MICROSTRIP ANTENNA DESIGN USING GENETIC ALGORITHMS COUPLED WITH ARTIFICIAL NEURAL NETWORKS

A THESIS

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ABSTRACT

Key Words: Microstrip Antenna, Resonant Frequency, Genetic Algorithm, Knowledge-based Crossover, Artificial Neural Networks, Tunneling, Finite Difference Time Domain Technique

In the changing scenario of wireless communication, where the demands are more on miniaturization and high data rate, microstrip antenna has become a major research topic. A microstrip antenna is a metallic patch on a dielectric magnetic slab mounted on a ground plane. Depending on the shape of the radiating metallic patch, they are classified as rectangular microstrip antenna, triangular microstrip antenna and circular microstrip antenna etc. There can be of any irregular structure also. They have many advantages like low cost, low profile, light weight and ease of fabrication etc. However, they have some shortcomings too. Major of which is their narrow bandwidth. Hence, the physical dimensions have to be accurately predicted. For impedance matching, the feed position has to be properly chosen. The spacing between antennas in antenna arrays has to be optimized. Therefore, there is a growing demand on use of Computer Aided Design(CAD) tools for antenna design. Current trend of RF design gives much emphasis on efficient CAD design of RF circuit, where antenna is an on board element. Most of the available simulation packages are based on solution of Maxwell's equation in order to characterize the RF circuit. The next generation CAD designs tool focus

on faster prediction of simulation results, which is generally not possible by field solution based packages. All these limitations have forced for development of an efficient optimizing soft computing tool for accurate and efficient miniaturized antenna design.

Soft computing techniques namely Genetic Algorithm(GA) and Artificial Neural Networks(ANN), have gained great importance in the field of electromagnetics. Genetic Algorithm is based on natural selection, i.e. on Darwinian principle of survival of the fittest. This is a stochastic, global and parallel in nature. On the other hand, Artificial Neural Networks is based on mimic of human brain. The most commonly used neural network algorithm is error back-propagation. This is a local search technique which uses gradient information of the error surface. Therefore, it's an attempt in this thesis to combine Genetic Algorithm with Artificial Neural Networks to get faster and highly accurate soft computing tools for antenna design. A GA can not be applied to problems where there is no proper fitness function to evaluate and select the individuals for next generation. Therefore, a trained ANN has been used as a fitness function of GA to overcome such problem in this thesis. While training ANN by GA, "the multiple representation problem" makes the algorithm slow when the chromosomal representation exceeds 300 bits. Keeping such problem in mind in this thesis, attempt has been made to train ANN by GA in different ways such as training ANN by the weights initialized by GA and by choosing different steepness of activation for different weights. It takes much man-time while selecting ANN parameters for training an ANN. A GA has been used to optimize those ANN parameters.

The Finite-Difference Time-Domain(FDTD) method, first applied by Yee in 1966, is a simple and elegant way to discretise the differential form of Maxwell's equations. Yee used an electric-field(E) grid, which was *offset both spatially and temporally from a magnetic-field(H) grid to obtain* update equations that yield the present fields throughout the computational domain in terms of the past fields. The update equations are used in a leap-frog scheme. Due to its Leap-Frog architecture, FDTD is inherently slow. Therefore, an attempt has been made to incorporate a temporal neural network for time series prediction of voltage and current of FDTD to improve the time efficiency and accuracy of FDTD technique. To further improve the scheme, GA is used to select the temporal neural networks parameters thus the GA-ANN-FDTD.

DECLARATION

I hereby declare that the thesis entitled "**MICROSTRIP ANTENNA DESIGN USING GENETIC ALGORITHMS COUPLED WITH ARTIFICIAL NEURAL NETWORKS**" submitted by me in partial fulfillment of the requirements of degree of Doctor of Philosophy is a record of my bonafide research work carried out under the guidance of Prof.(Dr.) Malayananda Dutta, Computer science & Engineering Department, Tezpur University, Assam, India and, Prof.(Dr.) Shyam S. Pattnaik, Head, Educational Television Centre, National Institute of Technical Teachers' Training and Research(NITTTR), Chandigarh, India.

The research work included in this thesis has not been submitted to any other university or institute for the award of any other degree.

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This is to certify that the thesis entitled "**MICROSTRIP ANTENNA DESIGN USING GENETIC ALGORITHMS COUPLED WITH ARTIFICIAL NEURAL NETWORKS**" submitted to Computer Science and Engineering Department, Tezpur University in partial fulfillment for the award of the degree of **Doctor of Philosophy in Engineering** is a record of research work carried out by Mr. Bonomali Khuntia under our supervision and guidance.

All the helps received by him from various sources have been duly acknowledged.

No part of this thesis has been submitted elsewhere for award of any other degree.

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List of Abbreviations

ANN	Artificial Neural Networks
MLP	Multi Layer Percptron
NBP	Normal Backpropagation
MSE	Mean Square Error
LMS	Least Mean Square
E_{abs}	Absolute Error
E_{rms}	Root Mean Square Error
TBP	Tunnel Based Neural Network
GA	Genetic Algorithm
SGA	Sample Genetic Algorithm
CGA	Continuous Genetic Algorithm
ABC	Absorbing Boundary Condition
NFDTD	Neural Network Based Finite Difference Time Domain Method
FIR	Finite Impulse Response
FDTD	Finite Difference Time Domain
FEM	Finite Element Method
MoM	Method of Moments
RMSA	Rectangular Microstrip Antenna
FFT	Fast Fourier Transform
DRNN	Dynamical Recurrent Neural Network
CAD	Computer Aided Design

List of Symbols

μ	Permeability
μ_r	Relative Permeability
μ_{eff}	Effective Permeability
λ	Wavelength
F, φ	Activation Function
ε	Permitivity
ε_r	Dielectric Constant
ε_{eff}	Effective Dielectric Constant
L	Length of Rectangular Patch Antenna
W	Width of Patch Antenna
h	Height of Dielectric Substrate
f_r	Resonant Frequency
f	Operating Frequency
f_p	Plasma Frequency
ε	Small Perturbation for Tunnel based neural network
λ	Steepness of Activation Function for Neural Network
α	Learning Constant
η	Momentum Factor
(m,n)	Mode of Resonant Frequency
ρ	Strength of Learning

List of Publication out of The Thesis Work

a) International Journals

1. S. S. Pattnaik, **B. Khuntia**, D. C. Panda, and S. Devi, "Calculation of optimized parameters of rectangular microstrip patch antenna using genetic algorithm", Microwave and Optical Technology Letters, USA, Vol. 23, No. 4, 20th June' 2003, pp. 431-433.
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3. D. K. Neog, S. S. Pattnaik, M. Dutta, S. Devi, **B. Khuntia** and D. C. Panda, "Inverted L-Shaped and Parasitically Coupled Inverted L-Shaped Microstrip Patch Antenna for wide Bandwidth," Microwave and Optical Technology Letters, vol. 42, no. 3, 5th Aug.' 2004, pp. 190-192.
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b) International Conferences

8. S. Devi D. C. Panda, S. S. Pattnaik, **B. Khuntia**, and D. K Neog, "Initializing Artificial Neural Networks by Genetic Algorithm to Calculate the Resonant Frequency of Single Shorting Post Rectangular Patch Antenna," *IEEE Proceedings Antennas and Propagation Society*, vol. 3, 2003, pp 144-147.
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Pattern of Cell Phone Antenna in Presence of Human Head, *IEEE-ASPW*, Delhi, 2002, pp.330-334.

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11. S. Devi, S. S. Pattnaik, **B. Khuntia**, D. C. Panda, M. Dutta, and D. K. Neog, "Design of Knowledge Based Continuous Genetic Algorithm to Train Artificial Neural Networks and its Application on Rectangular Microstrip Antenna," *International Conference on Antenna Technologies*, Ahmedabad, Feb. 21-22, 2005.

c) National Conferences

12. S. S. Pattnaik, D. C. Panda, **B. Khuntia**, and S. Devi, "Calculation of Parameters of Microstrip Antenna Using Artificial Neural Networks," *Proceedings APSYM*, Coachin University, 2002, pp. 27-31.
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CHAPTER 1

REVIEW OF MICROSTRIP PATCH ANTENNA AND SOFT COMPUTING TECHNIQUES

1.1 Introduction

Microstrip antennas proposed by Deschamp in the year 1953[1], have gained a great attention in last few decades. Due to Its advantages like, low profile, low cost, ease of construction, conformal geometry and flexibility in terms of radiation pattern, gain and polarization etc. Microstrip patch antennas are also used in most of the modern handsets, personal digital devices and laptop computers[2,3,4]. It is a potential radiator for miniaturized portable or hand-held devices. Many methods have been developed for analysis of microstrip antenna[4,5]. They fall in to two broad categories: approximate methods and full wave methods. The approximate method include the transmission line model and cavity model. The full wave methods that can be used to model microstrip patch antennas are the method of moments (MoM), the finite element method(FEM) and the finite-difference time-domain(FDTD)method.

1.1.1 Transmission Line Model

Microstrip antennas have a physical structure derived from microstrip transmission lines [6-9]. Therefore, a transmission-line model is one of the most obvious choices for the analysis and the design of microstrip antennas.

The transmission line model representation of the microstrip antenna is shown in figure 1.1. The microstrip patch antenna is represented by two slots, separated by a transmission line of length '*L*' and open circuited at both the ends. Along the width of the patch, the current is minimum and voltage appears maximum due to the open ends. The fields at the edges can be resolved into normal and tangential components with respect to the ground plane. The fields vary along the non-radiating edge of the patch, which is approximately half a wave length, and remain constant across the width. Variation of fields along the length depends on the propagation constant of the line. Radiation occurs mainly due to the fringing fields at the open ends.

However, this model is often regarded as over simplified and somewhat outdated[10]. This is true for the original, simple transmission-line model; but the accuracy of the improved transmission-line model is comparable to those of other more complicated methods[11].

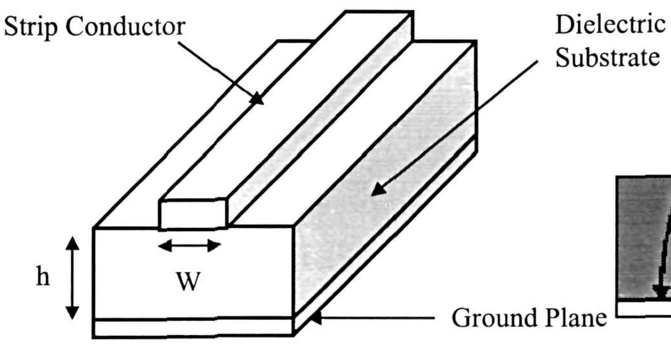

Fig. 1.1(a) Microstrip Line

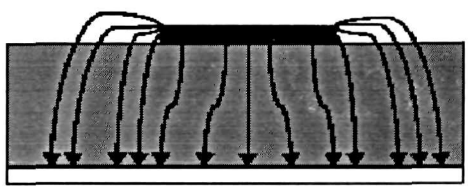

Fig. 1.1(b) Electric Field Line

Improved transmission-line models include substrate and conductor losses, aperture coupling, reactive effects, and the mutual coupling between the radiating apertures. The concept of the transmission-line model can be applied to any microstrip antenna configuration for which separation of variables is possible. Surface waves are not taken into account in the transmission-line model, which limits its use to thick and low substrate permittivity[12].

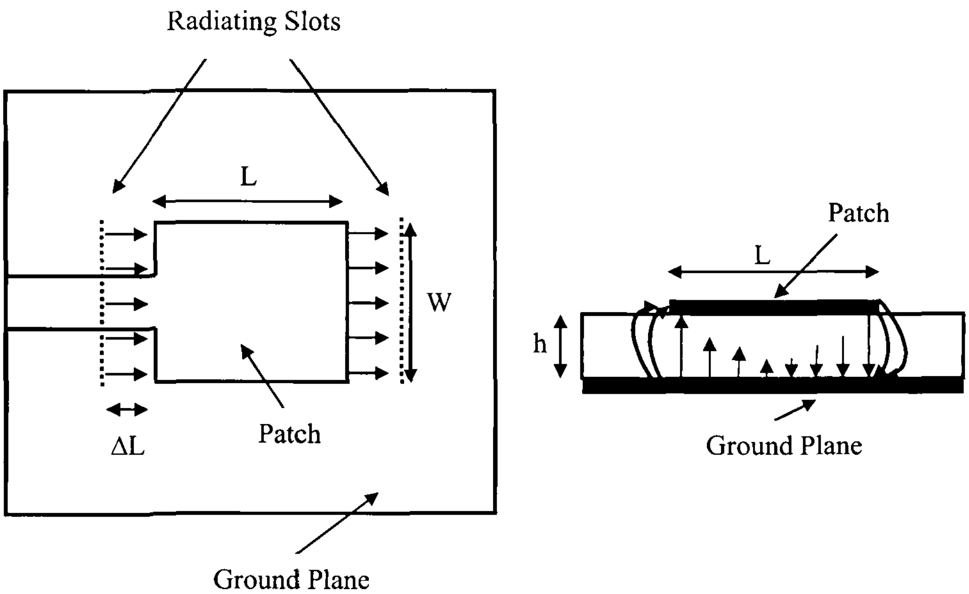

Fig. 1.2 Top and Side View of Rectangular Microstrip Antenna

1.1.2 Cavity Model

Transmission line model is useful for patches of rectangular design and it ignores field variations along the radiating edges. These disadvantages can be overcome by using the cavity model [13-21]. The microstrip patch antennas being narrow-band resonant antennas can be treated as lossy cavity. Therefore, cavity model becomes a natural choice to analyze the patch antennas. This model is suitable for regular geometries for which the Helhmoltz equation possesses an analytical solution, such as disks, rings, rectangles, triangles, and ellipses.

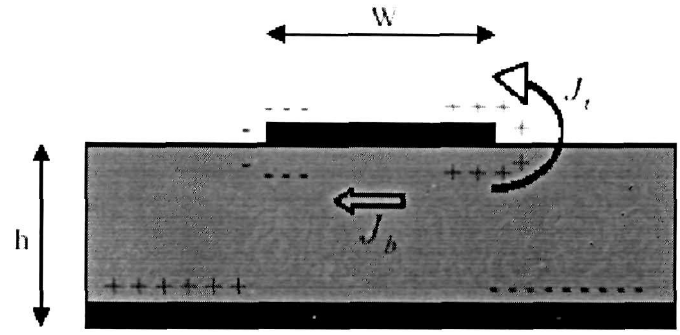

Fig. 1.3 Charge Distributions and Current Density on a Microstrip Antenna

When the microstrip patch is provided with power, the charge distribution occurs on the upper and lower surfaces of the patch and on the ground plane. This charge distribution is controlled by two mechanisms namely attractive mechanism and a repulsive mechanism[22]. The attractive mechanism is between the opposite charges on the bottom side of the patch and the ground plane, which helps in keeping the charge concentration intact at the bottom of the patch. Whereas, the repulsive mechanism occurs between the like charges on the bottom surface of the patch, which causes pushing out of some charges from the bottom, to the top of the patch. As a result of this charge movement, currents flow at the top and bottom surface of the patch.

The cavity model assumes that the height to width ratio (i.e. height of substrate and width of the patch) is very small and as a result of this the attractive mechanism dominates and causes most of the charge concentration and the current to be below the patch surface. Much less current flows on the top surface of the patch. As the height to width ratio further decreases, the current on the top surface of the patch becomes negligible. This does not allow the creation of any tangential magnetic field components to the patch edges. Hence, the four side walls are modeled as perfectly magnetic conducting surfaces. This implies that the magnetic fields and the electric field distribution beneath the patch are not disturbed. However, in practice, a finite width to height ratio exists and this does not make the tangential magnetic fields to be completely zero, but they being very small, the side walls can be approximated to be perfectly magnetic conducting.

This model has limitation due to its applicability only in low frequencies or electrically thin substrates; this is because the formulation inherently does not account for losses due to radiation and surface waves rigorously.

1.1.3 Full Wave Method – Moment Method

The most popular method, that provides the full wave analysis for the microstrip patch antenna, is the moment method[23]. In mathematical literature, Moment Method is known as Weighted residuals and can be applied to the solution of both differential and integral equations. The method owes its name to the process of taking moments by multiplying the function with an appropriate weighting function and integrating. On microstrip antenna analysis with this method, the surface currents are used to model the microstrip patch and the volume polarization currents are used to model the fields in the dielectric slab. It has been shown by Newman and Tulyathan[23] how an integral equation is obtained for these unknown currents and using the method of moments, these electric field integral equations are converted into matrix equations which can then be solved by various techniques of algebra to provide the result. In electromagnetic theory, the method became popular after the pioneering work done by R.F.Harrington in 1967. Since than it has been one of the most popular methods for solving the electromagnetic boundary value problem.

1.1.4 Finite Element Method (FEM) of Analysis

The basic concept of Finite Element Method (FEM) [24] lies in the fact that although the behavior of a function may be complex when viewed over a larger region, a simple approximation may suffice for a small sub region. The total region is divided into a number of non-overlapping sub-regions called finite elements. In two dimensions usually polygons like triangles or squares or combinations of triangles and squares are used for approximating the total surface. Regardless of the shape of the elements, the field is approximated by a different expression over each element, but where the edges of adjoining elements overlap, the field representation must agree to maintain continuity of the field. The equations to be solved are usually stated in terms not of the field variables but in terms of an integral type function such as energy. The function is chosen such that the field solution makes the functional stationary.

Finite element method is employed in many software packages for design and evaluation of microwave circuit performance. Its precision depends on developing proper meshing for the structure under consideration. So it is important to develop a tool that can provide a good mesh.

1.1.5 Finite-Difference Time-Domain (FDTD) Method

The FDTD method of analysis of an electromagnetic problem is a volumetric computational method. The FDTD technique is a numerical method for the solution of electromagnetic field problems with large numerical but a low analytical expenses. Despite the large numerical expenses, it is believed to be one of the most efficient techniques, because it stores only the field distribution at one moment in memory instead of working with a very large equation system matrix. The field solution for each time instant is then determined from

Maxwell's equations and is calculated using a time stepping procedure based on the finite difference formulation of Maxwell's equations in space and time[25-28]. In this method, Maxwell's equations are discretized in space and time over a finite volume, and the derivatives are approximated by finite differences. By appropriately selecting the points at which the various field components are to be evaluated, the resulting set of finite-difference equations can then be solved, and a solution that satisfies the boundary conditions can be obtained[29]. The method can efficiently be implemented on vector or on parallel computers. Sufficiently accurate results can be obtained by using a single precision floating point expression requiring only four bytes. FDTD method has been used for microstrip antenna analysis. Details of implementation reported by various authors differ in respect of excitation treatment, boundary conditions and post processing of results to obtain frequency parameters of interest[25-30]. The EM field in the space, which has to be analyzed, can be excited in different ways. A transient analysis, where pulse in space and time, *e.g.,* in the form of a Gaussian pulse, is excited inside the circuit or component, is mostly used for the analysis of the microstrip antenna.

1.2 Motivation

In the era of 3G and upcoming 4G and 5G wireless applications, the demands are for miniaturized, high directional, high gain and flexible conformal microstrip patch antenna. The microstrip antenna analysis performed by traditional methods are either less accurate or, computationally expensive. Therefore, design of microstrip antenna by such field analysis techniques is a difficult task for the researcher or engineers. At the same time, the bio-inspired soft-computing techniques like, Genetic Algorithm(GA), Particle swarm Optimization(PSO) and Artificial Neural Networks(ANN) etc. have received much interest in all areas of research[31-39]. Their extensive application to electromagnetic problem is yet to be achieved. The body centric communication demands for antennas with size reduction and with high efficiency. To design such antennas there is a tremendous demand on development of accurate computational tools. Looking into the needs of antenna and development of computationally efficient tool, the thesis is planned to address these issues.

1.3 Dissertation Overview

This dissertation consists of seven chapters. The first chapter is an introduction. It describes an overall outline of the thesis. Firstly it describes Microstrip Antenna and various analytical methods used for analysis. Then it explains about Genetic Algorithm and Artificial Neural Networks. A brief introduction to the combination of Genetic Algorithm and Artificial Neural Networks and its problem is also outlined. Further, a brief introduction to Finite Difference Time Domain technique for microstrip antenna analysis, is presented to build the background of the thesis. The objectives and methodologies are also presented.

Chapter two includes literature review of Genetic Algorithm and Artificial Neural Networks. It gives basic concept of Genetic Algorithm and Continuous Genetic Algorithm. It also describes different types of crossover. Advantages and care to be taken while implementing GA. It also outlines artificial neural networks and algorithms more specifically error back propagation.

Chapter three describes application of Genetic Algorithm on Microstrip Antenna designing as proposed by the candidate[40]. This chapter presents how the accuracy of the designing of Microstrip antenna can be improved using GA. The developed algorithm is used for designing rectangular, circular and triangular Microstrip antenna. The results found are validated by IE3D software of the Zealand Inc., USA and with the experimental results. The outcomes have been published for the benefit of the research community.

Chapter four starts with an introduction to Artificial Neural Networks. A tunnel-based Artificial Neural Networks is proposed to overcome the local minima. This is used to find out the radiation pattern of rectangular Microstrip antenna [41]. Proper selection of fitness function of genetic Algorithm is one of the major limitations of

GA. Hence, ANN is efficiently used to overcome such problems. A trained ANN is used as fitness function of GA which has been applied to design Microstrip antenna[42].

Chapter five shows how GA can be combined with ANN for weight optimization. Firstly Genetic Algorithm is used to fix the initial weight set of ANN and result is analyzed[43]. It is seen that 45% of computational time has been reduced with better accuracy. Then continuous/real valued crossover is replaced by introducing knowledge-based continuous Genetic Algorithm for training Artificial Neural Networks efficiently. The proposed technique is used to design Microstrip antenna[44]. Taking different steepness of activation for different neuron the problem of competing convention is taken care of while training Artificial Neural Networks using Genetic Algorithm. Here higher accuracy is achieved with 34% of computational time reduction. This technique is used to calculate resonant frequency of rectangular Microstrip antenna on thick substrate[45]. Finally, various parameters of Artificial Neural Networks are optimized by Genetic Algorithm. In this method, the man-time required to select the ANN parameters has been reduced considerably. Further, accuracy is improved by 30%. The proposed algorithm is applied to calculate resonant frequency of tunable single shorting post rectangular patch antenna[46].

Finite Difference Time Domain Technique and its use in analysis of microstrip antenna is described in chapter six. The presently used FDTD algorithm takes long computational time for simulation of high Q passive structure. In this thesis, the temporal neural networks is introduced which is then applied with FDTD technique, and is named as NFDTD[42]. Further to improve the time efficiency and accuracy using the approach of soft fusion, GA coupled ANN is incorporated with FDTD to develop GA-ANN-FDTD. The proposed technique is applied for the calculation of input impedance of rectangular patch antenna[47].

The conclusion and future scopes are presented in chapter seven.

1.4 Need for GA and ANN

Genetic Algorithm is a global search technique[31-33]. It is parallel in nature, i.e., the search is population to population but not point to point. It operates on encoded parameter instead of the parameters itself. Thus, non-differentiable functions as well as functions with multiple local optima represent classes of problems to which genetic algorithms can be applied[48,49]. On the other hand, Artificial Neural Networks is a mathematical model that learns from experience(training) and applies its knowledge for new unknown situations[50-52]. In the field of electromagnetics, there are various problems, where it is required to optimize many parameters simultaneously. These problems are efficiently handled by using Genetic Algorithm. There are cases such as body centric devices, hand held devices etc., where it is very difficult to define the problem mathematically. In such cases, we take help of bio-inspired computing.

1.5 Connection Weight Determination

GAs are used to find a set of connection weights. The fitness of the network is determined solely by minimizing error. However, sometimes GA is used to select a suitable initial set of weights, that is, a set of weights which leads to a successful ANN after training with some standard training routines. In this case, the training time plays an important role[43-45,53].

1.6 Network Architecture Design

The network architecture is of great importance for the success of an ANN. For some problems, a big network is unavoidable, while for others smaller networks are more suitable. The space of all possible networks is infinite, and as yet there is little or no theory about what architecture works well for what problem. This makes GAs a viable tool to search for a better ANN solution.

1.7 Problems in Training of ANN by Means of GA

When the length of the chromosome is small, the ANN with GA approach works well. When the length of chromosome increases, a problem arises which is called, *The Problem of Competing Conventions*, or, permutation problem[53-55,56]. They are of two types:

Hidden Node Redundancy: A neuron sums the weighted inputs and applies an odd activation function to the sum to produce the output values. The output of the total network doesn't change if the signs of all the incoming and outgoing weights are fliped. Since for every node in the ANN there are two possibilities, for the ANN as a whole, if there are n hidden nodes, there are 2^n different combinations.

(Two different but functionally equivalent neurons)

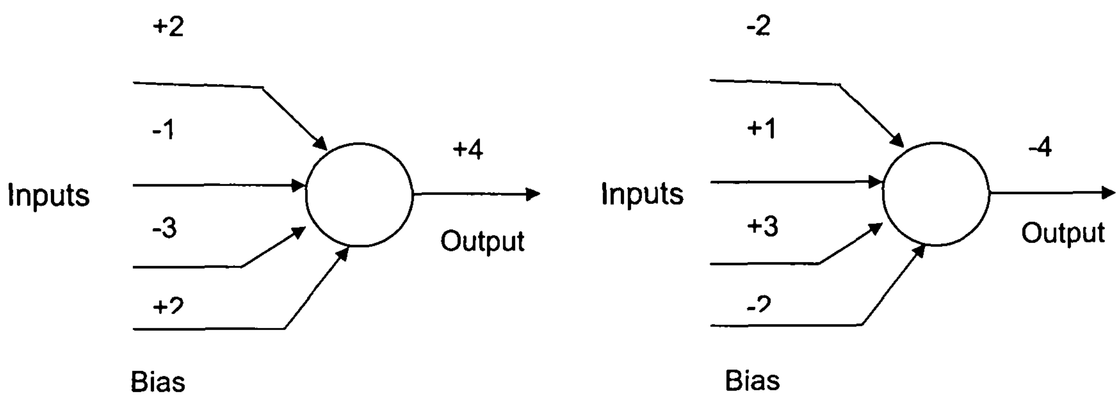

Fig. 1.4 Hidden Node Redundancy (In case of an Odd Function)

Hidden Layer Redundancy: If a hidden neuron, with all its incoming and outgoing connections, is exchanged with another neuron with all its incoming and outgoing connections, we have a different structural representation of ANN, but functionally the ANN remains exactly the same. In a network with n hidden neurons, there are n! different combinations of these hidden nodes.

(Two different but functionally equivalent neurons)

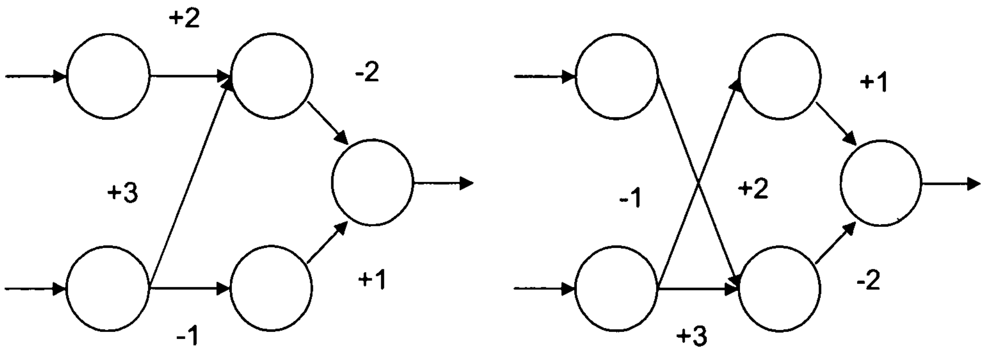

Figure. 1.5 Hidden Layer Redundancy

Since these two transformations are independent of each other, for a network with n hidden nodes, there are 2^n n! functionally equivalent but structurally different representations, if the activation function is odd, and otherwise n! different representations.

1.8 Competing Convention as a Big Problem

First, its existence dramatically increases the size of the solution space. That means, it takes a lot more time to converge to an acceptable solution. Secondly, it almost completely destroys the usefulness of the crossover operator which is the most important operator in GA.

For instance, suppose that each character in the string codes one hidden node, and the string "abcdef" codes the fittest possible ANN. In the population are the strings "abcdeg" and "hbcdef". If we cross these two strings, we might get the desired ANN. However, the second string may reside in the population as, for example, "fedcbh". Crossing may now leave us with something like the strings "abccbh" and "feddeg", which may not fit at all.

1.9 Handling the Problem of Competing Convention

It may be noted that some researches ignore the problem of competing conventions, and simply use the crossover operator. Ultimately, the performance reduces. However, there are some ways to overcome this problem[53] which are listed below.

i. Genetic Hill-climbing: To deal with hidden layer redundancy, many researchers have just left the crossover operator, and evolve ANNs with reproduction and mutation only. The GA process then becomes a kind of random. This is sometimes called *Genetic Hill-climbing*.

ii. Another simple way of dealing with the problem of hidden layer redundancy is using small populations. How ever, crossover is of no use any more, and the process is evolved with big mutation rate, strengthening the *hill-climbing* features.

iii. Restrictive Mating: Some literatures only use the crossover operator if the parents are not too different. This is sometimes called *Restrictive Mating.*

iv. Rearranging the Hidden Nodes in the Parent Individuals: It can also be handled by rearranging the hidden nodes in the parent individuals to place functionally equivalent hidden nodes in the same positions on both parent chromosomes.

Rearranging the hidden nodes seems to be the most effective. Since, it leaves all the aspects of GAs intact and is relatively easy to analyze and understand. The reason it is not always used is that it depends on the theory behind the determination of equivalent nodes of ANNs, how difficult the method is to implement and how much time it will cost. Most methods are very time consuming and difficult to implement. Montana and Davis[57] have also designed two techniques independently giving good results for small networks. But, they have also ignored the problem of compete conventions.

1.10 Finite Difference Time Domain Technique

In this section Yee's FDTD scheme[25-30] in brief is discussed to implement for patch antenna. The FDTD update scheme is based on two spatial and temporal dependent equations. In a linear, isotropic, non-dispersive dielectrics, and non magnetic medium the time depended Maxwell's equations are

$$\frac{\partial \vec{E}}{\partial t} = \frac{1}{\varepsilon} \nabla \vec{H} \qquad (1.1)$$

$$\frac{\partial \vec{H}}{\partial t} = -\frac{1}{\mu} \nabla \vec{E} \qquad (1.2)$$

where,

E - Electric field intensity

H- Magnetic field intensity

ε- Permittivity of the medium

μ-Permeability of the medium

Under Cartesian coordinate system, these can be further expanded as:

$$\frac{\partial H_x}{\partial t} = -\frac{1}{\mu}\left(\frac{\partial E_x}{\partial y} - \frac{\partial E_y}{\partial z}\right)$$

$$\frac{\partial H_y}{\partial t} = -\frac{1}{\mu}\left(\frac{\partial E_x}{\partial z} - \frac{\partial E_z}{\partial x}\right)$$

$$\frac{\partial H_z}{\partial t} = -\frac{1}{\mu}\left(\frac{\partial E_y}{\partial x} - \frac{\partial E_x}{\partial y}\right)$$

$$\frac{\partial E_x}{\partial t} = \frac{1}{\varepsilon}\left(\frac{\partial H_z}{\partial y} - \frac{\partial H_y}{\partial z}\right)$$

$$\frac{\partial E_y}{\partial t} = \frac{1}{\varepsilon}\left(\frac{\partial H_x}{\partial z} - \frac{\partial H_z}{\partial x}\right)$$

$$\frac{\partial E_z}{\partial t} = \frac{1}{\varepsilon}\left(\frac{\partial H_y}{\partial x} - \frac{\partial H_x}{\partial y}\right)$$

(1.3)

The 2nd order accurate central difference scheme as proposed by Yee is given by[29,30]

$$\frac{\partial u}{\partial t}(i\Delta x, j\Delta y, k\Delta z, n\Delta t) = \frac{u_{i,j,k}^{n+1/2} - u_{i,j,k}^{n-1/2}}{\Delta t} \tag{1.4}$$

Simplifying these equations by central difference scheme one will get,

$$E_x^{n+1}(i,j,k) = E_x^n(i,j,k) +$$
$$\frac{\Delta t}{\varepsilon}\left[\frac{H_z^{n+1/2}(i,j+1,k) - H_z^{n+1/2}(i,j,k)}{\Delta y} - \frac{H_y^{n+1/2}(i,j,k+1) - H_y^{n+1/2}(i,j,k)}{\Delta z}\right]$$

$$E_y^{n+1}(i,j,k) = E_y^n(i,j,k) +$$
$$\frac{\Delta t}{\varepsilon}\left[\frac{H_x^{n+1/2}(i,j,k+1) - H_x^{n+1/2}(i,j,k)}{\Delta z} - \frac{H_z^{n+1/2}(i+1,j,k) - H_z^{n+1/2}(i,j,k)}{\Delta x}\right]$$

$$E_z^{n+1}(i,j,k) = E_z^n(i,j,k) +$$
$$\frac{\Delta t}{\varepsilon}\left[\frac{H_y^{n+1/2}(i+1,j,k) - H_y^{n+1/2}(i,j,k)}{\Delta x} - \frac{H_x^{n+1/2}(i,j+1,k) - H_x^{n+1/2}(i,j,k)}{\Delta y}\right]$$

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

$$H_y^{n+1/2}(i,j,k) = H_y^{n-1/2}(i,j,k) -$$

$$\frac{\Delta t}{\mu}\left[\frac{E_x^n(i,j,k)-E_x^n(i,j,k-1)}{\Delta z}-\frac{E_z^n(i,j,k)-E_z^n(i-1,j,k)}{\Delta x}\right]$$

$$H_z^{n+1/2}(i,j,k)=H_z^{n-1/2}(i,j,k)-$$

$$\frac{\Delta t}{\mu}\left[\frac{E_y^n(i,j,k)-E_y^n(i-1,j,k)}{\Delta x}-\frac{E_x^n(i,j,k)-E_x^n(i,j-1,k)}{\Delta y}\right] \qquad (1.5)$$

The numerical algorithm for Maxwell's curl equations as defined by above equations requires that the time increment Δt have a specific bound relative to the spatial discretization Δx, Δy and Δz [25]. For a linear, isotropic, non-dispersive and homogeneous dielectric with permittivity (ε)and permeability(μ) the time increment has to obey the following bound, known as Courant-Freidrichs-Lewy (CFL) Stability Criterion and is expressed as

$$\Delta t \le \frac{1}{c\sqrt{\frac{1}{\Delta x^2}+\frac{1}{\Delta y^2}+\frac{1}{\Delta z^2}}} \qquad (1.6)$$

The structure and surrounding space are decomposed in parallelepipeds called elementary cells. The six components of the electromagnetic field are determined in each cell as shown in figure 1.6.

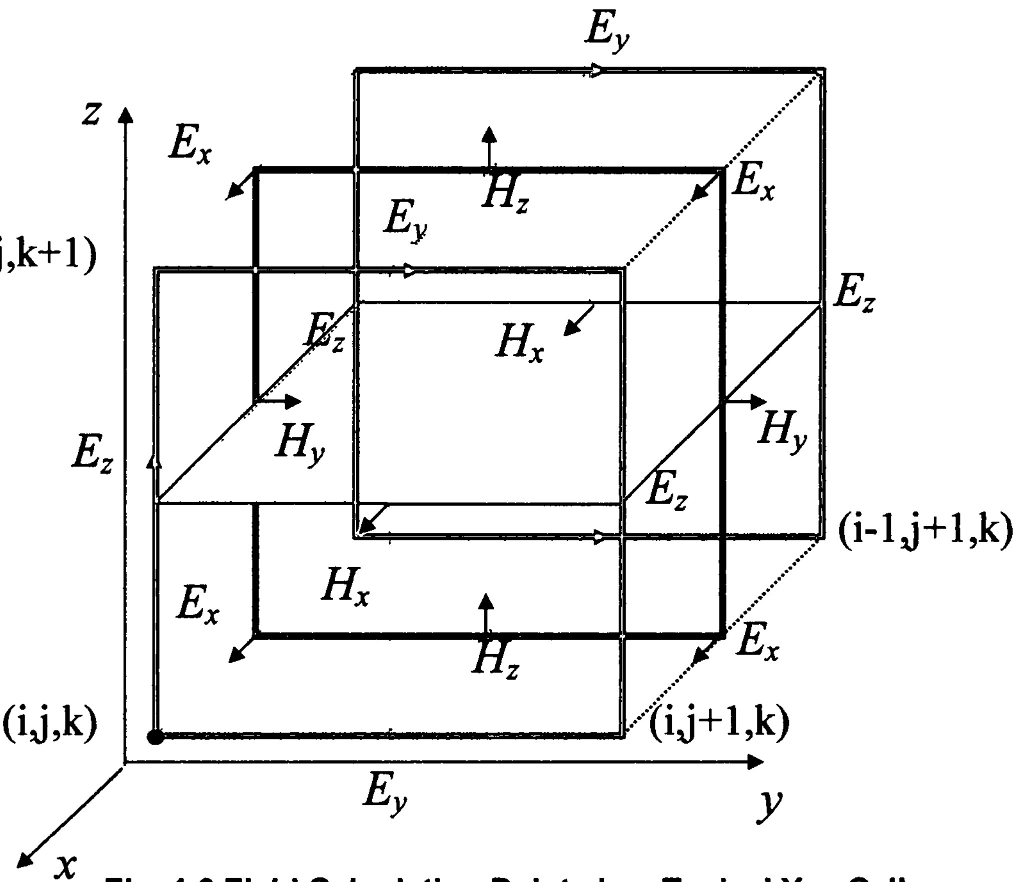

Fig. 1.6 Field Calculation Points in a Typical Yee Cell

Due to finite capability of the computer used to implement the finite-difference equations, the mesh must be limited in the x, y and z directions. The difference equations cannot be used to evaluate the field components tangential to the outer boundaries since they would require the values of the field components outside of the mesh. One of the six mesh boundaries is a ground plane and its tangential fields are forced to be zero. Tangential electric field components on the other five walls must be specified in such a way that outgoing fields are not reflected using the absorbing boundary condition[58-62]. For the structures considered in this work, the pulses on the microstrip lines will be normally incident to the mesh walls. Mur first order boundary condition[56] is applied at the boundary walls.

A raised cosine pulse is used at the feed point. At the feed gap the source is associated with an internal resistance[63] as shown in figure 1.7.

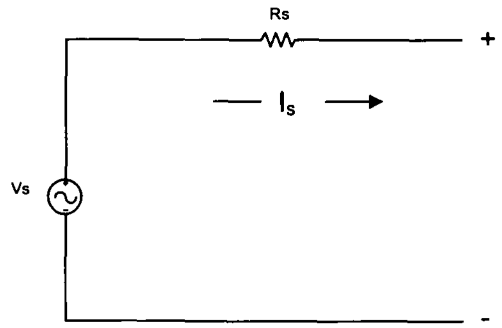

Fig. 1.7 FDTD Source with Source Resistance R_s

The current through the source is then given by

$$I_s^{n-1/2} = (H_x^{n-1/2}(i_s, j_s - 1, k_s) - H_x^{n-1/2}(i_s, j_s, k_s))\Delta x$$

$$(H_y^{n-1/2}(i_s, j_s, k_s) - H_y^{n-1/2}(i_s - 1, j_s, k_s))\Delta y \qquad (1.7)$$

The field at the source is given by

$$E_s^n(i_s, j_s, k_s) = V_s(n\Delta t) / \Delta Z + I_s^{n-1/2} R_s / \Delta z \qquad (1.8)$$

The current at the feed point is calculated by integrating the magnetic field around the feed location. Which is given by

$$I = \int H.dl \qquad (1.9)$$

and voltage at the feed location is given by

$$V = -\int E.dl \qquad (1.10)$$

Finally the current and voltage are transformed to the Fourier domain.

The input impedance of the antennas is obtained from

$$Z_{in} = \frac{V(f)}{I(f)} - R_s \qquad (1.11)$$

The implementation of FDTD algorithm is as shown in figure 1.8.

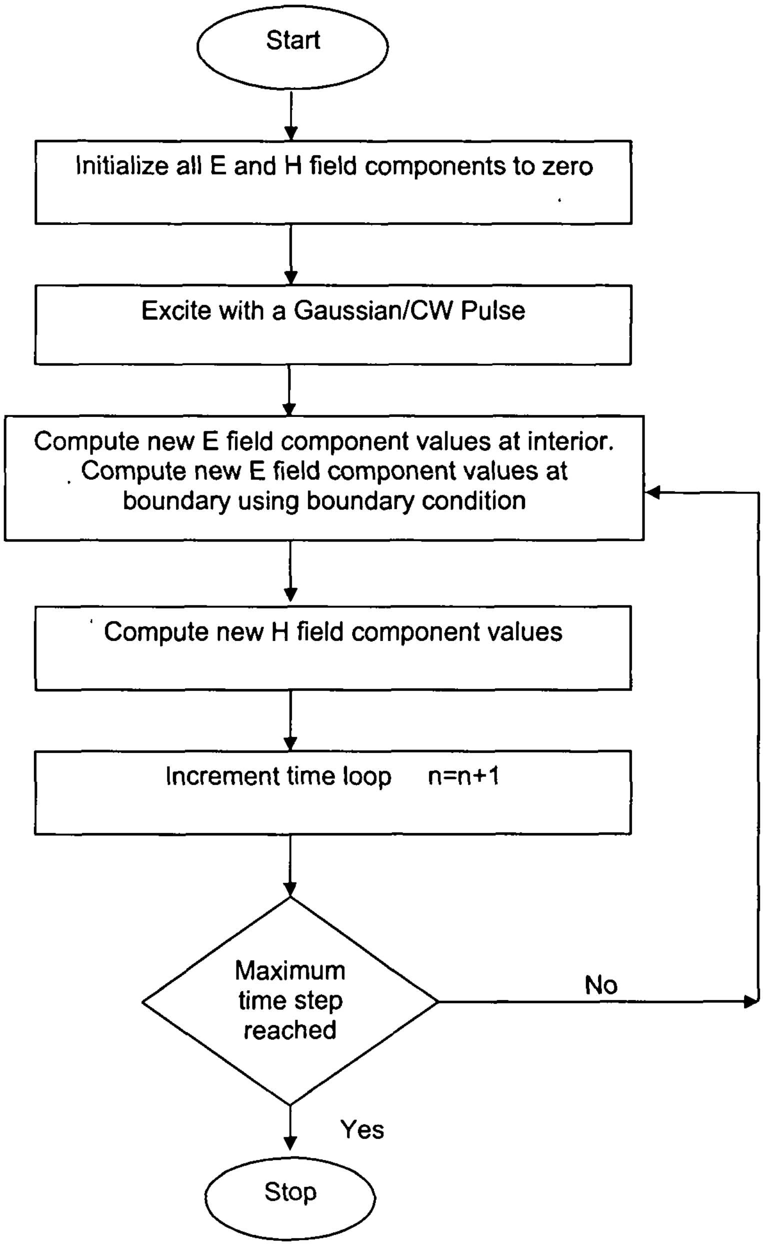

Fig. 1.8 Basic FDTD Algorithm

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CHAPTER 2

BRIEF OF GENETIC ALGORITHM AND ARTIFICIAL NEURAL NETWORKS

2.1 Introduction

Optimization is the minimization or maximization of a function. Ie adjusting the variables of the function such that the function gives its minimum or maximum result[1]. Root finding is search for zeros of a function whereas, an optimization is search for zeros of the derivative of the function. Finding derivative is not always easy. This becomes more difficult when the function is highly nonlinear and discontinuous. There we need use of optimization techniques like Genetic Algorithm. Genetic Algorithm is based on natural selection procedure, ie survival of the fittest or Darwinian principle. This is under the class of Evolutionary Computing. In recent times, a large number of biologically motivated algorithms have been invented and have been applied for different complex problems. These are known as Bio-inspired Soft-computing. Some of these techniques are Particle Swarm Optimization(PSO)[2,3], Ant Colony Optimization(ACO)[4,5], Bacterial Foraging Optimization(BFO)[6], Bio-geography Based Optimization (BBO)[7] and Artificial Neural Networks(ANN)[8] etc.

