PREDICTING TRANSMISSION LINE CHARACTERISTICS USING ANN

A Thesis submitted in partial fulfilment of the requirements for the awards of the Degree of

B.Tech

in

Electronics and Communication Engineering

By

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BONAFIDE CERTIFICATE

This is to certify that the project titled **‘Predicting Transmission Line Characteristics using ANN’** is a bonafide record of the work done by

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in partial fulfilment of the requirements for the award of the degree of **Bachelor of Technology** in **Electronics and Communication Engineering** of the **NATIONAL INSTITUTE OF TECHNOLOGY, TIRUCHIRAPALLI,** during the year 2016-2017.

Dr. S. Raghavan — Project Guide

Dr. G. Lakshmi Narayanan — Head of the Department

Project Viva-voce held on ______________________

Internal Examiner

External Examiner

ABSTRACT

Neural networks have recently been introduced to the microwave area as a fast and flexible vehicle for microwave modelling, simulation and optimization. This thesis represents a research direction that uses Neural networks to model Transmission Line characteristics.

The goal is to train Neural Networks using PYTHON, to predict characteristics such as impedance or resonant frequency against design parameters of 6 types of transmission lines.

Using formula and equations that define characteristics of Transmission lines, training data is to be generated. Training of the Neural Network is to be done using 6 different algorithms. The extent of deviation of predicted output from the actual output is to be measured in terms of maximum error percentage and average error percentage. This helps determine how well an algorithm worked for a particular transmission line. Secondary objective is to determine which algorithm is best suited for a particular transmission line based on error values.

During the training process one of the challenges is to find a balance between number of training samples, number of iterations, time for training and error percentage. Number of samples and iterations have direct relationship with training time and inverse relationship with error percentage. Optimising the algorithm involves finding the right numbers such that the training time and error are minimized.

ACKNOWLEDGEMENTS

We would like to express our sincere gratitude to our project guide, **Dr. S. Raghavan**, **Professor**, Department of Electronics and Communication Engineering, National Institute of Technology, Tiruchirappalli for his valuable guidance and constant encouragement throughout the course of the project work. We take immense pleasure in thanking **Dr. G. Lakshmi Narayanan, Head of the Department,** Electronics and Communication Engineering for his inspiration and support.

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The characteristics of the following planar transmission lines have been predicted:

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3. Slotline
4. Co Planar Waveguide(CPW)
5. Co Planar Strip
6. Microstrip Patch Antenna

1.2 ANN Algorithms used

The characteristics have been predicted using five different methodologies of Artificial Neural Networks namely:

1. Backpropagation
2. Linear Regression
3. Logistic Regression
4. MLP Classifier
5. SGD - Stochastic Gradient Descent

Chapter 2

Artificial Neural Networks

ANNs are processing devices (algorithms or actual hardware) that are loosely modeled after the neuronal structure of the mamalian cerebral cortex but on much smaller scales. A large ANN might have hundreds or thousands of processor units, whereas a mamalian brain has billions of neurons with a corresponding increase in magnitude of their overall interaction and emergent behavior.

The simplest definition of a neural network, more properly referred to as an 'artificial' neural network (ANN), is provided by the inventor of one of the first neurocomputers, Dr. Robert Hecht-Nielsen. He defines a neural network as: A computing system made up of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs.

2.1 Basic features of Artificial Neural Networks

Neural neworks are typically organized in layers. Layers are made up of a number of interconnected 'nodes' which contain an 'activation function'. Patterns are presented to the network via the 'input layer', which communicates to one or more 'hidden layers' where the actual processing is done via a system of weighted 'connections'. The hidden layers then link to an 'output layer'.

Most ANNs contain some form of 'learning rule' which modifies the weights of the connections according to the input patterns that it is presented with. ANNs learn by example as do their biological counterparts.

Since the nature of the error space can not be known a prioi, neural network analysis often requires a large number of individual runs to determine the best solution. Most learning rules have built-in mathematical terms to assist in this process which control the 'speed' and the 'momentum' of the learning. The speed of learning is actually the rate of convergence between the current solution and the global minimum. Momentum helps the network to overcome obstacles (local minima) in the error surface and settle down at or near the global miniumum.

Once a neural network is 'trained' to a satisfactory level it may be used as an analytical tool on other data. To do this, the user no longer specifies any training runs and instead allows the network to work in forward propagation mode only. New inputs are presented to the input pattern where they filter into and are processed by the middle layers as though training were taking place, however, at this point the output is retained and no backpropagation occurs. The output of a forward propagation run is the predicted model for the data which can then be used for further analysis and interpretation.

2.2 Artificial Neural Networks Vs. Conventional Computing

A serial computer has a central processor that can address an array of memory locations where data and instructions are stored. Computations are made by the processor reading an instruction as well as any data the instruction requires from memory addresses, the instruction is then executed and the results are saved in a specified memory location as required. In a serial system (and a standard parallel one as well) the computational steps are deterministic, sequential and logical, and the state of a given variable can be tracked from one operation to another.

In comparison, ANNs are not sequential or necessarily deterministic. There are no complex central processors, rather there are many simple ones which generally do nothing more than take the weighted sum of their inputs from other processors. ANNs do not execute programed instructions; they respond in parallel (either simulated or actual) to the pattern of inputs presented to it. There are also no separate memory addresses for storing data. Instead, information is contained in the overall activation 'state' of the network. 'Knowledge' is thus represented by the network itself, which is quite literally more than the sum of its individual components.

