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 Zeland 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 probability nature. GAs are capable of optimizing nonlinear multimoal 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.

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

Figure 2 Return loss plot for antenna no 1

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mutation is equal to 0.01. Thus, it is suitable for the calculation of the resonant frequencies for antenna elements with \( h \leq 0.0815L \). Hence, in this paper, we have used Eq (1) for designing antennas with thin substrates.

Resonant frequency \( f_r \), dielectric constant \( e_r \), 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 \( (L, W, h, e_r) \) 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 antennas.

**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.

**ACKNOWLEDGMENT**

The authors are thankful to MHRD, Govt. of India for sponsoring the project.
## Table 1: Resonant Frequency Results and Dimensions for Rectangular Microstrip Antennas

<table>
<thead>
<tr>
<th>Antenna No</th>
<th>II Theoretical Resonant Frequency ($f_r$) in GHz as Input</th>
<th>III Permittivity of Substrate ($\varepsilon_r$) as Input</th>
<th>IV Height (H) in mm as Input</th>
<th>V Calculated Length (L) in mm Using GA as Input</th>
<th>VI Calculated Width (W) in mm Using GA as Output</th>
<th>VII Experimental Length (L) in mm from [1]</th>
<th>VIII E3D Simulated Resonant Frequency ($f_r$) in GHz Using Calculated (L and W as in V and VI)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6.2</td>
<td>2.55</td>
<td>2.0</td>
<td>14.382</td>
<td>8.975</td>
<td>14.12</td>
<td>6.13</td>
</tr>
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<td>2</td>
<td>8.45</td>
<td>2.22</td>
<td>0.17</td>
<td>11.867</td>
<td>9.456</td>
<td>11.85</td>
<td>8.32</td>
</tr>
<tr>
<td>3</td>
<td>7.74</td>
<td>2.22</td>
<td>0.17</td>
<td>12.19</td>
<td>19.337</td>
<td>12.9</td>
<td>7.6</td>
</tr>
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<td>4</td>
<td>5.97</td>
<td>2.22</td>
<td>0.79</td>
<td>25.306</td>
<td>13.007</td>
<td>25</td>
<td>5.92</td>
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<td>5</td>
<td>5.06</td>
<td>2.33</td>
<td>1.57</td>
<td>18.6</td>
<td>18.4</td>
<td>18.6</td>
<td>4.08</td>
</tr>
<tr>
<td>6</td>
<td>5.6</td>
<td>2.55</td>
<td>1.63</td>
<td>16.07</td>
<td>13.34</td>
<td>16.21</td>
<td>5.3</td>
</tr>
<tr>
<td>7</td>
<td>4.805</td>
<td>2.33</td>
<td>1.57</td>
<td>19.573</td>
<td>21.696</td>
<td>19.6</td>
<td>4.6</td>
</tr>
</tbody>
</table>

The return loss and VSWR plots calculated using E3D Simulation Software for antenna number 1 are shown in Figs 2 and 3, respectively, Figs 4 and 5 show that of antenna number 5.

## References

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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-Gaussian 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, Rayleigh–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 eigenvectors 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. 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...
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 conventions 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-dimensional, multimodal function, in which the number of variables tends to be high, 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 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]
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

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

where $\lambda$ 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

$$E(w) = \frac{1}{2} \sum_{p=1}^{P} \sum_{k=1}^{N} \left( y_k^p - d_k^p \right)^2,$$  \hspace{1cm} (2)

where $y_k^p$ is the output of the $k^{th}$ 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 $l-1$, $x_k$ is the $p^{th}$ training sample, $d_k^p$ is the desired response of the $j^{th}$ output node for the $p^{th}$ training sample, $N$ 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, $w_{j,k}^l = 1$ 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 $\lambda$ 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, speci-
TABLE 1 Comparison of the Results of Using the Present Method, the Feed-Forward Backpropagation Algorithm, and Experimental Resonant Frequency

<table>
<thead>
<tr>
<th>Patch No</th>
<th>Experimental Resonant Frequency (GHz)</th>
<th>Resonant Frequency (GHz) (Present Method)</th>
<th>Resonant Frequency (GHz) (Backpropagation Algorithm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5.820</td>
<td>5.8251</td>
<td>5.7964</td>
</tr>
<tr>
<td>2</td>
<td>4.660</td>
<td>4.67353</td>
<td>4.5259</td>
</tr>
<tr>
<td>3</td>
<td>3.980</td>
<td>3.95329</td>
<td>3.9308</td>
</tr>
<tr>
<td>4</td>
<td>3.900</td>
<td>3.87665</td>
<td>3.9149</td>
</tr>
<tr>
<td>5</td>
<td>2.980</td>
<td>3.02413</td>
<td>2.9927</td>
</tr>
</tbody>
</table>

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

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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(−iωt) 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

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

(1)

The sign of $n_r$ gives the phase-velocity direction, whereas the sign of the real part of $n\mu$, given by

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INVERTED L-SHAPED AND PARA-SITICALLY 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. © 2004 Wiley Periodicals, Inc. 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, and suitable polarization of microstrip antennas for wireless communication systems. To enlarge the inherent narrow band 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 (thick 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.