2.2 Simple Genetic Algorithm

A Genetic Algorithm is a global search technique based on Darwinian principle, i.e., survival of the fittest[1,9-12]. It performs following six basic tasks:-

a) *Encode the solution parameters as genes,*

Example: We adopt the test function $f(x,y)=x^2+y^2$ to illustrate the encoding operation. The test function would be maximized. Suppose the range of *x* is [5-8] and that of *y* is [2-4]. Let us first consider the first variable *x*. If the precession requirement is up to two decimal points, we have (4-2)x10^2 values within the range. To represent any value within this range, we require nine binary bits. The mapping is such that nine zeros represent the lower bound and nine ones represent the upper bound of the variable. Suppose, the randomly generates string of binary bits is [0 1 0 0 1 1 0 1 1]. Its decimal equivalent is 155 which represents 2.6067 after mapping to its real value.

b) *Create a string of genes to form a chromosome,*

Considering the same example, we can create a string of binary bits for the second variable in same manner. Suppose, the string of binary bits is [1 0 0 0 1 0 1 0 1]. A chromosome is formed by concatenating strings of all variables. Therefore, the first individual or a chromosome becomes [0 1 0 0 1 1 0 1 1 1 0 0 0 1 0 1 0 1] where, the length of chromosome is eighteen.

c) *Initialize a starting population,*

If the population size is set to *popsize,* we can get a population of solution by repeating previous steps *popsize* times.

d) Evaluate and assign fitness values to individuals in the population,

The fitness value is calculated by putting the real values of the variables in the cost function for all the individuals or chromosomes in the population. For a population of five individuals [p_1, p_2, p_3, p_4, p_5] the fitness value for above example is as given below

	Chromosomes		Real Values		Fitness Value
			x	y	$f(x,y)$
Population	[010011011	100010101]	2.6067	6.6262	50.7015
	[011000001	110111000]	2.7554	7.5832	65.0966
	[001001101	101100101]	2.3014	7.0959	55.6480
	[001100011	101011101]	2.3875	7.0489	55.3874
	[110110101	100101111]	3.7104	6.7789	59.7199

e) Perform reproduction through the fitness-weighted selection of individuals from the population,

In this step, the individuals of the population are first rearranged according to their fitness value in ascending order. Then the fitness values are ranked between zero to one by calculating the cumulative factor so that, the individual having highest fitness value is assigned to one. After ranking, the individuals are selected by one of the procedures such as population decimation, tournament selection and proportionate selection. The detail of those selection procedures are narrated in the subsequent sections. The ranking of fitness value of the population in above example is given as:

Individuals having increasing fitness value	**Cumulative Factor** (f_i)	**Ranked Fitness Value** ($\frac{f_i}{\sum f_i}$)
p_1=50.7015	50.7015	0.1933
p_4=55.3874	106.0888	0.3702
p_3=55.6480	161.7368	0.5644
p_5=59.7199	226.8334	0.7916
p_2=65.0966	286.5533	1.0000

f) *Perform crossover and mutation to produce members of new generation.* The details crossover and mutation are described in subsequent sections.

The flow-chart is as shown in figure. 2.1.

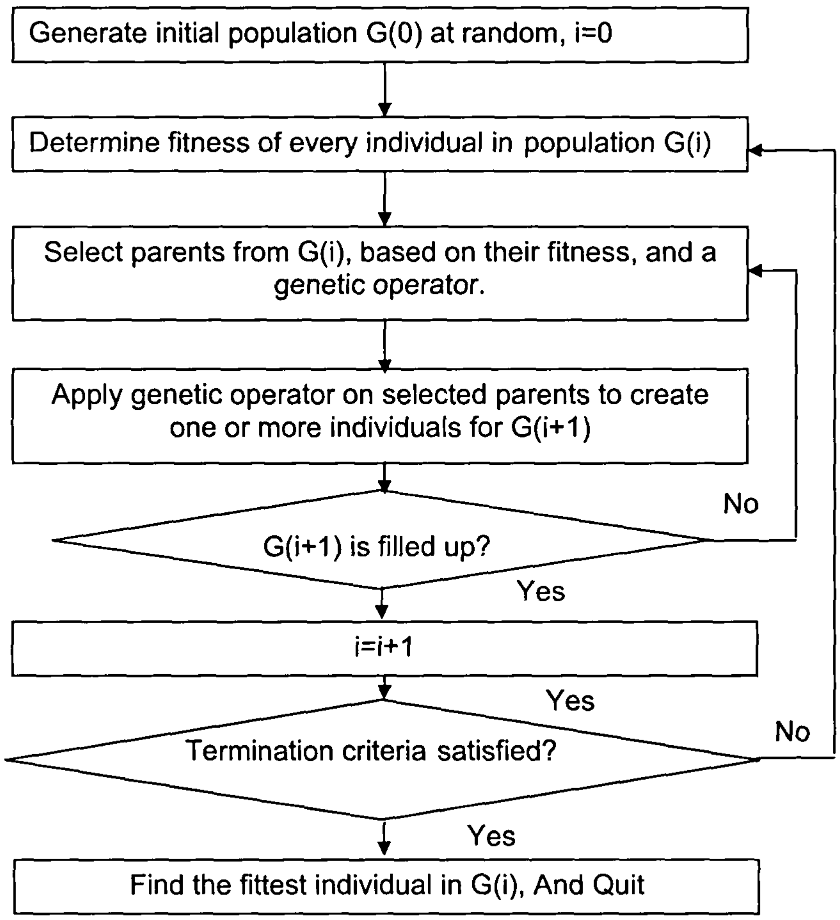

Fig. 2.1 Flow Chart of Genetic Algorithm

The pseudo code of a genetic algorithm program is depicted as below.

```
Simple Genetic Algorithm ()
{
        Initialize the Population;
        Calculate Fitness function;
        While (Fitness Value != Optimal Value)
        {
                Selection;
                Crossover;
                Mutation;
                Calculate fitness Function;
        }
}
```

2.2.1 Chromosomes and Parameter Coding

Genetic algorithm is a function optimizer. It gives the solutions of the derivative of the function. One important feature of GA is that it operates on encoded parameter instead of the parameters itself. The parameters are represented or encoded as genes. They can be binary or real value representation. Typically, a binary coding is used. The bits, 0's and 1's are called as genes. By concatenating genes of all the parameters, forms a chromosome. GA doesn't search single solution point at a time; rather it searches a population of solution.

2.2.2 Selection Procedure

A number of selection strategies have been developed and have been utilized for genetic algorithm optimization[9-14]. These strategies are generally classified as either stochastic or deterministic. Usually, selection results in the choice of parents for participation in the reproduction system. Some widely used selection strategies are discussed below.

i.*Population Decimation[10]:*

The simplest of the deterministic strategies is population decimation in which, individuals are ranked from largest to smallest, according to their fitness values. An arbitrary minimum fitness is chosen as a cut off point, and any individual with a lower fitness than the minimum is removed from the population. The remaining individuals are then used to generate the new generation through random pairing. The pairing and application of GA operators are repeated until the new generation is filled.

The advantage of population-decimation selection lies in its simplicity. Its disadvantage is that once an individual has been removed from the population, any unique characteristic of the population possessed by that individual is lost.

ii.Proportionate Selection:

The most popular of the stochastic-selection strategies is proportionate selection, sometimes called roulette-selection. In proportionate selection, individuals are selected based on their probability of selection given by

$$P_i = \frac{f_i}{\sum f_i} \tag{2.1}$$

where f_i is the fitness of the i^{th} parent. And, $\sum f_i$ is the sum of the population's fitness.

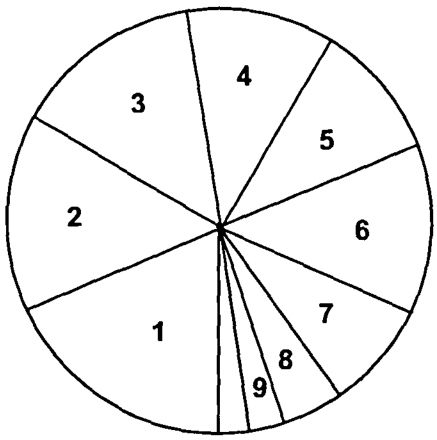

Fig. 2.2 Rowlette Wheel Selection

The probability of selecting an individual from a population is purely a function of the relative fitness of the individual. Individuals with high fitness will participate in the creation of the next generation more often than less-fit individuals. The distinction between population decimation and proportionate selection is that in proportionate selection, there is still a finite probability that highly unfit individuals will participate in at least some of the matings, thereby preserving their genetic information.

iii. Tournament Selection[10]:

A second popular strategy is tournament selection. In this selection, a sub-population of N individuals is chosen at random from the population. The individuals of this sub-population compete on the basis of their fitness. The individual in the sub-population with the highest fitness wins the tournament, and becomes the selected individual. All of the sub-population members are then placed back into the general population, and the process is repeated until the new population is full. The most commonly used form of tournament selection is binary tournament selection, in which N equals two.

Both tournament selection and proportionate selection use selection with replacement, so that individuals may, and usually do, participate in multiple pairings. Tournament selection also has a some what faster execution time. The time complexity of proportionate selection is $O(n^2)$, while tournament selection has $O(n)$ time complexity.

2.2.3 GA Operators

Once a pair of individuals has been selected as parents, a pair of children is created by recombining and mutating the chromosomes of the parents, utilizing the basic genetic-algorithm operators, cross over and mutation. Crossover and mutation are applied with probability p_{cross} and $p_{mutation}$, respectively.

2.2.3.1 Crossover

The crossover is applied to selected mating pool with a hope that they will produce better offspring[13]. It accepts two parents and generates two children having mixed genetic information of two parents. Many variations of crossover have been developed. Different types of crossovers are a) One-point crossover, b) Two-point crossover, c) N-point crossover and d) Uniform crossover[14]. The simplest of these is single-point crossover.

One-point crossover: In single-point crossover, if $p>p_{cross}$, a random location in the parent's chromosomes is selected. The portion of the chromosome preceding the selected point is copied from parent A to child A, and from parent B to child B. The portion of the chromosome of parent A following the randomly selected point is placed in the corresponding positions in child B and vice versa for the remaining portion of parent B's chromosome. If $p<p_{cross}$, the entire chromosome of parent A is copied into child A, and similarly for parent B and child B. Typically, it has been found that probability p_{cross} values of 0.6-0.8 are optimal.

Example:

Parent A 1 1 0 | **1 0** offspring A 1 1 0 | **0 1**

Parent B 1 0 0 | **0 1** offspring B 1 0 0 | **1 0**

***Two-point crossover*:** In Two-point crossover, two points are selected randomly and the bits within the points are exchanged as shown below:-

Parent A 1 1 0 | **1 0** | 1 0 offspring A 1 1 0 | **0 1** | 1 0

Parent B 1 0 0 | **0 1** | 0 0 offspring B 1 0 0 | **1 0** | 0 0

N-point crossover: It uses the same technique having N-crossover points. Here the offspring are created by swapping parts of the chromosomes between every other crossover point.

***Uniform crossover*:** Here, for each bit, it is randomly decided, if it is copied from parent one or two

2.2.3.2 Mutation

The mutation operator is applied to maintain genetic diversity. In mutation, if $p>p_{mutation}$, an element in the string making up the chromosome is randomly selected and changed. In case of binary coding, this amounts to selecting a bit from the chromosome string and inverting it. In other words, a "1" becomes a "0" and a "0" becomes a "1". If higher-order alphabets are used, slightly more complicated mutations are required.

Generally, it has been seen that mutation occurs with a low probability, usually on the order of $p_{mutation}$ =0.01-0.1.The action of mutation is as shown below.

Offspring: 1 1 0 **0** 0 1

Mutate 4th gene (bit flip)

Mutated offspring: 1 1 0 **1** 0 1

2.2.3.3 Fitness Function

The fitness function, or object function, is used to assign a fitness value to each of the individuals in the GA population. The fitness function is the only connection between the physical problem being optimized and genetic algorithm.

2.3 Continuous Genetic Algorithm

A Continuous Genetic Algorithm[1,11-15] also, termed as real coded Genetic Algorithm uses the real value of the parameters instead of binary codes. It employs a reproduction strategy based on roulette wheel selection. However, this strategy may lose genetic diversity of population in an early stage [16], because it can not generate new chromosomes which are different from present chromosomes. A number of new crossover strategies have been suggested[17].

The simplest one-point crossover for parents P_A and P_B is carried out by combining the parameter values from the two parents which are selected for swapping, into the new parameter values in the offspring.

$$\begin{aligned} P_A &= [p_{1a}, p_{2a}, p_{3a} \cdots p_{na}] \\ P_B &= [p_{1b}, p_{2b}, p_{3b} \cdots p_{nb}] \\ p_{newa} &= \beta p_{1a} + (1-\beta) p_{1b} \\ p_{newb} &= \beta p_{1b} + (1-\beta) p_{1a} \end{aligned} \tag{2.2}$$

Where, p_{newa}=First new offspring,

p_{newb}=Second new offspring and,

β=Random number between 0 and 1.

2.4 Basic Concept of Artificial Neural Networks

Artificial Neural Network is a mathematical model of human brain[8,13,18,19]. As our brain learns from experience, an ANN also learns form experience and applies its knowledge at new and unknown environment. To understand the basic function of ANN, it is necessary to have a look at human brain.

A human brain consists of approximately 10^{11} computing elements known as neurons. A neuron consists of a *Cell body* to sum and threshold those incoming signals, *dendrite*: to carry electrical signals into cell body and an *Axon* to carry the signal from the cell body out to other neurons[20]. Signals are communicated from one neuron to another by *Synapse* which connects an axon of one cell and a dendrite of another cell. The schematic diagram of a biological neuron is as shown in figure 2.3.

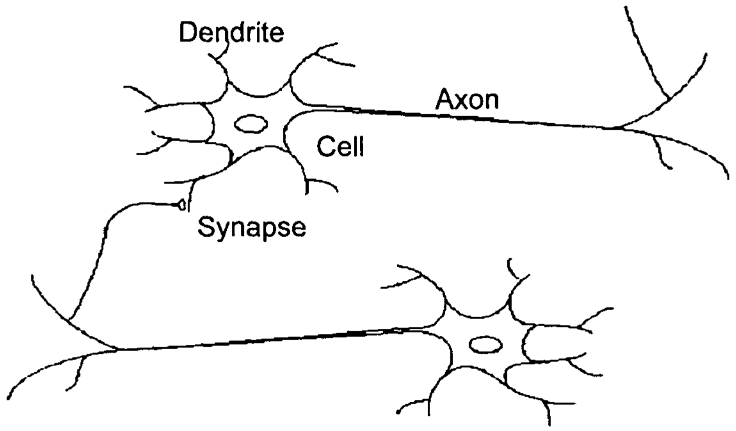

Fig. 2.3 Biological Neuron Artificial Neuron

A neuron is an information-processing unit that is fundamental to the operation of a neural network. The block-diagram of an artificial neural network is shown in figure 2.4. The basic elements of ANN are:

Input: Analogous to signal on the dendrites,

Weight: Analogous to strength of a synapse,

Summation and transfer function or activation function: Analogous to cell body,

Output: Analogous to signal on the axon.

Biological Neural Network	**Artificial Neural Network**
Cell body	Neurons
Dendrite	Weights or interconnections
Soma	Net input
Axon	Output

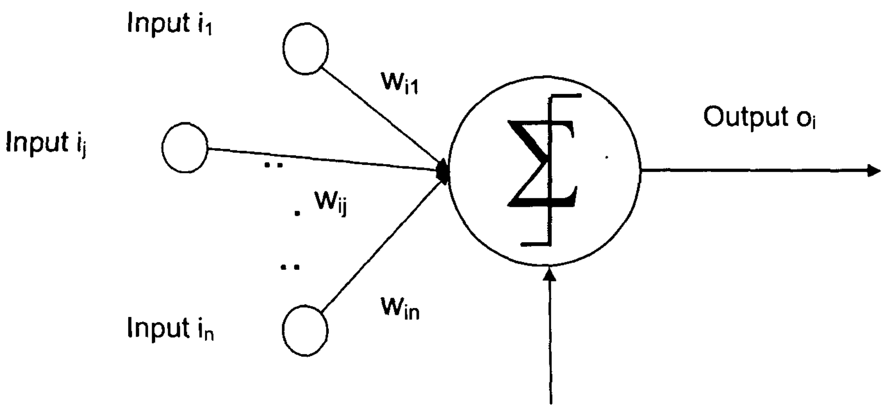

Fig. 2.4 Block-Diagram of an Artificial Neural Network

The neuron model also includes an externally applied bias. The function of the neuron (k) can be described mathematically as follows,

$$v_k = \sum_{j=0}^{m} w_{kj} x_j,$$
$$y_k = \varphi(v_k + b_k). \tag{2.3}$$

Where $x_1, x_2, \ldots, x_m$ are the input signals; $w_{k1}, w_{k2}, \ldots, w_{km}$ are the synaptic weights of the neuron k; u_k is the linear combiner output due to the input signals; b_k is the bias; $\varphi(v)$ is the activation function; and y_k is the output signal of the neuron. A common activation function is the sigmoid function as shown in figure 2.5. And mathematically given by,

$$\varphi(x_j, \lambda) = \frac{1}{1 + e^{-\lambda x_j}} \tag{2.4}$$

Where, λ is the steepness of activation function.

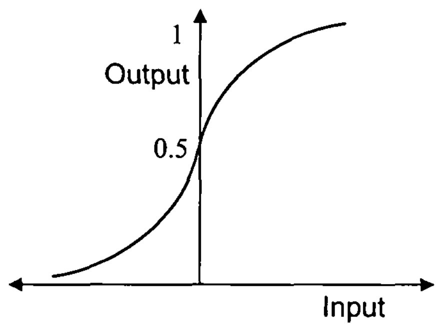

Fig. 2.5 Sigmoid Activation Function

Typical example of a multi-layered neural network is shown in figure 2.6. A three layer neural network, in principle, is sufficient to model a problem[20]. In the example, every neuron in a layer is connected to every neuron in the next layer. Also, every neuron is connected only to successive layers, but not to preceding ones. This network is therefore called a *feed forward network.*

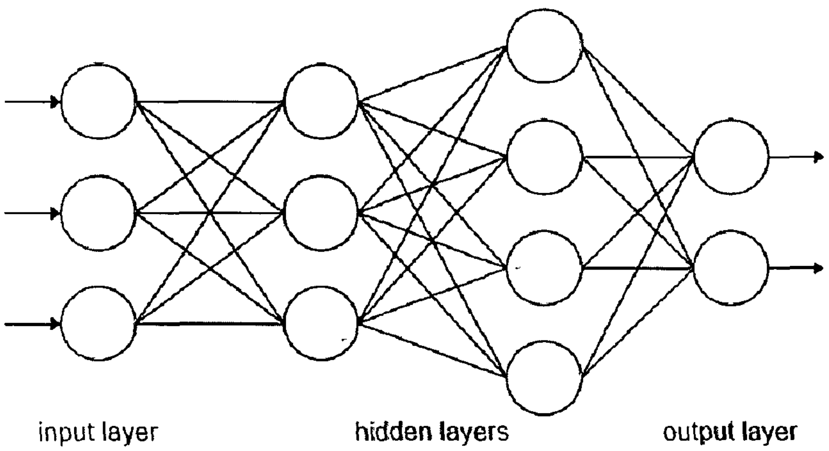

Fig. 2.6 Multi-Layered Neural Network

2.4.1 Learning Rules

Learning means simply to get information and remember from experience. In case of an Artificial Neural Network, learning is to adjust the weights to satisfy a function which is the input-output relation. If w_i be the weight vector and, $w_{i,j}$ is the component connecting the j'th input with the i'th neuron, according the general learning rule, the weight vector w_i increases in proportion to the product of input x and learning signal r. The learning signal r is a function of w_i, x and the teacher's signal d_i in case of supervised learning. Mathematically it can be written as,

$$r = r(w_i, x_i, d_i). \qquad (2.5)$$

Therefore, the increment of the weight vector w_i produced by the learning step at time *t* according to the general learning rule is

$$\nabla w_i(t) = cr[w_i(t), x_i(t), d_i(t)]x(t).$$

Where *c* is a positive number called the learning constant that determines the learning rate. The weight vector adopted at time *t* becomes

$$w_i(t+1) = w_i(t) + cr[w_i(t), x_i(t), d_i(t)]x(t) \qquad (2.6)$$

at the next instant or, learning step.

Based on the learning signals, there are different types of learning rules[8,20] such as *Hebbian learning rule, Perceptron learning rule, Delta learning rule, Widrow-Hoff learning rule, Correlation learning rule and Winner-Take-All learning rule etc.*

2.4.2 Delta-Learning Rule [21,22]

The learning rule is only valid for continuous activation function and, in the supervised training mode. This minimizes the squared error. The learning signal of this delta-learning rule is termed as delta which is defined as:

$$r \stackrel{\Delta}{=} [di - f(w^t{}_i x)] f'(w^t{}_i x). \tag{2.7}$$

The term $f'(w^t{}_i x)$ is the derivative of the activation function $f(net)$ computed for $net = w^t{}_i x$.

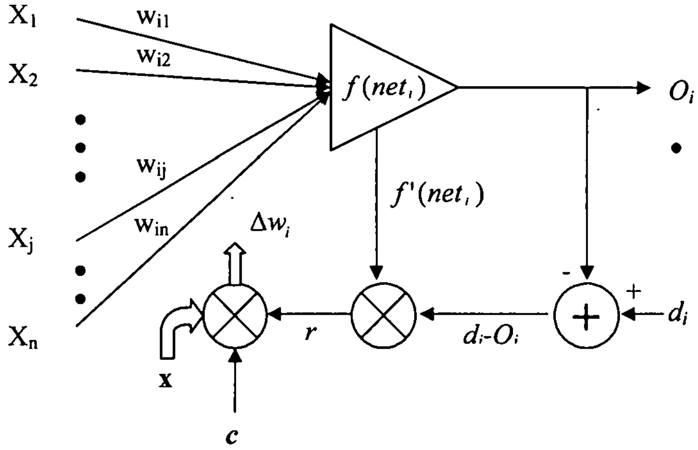

Fig. 2.7 Delta Learning Rule

In this method, the squared error is first calculated as

$$E \stackrel{\Delta}{=} \frac{1}{2}(d_i - o_i)^2 = \frac{1}{2}[d_i - f(w^t{}_i x)]^2. \tag{2.8}$$

Therefore, the gradient of the error field is,

$$\nabla E = -(d_i - o_i) f'(w^t{}_i x) x \tag{2.9}$$

And the components of gradient vector are

$$\frac{\partial E}{\partial w_{ij}} = -(d_i - o_i) f'(w^t_i x) x_j, \text{ for } j = 1,2, \dots, n. \qquad (2.10)$$

Since the minimization of the error requires the weight changes to be in the negative gradient direction, the weight correction factor is given by,

$$\Delta w_{ij} = -\eta \nabla E = (d_i - o_i) f'(net_i) x_j. \qquad (2.11)$$

Where, η is a positive learning constant.

2.5 Back-Propagation Algorithm[21-23]

Normal feed forward back-propagation algorithm is the most popular, efficient and most widely used algorithm in Artificial Neural networks because of its ease in developing the code.

It is a supervised training method having at least two layers: the hidden layer and the output layer. Let's consider the network shown in figure. 2.8.

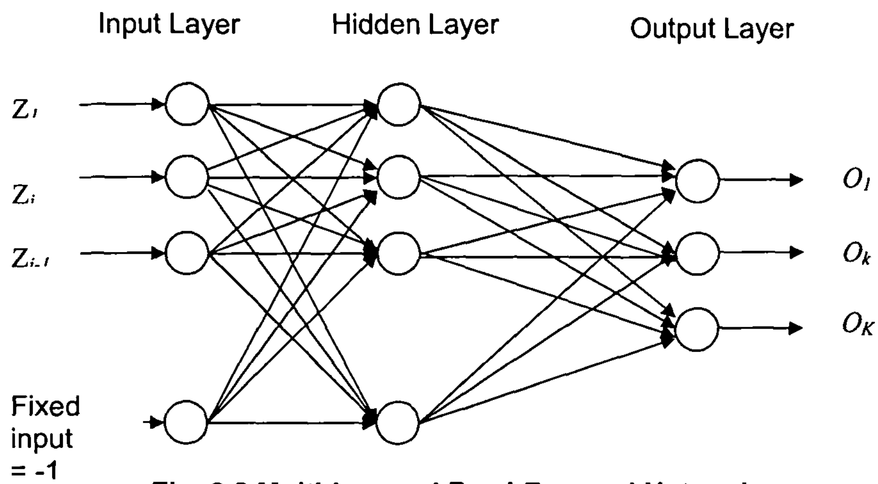

Fig. 2.8 Multi-Layered Feed-Forward Network

Here Z_l is the input vector; y_j is the output of hidden neurons and O_K is the output vector. The connecting weight vectors of hidden layer and output layer are v_{jl} and w_{kj} respectively. The fixed bias input is -1. Now the back-propagation algorithm involves five basic tasks as follows:

- Initialize the weights to small random numbers
- Randomly select a training pattern pair (xp, tp) and present the input pattern xp to the network; compute the corresponding network output zp
- Compute the error Ep = zp - tp for pattern (xp, tp)
- Back propagate the errors according to the BP weight adjustment formulas
- Test the mean square error (MSE); if the MSE is below the required threshold, stop; otherwise, repeat step 2-5.

1. *Weight initialization*

Set all weights & node thresholds to small random numbers

(repeat step 2,3 until error criterion is met)

2.. *Calculation of output levels*

Output level *oj* of a hidden neuron is

$$O_j = (\sum W_{ji} O_i - \theta_j) = \frac{1}{1 + e^{-\alpha(\sum W_{ji} O_i - \theta_j)}} \qquad (2.12)$$

Where, W_{ij}= Weight of input *i* to neuron *j*.

3. *Weight training*

i. *Error gradient* is computed as

For the output neurons

$\delta_j = o_j\,(1 - o_j)(d_j - o_j)$ (2.13)

d_j : desired output, o_j : actual output for the hidden neurons

$\delta_j = o_j\,(1 - o_j) \sum \delta_k w_{kj}$ (2.14)

δ_k : error gradient at neuron k to which a connection points from hidden neuron j

ii. *Weight adjustment* is computed as

$\Delta w_{ji} = \eta \delta_j\, o_i$ (2.15)

η : trial-independent learning rate (0< η <1)

iii. *Adjust weights* is computed as

$\Delta w_{ji}\,(t+1) = \Delta w_{ji}(t) + \Delta w_{ji}$ (2.16)

$\Delta w_{ji}(t)$: weight from i to j at iteration t.

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CHAPTER 3

DESIGN OF MICROSTRIP PATCH ANTENNA USING GENETIC ALGORITHM

3.1 Introduction

Microstrip antenna inherently has very low bandwidth. Hence it is very important to find accurate dimension and its feed position to efficiently operate such antenna. There are many empirical formulae[1-4] for different regular structure microstrip patch antenna for calculating the resonant frequency. However, resonant frequency being a non-linear function of parameters like the physical dimensions and material property of the antenna, it is quite difficult to adjust all these parameters simultaneously to design a microstrip patch antenna for a particular operating frequency. Therefore, optimization tool like GA. may lead an important role in such problems. GA performs its searching process through population to population instead of point-to-point search. The most favorite advantage of GA is its parallel architecture. They use probabilistic and deterministic rules[5-7].

In this chapter, GA has been efficiently used to design rectangular, circular and triangular microstrip patch antennae.

3.2 Design of Rectangular Microstrip Patch Antenna Using GA

The length (L), width (W), height (h) and the feed point location (a) for a rectangular microstrip antenna are shown in the figure 3.1.

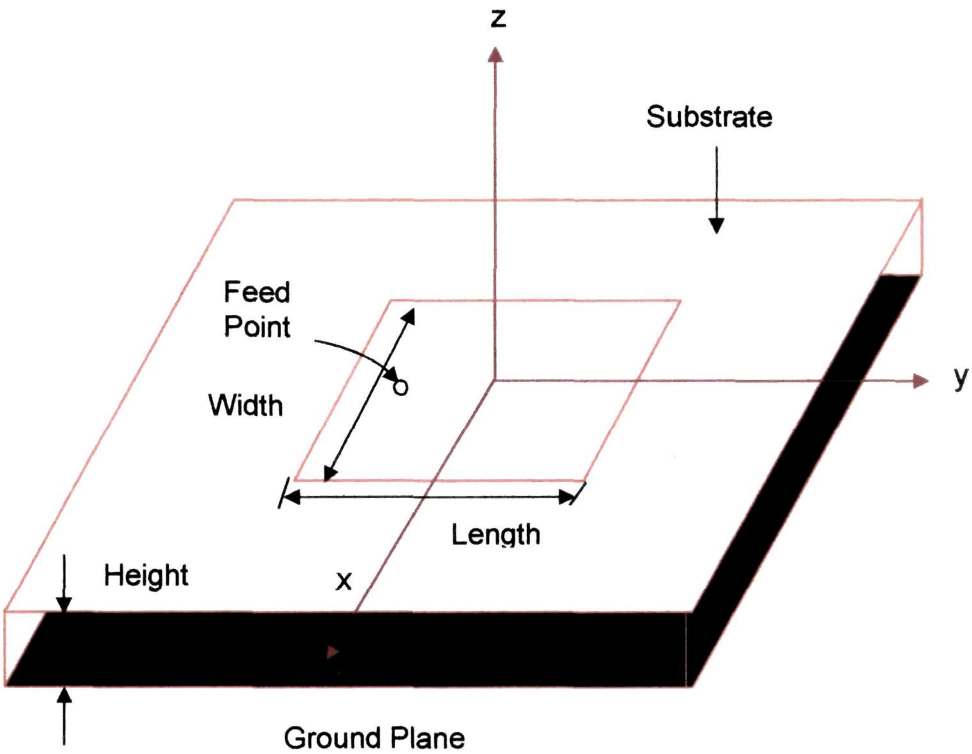

Fig. 3.1 Rectangular Patch Antenna

The resonant frequency of the rectangular microstrip antenna[8] is expressed as,

$$f_r = \frac{c_o}{2(L + \Delta W)\sqrt{\varepsilon_e(W)}}, \tag{3.1}$$

where, c_0 is the velocity of the electromagnetic waves in free space and $\varepsilon_e(W)$ is the effective dielectric constant, which is given by

$$\varepsilon_e(W) = \frac{\varepsilon_r + 1}{2} + \frac{\varepsilon_r - 1}{2\sqrt{1 + 10\, h / W}}, \tag{3.2}$$

ΔW is the line extension and is given by

$$\Delta W = 0.412\, h \frac{[\varepsilon_e(W) + 0.300](W / h + 0.264)}{[\varepsilon_e(W) - 0.258](W / h + 0.813)}, \tag{3.3}$$

Equation (3.1) is used as the fitness function of GA. The two independent variables are the length (L) and width (W). The population size is taken as 20 individuals and 200 generations are produced. The probability of crossover is set at 0.7, while the probability of mutation is equal to 0.01. Thus, it is suitable for the calculation of the resonant frequencies for antenna elements with h $\leq$ 0.0815λ_d. Resonant frequency (f_r), dielectric constant (ε_r) and thickness of the substrate (h) are given as inputs to GA, which gives the optimized values for the length and width of the antennae[9]. The optimized lengths (L) obtained using GA are in good agreement with the experimental results as listed in column 'VII' of Table 3.1. Using these calculated parameters, i.e. 'L', 'W', 'h' and 'ε_r' in IE3D simulation software, resonant frequencies are calculated which almost match with the input resonant frequencies considered, thus, validating the results of GA. The theoretical results obtained by GA and IE3D software are listed in table 3.1 for 7 different rectangular microstrip antennae.

Table 3.1 Resonant Frequency Results and Dimensions for Rectangular Microstrip Antennae

I	II	III	IV	V	VI	VII	VIII
Antenna No.	f_r In GHz (Expt.)	ε_r	h In mm	L In mm (GA)	W In mm (GA)	L_{expt} In mm [3]	f_{IE3D} In GHz
1	6.2	2.55	2.0	14.382	8.975	14.12	6.13
2	8.45	2.22	0.17	11.867	9.456	11.85	8.32
3	7.74	2.22	0.17	12.9	19.337	12.9	7.6
4	3.97	2.22	0.79	25.306	13.007	25	3.92
5	5.06	2.33	1.57	18.6	18.4	18.6	4.98
6	5.6	2.55	1.63	16.07	13.34	16.21	5.3
7	4.805	2.33	1.57	19.573	21.696	19.6	4.6

The return loss and VSWR plots calculated using IE3D simulation software for antenna number 1 (L=14.382 mm, W=8.975 mm, h=2 mm and ε_r=2.55)are shown in figure 3.2 and figure 3.3 respectively where as, figure 3.4 and figure 3.5 show that of antenna number 5 (L=18.6 mm, W=18.4 mm, h=1.57 mm and ε_r=2.33).

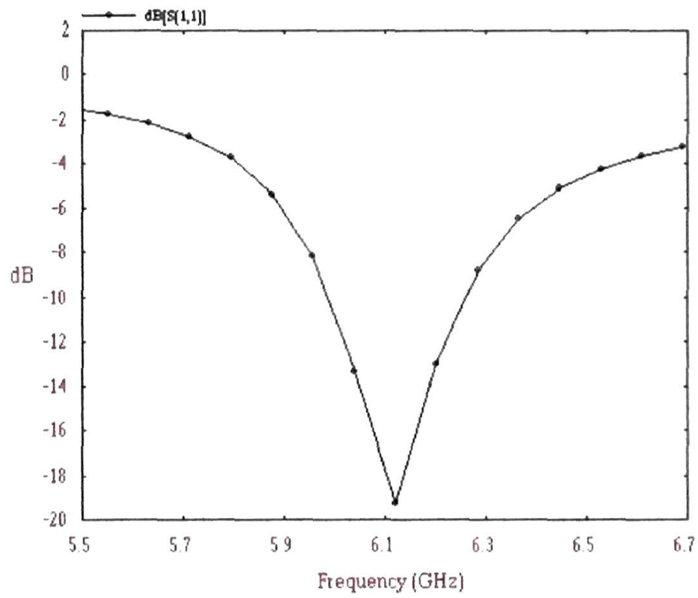

Figure 3.2 Return Loss Plot for Antenna No. 1

(L=14.382 mm, W=8.975 mm, h=2 mm and ε_r=2.55)

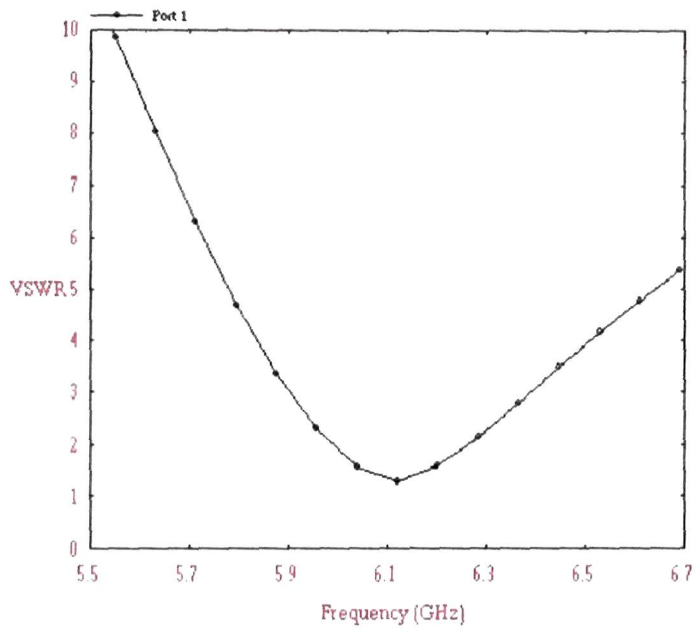

Fig. 3.3 VSWR Plot for Antenna No. 1

(L=14.382 mm, W=8.975 mm, h=2 mm and ε_r=2.55)

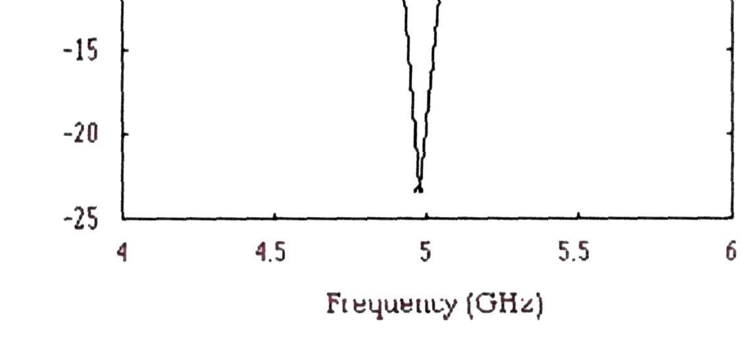

Fig. 3.4 Return Loss Plot for Antenna No. 5

(L=18.6 mm, W=18.4 mm, h=1.57 mm and ε_r=2.33)

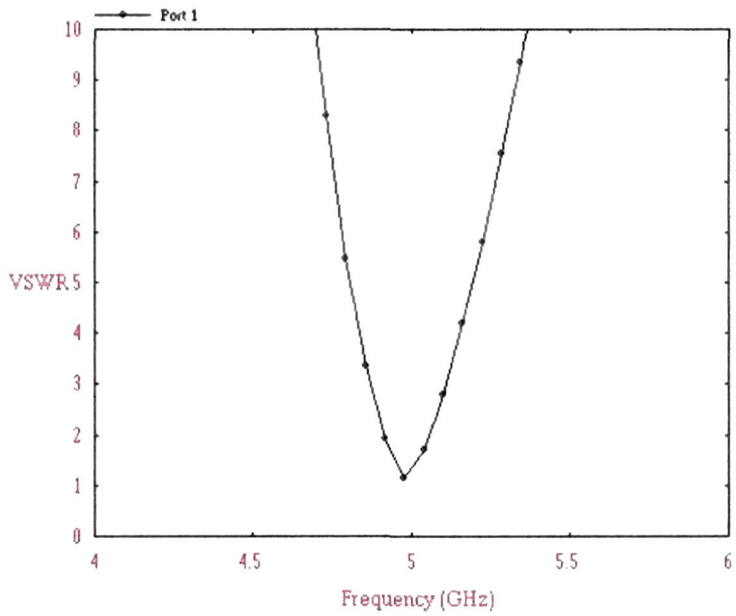

Fig. 3.5 VSWR Plot for Antenna No. 5

(L=18.6 mm, W=18.4 mm, h=1.57 mm and ε_r=2.33)

Simultaneous variation of length and width of a microstrip antenna to obtain optimized length and width for calculating the resonant frequency of a said antenna that matches with the experimental resonant frequency is a computationally tedious and time consuming process. As seen from the table, using GA this can be achieved without much computational time. The return loss plot and VSWR plot obtained using IE3D Simulation package for two antennae are also presented. These results have good agreement with that of experimental results. Thus, application of GA to calculate optimized length and width of microstrip antenna seems to be an accurate and simple method. This will go a long way in helping antenna designs especially for small pack antenna system where due to space limitation both length and width are to be adjusted simultaneously to achieve the required resonant frequency. This is a forced situation in the present scenario of miniaturization.

3.3 Design of Circular Microstrip Patch Antenna Using GA

Circular microstrip antenna, due to its simple design features is still popular in industrial and commercial applications[10-12]. However, due to inherent narrow bandwidth, the resonant frequency or the dimension of the patch antenna is to be predicted accurately.

Genetic Algorithm (GA) has been applied to calculate the optimized radius of Circular Microstrip Antennae. Resonant frequency (f) in the dominant TM_{11} mode, dielectric constant (ε_r) and thickness of the substrate (h) are taken as inputs to GA, which gives the optimized radii (a) of the antennae. Method of Moment (MOM) based IE3D software of the Zealand Inc., USA, and experimental results are used to validate the GA based code. It is seen that the GA results are more accurate while taking less computational time. The results are in good agreement with experimental findings[13].

The circular patch antenna with its design parameters i.e. thickness of substrate 'h' and radius of circular patch 'a', is shown in figure 3.6.