2.3 Advantages over Conventional Computing

Depending on the nature of the application and the strength of the internal data patterns you can generally expect a network to train quite well. This applies to problems where the relationships may be quite dynamic or non-linear. ANNs provide an analytical alternative to conventional techniques which are often limited by strict assumptions of normality, linearity, variable independence etc. Because an ANN can capture many kinds of relationships it allows the user to quickly and relatively easily model phenomena which otherwise may have been very difficult or impossible to explain otherwise.

2.4 Applications of Neural Networks

Neural networks are universal approximators, and they work best if the system you are using them to model has a high tolerance to error. They work very well for:

- capturing associations or discovering regularities within a set of patterns;
- where the volume, number of variables or diversity of the data is very great;
- the relationships between variables are vaguely understood; or,
- the relationships are difficult to describe adequately with conventional approaches.

Chapter 3

Algorithms of Artificial Neural Networks

3.1 Backpropagation

The principle of the backpropagation approach is to model a given function by modifying internal weightings of input signals to produce an expected output signal. The system is trained using a supervised learning method, where the error between the systems output and a known expected output is presented to the system and used to modify its internal state.

Technically, the backpropagation algorithm is a method for training the weights in a multilayer feed-forward neural network. As such, it requires a network structure to be defined of one or more layers where one layer is fully connected to the next layer.

Backpropagation uses these error values to calculate the gradient of the loss function with respect to the weights in the network. In the second phase, this gradient is fed to the optimization method, which in turn uses it to update the weights, in an attempt to minimize the loss function.

3.2 Linear Regression

Linear regression is a linear model, e.g. a model that assumes a linear relationship between the input variables (x) and the single output variable (y).

There are four techniques to prepare a linear regression model.In our project we used Gradient Descent technique.

As there are more than one inputs we chose to use a process of optimizing the values of the coefficients by iteratively minimizing the error of the model on our training data.

Gradient Descent works by starting with random values for each coefficient. The sum of the squared errors are calculated for each pair of input and output values. A learning rate is used as a scale factor and the coefficients are updated in the direction towards minimizing the error. The process is repeated until a minimum sum squared error is achieved or no further improvement is possible.

When using this method, you must select a learning rate (alpha) parameter that determines the size of the improvement step to take on each iteration of the procedure.

The linear regression model fits a linear function to a set of data points. The form of the function is:

$$Y = \beta_0 + \beta_1 * X_1 + \beta_2 * X_2 + ... + \beta_n * X_n$$

Where Y is the target variable, and X_1, X_2, ... X_n are the predictor variables and β_0, β_1, β_2 β_n are the coefficients that multiply the predictor variables. β_0 is constant.

3.3 Logistic Regression

Logistic Regression is a type of regression that predicts the probability of ocurrence of an event by fitting data to a logistic function. Logistic regression uses an equation as the representation, very much like linear regression. Input values (X) are combined linearly using weights or coefficient values to predict an output value (y). A key difference from linear regression is that the output value being modeled is a binary value (0 or 1) rather than a numeric value.

3.4 SGD Regression

Stochastic Gradient Descent (SGD), a simple modification to the standard gradient descent algorithm that computes the gradient and updates weight matrix W on small batches of training data, rather than the entire training set itself.

SGD has been successfully applied to large-scale and sparse machine learning problems often encountered in text classification and natural language processing.

The advantages of Stochastic Gradient Descent are Efficiency and ease of implementation.While this leads to noiser weight updates, it also allows us to take more steps along the gradient , ultimately leading to faster convergence and no negative affects to loss and classification accuracy.

In Stochastic Gradient Descent (SGD), the weight vector gets updated every time you read process a sample, whereas in Gradient Descent (GD) the update is only made after all samples are processed in the iteration. Thus, in an iteration in SGD, the weights number of times the weights are updated is equal to the number of examples, while in GD it only happens once. SGD is beneficial when it is not possible to process all the data multiple times because the data is huge. It is also possible for SGD to converge in fewer iterations than GD, and depending on the data size, it can be more efficient than GD from a processing point of view.

Chapter 4

Features of Planar Transmission Lines

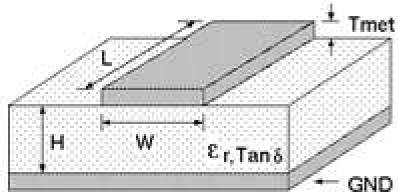
4.1 Microstrip

Microstrip is a planar transmission line used to carry Electro-Magnetic Waves (EM waves) or microwave frequency signals. It consists of 3 layers, conducting strip, dielectric and Ground plane. It is used to design and fabricate RF and microwave components such as directional coupler, power divider/combiner, filter, antenna, MMIC etc.

Microstrip line will have low to high radiation, will support 20 to 120 ohm impedance, supports Q factor of about 250.

Microstrip lines are also used in high-speed digital PCB designs, where signals need to be routed from one part of the assembly to another with minimal distortion, and avoiding high cross-talk and radiation.