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

The thickness of the substrate used is 2 mm, while $e_r = 2.2$. 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 band-

width. 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 Zeland, 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].
REFERENCES


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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 crosstalk 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.

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, 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

$$Fitness = \frac{1}{1 + E_{abs}}.$$  \hspace{1cm} (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

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

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

$$= \sum_{i=1}^{m} w_{ij}z_j(n),$$

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

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.

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 ($\varepsilon_r$), 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 ($\lambda$) is 5.382164;

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

Figure 3. Number of cycles vs. error.
Table I. Resonant Frequency of a Microstrip Antenna Using Single Shorting Pin Applying GA on ANN*  

<table>
<thead>
<tr>
<th>(L/L_t)</th>
<th>(L (\text{cm}))</th>
<th>(W (\text{cm}))</th>
<th>(e_r)</th>
<th>(h (\text{cm}))</th>
<th>Resonant Frequency (Experimental) (GHz)</th>
<th>Resonant Frequency (Eqn. (10)) of [13] (GHz)</th>
<th>Resonant Frequency (Normal Back-propagation) (GHz)</th>
<th>Resonant Frequency (Presented Method) (GHz)</th>
</tr>
</thead>
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<tr>
<td>0.1</td>
<td>62</td>
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<td>2.55</td>
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<td>1.594</td>
<td>1.64</td>
<td>1.619</td>
<td>1.607</td>
</tr>
<tr>
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<td>7.424</td>
<td>22</td>
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<td>2.788</td>
<td>—</td>
<td>2.808</td>
<td>2.798</td>
</tr>
<tr>
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<td>62</td>
<td>9</td>
<td>2.55</td>
<td>0.16</td>
<td>1.525</td>
<td>1.544</td>
<td>1.493</td>
<td>1.517</td>
</tr>
<tr>
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<td>375</td>
<td>7.424</td>
<td>22</td>
<td>0.1524</td>
<td>3.13</td>
<td>—</td>
<td>3.014</td>
<td>3.028</td>
</tr>
</tbody>
</table>

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

• the learning constant \((\eta)\) is 0.106955,  
• the momentum factor \((\alpha)\) 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 \((3 \times 20 \times 1)\) 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.

ACKNOWLEDGMENTS

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REFERENCES

8. S. S. Pattnaik, D. C. Panda, and S. Devi, Radiation resistance of cox-fed rectangular microstrip patch an-
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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 multidimensional, 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-dimensional, 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 imputation 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 $\lambda_0$ 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...
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 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:

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

**RESULTS AND DISCUSSION**

The optimized design parameters of the five antennas considered for testing are 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 2nd and the 3rd columns. The experimental dimensions of length and width are shown in the 4th and 7th columns, respectively, while the optimized output of our GA-ANN-based dimensions are listed in the 6th 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>
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**TABLE 1 Dimensions of Thick-Substrate Rectangular-Microstrip Antenna ($\varepsilon_r = 2.55$)**

**Figure 3** Block diagram of the presented algorithm
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 efficiency of training 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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REFERENCES

2 J M Johnson and Y Rahmat-Samii, Genetic algorithms in electromagnetic design, IEEE Antennas Propagat Mag 39 (1997), 7–21
4 M. Kara, Empirical formulas for the computation of the physical properties of rectangular microstrip antenna elements with thick substrates, Microwave Opt Technol Lett 14 (1997), 115–120

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.20971

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](https://wds1.wiley.com/doi/figure/10.1002/mop.20971)
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 ($L_s$), width ($W_s$), and position ($P_s$) 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. FEKO 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: $l = 45 mm$, $W = 71 mm$, $h = 2 mm$, $L_s = 17.5 mm$, $W_s = 4 mm$, 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 $L_s = 19.5 mm$, i.e., for an increased slot length. This figure also shows the $S_{11}$ values in dB with a slot width of $W_s = 3 mm$, i.e., for a decreased slot width. These plots clearly show the effects of $L_s$ and $W_s$ 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 $5 \times 10^{-15}$, and strength of learning for tunneling of 0.08.
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]

$$\frac{dw}{dt} = \rho (w - w^*)^{1/3},$$  \hspace{1cm} (1)

where $\rho$ 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 tunnelled according to the above equation. If the error was less than the last local minimum, then the weights were updated according to the relation