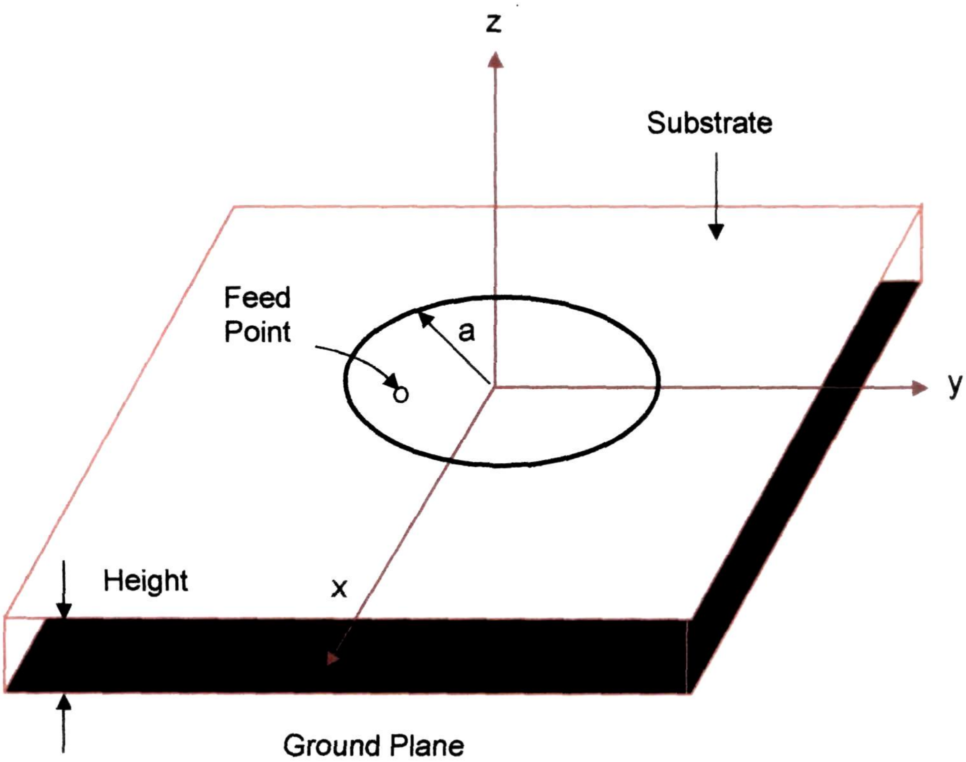

Fig. 3.6 Circular Patch Antenna

The resonant frequency of circular microstrip antenna[13] is expressed as

$$f_r = \frac{1.84118\ c_0}{2\pi a[\varepsilon_{eff}\{1+\frac{2h}{\pi\varepsilon_r a}(\ln(\frac{a}{2h})+(1.44\,\varepsilon_r+1.77)+\frac{h}{a}(0.268\,\varepsilon_r+1.65))\}]^{1/2}} \quad (3.4)$$

Where, the effective dielectric constant (ε_{eff}), is given by

$$\varepsilon_{eff} = \frac{\varepsilon_r+1}{2}+\frac{\varepsilon_r-1}{2}\left[1+\frac{12\,h}{a\sqrt{\pi}}\right]^{-1/2} \quad (3.5)$$

And c_0 is the velocity of light.

Equation (3.4) is used as the fitness function of GA to optimize radius of the patch of the antennae. The population size is taken 20 individuals, and 200 generations are produced. The probability of crossover is set at 0.25, while the probability of mutation was equal to 0.01. Resonant frequency (f_r), dielectric constant (ε_r) and thickness of the substrate (h) are given as inputs to GA, which gives the optimized radii (a) of the antennae. The comparisons of GA and results obtained by IE3D software are listed in table 3.2 for nine different fabricated circular microstrip antennae. The optimized radii (a) obtained using GA are in good agreement with the experimental results as listed in column 'VII' of table 3.2.

Using these calculated radius (a) in IE3D simulation software, resonant frequencies are calculated which almost match with the input resonant frequencies used as input, thus, validating the results of GA. The percentage of error for calculation of radius using GA, are listed in column VI. Average error obtained using GA is only 0.65 for seven antennas.

Table 3.2 Comparison of Results

I	II	III	IV	V	VI	VII
Antenna No.	f_r In GHz	ε_r	h In mm	a In mm By GA	*Error* In %	f_{IE3D} In GHz
1	4.945	4.55	2.35	7.6742	0.306234	4.94
2	3.75	4.55	2.35	10.3837	0.156731	3.735
3	2.003	4.55	2.35	20.0659	0.3295	2.02
4	1.03	4.55	2.35	39.5602	0.477484	1.05
5	0.825	4.55	2.35	49.502	0.0040404	0.82
6	1.51	2.33	3.175	35.2043	0.785285	1.53
7	4.07	2.33	0.794	13.0196	2.51654	4.12

[+] Measured by Abboud *et al* [14], reminder measured by Howell [15].

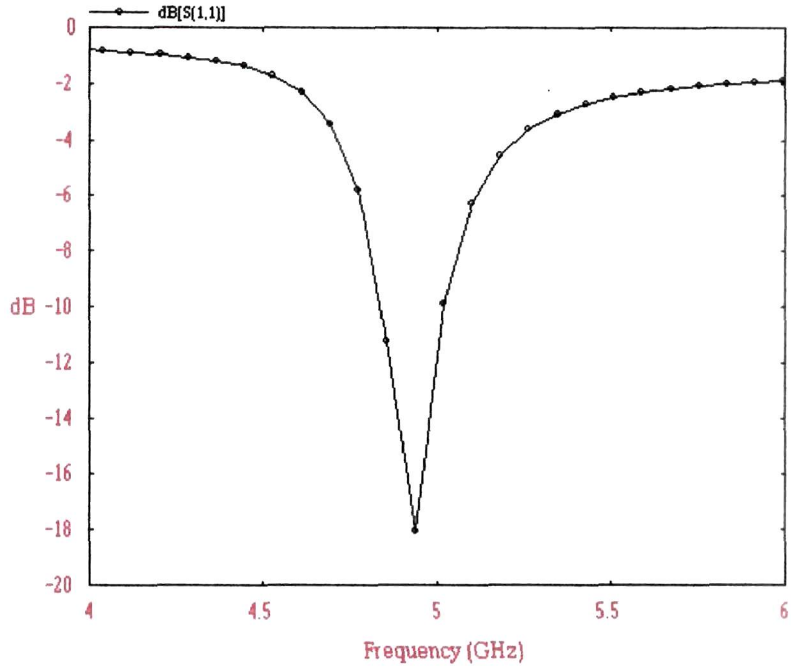

Fig. 3.7 Return Loss Plot for Antenna No. 1

(a=7.6742 mm, h=2.35 mm and ε_r= 4.55)

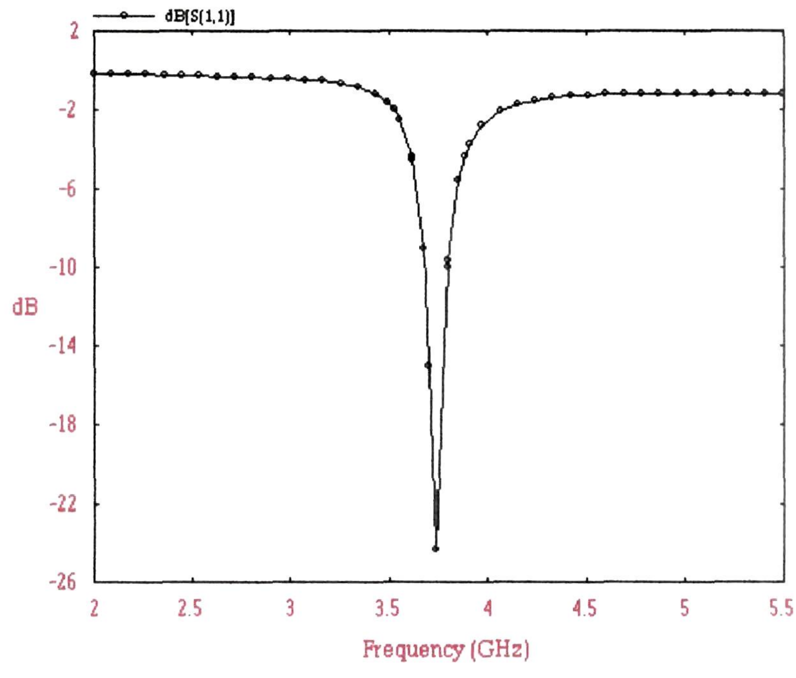

Fig. 3.8 Return Loss Plot for Antenna No. 2

(a=10.3837 mm, h=2.35 mm and ε_r= 4.55)

The return loss plots calculated using IE3D simulation software for antenna number 1 (a=7.6742 mm, h=2.35 mm and ε_r = 4.55) and antenna number 2 (a=10.3837 mm, h=2.35 mm and ε_r = 4.55) are shown in figure 3.7 and figure 3.8 respectively.

Seven antennae are optimized to validate the developed code using GA. IE3D software and experimental results are used to compare and hence, to validate the obtained results by GA. Design parameter obtained using GA are used to simulate the antenna using IE3D. Return loss plots are presented for simulated antennas. As seen, the results obtained using GA are more close to experimental results. Thus, a highly selected fitness function in GA gives much accurate result. Application of GA to microstrip antenna design seems to be an accurate, computationally simple and cost effective method, which may go a long way in antenna design.

3.4 Design of Triangular Microstrip Patch Antenna Using GA

Triangular microstrip antenna, due to its simple design features and patch area has gained much interest for investigation by researchers since last few decades[16-23]. Most importantly they are advantageous in arranging in such a way to reduce the coupling as well as the spacing between two adjacent elements when used as elements of a periodic array. Since they have very narrow bandwidth the resonant frequency or design parameter has to be predicted accurately.

Genetic Algorithm (GA) has been applied to calculate the optimized side length of Triangular Microstrip Antennae. The inputs to the problem are the desired resonant frequency, dielectric constant and thickness of the substrate. And output is the optimized side length. Method of Moment (MOM) based IE3D software of the Zealand Inc., USA, and experimental results are used to validate the GA based code. The basic formula developed in [24] is used to determine the resonant frequency of Triangular microstrip antenna.

The side length (*r*), height (h) and the feed point location (a) for a Triangular microstrip antenna are shown in the figure 3.9.

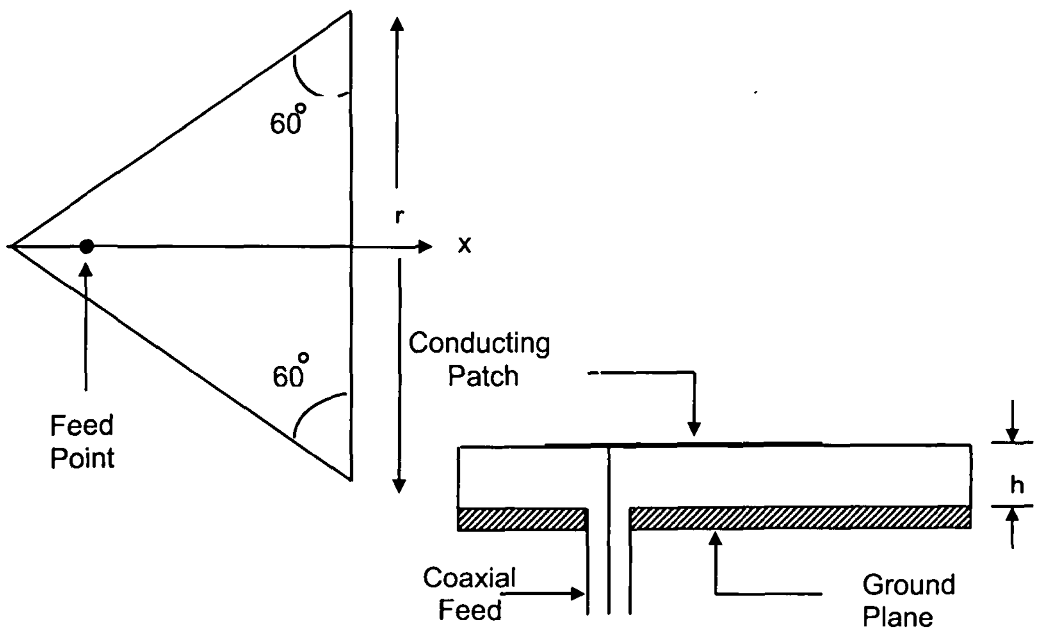

Fig. 3.9 Triangular Patch Antenna

The fitness function used in GA to optimize the Triangular patch antenna is the resonant frequency expression [24], given as

$$f_{n,m,l} = \frac{2c}{3r_{eff}\sqrt{\varepsilon_{reff}}}\left(n^2 + nm + m^2\right)^{1/2} \tag{3.6}$$

Where c is the velocity of the electromagnetic waves in free, and ε_{reff} is given by

$$r_{eff} = \frac{2\pi}{3} a\sqrt{(1+q)} \tag{3.7}$$

Equation (3.6) is used as the fitness function since it is more accurate as compared to earlier empirical formulae. The variable to be optimized is '*r*'. The population size is taken as 20 individuals, and 200 generations are produced. The probability of crossover is set at 0.25, while the probability of mutation is set equal to 0.01.

Resonant frequency (f_r), dielectric constant (ε_r) and thickness of the substrate (h) are given as inputs to GA, which gives the optimized side length of the antennae. The optimized side lengths (*r*) obtained using GA are in good agreement with the experimental results as listed in column 'VI' of the Table. Using these calculated parameters, i.e. '*r*', 'h' and 'ε_r' in IE3D smulation software, resonant frequencies are calculated which almost match with the input resonant frequencies considered, thus, validating the results of GA. The theoretical results obtained by GA and results obtained by IE3D software are listed in table 3.3 for 5 different Triangular Microstrip Antennas.

Table 3.3 Resonant Frequency Results and Dimensions for Triangular Microstrip Antennae

I	II	III	IV	V	VI
Antenna No.	f_r In GHz	ε_r	h In cm	R_{GA} In cm	R_{EXPT} In cm From[23]
1	4.1	10.5	0.07	4.086	4.1
2	8.7	2.32	0.078	8.876	8.7
3	10.0	2.32	0.159	10.158	10.0
4	6.65	4.3	0.159	6.73	6.65
5	4.33	2.33	0.159	4.648	4.33

The mathematical expressions available for determination of resonant frequency of Triangular Microstrip Antenna show that for higher accuracy the effective permittivity of the dielectric substrate must be considered. Hence, in such situation, it is difficult to calculate the side length of the Triangular microstrip antenna. As seen from the table, using GA this can be achieved without much computational time. In proposed approach, five antennae are optimized to validate the developed code using GA. IE3D software and experimental results are used to compare and hence to validate the obtained results by GA. The return loss plot and VSWR plot obtained using IE3D Simulation package for two antennae are also presented.

3.5 Conclusion

This chapter presents design of different regular structure microstrip antenna using GA. The results obtained are close to experimental results. This method can be applied for other irregular structures which are having empirical formulae to find the resonant frequency. The technique can be further improved by choosing proper selection of fitness function or, by developing new better empirical formula where it is not available. This is a simple and efficient technique for design a microstrip antenna.

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CHAPTER 4

ANN AND ITS COUPLING WITH GA FOR ANTENNA DESIGN

4.1 Introduction

In this chapter, Artificial Neural Networks (ANNs) is used for design of microstrip antenna. Firstly, backpropagation algorithm is applied to calculate resonant frequency of rectangular microstrip antenna with shorting post. To further improve the backpropagation algorithm, Tunnel Based Artificial Neural Networks (ANNs) is also developed to calculate the radiation patterns of the antenna. In the second phase, ANN is used to improve Genetic Algorithm(GA) for problems those are not having a proper fitness function. The proposed technique of using ANN as fitness function of GA is applied to calculate the design parameters of a thick substrate rectangular microstrip antenna. A Multi-Layer Feed-Forward Neural Network is used as fitness function in a binary coded genetic algorithm. The results are in very good agreement with experimental findings.

4.2 Calculation of Resonant Frequency of Single Shorting Post Microstrip Patch Antenna

One of the major disadvantages of microstrip patch antenna is its inherent narrow bandwidth, which restricts its wide applications. A number of techniques have been developed for band width enhancement[1-9].

Use of shorting pins[10] is a simple and efficient method to handle such problems. By changing the number and location of the shorting posts, the operating frequency can be tuned, and the polarization can also be changed. Figure 4.1 represents the schematic diagram of the single shorting post rectangular microstrip antenna. Depending on the position of the shorting post, the resonant frequency of the rectangular microstrip antenna can be tuned.

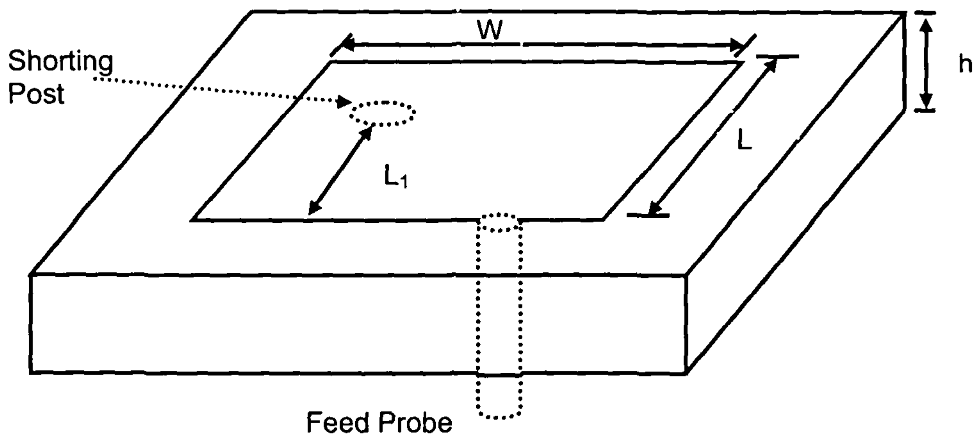

Fig. 4.1 Rectangular Microstrip Patch Antenna with a Shorting Post

The network 5x20x1 is trained by normal feed forward back-propagation algorithm having steepness of activation function, lambda(λ) = 1, learning constant(η) = 0.3 and, momentum factor(α) = 0.1. In this case, all the four parameters are chosen by hit and trial method. The error vs. epoch for the training is shown in figure 2.10. The training time is found to be 889 seconds for an error tolerance of 0.05. The average error per pattern for four patterns is found to be 0.0482 GHz.

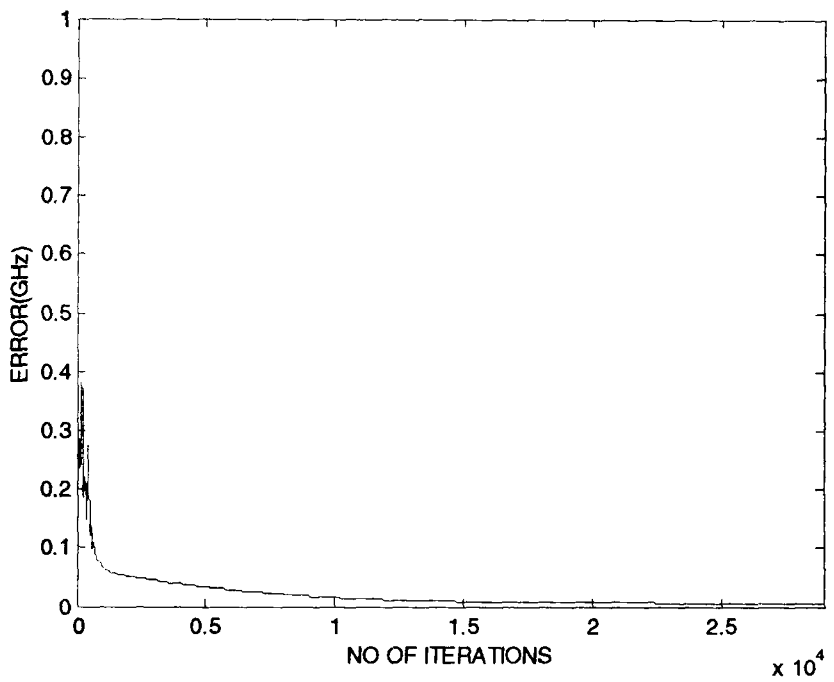

Fig. 4.2 No. of Cycles vs. Error

As shown in table 4.1, the results obtained by ANN are close to experimental data.

Table 4.1 Resonant Frequency of a Microstrip Antenna Using Single Shorting Pin Applying ANN

L_1/L	L In cm	W In cm	ε_r	h In cm	$f_{r(EXPT)}$ In GHz	f_r (Eqn. 10 of[10]) In GHz	$f_{r(Back\text{-}propagation)}$ In GHz
0.1	6.2	9	2.55	0.16	1.594	1.64	1.619
0.3	3.75	7.424	2.2	0.1524	2.788	-	2.808
0.7	6.2	9	2.55	0.16	1.525	1.544	1.493
0.9	3.75	7.424	2.2	0.1524	3.13	-	3.014

* The radius of the metallic post (r_0) = 0.064cm

4.3 Application of Tunnel-Based ANN on Microstrip Patch Antenna Design

Backpropagation algorithm i.e. the gradient decent method is modified using the tunneling technique. The concept of tunneling[11,12] technique is based on violation of Lipschitz condition[12] at equilibrium position, which is governed by the fact that any particle placed at small perturbation from the point of equilibrium will move away from the current point to another within a finite amount of time. The tunneling is implemented by solving the differential equation given by[12],

$$dw/dt=\rho(w-w^*)^{1/3} \qquad (4.1)$$

Where, 'ρ' and 'w*' represent the strength of learning and last local minima for 'w' respectively. The differential equation is solved for some time till it attains the next minima position. To start with the training cycle, some perturbation is added to the weights. Then, the sum of square errors(E) for all the training patterns is calculated. If it is greater than the last minima than it is tunneled according to above equation. If the error is less than the last local minima than the weights are updated according to the relation,

$$\Delta w(t)=-\eta\nabla E(t)+\alpha\Delta w(t-1) \qquad (4.2)$$

Where, 'η' is called learning factor and 'α' is called momentum factor. 't' and '(t-1)' indicate current and the most recent training steps respectively. This technique is validated by implementing it for calculating radiation pattern of a wide-band microstrip patch antenna as shown in figure 4.1.

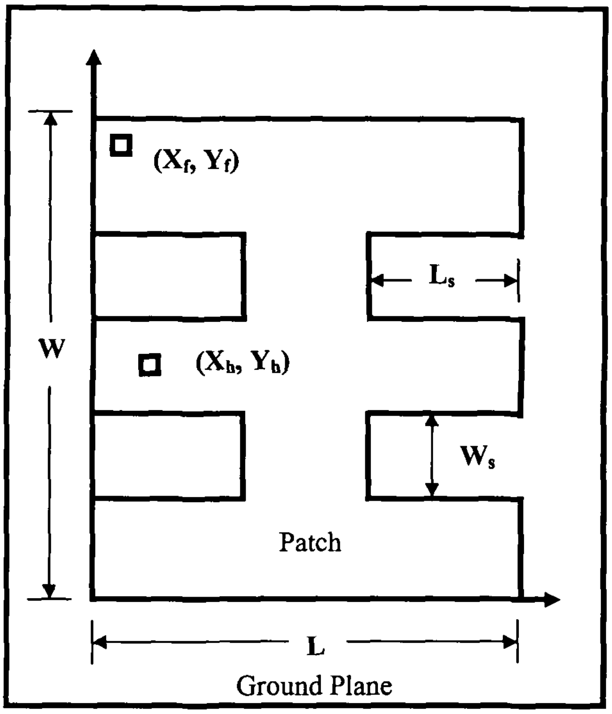

Fig. 4.3 Geometry of the Multi-Slots Hole-Coupled Microstrip Antenna

(The antenna parameters are L= 45 mm, W=71 mm, h=2 mm, Ls=17.5 mm, Ws=04 mm, Feed position(x_f, y_f)=(0.75 mm, 69 mm))

The antenna has been designed on a substrate of thickness 2 mm with ε_r=2.2. The patch size is characterized by length, width and thickness (L, W, h) and is fed by a coaxial probe at position (x_f, y_f). A hole of 0.2mm diameter has been made at location (x_h, y_h) for impedance matching. Four slots are incorporated into this patch and are positioned on both sides of feed position. The structure resembles to the geometry as if an E-shaped patch has been joined with another inverted E-shaped patch. The slot length (Ls), width (Ws) and position (Ps) are important parameters in controlling the bandwidth. Due to slots, the length of the current path is increased[13], which leads to additional inductance in series. Hence, the wide band is generated as resonant circuits get coupled. The slots aggregate the currents, which give additional inductance, which is controlled by patch width (W). For impedance compensation and for better matching, a hole is made at (x_h= 6.75 mm., y_h= 35 mm.). The approach of creating a hole gives the flexibility of changing the reactive component for impedance matching. IE3D software is used to calculate the return loss and VSWR of the considered antenna.

A multilayer 2x80x1 structure, shown in figure 4.4, is used for training the network. The other network parameters used are as follows,

The network is trained by taking 36 patterns each for 6.0GHz, 6.5GHz, 10.5GHz and 12GHz. The training time required is 7.35 minutes. The network is tested for 480 patterns. Figure 4.3 shows the radiation at 6GHz and 10.5GHz whereas Figure 4.4 shows the radiation pattern at 6.5GHz and 12GHz.

Noise Factor=0.004	Time Step for Integrating for the Differential Equation=$5x10^{-15}$
Momentum Factor=0.075	Strength of Learning for Tunneling=0.08
Learning Constant=0.08	

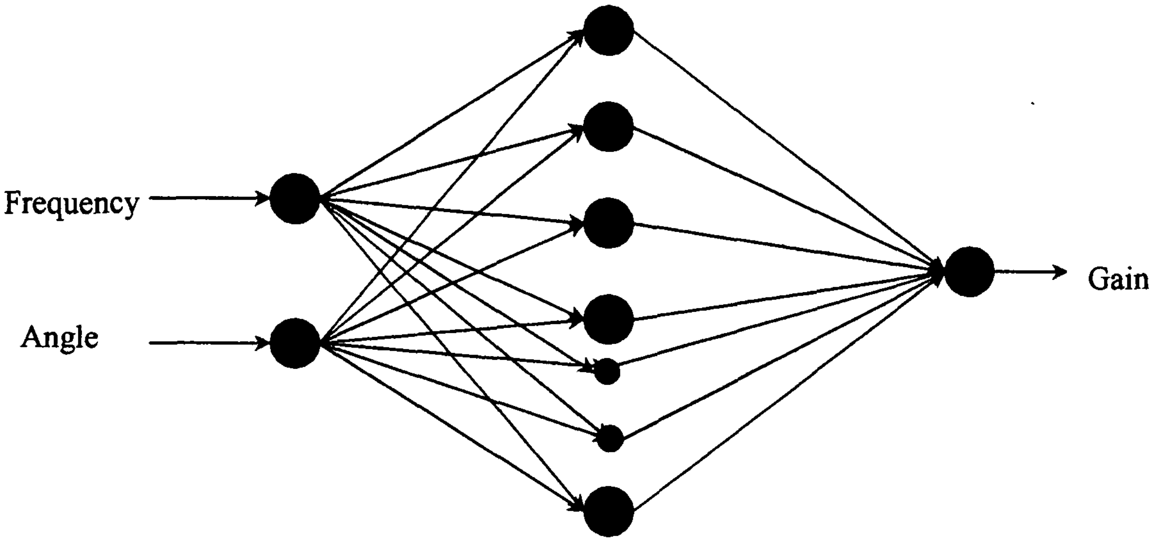

Fig. 4.4 Network Architecture Showing Angle and Frequency as Input and Gain as Output

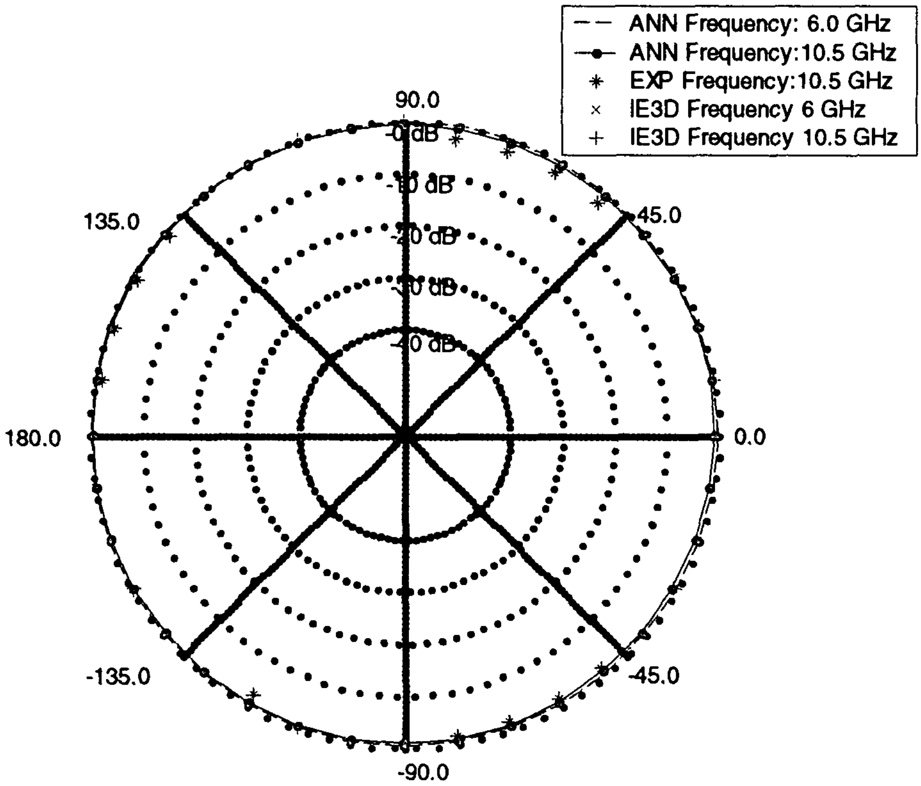

Fig.4.5 Radiation Pattern for E-Total, theta=0 at 6 GHz and 10.5GHz

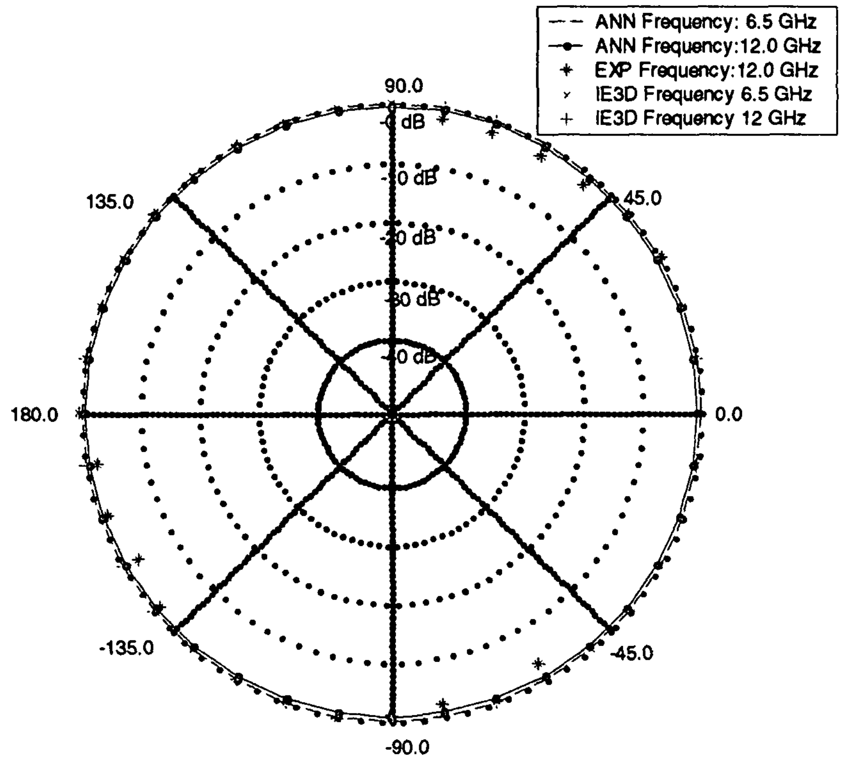

Fig. 4.6 Radiation Pattern for E-Total, theta=0 at 6.5GHz and 12.0GHz

The total average errors at different frequencies are 6GHz is 0.0408, at 6.5GHz is 0.0520241, at 10.5 GHz is 0.0745005 and at 12 GHz is 0.0181725. Experimental measurements are carried out to see the radiation patterns at 10.5GHz and at 12GHz. The results are in good agreement with the results of IE3D and with ANN.

The variation of slot parameters, hole size and positions gives the flexibility to shift the frequency and match the impedance, which is a notable feature of the referred antenna.

4.4 ANN Used as Fitness Function of GA and Its Application to Microstrip Patch Antenna Design

Over the years, genetic algorithm has been applied in many applications. But lack of proper fitness function acts as a hindrance for its wide spread application in many cases. Often in electromagnetics, the objective function (fitness function) arises for optimization is multimodal, stiff and non-differentiable. In addition, they are computationally expensive to evaluate. Tentativeness of the objective function cannot be relied upon when accuracy cannot be compromised. The deterministic optimization technique like Monte Carlo technique, simulated annealing and hill climbing, or evolutionary optimization technique like Genetic algorithm (GA) [14-16,23] mostly rely upon objective function, without which the optimization technique has no meaning. Here a new class of objective function formulation technique is presented in which trained Artificial Neural Networks (ANN) is used as fitness function. The presented technique can be used everywhere particularly in those cases, where the objective function formulation is difficult, or the objective function is erroneous.

4.4.1 Application on Microstrip Patch Antenna

A novel technique of using Artificial Neural Networks as fitness function of Genetic algorithm to calculate the design parameters of a thick substrate rectangular microstrip antenna is presented here for which there is no closed form mathematical formula to calculate the resonant frequency. A Multi-Layer Feed-Forward Neural Network is used as fitness function in a binary coded genetic algorithm. It is seen that the results obtained by this method are closer to experimental value compared to earlier results obtained by curve fitting method. To validate this, the results are compared with experimental values for five fabricated antennae. The results are in very good agreement with experimental findings.

With $h/\lambda_0>0.0815$, the properties of the patch antenna changes drastically[24,25], where 'h' is the thickness of the substrate and λ_0 is the free space wavelength. The standard formulae available in the literature are valid for $h/\lambda_0<0.0815$. So, for $h/\lambda_0>0.0815$, the designer, thus, forced to obtain the physical characteristics by trial and error method or numerical method. But these formulae are derived by curve fitting method which can be extrapolated to a certain extent only. Thus, there is a need for a robust numerical approximation for the calculation of the dimensions. A typical microstrip antenna with length (L), width (W), height (h), and the feed point location (a) are shown in the figure 3.1.

The approach[26] is basically a two step calculation procedure. In the first step a suitable network is selected and trained for a set of training data. After successful training the network will learn the input-output relation among length, width, thickness, permittivity and resonant frequency of the antenna. In the second step the network will be used as objective function and GA will be used for calculation of the optimized dimension.

4.4.2 Training Phase

The back propagation algorithm, using gradient decent method is used for training the network. A three layers neural network, consisting of four input neurons, thirty hidden neurons and one output neuron(i.e 4 x 30 x 1) has been used. For this network, length, width, substrate thickness and dielectric constant of the substrate are taken as inputs where as, resonant frequency is taken as output. The proposed model is as shown in the figure 4.7.

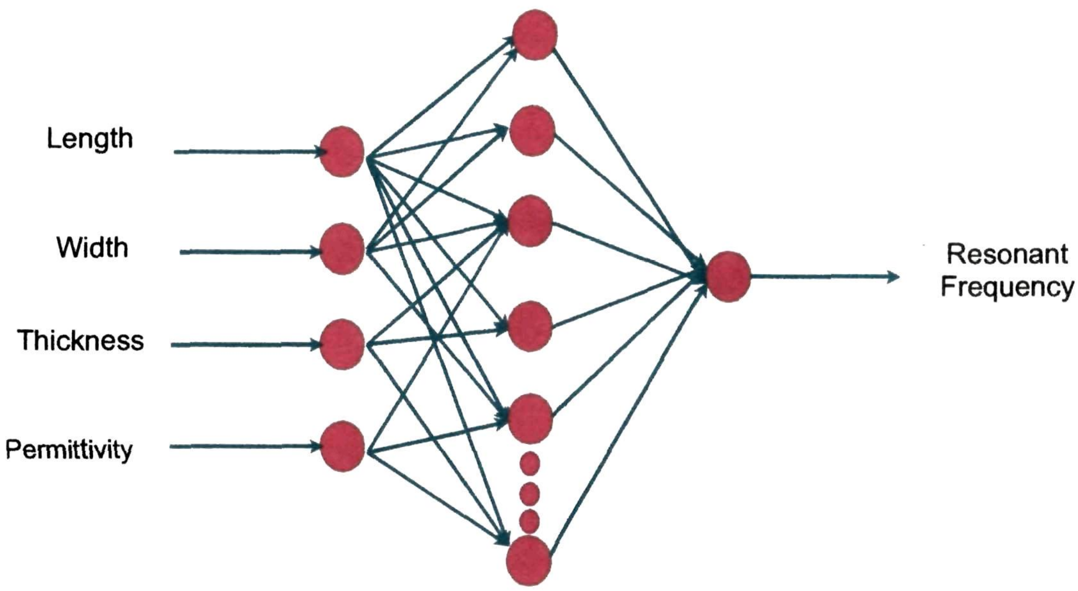

Fig. 4.7 Network Structure

Twelve patterns from [24] are taken for training the networks and rest five patterns are used for testing the networks and the ANN based GA code. The parameters considered for training the network are,

Noise factor parameters = 0.0003

Learning Constant (parameter) = 4

Momentum factor = 0.0205.

Noise factor of 0.0003 is used during training of ANN to increase its generalization capability. The number of hidden neurons and various parameters are chosen by hit-and-trial method.

4.4.3 Optimization Phase

The two independent variables to be optimized are the length and width of the antenna. The population size of 20 individuals, and 200 generations are produced. Roulette wheel selection procedure is adopted to select new population. The probability of crossover is set to 0.7, while the probability of mutation is equal to 0.01. The fitness of the selected population is calculated from the trained neural network. The process is repeated until the termination criterion is met. The flow chart of the proposed algorithm is presented in figure 4.6. The fitness of an individual is decided according to following relation,

$$\begin{aligned} \text{Fitness} &= f(\mathrm{L}, \mathrm{W}, \varepsilon_r, h) = 1/(1+ \mid \mathrm{f}_r - \text{desired frequency} \mid) \\ &= 1/(1+ \mid \text{output of ANN} - \text{desired frequency} \mid) \end{aligned} \tag{4.3}$$

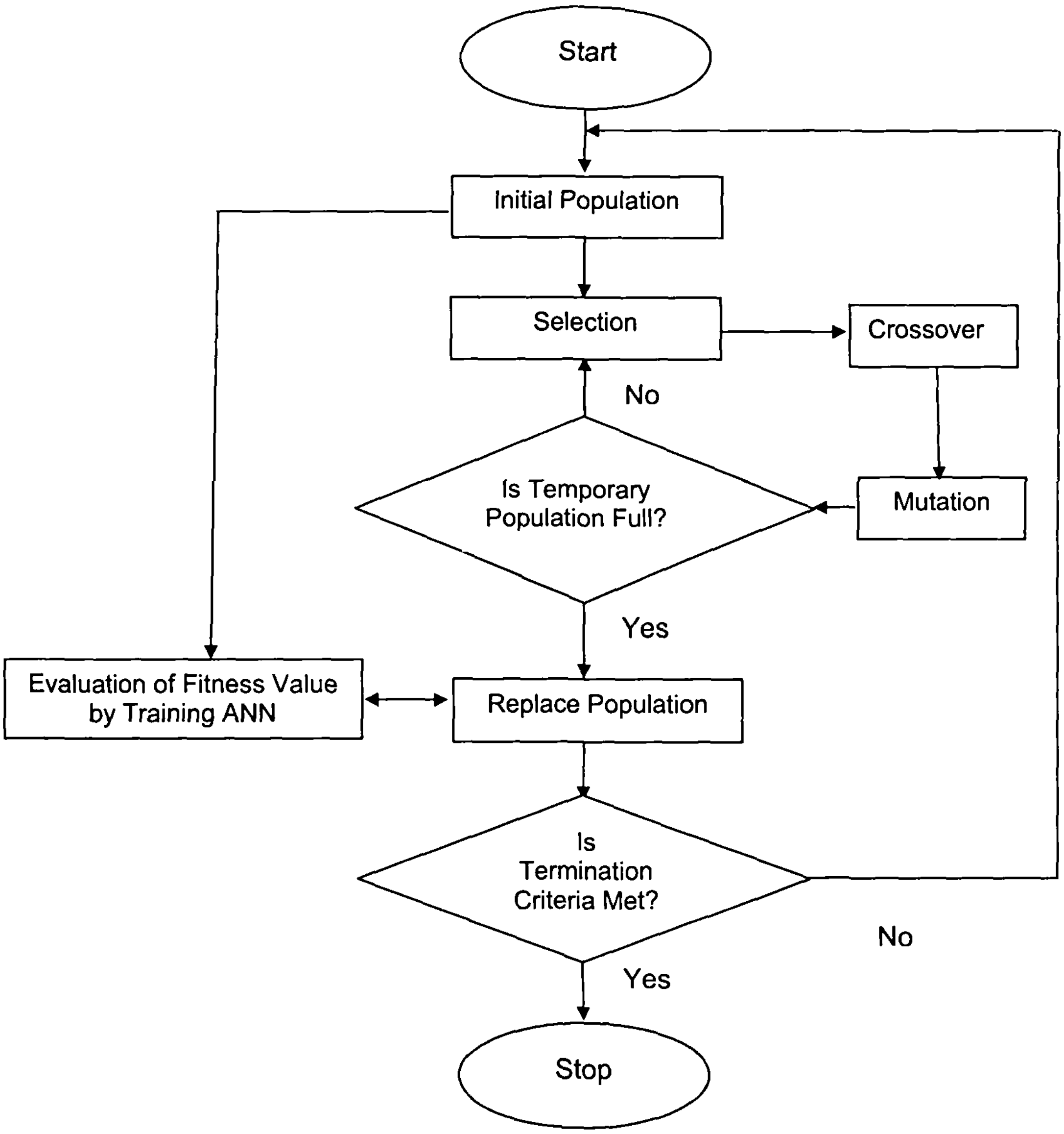

Fig. 4.8 Flow chart of the Proposed Algorithm

The optimized design parameters of five antennae considered for testing is tabulated in Table 4.2. Out of three inputs, one is dielectric constant (ε_r = 2.55) of the substrate. The other two inputs are listed in 2nd, 3rd column. The experimental dimensions of length and width are shown in 4th and 7th column respectively, while optimized output of our GA-ANN based dimensions are listed in 6th and in the last column of the table. By using empirical formulae derived by curve fitting method [24], the average error in calculating length and width of thick substrate microstrip antenna is found to be 0.06 and 0.074 respectively where as, the presented method shows an average error of 0.032 for length and that of for width is 0.018. Thus, an ANN coupled GA gives better results compared to formulae derived in [24].