4.1.1 Schematic Diagram



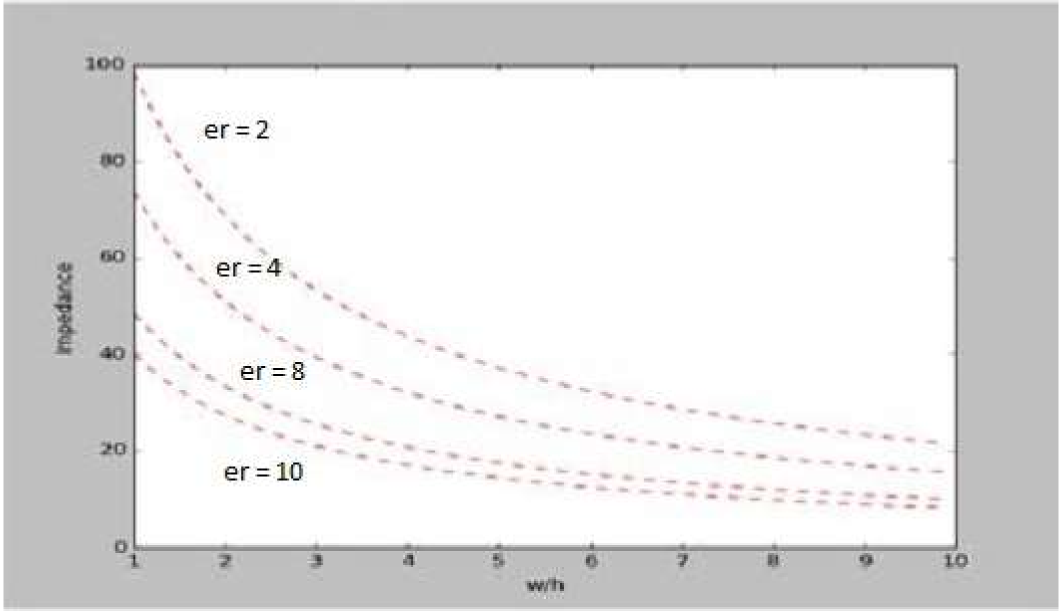
4.1.2 Formula used

for $\frac{W}{H} \geq 1$

$$\varepsilon_{eff} = \frac{\varepsilon_r + 1}{2} + \frac{\varepsilon_r - 1}{2\sqrt{1 + 12\frac{H}{W}}}$$

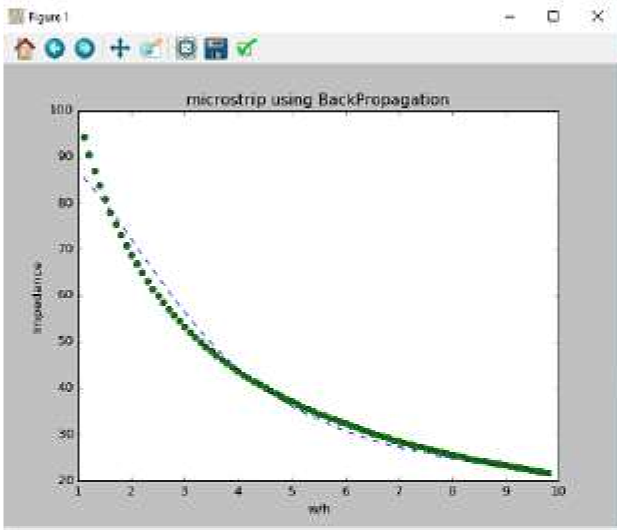
$$Z_0 = \frac{120\pi}{\sqrt{\varepsilon_{eff}}\left[\frac{W}{H} + 1.393 + \frac{2}{3}\ln\left(\frac{W}{H} + 1.444\right)\right]} \quad \Omega$$

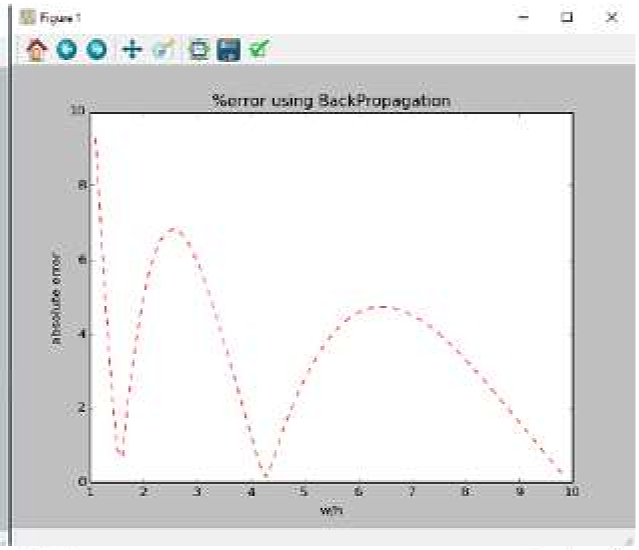
4.1.3 Graphical plot using formula method

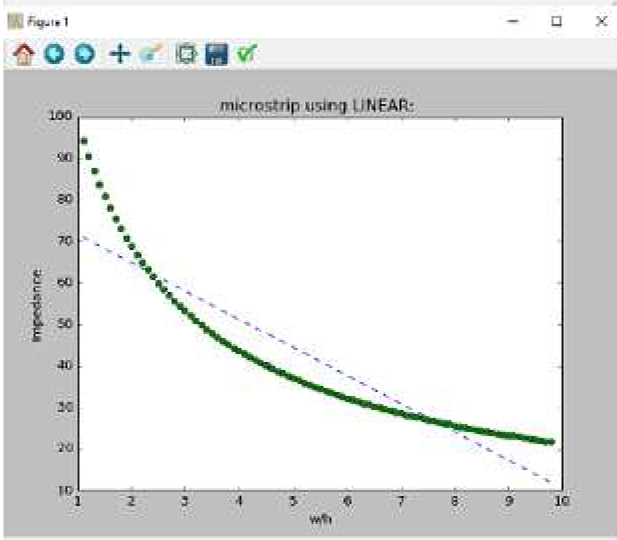


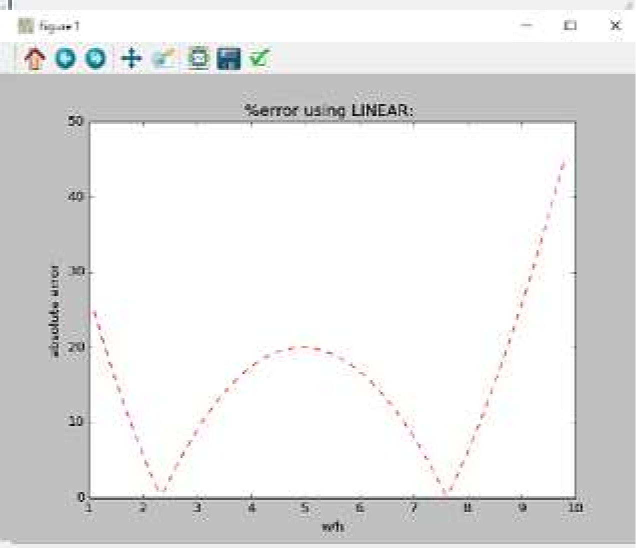
4.1.4 Graphical plots using different ANN methods

