cross each other. We should mention by constraining these angles we are limiting our feasibility region more than what actually is needed, and we are losing some possible solutions to our problem, but still we can find some points, which can satisfy the specifications for the antenna design. We can calculate an expression for the values of a_i based on the coordinates of the control points:

$$a_i = \arctan\left(\frac{(y_{i+1} - y_0)}{(x_{i+1} - x_0)}\right) - \arctan\left(\frac{(y_i - y_0)}{(x_i - x_0)}\right), \tag{2.2}$$

where y_0 and x_0 are the coordinates of the origin.

To be able to use a gradient-based optimizer we also need to derive expressions for the derivatives of the a_i based on the optimization parameters, to evaluate the gradient of a_i and use it in the optimizer. So, to wrap-up the calculation, there is *M-1* angles and their gradients are vectors with length of *2N*, which is the length of the vector of optimization parameters, and we need to calculate their gradient vectors. The derivatives of a_i with respect to all the optimization parameters are zero except x_i, y_i, x_{i+1}, and y_{i+1}, which $i=1, 2, \ldots, M-1$. So, the elements of vectors of gradients are zero except four elements. We can derive their expressions using equation (2.2):

$$\frac{\partial a_i}{\partial x_i} = \frac{y_i - y_0}{\left(x_i - x_0\right)^2 \left(\frac{\left(y_i - y_0\right)^2}{\left(x_i - x_0\right)^2} + 1 \right)}, \tag{2.3}$$

$$\frac{\partial a_i}{\partial y_i} = -\frac{1}{\left(x_i - x_0\right) \left(\frac{\left(y_i - y_0\right)^2}{\left(x_i - x_0\right)^2} + 1 \right)}, \tag{2.4}$$

$$\frac{\partial a_i}{\partial x_{i+1}} = -\frac{y_{i+1} - y_0}{\left(x_{i+1} - x_0\right)^2 \left(\frac{\left(y_{i+1} - y_0\right)^2}{\left(x_{i+1} - x_0\right)^2} + 1 \right)}, \tag{2.5}$$

$$\frac{\partial a_i}{\partial y_{i+1}} = \frac{1}{\left(x_{i+1} - x_0\right) \left(\frac{\left(y_{i+1} - y_0\right)^2}{\left(x_{i+1} - x_0\right)^2} + 1 \right)}, \tag{2.6}$$

Using these expressions, and the Matlab code that derives HFSS to simulate the antenna structure in every iteration and exports the values of *S*-parameters and their derivatives with respect to all the optimization parameters alongside, we can implement the optimization problem in Matlab and solve it using a gradient-based optimizer.

C. MIMO Antenna Array Optimization

In this stage of our approach we form a linear MIMO antenna array using the structure resulted from previous stage with a larger spacing that ensures the coupling antenna elements is low. Then, we minimize the spacing between antenna elements in the MIMO antenna array, such that the $|S_{11}|$ and coupling between all the antenna elements to be less than -10 dB. Notice that we also need the constraint in the optimization problem which we had in previous stage for single element antenna design, because in this stage also we want to let the antenna structure to evolve during the optimization process. But in the vector optimization parameters in this stage in addition to the coordinates of the control points we also have one extra parameter which is for spacing between antenna elements of the MIMO antenna array. Finally the optimization problem is in this form:

$$
\begin{aligned}
& \min_{\boldsymbol{x}} \; d \\
\textit{subject to:} \quad & f_j(\boldsymbol{p}) < 10^{-0.5} \qquad j = 1, 2, \ldots, N, \\
& h_j(\boldsymbol{p}) < 10^{-0.5} \\
& \boldsymbol{p}_{lb} < \boldsymbol{p} < \boldsymbol{p}_{ub} \\
& a_i > 0 \qquad i = 1, 2, \ldots, M\text{-}1,
\end{aligned}
\tag{2.7}
$$

where $\boldsymbol{p}$ is the vector of optimization parameters, which in addition to the coordinates of the control points, it includes the spacing between antenna elements of the MIMO antenna array. It is given by $\boldsymbol{p}=[x_1 \; y_1 \; x_2 \; y_2 \; \ldots \; x_M \; y_M \; d]^T$, where d is the spacing, which we want to minimize it. The values $f_j(\boldsymbol{p})$ and $h_j(\boldsymbol{p})$ are $|S_{11}|$ and $|S_{12}|$ of the antenna structure, which we constrain them to be less than -10 dB during the optimization process. We also have constraints on the upper and lower band for the optimization parameters in $\boldsymbol{p}_{ub}$ and $\boldsymbol{p}_{lb}$ vectors, which are defined by the dimensions of the antenna structure, and constraints on the hypothetical angles.

To be able to use a gradient-based optimizer we need to use the derived expression for the derivatives of the hypothetical angles from previous section, and implement them in Matlab. Also to solve this problem, we need to calculate the $|S_{11}|$ and $|S_{12}|$ of the antenna structure and their derivatives with respect to all the optimization parameters using EM simulator, which is driven by the Matlab code.

4.4. EXAMPLES

In this section for elaborating the new approach in MIMO antenna design, we apply it to design a single element UWB antenna. Then using that single element we design a 1-by-2 and a 1-by-3 UWB antenna array for MIMO systems, by solving the optimization problems, which was described in previous section.

A. UWB Single Element Antenna Design

In this example we apply our approach to a microstrip monopole to design a UWB microstrip monopole antenna. The antenna structure consists of on a normal FR4 substrate with 4.4 relative permittivity, and dimensions of 30×35×1.5 mm^3, and a microstrip patch, which is fed by a 12.5 mm long microstrip feed line, and the ground plane under the feed line on the other side of the substrate. We start the optimization process with a 16×17.5 mm^2 rectangular patch (Figure 4.1). This structure has been used previously in [17]. We choose five control points on one side of the rectangular shaped patch, which they have been shown by red “x” on Figure 4.1. The other side of the microstrip patch would change symmetrically so that after optimization the antenna structure has a symmetric radiation pattern.

Since there is five control points, with the notation of previous section in this example M is equal five. Thus, the vector of optimization parameters would have 10 elements and it would be given by $\boldsymbol{p}=[x_1\ \ y_1\ \ x_2\ \ y_2\ \ x_3\ \ y_3\ \ x_4\ \ y_4\ \ x_5\ \ y_5]^T$. The vectors of lower and upper bounds of the optimization variables would be $\boldsymbol{p}_{lb}=[0\ \ 12.5\ \ 0\ \ 12.5\ \ 0\ \ 12.5\ \ 0\ \ 12.5\ \ 0\ \ 12.5]^T$ and $\boldsymbol{p}_{ub}=[15\ \ 35\ \ 15\ \ 35\ \ 15\ \ 35\ \ 15\ \ 35\ \ 15\ \ 35]^T$.

Table 4.1. Initial and Final Parameters of The Single Element Antenna Optimization Problem

point	initial design (mm)	final design (mm)
(x_1, y_1)	(8.0, 12.5)	(8.7841, 15.1650)
(x_2, y_2)	(8.0, 17.0)	(6.5030, 17.4784)
(x_3, y_3)	(8.0, 21.5)	(11.0579, 20.9659)
(x_4, y_4)	(8.0, 26.0)	(12.9389, 25.7970)
(x_5, y_5)	(8.0, 30.0)	(9.8854, 33.8692)

In this example N is equal nine, which means the EM simulations are done on nine frequencies over the UWB frequency band (3.1 - 10.6 GHz). So, starting from 3 GHz the nine frequency points are going to be, 3, 4… 11 GHz. Also in this example for the expressions of constraints on the hypothetical angles, we assumed the origin to be the end of the microstrip feed line, which has coordination of (12.5, 0). So the expressions for the angles are in going to be in this form:

$$a_1 = \arctan((y_2 - 12.5)/x_2) - \arctan((y_1 - 12.5)/x_1), \tag{2.8}$$

$$a_2 = \arctan((y_3 - 12.5)/x_3) - \arctan((y_2 - 12.5)/x_2), \tag{2.9}$$

$$a_3 = \arctan((y_4 - 12.5)/x_4) - \arctan((y_3 - 12.5)/x_3), \tag{2.10}$$

$$a_4 = \arctan((y_5 - 12.5)/x_5) - \arctan((y_4 - 12.5)/x_4), \tag{2.11}$$

Also the expression for their gradients can be developed in this form:

$$\begin{aligned}\nabla a_1 = \Bigg[& \frac{(y_1 - 12.5)}{x_1^{\,2}\left(\frac{(y_1-12.5)^2}{x_1^{\,2}}+1\right)}, -\frac{1}{x_1\left(\frac{(y_1-12.5)^2}{x_1^{\,2}}+1\right)}, \cdots \\ & -\frac{(y_2 - 12.5)}{x_2^{\,2}\left(\frac{(y_2-12.5)^2}{x_2^{\,2}}+1\right)}, \frac{1}{x_2\left(\frac{(y_2-12.5)^2}{x_2^{\,2}}+1\right)}, 0,0,0,0,0,0 \Bigg]^T,\end{aligned} \tag{2.12}$$

$$\begin{aligned}\nabla a_2 = \Bigg[& 0,0, \frac{(y_2 - 12.5)}{x_2^{\,2}\left(\frac{(y_2-12.5)^2}{x_2^{\,2}}+1\right)}, -\frac{1}{x_2\left(\frac{(y_2-12.5)^2}{x_2^{\,2}}+1\right)}, \cdots \\ & -\frac{(y_3 - 12.5)}{x_3^{\,2}\left(\frac{(y_3-12.5)^2}{x_3^{\,2}}+1\right)}, \frac{1}{x_3\left(\frac{(y_3-12.5)^2}{x_3^{\,2}}+1\right)}, 0,0,0,0 \Bigg]^T,\end{aligned} \tag{2.13}$$