Table 4.2 Dimensions of Thick Substrate Rectangular Microstrip Antenna (ε_r = 2.55)

L_1/L	L In cm	W In cm	ε_r	h In cm	$f_{r(EXPT)}$ In GHz	f_r (Eqn. 10 of [10]) In GHz	$f_{r(Back\text{-}propagation)}$ In GHz
0.1	6.2	9	2.55	0.16	1.594	1.64	1.619
0.3	3.75	7.424	2.2	0.1524	2.788	-	2.808
0.7	6.2	9	2.55	0.16	1.525	1.544	1.493
0.9	3.75	7.424	2.2	0.1524	3.13	-	3.014

* The radius of the metallic post (r_0) = 0.064cm

The measure of accuracy of the solution obtained by GA depends directly upon the efficient training of the neural networks. So, care must be taken for efficient training of the network. Cases where, there is no accurate theoretical formulation for objective function, this technique can be used for optimization purpose.

Simultaneous optimization of dielectric constant, height of the substrate and dimensions etc. is possible in the proposed method where as, in conventional method it is either computationally complex or, not possible. The results obtained by the ANN coupled GA is compared with experimental results. The results are in very good agreement with experimental findings.

4.5 Conclusion

A back-propagation algorithm is used to calculate the resonant frequency of single shorting post tunable microstrip antenna. This technique to calculate resonant frequency of shorted microstrip antenna seems to be a simple, inexpensive and highly accurate method. Accuracy can be improved by choosing smaller error tolerance and/or training the network for more number of iterations while evaluating the fitness value.

The radiation patterns of the antenna calculated by Tunnel based Artificial Neural Networks (ANNs) is compared with experimental results measured. The experimental results are in good agreement with the simulated results of IE3D and that of ANNs. This simple method saves computational time considerably giving better accuracy.

In proposed method of coupling ANN with GA, the simulation time is very less as compared to the simulation time of methods like Method of Moments (MoM), Finite Difference Time Domain (FDTD) and Finite Element Technique (FET) without compromising with the error. The accuracy of the proposed model can be increased by using a more effective ANN algorithm. Further, the accuracy can be increased by taking more experimental results for training the artificial neural network. This method may go a long way in improving the ANN based techniques to solve problems like array factor correction, cross polarization reduction, band width enhancement and array optimization etc.

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CHAPTER 5

APPLICATION OF GA COUPLED ANN

5.1 Introduction

As seen in previous chapters, both Genetic Algorithm and Neural Network independently has become an efficient tool to solve various problems in electromagnetics[1,2]. Genetic Algorithm is a global search technique where as Neural Network uses the gradient information of the error surface. In this chapter, attempt is made to take the advantages of both by coupling them together.

5.2 GA Used to Find Initial Weight Set of ANN for Microstrip Antenna Design and Analysis

The multilayer neural network trained with gradient decent back-propagation method is unique due to its high generalization capability. Owing to its gradient-descent nature, back-propagation is very sensitive to initial conditions[3,4]. If the choice of the initial weight vector happens to be located within the attraction basin of a strong local minima attractor (one where the minima is at the bottom of a steep-sided valley of the error surface) then the convergence of back-propagation will be fast. On the other hand the, back-propagation converges very slowly if the initial weight vector starts the search in a relatively flat region of the error surface. Here Genetic Algorithm is used to fix the initial weights of a multilayer neural network. GAs are capable of optimizing nonlinear multi-modal functions of many variables[5-7]. They require no derivative information and they robustly find global or very strong local optima. Numerical experiments indicate that using GA good solutions to highly non-linear equations can be obtained quickly even in time comparable to that taken by analytical methods such as steepest descent. Previously, attempt has been made to train the network by evolutionary approach. As these method is ignorant about the gradient information of the weight surface. The main drawback of the evolutionary approach of the neural network training is the training time. The back-propagation algorithm takes only several minutes on average to its lowest error, on the other hand the evolution approach takes over an hour[3,4,8].

A simple and accurate method for calculating the resonant frequency of a rectangular microstrip patch antenna with a single shorting post is proposed here[2]. By changing the location of the shorting post the resonant frequency of the patch antenna can be tuned. The microstrip patch antenna with single shorting post is shown in figure 5.1.

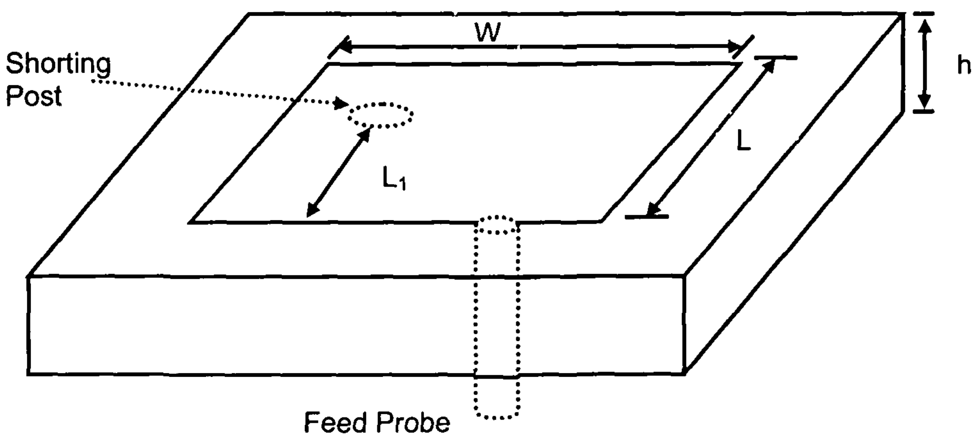

Fig. 5.1 Rectangular Microstrip Patch Antenna with Shorting Post

But, so far all the numerical and theoretical methods proposed failed to agree with the experimental results. Here Neural Networks is used to predict the resonant frequency and Genetic Algorithm is used to fix the initial weight set to start the training by back-propagation.

The ERMS error of a multilayer neural network is given by,

$$E(w) = 0.5 * \left(\sum_{p=1,P} \sum_{q=1,N^L} (u_q^L(x_p) - d_q(x_p))^2 \right) \tag{5.1}$$

where,

u_j^l Output of j^{th} node in layer l.

$w_{j,k}^l$ Weighting connecting the j^{th} node in layer l to k^{th} node in layer (l-1)

x_p p^{th} training sample.

$d_q(x_p)$ Desired response of the j^{th} output node for the p^{th} training sample.

N^l Number of nodes in layer l.

L Number of layers.

P Number of training patterns.

In the above notation u_o^l is=1 and $w_{j,0}^l$ represents the bias weights, where $l \neq 1$.

Equation (5.1) is taken as the fitness function of the genetic algorithm. The function is minimized to its saturation level. The corresponding weights are taken as initial weights of the neural network. For the training of the neural network the backpropagation algorithm[9] is used. Depending on the position of the shorting post the resonant frequency of the rectangular microstrip antenna can be tuned. Width of the patch(W), length of the patch(L), position of the shorting post(L1), permittivity of the substrate(ε_r) and height of the substrate are taken as input to a 5x30x1 network and resonant frequency of the patch is taken as the output. Experimental results from[10] is taken fro training the network.

To make the Network more generalized, mixed patterns training in non-homogeneity is developed. For training the network in a non-homogeneity data nine patterns from [10] and eleven patterns generated by IE3D with little change in configuration are taken for training the network. The network structure is selected on trial and error basis. The various parameters taken for training the network and genetic algorithm are selected on trial and error basis. These parameters are,

GA initialized ANN		**ANN**	
Learning constant	3	learning constant	3
momentum factor	0.1	momentum factor	0.1
noise factor	0.004	noise factor	0.004
No. of population	1000		
No. of generation	20		
probability of cross over	0.6		
probability of mutation	0.001		

The training time for the network is 346 seconds(5.76 minutes) in the GA coupled model and 642 seconds(10.7 minutes) for the ANN model in a P-III HP PC. Figure 5.2 shows the graph between error and number of training cycles in both the approach (with and with out GA).

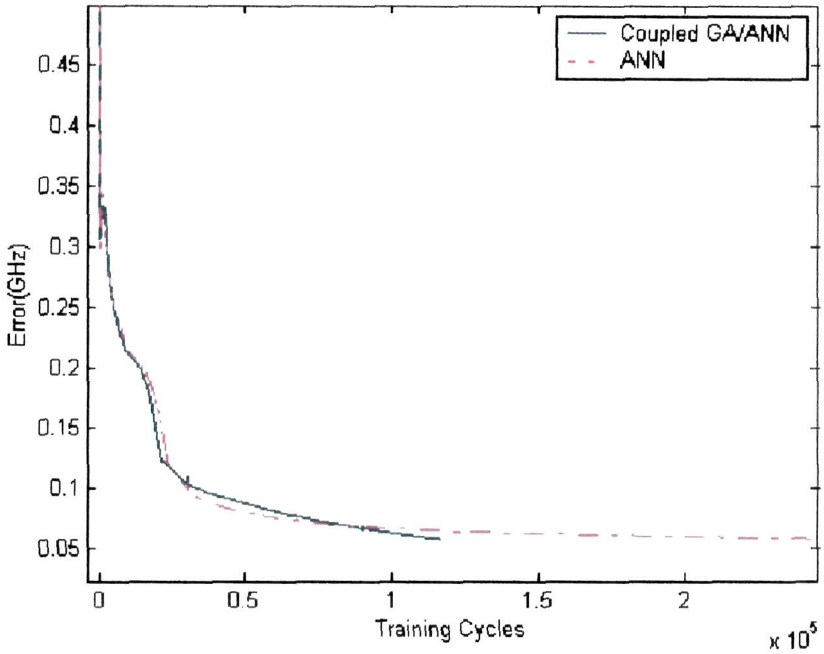

Fig. 5.2 No. of Cycles vs. Error

It shows that the proposed approach takes nearly half computational time compared to the algorithm presented in [9] to get the same accuracy. It may be due to the fact that the network starts training from the attractor basin in the weight space.

To test the generalization of the presented model, the antenna presented in [11] is used for testing. The output of the network for those four patterns is shown in the table 5.1. The average error per pattern is found to be 0.013545GHz.

Table-5.1 Resonant Frequency of Single Shorting Post MSA by GA Initialized ANN

$L1/L$	L	W	ε_r	H	$f_{r(EXPT)}$ In GHz	$f_{r(GA\text{-}init\text{-}ANN)}$ In GHz
0.5	6.2	9	2.55	0.16	1.466	1.46789
0.6	6.2	9	2.55	0.16	1.480	1.48859
0.3	3.75	7.424	2.20	0.1524	2.788	2.81575
0.4	0.16	7.424	2.20	0.1524	2.664	2.67995

The results obtained in present technique is more close to the experimental results compared to the numerical and analytical results presented in[10]. The input-output relation is also checked for the experimental results for (L=3.75cm, W=7.424cm, h=0.1524cm and ε_r=2.2).

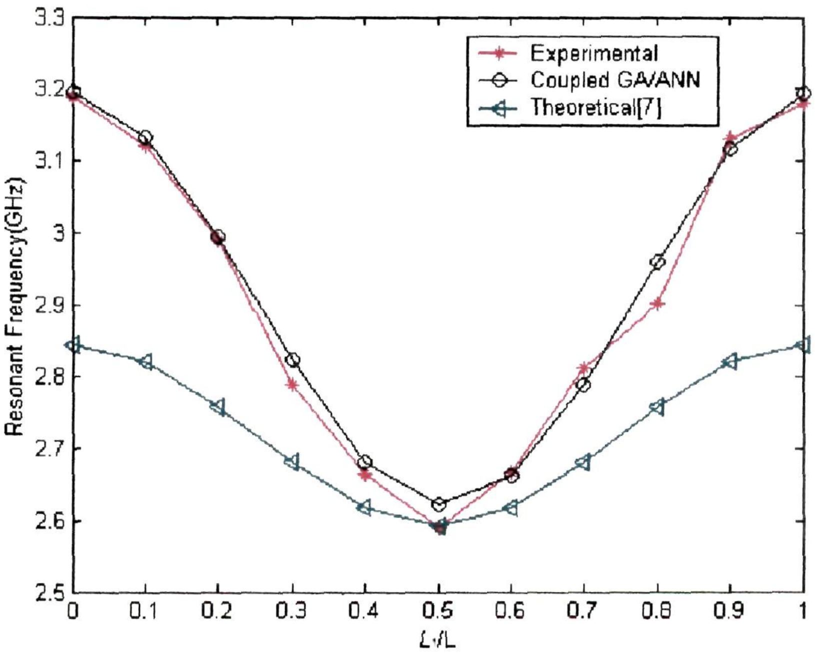

Fig. 5.3 Resonant Frequency of Tuned Antenna vs Post Position

Figure 5.3 shows the graph between the experimental results, theoretical results and the results with present approach for the above said antenna for different positions of the post. Experimentally, it is verified that the resonant frequency is slight asymmetric about L_1/L, whereas the calculated results using[10] are symmetric. The results obtained using proposed approach, follows the experimental trend.

5.3 Training ANN by GA Considering Competing Convention for Resonant Frequency of RMA on Thick Substrate

A normal feed forward back propagation algorithm is widely used in electromagnetic applications because of its ease in implementation and low computational cost. However, selection of a suitable architecture and parameters such as the number of hidden neurons, steepness of activation function, momentum factor, learning constant etc. is a cumbersome job. Hence, combination of GA and ANN in various ways is present problem of research. GAs are applied in the design of ANNs in a number of areas as discussed in previous section[1,2]. Most importantly, they are applied in weight optimization and architecture optimization. But, especially, for long chromosomes, the problem of competing conventions almost destroys the cross over operator, the most important operator in GA. This is the reason, why it takes a huge amount of computational time to train a neural network by GA. However, an attempt has been made to overcome this limitation.

While GA is used for weight optimization, its performance gradually reduces with increase in the length of chromosome [3]. This is because of the permutation problem namely, hidden node redundancy and hidden layer redundancy. As discussed earlier, for a network with n hidden nodes, there are 2^n n! functionally equivalent but structurally different representations, if the activation functionn is odd, and otherwise n! different representations. This increases the solution space which leads to a high computational cost. However, using an even activation function, hidden node redundancy can be overcome. To handle the hidden layer redundancy, either it is ignored, or the crossover is removed from GA which is not the right solution [4].

GA has been used for connection weight determination considering the hidden layer redundancy. If a hidden neuron, with all its incoming and outgoing connections, is exchanged with another neuron with all its incoming and outgoing connections, we have a different structural representation of ANN. But functionally the ANN remains the same resulting hidden layer redundancy. To make them functionally different, the network should be chosen so that, for same input, each node would give different output after applying the activation function. This is possible if different steepness of activation function(λ) is chosen for each node.

The proposed method is applied to rectangular microstrip antenna. The length (L), width (W), height (h), permittivity of the substrate (ε_r) and the feed point location (a) for a typical thick RMA are shown in the figure 5.4. Since its bandwidth is narrow, the resonant frequency must be predicted accurately. The simplest method to increase the bandwidth is to increase the substrate thickness. Existing formulas can predict resonant frequency with good accuracy when the antenna substrates are electrically thin [12,13]. But when the thickness increases, the predicted resonant frequency diverges from its experimental value. ANN is well suited for such situation.

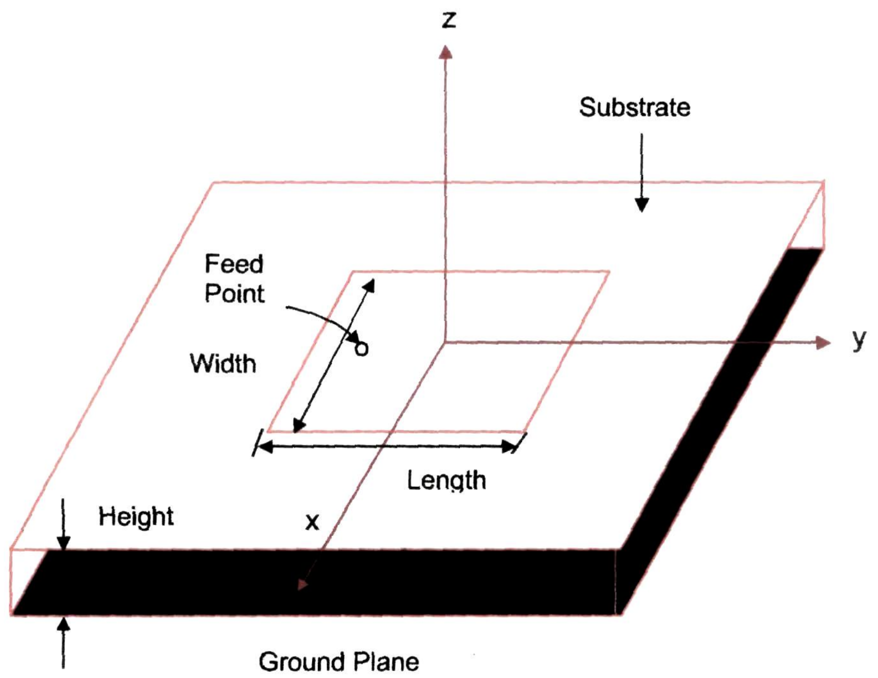

Fig. 5.4 Rectangular Microstrip Antenna on Thick Substrate

The resonant frequency of a microstrip patch antenna depends mainly on its length, width, thickness, feed point location and permittivity of the substrate. So, these five parameters are taken as input and, resonant frequency(f_r) is considered as the target output for training the designed neural network. The network (5x20x1) is as shown in figure 5.5.

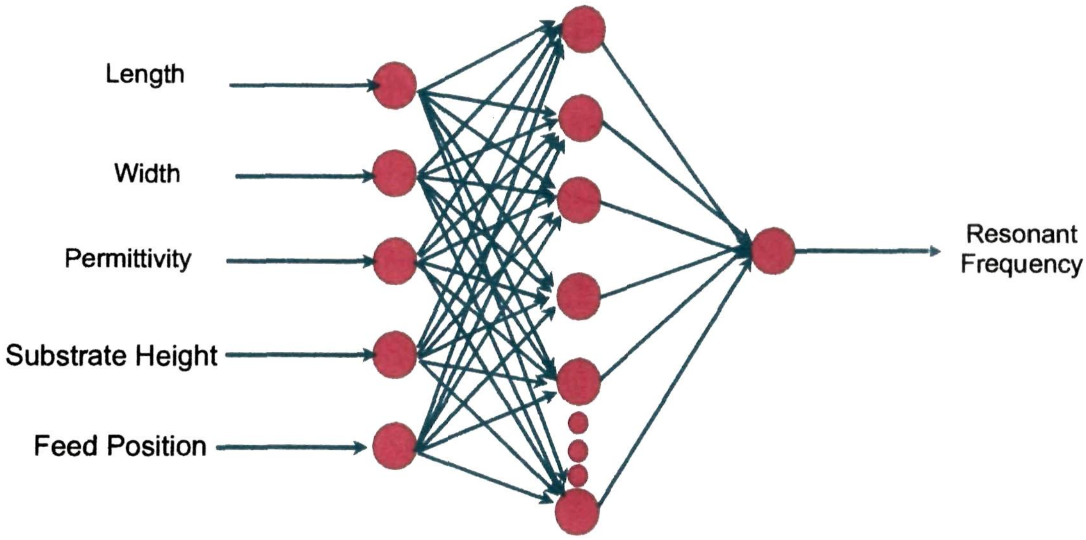

Fig. 5.5 Network Structure

GA has been used to find the optimized weight set. A logarithmic sigmoid function is used as activation function which is expressed as

$$f(x) = \frac{1}{1+e^{-\lambda(x)}} \tag{5.2}$$

where,

λ = Steepness of activation function, chosen different for different hidden node.

The E_{RMS} error of a multilayer neural network that gives the fitness value, can be written as,

$$E(w) = \frac{1}{2}\left(\sum_{p=1,P}\sum_{q=1,N^L}(u_q^L(x_p) - d_q(x_p))^2\right) \tag{5.3}$$

where,

u_j^l = Output of j^{th} node in layer l.

$w_{j,k}^l$ = Weighting connecting the j^{th} node in layer l to k^{th} node in layer (l-1)

x_p = p^{th} training sample.

$d_q(x_p)$ = Desired response of the j^{th} output node for the p^{th} training sample.

N^l = Number of nodes in layer l.

l= Number of layers.

p = Number of training patterns.

In the above notation u_0^l =1 and $w_{j,0}^l$ represents the bias weights, where $l \neq 1$.

The population size is taken 30 individuals. It took 1395 generations to achieve the accepted error tolerance. The probability of crossover is set at 0.30, while the probability of mutation is equal to 0.01. The algorithm presented in [6,7] for GA is used to train the network. Twelve out of 17 patterns from [12] are taken for training and the rest are taken to test the result.

While training ANN by GA keeping steepness of activation (λ=1) fixed, the error gets saturated above desired error tolerance after certain generations of GA. By taking different values of steepness of activation (λ) for different hidden node, error goes on reducing with number of generations. Figure 5.6 shows the graph between number of generations and E_{RMS} error for both the cases.

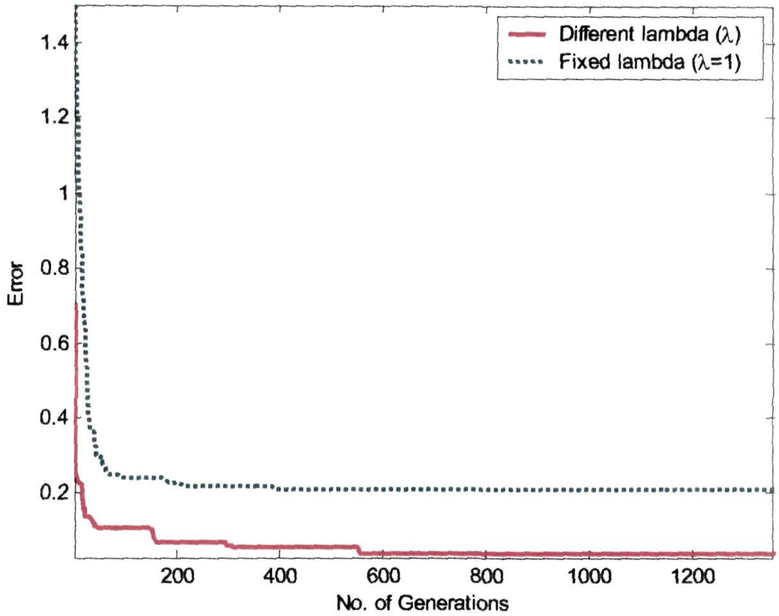

Fig. 5.6 No. of Generations vs. Error

The average error per pattern for five patterns is found to be 0.02257 GHz. Time taken for training the network is 122 seconds. The same network is trained by normal feed forward back propagation algorithm. The Network parameters taken are,

Lambda (λ)	1
Learning constant (η)	0.08
Momentum factor (α)	0.205

The average error per pattern for those five patterns is found to be 0.0457 GHz whereas, training time is 181 seconds. The graph between the number of training cycles and the E_{RMS} error for normal feed forward back propagation is as shown in the figure 5.7.

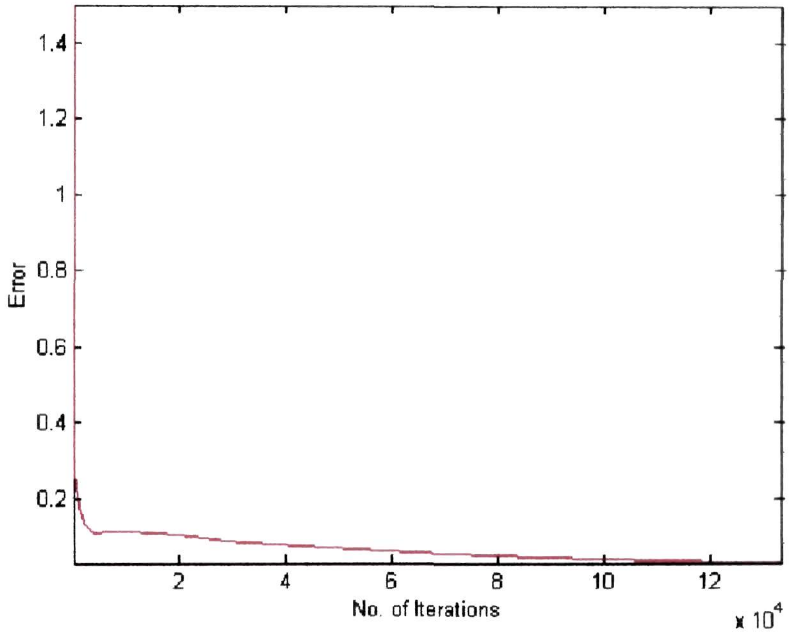

Fig. 5.7 No. of Cycles vs. Error

The comparison of results obtained by present method with experimental resonant frequency and that of normal feed forward back propagation is as shown in the table 5.2.

Table-5.2 Comparison of Results of Proposed Method and Feed Forward Back Propagation Algorithm with Experimental Results

Patch No.	$f_{r(Expt.)}$ In GHz	$f_{r(Present\ Method)}$ In GHz	$f_{r(Back\text{-}propagation)}$ In GHz
1	5.820	5.82515	5.79649
2	4.660	4.67353	4.52594
3	3.980	3.95329	3.93908
4	3.900	3.87665	3.91498
5	2.980	3.02413	2.99279

In a gradient descent feed forward back propagation method, there is a chance that the solution may be trapped by local minima which does not happen in case of GA. Hence, proposed algorithm of training ANN by GA takes the advantage of population-to-population search of GA by overcoming the competing convention. This model can be used as a CAD model for designing antennas.

5.4 Optimization of Parameters of ANN Using GA and Its Application on RMA with Shorting Post

A lot has been tried to control various features of ANN by GA[8], but all the efforts have their own limitations. The strategy for optimizing the neural network using Genetic Algorithm is an open issue. Literature survey shows that Genetic Algorithm has been used to provide a model of evolution of the topology of ANN while supervised learning is used for learning [3,14]. Yet another way of using Genetic Algorithm is the weight optimization technique [4,15,16], where a network is trained by using GA without any gradient information. The authors report that ANN becomes victim of the parameters of GA. Mutation and Crossover, the main parameters of GA arise the encoding problem. The third way of dealing optimization of neural network is to associate the gradient information of the network while training with ANN learning rules. In[2] Genetic Algorithm has been used to assign/find out the initial weight set, which are subsequently processed using back-propagation algorithm. The algorithm takes much time to select an optimized model.

Although there are some numerical approximations to initialize various parameters of ANN, it is not true in all cases. In a gist, it is a tedious job for a programmer to select an efficient model for a particular problem thus, increasing man-time. Keeping these in view, GA has been used in this problem to select an optimized trained ANN model. In the present paper, Genetic Algorithm has been used to optimize number of hidden neurons, steepness of activation function, learning constant and momentum factor to achieve the output. In other words, in the present paper, Genetic Algorithm has been used continuously to optimize the Artificial Neural Networks to achieve the best result. Hence, it is seen that GA takes less computational time for training the network while giving high accuracy.

Here, genetic algorithm has been used to optimize number of hidden neurons, steepness of activation function, momentum factor and learning constant while training the network. A network with a single hidden layer has been chosen for the present problem, as it is sufficient to solve most of the problems. The model can be generalized for multi hidden layer network. Initially, a set of networks, which is the population size of genetic algorithm, is trained for chosen minimum number of cycles/iterations by normal feed-forward back-propagation algorithm. The fitness value of the individuals of the population is calculated in terms of the lowest Absolute Error E_{Abs} obtained by back-propagation algorithm for given minimum number of cycles/iteration. Thus, the fitness function is expressed as:

$$Fitness = \frac{1}{(1 + E_{Abs})} \tag{5.4}$$

Then applying genetic operators such as cross over and mutation, the E_{Abs} error is further reduced up to an accepted error tolerance. And, the fittest trained network is selected which has been trained while optimizing those four ANN parameters. However, as the network is trained by delta learning rule, the weights are adjusted depending on the root mean squared error E_{RMS} which is as given below,

$$E_{RMS} = \frac{1}{2N}\sum_{n=1}^{N}\sum_{k=1}^{M}(d_k(n) - y_k(n))^2 \tag{5.5}$$

where,

N = Number of patterns,

M = Number of outputs,

$d_k(n)$ = Desired output for k^{th} output neuron for n^{th} training pattern,

$y_k(n)$ = Output of k^{th} output neuron for n^{th} training pattern,

$$= \sum_{j=1}^{m} w_{kj} z_j(n),$$

where,

m = Number of hidden neurons,

w_{kj} = Weight connected between j^{th} hidden neuron and k^{th} output neuron,

w_{k0} = Bias applied to k^{th} neuron and,

$z_j(n)$ = Output of jth hidden neuron for n^{th} training pattern.

The flow-chart of presented algorithm is shown in figure 5.8.

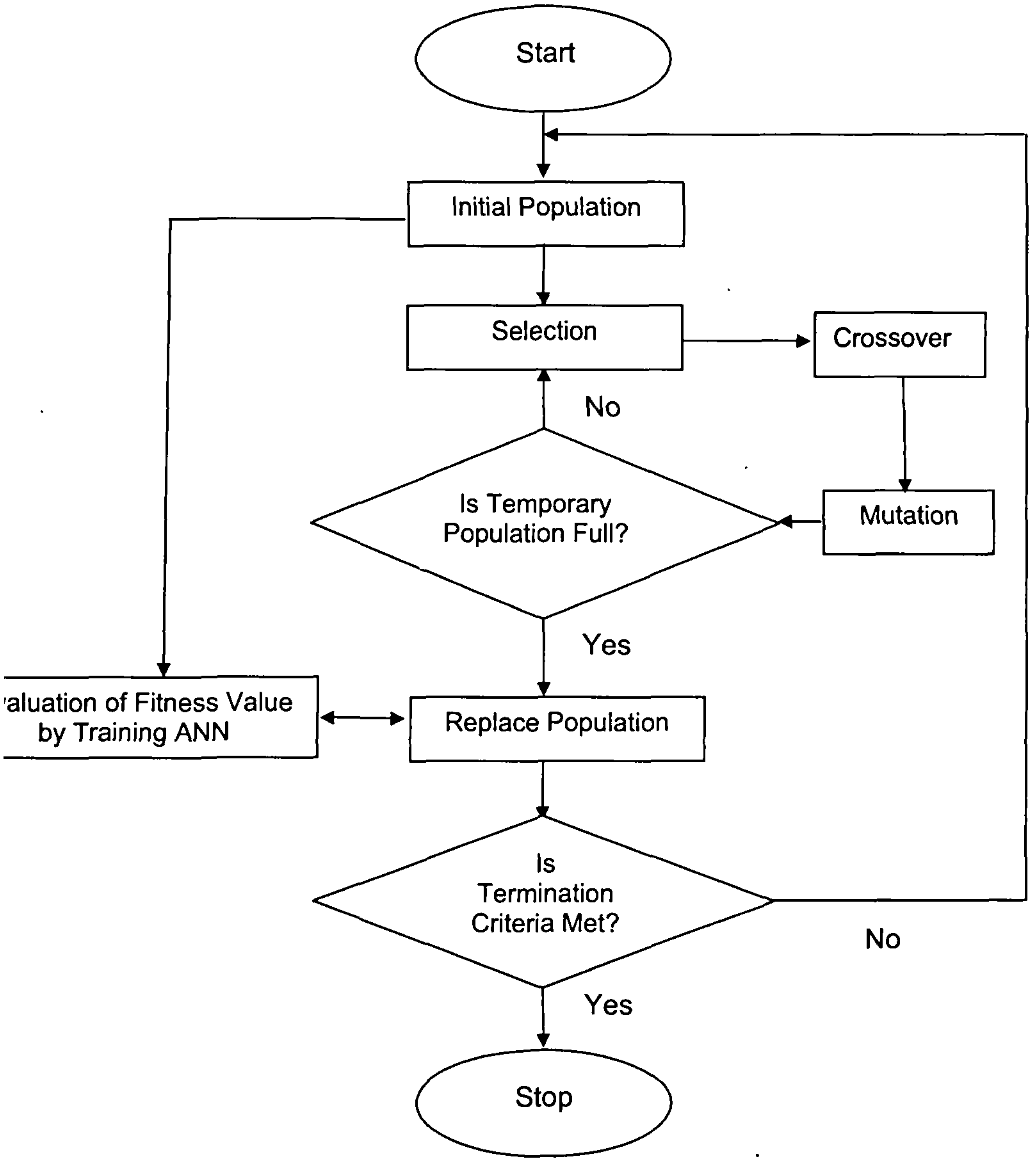

Fig. 5.8 Flow Chart of Presented Algorithm

One of the major disadvantages of microstrip patch antenna is its inherent narrow bandwidth, which restricts its wide applications. A number of techniques have been developed for band width enhancement. Use of shorting pins is a simple and efficient method to handle such problems[17]. By changing the number and location of the shorting posts, the operating frequency can be tuned, and the polarization can also be changed. Figure 5.9 represents the schematic diagram of the single shorting post rectangular microstip antenna. Depending on the position of the shorting post, the resonant frequency of the rectangular microstrip antenna can be tuned.

While optimizing those four ANN parameters(number of hidden neurons, steepness of activation function, momentum factor and learning constant) by GA, the population size taken is 30 individuals, and the maximum number of generations is set at 30, 000. The probability of crossover is set at 0.7, while the probability of mutation is equal to 0.01. The length of chromosome is 43 bits. For each set of ANN parameters selected by GA, the network is set to train which measures the fitness value in terms of error obtained after completion of all cycles. Absolute error tolerance considered is 0.02 to give the desired set of ANN parameters and once it is achieved, the network training is continued till saturation.

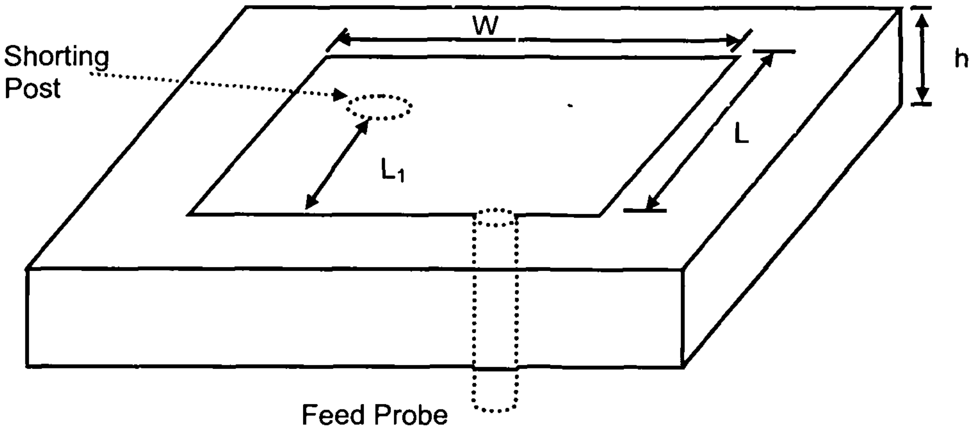

Fig. 5.9 Rectangular Microstrip Patch Antenna with a Shorting Post

To train the neural network for evaluating the fitness value, the backpropagation algorithm is used. The number of inputs and outputs in the input layer and output layer respectively are fixed in the model. Width of the patch(W), length of the patch(L), position of the shorting post(L_1), permittivity of the substrate(ε_r) and height of the substrate(h) are taken as inputs to the networks and resonant frequency of the patch is taken as the output. In[10], experimental data has been provided for fixed r_o=0.064 cm. The proposed technique has been validated with the experimental data to see the accuracy of the method. Therefore, it has been considered for fixed r_o=0.064 cm only. However, using equation 10 of[10], and varying r_o more data sets can be generated to incorporate the dependency of r_o. But the validation shall not be with experimental data. 18 patterns out of 22 patterns presented in[10,11] are taken for training the network. Four antennas are taken for testing the best trained neural network model selected by GA. The optimized parameters of ANN by applying GA are found as:

No. of hidden neurons	35
Steepness of activation function (λ)	5.382164
Learning constant (η)	0.106955
Momentum factor (α)	0.58947

As far as selection of ANN parameters is concerned, it takes much time by hit and trial method to get the best trained network as in chapter 4.2. i.e. the simulation time is less but the man-time is excessive while training a network by normal feed forward back propagation algorithm. But using GA, this man-time has been reduced to 3856 seconds in presented algorithm. For the sake of comparison of training time, the network 5x20x1 trained by normal feed forward back-propagation algorithm in chapter 4.2 having steepness of activation function, lambda(λ) = 1, learning constant(η) = 0.3 and, momentum factor(α) = 0.1 may be considered. In that case, all the four parameters were chosen by hit and trial method. The training time was found to be 889 seconds for an error tolerance of 0.05. The average error per pattern for four patterns was found to be 0.0482 GHz.

But in case of this proposed algorithm, it takes only 41 seconds (30, 000 training cycles) to train the network even for a less error tolerance of 0.02. And, the average error for those four antennas is found to be 0.0332 GHz. Figure 5.10 shows the graph between number of cycles and error for both the cases. As shown in Table. 5.3, the results are more close to the experimental results compared to the numerical and analytical results presented in[10].

Table 5.3 Resonant Frequency of a Microstrip Antenna Using Single Shorting Pin Applying GA on ANN

L_1/L	L In cm	W In cm	ε_r	h In cm	$f_{r(EXPT)}$ In GHz	f_r (*Eqn. 10 of [4]*) In GHz	$f_{r(Back-propagation)}$ In GHz (Chapter 4.2)	$f_{r(Present\ Method)}$ In GHz
0.1	6.2	9	2.55	0.16	1.594	1.64	1.619	1.607
0.3	3.75	7.424	2.2	0.1524	2.788	-	2.808	2.798
0.7	6.2	9	2.55	0.16	1.525	1.544	1.493	1.517
0.9	3.75	7.424	2.2	0.1524	3.13	-	3.014	3.028

* The radius of the metallic post (r_0) = 0.064cm

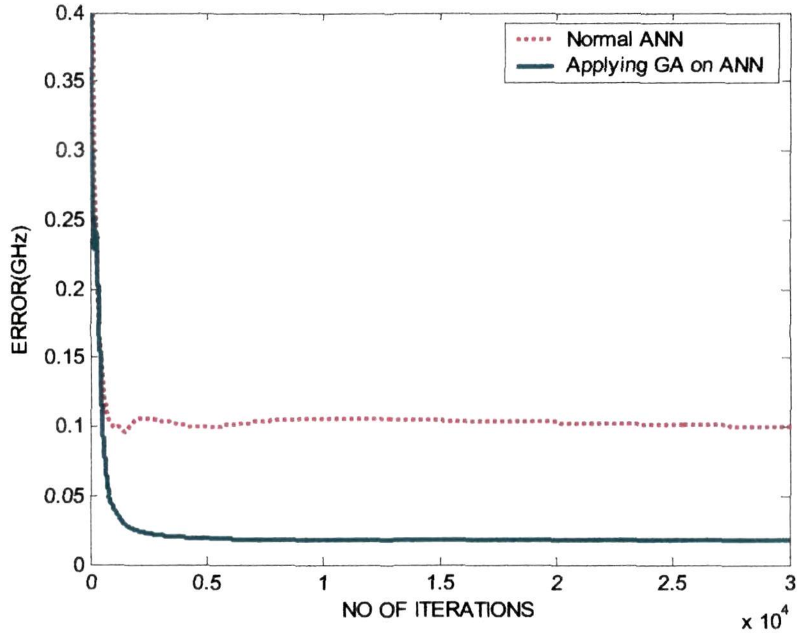

Fig. 5.10 No. of Cycles vs. Error

GA has been applied on back-propagation algorithm to calculate the resonant frequency of single shorting post tunable microstrip antenna. The presented technique to calculate resonant frequency of shorted microstrip antenna seems to be a simple, inexpensive and highly accurate method. Accuracy can be improved by choosing smaller error tolerance and/or training the network for more number of iterations while evaluating the fitness value. Further improvement to the model can be done by taking a multi layer network considering the number of hidden layers as another parameter to be optimized. This model can be used as a potential simulator technique for designing microstrip antennas.

5.5 Design of Knowledge-Based Continuous Genetic Algorithm and Its Application to Microstrip Patch Antenna Design and Analysis

Genetic Algorithm(GA) and Artificial Neural Networks(ANN) have been combined in a number of ways. One of the limitations of binary representation, in GA, is that the solution space depends on the precision chosen for the variable (weight of ANN) value. A higher precision increases the length of the chromosome. This reduces the effectiveness of crossover. Therefore, Continuous GA(CGA)[18,19] is preferred to train a neural network. The number of variables in CGA depends on the architecture of ANN. Instead of using the default crossover, a new type of *knowledge based recombination technique* is proposed here. Delta training rule of ANN is used for *knowledge based recombination*[20].

Initially, a set of weight set is randomly picked up. This is called as the initial population. The number of individuals/chromosomes gives the population size. Then they are fed to evaluation function that gives the fitness value of each individual. The fitness value is calculated in terms of the root mean squared error (E_{RMS}). It is given by

$$Fitness = \frac{1}{(1+E_{RMS})} \tag{5.6}$$

Proportionate selection is the most effective selection strategy. Theoretically the higher is the fitness value of an individual, the more is the probability of being selected of that individual. Based on this selection strategy, multiple copies of this population are selected for new generation. In each generation one of the training patterns is sequentially selected to compute the correction factor (Δw_i) for each weight(w_i) by using delta learning rule where, *i* represents the weight number. Then a number less than the length of chromosome(cross-point) is randomly chosen and the genes after the cross-point are computed by adding these correction factors as follows

$$w_i' = w_i + \Delta w_i \tag{5.7}$$

Finally, mutation is performed by simply inserting the new gene. This is done gene wise depending on the probability of mutation. Once it completes mutation, next generation starts repeating selection, knowledge-based recombination and mutation and it is continued till termination criteria is met.