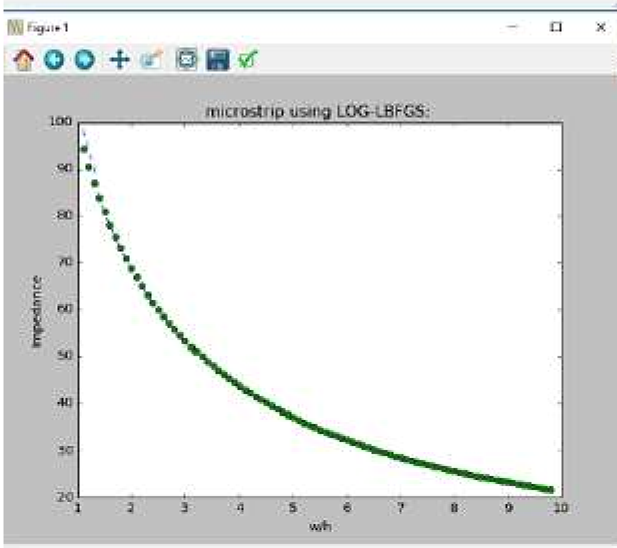
$\epsilon r = 2$ for all the plots using ANN
Dashed line implies Predicted Output
Dotted line implies Actual Output