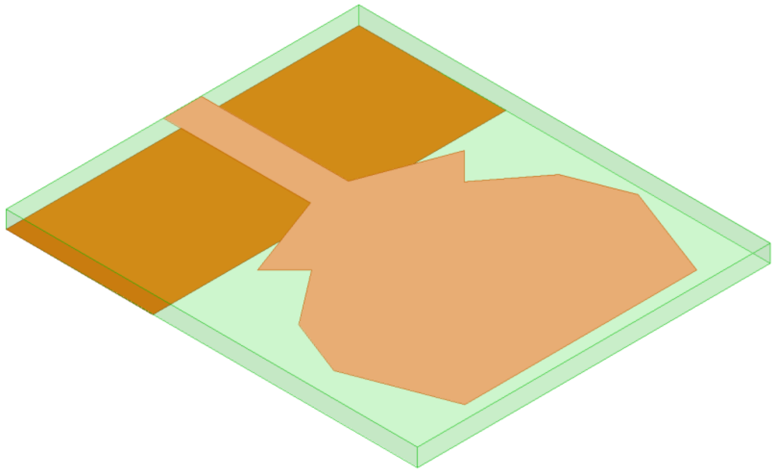


Figure 4.2. The final geometry of the UWB single element antenna structure.

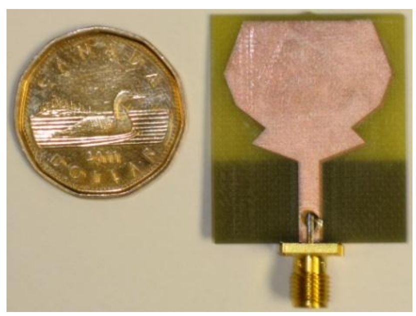


Figure 4.3. The fabricated UWB single element antenna structure.

$$\nabla a_3 = \left[0,0,0,0, \frac{(y_3-12.5)}{x_3^{\,2}\left(\frac{(y_3-12.5)^2}{x_3^{\,2}}+1\right)}, -\frac{1}{x_3\left(\frac{(y_3-12.5)^2}{x_3^{\,2}}+1\right)}, \cdots \right. \tag{2.14}$$

$$\left. -\frac{(y_4-12.5)}{x_4^{\,2}\left(\frac{(y_4-12.5)^2}{x_4^{\,2}}+1\right)}, \frac{1}{x_4\left(\frac{(y_4-12.5)^2}{x_4^{\,2}}+1\right)}, 0, 0 \right]^T,$$

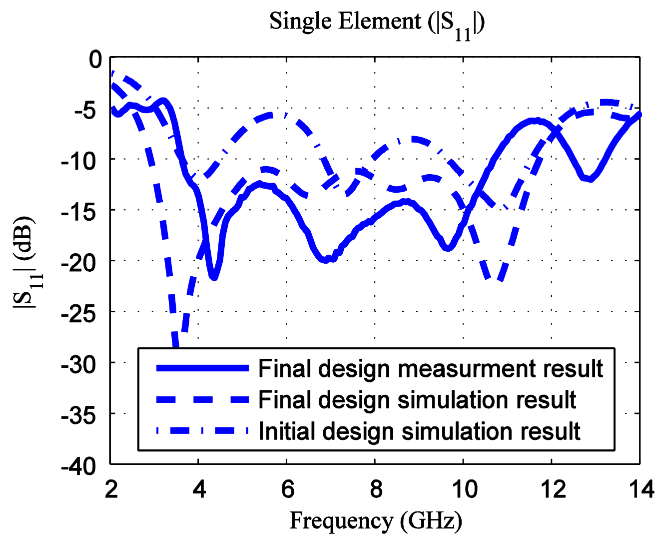


Figure 4.4. The values of the $|S_{11}|$ in dB at the initial and final designs of the UWB single element antenna structure.

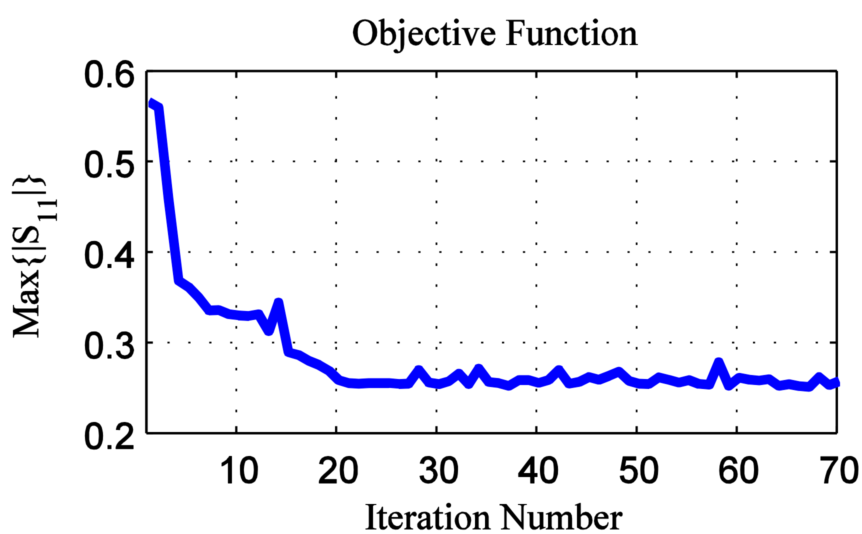


Figure 4.5. The values of the objective function at each iteration for the UWB single element antenna structure.

$$\nabla a_4 = \left[0,0,0,0,0,0, \frac{(y_4 - 12.5)}{x_4^{\,2}\left(\frac{(y_4-12.5)^2}{x_4^{\,2}}+1\right)}, -\frac{1}{x_4\left(\frac{(y_4-12.5)^2}{x_4^{\,2}}+1\right)}, \cdots \right. \tag{2.15}$$

$$\left. -\frac{(y_5 - 12.5)}{x_5^{\,2}\left(\frac{(y_5-12.5)^2}{x_5^{\,2}}+1\right)}, \frac{1}{x_5\left(\frac{(y_5-12.5)^2}{x_5^{\,2}}+1\right)} \right]^T,$$

Finally using the Matlab code to derive HFSS as the EM solver and fminimax function in Matlab as the gradient-based optimizer, the antenna structure can evolve in 70 iterations to a UWB monopole (see Figure 4.2 and Figure 4.3). In Figure 4.4 we can see the $|S_{11}|$ of the antenna for the first and last iterations. Notice, the difference between the simulation and measurement result is not using a homogeneous substrate with uniform permittivity, and using normal FR4 substrate for general electronic circuits. In Figure 4.5 we can see the objective function of the optimization problem in different iterations, which is maximum $|S_{11}|$ between the working frequencies. In this figure, and in this work, iteration number is defined number of function evaluations, since in optimization of antenna structures number of function evaluations is important and time consuming, which is reduced in this work because of utilizing gradient-based optimizatoin. Also in Table 4.1 we can see how coordinate of the control points change during the optimization process.