In the present work, a knowledge based continuous genetic algorithm is used to train an artificial neural network to calculate resonant frequency of rectangular microstrip antenna(RMA) with shorting walls. The results obtained using present technique is close to experimental results with in less time.

The schematic diagram of the microstrip antenna with shorting wall is shown in figure 5.11.

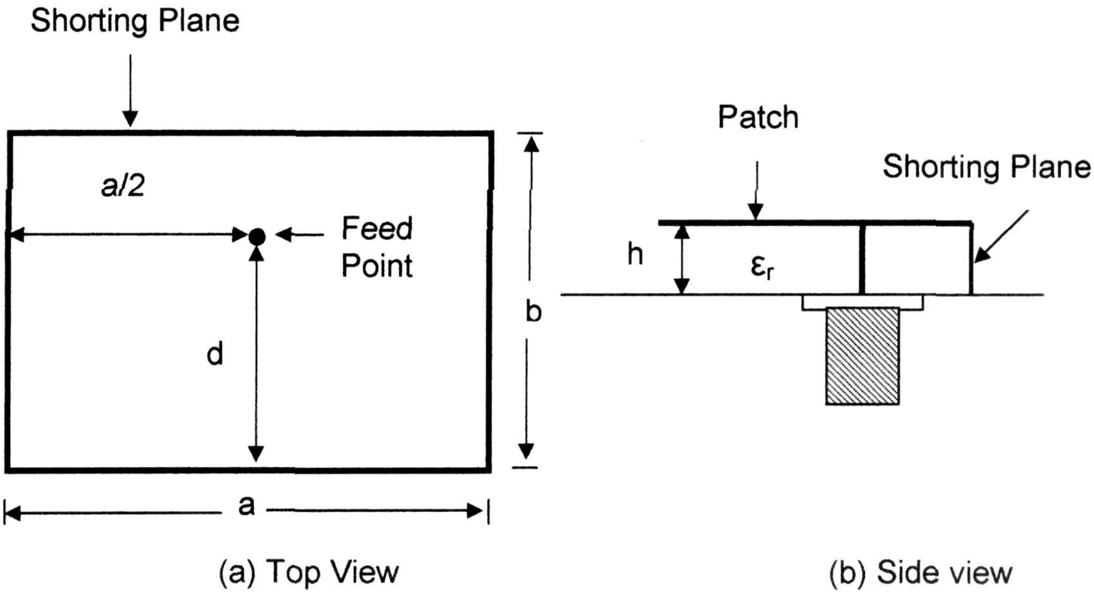

Fig. 5.11 Geometry of Shorted Wall Patch

The length(a), width(b), d/b, height(h) and permittivity of the dielectric substrate (ε_r) are taken as inputs to the network(figure 5.12) and resonant frequency as the output of the network. The experimental data are taken for training from [22].

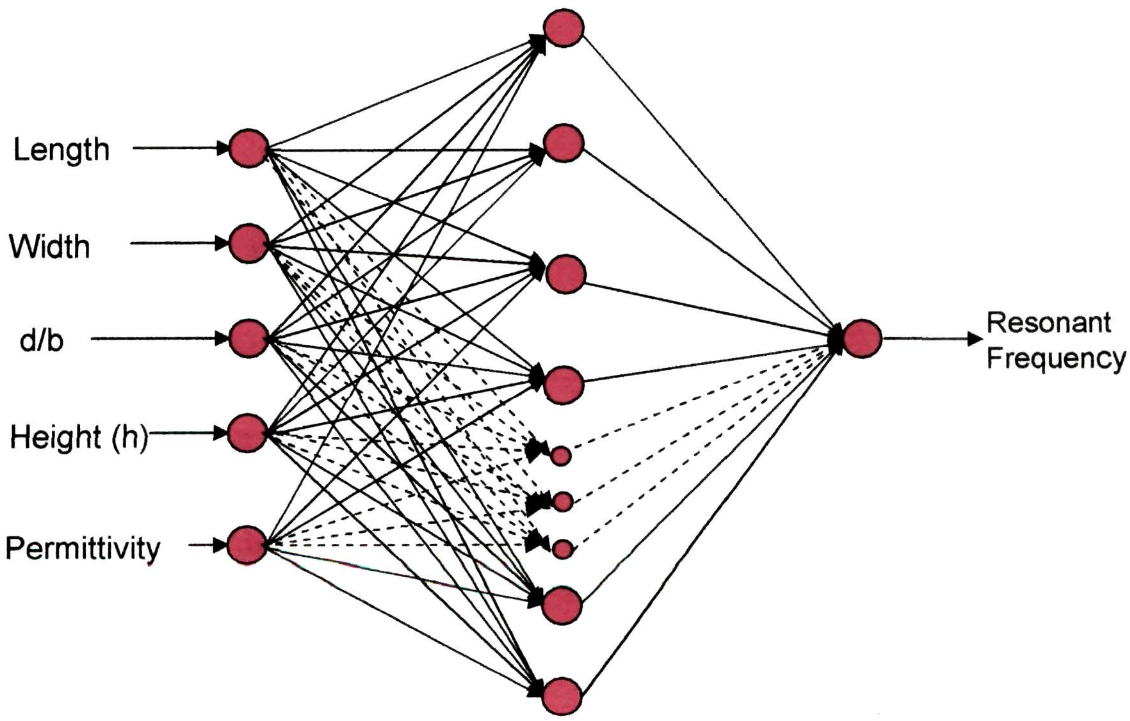

Fig. 5.12 Network Structure

While training ANN by CGA, the population size taken is 20 individuals, and the maximum number of generations is set at 15, 000. The probability of mutation is equal to 0.001. The length of chromosome or, the number of weights is 181 real numbers. Using present technique in a CGA the training time is 89 secs, while giving an average error of 0.023 GHz per training pattern. The results are shown in Table- 5.4.

Table 5.4. Resonant Frequency of a Microstrip Antenna Using Shorting Walls Applying CGA on ANN

a In mm	*b* In mm	d/b	*h* In mm	ε_r	$f_{r(EXPT)}$ In GHz	$f_{r(Present\ Method)}$ In GHz
3.06	3.06	0.65	4	1.08	2.11	2.129
3.06	6.12	0.75	2	1.08	2.20	2.118
3.06	6.12	0.65	5	1.08	2.15	2.163
2.4	1.6	0.78	3.2	2.32	2.89	2.890
1.9	1.25	0.81	0.8	4	2.95	2.949

5.6 Conclusion

In the first phase, this chapter presents the utility of GA in artificial neural networks to select the initial weights for efficient training of neural networks. By using this coupled technique, substantial amount of accuracy is achieved with less computational time. It reduces the simulation time to approximately half then the case where the initial weights are selected randomly. The proposed technique to calculate resonant frequency of shorted microstrip antenna is a simple, inexpensive and highly accurate method. Similar approach can also be extended to calculate resonant frequency where more then one shorting posts are present. This will reduce the experimental cost and computational time to a greater extent while giving accurate results.

In the second phase, Hidden node redundancy has been handled by taking different steepness of activation function for different neuron. Applying two-point crossover or uniform crossover and replacing simple GA by micro-GA[22-23], the computational time may be reduced. Further improvement can be done by considering architecture optimization.

In the third phase, GA is used to optimize the parameters of ANN to reduce the man-time while selecting appropriate values.

Finally, Continuous GA is used to train ANN. To improve its performance, a new crossover ie, *Knowledge Based Crossover* is proposed which is based on Delta learning rule. It is seen that the proposed recombination technique increases the convergence speed giving higher accuracy. This method is applied to calculate resonant frequency of rectangular microstrip antenna with shorting walls. The results are close to experimental findings.

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CHAPTER 6

APPLICATION OF GA COUPLED ANN ON FDTD

6.1 Introduction

In the previous chapter, GA is coupled with ANN in different ways to take advantages of their behavior. In this chapter, attempt is made to use time series prediction capability of temporal neural networks on FDTD, called NFDTD. Further, GA is coupled with the NFDTD and, applied in the analysis of a microstrip antenna.

The Finite-Difference Time-Domain(FDTD) method, first applied by Yee in 1966[1], is a simple and elegant way to discretise the differential form of Maxwell's equations. Yee used an electric-field(E) grid, which was offset both spatially and temporally from a magnetic-field(H) grid, to obtain update equations that yield the present fields throughout the computational domain, in terms of the past fields. The update equations are used in a leap-frog scheme.

As the cost of computation decreases and shortcomings of the original FDTD implementation were alleviated, FDTD gained interest. It has become an increasingly popular approach for analyzing the electromagnetic performance of antennas and microstrip devices. With transient excitation, it provides impedance and scattering parameters over a wide frequency band with one calculation by applying Fast Fourier Transformation(FFT). Reineix and Jecko[2] in 1989 were the first to apply the FDTD method to the analysis of microstrip antennas. Since then, many different configurations such as parasitically coupled patches [3], active antennas [4], two element arrays[5], and microstrip antenna mounted on curved surfaces[6] have been successfully analyzed with this approach. Wu *etal* considerably improved the modeling technique that enabled it to accurately characterize mulitalyer patch antennas with various feed structures such as microstrip, coaxial, and aperture coupled feeds[7,8].

However, It is well known that FDTD method requires long computational time for solving the resonant type of high-Q-passive structures. This is due to the fact the algorithm is based on the leap-frog technique. The computational cost shoots up in whole body simulation, computation of fields with in missile guidance section, SAR calculation of human head in presence of cell phone *etc*[9].

In this chapter Artificial Neural Network(FIR ANN)[8,10,11] is applied as a nonlinear predictor to predict time series signal for speeding up the FDTD simulations. The FIR NN is trained by temporal backpropagation learning algorithm. Neural network based FDTD(NFDTD)[12-17] has been implemented to calculate the parameters of patch antenna. One of the main advantages of NFDTD is less storage requirement. But for less number of time steps data collected from FDTD, the temporal neural network training time can exceed the normal FDTD computing time. On the other hand, the major disadvantage is that selection of parameters requires much man-time. Hence, GA has been used with NFDTD to speed up the simulation time while meeting the accuracy requirement.

6.2 Temporal Neural Networks

A temporal neural network is used for time series data prediction. A time series data consist of a sequence of values changing with time. Therefore, a memory structure is needed in the traditional neural network to change it from static to dynamic. This memory structure is incorporated in neural networks by introducing a Finite Impulse Response(FIR) in between the weights. i.e., weights are replaced by FIRs. The FIR network is feed forward neural network architecture with internal time delay lines[4]. It is a modification of the basic multi-layer network in which each weight is replaced by a FIR linear filter as shown in figure 6.1(a).

The coefficients of a synaptic FIR filter connecting neuron *i* to *j* is specified by the vector

$$w_{ji} = [w_{ji}(0), w_{ji}(1), \ldots., w_{ji}(p)]^T \tag{6.1}$$

And,

$$x_i(n) = [x_i(n), x_i(n-1), \ldots., x_i(n-p)]^T \tag{6.2}$$

denotes the vector of delayed states along the FIR.

Output of neuron *j* is given by[17]

$$s_j(n) = \sum_{k=0}^{p} w_{ji}(k) x_i(n-k) \tag{6.3}$$

For the filter, the output $y_j(n)$ corresponds to a weighted sum of past delayed values of the input as shown in figure 6.1(b).

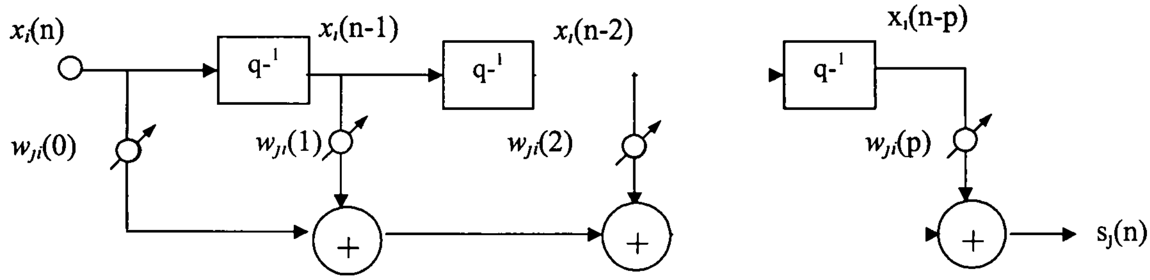

Fig. 6.1 (a) Filter Model of FIR Network

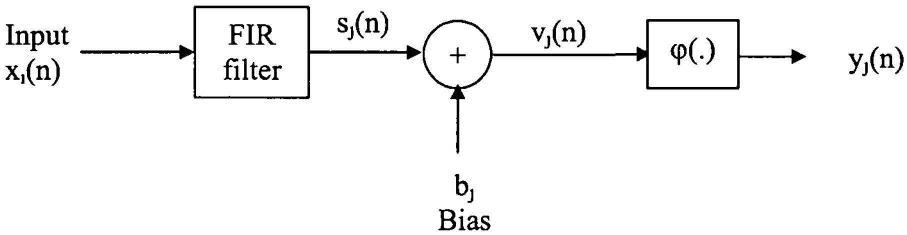

Fig. 6.1 (b) Output of a Neuron of FIR Network

The weights of the output layer neuron are updated as,

$$w_{ji}(n+1) = w_{ji}(n) + \eta \delta_j(n) x_i(n) \tag{6.4}$$

where, η is learning constant

$$\delta_j(n) = -\frac{\partial E_{total}}{\partial v_j} \tag{6.5}$$

$$E_{total} = \sum_{n} E(n) \tag{6.6}$$

$$E(n) = \frac{1}{2}\sum_{j} e_j^2(n) \tag{6.7}$$

$$e_j(n) = d_j(n) - y_j(n) \tag{6.8}$$

$d_j(n)$ =Desired output at time stem *n*(Obtained from FDTD).

The weights of the hidden layer neurons are updated as,

$$w_{ji}(n+1) = w_{ji}(n) + \eta\delta_j(n-p)x_i(n-p) \tag{6.9}$$

$$\delta_j(n-p) = \varphi'(v_j(n-p))\sum_{r\in A}\Delta_r^T(n-p)w_{rj} \tag{6.10}$$

$$\Delta_r(n-p) = [\delta_r(n-p), \delta_r(n+1-p), \ldots\ldots\ldots, \delta_r(n)]^T \tag{6.11}$$

Where, *A* is the set of all neurons whose inputs are fed by neuron *j* in a forward manner.

P is the order of each synaptic FIR filter

v_r denote induced local field of neuron *r* that belongs to the set *A*.

6.3 Application of NFDTD for the Calculation of S-Parameter of Microstrip Antenna

Application of FDTD saw a great degree of pros and cons during last decade. FDTD simulation time for higher frequency range is very large. In this work a novel technique is chosen to reduce the simulation time step. FDTD is coupled with ANN, that is why the name NFDTD. The NFDTD is applied to calculate the S parameter of a rectangular microstrip antenna as shown in figure 6.2. The dimensions of the rectangular microstrip antenna are Length 14.12 mm, Width 8.975 mm, height 2 mm, dielectric constant 2.55 and the patch is resonating at 6.13 GHz.

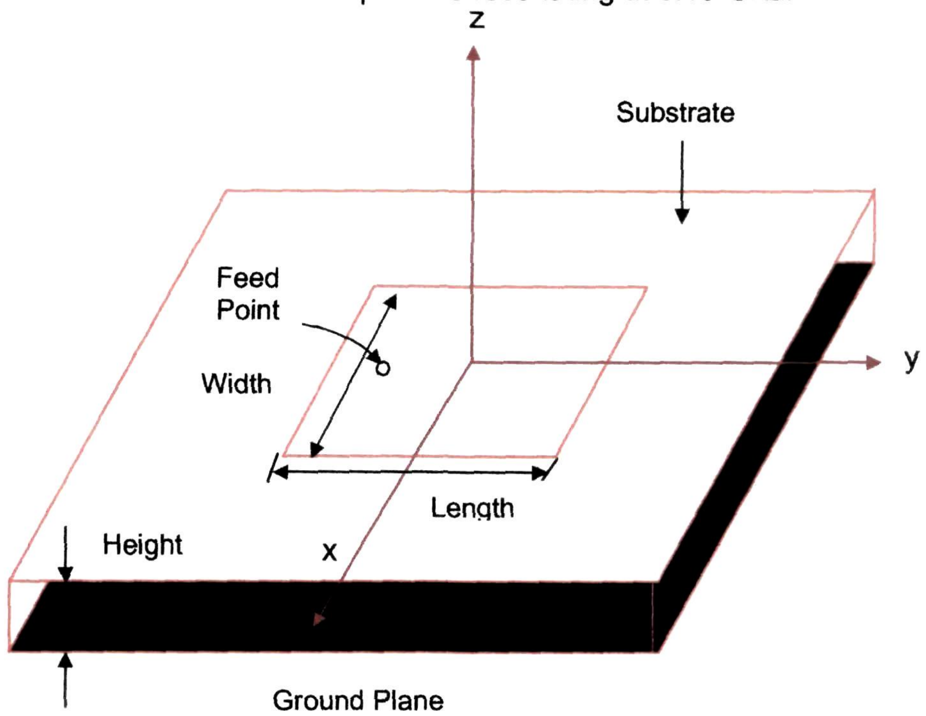

Fig. 6.2 Rectangular Patch Antenna

An Artificial Neural Network(ANN) whose each weights are replaced by coefficient of FIR filter can predict a time series easily[17]. The time series prediction capability of an FIR filter is well established, where the current inputs depend upon previous inputs and outputs. In this work the patch antenna is first simulated with help of FDTD Engine up to certain time steps(till the transient die down). The information is collected for that time steps, after the decay of transient, which in turn is fed to an ANN at the observation points for training. Figure 6.3 shows flow-chart of the NFDTD algorithm where as the architecture chosen for temporal neural networks is shown in figure 6.4.

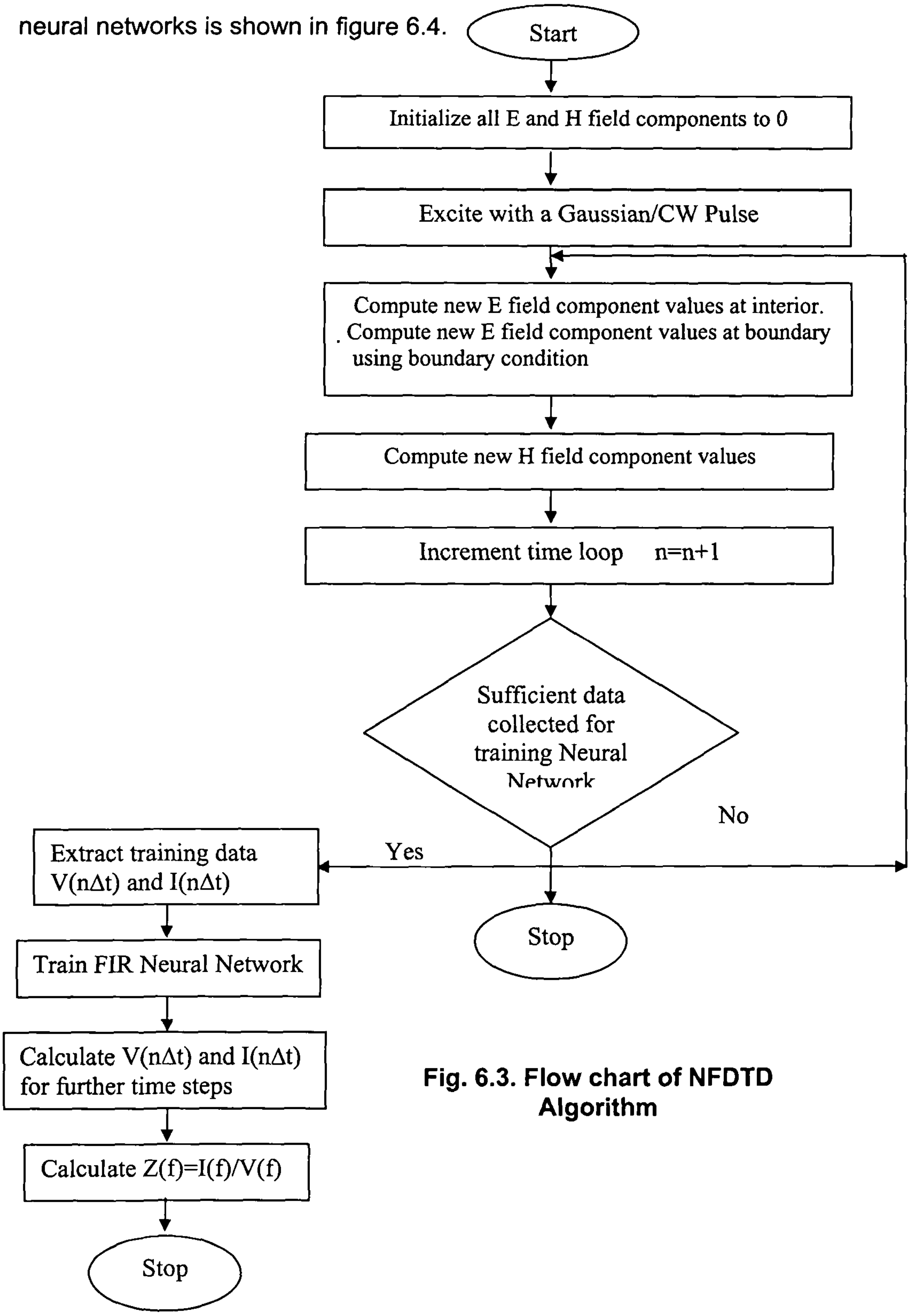

Fig. 6.3. Flow chart of NFDTD Algorithm

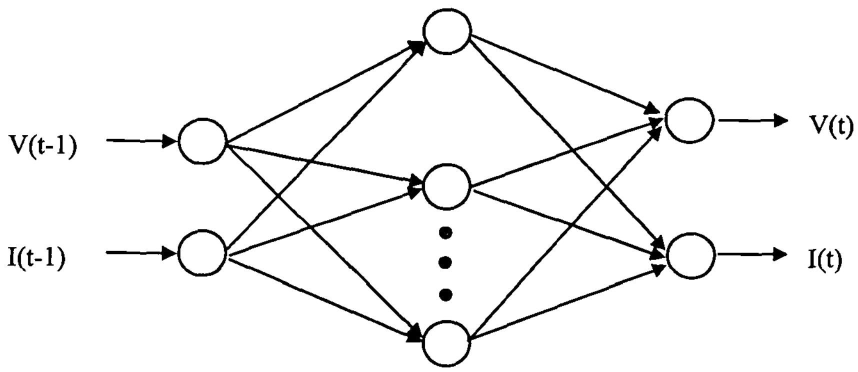

Fig. 6.4 FIR-Neural Network Architecture

The FDTD is similar to [19] except the boundary condition. A raised Gaussian pulse is used for excitation. The cell size is 0.5mm. The time step is 2.5 ps. Cells per wave length taken is 20. The dimension of the computational domain is 68x58x24. Patch dimension is 28x18. The FDTD is run up to 8000 time steps. After 1500 time steps from the beginning, for the next 3000 time step ANN is trained. The FIR-ANN parameters such as the number of hidden neurons, depth of memory, learning constant and momentum factor are chosen by hit and trial basis which depends purely on experience of the programmer. The FIR-ANN parameters are, Depth of memory in each FIR filters 60, No. of hidden neurons 40, Learning constant 0.821, Momentum factor 0.0001. Accuracy of the model depends upon the selection of those parameters. For the next 3500 time step the results are extracted form FIR-ANN. The current at an observation point with both the FDTD and NFDTD are as shown in figure 6.5.

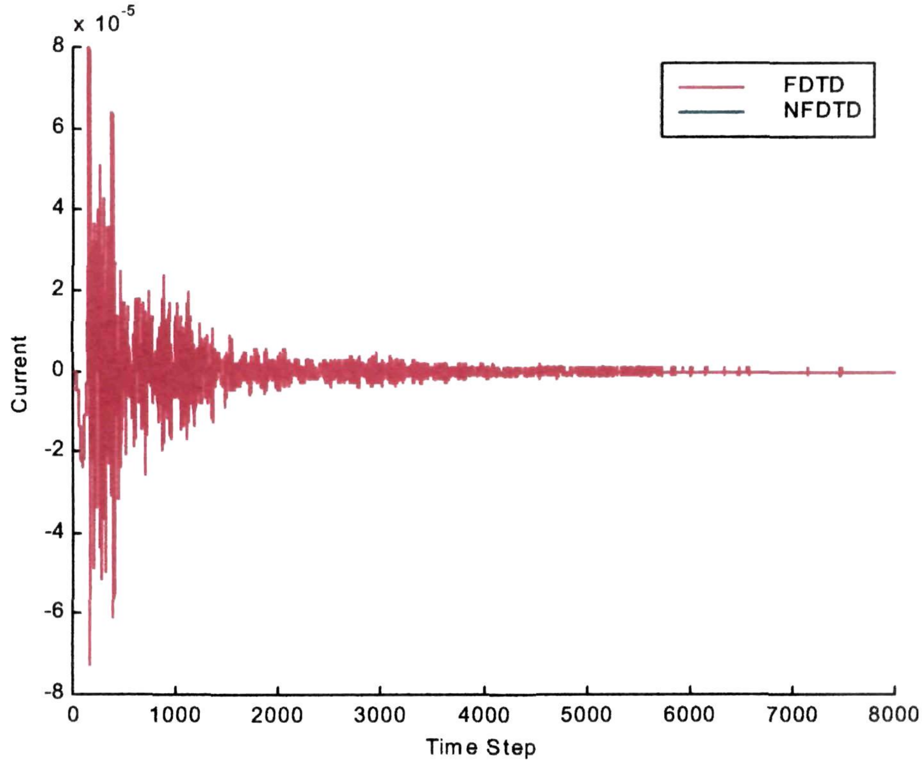

Fig. 6.5 No. of Time Step Vs. Current at an Observation Point

S parameters are studied using FDTD, NFDTD and with IE3D. The results obtained using NFDTD are better in terms of simulation time as shown in figure 6.6. The memory management of presented technique is better than FDTD at the expense of the code complexity.

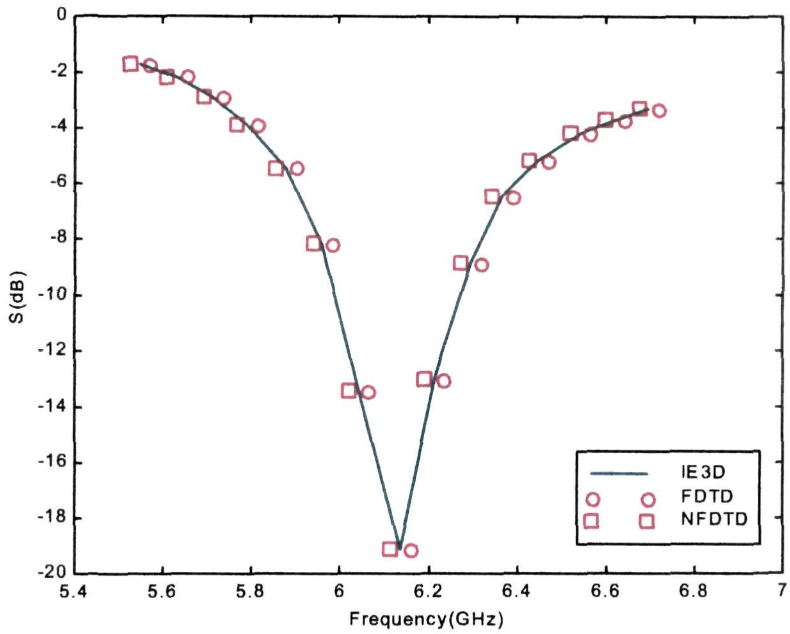

Fig. 6.6 S-Parameter of the Microstrip Antenna

A reduction of 3 minutes is achieved for the above problem. The method is suitable for the case where the simulation takes hours using FDTD. To further reduce computational time parallel simulation of FIR-ANN and FDTD can be done. This type of technique is employed to study Plant response. Optimization techniques can also be employed to select suitable architecture. The proposed technique will go a long way to use as a CAD technique.

6.4 GA Coupled NFDTD for Input Impedance Calculation

The objective of this section is to investigate the suitability of incorporating optimizing technique, GA with NFDTD for characterization of microstrip patch antenna. FIR-ANN has been used as a nonlinear predictor to predict time series signal for speeding up the FDTD simulations for calculating S-parameter of a microstrip patch antenna[17]. It has been observed that the man-time required finding a suitable architecture and parameter of NFDTD much more than the normal simulation time of FDTD engine. The NFDTD is approximating the voltage and current across the co-axial feed at different time steps in the co-axially fed square patch antenna for which the architecture and parameters of NFDTD are optimized by Continuous Genetic Algorithm. The GA-NFDTD is used to calculate the input impedance of the square patch microstrip antenna and the result is compared with those of the traditional FDTD, NFDTD and experimental result. It has been observed that the GA-NFDTD provides an accurate result with considerable reduction in computational time.

A coaxially fed square patch antenna as shown in figure 6.7, is considered to validate the technique. The dimensions of the patch antenna are side length L 10mm, dielectric constant(ε_r) 2.33, height of the substrate(h) 1.57 mm. The antenna is fed at 0.25 mm from corner(x_o=y_o=0.25mm).

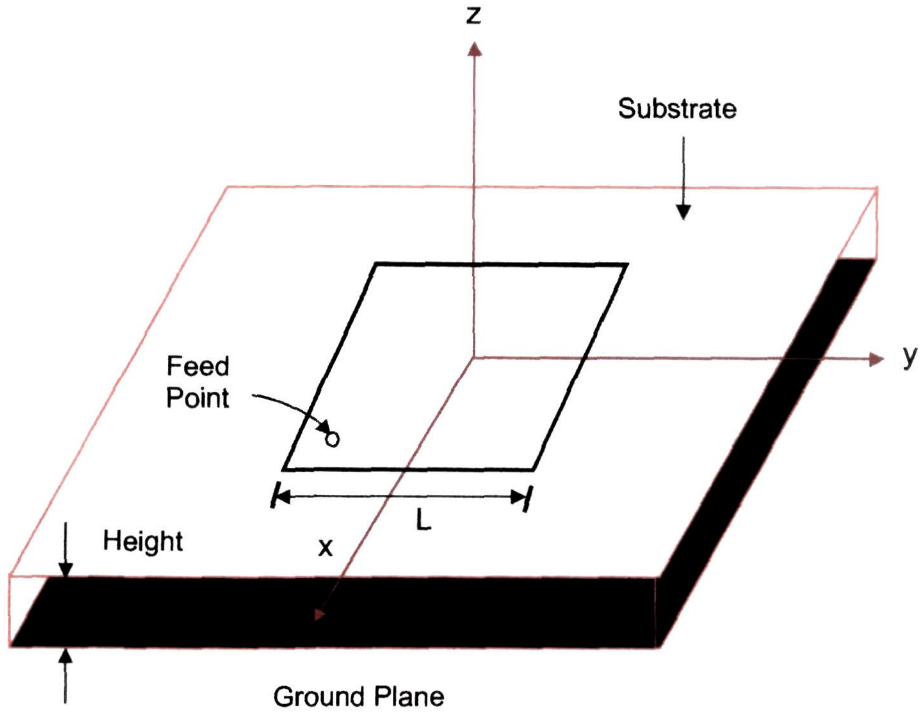

Fig. 6.7 Coaxially Fed Square Patch Antenna

To model the dimensions of the antenna, the space descritization is chosen to be Δx = Δy = Δz =0.25mm. The total mesh dimensions are 80x80x26. The time step used is Δt =0.48ps. The simulation is performed for 10000 time steps. The experimental result for comparison is taken from [20]. The antenna is fed using a z-directed electric field at (21 Δx , 21 Δy , 6 Δz) by a raised cosine pulse. The internal source resistance R_s is kept at 50 ohm. Transient current and voltage for 500 steps from the FDTD simulation are collected. The FIR based feed forward neural network is trained with data set comprising current and voltage with 500 samples.

Genetic algorithm found the optimized architecture in 24 generations. In each generation GA runs FIR-ANN for 100 cycles. The absolute error is set to 0.6. After obtaining the optimized architecture the FIR-ANN continued to obtain an absolute error tolerance level of 0.5.

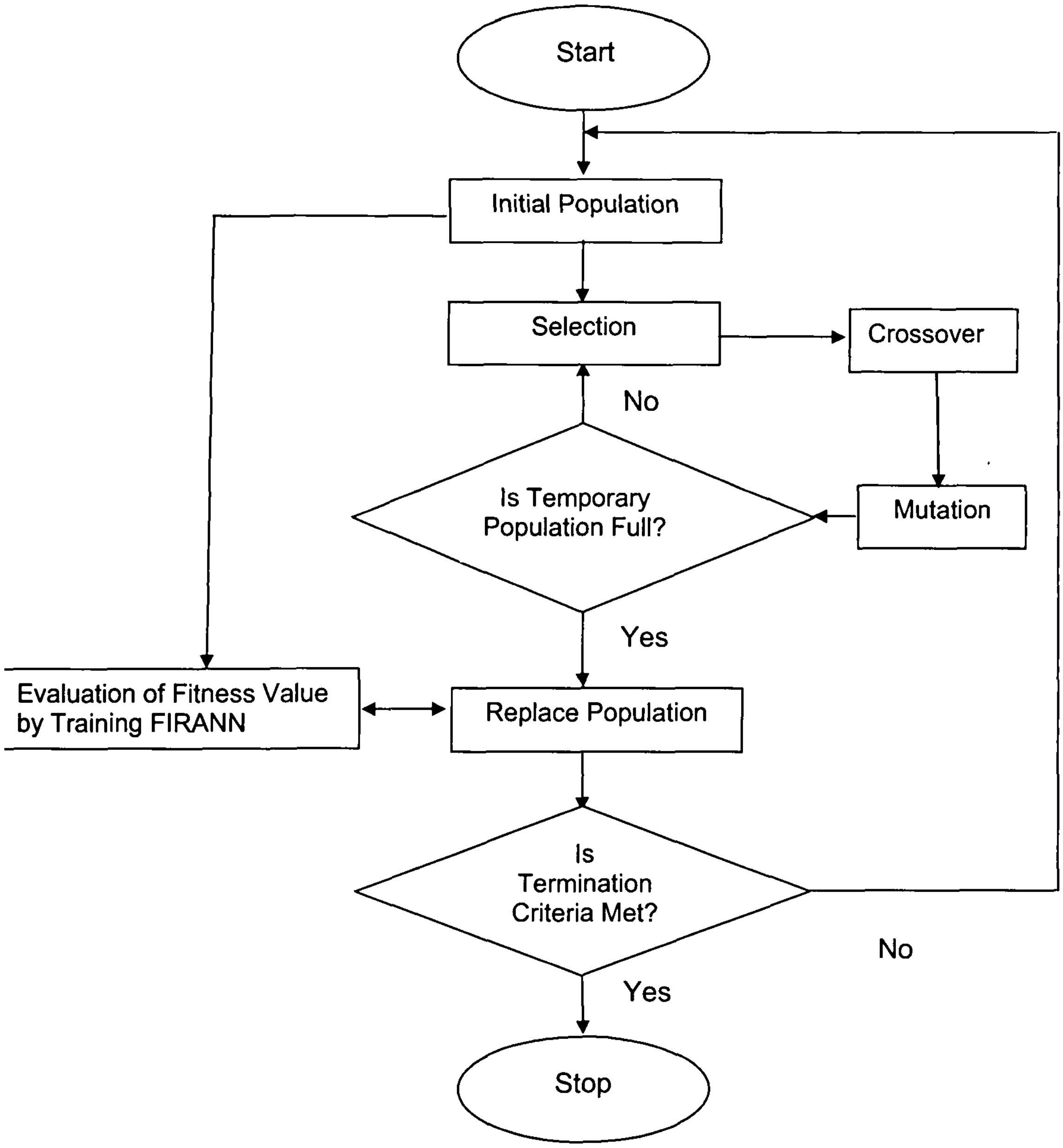

Fig. 6.8 Flow chart of GA-NFDTD Algorithm

The operation of the scheme is as shown in the flow chart figure 6.8.

The parameters of GA are set to as:

Population size: 20

Probability of crossover(P_{cross}): 0.7

Probability of mutation(P_{mut}): 0.001

The parameters found for training the FIR-ANN is as shown in table-6.1.

Table 6.1. Parameters of NFDTD Optimized by GA

Number of Hidden Neurons:	08
Depth of memory:	59
Learning Constant:	0.888519
Momentum factor:	0.0539589

The network is tested for 9500 samples. FFT is applied on 10, 000 samples(500 samples of FDTD and output of 9500 samples of NFDTD). Figure 6.9 shows the absolute error vs epoch curve. Figure 6.10 and 6.11 shows the comparison of Impedance for both real and imaginary part of FDTD, NFDTD and experimental result and GA-NFDTD result. GA-NFDTD results are close to experimental results[2].

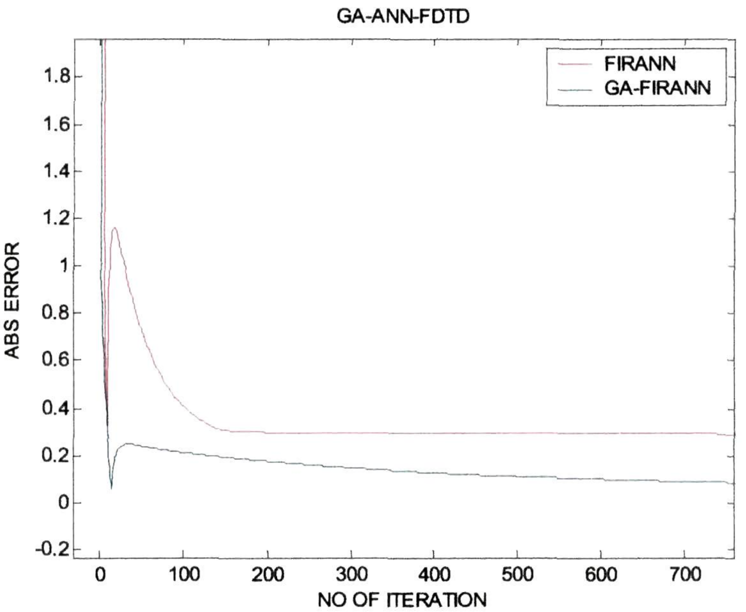

Fig. 6.9 Absolute Error vs. Epochs

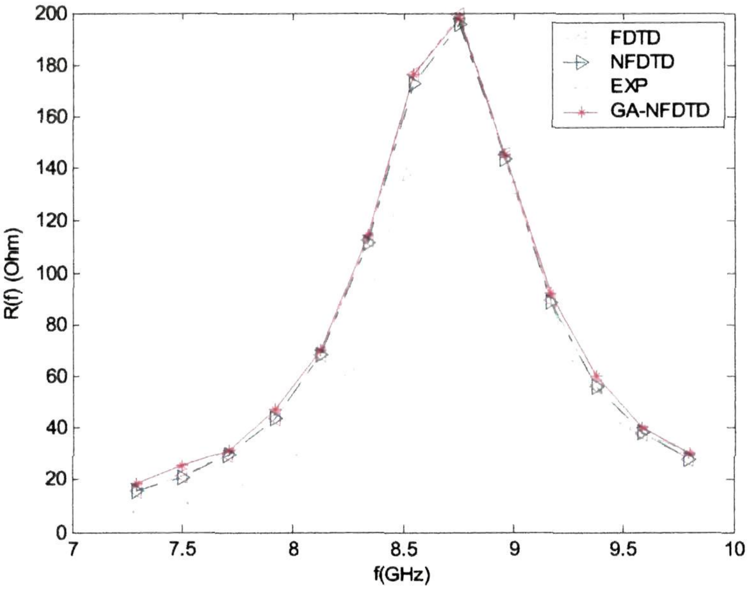

Fig. 6.10 Comparison of Input Impedance(Real) of FDTD, NFDTD and Measured Results of Square Patch Antenna

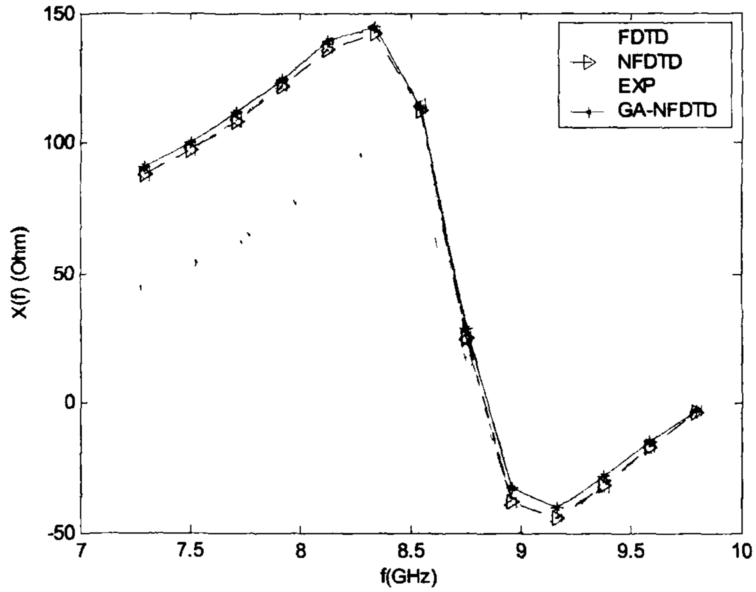

Fig. 6.11 Comparison of Input Impedance(Imaginary) of FDTD, NFDTD and Measured Results of Square Patch Antenna

The purpose of this work is to establish the suitability of ANN and GA with FDTD for analysis of electromagnetic problems. A co-axial feed square patch antenna is used to explain the implementation procedure. FDTD results for 500 time steps have been considered for training the FIR-ANN(NFDTD). GA decides the architecture and parameters of NFDTD by setting minimum training cycles. Once the parameters are decided, the network is further trained to reduce the error. Finally, for remaining time steps the current and voltage are calculated using trained-NFDTD. This technique will have immense potential when the number of time steps is more and for high-Q passive structures. One of the main advantages of NFDTD is storage requirement. When, the number of time steps is few, the training time can exceed the normal FDTD computing time. On the other hand, the major disadvantage is that selection of parameters requires too much man time. Hence, use of GA with NFDTD speeds up the simulation time[21].