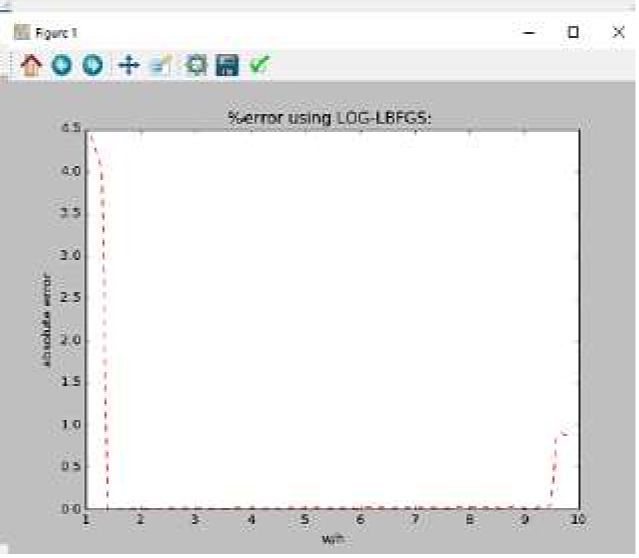


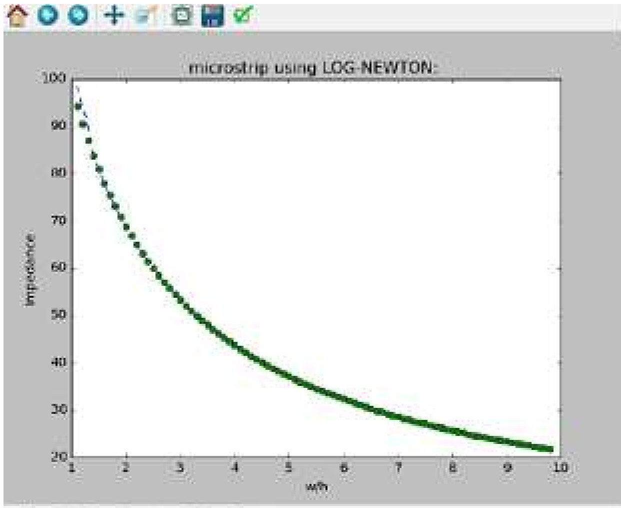


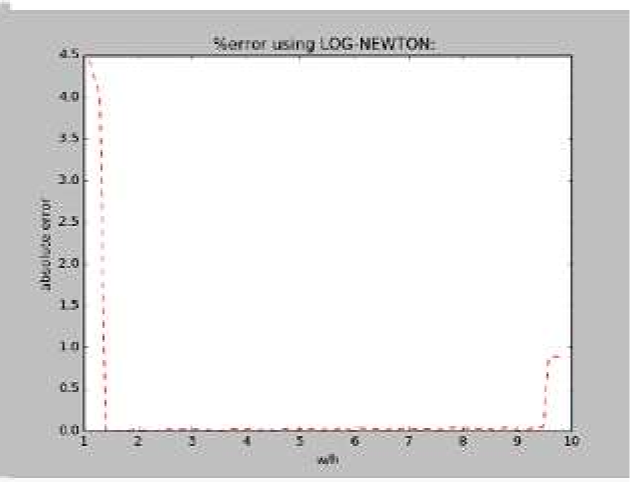


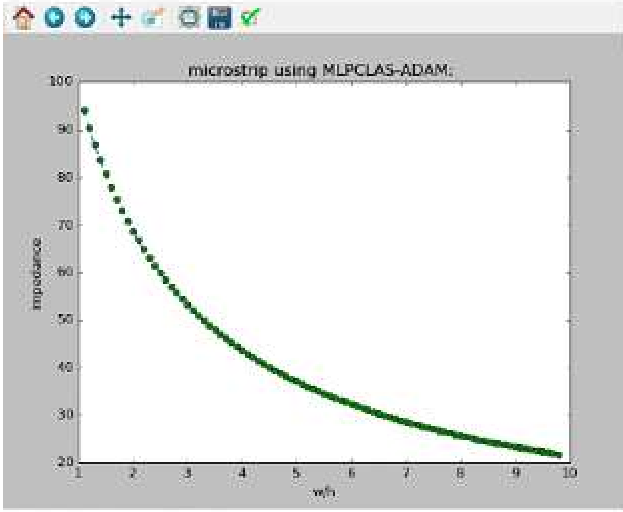


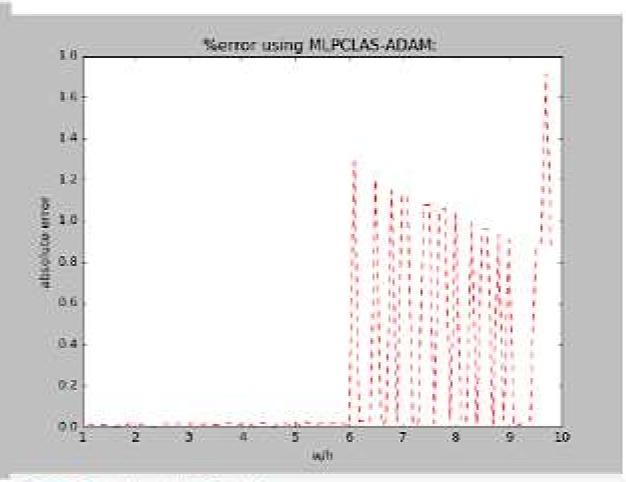


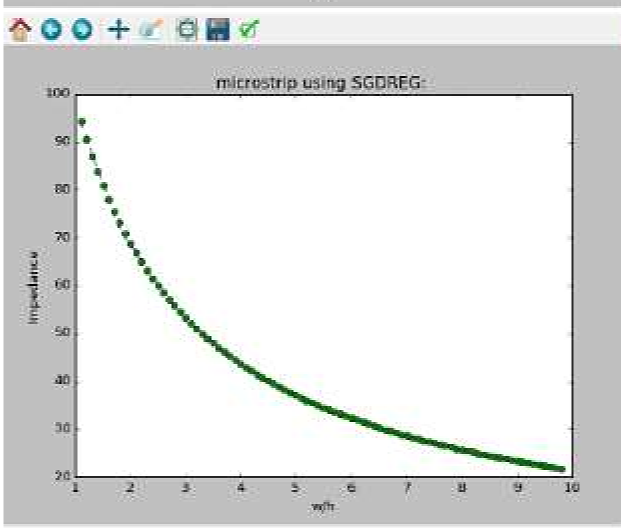


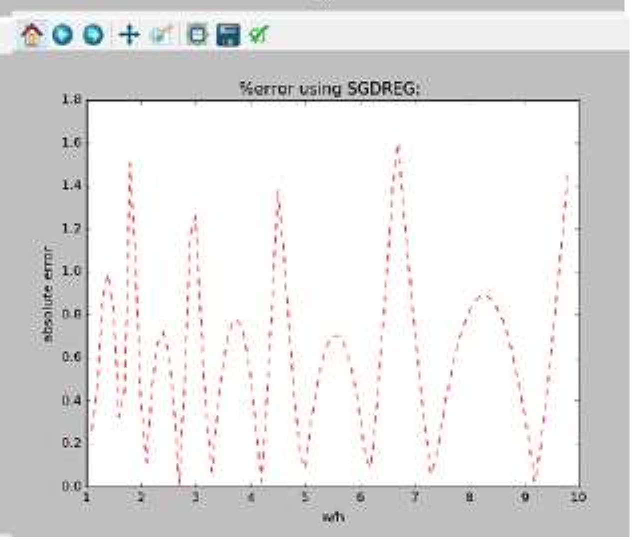

microstrip using LOG-NEWTON:
impedance
w/h


%error using LOG-NEWTON:
absolute error
w/h


microstrip using MLPCLAS-ADAM:
impedance
w/h


%error using MLPCLAS-ADAM:
absolute error
w/h


microstrip using SGDREG:
impedance
w/h


%error using SGDREG:
absolute error
w/h

4.1.5 Predicted Impedance values for different ANN Algorithms

w/h	Impedance (actual)	SGD Regression	Linear Regression	Back Propagation	Logistic Regression
1	98.525	97.323	71.658	88.109	98.52
1.5	80.819	81.450	68.265	80.773	80.81
2	68.774	68.488	64.871	71.992	68.77
2.5	59.999	60.280	61.477	63.074	59.99
3	53.296	53.129	58.084	55.066	53.29
3.5	47.993	48.268	54.690	48.439	47.99
4	43.686	43.408	51.297	43.208	43.68
4.5	40.113	39.950	47.903	39.162	40.11
5	37.098	37.376	44.509	36.033	37.09
5.5	34.517	34.802	41.116	33.573	34.51
6	32.281	32.228	37.722	31.584	32.28
7	30.325	29.801	34.329	29.918	30.32
7.5	28.598	28.517	30.935	28.468	28.59
8	27.061	27.233	27.541	27.157	27.06
8.5	25.685	25.949	24.148	25.933	25.68
9	24.445	24.665	20.754	24.761	24.44