B. UWB-MIMO Antenna Array Design

In this section using the antenna structure which resulted from the previous stage we form a linear antenna array. The antenna elements are on one substrate, and they have symmetric structure, which means in this part we also have five control points in one side of one of the antenna elements and the other side of the antenna change symmetrically. The other antenna elements also change symmetrically and they are identical. Thus, the vector of optimization parameters in this section includes coordinates of the five control points, similar to the previous stage, plus one more parameter for the spacing between the elements, and it is given by $\boldsymbol{p}=[x_1\ \ y_1\ \ x_2\ \ y_2\ \ x_3\ \ y_3\ \ x_4\ \ y_4\ \ x_5\ \ y_5\ \ d]^T$. Similarly M is equal to five, and we have 4 hypothetical angles in the constraints, and we can use the same expressions, which was derived in previous section, for the angles and their derivatives. The vectors of lower and upper bound of the optimization parameters are the same, but with one more element, $\boldsymbol{p}_{lb}=[0\ \ 12.5\ \ 0\ \ 12.5\ \ 0\ \ 12.5\ \ 0\ \ 12.5\ \ 0\ \ 12.5\ \ 30.02]^T$ and $\boldsymbol{p}_{ub}=[15\ \ 35\ \ 15\ \ 35\ \ 15\ \ 35\ \ 15\ \ 35\ \ 15\ \ 35\ \ \infty]^T$. The upper limit for the spacing parameter is infinite, but its lower limit should be large enough that the ground planes of antenna elements would not overlap. The width of the ground planes are 30 mm and the thinnest track for fabrication could be with 0.02 mm thickness, so the lower limit for the spacing parameter is 30.02 mm.

In this part because of the antenna structure is more complicated than previous stage and there are more resonance frequencies, the EM simulation is

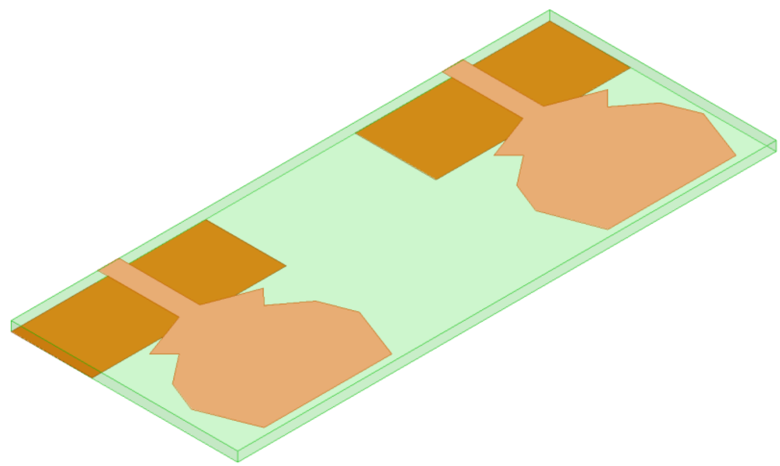


Figure 4.6. The starting geometry of the 1-by-2 UWB-MIMO antenna array.

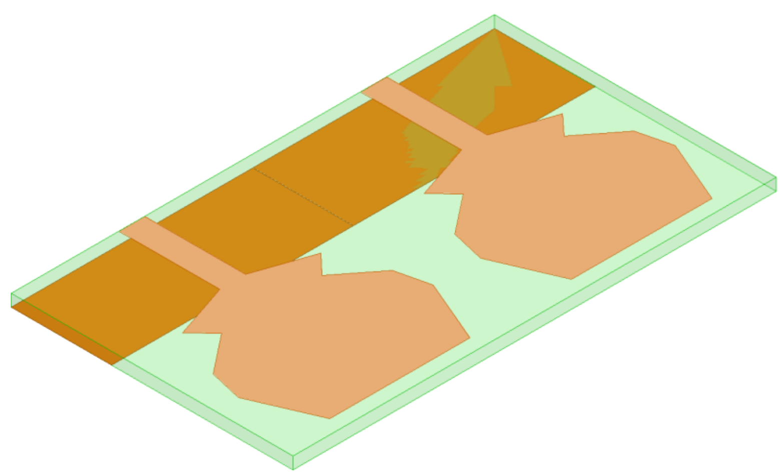


Figure 4.7. The final geometry of the 1-by-2 UWB-MIMO antenna array.

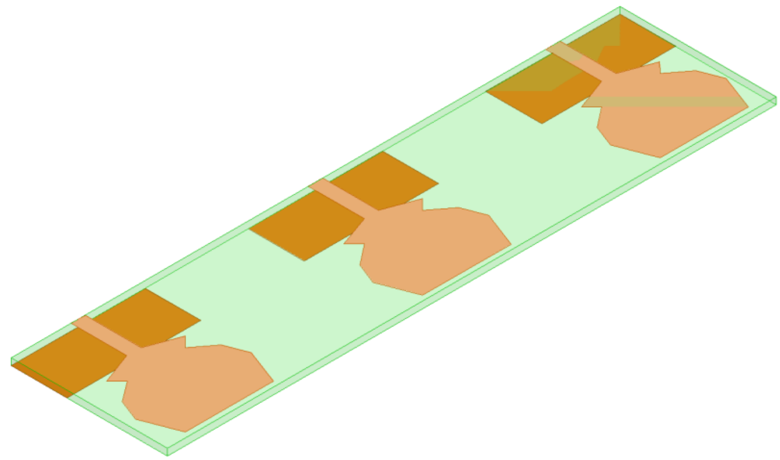


Figure 4.8. The starting geometry of the 1-by-3 UWB-MIMO antenna array.

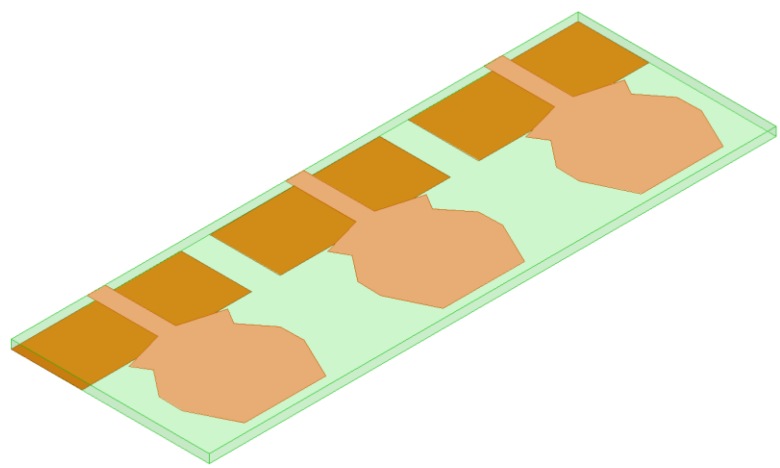


Figure 4.9. The final geometry of the 1-by-2 UWB-MIMO antenna array.

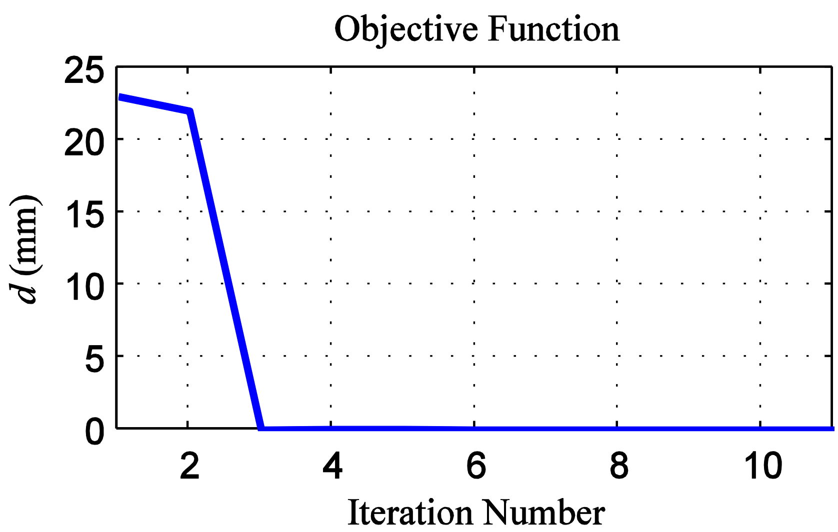


Figure 4.10. The values of the objective function at each iteration for the 1-by-2 UWB-MIMO antenna array.

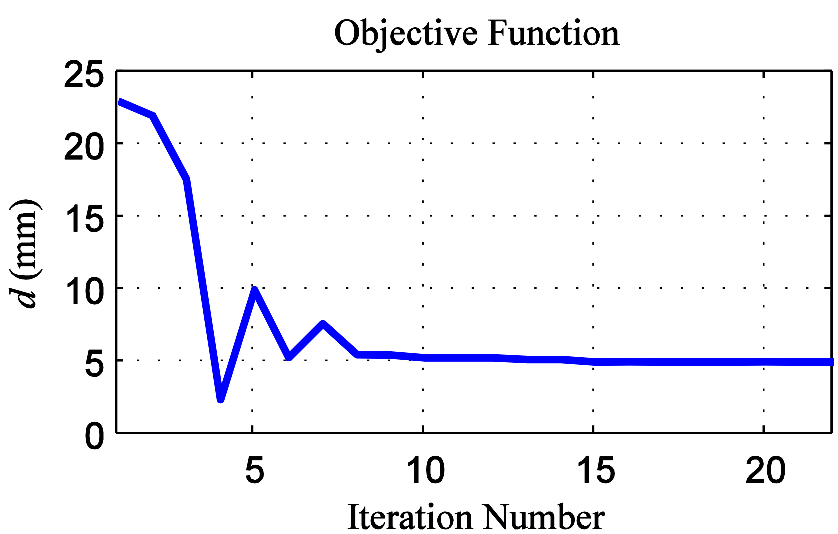


Figure 4.11. The values of the objective function at each iteration for the 1-by-3 UWB-MIMO antenna array.