6.5 Conclusion

In this chapter, time reduction is achieved for solving FDTD by using FIR-ANN. The method is suitable for the case where the simulation takes hours using FDTD. To further reduce computational time parallel simulation of FIR-ANN and FDTD can be done. An optimization technique can also be used to make the system faster by selecting proper architecture of the neural networks. This is also done in second phase of this chapter and applied the same to a square patch microstrip antenna. The purpose of this work is to establish the suitability of ANN and GA with FDTD for analysis of electromagnetic problems in time domain. FDTD results for 500 time steps have been considered for training the FIR-ANN(NFDTD). GA decides the architecture and parameters of NFDTD by setting minimum training cycles. Once the parameters are decided, the network is further trained to reduce the error. Finally, for remaining time steps, the current and voltage are calculated using trained-NFDTD. This technique will have immense potential when the number of time steps is more and for high-Q passive structures. The technique can further be improved by replacing GA by faster soft-computing algorithms like Particle Swarm Optimization(PSO), Bacterial Foraging Optimization(BFO) etc.

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CHAPTER 7

CONCLUSION AND FUTURE SCOPE

7.1 Conclusion

Recent trends of miniaturized microstrip antenna design and computational electromagnetic analysis demands efficient soft computing tools that give high accuracy with less computational time. In this scenario, genetic algorithm, neural networks and finite difference time domain technique have become good tools for the researchers. In this thesis, these tools have been used efficiently for the design of microstrip antennas.

In chapter 1, review of microstrip antenna analysis, genetic algorithm and artificial neural networks is presented. In chapter 2, detail of genetic algorithm and artificial neural network is described. In chapter 3, genetic algorithm has been used to design different regular structure microstrip antennas. In chapter 4, neural networks has been used to find out the resonant frequency of single shorting post microstrip antenna and also, a tunnel-based neural networks is used to find the radiation pattern of dual-band E-shaped microstrip antenna. Further, neural networks is used as fitness function of genetic algorithm and the proposed technique is applied to calculate resonant frequency of rectangular microstrip antenna on thick substrate.

In chapter 5, genetic algorithm is used to train artificial neural networks in a number of ways. First, genetic algorithm is used to find the initial weight set of neural networks. The proposed method is applied to find out resonant frequency of microstrip antenna. Then, the problem of competing convention is handled by choosing different steepness of activation function for different neuron while training. Genetic algorithm is also used to select the neural networks parameters while training by backpropagation algorithm. These methods have been used to find out resonant frequencies of microstrip antennas.

In chapter 6, a temporal neural networks is used to predict the time series data generated during simulation of finite difference time domain technique. This has been used to calculate s-parameter of microstrip antenna. Then genetic algorithm is incorporated with the proposed algorithm to select the FIR-neural network parameters during training. This method is used to calculate input impedance of microstrip antennas.

This thesis describes the benefits of soft computing fusion and its application to antenna design. The reduction in computational time, enhanced accuracy and simplicity are the main features of this thesis which are highly relevant in the present scenario of miniaturization and portability.

7.2 Future Scope

In this thesis, three computational techniques are used separately as well as by coupling them with one another. Therefore, this work can be extended by improving in two ways, ie by developing them individually and coupling them in more efficient ways. In case of design part of microstrip antennas, new better empirical formulas may be formulated that can give better accuracy while using those as fitness function of genetic algorithm. Genetic algorithm may be improved by taking new crossover and mutation operators in continuous micro-genetic algorithms. While coupling with neural networks and finite difference time domain technique, faster techniques like particle swarm optimization, bacteria foraging optimization etc. may be used. The proposed methods may be applied in wide range applications like calculation of radiation pattern, gain etc. of microstrip antennas. Apart from regular single element, some irregular structures may be investigated and antenna arrays may also be designed and analyzed by using proposed techniques.

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CALCULATION OF OPTIMIZED PARAMETERS OF RECTANGULAR MICROSTRIP PATCH ANTENNA USING GENETIC ALGORITHM

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ABSTRACT: *In this paper, the genetic algorithm (GA) has been applied to calculate the optimized length and width of rectangular microstrip antennas The inputs to the problem are the desired resonant frequency, dielectric constant, and thickness of the substrate, the outputs are the optimized length and width The antennas considered are electrically thin Method of moments (MoM) based IE3D software from Zealand Inc, USA, and experimental results are used to validate the GA-based code The results are in good agreement* © 2003 Wiley Periodicals, Inc Microwave Opt Technol Lett 37 431–433, 2003, Published online in Wiley InterScience (www interscience wiley com) DOI 10 1002/mop 10940

Key words: *genetic algorithm, rectangular microstrip antenna, resonant frequency*

INTRODUCTION

The rectangular microstrip antenna, due to its simple design features, is still currently popular in industrial and commercial applications However, due to its inherent narrow bandwidth, the resonant frequency or dimension of the patch antenna must be predicted accurately In this paper, the genetic algorithm (GA) is applied in order to calculate the design parameters such as length and width of these antennas

GA are search techniques based on biological genetics In recent years, GAs have gained popularity in electromagnetic applications, in which the number of variables tend to be higher, for their easy searching process, global optimality, searching-space independence, and probabilistic nature [1] GAs are capable of optimizing nonlinear multi-modal functions of many variables They require no derivative information and they robustly find global or very strong local optima Numerical experiments indicate that by using GA good solutions for difficult antennas can be obtained, quickly, comparable even to the time necessary for analytical methods such as steepest descent

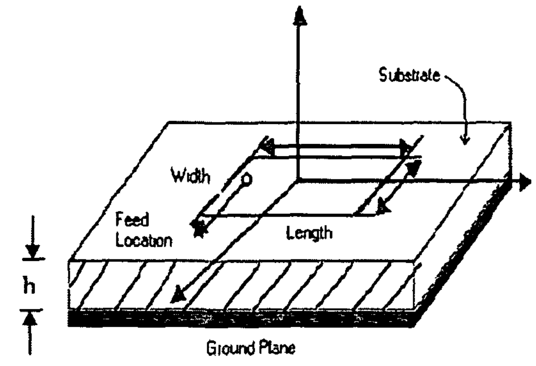

Figure 1 Rectangular patch antenna [Color figure can be viewed in the online issue, which is available at www interscience wiley com]

The length L, width W, height h, and feed-point location a for a rectangular microstrip antenna are shown in Figure 1 The fitness function used in GA to optimize the rectangular patch is taken from [2]

PROBLEM FORMULATION AND DEVELOPMENT OF THE MODEL

GA performs its searching process via a population-to-population (instead of point-to-point) search The most favored advantage of GA is its parallel architecture, which uses probabilistic and deterministic rules A member in a population, called a chromosome, is represented by a binary string comprised of 0, 1 bits Bits of the chromosome are randomly selected and the length of bit strings is defined in relevance An initial randomly generated population is required at first in order to start the methodology From the initial population, a child population is born and guided by three operators such as reproduction, crossover, and mutation Newborn child members are judged by their fitness function values The fitness function is formulated as per the ultimate goal concerned These child members act as parents in the next iteration In GA, the iteration is called a generation A detailed analysis of the methods and process of GA can be found in [3]

The resonant frequency of the rectangular microstrip antenna is

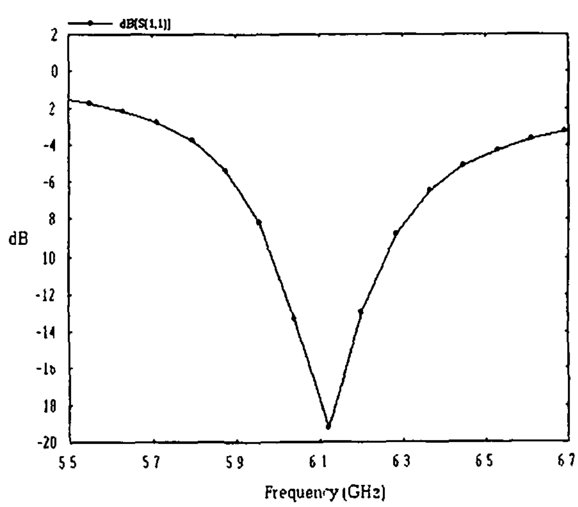

Figure 2 Return loss plot for antenna no 1

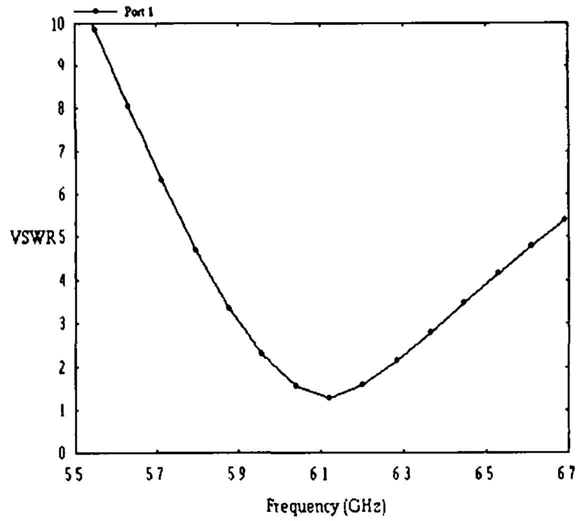

Figure 3 VSWR plot for antenna no 1

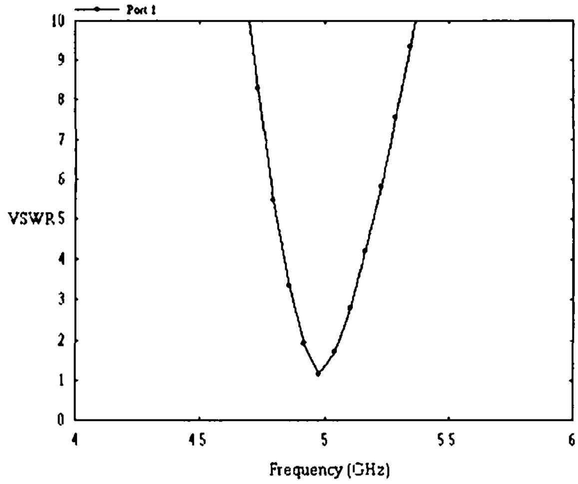

Figure 5 VSWR plot for antenna no 5

$$f_r = \frac{c_0}{2(L + \Delta W)\sqrt{\varepsilon_e(W)}}, \qquad (1)$$

where c_0 is the velocity of the electromagnetic waves in free space and $\varepsilon_e(W)$ is the effective dielectric constant, which is given by

$$\varepsilon_e(W) = \frac{\varepsilon_r + 1}{2} + \frac{\varepsilon_r - 1}{2\sqrt{1 + 10h/W}}, \qquad (2)$$

and ΔW is the line extension and is given by

$$\Delta W = 0\ 412h \frac{[\varepsilon_e(W) + 0\ 300](W/h + 0\ 264)}{[\varepsilon_e(W) - 0\ 258](W/h + 0\ 813)} \qquad (3)$$

Eq (1) is used as the fitness function The two independent variables are the length L and width W The population size is taken to be 20 individuals, and 200 generations are produced The probability of crossover is set at 0 25, while the probability of

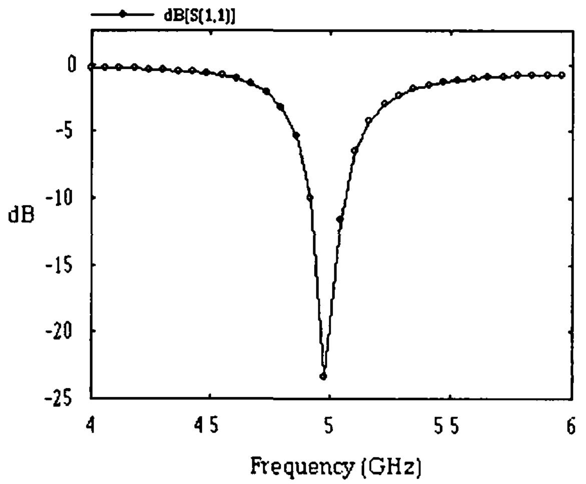

Figure 4 Return loss plot for antenna no 5

mutation is equal to 0 01 Thus, it is suitable for the calculation of the resonant frequencies for antenna elements with $h \leq 0\ 0815\lambda_d$ Hence, in this paper, we have used Eq (1) for designing antennas with thin substrates

Resonant frequency f_r, dielectric constant ε_r, and thickness of the substrate h are given as inputs to GA, which gives the optimized values for the length and width of the antennas The optimized lengths L obtained using GA are in good agreement with the experimental results, as listed in column VII of Table 1 Using these calculated parameters (L, W, h, and ε_r) in IE3D simulation software, resonant frequencies, which almost match the input resonant frequencies considered, are calculated, thus, validating the results of GA The theoretical results obtained by GA and results obtained by the IE3D software are listed in Table 1 for seven different rectangular microstrip antennae

CONCLUSION

Using simultaneous variation of the length and width of a microstrip antenna to obtain optimized length and width, in order calculating the resonant frequency of said antenna that will match the experimental resonant frequency, is a computationally tedious and time-consuming process As seen from Table 1, by using GA, this can be achieved without much computational time In this paper, only seven antennas are optimized to validate the code developed using GA IE3D software and experimental results are used to compare and validate the results obtained by GA The return-loss plot and VSWR plot obtained using the IE3D simulation package for two antennas are also presented These results are in good agreement with those of experimental results Thus, application of GA to calculate the optimized length and width of microstrip antennas seems to be an accurate and simple method This will contribute to helping facilitate improved antenna designs, especially for small pack antenna systems where, due to space limitations, both length and width are to be adjusted simultaneously in order to achieve the required resonant frequency

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TABLE 1 Resonant Frequency Results and Dimensions for Rectangular Microstrip Antennae

I Antenna No	II Theoretical Resonant Frequency (f_r) in GHz as Input	III Permittivity of Substrate (ε_r) as Input	IV Height (h) in mm as Input	V Calculated Length (L) in mm Using GA as Output	VI Calculated Width (W) in mm Using GA as Output	VII Experimental Length (L) in mm from [1]	VIII IE3D Simulated Resonant Frequency (f_r) in GHz Using Calculated (L and W as in V and VI)
1	6.2	2.55	2.0	14.382	8.975	14.12	6.13
2	8.45	2.22	0.17	11.867	9.456	11.85	8.32
3	7.74	2.22	0.17	12.9	19.337	12.9	7.6
4	3.97	2.22	0.79	25.306	13.007	25	3.92
5	5.06	2.33	1.57	18.6	18.4	18.6	4.98
6	5.6	2.55	1.63	16.07	13.34	16.21	5.3
7	4.805	2.33	1.57	19.573	21.696	19.6	4.6

The return loss and VSWR plots calculated using IE3D Simulation Software for antenna number 1 are shown in Figs. 2 and 3, respectively, Figs. 4 and 5 show that of antenna number 5.

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IMPROVED RITZ–GALERKIN METHOD FOR FIELD DISTRIBUTION OF GRADED-INDEX OPTICAL FIBERS

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ABSTRACT: *Having obtained the eigenvalue and the modal field by using the Ritz–Galerkin method, we quit the cladding-field expression in the form of a Laguerre–Gaussian function and reconstruct it with a modified Bessel function. The accuracy of the cladding field is thus improved. We also show its application to the calculation of the coupling coefficient.* © 2003 Wiley Periodicals, Inc. Microwave Opt Technol Lett 37: 433–436, 2003; Published online in Wiley InterScience (www.interscience.wiley.com). DOI 10.1002/mop.10941

Key words: *optical fibers; modal fields; Laguerre–Gauss expansion; coupling coefficient*

1. INTRODUCTION

In order to properly design and use an optical-fiber link, the propagation characteristics and field distributions of the propagating modes in the optical fiber must be known. An accurate description of the transverse field of the mode propagating in such fibers is essential for characterisation and the evaluation of splice loss, microbending loss, coupling coefficients, and so on.

Except for a few special refractive index profile shapes that allow explicit field solutions, the guided modes capable of propagating along the fiber must be determined by approximate methods, such as the perturbation method [1, 2], the WKB method [3, 4] or the variational method [5–10], which are reviewed in [11].

The perturbation method gives good results only if the refractive index profile of the fiber is very close to that of the fiber for which the exact modes are analytically known, while the WKB method gives accurate results only for multimode fibers. Among variational methods, approximation [5] is very simple, but its accuracy is not sufficiently high, especially for modal fields. Other analytical formulas, such as the Gaussian-exponential approximation [7, 9, 10] and the Gaussian–Hankel approximation [8], have been shown to give quite accurate results for both the fundamental mode field and the propagation constant at low V values. However, they need two-parameter optimisation and cannot be applied to multimode optical fibers.

There are numerical methods, for example, Rayleign–Ritz method [12], power-series expansion method [13], finite element method [14], staircase approximation method [15], and so on. Though numerical methods are exact methods, they usually are cumbersome and take more computation time. The Ritz–Galerkin method [16] or variational method [17], using Laguerre–Gaussian basis function, seem to have both merits of simplicity and accuracy. Because these basis functions approximate the electromagnetic field very well, only a few terms are needed. Besides, finding the eigenvalues and eigenvactors can be easily done by a routine program for a square matrix. However, there is one drawback: the Gaussian function behavior of the basis function allows the modal field in cladding to decay too quickly, thus it is only a good approximation in the core region [18]. Although the modal field in the core region is accurate enough, if a few terms used, the accuracy of the cladding field is poor. Certainly, we can add more terms, but this will require more computation time and the convergence of the cladding field will occur much more slowly with increasing terms.

In this paper, we present an improvement on the Ritz–Galerkin method by expressing the core field with a Laguerre–Gaussian function and the cladding field with a modified Bessel function, respectively. Having obtained the eigenvalue and the modal field by using the Ritz–Galerkin method, we quit the cladding field expression in the form of a Laguerre–Gaussian function and reconstruct it with a modified Bessel function. In this way, the accuracy for cladding field is improved and the cladding field

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A SIMPLE AND EFFICIENT APPROACH TO TRAIN ARTIFICIAL NEURAL NETWORKS USING A GENETIC ALGORITHM TO CALCULATE THE RESONANT FREQUENCY OF AN RMA ON THICK SUBSTRATE

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ABSTRACT: *Both genetic algorithms (GAs) and artificial neural networks (ANNs) have been used in the field of computational electromagnetics as the most powerful optimizing tools In this paper, a simple and efficient method is presented to handle the problem of competing convention while training an ANN by using a GA This technique is applied to calculate the resonant frequency of a thick-substrate rectangular microstrip antenna (RMA) The training time is less than that of a normal feed-forward backpropagation algorithm. The measured results are in very good agreement with experimental results* © 2004 Wiley Periodicals, Inc Microwave Opt Technol Lett 41 313–315, 2004, Published online in Wiley InterScience (www interscience wiley com) DOI 10 1002/mop 20126

Key words: *genetic algorithm, artificial neural networks, problem of competing conventions, microstrip antenna, resonant frequency*

1. INTRODUCTION

A genetic algorithm (GA) is a global search method based on a natural-selection procedure that consists of genetic operators such as selection, crossover, and mutation GA optimizers are particularly effective in a high-dimension, multimodal function, in which the number of variables tends to be higher, for their easy searching process A GA performs its searching process via population-to-population (instead of point-to-point) search GAs are robust due to their parallel architecture They use probabilistic and deterministic rules A member in a population, called a chromosome, is represented by a binary string comprising 0, 1 bits Bits of the chromosome are randomly selected and the length of bit strings is defined according to relevance An initial randomly generated population is required, at first, to start the methodology From the initial population, a child population guided by three operators (such as reproduction, crossover, and mutation) is born Newborn child members are judged by their fitness-function values These child members act as parents in the next iteration [1, 2]

Since the last decade, application of ANNs is taking place in electromagnetics due to their versatile features and ease of implementation [3, 4] A normal feed-forward backpropagation algorithm [5] is widely used in electromagnetic applications because of its ease of implementation and low computational cost However, selection of a suitable architecture and parameters such as the number of hidden neurons, steepness of activation function, momentum factor, learning constant, and so forth is a cumbersome job Hence, combination of GAs and ANNs in various ways is a current problem of research GAs are applied to the design of ANNs in a number of areas [6] Most importantly, they are applied in weight optimization and architecture optimization But, especially, for long chromosomes, the problem of competing conventions almost destroys the crossover operator, the most important operator in a GA This is why it takes a huge amount of computational time to train a neural network using a GA However, in this paper, an attempt has been made to overcome this limitation

2. PRESENT APPROACH

When a GA is used for weight optimization, its performance is gradually reduced with an increase in chromosome length [7] This is because of the permutation problem, namely, hidden node redundancy and hidden layer redundancy Literature shows that, for a network with n hidden nodes, there are $2^n\ n!$ functionally equivalent but structurally different representations, if the activation function is odd, and otherwise there are $n!$ different representations This increases the solution space, which leads to a high computational cost However, using an even activation function, hidden node redundancy can be overcome To handle the hidden layer redundancy, either it is ignored, or the crossover is removed from the GA, which is not the correct solution [8]

In this paper, a GA has been used for connection-weight determination, taking the hidden layer redundancy into consideration If a hidden neuron, with all its incoming and outgoing connections, is exchanged with another neuron with all its incoming and outgoing connections, we have a different structural representation of the ANN However, the ANN remains functionally the same, which results in hidden layer redundancy To make them functionally different, the network should be chosen so that, for the same input, each node would give a different output after applying the activation function This is possible if we choose different values for the activation-function steepness λ for each node

3. RESONANT FREQUENCY OF RMA ON THICK SUBSTRATE

Because of advantages like low profile, low cost, light weight, conformal structure, and ease of fabrication, the rectangular microstrip antenna (RMA) has become popular in industrial applications The length L, width W, height h, permittivity ε_r of the substrate, and the feed-point location a for a typical thick RMA are shown in the Figure 1 Since its bandwidth is narrow, the resonant frequency must be predicted accurately The simplest method to increase the bandwidth is to increase the substrate thickness Existing formulas can the predict resonant frequency with good

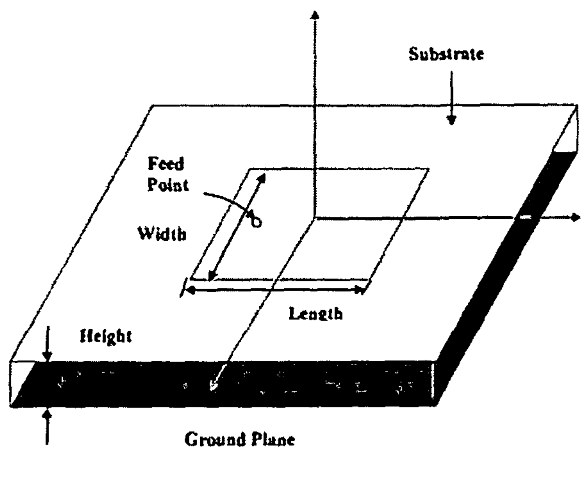

Figure 1 Rectangular microstrip antenna on thick substrate [Color figure can be viewed in the online issue, which is available at www interscience wiley com]

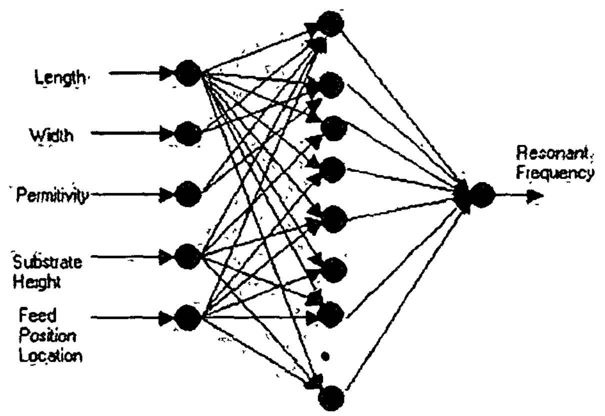

Figure 2 Network structure. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com.]

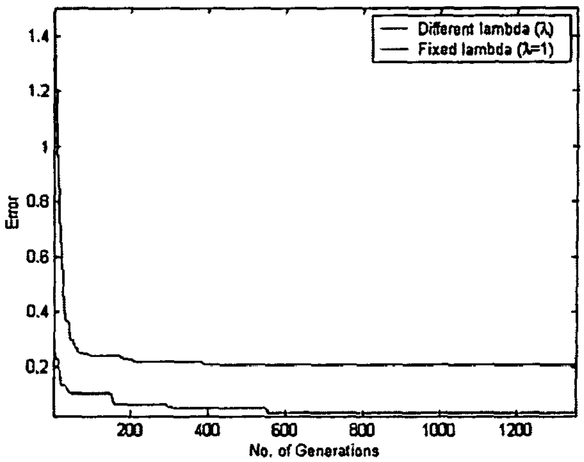

Figure 3 Number of generations vs. error. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com.]

accuracy when the antenna substrates are electrically thin [9, 10]. But when the thickness increases, the predicted resonant frequency diverges from its experimental value. ANNs are well suited for such a situation.

The resonant frequency of a microstrip patch antenna depends mainly on its length, width, thickness, feed-point location, and permittivity of the substrate. Thus, these five parameters are taken as input and the resonant frequency f_r is considered as the target output for training the designed neural network. The $5 \times 20 \times 1$ network is shown in Figure 2.

A GA has been used to find the optimized weight set. A logarithmic sigmoid function is used as activation function, which is expressed as

$$f(x) = \frac{1}{1 + e^{-\lambda(x)}}, \qquad (1)$$

where λ is the steepness of activation function, chosen separately for different hidden nodes.

The E_{RMS} error of a multilayer neural network that gives the fitness value, can be written as

$$E(w) = \frac{1}{2}\left(\sum_{p=1,P}\sum_{q=1,N^L}(u_q^L(x_p) - d_q(x_p))^2\right), \qquad (2)$$

where u_j^l is the output of j^{th} node in layer l, $w_{j,k}^l$ is the weight connecting the j^{th} node in layer l to the k^{th} node in layer $l-1$, x_p is the p^{th} training sample, $d_q(x_p)$ is the desired response of the j^{th} output node for the p^{th} training sample, N^l is the number of nodes in layer l, l is the number of layers, and p is the number of training patterns. In the above notation, $u_o^l = 1$ and $w_{j,0}^l$ represents the bias weights, where $l \neq 1$.

The population size is taken 30 individuals. It took 1395 generations to achieve the accepted error tolerance. The probability of crossover is set at 0.30, while the probability of mutation is equal to 0.01. The algorithm presented in [1] is the GA used to train the network. Twelve out of 17 patterns from [9] are taken for training and the rest are taken to test the result.

4. NUMERICAL RESULTS AND DISCUSSION

While training ANNs by using a GA and keeping the steepness of activation (with $\lambda = 1$) fixed, the error becomes saturated above the desired error tolerance after a certain number of generations of the GA. By taking different values of steepness of activation λ for different hidden nodes, the error continues to be reduced with the number of generations. Figure 3 shows the graph of the number of generations versus E_{RMS} error for both cases.

The average error per pattern for the five patterns is found to be 0.02257 GHz. The time taken for training the network is 122 s. The same network is trained by a normal feed-forward backpropagation algorithm. The network parameters used are $\lambda = 1$, learning constant $\eta = 0.08$, and momentum factor $\alpha = 0.205$.

The average error per pattern for those five patterns is found to be 0.0457 GHz, whereas the training time is 181 s. The graph of the number of training cycles versus E_{RMS} error for normal feed-forward backpropagation is shown in Figure 4.

A comparison of the results obtained by using the present method, experimental resonant frequency, and normal feed-forward backpropagation is shown in Table 1.

5. CONCLUSION

In this paper, the connection weights of an ANN are optimized by using a GA, taking the competing-convention problem, specifi-

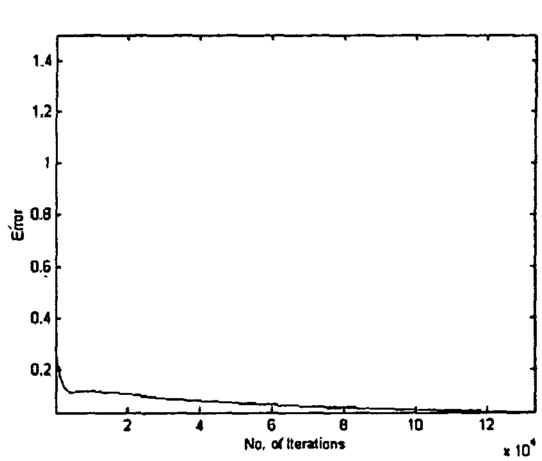

Figure 4 Number of cycles vs. error. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com.]

TABLE 1 Comparison of the Results of Using the Present Method, the Feed-Forward Backpropagation Algorithm, and *Experimental Resonant Frequency*

Patch No	Experimental Resonant Frequency (GHz)	Resonant Frequency (GHz) (Present Method)	Resonant Frequency (GHz) (Backpropagation Algorithm)
1	5 820	5 82515	5 79649
2	4 660	4 67353	4 52594
3	3 980	3 95329	3 93908
4	3 900	3 87665	3 91498
5	2 980	3 02413	2 99279

cally, the hidden-node redundancy into consideration In a gradient-descent feed-forward backpropagation method, there is a chance that the solution may be trapped by local minima, which does not happen in the case of the GA Hence, the present algorithm of training ANNs by using a GA takes advantage of the population-to-population GA search Hidden-node redundancy has been handled by taking different values of the steepness of activation function Applying two-point crossover or uniform crossover and replacing simple the GA by a micro-GA, the computational time may be reduced Further improvement can be done by considering architecture optimization This model can be used as a CAD model for antenna design

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A NEW CONDITION TO IDENTIFY ISOTROPIC DIELECTRIC-MAGNETIC MATERIALS DISPLAYING NEGATIVE PHASE VELOCITY

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ABSTRACT: *The derivation of a new condition for characterizing isotropic dielectric-magnetic materials exhibiting negative phase velocity, and the equivalence of that condition with previously derived conditions, are presented* © 2004 Wiley Periodicals, Inc Microwave Opt Technol Lett 41 315–316, 2004, Published online in Wiley InterScience (www interscience wiley com) DOI 10 1002/mop 20127

Key words: *negative phase velocity, power flow*

1. INTRODUCTION

Nondissipative media with both simultaneously negative permittivity and permeability were first investigated by Veselago [1] in 1968 These media support electromagnetic-wave propagation, in which the phase velocity is antiparallel to the direction of energy flow, and other unusual electromagnetic effects, such as the reversal of the Doppler effect and Cerenkov radiation After the publication of Veselago's work, more than three decades went by before the actual realization of artificial materials that are effectively isotropic, homogeneous, and possess negative real permittivity and permeability in some frequency range [2, 3]

A general condition for the constitutive parameters of an isotropic dielectric-magnetic medium to have phase velocity directed oppositely to the power flow, when dissipation is included in the analysis, was reported about two years ago [4] Most importantly, according to that condition, the real parts of both the permittivity and the permeability need not be both negative

In this paper, we derive a new condition for characterizing isotropic materials with negative phase velocity Although this new condition looks very different from its predecessor [4], we also show the equivalence between both conditions

2. THE NEW CONDITION

Let us consider a linear isotropic dielectric-magnetic medium characterized by complex-valued relative permittivity and relative permeability scalars $\varepsilon = \varepsilon_r + i\varepsilon_i$ and $\mu = \mu_r + i\mu_i$ An $\exp(-i\omega t)$ time dependence is implicit, with ω as the angular frequency

The wave equation gives the square of the complex-valued refractive index $n = n_r + in_i$ as

$$n^2 = \varepsilon\mu \Rightarrow n_r^2 - n_i^2 + 2in_rn_i = \mu_r\varepsilon_r - \mu_i\varepsilon_i + i(\mu_i\varepsilon_r + \mu_r\varepsilon_i) \tag{1}$$

The sign of n_r gives the phase-velocity direction, whereas the sign of the real part of n/μ, given by

INVERTED L-SHAPED AND PARASITICALLY COUPLED INVERTED L-SHAPED MICROSTRIP PATCH ANTENNAS FOR WIDE BANDWIDTH

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ABSTRACT: *Coax-fed inverted L-shaped microstrip antennas and parasitically coupled inverted L-microstrip antennas are presented. The inverted L-shaped microstrip antenna gives an impedance bandwidth of 30.6%, which is increased to 33.7% by parasitic coupling. The bandwidth has been achieved with a substrate thickness of 2 mm. Radiation patterns and gains are also studied and presented.* Microwave Opt Technol Lett 42: 190–192, 2004; Published online in Wiley InterScience (www.interscience.wiley.com). DOI 10.1002/mop.20248

Key words: *inverted L-microstrip antenna; parasitically coupled; radiation pattern; wide bandwidth*

INTRODUCTION

Microstrip antennas in various forms and geometries have been extensively used in many applications [1, 2]. In the recent past, significant work has been reported on small size, broadband width, and suitable polarization of microstrip antennas for wireless communication systems. To enlarge the inherent narrowband width of microstrip patch antennas, a large number of techniques have been proposed. The use of thick substrate, stacking, and so on, is among the acceptable techniques in broadband design. In this paper, the authors have successfully generated a wide-bandwidth 30.6% impedance bandwidth and a 26.5% pattern bandwidth by the asymmetric feeding of an inverted L-microstrip patch antenna in its narrow side. The large bandwidth has been achieved on a substrate thickness of 2 mm (thin substrate) without any stacking or parasitic elements. Upon seeing the current distribution of the inverted L-microstrip patch, a parasitic strip is placed on the side of the notched edge to compensate the reactance component in order to generate further wideband width. An impedance bandwidth of 33.7% and a pattern bandwidth of 33.7% are achieved by this method while occupying a space similar to that of a rectangular microstrip antenna. The size of the antenna is also 1/3rd of the wavelength.

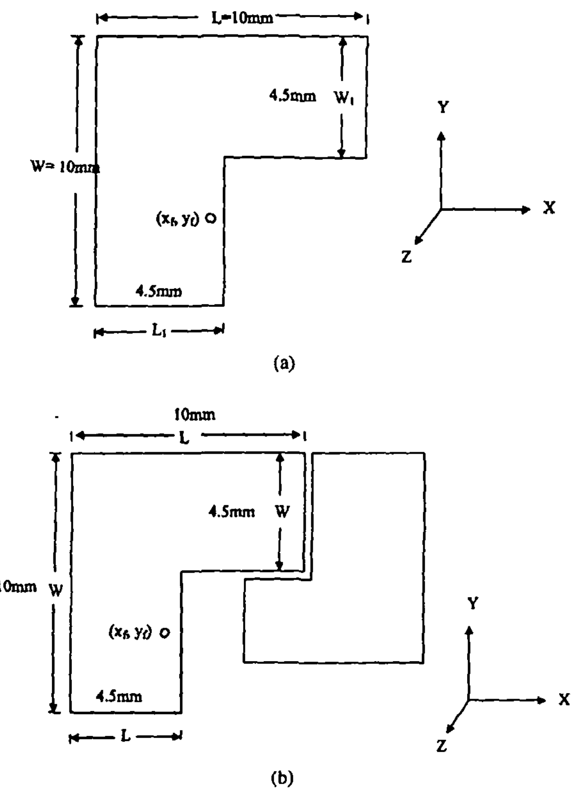

Figure 1 (a) Inverted L-shaped microstrip antenna; (b) parasitic coupled inverted L-shaped microstrip antenna

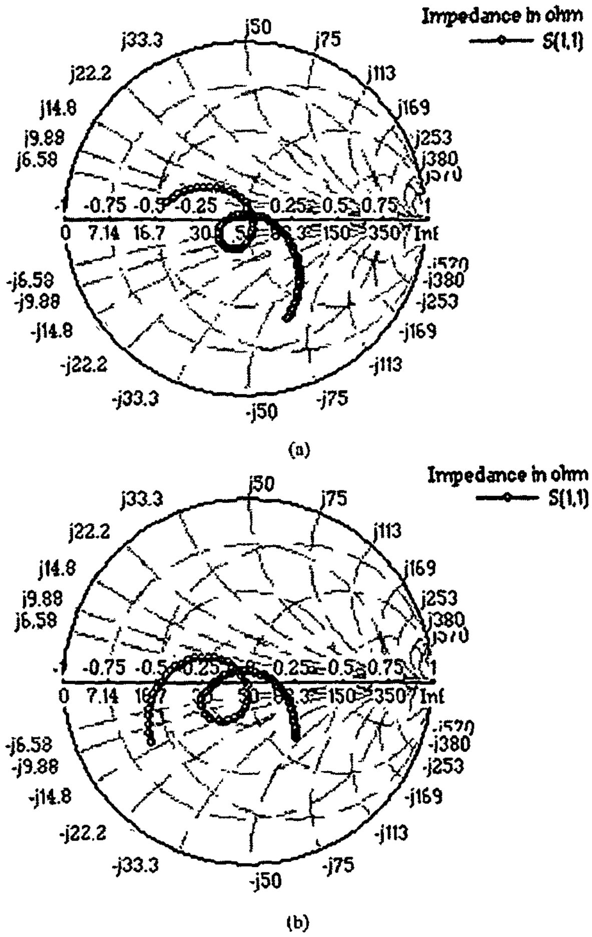

Figure 2 Smith Chart plot of (a) inverted L-shaped microstrip patch antenna; (b) parasitically coupled inverted L-shaped microstrip patch antenna. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com.]

DESCRIPTION OF ANTENNAS

Figure 1(a) depicts the geometry of the inverted L-microstrip antenna, which is fed at a point (x_f = 3.8 mm, y_f = 3.2 mm), whereas Figure 1(b) represents the parasitically coupled inverted

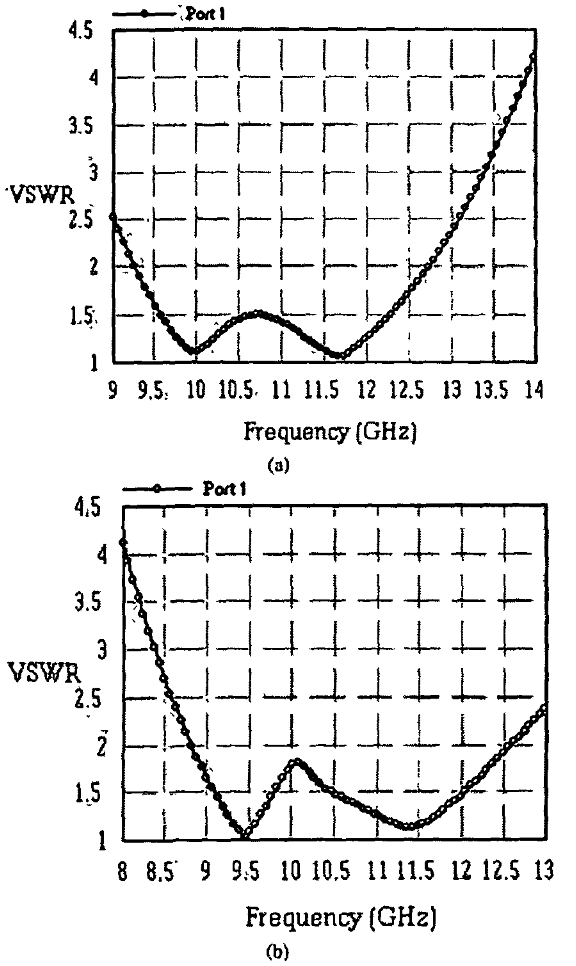

Figure 3 VSWR plot of (a) inverted L-shaped microstrip patch antenna; (b) parasitically coupled inverted L-shaped microstrip patch antenna. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com]

L-microstrip patch antenna with a feed point at (x_f = 3.8 mm, y_f = 3.2 mm).

The thickness of the substrate used is 2 mm, while ε_r = 2.2. The value of L_1 and W_1 are the optimized values selected based on current distribution. The feed point is highly dependent on L_1 and W_1. The width of the parasitic strip and spacing from the main patch are selected based upon the current distribution on the patch.

RESULTS AND DISCUSSION

Figures 2(a) and 2(b) show the Smith-chart plots of the inverted L-microstrip patch antenna and parasitically coupled inverted L-microstrip patch antenna, respectively, whereas Figures 3(a) and 3(b) show the VSWR plots. As seen from the figures, the inverted L-microstrip antenna offers an impedance bandwidth of 3.35 GHz, while the parasitically coupled inverted L-microstrip patch antenna offers 3.60 GHz. It is seen that the probe dimension affects impedance. The practical radius of a central conductor of a SMA connector is 0.6 mm. In the present problem, we present our result using this value.

The selection of parasitic element is based on the idea of offering capacitive reactance in order to compensate for the inductive reactance due to the feeding probe, thus, increasing the bandwidth. The current distributions are calculated using the method of moments (MoM). For viewing the pattern bandwidth, these antennas are simulated at different frequencies in order to study the radiation patterns in both azimuth and elevation planes. Figures 4(a) and 4(b) represent the azimuth radiation pattern and elevation radiation pattern of the inverted L-microstrip patch antenna, respectively. The 3-dB pattern bandwidth is calculated to be 2.5 GHz. The azimuth and elevation patterns of the parasitically coupled inverted L-microstrip patch antenna are plotted in Figures 5(a) and 5(b), respectively. The 3-dB pattern bandwidth is found to be 3.61 GHz. The simulations are carried out using IE3D software by Zeeland, Inc. The linear gain of the inverted L-microstrip antenna is calculated to be 5.35 dBi, while that for parasitically coupled one is 5.71 dBi. The large bandwidth has been achieved with a substrate of 2-mm thickness compared to that of the L-shaped plate antenna (10 mm) [3].