4.1.6 Error Tabulations for different ANN Algorithms

Error %	Back Propagation	Linear Regression	Log.Regr. LBFGS	Log.Regr. NEWTON	MLP Classifier	SGD Regression
max	9.28	15.08	4.43	4.43	1.714	1.60
avg	3.51	8.08	0.18	0.18	0.24	0.61

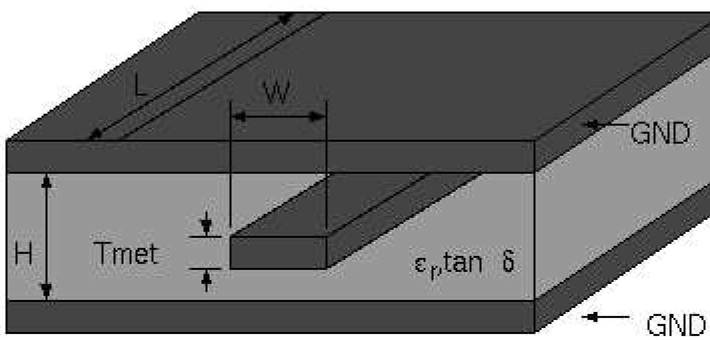
4.2 Stripline

A stripline circuit uses a flat strip of metal which is sandwiched between two parallel ground planes. The insulating material of the substrate forms a dielectric. The width of the strip, the thickness of the substrate and the relative permittivity of the substrate determine the characteristic impedance of the strip which is a transmission line. The central conductor need not be equally spaced between the ground planes. In the general case, the dielectric material may be different above and below the central conductor.

The first planar line to be widely used was stripline, a conductor sandwiched between dielectric slabs between metal ground planes. Stripline was successful because its electrical characteristics were quite predictable and its attenuation was reasonably low. It supports a true transverse electromagnetic (TEM) mode; that is, the electric and magnetic fields have no component in the direction of propagation, and the transverse field configurations do not change with frequency.

Stripline is considered as extended version of microstrip line with low radiation, Q factor of about 400 and will support 35 to 250 ohm impedance range. Stripline provides homogeneous medium for EM waves compare to uncovered microstrip line structure. Stripline is formed by etching one one side of grounded substrate and later covered with another grounded substrate of same height.