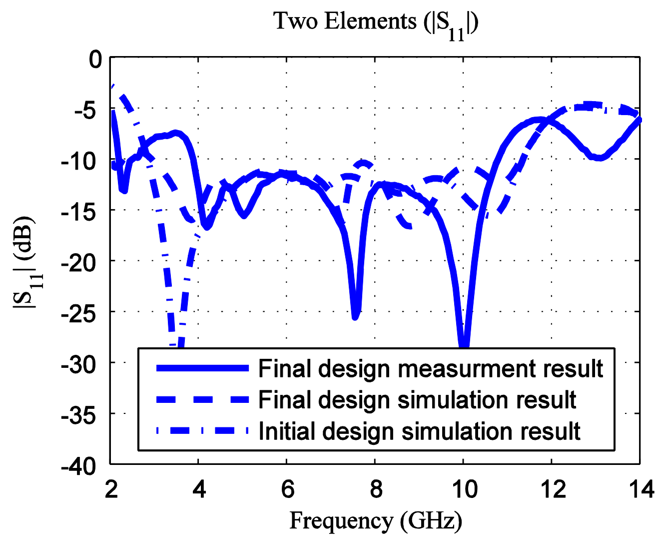


Figure 4.12. The value of the $|S_{11}|$ in dB at the initial and final designs of the 1-by-2 UWB-MIMO antenna array.

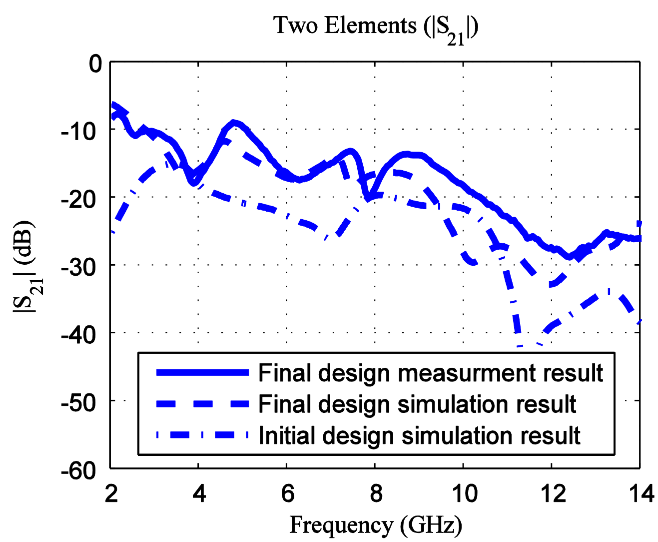


Figure 4.13. The value of the $|S_{12}|$ in dB at the initial and final designs of the 1-by-2 UWB-MIMO antenna array.

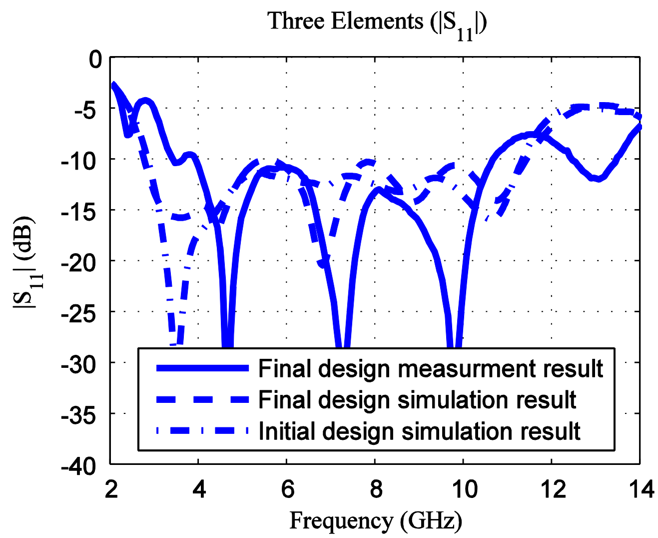


Figure 4.14. The value of the $|S_{11}|$ in dB at the initial and final designs of the 1-by-3 UWB-MIMO antenna array.

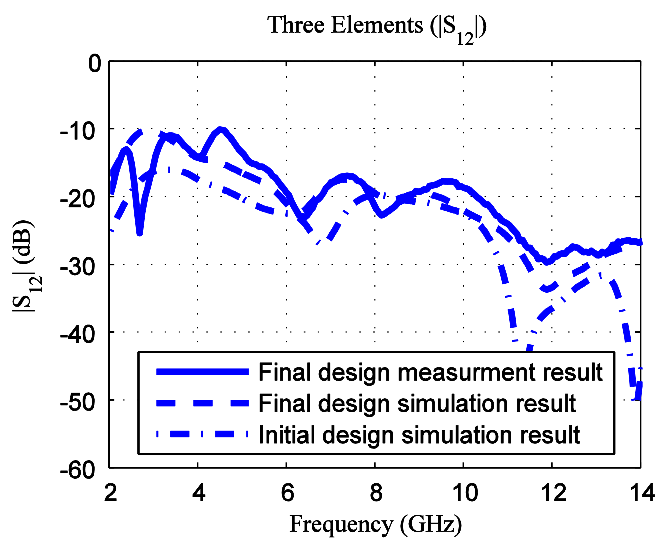


Figure 4.15. The value of the $|S_{12}|$ in dB at the initial and final designs of the 1-by-3 UWB-MIMO antenna array.

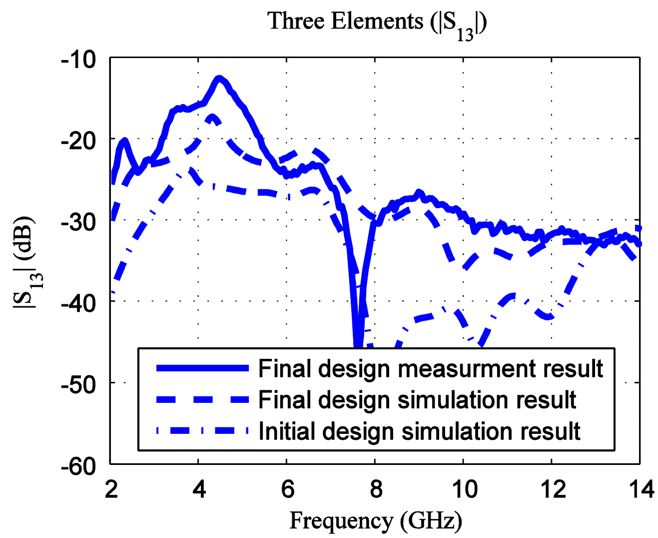


Figure 4.16. The value of the $|S_{13}|$ in dB at the initial and final designs of the 1-by-3 UWB-MIMO antenna array.

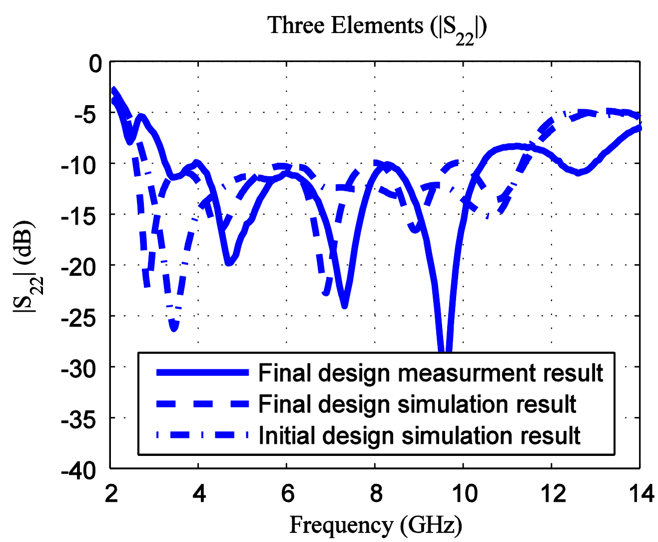


Figure 4.17. The value of the $|S_{22}|$ in dB at the initial and final designs of the 1-by-3 UWB-MIMO antenna array.