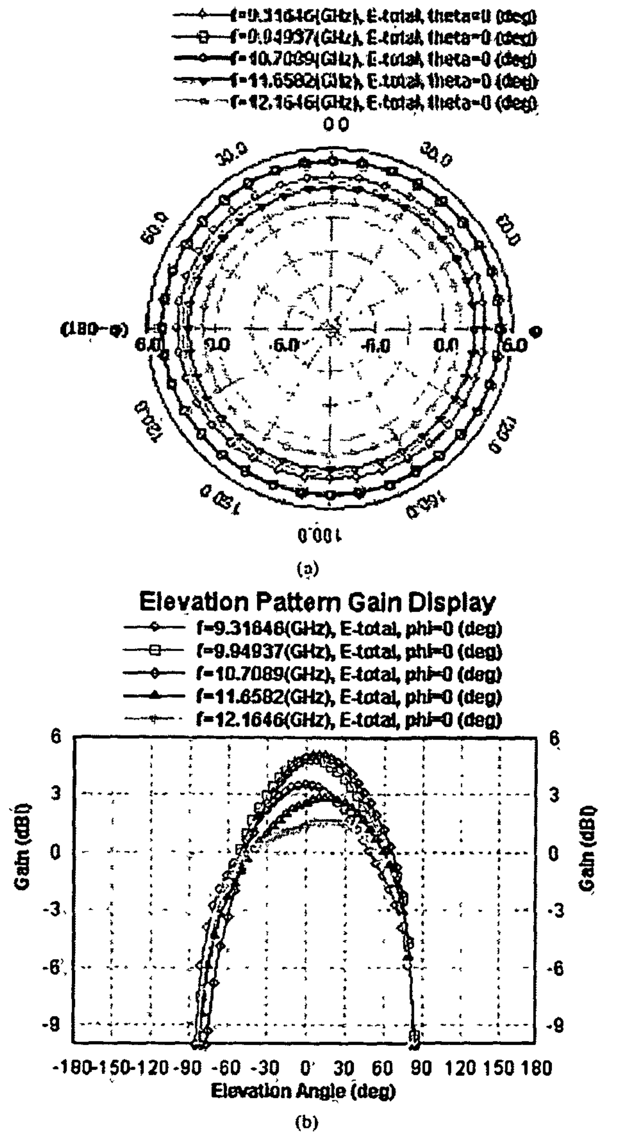

Figure 4 (a) Azimuth pattern of inverted L-shaped microstrip patch antenna, (b) elevation pattern of inverted L-shaped microstrip patch antenna. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com.]

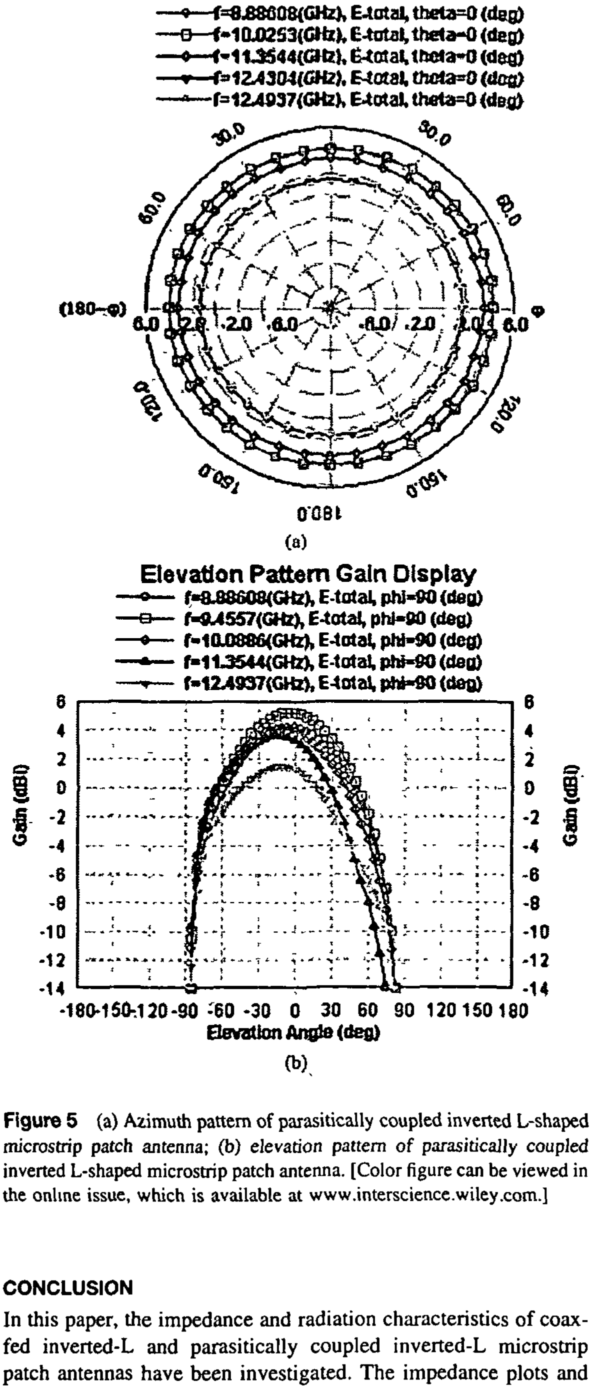

Figure 5 (a) Azimuth pattern of parasitically coupled inverted L-shaped microstrip patch antenna; (b) elevation pattern of parasitically coupled inverted L-shaped microstrip patch antenna. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com.]

CONCLUSION

In this paper, the impedance and radiation characteristics of coax-fed inverted-L and parasitically coupled inverted-L microstrip patch antennas have been investigated. The impedance plots and radiation patterns show that these antennas exhibit wider bandwidth. The study of current distribution has provided insights regarding the technique of choosing the shape (width) and spacing of the parasitic element and hence increasing the efficiency and bandwidth. The inverted L-shaped microstrip patch antenna with simple structure and large bandwidth seems to be a potential radiator for wireless communication and for biomedical applications where large bandwidth is an essential requirement.

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32-CHANNEL ARRAYED-WAVEGUIDE-GRATING MULTIPLEXER USING FLUORINATED POLYMERS WITH HIGH THERMAL STABILITY

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ABSTRACT: *A 32-channel arrayed-waveguide-grating (AWG) multiplexer operating around 1550 nm has been designed and fabricated using synthesized cross-linkable fluorinated poly (ether ether ketone). The channel spacing is 0.8 nm (100 GHz). The insertion loss of the multiplexer is 12–17 dB and the cross talk is less than −20 dB.* © 2004 Wiley Periodicals, Inc. Microwave Opt Technol Lett 42: 192–196, 2004; Published online in Wiley InterScience (www.interscience.wiley.com). DOI 10.1002/mop.20249

Key words: *arrayed waveguide grating; wavelength division multiplexing (WDM); fluorinated poly (ether ether ketone); reaction ion etching*

1. INTRODUCTION

It is inevitable that transmission capacity will increase in highly developed telecommunication systems. The wavelength-division multiplexing (WDM) system has become the preferred technology for further increasing the capacity of the optical-fiber telecommunication infrastructure [1, 2]. The arrayed-waveguide-grating (AWG) multiplexer is a key component for wavelength-division multiplexing (WDM) systems [3, 4] because both add-drop multiplexing and wavelength routing require its use. AWG multiplexers have been fabricated using silicas [5], semiconductors (InP) [6], and polymers [7, 8]. Among them, a polymeric AWG multiplexer has recently attracted much attention due to its low-cost processing and a variety of optical functions [9].

However, polymers have high optical loss in the infrared region due to the carbon-hydrogen (C–H) bond vibrational absorption. By modifying a molecule via the substitution of fluorine or deuterium for hydrogen in the C–H greatly reduces optical loss [10]. To overcome the abovementioned problems, we designed and synthesized cross-linkable fluorinated poly (ether ether ketone) (FPEEK) to fabricate the AWG multiplexer.

The multiplexer is composed of an arrayed waveguide grating, input-output (I-O) waveguides, and focusing-slab waveguides. The AWG consists of regularly arranged waveguides joining the two slabs, with the lengths of adjacent waveguides differing by a constant value. The length difference results in wavelength-depen-

Application of a Genetic Algorithm in an Artificial Neural Network to Calculate the Resonant Frequency of a Tunable Single-Shorting-Post Rectangular-Patch Antenna

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ABSTRACT: In this article, an efficient application of a genetic algorithm (GA) in an artificial neural network (ANN) to calculate the resonant frequency of a coaxially-fed tunable rectangular microstrip-patch antenna is presented. For a normal feed-forward back-propagation algorithm, with a compromise between time and accuracy, it is difficult to train the network to achieve an acceptable error tolerance. The selection of suitable parameters of ANNs in a feed-forward network leads to a high number of man-hours necessary to train a network efficiently. However, in the present method, the GA is used to reduce the man-hours while training a neural network using the feed forward-back-propagation algorithm. It is seen that the training time has also been reduced to a great extent while giving high accuracy. The results are in very good agreement with the experimental results. © 2004 Wiley Periodicals, Inc. Int J RF and Microwave CAE 15: 140–144, 2005.

Keywords: artificial neural networks; genetic algorithm; microstrip antenna; shorting post; resonant frequency

I. INTRODUCTION

Artificial neural networks (ANNs) and genetic algorithms (GAs) have become very important in the field of computational electromagnetics due to their many attractive features. Much effort has been made to control various features of ANNs by using GAs [1], but each of these efforts has its own limitations. The strategy of optimizing neural networks using GAs is an open issue. A literature survey shows that GAs have been used to provide a model of the evolution of the ANN topology, while supervised learning is used for learning [2, 3]. Yet another way of using the GA is the weight-optimization technique [4–6], where a network is trained by using a GA without any gradient information. The authors report that the ANN becomes a victim of the parameters of the GA. Mutation and crossover, the main parameters of the GA, emerge as an encoding problem. The third way of addressing the optimization of neural networks is to associate the gradient information of the network while training with the ANN learning rules [6]. In [7], the GA was used to assign/find out the initial weight set, which is subsequently processed using a back-propagation algorithm. The algorithm presented in [8] takes a long

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time to select an optimized model. Although there are some numerical approximations to initialize the various ANN parameters, this is not true in all cases. In essence, the selection of an efficient model for a particular problem is a tedious job for a programmer, which increases man-hours. Keeping these factors in view, the GA is used in this problem to select an optimized trained ANN model. In the present article, the GA optimizes the number of hidden neurons, steepness of activation function, learning constant, and momentum factor to achieve the output. In other words, in the present article, the GA has been used to optimize the ANN continuously in order to achieve the best result. Hence, it is seen that the GA takes less computational time for training the network while providing high accuracy.

II. ALGORITHM DESCRIPTION

The genetic algorithm performs its search process through a population-to-population (instead of point-to-point) search. The most popular advantage of the GA is its parallel architecture, which uses probabilistic and deterministic rules. A member in a population called a chromosome is represented by a binary string comprising 0,1 bits in a simple GA. Bits of the chromosome are randomly selected and the length of the bit strings is defined with regard to relevance. Real values are also represented in the continuous/decimal GA, which gives a better result, especially when the number of variables to be optimized is increased. The increase in the number of variables increases the length of chromosome, that is, the number of binary bits in the GA that negatively affects crossover. However, in the present article, as the number of variables is only four, binary representation is therefore considered.

First, an initial randomly generated population is required to start the methodology. From the initial population, a child population is born and guided by three operators, such as reproduction, crossover, and mutation. Newborn child members are judged by their fitness-function values. These child members act as parents in the next iteration. The algorithm presented in [9] is used in the present problem. A detailed analysis of the methods and process of GA can be found in [10, 11].

In this article, the GA is used to optimize the number of hidden neurons, steepness of activation function, momentum factor, and learning constant while training the network. A network with a single hidden layer is chosen for the present problem, as it is sufficient to solve most of the problems. The model can be generalized for a multi-hidden-layer network. Initially, a set of networks, which is the population size of the GA, is trained for a chosen minimum number of cycles/iterations using a normal feed-forward back-propagation algorithm. The fitness value of the individuals of the population is calculated in terms of the lowest absolute error E_{Abs}, obtained by using a back-propagation algorithm for a given minimum number of cycles/iterations. Thus, the fitness function is expressed as

$$Fitness = \frac{1}{(1 + E_{Abs})}. \tag{1}$$

Then, by applying genetic operators such as crossover and mutation, the E_{Abs} error is further reduced up to an accepted error tolerance. Also, the fittest trained network, which has been trained while optimizing those four ANN parameters, is selected. However, as the network is trained by the delta learning rule, the weights are adjusted depending upon the root-mean-squared error E_{RMS}, given by

$$E_{RMS} = \frac{1}{2N} \sum_{n=1}^{N} \sum_{k=1}^{M} (d_k(n) - y_k(n))^2, \tag{2}$$

where N = number of patterns, M = number of outputs, $d_k\ (n)$ = desired output for the k^{th} output neuron for the n^{th} training pattern, and $y_k\ (n)$ = output of the k^{th} output neuron for the n^{th} training pattern,

$$= \sum_{j=1}^{m} w_{kj} z_j(n),$$

where m = number of hidden neurons, w_{kj} = weight connected between the j^{th} hidden neuron and the k^{th} output neuron, w_{k0} = bias applied to the k^{th} neuron, and $z_j\ (n)$ = output of the j^{th} hidden neuron for the n^{th} training pattern.

The flow chart of presented algorithm is shown in Figure 1.

III. PROBLEM FORMULATION

One of the major disadvantages of the microstrip-patch antenna is its inherent narrow bandwidth, which restricts its wide applications. A number of techniques have been developed for bandwidth enhancement. The use of shorting pins [12] is a simple and efficient method to handle such problems. By changing the

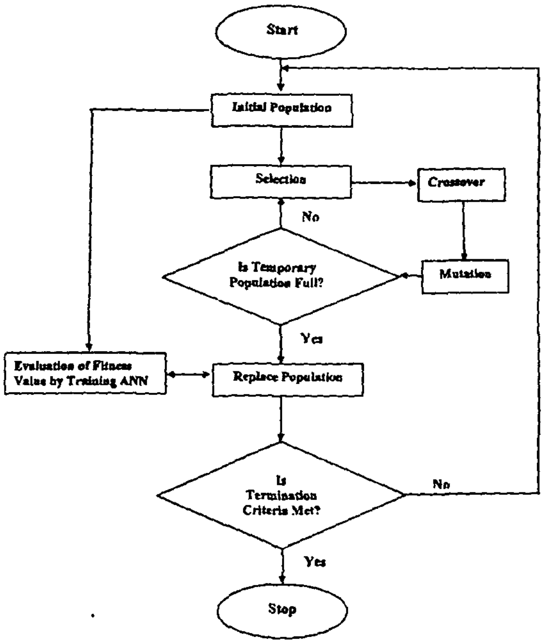

Figure 1. Flow chart of the presented algorithm.

number and location of the shorting posts, the operating frequency can be tuned and the polarization can also be changed. Figure 2 represents a schematic diagram of the single-shorting-post rectangular-microstrip antenna. Depending on the position of the shorting post, the resonant frequency of the rectangular-microstrip antenna can be tuned.

For optimizing these four ANN parameters — number of hidden neurons, steepness of activation function, momentum factor, and learning constant — using the GA, the population size taken is 30 individuals and the maximum number of generations is set at 30,000. The probability of crossover is set at 0.7, while the probability of mutation is equal to 0.01. The length of each chromosome is 43 bits. For each set of ANN parameters selected by the GA, the network is set to train that which measures the fitness value in terms of error obtained, after completion of all cycles.

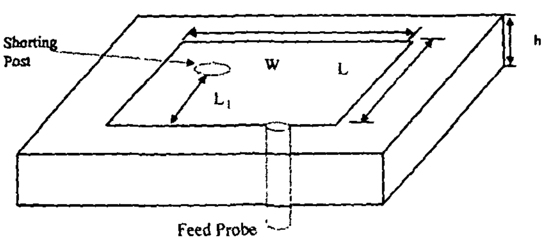

Figure 2. Rectangular microstrip-patch antenna with a shorting post.

The absolute error-tolerance considered is 0.02 in order to obtain the desired set of ANN parameters and, once this is achieved, the network training is continued until saturation.

To train the neural network for evaluating the fitness value, the algorithm presented in [7] is used. The number of inputs and outputs in the respective input and output layers are fixed in the model. The width of the patch (W), length of the patch (L), position of the shorting post (L_1), permittivity of the substrate (ε_r), and height of the substrate (h) are taken as inputs to the networks and the resonant frequency of the patch is taken as the output. In [13], experimental data were provided for fixed $r_0 = 0.064$ cm. The proposed technique presented in this article has been validated with the experimental data to examine the accuracy of the method. Therefore, it has been considered for fixed $r_0 = 0.064$ cm only. However, using eq. 10 of [13], and varying r_0, more data sets can be generated to incorporate the dependency of r_0. But the validation will not occur with the experimental data. Eighteen out of 22 patterns presented in [13, 14] are taken for training the network, and four antennas are taken for testing the best-trained neural network model selected by the GA. The optimized parameters of the ANN obtained by applying the GA are as follows:

- the number of hidden neurons is 35;
- the steepness of activation function (λ) is 5.382164;

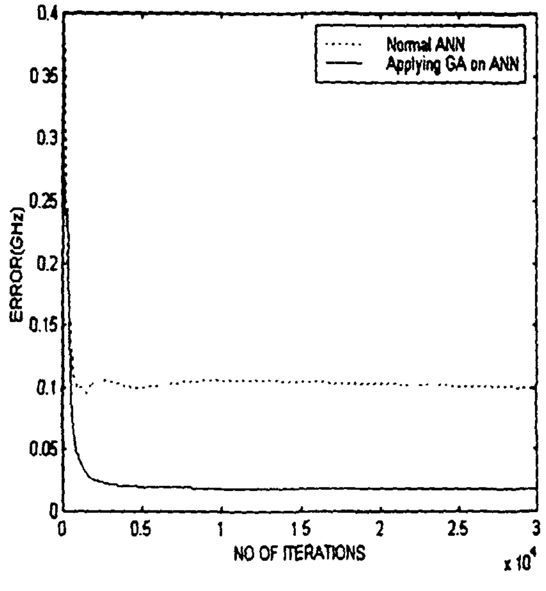

Figure 3. Number of cycles vs. error.

Table I. Resonant Frequency of a Microstrip Antenna Using Single Shorting Pin Applying GA on ANN*

L_1/L	L (cm)	W (cm)	ε_r	h (cm)	Resonant Frequency (Experimental) (GHz)	Resonant Frequency (Eqn (10) of [13]) (GHz)	Resonant Frequency (Normal Back-propagation) (GHz)	Resonant Frequency (Presented Method) (GHz)
0 1	6 2	9	2 55	0 16	1 594	1 64	1 619	1 607
0 3	3 75	7 424	2 2	0 1524	2 788	—	2 808	2 798
0 7	6 2	9	2 55	0 16	1 525	1 544	1 493	1 517
0 9	3 75	7 424	2 2	0 1524	3 13	—	3 014	3 028

* The radius of the metallic post (r_0) = 0 064 cm

- the learning constant (η) is 0 106955,
- the momentum factor (α) is 0 58947

IV. RESULTS AND DISCUSSION

Selection of the ANN parameters takes a long time via trial-and-error method to obtain the best-trained network, that is, the simulation time is less, but the man-hours are excessive while training a network using the normal feed-forward back-propagation algorithm However, by using a GA, these man-hours have been reduced to 3856 s in the presented algorithm In order to compare the training times, the network (5×20×1) is trained using a normal feed-forward back-propagation algorithm with a steepness of activation function $\lambda = 1$, learning constant $\eta = 0$ 3, and momentum factor $\alpha = 0$ 1 In this case, all four parameters are chosen using the trial-and-error method The training time is found to be 889 s for an error tolerance of 0 05 The average error per pattern for four patterns is found to be 0 0482 GHz

In the case of the algorithm presented in this article, it takes only 41 s (30,000 training cycles) to train the network, even for a lower error tolerance of 0 02 And the average error for these four antennas is found to be 0.0332 GHz Figure 3 shows the comparison between the number of cycles and the error for both cases As shown in Table I, the results are closer to the experimental results, as compared to the numerical and analytical results presented in [8, 9]

V. CONCLUSION

In this article, a genetic algorithm (GA) has been applied to a back-propagation algorithm in order to calculate the resonant frequency of a single-shorting-post tunable microstrip antenna The presented technique to calculate the resonant frequency of a shorted-microstrip antenna was found to be a simple, inexpensive, and highly accurate method The accuracy can be improved by choosing a smaller error tolerance and/or by training the network for a larger number of iterations while evaluating the fitness value Further improvement to the model may involve taking a multilayer network that considers the number of hidden layers as another parameter to be optimized This model can be used as a potential simulator technique for the design of microstrip antennas

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GENETIC ALGORITHM WITH ARTIFICIAL NEURAL NETWORKS AS ITS FITNESS FUNCTION TO DESIGN RECTANGULAR MICROSTRIP ANTENNA ON THICK SUBSTRATE

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ABSTRACT: *Over the years genetic algorithms (GAs) have been applied in many applications But the lack of a proper fitness function has been a hindrance to its widespread application in many cases In this paper, a novel technique of using artificial neural networks (ANNs) as the fitness function of a genetic algorithm in order to calculate the design parameters of a thick substrate rectangular microstrip antenna is presented A multilayer feed forward neural network is used as the fitness function in a binary coded genetic algorithm The results obtained using this method are found to be closer to the experimental value as compared to previous results obtained using the curve-fitting method To validate this the results are compared with the experimental values for five fabricated antennas The results are in very good agreement with the experimental findings* © 2004 Wiley Periodicals, Inc Microwave Opt Technol Lett 44 144–146, 2005, Published online in Wiley InterScience (www interscience wiley com) DOI 10 1002/mop 20570

Key words: *genetic algorithm artificial neural networks, microstrip antenna resonant frequency*

INTRODUCTION

In the recent past, the field of theoretical electromagnetics has shifted towards computational electromagnetics due to the development of high-speed digital processors, that is, these high-speed mathematical processors have helped to serve as a catalyst for this shift Often in electromagnetics, the objective function (fitness function) that arises for optimization is multimodal, stiff, and nondifferentiable In addition, it is computationally expensive to evaluate The objective function cannot be relied upon due to its tentativeness, especially when accuracy cannot be compromised Deterministic optimization techniques such as the Monte Carlo technique, simulated annealing, and hill climbing, or an evolutionary optimization technique such as the genetic algorithm (GA) [1–3], mostly rely upon the objective function, without which the optimization technique has no meaning In this paper, a new class of objective-function formulation is presented in which artificial neural networks (ANNs) are used as the fitness function The technique presented can be used everywhere, particularly in those cases where the objective-function formulation is difficult, or the objective function is erroneous For instance, in the present work we use this technique to calculate the optimized dimension of a rectangular patch antenna on thick substrate [4, 5], since there is no closed-form mathematical formula to calculate the resonant frequency of a thick-substrate rectangular microstrip antenna

The GA is a global search method based on a natural-selection procedure that consists of genetic operators such as selection, crossover, and mutation GA optimizers are particularly effective in a high-dimension, multimodal function, that is, where the number of optimizing parameters are large Since the last decade, application of the ANN has occurred in electromagnetics due to its versatility and ease of implementation [6–8] An ANN trained by the back-propagation algorithm has been introduced as a fitness function Coupling of ANNs with a GA can avoid the limitation encountered for objective-function formulation in the GA The global-function approximation capability [9] and greater generalization capability of ANNs further facilitate the coupling phenomenon

PROBLEM FORMULATION AND DEVELOPMENT OF THE MODEL

The GA, due to its parallel architecture and probabilistic and deterministic nature, is used to solve problems in many applications The GA performs its searching process via a population-to-population (instead of point-to-point) search A member in a population, called a chromosome, is represented by a binary string comprising 0, 1 bits Bits of the chromosome are randomly selected and the length of the bit strings is defined according to relevance An initial randomly generated population is required at first to start the methodology From the initial population, a child population, guided by three operators such as reproduction, crossover, and mutation, is born Newborn child members are judged by their fitness-function values The fitness function is formulated as per the ultimate goal concerned These child members act as parents in the next generation

With $h/\lambda_0 > 0.0815$, the properties of the patch antenna change drastically [4, 5], where h is the thickness of the substrate and λ_0 is the free-space wavelength The standard formulas available in the literature are valid for $h/\lambda_0 < 0.0815$ So, for $h/\lambda_0 > 0.0815$, the designer is thus forced to obtain the physical characteristics using the trial-and-error method or the numerical method [4] But these formulas are derived using the curve-fitting method, which can be extrapolated only to a certain extent Thus, there is a need for a robust numerical approximation for the calculation of

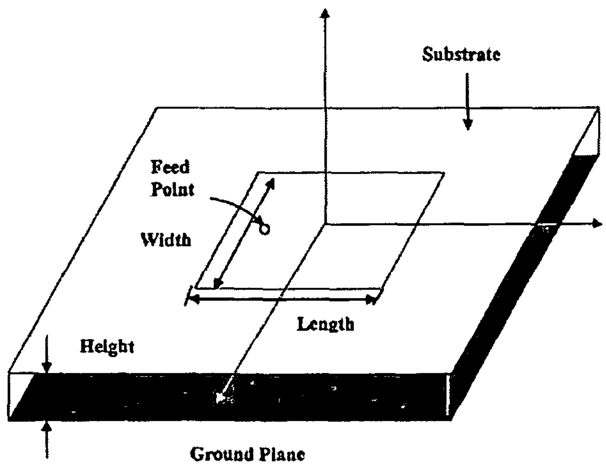

Figure 1 Rectangular microstrip antenna on thick substrate [Color figure can be viewed in the online issue, which is available at www interscience wiley com]

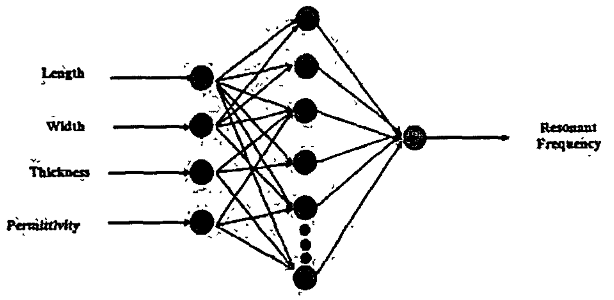

Figure 2 Network structure. [Color figure can be viewed in the online issue, which is available at www.interscience.wiley.com]

the dimensions. A typical microstrip antenna with length L, width W, height h, and the feed-point location a are shown in Figure 1.

The present is approach is basically a two-step calculation procedure. In the first step, a suitable network is selected and trained for a set of training data. After being successfully trained, the network will learn the input-output relation among the length, width, thickness, permittivity, and resonant frequency of the antenna. In the second step, the network will be used as the objective function and the GA will be used for calculation of the optimized dimension.

Training Phase

The back-propagation algorithm [6] using the gradient descent method is used for training the network. A three-layer neural network, consisting of four input neurons, 30 hidden neurons, and one output neuron (that is, $4 \times 30 \times 1$) has been used. For this network, the length, width, substrate thickness, and dielectric constant of the substrate are taken as inputs, whereas the resonant frequency is taken as the output. The proposed model is shown in Figure 2.

Twelve patterns from [4] are taken for training the networks and five other patterns are used for testing the networks and the ANN-based GA code. The parameters considered for training the network are as follows:

noise-factor parameters = 0.0003,
learning constant (parameter) = 4,
momentum factor = 0.0205.

Noise factor is used during the ANN training to increase its generalization capability. The number of hidden neurons and various parameters are chosen using the trial-and-error method. The training time of the network to obtain the best result using an HP 850-MHz 128-MB PC is 375 s (6.25 min).

Optimization Phase

The two independent variables to be optimized are the length and width of the antenna. A population size of 20 individuals and 200 generations is produced. A roulette-wheel selection procedure is adopted to select the new population. The probability of crossover is set to 0.7, while the probability of mutation is equal to 0.01. The fitness of the selected population is calculated from the trained neural network. The process is repeated until the termination criterion is met. The block diagram of the proposed algorithm is presented in Figure 3. The fitness of an individual is decided according to the following relation:

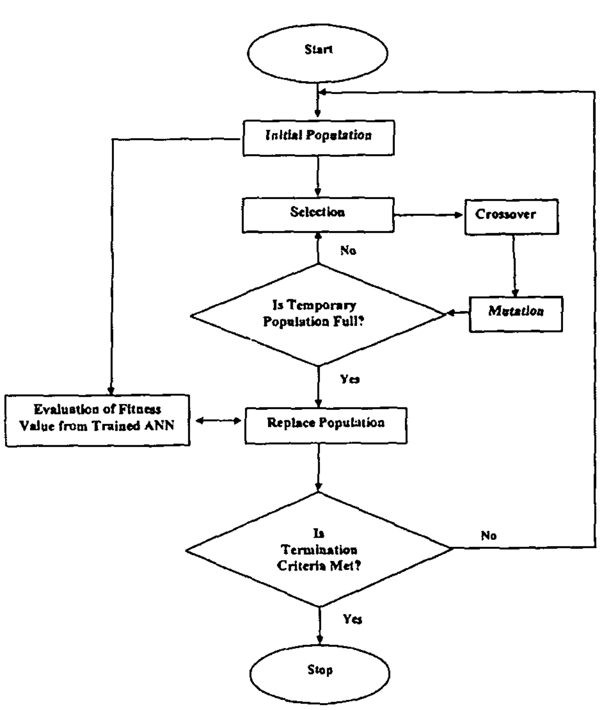

Figure 3 Block diagram of the presented algorithm

$$\text{Fitness} = f(L, W, \varepsilon_r, h) = 1/(1 + |f_r - \text{desired frequency}|)$$
$$= 1/(1 + |\text{output of ANN} - \text{desired frequency}|).$$

RESULTS AND DISCUSSION

The optimized design parameters of the five antennas considered for testing is tabulated in Table 1. Of the three inputs, one is the dielectric constant ($\varepsilon_r = 2.55$) of the substrate. The other two inputs are listed in the 2[nd] and the 3[rd] columns. The experimental dimensions of length and width are shown in the 4[th] and 7[th] columns, respectively, while the optimized output of our GA–ANN-based dimensions are listed in the 6[th] and last columns of the table. By using empirical formulas derived using the curve-fitting method [4], the average error in calculating the length and width of the thick-substrate microstrip antenna

TABLE 1 Dimensions of Thick-Substrate Rectangular-Microstrip Antenna (ε_r = 2.55)

Patch No.	Resonant Frequency f_r in GHz	Height h in mm	Length L Experiment [4] in mm	Length L Using Eq. (18) [4] in mm	Length L Using Present Method in mm	Width W Experiment [4] in mm	Width W Using Eq. (19) [4] in mm	Width W Using Present Method in mm
1	5.82	4.76	15.2	15.27	15.21	10.0	10.13	10.02
2	4.66	6.26	19.7	19.57	19.65	12.0	11.92	11.99
3	3.98	9.52	26.2	26.12	26.15	9.74	9.64	9.70
4	3.90	11.0	28.35	28.36	28.37	7.77	7.77	7.76
5	2.98	12.81	35.0	35.01	35.03	12.65	12.71	12.66

is found to be 0.06 and 0.074, respectively, whereas the presented method shows an average error of 0.032 for length and 0.018 for width. Thus, an ANN-coupled GA gives better results, as compared to the formulas derived in [4].

CONCLUSION

A novel method of coupling an ANN with a GA in order to calculate the dimensions of a thick-substrate microstrip antenna has been discussed in this paper. The measure of accuracy of the solution obtained by the GA depends directly upon the efficient training of the neural networks. Thus, care must be taken for an efficient training of the network. In cases where there is no accurate theoretical formulation for the objective function, this technique can be used for optimization purposes.

Simultaneous optimization of the dielectric constant, height of the substrate, dimensions, and so forth is possible in the present method, whereas in the conventional method, it is either computationally complex or not possible. The results obtained by the ANN-coupled GA are compared with the experimental results. The results are in very good agreement with the experimental findings. In the presented method, the simulation time is less than the simulation times of methods such as the method of moments (MoM), finite-difference time-domain (FDTD), and finite-element technique (FET), without compromising the error. The accuracy of the proposed model can be increased by using a more effective ANN algorithm. Furthermore, the accuracy can be increased by taking more experimental results for training the ANN. This method may contribute to the improvement of ANN-based techniques for solving problems such as array-factor correction, cross-polarization reduction, bandwidth enhancement, array optimization, and so on.

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A LOW-VOLTAGE FAST-SWITCHING FREQUENCY SYNTHESIZER AT 2.4 GHz

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ABSTRACT: *A low voltage fast switching frequency synthesizer at 2.4 GHz is presented. The phase noise is analyzed and measured to be −96 dBc/Hz at 100 KHz offset. The measured spectral purity is also good. This synthesizer can be used for frequency hopping spread spectrum applications.* © 2004 Wiley Periodicals, Inc. Microwave Opt Technol Lett 44: 146–148, 2005; Published online in Wiley InterScience (www.interscience.wiley.com). DOI 10.1002/mop.20571

Key words: *frequency synthesizer; phase locked loop; PLL*

1. INTRODUCTION

Recently, frequency-hopping spread-spectrum (FH-SS) communication has been developing rapidly. The frequency synthesizer in a transceiver plays a key role in system performance [1]. During signal reception, the synthesizer usually functions as the first-stage local oscillator. During signal transmission, the synthesizer generates the carrier. For better jamming susceptibility, the hop rate needs to be high [2]. In the case of fixed channel-switching time, the channel efficiency drops as the hop rate increases. Hence, a fast-switching synthesizer is desirable. Usually, the phase noise of a low-voltage fast-switching synthesizer is high at low offset frequencies from the carrier. It should be noted that, for fast-switching application, low phase noise at close-in frequencies is not required. This paper reports a fast-switching frequency synthesizer dedicated to FH-SS communication. Phase-noise analysis and measurement are conducted to show that satisfactory noise has been achieved.

2. SYSTEM ANALYSIS AND DESIGN

In practice, implementing fast-switching synthesizers under low voltage is a difficult task. A special technique must be employed to achieve this goal. In this paper, the direct memory-access technique is used. Resembling the technique, the resultant synthesizer is referred to as the direct memory-access frequency synthesizer (DMAFS). The DMAFS is based on a conventional charge-pump phase-locked loop (PLL) frequency synthesizer [3, 4]. The block diagram of the DMAFS is shown in Figure 1. The DMAFS will undergo a calibration mode and a normal-measurement mode. To minimize the channel-switching time during frequency hopping, data conversion and memory-access circuits are inserted between

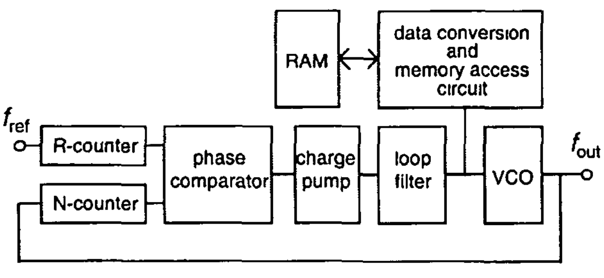

Figure 1 Block diagram of the DMAFS

Design of a Wideband Microstrip Antenna and the Use of Artificial Neural Networks in Parameter Calculation

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Abstract

This paper deals with the design of a multi-slot hole-coupled microstrip antenna on a substrate of 2 mm thickness that gives multi-frequency (wideband) characteristics. The Method of Moments (MoM)-based *IE3D* software was used to simulate the results for return loss, VSWR, the Smith chart, and the radiation patterns. A tunnel-based artificial neural network (ANN) was also developed to calculate the radiation patterns of the antenna. The radiation patterns were measured experimentally at 10.5 GHz and 12 GHz. The experimental results were in good agreement with the simulated results from *IE3D* and those of the artificial neural network. A new method of using a genetic algorithm (GA) in an artificial neural network is also discussed. This new method was used to calculate the resonant frequency of a single-shorting-post microstrip antenna. The resonant frequency calculated using the genetic-algorithm-coupled artificial neural network was compared with the analytical and experimental results. The results obtained were in very good agreement with the experimental results.

Keywords: Microstrip antennas; slot antennas; wideband antennas; neural networks; tunneling; genetic algorithms

1. Introduction

Due to their many attractive features, microstrip antennas have drawn the attention of researchers over the past decades [1-4]. Microstrip antennas are used in an increasing number of applications, ranging from biomedical diagnosis to wireless communications [5]. Such a wide range of applications, coupled with the fact that microstrip structures are relatively easy to manufacture, have turned microstrip analysis into an extensive research problem. Research on microstrip antenna in the 21st century aims at size reduction, high gain, wide bandwidth, multiple functionality, and system-level integration. Significant research work has been reported on the enhancement of the bandwidth of microstrip antennas, which are otherwise inherently narrowband. Many techniques have been suggested for achieving wide bandwidth [6-9]. Stacked patches, parasitic loading, and U-shaped microstrip antennas have been used to enhance the bandwidth. But the present trends of the size reduction of wireless handheld devices and multiple functionality present challenges for the antenna designer to design multi-frequency antennas in a simple manner and for easy fabrication. Complex geometries and complexity in the designs are not in the interest of the rapidly growing wireless industries. In this paper, an attempt has been made to design a wideband microstrip antenna without any geometrical complexities.

Due to its greater generalization capability, an artificial neural network has been used to calculate the radiation patterns of the designed antenna. A back-propagation algorithm has been used to train the network, which learns using the gradient-descent method. The training time has been considerably reduced by using the tunneling technique in the fast artificial neural network algorithm. Owing to its gradient-descent nature, back-propagation is very sensitive to the initial conditions [10]. If the choice of the initial weight vector happens to be located within the attraction basin of a strong local-minimum attractor (one where the minimum is at the bottom of a steep-sided valley of the error surface), then the convergence of back-propagation will be fast. On the other hand, back-propagation converges very slowly if the initial weight vector starts the search in a relatively flat region of the error surface [2].

In this paper, a genetic algorithm is used to fix the initial weights of a multilayer neural network for faster convergence, by coupling the genetic algorithm with the artificial neural network to select the initial weights. This is a new approach.

Genetic algorithms are capable of optimizing nonlinear multi-modal functions of many variables [11, 12]. They require no derivative information, and they robustly find global or very strong local optima. Numerical experiments indicate that using a genetic algorithm, good solutions to highly nonlinear equations can be quickly obtained, even in times comparable to those taken by analytical methods, such as steepest descent. Previously, an attempt was made to train the artificial neural network via an evolutionary approach using a genetic algorithm, as these methods are ignorant about the gradient information of the weight surface. The main drawback of the evolutionary approach for neural-network training is the training time. The back-propagation algorithm takes only several minutes, on average, to reach its lowest error. On the other hand, the evolutionary approach takes a longer time [13].

This paper consists of two major subsequent sections. In the first section, a simple and novel design is presented for achieving wide bandwidth in a microstrip antenna. A tunnel-based artificial neural network is applied to calculate the radiation pattern of the antenna. In the second section, a new approach for using an artificial neural network and a coupled genetic algorithm technique for calculating the resonant frequency of a single shorted rectangular microstrip antenna is presented.

2. Wideband Multi-Slot Hole-Coupled Microstrip Antenna

2.1 Design and Performance Features

In a microstrip antenna, some parts of the radiating surface or ground plane can be removed without any significant changes in the antenna's performance in terms of the radiation patterns, as the current distributions remain relatively intact [14]. It is also known that the frequency of a patch antenna can be increased or decreased by a capacitive or inductive load [15]. In this paper, a multi-slot microstrip antenna has been designed implementing the above facts to achieve a wide bandwidth.

The antenna is designed on a substrate of thickness 2 mm, with $\varepsilon_r = 2.2$. The patch size is characterized by its length, width, and thickness (*L*, *W*, *h*), and is fed by a coaxial probe at position (x_f, y_f). A hole of diameter 0.2 mm is made at location (x_h, y_h) for impedance matching. Four slots are incorporated into this patch, and are positioned on both sides of the feed. The structure resembles the geometry that would result if an E-shaped patch is joined with another, inverted E-shaped patch (Figure 1). The slot's length (*Ls*), width (*Ws*), and position (*Ps*) are important parameters in controlling the bandwidth. The length of the current path is increased due to the slots [16], which leads to additional inductance in series. Hence, the wide bandwidth is generated as the resonant circuits become coupled. The slots aggregate the currents, which give additional inductance, which is controlled by the patch width (*W*). A hole is made at ($x_h = 6.75$ mm, $y_h = 35$ mm) for impedance compensation and for better matching. The approach of creating a hole gives the flexibility to change the reactive component for impedance matching. *IE3D* software from Zeland Corp. was used to calculate the return loss and the VSWR of the antenna.

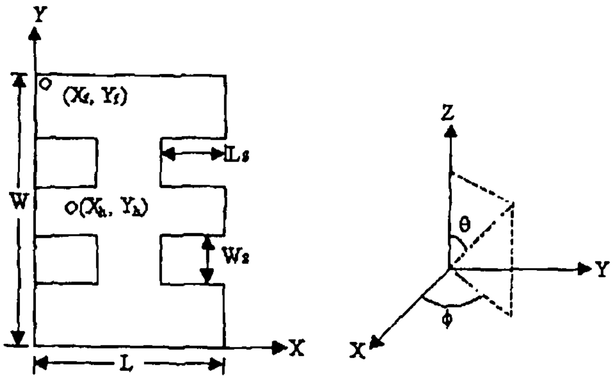

Figure 1. The geometry of the multi-slot hole-coupled microstrip antenna: $l = 45$ **mm,** $W = 71$ **mm,** $h = 2$ **mm,** $Ls = 17.5$ **mm,** $Ws = 4$ **mm, feed position** $(x_f, y_f) =$ **(0.75 mm, 69 mm).**

Figure 2 shows the return loss and VSWR of the multiple-slot hole-coupled microstrip patch antenna.

As can be seen, the antenna operated in distinct multiple frequency bands, with center frequencies at 6 GHz, 6.5 GHz, 9 GHz, 10.5 GHz, and 12 GHz. The calculation of the radiation patterns shows that the radiation patterns for 6 GHz, 6.5 GHz, 10.5 GHz, and 12 GHz were well within 3 dB. Interestingly, the gain, beamwidth, shape, and efficiency at 6 GHz completely matched with those values at 10.5 GHz, whereas the values for 6.5 GHz matched with the values for 12 GHz. The $-10\text{dB}(S_{11})$ bandwidth was nearly 800 MHz at each of those frequencies. There was also perfect isolation between these bands.

The slot lengths, widths, and the positions of the hole were varied to see the effects on return loss, VSWR, and on the radiation patterns. It was observed that the antenna's performance could be controlled by changing these parameters. The dimensions presented in this paper were the optimum dimensions after considering all these effects to achieve the best results. Figure 3 shows the S_{11} values in dB for a slot length of $Ls = 19.5$ mm, i.e., for an increased slot length. This figure also shows the S_{11} values in dB with a slot width of $Ws = 3$ mm, i.e., for a decreased slot width. These plots clearly show the effects of *Ls* and *Ws* on the S_{11} values.