4.2.1 Schematic Diagram



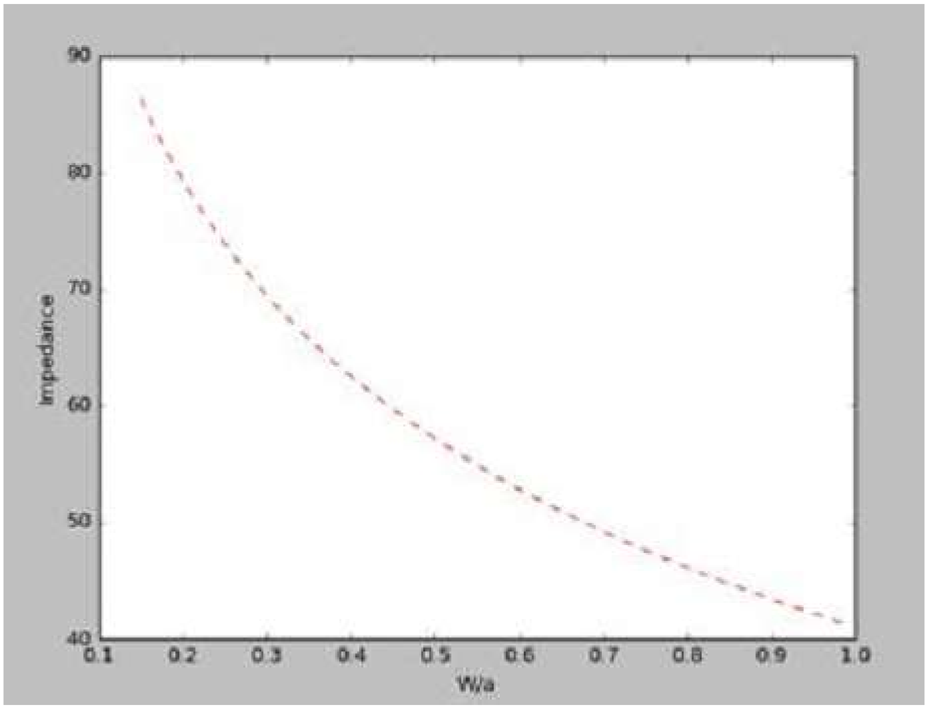
4.2.2 Formula used

$$Z_o = \frac{30\pi}{\sqrt{\varepsilon_r}} \frac{K(k')}{K(k)}$$

$$k = \tanh\left(\frac{\pi W}{4a}\right)$$

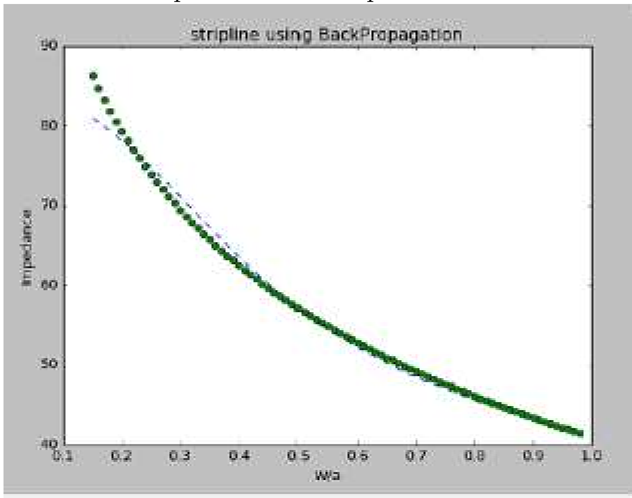
$$k' = \sqrt{1 - k^2}$$

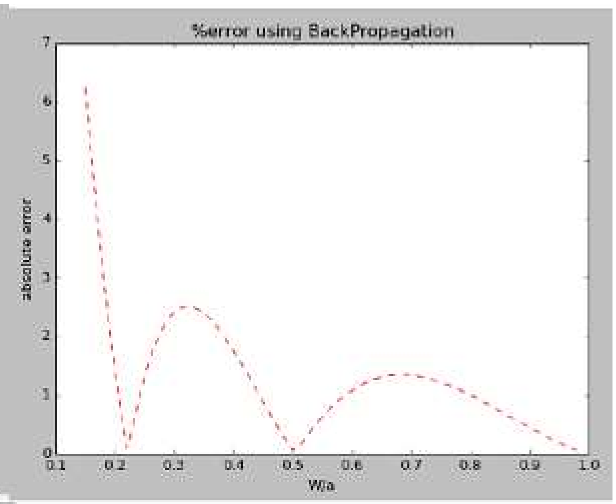
4.2.3 Graphical plot using formula method

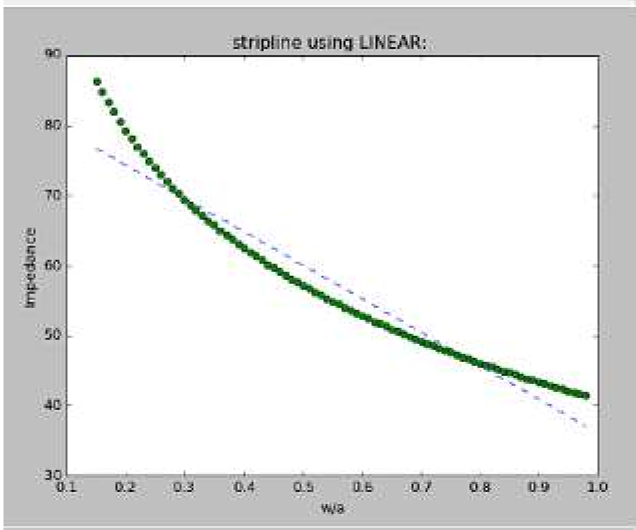


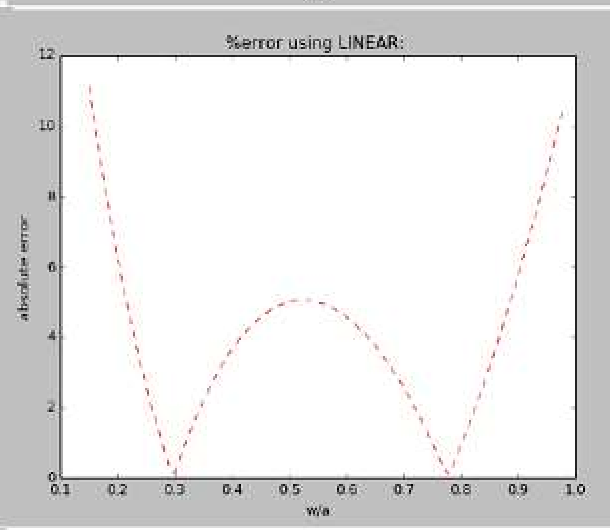
4.2.4 Graphical plots using different ANN methods

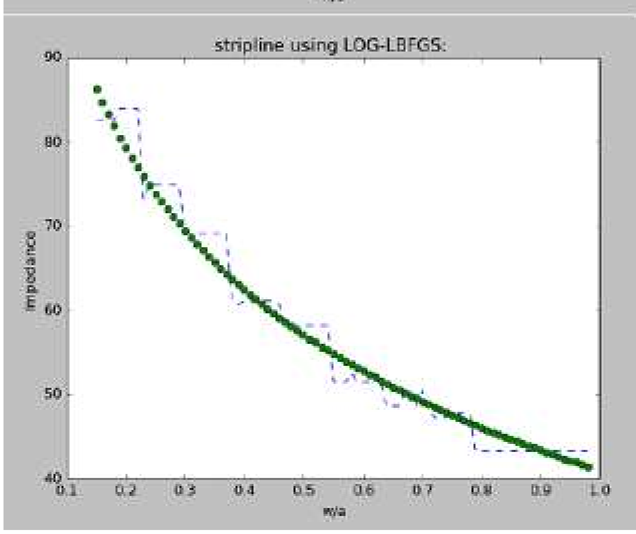
$\epsilon r = 6$ for all the plots using ANN
Dashed line implies Predicted Output
Dotted line implies Actual Output