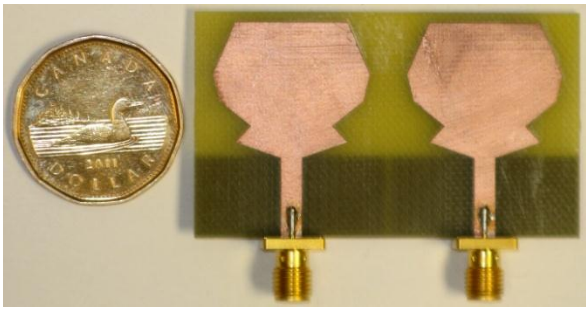


Figure 4.18. The starting geometry of the 1-by-2 UWB-MIMO antenna array.

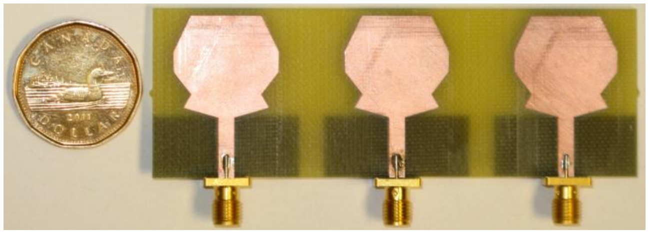


Figure 4.19. The starting geometry of the 1-by-2 UWB-MIMO antenna array.

done in 18 frequency points. So in this part *N* is equal 18 and starting from 3 GHz the frequencies of the EM simulations are 3, 3.5, 4, 4.5… 11 GHz.

In this part because the objective function is just a single parameter, we can use fmincon functions in Matlab as the gradient-based optimizer. Using the Matlab code to derive HFSS as the EM solver and the gradient-based optimizer, for the 1-by-2 antenna array the spacing between antenna elements is minimized in 11 iterations and the final value is equal to the lower bound specified in the optimization problem. But for the 1-by-3 antenna array in 22 iterations the spacing was reduced to 5 mm. In Figure 4.6 and Figure 4.7 respectively we can see the initial and final antenna structure for 1-by-2 antenna array and in Figure 4.8 and Figure 4.9 we can see the initial and final antenna structure for 1-by-3

Table 4.2. Initial and Final Parameters of The 1-by-2 Antenna Array Optimization Problem

Point	initial design (mm)	final design (mm)
(x_1, y_1)	(8.7841, 15.1650)	(8.5843, 14.8804)
(x_2, y_2)	(6.5030, 17.4784)	(6.2381, 17.3823)
(x_3, y_3)	(11.0579, 20.9659)	(11.1207, 21.2035)
(x_4, y_4)	(12.9389, 25.7970)	(12.0941, 25.3263)
(x_5, y_5)	(9.8854, 33.8692)	(8.7082, 33.2925)
d	53.0700	30.0200

Table 4.3. Initial and Final Parameters of The 1-by-3 Antenna Array Optimization Problem

point	initial design (mm)	final design (mm)
(x_1, y_1)	(8.7841, 15.1650)	(8.7262, 14.5307)
(x_2, y_2)	(6.5030, 17.4784)	(7.0934, 17.2881)
(x_3, y_3)	(11.0579, 20.9659)	(10.6603, 21.8127)
(x_4, y_4)	(12.9389, 25.7970)	(10.7491, 25.9661)
(x_5, y_5)	(9.8854, 33.8692)	(7.2240, 33.3379)
d	53.0700	35.0447

antenna array. The objective functions of two optimization problems for antenna arrays are shown in Figure 4.10 and Figure 4.11. In Figure 4.12 and Figure 4.13 the $|S_{11}|$ and $|S_{21}|$ of the 1-by-2 antenna array are shown and in Figure 4.14, Figure

4.15, Figure 4.16, and Figure 4.17 respectively, $|S_{11}|$, $|S_{12}|$, $|S_{13}|$, $|S_{21}|$, and $|S_{22}|$ of antenna structure are shown in first and last. The measurement results are for the final antenna structure, which is fabricated and are shown in Figure 4.18 and Figure 4.19. Also in Table 4.2 and Table 4.3 we can see the optimization parameters in initial and final structure of the antenna arrays.

4.5. CONCLUSION

A new evolutionary approach to design MIMO antenna arrays is introduced. In this approach using coordinates of control points as the optimization parameters, we let the antenna structure to evolve during an optimization process. The optimization process is a constrained gradient-based optimization, and the constraints are based on hypothetical angles in the antenna structure, which can be calculated based on the optimization parameters. We use the readily available derivatives of the *S*-parameters of the antenna structure provided by commercial software, during the optimization process. Finally for illustration a 1-by-2 and a 1-by-3 UWB antenna array for MIMO systems are designed using this approach.

REFERENCES

[1] G. J. Foschini and M. J. Gans. "On limits of wireless communications in a fading environment when using multiple antennas," *Wireless Personal Communications*, vol. 6, no. 3, pp. 311–335, 1998.

[2] Federal Communication Commission (FCC), "Revision of part 15 of the commission's rules regarding ultra-wideband transmission systems," First report and order, ET Docket 98–153, FCC 02–48, adopted: Feb. 2002, released in April 2002.

[3] A. Diallo, C. Luxey, P. Le Thuc, R. Staraj, and G. Kossiavas, "Study and reduction of the mutual coupling between two mobile phone PIFAs operating in the DCS1800 and UMTS bands", *IEEE Trans. Antennas Propag.*, vol. 54, no. 11, pp. 3063–3074, 2006.

[4] A. C. K. Mak, C. R. Rowell, and R. D. Murch, "Isolation enhancement between two closely packed antennas," *IEEE Trans. Antennas Propag.*, vol. 56, no. 11, pp. 3411–3419, 2008.

[5] T. Kokkinos, E. Liakou, and A. P. Feresidis, "Decoupling antenna elements of PIFA arrays on handheld devices," *IEEE Electronic Letters*, vol. 44, no. 25, 2008.

[6] A. I. Najam, Y. Duroc, S. Tedjini, "Design & characterization of an antenna system for UWB-MIMO communication systems", Proceeding of the forth European Conference on Antenna and Propagation (EuCAP) 2010, pp. 1-5, July 2010.

[7] M. Ghassemi, M. H. Bakr, and N. Sangary, "Antenna Design Exploiting Adjoint Sensitivity Based Geometry Evolution," *IEEE Trans. Antennas Propag.*, 2011. (submitted)

[8] H. Akel, J. P. Webb, "Design sensitivities for scattering-matrix calculation with tetrahedral edge elements," *IEEE Transactions on Magnetics*, vol. 36, no. 4, pp. 1043–1046, 2000.

[9] M.H. Bakr and N.K. Nikolova, "An adjoint variable method for time domain TLM with wideband Johns matrix boundaries," *IEEE Trans. Microwave Theory Tech.*, vol. 52, pp. 678-685, February 2004.

[10] N.K. Nikolova, H.W. Tam, and M.H. Bakr, "Sensitivity analysis with the FDTD method on structured grids," *IEEE Trans. Microwave Theory Tech.*, vol. 52, pp. 1207-1216, April 2004.

[11] E.A. Soliman, M.H. Bakr, and N.K. Nikolova, "An adjoint variable method for sensitivity calculations of multiport devices," *IEEE Trans. Microwave Theory Tech.*, vol. 52, pp. 589-599, February 2004.

[12] M.A. Swillam, M.H. Bakr, and X. Li , "Efficient adjoint sensitivity analysis exploiting the FD-BPM," *IEEE/OSA Journal of Lightwave Technology*, vol. 25, no. 7, pp. 1861 – 1869, July 2007.

[13] M.H. Bakr, N.K. Nikolova, and P.A.W. Basl, "Self-Adjoint S-Parameter Sensitivities for Lossless Homogeneous TLM Problems," *International Journal of Numerical Modelling: Electronic Networks, Devices and Fields*, vol. 18, issue 6, pp. 441-455, November 2005.

[14] "HFSS" ver. 13, ANSYS, Inc., Canonsburg, PA, 2010.

[15] "CST" ver. 2010.00, CST, Inc., Framingham, MA, 2010.

[16] "Matlab" ver. 7, The MathWorks Inc., Natick, MA. 2010.

[17] N. P. Agrawall, G. Kumar, and K. P. Ray, "Wide-band planar monopole antennas", *IEEE Trans. Antennas Propag.*, vol. 46, no. 2, 1998.

[18] G. J. Foschini, "Layered space-time architecture for wireless communication in a fading environment when using multielement antennas," *Bell Lab Tech. Journal*, pp. 41−59, 1996.

[19] I. E. Telatar, "Capacity of multi-antenna gaussian channels," *AT&T Bell Labs Internal Report*, 1995.

[20] M. A. Jensen and J. W. Wallace, "A review of antennas and propagation for MIMO wireless communications," *IEEE Trans. Antennas Propag.*, vol. 52, no. 11, pp. 2810−2824, 2004.

