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 et al considerably improved the modeling technique that enabled it to accurately characterize multilayer 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

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

And,

$$x_i(n)=[x_i(n), x_i(n-1), ..., x_i(n-p)]^T$$  \hfill (6.2)

denotes the vector of delayed states along the FIR.

Output of neuron $j$ is given by[17]
\[ s_j(n) = \sum_{k=0}^{p} w_{j,k}(k)x_j(n-k) \quad (6.3) \]

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).

![Diagram of Filter Model of FIR Network](image)

**Fig. 6.1 (a) Filter Model of FIR Network**

![Diagram of Output of a Neuron of FIR Network](image)

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

The weights of the output layer neuron are updated as,

\[ w_{j}(n+1) = w_{j}(n) + \eta \delta_j(n) x_j(n) \quad (6.4) \]

where, \( \eta \) is learning constant

\[ \delta_j(n) = -\frac{\partial E_{\text{total}}}{\partial v_j} \quad (6.5) \]
\[ E_{\text{total}} = \sum_n E(n) \] (6.6)

\[ E(n) = \frac{1}{2} \sum_j \varepsilon_j^2(n) \] (6.7)

\[ \varepsilon_j(n) = d_j(n) - y_j(n) \] (6.8)

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

The weights of the hidden layer neurons are updated as,

\[ w_{ji}(n+1) = w_{ji}(n) + \eta \delta_j(n-p) x_j(n-p) \] (6.9)

\[ \delta_j(n-p) = \varphi'(y_j(n-p)) \sum_{r \in A} \Delta^T_r(n-p) w_{\eta} \] (6.10)

\[ \Delta_j(n-p) = [\delta_j(n-p), \delta_j(n+1-p), \ldots, \delta_j(n)]^T \] (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

\( y_r \) 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.

Start

Initialize all E and H field components to 0

Excite with a Gaussian/CW Pulse

Compute new E field component values at interior. Compute new E field component values at boundary using boundary condition

Compute new H field component values

Increment time loop $n = n + 1$

Sufficient data collected for training Neural Network

Yes

Extract training data $V(n\Delta t)$ and $I(n\Delta t)$

Train FIR Neural Network

Calculate $V(n\Delta t)$ and $I(n\Delta t)$ for further time steps

Calculate $Z(f) = I(f)/V(f)$

No

Stop

Fig. 6.3. Flow chart of NFDTD Algorithm
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($\varepsilon_r$) 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 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 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 $(21 \Delta x, 21 \Delta y, 6 \Delta z)$ 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.
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.

![Flow chart of GA-NFDTD Algorithm](image)

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\( (P_{\text{cross}}) \): 0.7

Probability of mutation\( (P_{\text{mut}}) \): 0.001

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

<table>
<thead>
<tr>
<th>Number of Hidden Neurons:</th>
<th>08</th>
</tr>
</thead>
<tbody>
<tr>
<td>Depth of memory:</td>
<td>59</td>
</tr>
<tr>
<td>Learning Constant:</td>
<td>0.888519</td>
</tr>
<tr>
<td>Momentum factor:</td>
<td>0.0539589</td>
</tr>
</tbody>
</table>

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.
References