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

where $\eta$ is called the learning factor, and $\alpha$ is called the momentum factor. $t$ and $(t-1)$ indicate training steps. Using IEDJ, 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 × 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 IEDJ and with those of 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 favorable 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

$$E(w) = 0.5 \sum_{p=1}^{N_t} \sum_{k=1}^{N_l} \left[ \frac{w_{jk}^{l}(x_p) - d_p(x_p)}{d_p(x_p)} \right]^2,$$  \hspace{1cm} (3)

where $w_{jk}^{l}$ is the output of the $j$th node in layer $l$, $w_{jk}^{l}$ is the weighting 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, $d_p(x_p)$ is the desired response of the $j$th output node for the $p$th training sample, $N_t$ is the number of nodes in layer $l$, $N_l$ is the number of layers, and $P$ is the number of training patterns. In the above notation, $w_{jk}^{0} = 1$ and $w_{jk}^{1,0}$ 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 $L_s$, 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 $L_2$ and $W_2$: solid dots, $L_2 = 19.5$ mm, $W_2 = 4$ mm; circles, $L_2 = 17$ mm, $W_2 = 3$ 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.

<table>
<thead>
<tr>
<th>$L_x/L$</th>
<th>$L$ (cm)</th>
<th>$W$ (cm)</th>
<th>$h$ (cm)</th>
<th>Resonant Frequency: Theory (GHz)</th>
<th>Resonant Frequency: Experiment (GHz)</th>
<th>Resonant Frequency: GA-ANN (GHz)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.5</td>
<td>6.2</td>
<td>9</td>
<td>2.55</td>
<td>0.16</td>
<td>1.48439</td>
<td>1.466</td>
</tr>
<tr>
<td>0.6</td>
<td>6.2</td>
<td>9</td>
<td>2.55</td>
<td>0.16</td>
<td>1.50073</td>
<td>1.480</td>
</tr>
<tr>
<td>0.3</td>
<td>3.75</td>
<td>7.424</td>
<td>2.2</td>
<td>0.1524</td>
<td>2.68041</td>
<td>2.788</td>
</tr>
<tr>
<td>0.4</td>
<td>3.75</td>
<td>7.424</td>
<td>2.2</td>
<td>0.1524</td>
<td>2.61531</td>
<td>2.664</td>
</tr>
</tbody>
</table>

$\varepsilon_r$ and the height of the substrate were taken as inputs to a 5x30x1 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 $L_x/L_x$, whereas the calculated results using [19] were symmetric. The results obtained using the present 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.

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6. References


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.

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

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

(1)

And,

\[
x_j(n) = [x_j(n), x_j(n-1), ..., x_j(n-p)]^T
\]

(2)

denotes the vector of delayed states along the FIR.

Output of neuron \(j\) is given by

\[
s_j(n) = \sum_{k=0}^{p} w_{ji}(k)x_j(n-k)
\]

(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

3
The weights of the output layer neuron are updated as,

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

where, $\eta$ is learning constant.

$$\delta_j(n) = -\frac{\partial E_{\text{total}}}{\partial v_j}$$  \hspace{1cm} (5)

$$E_{\text{total}} = \sum_n E(n)$$  \hspace{1cm} (6)

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

$$e_j(n) = d_j(n) - y_j(n)$$  \hspace{1cm} (8)

d_j(n) = \text{Desired output at time stem n (Obtained from FDTD)}.$$

The weights of the hidden layer neurons are updated as,

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

$$\delta_j(n-p) = \varphi'(v_j(n-p))\sum_{r \in A} \Delta_r^r(n-p)w_{jr}$$  \hspace{1cm} (10)

$$\Delta_r(n-p) = [\delta_r(n-p), \delta_r(n+1-p), \ldots \ldots, \delta_r(n)]^T$$  \hspace{1cm} (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.
\( y \) 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 \( (\varepsilon_r) \) 2.33, (iii) height of the substrate \( (h) \) 1.57 mm. The antenna is fed at 0.25 mm from corner \( (x_0,y_0)=0.25\text{mm} \).

![Coaxially Fed Square Patch Antenna](image)

**Figure 2. Coaxially Fed Square Patch Antenna**

To model the dimensions of the antenna, the space discretization is chosen to be \( \Delta x = \Delta y = \Delta z = 0.25\text{mm} \). The total mesh dimensions are 80x80x26. The time step used is
\( \Delta t = 0.48 \text{ps} \). 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 \((21 \Delta x, 21 \Delta y, 6 \Delta z)\) 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.

![FIR-Neural Network Architecture](image)

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 \( P_{\text{cross}} \): 0.7,
- Probability of mutation \( P_{\text{mut}} \): 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.
REFERENCE