[21] S. Schulteis, C. Waldschmidt, W. Sorgel, and W. Wiesbeck, "A Small Planar Inverted F Antenna with Capacitive and Inductive Loading", *Proc. Antennas and Propagation Society International Symposium 2004*, Vol. 4, pp. 4148-4151, June 2004.

[22] S. C. K. Ko and R. D. Murch, "Compact integrated diversity antenna for wireless communicaitons," *IEEE Trans. Antennas Propag.*, vol. 49, no. 6, pp. 954−960, 2001.

[23] Q.-J. Rao and D. Wang, "A compact dual-port diversity antenna for handheld devices," *Antennas & Propagation Conference 2009*, Loughborough, pp. 181−184, 2009.

[24] S. K. Chaudhury, H. J. Chaloupka, and A. Ziroff, "Novel MIMO antennas for mobile terminal," *2008. EuWiT 2008. European Conference on Wireless Technology*, pp. 330−333, Oct. 2008.

CHAPTER 5

CONCLUSION

In this thesis a novel approach for optimizing the antenna structure have been presented. Using coordinates of control points as the optimization variables and then optimizing them, the antenna structure evolves during the optimization process. In this method we use the readily available adjoint sensitivities in the commercial electromagnetic software to solve the optimization problem with a gradient-based optimization algorithm. We have implemented this approach using HFSS [1] as the electromagnetic simulator and MATLAB [2] as the optimizer. The optimizer will run the electromagnetic simulator to get the antenna response and the sensitivities and then export them, after that it would import them again in for the optimization algorithm. This method has been explained and illustrated in chapter 3 with three antenna examples. These examples have been fabricated and tested to confirm the simulation results.

In chapter 4, the aforementioned approach in antenna design has been modified. In the new modification some angles have been defined between hypothetical lines from an origin to the control points. These angles are constrained to be always positive. Also, they can be calculated mathematically with respect to the optimization variables. So by defining these constraints we can make sure the antenna structure remains physical during the optimization process. That modified antenna optimization approach has been used to design a UWB microstrip monopole antenna.

Also in chapter 4, a new optimization problem has been defined to reduce the spacing between antenna elements in a MIMO antenna array. This problem includes the constraints for single element antenna design in addition to new constraints for antenna array. We solved this new optimization problem by using the aforementioned single element UWB microstrip monopole antenna, as the starting point for the antenna arrays. For this problem also like the previous problem, we developed a MATLAB code to derive HFSS as the electromagnetic simulator and import the *S*-parameters of the antenna along with the sensitivities for the optimization, in each iteration. Once we solved this problem for a 1 by 2 MIMO antenna array which resulted in almost zero spacing between the two antenna elements. In the next step antenna structure was optimized for a 1 by 3 MIMO antenna array. In this case the spacing was dramatically reduced, but not to zero, because of the complexity of the antenna structure.

All the antenna examples in this thesis was fabricated and tested to verify the simulation results. In chapter 3, three examples have been presented for the optimization of single elements antenna. In chapter 4, two antenna arrays have been designed and fabricated using our method and measurements verify the simulation results.

Having the experience gained through the course of this work, and the review on the previous optimization algorithms, the author suggests improving this optimization algorithm with mixing it with other global optimization methods. The advantage of this method, which is using a gradient-based optimization method, can be used in the other global optimization methods, such as particle swarm optimization method, genetic algorithm, etc.

REFERENCES

[1] “HFSS” ver. 13, ANSYS, Inc., Canonsburg, PA, 2010.

[2] “Matlab” ver. 7, The MathWorks Inc., Natick, MA. 2010.

COMPLETE REFERENCE LIST

[1] J. Kennedy and R. Eberhart, “Particle swarm optimization,” in Proc. 9th Int. Conf. on Neural Networks, Nov. 1995, vol. 4, pp. 1942–1948.

[2] R. Eberhart and J. Kennedy, “A new optimizer using particle swarm theory,” in IEEE Proc. 6h Int. Symp. on Micro Machine and Human Science, Oct. 1995, pp. 39–43.

[3] J. Robinson and Y. Rahmat-Samii, “Particle swarm optimization in electromagnetics,” IEEE Trans. Antennas Propag., vol. 52, pp. 397–407, Feb. 2004.

[4] D. Gies, “Particle swarm optimization: applications in electromagnetic design,” M. Eng. thesis, UCLA, Los Angeles, CA, 2004.

[5] J. Kennedy and R. Eberhart, Swarm Intelligence. New York: Morgan Kaufmann and Academic Press, 2001.

[6] J. H. Holland, “Genetic algorithms and the optimal allocation of trials,” SIAM J. Comput., vol. 2, no. 2, Jun. 1973.

[7] Y. Rahmat-Samii and E. Michielssen, Eds., Electromagnetic Optimization by Genetic Algorithms. New York: Wiley, 1999.

[8] R. L. Haupt and D. H. Werner, Genetic Algorithms in Electromagnetics. Hoboken, NJ: Wiley, 2007.

[9] D. S. Weile and E. Michielssen, “Genetic algorithm optimization applied to electromagnetics: A review,” IEEE Trans. Antennas Propag., vol. 45, pp. 343–353, Mar. 1997.

[10] R. Storn and K. Price, “Differential evolution—A simple and efficient heuristic for global optimization over continuous spaces,” J. Global Optim., vol. 11, no. 4, pp. 341–359, Dec. 1997.

[11] K. V. Price, R. M. Storn, and J. A. Lampinen, Differential Evolution: A Practical Approach to Global Optimization, in Natural Computing. Heidelberg: Springer-Verlag, 2005.

[12] N. Jin and Y. Rahmat-Samii, “Parallel particle swarm optimization and finite difference time-domain (PSO/FDTD) algorithm for multiband and wide-band patch antenna designs,” IEEE Trans. Antennas Propag., vol. 53, pp. 3459–3468, Nov. 2005.

[13] N. Jin and Y. Rahmat-Samii, “Advances in particle swarm optimization for antenna designs: Real-number, binary, single-objective and multiobjective implementations,” IEEE Trans. Antennas Propag., vol. 55, pp. 556–567, Mar. 2007.

[14] N. Jin and Y. Rahmat-Samii, “Particle swarm optimization for antenna designs in engineering electromagnetics,” J. Artif. Evol. Applicat., vol. 2008, no. 9, Jan. 2008.

[15] F. J. Villegas, T. Cwik, Y. Rahmat-Samii, and M. Manteghi, "A parallel electromagnetic genetic-algorithm optimization (EGO) application for patch antenna design," IEEE Trans. Antennas Propag., vol. 52, pp. 2424–2435, Sep. 2004.

[16] D. H.Werner, P. L.Werner, and K. H. Church, "Genetically engineered multiband fractal antennas," IEEE Electron. Lett., vol. 37, no. 19, pp. 1150–1151, Sep. 2001.

[17] B. Schlobohm, F. Arndt, and J. Kless, "Direct PO optimized dual-offset reflector antennas for small earth stations and for millimeter wave atmospheric sensors," IEEE Trans. Microwave Theory Tech., vol. 40, pp. 1310–1317, Jun. 1992.

[18] A. Hoorfar and Y. Liu, "Antenna optimization using an evolutionary programming algorithm with a hybrid mutation operator," in Proc. IEEE Int. Symp. on Antennas Propag., 2000, vol. 2, p. 1029.

[19] M. John and M. J. Ammann, "Antenna optimization with a computationally efficient multiobjective evolutionary algorithm," IEEE Trans. Antennas Propag., vol. 57, pp. 260–263, Jan. 2009.

[20] D. S. Weile and E. Michielssen, "Integer coded Pareto genetic algorithm design of constrained antenna arrays," IEEE Electron. Lett., vol. 32, no. 19, pp. 1744–1745, Sep. 1996.

[21] T. G. Spence and D. H. Werner, "Design of broadband planar arrays based on the optimization of aperiodic tilings," IEEE Trans. Antennas Propag., vol. 56, pp. 76–86, Jan. 2008.

[22] R. L. Haupt, "Thinned arrays using genetic algorithms," IEEE Trans. Antennas Propag., vol. 42, pp. 993–999, Jul. 1994.

[23] J. S. Petko and D. H. Werner, "The evolution of optimal linear polyfractal arrays using genetic algorithms," IEEE Trans. Antennas Propag., vol. 53, pp. 3604–3615, Nov. 2005.

[24] J. S. Petko and D. H. Werner, "An autopolyploidy-based genetic algorithm for enhanced evolution of linear polyfractal arrays," IEEE Trans. Antennas Propag., vol. 55, pp. 583–593, Mar. 2007.