The ground plane size is a critical parameter. In the present design, the ground plane was selected with respect to the lowest frequency, i.e., 6.5 GHz. It had dimensions of $L = 55$mm and $W = 81$mm.

2.2 Radiation Pattern of Microstrip Antenna Using Tunnel-Based Artificial Neural Network

A multilayer $2 \times 80 \times 1$ structure, shown in Figure 4, was used for training the network. The other network parameters used were a noise factor of 0.004, a momentum factor of 0.075, a learning constant of 0.08, a time step for integrating the differential equation of 5×10^{-15}, and strength of learning for tunneling of 0.08.

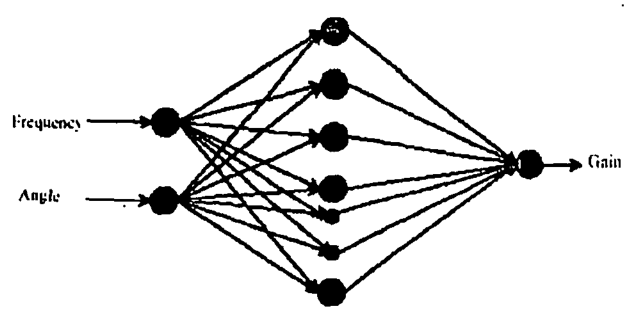

Figure 4. The network architecture, showing the angle and *frequency as inputs and the gain as output.*

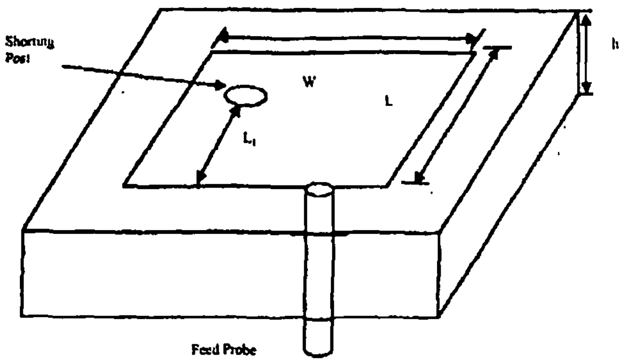

Figure 7. The rectangular microstrip patch antenna with a shorting post.

The back-propagation algorithm – the gradient descent method – was modified using the tunneling technique. The concept of the tunneling technique is based on violation of the Lipschitz condition [18] at the equilibrium position. This is governed by the fact that any particle placed at a small perturbation from the point of equilibrium will move away from the current point to another within a finite amount of time. Tunneling was implemented by solving the differential equation given by [18]

$$\frac{dw}{dt} = \rho\left(w - w^*\right)^{1/3}, \tag{1}$$

where ρ and w^* represent the strength of learning and the last local minimum for w, respectively. The differential equation was solved for some time until it attained the next minimum position. To start the training cycle, some perturbation was added to the weights. Then, the sum of the square errors (E) for all of the training patterns was calculated. If it was greater than the last minimum, then it is tunneled according to the above equation. If the error was less than the last local minimum, then the weights were updated according to the relation

$$\Delta w(t) = -\eta \nabla E(t) + \alpha \Delta w(t-1), \tag{2}$$

where η is called the learning factor, and α is called the momentum factor. t and '$(t-1)$ indicate training steps. Using *IE3D*, 36 patterns, each at a step angle of 10°, for frequencies of 6 GHz, 6.5 GHz, 10.5 GHz, and 12 GHz were generated. These ($36 \times 4 = 144$) patterns (the gain in dB at a given angle) were used to train the network. Finally, the network was subjected to testing for 480 (120×4) patterns, which were generated at a step angle of 3° for each of the frequencies given above. Figure 5 shows the radiation patterns at 6 GHz and 10.5 GHz, whereas Figure 6 shows the radiation patterns at 6.5 GHz and 12 GHz.

The average error (the deviation from the data taken for testing) at 6 GHz was 0.0408, at 6.5 GHz it was 0.0520241, at 10.5 GHz it was 0.0745005, and at 12 GHz it was 0.0181725. Experimental measurements were carried out to see the radiation patterns at 10.5 GHz and at 12 GHz. The results (see Figures 5 and 6) were in good agreement with the results of *IE3D* and with those of the artificial neural network.

3. GA-Coupled ANN Model for Calculating the Resonant Frequency of a Post-Tuned Patch Antenna

3.1 Implementation Strategy

A genetic algorithm performs its searching process through population to population, instead of doing a point-to-point search. The most favorite advantage of a genetic algorithm is its parallel architecture. Genetic algorithms use probabilistic and deterministic rules. A binary string, called a chromosome, comprised of "0s" and "1s," represents a member in a population. Bits of the chromosome are randomly selected, and a relevant length of the bit strings is defined. An initial randomly generated population is required to start the method. From the initial population, a child population is born guided by three operators: reproduction, crossover, and mutation. Newborn child members are judged by their fitness-function values. These child members act as parents in the next iteration. A detailed analysis of the methods and processes of genetic algorithms can be obtained from [11-12].

The ERMS error of a multilayer neural network can be written as

$$E(w) = 0.5 \sum_{p=1,P} \sum_{q=1,N^L} \left[u_q^L(x_p) - d_q(x_p)\right]^2, \tag{3}$$

where u_j^l is the output of the jth node in layer l, $w_{j,k}^l$ is the weighting connecting the jth node in layer l to the kth node in layer $(l-1)$, x_p is the pth training sample, $d_q(x_p)$ is the desired response of the jth output node for the pth training sample, N^l is the number of nodes in layer l, L is the number of layers, and P is the number of training patterns. In the above notation, $u_0^l = 1$ and $w_{j,0}^l$ represents the bias weights, where $l \neq 1$.

Equation (3) was taken as the fitness function of the genetic algorithm. The function was minimized to its saturation level. The corresponding weights were taken as the initial weights for the neural-network training. The network structure used in the present model was $5 \times 30 \times 1$. The algorithm presented in [5] was used for training the neural network.

The resonant frequency of the rectangular microstrip antenna (Figure 7) can be tuned, depending on the position of the shorting post. The width of the patch, W, the length of the patch, L, the position of the shorting post L_1, the permittivity of the substrate,

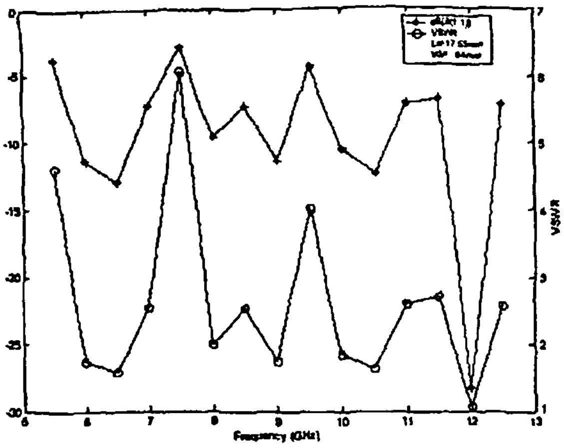

Figure 2. The return loss (S_{11}) in dB (solid dots) and the VSWR (circles) of the multiple-slot hole-coupled microstrip antenna.

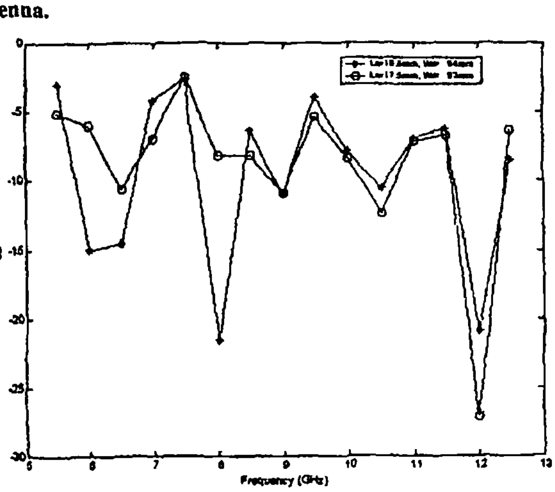

Figure 3. The return loss of the multiple-slot hole-coupled microstrip antenna for different values of Ls and Ws: solid dots, $Ls = 19.5$ mm, $Ws = 4$ mm; circles, $Ls = 17$ mm, $Ws = 3$ mm.

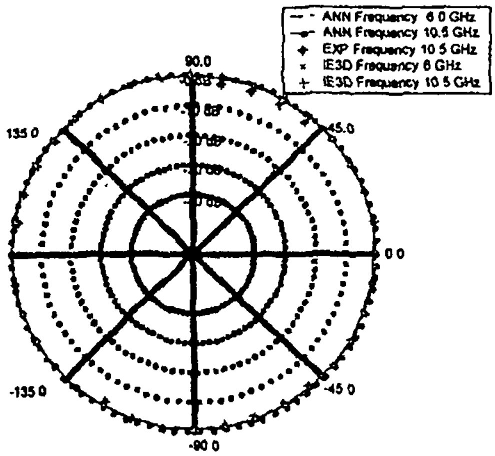

Figure 5. The radiation patterns for E-total, theta = 0°, at 6 GHz and 10.5 GHz. The dash-dotted line is the ANN results at 6 GHz, the solid black dots are the ANN results at 10.5 GHz, the red asterisks are the experimental results at 10.5 GHz, the green asterisks are the *IE3D* results at 6 GHz, and the green crosses are the *IE3D* results at 10.5 GHz.

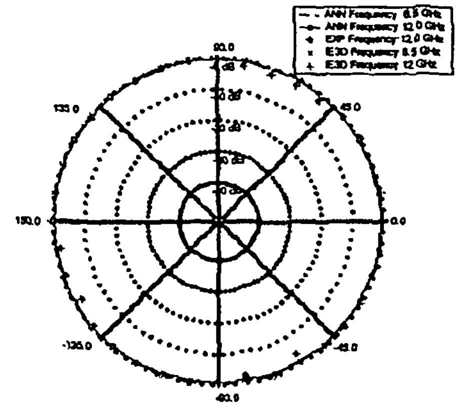

Figure 6. The radiation patterns for E-total, theta = 0°, at 6.5 GHz and 12.0 GHz. The dash-dotted line is the ANN results at 6.5 GHz, the solid black dots are the ANN results at 12 GHz, the red asterisks are the experimental results at 12 GHz, the green asterisks are the *IE3D* results at 6.5 GHz, and the green crosses are the *IE3D* results at 12 GHz.

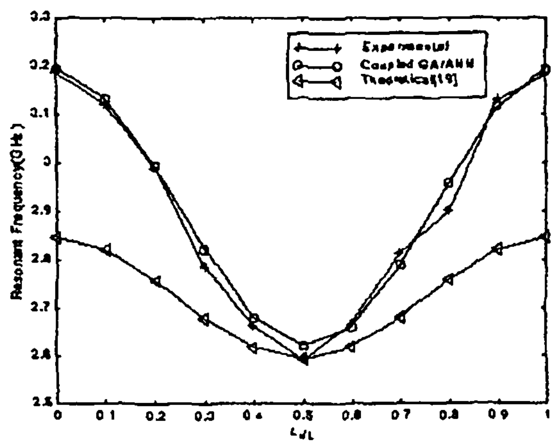

Figure 8. The resonant frequency (vertical axis, in GHz) of the tuned antenna as a function of the post position (horizontal axis, L_1/L). The asterisks are the experimental results, the circles are the results from the coupled genetic algorithm-artificial neural network, and the triangles are the theoretical results from [19].

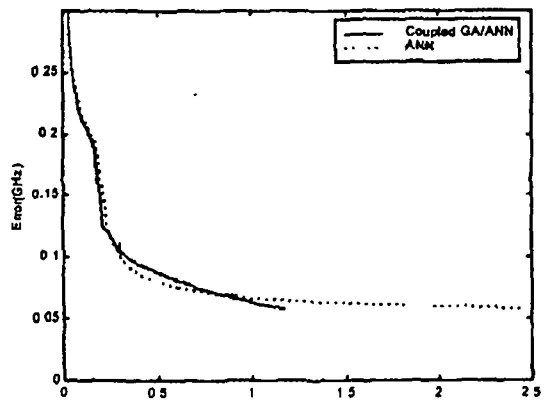

Figure 9. The error (vertical axis, GHz) as a function of the number of training cycles (horizontal axis) for the coupled genetic algorithm-artificial neural network (solid line) and the artificial neural network (dotted line).

Table 1. The resonant frequency of a microstrip antenna using a single shorting pin: results from theory, experiment, and genetic-algorithm-coupled artificial neural network calculation.

L_1/L	L (cm)	W (cm)	ε_r	h (cm)	Resonant Frequency: Theory (GHz)	Resonant Frequency: Experiment (GHz)	Resonant Frequency: GA-ANN (GHz)
0.5	6.2	9	2.55	0.16	1.48439	1.466	1.46789
0.6	6.2	9	2.55	0.16	1.50073	1.480	1.48859
0.3	3.75	7.424	2.20	0.1524	2.68041	2.788	2.81575
0.4	3.75	7.424	2.20	0.1524	2.61531	2.664	2.67995

ε_r, and the height of the substrate were taken as inputs to a $5\times30\times1$ network, and the resonant frequency of the patch was taken as the output. Experimental results from [19] were used for training the network. The network structure was selected on a trial and error basis. The various parameters used for training the network and the genetic algorithm were selected on a trial and error basis. These parameters were a learning constant of 3, a momentum factor of 0.1, a noise factor of 0.004, the size of the population was 20, the number of generations was 1000, the probability of crossover was 1, and the probability of mutation was 0.001.

To make the network more generalized, mixed-pattern training in inhomogeneity was developed. For training the network on inhomogeneous data, nine patterns from [19] and eleven patterns generated by *IE3D* with little change in configuration were used for training the network. To see the validity of the network, the network was tested with four patterns from [20] (Table 1).

3.2 Results

The average error per pattern was found to be 0.013545 GHz. The output of the network for those four patterns is shown in Table 1. The training time for the network was 346 seconds with the genetic-algorithm coupled model, and 642 seconds for the artificial neural network model, using a P-III HP PC.

The results obtained with the present technique were closer to the experimental results, compared to the numerical and analytical results presented in [19]. To test the generalization of the presented model, the antenna presented in [20] was used for testing. The input-output relation was also checked for the experimental results presented in [19], for $L = 3.75$ cm, $W = 7.424$ cm, $h = 0.1524$ cm, and $\varepsilon_r = 2.2$). Figure 8 shows a plot comparing the experimental results, the theoretical results, and the results from the present approach for the above antenna, for different positions of the post. Figure 9 shows comparing the error and the number of training cycles in the approach with and without the genetic algorithm). Figure 9 shows that the present approach took nearly half the computational time compared to the algorithm presented in [20] to get the same accuracy. This may be due to the fact that the network started training from the attractor basin in the weight space. Experimentally, it was verified that the resonant frequency was slight asymmetric about L_1/L, whereas the calculated results using [19] were symmetric. The results obtained using present the approach followed the experimental trend.

4. Conclusion

The return loss and radiation patterns of the multiple-slot hole-coupled microstrip antenna presented in this paper clearly showed that the antenna is a wideband, multiple frequency antenna. It has the attractive features of simplicity and flexibility in controlling the bandwidth, with high isolation between frequency bands. With almost omni-directional radiation patterns, the multiple-slot hole-coupled microstrip antenna seems to be a good antenna for wireless communications, especially for cellular telephone applications. The achievement of a wide bandwidth with a substrate thickness of 2 mm is a focus of attention. Careful study of the current distribution may help in housing the active components in the etched region of the patch, for possible system-level integration of this antenna. The variation of the slot parameters, and the hole size and positions, gives the flexibility to shift the frequency and match the impedance, which is a notable feature of this antenna. The calculation of radiation patterns using artificial neural networks is a new and interesting part of the paper, which reflects the simplicity and accuracy of the method. The calculation of radiation patterns using tunnel-based artificial neural networks can save considerable computational time while giving accurate results.

Further, this paper has demonstrated the utility of the genetic algorithm in an artificial neural network for selecting the initial weights for efficient training of a neural network. By using this coupled technique, a substantial amount of accuracy is achieved with less computational time. It reduces the simulation time to approximately half of the case where the initial weights are selected randomly. The technique presented for calculating the resonant frequency of a shorted microstrip antenna seems to be a simple, inexpensive, and highly accurate method. A similar approach can also be extended to calculating the resonant frequency where more than one shorting post is present. This will reduce the experimental cost and computational time to a greater extent, while giving accurate results.

5. Acknowledgement

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GA-FIR-Neural Network Based FDTD Technique For Input Impedance Calculation

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Abstract: **Finite Difference Time Domain Method (FDTD) is used as a potential tool for analysis of planar structure. This paper investigates the suitability of incorporating Genetic Algorithm(GA) on Finite Impulse Response Artificial Neural Networks(FIR-ANN) for impedance calculation of a co-axially fed square patch antenna. FIR-ANN is used as a nonlinear predictor to predict time series signal for speeding up the FDTD simulations. The NFDTD is used to approximate the voltage and current across the feed point at different time steps for which the architecture and parameters of NFDTD are optimized by GA. The GA-NFDTD result is compared with those of the traditional FDTD, NFDTD and experimental results.**

Index Terms: **Genetic Algorithm, Temporal Artificial Neural Networks, Filter Impulse Response, Finite Difference Time Domain Technique, Microstrip antenna and Resonant frequency.**

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I. INTRODUCTION

The Finite Difference Time Domain method, proposed by Yee in 1966[1], is a simple and elegant way to discretise the differential form of Maxwell's equations[2]. Yee used an electric-field(E) grid, which was offset both spatially and temporally from a magnetic-field(H) grid, to obtain update equations that yield the present fields throughout the computational domain, in terms of the past fields. The update equations are used in a leap-frog scheme. However, FDTD method requires long computational time for solving the resonant type of high-Q-passive structures. This is due to the fact that FDTD algorithm is based on the leap-frog technique. The computational cost shoots up in whole body simulation, computation of fields within missile guidance section, SAR calculation of human head in presence of cell phone[3] etc.

In [4] FIR-ANN is applied to calculate the input impedance of square patch antenna. The detailed concept of NFDTD is explained in[5]. But the man-time required in finding a suitable architecture in general and dept of memory in particular takes much time than the normal simulation time of FDTD engine. In this paper, Real Coded Genetic Algorithm is used to find the architecture and training parameter of FIR-ANN. The FIR-ANN is applied as a nonlinear predictor to predict time series signal for speeding up the FDTD simulations. One of the main advantages of NFDTD is less storage requirement. But for less number of time-steps data collected from FDTD, the temporal neural network training time can exceed the normal FDTD computing time. On the other hand, the major disadvantage is that selection of parameters requires much man-time. Hence, use of GA with NFDTD speeds up the simulation time while meeting the accuracy requirement.

II. PROBLEM STATEMENT AND IMPLEMENTATION

A temporal neural network is used for time series data prediction. A time series data consists of a sequence of values changing with time. Therefore, a memory structure is needed in the traditional neural network to change it from static to dynamic. This memory structure is incorporated in neural networks by introducing a Finite Impulse Response(FIR) in between the weights. i.e., weights are replaced by FIRs. The FIR network is feed forward neural network architecture with internal time delay lines[4]. It is a modification of the basic multi-layer network in which each weight is replaced by an FIR linear filter as shown in figure 1(a).

The coefficients of a synaptic FIR filter connecting neuron i to j is specified by the vector

$$\mathbf{w}_{ji} = [w_{ji}(0), w_{ji}(1), ..., w_{ji}(p)]^T \tag{1}$$

And,

$$\mathbf{x}_i(n) = [x_i(n), x_i(n-1), ..., x_i(n-p)]^T \tag{2}$$

denotes the vector of delayed states along the FIR.

Output of neuron j is given by

$$s_j(n) = \sum_{k=0}^{p} w_{ji}(k) x_i(n-k) \tag{3}$$

For the filter, the output $y_j(n)$ corresponds to a weighted sum of past delayed values of the input as shown in figure 1(b).

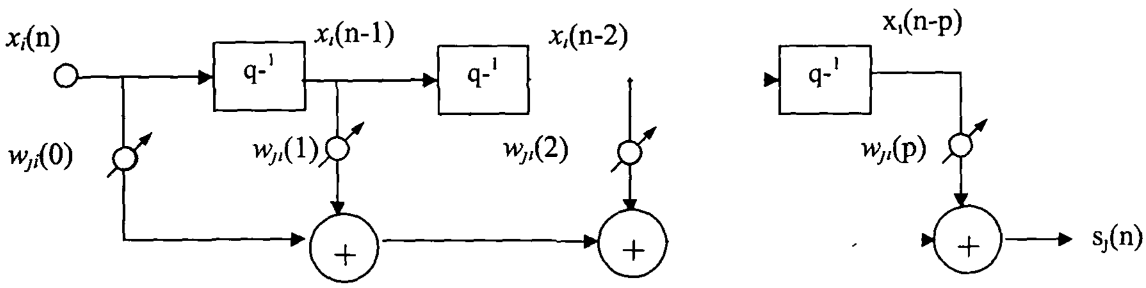

Fig. 1 (a) Filter Model of FIR Network

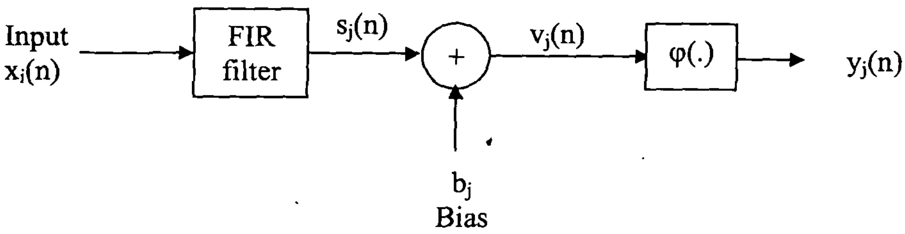

Fig. 1 (b) Output of a Neuron of FIR Network

The weights of the output layer neuron are updated as,

$$w_{ji}(n+1) = w_{ji}(n) + \eta\delta_j(n)x_i(n) \tag{4}$$

where, η is learning constant.

$$\delta_j(n) = -\frac{\partial E_{total}}{\partial v_j} \tag{5}$$

$$E_{total} = \sum_n E(n) \tag{6}$$

$$E(n) = \frac{1}{2}\sum_j e_j^2(n) \tag{7}$$

$$e_j(n) = d_j(n) - y_j(n) \tag{8}$$

$d_j(n)$ =Desired output at time stem n(Obtained from FDTD).

The weights of the hidden layer neurons are updated as,

$$w_{ji}(n+1) = w_{ji}(n) + \eta\delta_j(n-p)x_i(n-p) \tag{9}$$

$$\delta_j(n-p) = \varphi'(v_j(n-p))\sum_{r\in A}\Delta_r^T(n-p)w_{rj} \tag{10}$$

$$\Delta_r(n-p) = [\delta_r(n-p), \delta_r(n+1-p), \ldots\ldots, \delta_r(n)]^T \tag{11}$$

Where, A is the set of all neurons whose inputs are fed by neuron j in a forward manner.

P is the order of each synaptic FIR filter.

v_r denote induced local field of neuron r that belongs to the set A.

The operation of FIR-Neural networks is referred from [4].

The NFDTD parameters such as the number of hidden neurons, depth of memory, learning constant and momentum factor are chosen by hit and trial basis which depends purely on experience of the programmer. Proper selection takes much man-time. In this paper, Genetic Algorithm is used to set those parameters to reduce the man-time.

A coaxially fed square patch antenna as shown in figure 2, is considered to validate the proposed technique. The dimensions of the patch antenna are (i) side length L 10mm, (ii) dielectric constant(ε_r) 2.33, (iii) height of the substrate(h) 1.57 mm. The antenna is fed at 0.25 mm from corner(x_o=y_o=0.25mm).

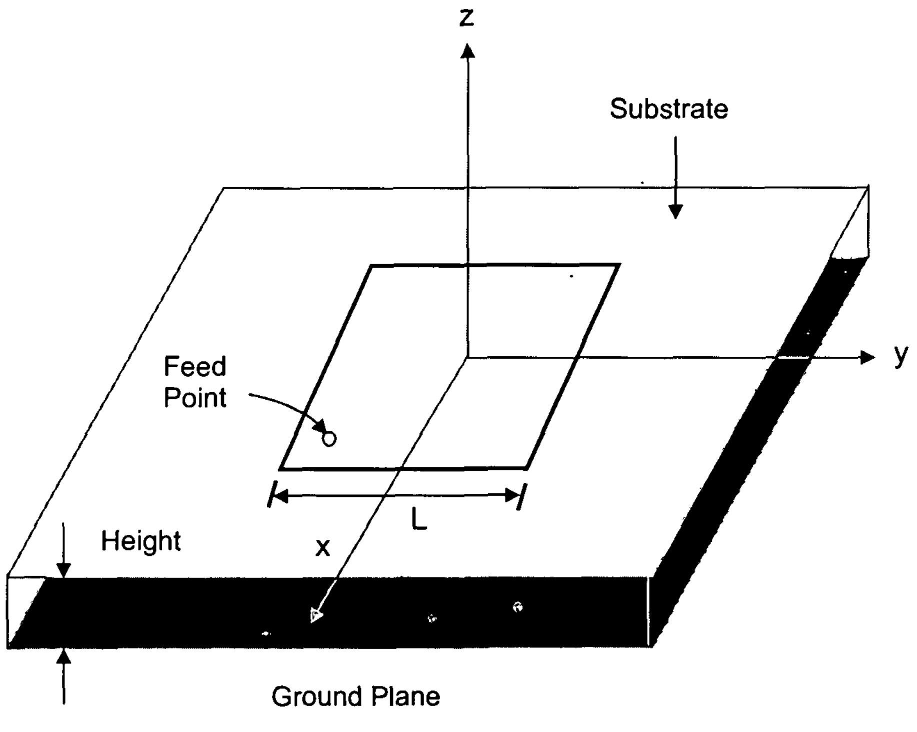

Figure 2. Coaxially Fed Square Patch Antenna

To model the dimensions of the antenna, the space descritization is chosen to be $\Delta x = \Delta y = \Delta z$ =0.25mm. The total mesh dimensions are 80x80x26. The time step used is

Δt =0.48ps. The FDTD simulation is performed for 10000 time steps. The experimental result for comparison is taken from [3]. The antenna is fed using a z-directed electric field at (21 Δx, 21 Δy, 6 Δz) by a raised cosine pulse. The internal source resistance R_s is kept at 50 ohm. Transient current and voltage for 500 steps from the FDTD simulation are collected. The FIR based feed forward neural network is trained with data set comprising current and voltage with 500 samples. The architecture chosen for temporal neural networks is shown in figure 3.

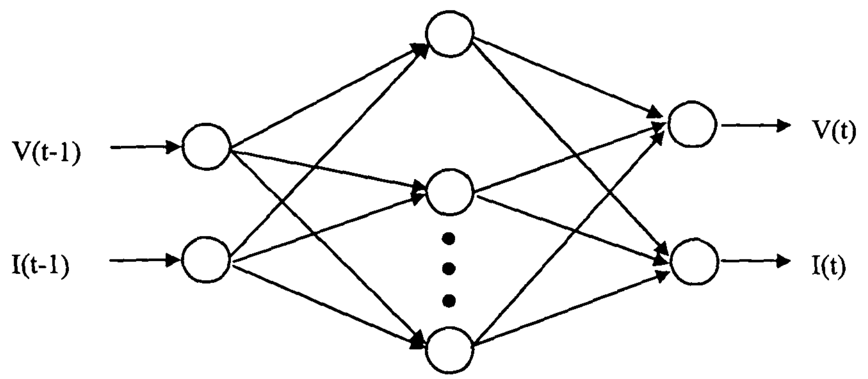

Fig. 3 FIR-Neural Network Architecture

Genetic algorithm is used to find the optimized FIR-ANN architecture. The training is done with temporal backpropagation algorithm. In each generation GA runs FIR-ANN for 100 cycles. The absolute error is set to 0.6. Genetic algorithm found the optimized architecture in 24 generations. After obtaining the optimized architecture, the FIR-ANN continued to obtain an absolute error tolerance level of 0.5.

The parameters of GA are set to as:

Population size: 20,

Probability of crossover(P_{cross}): 0.7,

Probability of mutation(P_{mut}): 0.001.

Figure 4 shows the flow-charts of the NFDTD algorithm where as the flow-chart of GA-NFDTD algorithm proposed by authors is shown in figure 5.

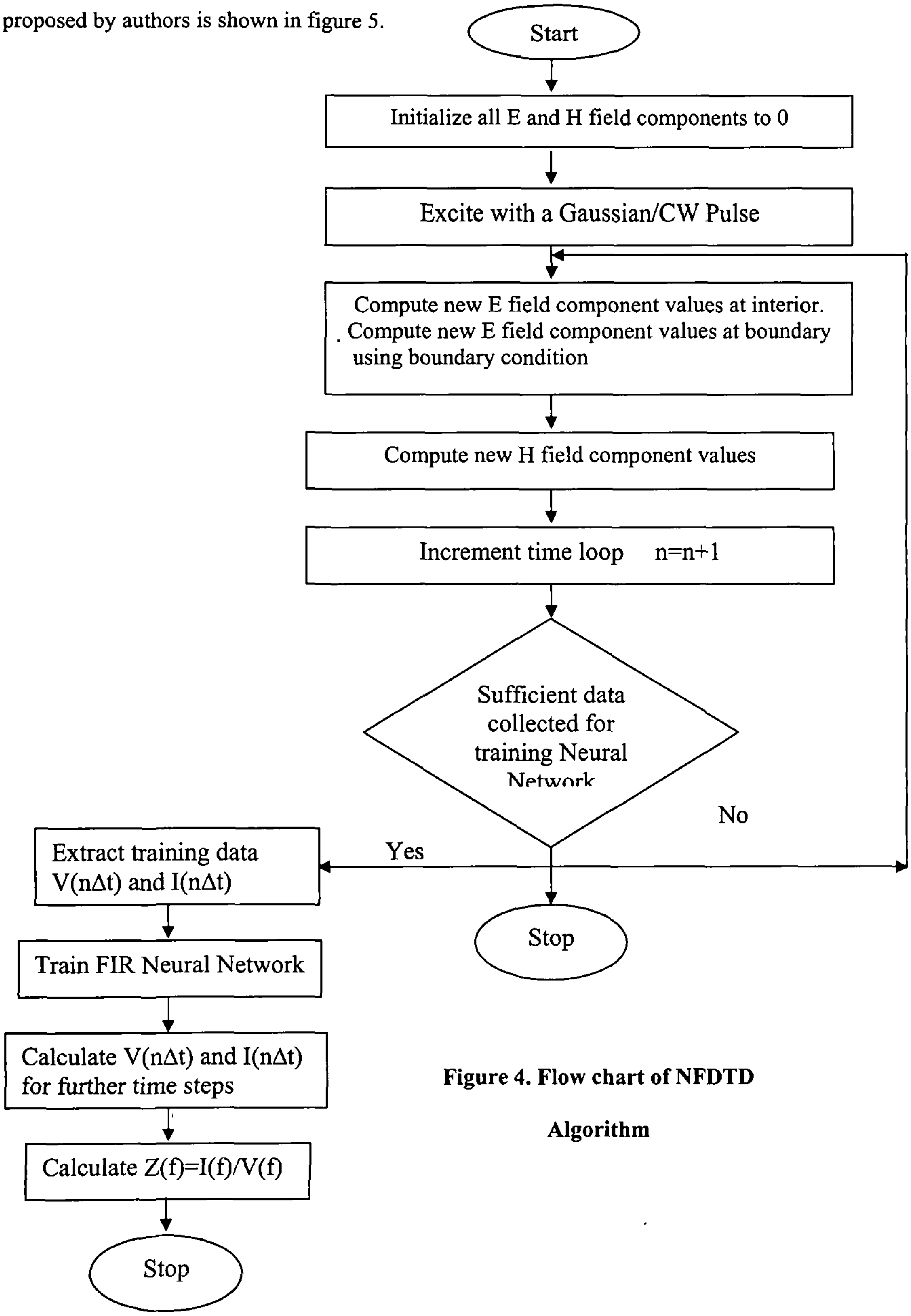

Figure 4. Flow chart of NFDTD Algorithm

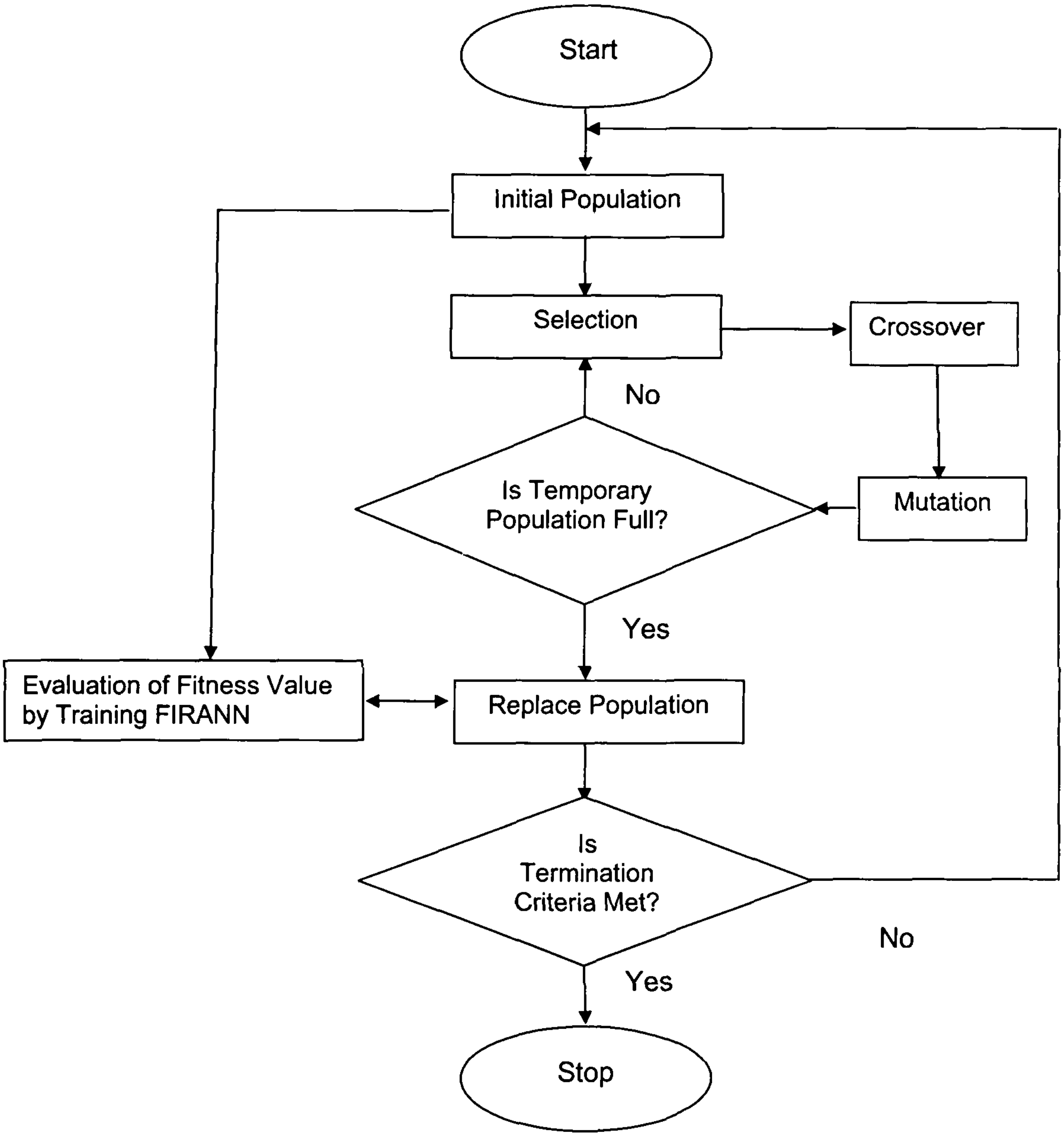

Figure 5. Flow chart of GA-NFDTD Algorithm

II. RESULTS AND DISCUSSION

The NFDTD parameters found by GA for training the FIR-ANN are as follows:

Number of Hidden Neurons: 08

Depth of memory: 59

Learning Constant: 0.888519

Momentum factor: 0.0539589

The network is tested for 9500 samples. FFT is applied on 10, 000 samples(500 samples of FDTD and output of 9500 samples of NFDTD). Figure 6 shows the absolute error vs epoch curve. Figure 7 and 8 shows the comparison of Impedance for both real and imaginary part of FDTD, NFDTD and experimental and GA-NFDTD results. GA-NFDTD results are close to experimental results and are in good agreement with the simulation results published in[6].

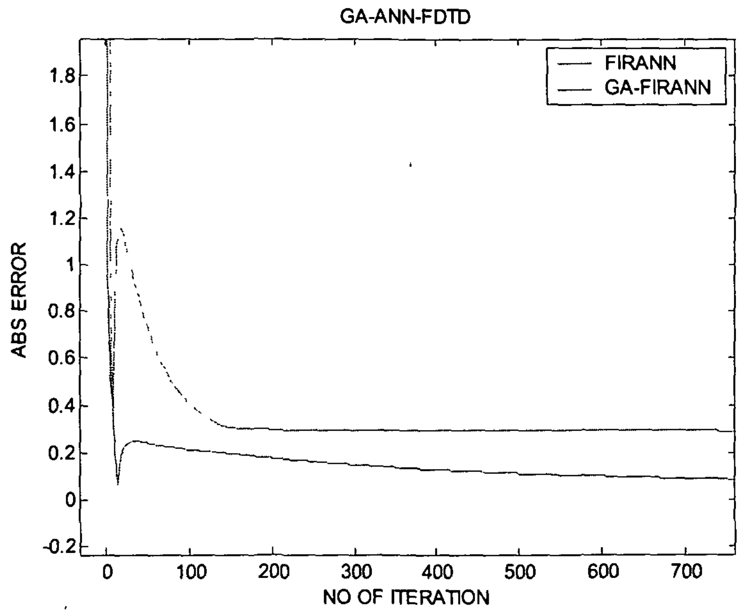

Figure 6. Error vs. Epochs

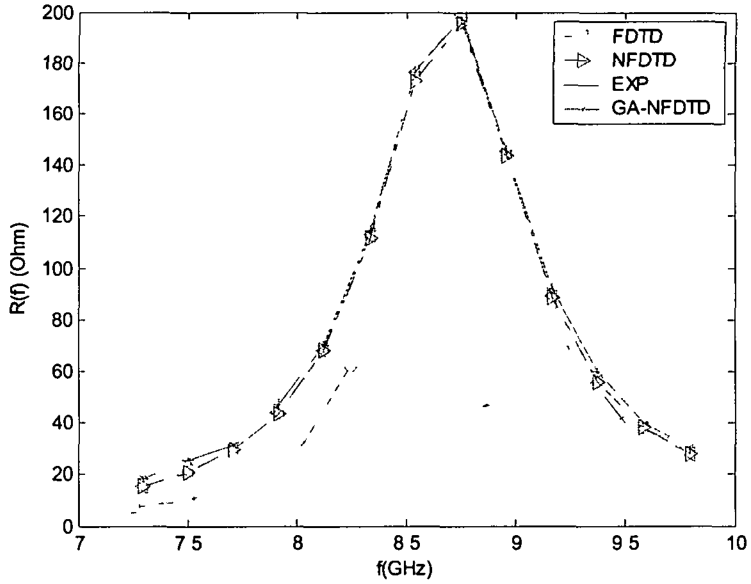

Figure 7. Comparison of Input Impedance(Real) of FDTD, NFDTD, GA-NFDTD and Experimental Results

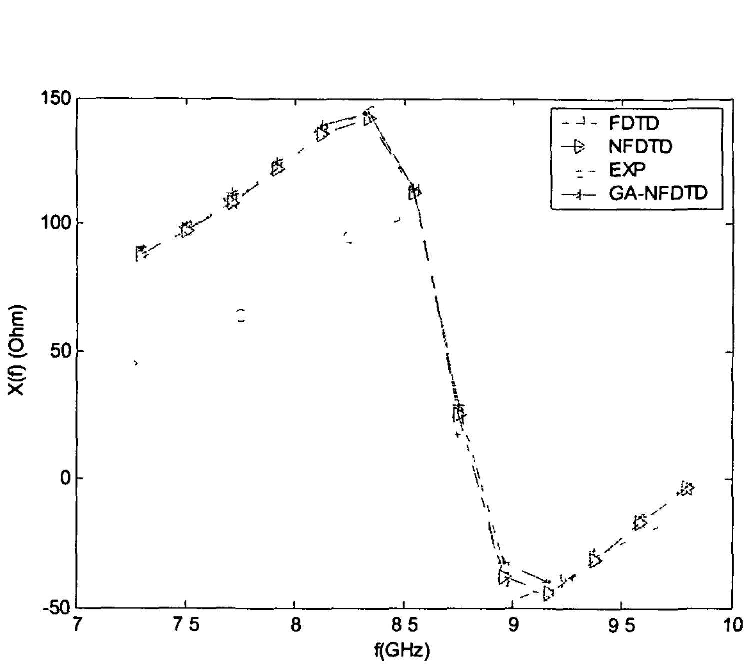

Figure 8. Comparison of Input Impedance(Imaginary) of FDTD, NFDTD, GA-NFDTD and Experimental Results

IV. CONCLUSION

The purpose of this work is to establish the suitability of ANN and GA with FDTD for analysis of electromagnetic problems in time domain. A co-axial feed square patch antenna is used to explain the implementation procedure. FDTD results for 500 time steps have been considered for training the FIR-ANN(NFDTD). GA decides the architecture and parameters of NFDTD by setting minimum training cycles. Once the parameters are decided, the network is further trained to reduce the error. Finally, for remaining time steps, the current and voltage are calculated using trained-NFDTD. This technique will have immense potential when the number of time steps is more and for high-Q passive structures. The technique can further be improved by replacing GA by faster soft-computing algorithms like Particle Swarm Optimization(PSO), Bacterial Foraging Optimization(BFO) etc.

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