[25] J. S. Petko and D. H. Werner, "The pareto optimization of ultrawideband polyfractal arrays," IEEE Trans. Antennas Propag., vol. 56, pp. 97–107, Jan. 2008.

[26] M. G. Bray, D. H.Werner, D.W. Boeringer, and D. W. Machuga, "Optimization of thinned aperiodic linear phased arrays using genetic algorithms to reduce grating lobes during scanning," IEEE Trans. Antennas Propag., vol. 50, pp. 1732–1742, Dec. 2002.

[27] M. D. Gregory and D. H. Werner, "Ultrawideband aperiodic antenna arrays based on optimized raised power series representations," IEEE Trans. Antennas Propag., vol. 58, Mar. 2010.

[28] D. W. Boeringer, D. H.Werner, and D. W. Machuga, “A simultaneous parameter adaptation scheme for genetic algorithms with application to phased array synthesis,” IEEE Trans. Antennas Propag., vol. 53, pp. 356–371, Jan. 2005.

[29] D. W. Boeringer and D. H. Werner, “Efficiency-constrained particle swarm optimization of a modified Bernstein polynomial for conformal array excitation amplitude synthesis,” IEEE Trans. Antennas Propag., vol. 53, pp. 2662–2673, Aug. 2005.

[30] J. A. Bossard, X. Liang, L. Li, S. Yun, D. H. Werner, B. Weiner, T. S. Mayer, P. F. Cristman, A. Diaz, and I. C. Khoo, “Tunable frequency selective surfaces and negative-zero-positive index metamaterials based on liquid crystals,” IEEE Trans. Antennas Propag., vol. 56, pp. 1308–1320, May 2008.

[31] J. A. Bossard, D. H.Werner, T. S.Mayer, J. A. Smith, Y. U. Tang, R. P. Drupp, and L. Li, “The design and fabrication of planar multiband metallodielectric frequency selective surfaces and infrared applications,” IEEE Trans. Antennas Propag., vol. 54, pp. 1265–1276, Apr. 2006.

[32] J. A. Bossard, D. H. Werner, T. S. Mayer, and R. P. Drupp, “A novel design methodology for reconfigurable frequency selective surfaces using genetic algorithms,” IEEE Trans. Antennas Propag., vol. 53, pp. 1390–1400, Apr. 2005.

[33] M. A. Gingrich and D. H. Werner, “Synthesis of low/zero index of refraction metamaterials from frequency selective surfaces using genetic algorithms,” IEEE Electron. Lett., vol. 41, no. 23, pp. 1266–1267, Nov. 2005.

[34] D. J. Kern, D. H. Werner, and M. Lisovich, “Metaferrites: Usign electromagnetic bandgap structures to synthesize metamaterial ferrites,” IEEE Trans. Antennas Propag., vol. 53, pp. 1382–1389, Apr. 2005.

[35] D. J. Kern, D. H. Werner, A. Monorchio, L. Lanuzza, and M. J. Wilhelm, “The design synthesis of multiband artificial magnetic conductors using high impedance frequency selective surfaces,” IEEE Trans. Antennas Propag., vol. 53, pp. 8–17, Jan. 2005.

[36] S. Genovesi, R. Mittra, A. Monorchio, and G. Manara, “Particle swarm optimization for the design of frequency selective surfaces,” IEEE Antennas Wireless Propag. Lett., vol. 5, pp. 277–279, 2006.

[37] M.-I. Lai and S.-K. Jeng, “Compact microstrip dual-band bandpass filter design using genetic algorithm techniques,” IEEE Trans. Microwave Theory Tech., vol. 54, pp. 160–168, Jan. 2006.

[38] S. K. Guodos and J. N. Sahalos, “Pareto optimal microwave filter design using multiobjective differential evolution,” IEEE Trans. Antennas Propag., vol. 58, pp. 132–144, Jan. 2010.

[39] Y. Rahmat-Samii, “Modern antenna designs using nature inspired optimization techniques: Let darwin and the bees help designing your multi band MIMO antennas," *Proceedings of IEEE Radio and Wireless Symposium (RWS)*, pp. 463–466, Jan. 2007.

[40] "HFSS" ver. 13, ANSYS, Inc., Canonsburg, PA, 2010.

[41] "Matlab" ver. 7, The MathWorks Inc., Natick, MA. 2010.

[42] N. V. Venkatarayalu and T. Ray, "Optimum design of yagi–uda antennas using computational intelligence," IEEE Trans. Antennas Propag., vol. 52, no. 7, pp. 1811–1818, July 2004.

[43] R. L. Haupt, "An introduction to genetic algorithms for electromagnetics", IEEE Antenna and Propag. Magazine, vol. 37, no. 2, pp. 7–15, April 1995.

[44] L. Y. Tseng, and T. Y. Han, "An Evolutionary Design Method Using Genetic Local Search Algorithm to Obtain Broad/Dual-Band Characteristics for Circular Polarization Slot Antennas" IEEE Trans. Antennas Propag., vol. 58, no. 5, pp. 1811–1818, May 2010.

[45] R. C. Eberhart and Y. Shi, "Evolving artificial neural networks," in Proc. 1998 Int. Conf. Neural Networks and Brain, Beijing, P.R.C., 1998.

[46] J. Robinson, S. Sinton, and Y. Rahmat-Samii, "Particle swarm, genetic algorithm, and their hybrids: optimization of a profiled corrugated horn antenna," in Proc. IEEE Int. Symp. Antennas Propagation, vol. 1, San Antonio, TX, 2002, pp. 314–317.

[47] J. Kennedy and W. M. Spears, "Matching algorithms to problems: an experimental test of the particle swarm and some genetic algorithms on multi modal problem generator," in Proc. IEEE Int. Conf. Evolutionary Computation, 1998.

[48] J. Kennedy and R. Eberhart, "A discrete binary version of the particle swarm algorithm," in Proc. 1997 Conf. Systems, Man, Cybernetics, Piscataway, NJ, 1997.

[49] Ó. Quevedo-Teruel and E. Rajo-Iglesias, "Ant colony optimization in thinned array synthesis with minimum sidelobe level," IEEE Trans. and Wireless Propag. Letters, vol. 5, no. 1, pp. 349–352, Dec. 2006.

[50] N. Jin and Y. Rahmat-Samii, "Parallel particle swarm optimization and finite-difference time-domain (PSO/FDTD) algorithm for multiband and wide-band patch antenna designs" IEEE Trans. Antennas Propag., vol. 53, no. 11, pp. 3459–3468, Nov. 2005.

[51] M. Dorigo, V. Maniezzo, and A. Colorni, "Ant system: Optimization by a colony of cooperating agents," IEEE Trans. Syst., Man, Cybern. B, Cybern., vol. 26, no. 1, pp. 29–41, Feb. 1996.

[52] M. Dorigo and T. Stutzle, Ant Colony Optimization. Cambridge, MA: MIT Press, 2004.

[53] S. Kirkpatrick, C. D. Gellatt, Jr., and M. P. Vecchi, "Optimization by simulated annealing," Sci., vol. 220, no. 4598, pp. 671480, 1983.

[54] W. A. Kuperman, M. D. Collins, J. S. Perkins, and N. R. Davis, "Optimal time-domain beamforming with simulated annealing including application of a priori information," J. Acoust. Soc. Amer., vol. 88, pp. 1802-1810, Oct. 1990.

[55] C. S. Ruf, "Numerical annealing of low-redundancy linear arrays," IEEE Trans. Antennas Propagat., vol. 41, pp. 85-90, Jan. 1993.

[56] T. J. Hayward, "Optimization of the hydrophone placement for acoustic arrays using simulated annealing," J. Acoust. Soc. Amer., vol. 95, pp. 201-212, Jan. 1994.

[57] J. Martínez-Fernández, J. M. Gil, and J. Zapata, "Ultrawideband Optimized Profile Monopole Antenna by Means of Simulated Annealing Algorithm and the Finite Element Method," IEEE Trans. Antennas Propag., vol. 55, no. 6, pp. 1826–1832, June 2007.

[58] A. R. Mehrabian and C. Lucas, "A novel numerical optimization algorithm inspired from weed colonization," Ecological Informatics, vol. 1, no. 4, pp. 355-366, Dec. 2006.

[59] B. Dadalipour, A. R. Mallahzadeh, and Z. Davoodi-Rad, "Application of the invasive weed optimization technique for antenna configurations," in Proc. 2008 Loughborough Antennas and Propag. Conf., UK, March 2008.

[60] Y. Shi and R. C. Eberhart, "Empirical study of particle swarm optimization," in Proc. Congr. Evolutionary Computation. Piscataway, NJ, 1999, pp. 1945–1950.

[61] T. Ray, K. Tai, and K. C. Seow, "An evolutionary algorithm for constrained optimization," in Proc. Genetic and Evolutionary Computation Conf.. San Matteo, CA, 2000, pp. 771–777.

[62] N. Srinivas and K. Deb, "Multiobjective optimization using non-dominated sorting in genetic algorithms," Evolutionary Comput., vol. 2, no. 3, pp. 221–248, 1994.

[63] T. Ray and P. Saini, "Engineering design optimization using a swarm with an intelligent information sharing among individuals," Eng. Optimization, vol. 33, no. 6, pp. 735–748, 2002.

[64] J. Aelterman, R. Goossens, F. Declercq, and H. Rogier, "Ant colony optimisation-based radiation pattern manipulation algorithm for Electronically Steerable Array Radiator Antennas," *IET Sci. Meas. Technol.*, vol. 3, no. 4, pp. 302–311, July 2009.

[65] C. Zhang, S. Yang, H. K. Pan, A.E. Fathy, S. El-Ghazaly, V. K. Nair, "A reconfigurable multiband patch antenna for wireless applications using MEMS switches," *Microwave and Optical Technology Letters*, vol. 51, no. 8, pp. 1892–1896, Aug. 2009

[66] H. Akel, J. P. Webb, "Design sensitivities for scattering-matrix calculation with tetrahedral edge elements," *IEEE Transactions on Magnetics*, vol. 36, no. 4, pp. 1043–1046, July 2000.

[67] M. H. Bakr and N.K. Nikolova, “An adjoint variable method for time domain TLM with wideband Johns matrix boundaries,” *IEEE Trans. Microwave Theory Tech.*, vol. 52, no. 2, pp. 678–685, Feb. 2004.

[68] N. K. Nikolova, H. W. Tam, and M. H. Bakr, “Sensitivity analysis with the FDTD method on structured grids,” *IEEE Trans. Microwave Theory Tech.*, vol. 52, no. 4, pp. 1207–1216, April 2004.

[69] E. A. Soliman, M. H. Bakr, and N. K. Nikolova, “An adjoint variable method for sensitivity calculations of multiport devices,” *IEEE Trans. Microwave Theory Tech.*, vol. 52, no. 2, pp. 589–599, Feb. 2004.

[70] M. A. Swillam, M. H. Bakr, and X. Li , “Efficient adjoint sensitivity analysis exploiting the FD-BPM,” *IEEE/OSA Journal of Lightwave Technology*, vol. 25, no. 7, pp. 1861–1869, July 2007.

[71] M. H. Bakr, N. K. Nikolova, and P. A. W. Basl, “Self-adjoint S-parameter sensitivities for lossless homogeneous TLM problems,” *International Journal of Numerical Modelling: Electronic Networks, Devices and Fields*, vol. 18, no. 6, pp. 441–455, Nov. 2005.

[72] G. Kiziltas, D. Psychoudakis, J. L. Volakis, N. Kikuchi, ”Topology design optimization of dielectric substrates for bandwidth improvement of a patch antenna,” *IEEE Trans. Antennas and Prop.*, vol. 51, no. 10, pp. 2732–2743, Oct. 2003.

[73] N. Uchida, S. Nishiwaki, K. Izui, M. Yoshimura, T. Nomura, and K. Sato ”Simultaneous shape and topology optimization for the design of patch antennas," Proceedings of Antennas and Prop. (EuCAP), pp. 103–107, March 2009.

[74] "CST" ver. 2010.00, CST, Inc., Framingham, MA, 2010.

[75] M. H. Bakr, M. Ghassemi, and N. Sangary, "Bandwidth enhancement of narrow band antennas exploiting adjoint-based geometry evolution," *Proceedings of IEEE International Symposium on Antennas and Propagation*, pp. 2909–2911, July 2011.

[76] J. W. Bandler, W. Kellermann, and K. Madsen, "A superlinearly convergent minimax algorithm for microwave circuit design," *Proceedings of IEEE Trans. Microwave Theory Tech.*, vol. 33, no. 12, pp. 1519–1530, June 1985.

[77] L. Wang, W. Wu, X.- W.Shi, F. Wei, and Q. Huang, "Design of novel monopole UWB antenna with a notched ground," *Progress In Electromagnetics Research (PIER) C*, vol. 5, pp. 13–20, 2008.

[78] N. P. Agrawall, G. Kumar, and K. P. Ray, "Wide-band planar monopole antennas", *IEEE Trans. Antennas Propag.*, vol. 46, no. 2, pp. 294–295, Feb. 1998.

[79] L. Zhang, Z. Cui, Yong-Chang Jiao, and Fu-Shun Zhang, "Broadband patch antenna design using differential evolution algorithm," *Microwave and Optical Technology Letters*, vol. 51, no. 7, pp. 1692–1695, July 2009.

[80] A. Khidre, K. F. Lee, F. Yang, and A. Elsherbeni, "Wideband circularly polarized E-shaped patch antenna for wireless applications," *IEEE*

Antennas and Propagation Magazine, vol. 52, no.5, pp. 219–229, Oct. 2010.

[81] G. Mayhew-Ridgers, J. W. Odendaal, and J. Joubert, “Single-layer capacitive feed for wideband probe-fed microstrip antenna elements,” *IEEE Trans. Antennas Propag.*, vol. 51, no. 6, pp. 1405–1407, June 2003.

[82] V. G. Kasabegoudar and K. J. Vinoy, “Coplanar capacitively coupled probe fed microstrip antennas for wideband applications,” *IEEE Trans. Antennas Propag.*, vol. 58, no. 10, pp. 3131–3138, Oct. 2010.

[83] G. J. Foschini and M. J. Gans. “On limits of wireless communications in a fading environment when using multiple antennas,” *Wireless Personal Communications*, vol. 6, no. 3, pp. 311–335, 1998.

[84] Federal Communication Commission (FCC), “Revision of part 15 of the commission’s rules regarding ultra-wideband transmission systems,” First report and order, ET Docket 98–153, FCC 02–48, adopted: Feb. 2002, released in April 2002.

[85] A. Diallo, C. Luxey, P. Le Thuc, R. Staraj, and G. Kossiavas, “Study and reduction of the mutual coupling between two mobile phone PIFAs operating in the DCS1800 and UMTS bands”, *IEEE Trans. Antennas Propag.*, vol. 54, no. 11, pp. 3063–3074, 2006.

[86] A. C. K. Mak, C. R. Rowell, and R. D. Murch, “Isolation enhancement between two closely packed antennas,” *IEEE Trans. Antennas Propag.*, vol. 56, no. 11, pp. 3411–3419, 2008.

[87] T. Kokkinos, E. Liakou, and A. P. Feresidis, “Decoupling antenna elements of PIFA arrays on handheld devices,” *IEEE Electronic Letters*, vol. 44, no. 25, 2008.

[88] A. I. Najam, Y. Duroc, S. Tedjini, “Design & characterization of an antenna system for UWB-MIMO communication systems”, Proceeding of the forth European Conference on Antenna and Propagation (EuCAP) 2010, pp. 1-5, July 2010.

[89] M. Ghassemi, M. H. Bakr, and N. Sangary, “Antenna Design Exploiting Adjoint Sensitivity Based Geometry Evolution,” *IEEE Trans. Antennas Propag.*, 2011. (submitted)

[90] G. J. Foschini, “Layered space-time architecture for wireless communication in a fading environment when using multielement antennas,” *Bell Lab Tech. Journal*, pp. 41−59, 1996.

[91] I. E. Telatar, “Capacity of multi-antenna gaussian channels,” *AT&T Bell Labs Internal Report*, 1995.

[92] M. A. Jensen and J. W. Wallace, “A review of antennas and propagation for MIMO wireless communications,” *IEEE Trans. Antennas Propag.*, vol. 52, no. 11, pp. 2810−2824, 2004.

[93] S. Schulteis, C. Waldschmidt, W. Sorgel, and W. Wiesbeck, “A Small Planar Inverted F Antenna with Capacitive and Inductive Loading”, *Proc. Antennas and Propagation Society International Symposium 2004*, Vol. 4, pp. 4148-4151, June 2004.

[94] S. C. K. Ko and R. D. Murch, "Compact integrated diversity antenna for wireless communicaitons," *IEEE Trans. Antennas Propag.*, vol. 49, no. 6, pp. 954–960, 2001.

[95] Q.-J. Rao and D. Wang, "A compact dual-port diversity antenna for handheld devices," *Antennas & Propagation Conference 2009*, Loughborough, pp. 181–184, 2009.

[96] S. K. Chaudhury, H. J. Chaloupka, and A. Ziroff, "Novel MIMO antennas for mobile terminal," *2008. EuWiT 2008. European Conference on Wireless Technology*, pp. 330–333, Oct. 2008.