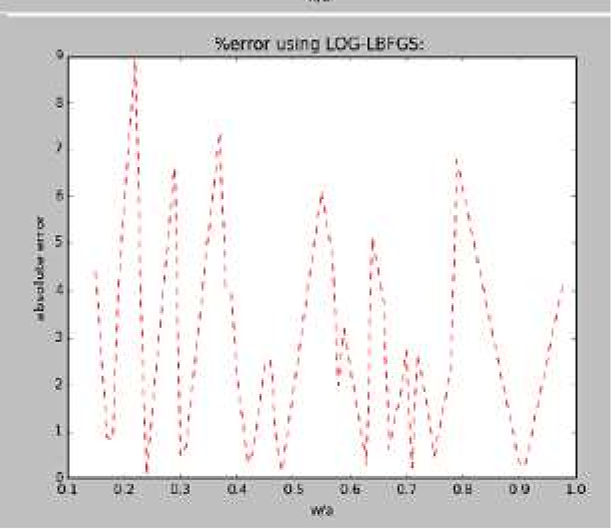


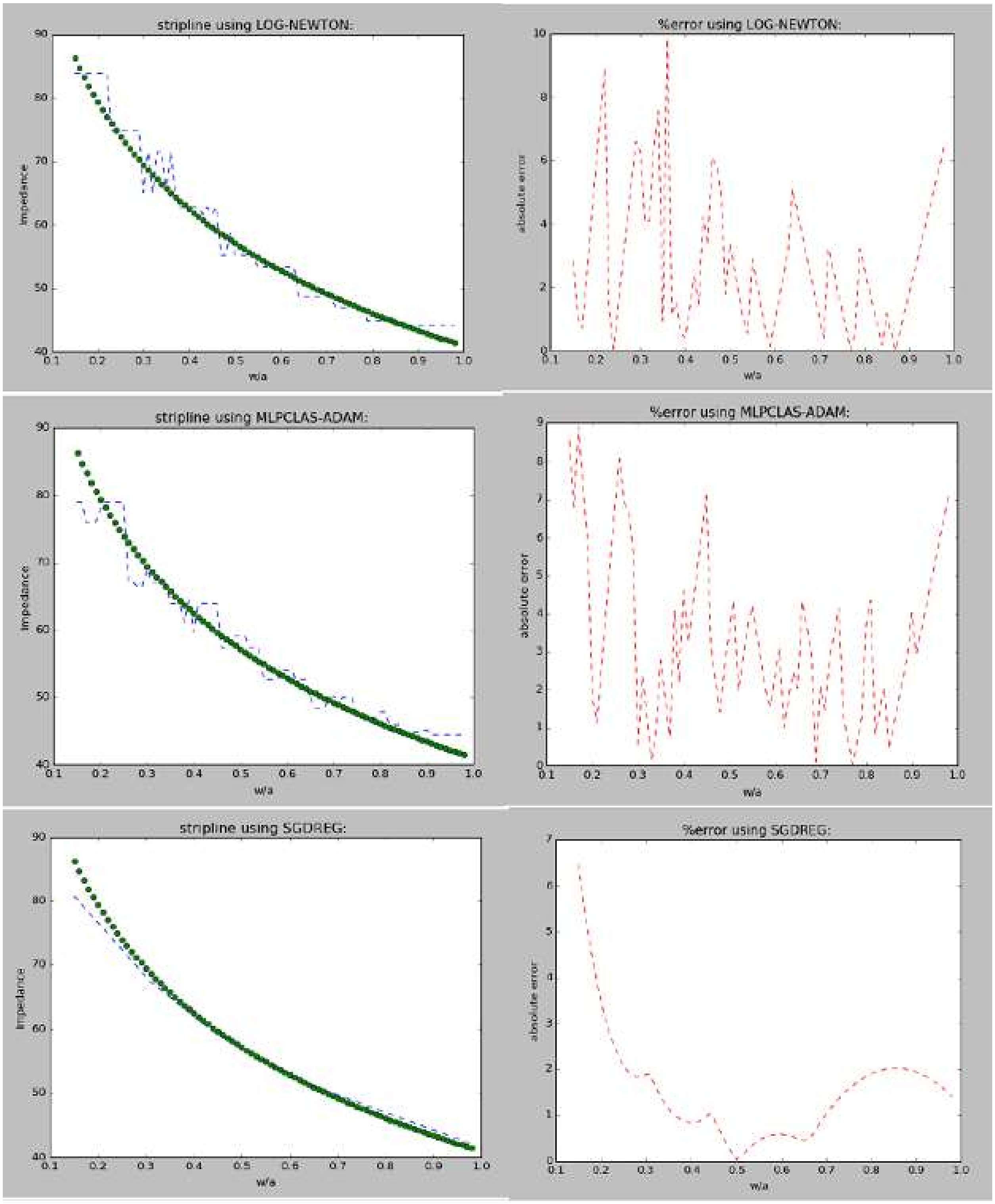











stripline using LOG-NEWTON:
Impedance
w/a
%error using LOG-NEWTON:
absolute error
w/a
stripline using MLPCLAS-ADAM:
Impedance
w/a
%error using MLPCLAS-ADAM:
absolute error
w/a
stripline using SGDREG:
Impedance
w/a
%error using SGDREG:
absolute error
w/a

4.2.5 Predicted Impedance values for different ANN Algorithms

W/a	Impedance (actual)	SGD Regression	Linear Regression	Back Propagation	Logistic Regression
0.2	79.347	74.690	72.354	77.975	81.91
0.25	73.909	70.400	69.966	74.817	72.95
0.3	69.477	66.110	67.577	71.289	69.47
0.35	65.742	62.431	65.188	67.609	63.12
0.4	62.517	60.000	62.800	63.984	59.68
0.45	59.683	57.568	60.411	60.572	60.77
0.5	57.160	55.136	58.022	57.468	53.22
0.55	54.888	52.705	55.634	54.711	51.3
0.6	52.825	50.926	53.245	52.299	51.3
0.65	50.938	49.456	50.856	50.203	46.68
0.7	49.201	47.986	48.468	48.383	46.68
0.75	47.594	46.516	46.079	46.795	44.97
0.8	46.101	45.046	43.691	45.399	42.9
0.85	44.708	43.576	41.302	44.155	42.18
0.9	43.405	42.106	38.913	43.033	42.18
0.95	42.181	40.729	36.525	42.005	42.18

4.2.6 Error Tabulations for different ANN Algorithms

Error %	Back Propagation	Linear Regression	Log.Regr. LBFGS	Log.Regr. NEWTON	MLP Classifier	SGD Regression
Max	6.25	11.14	8.94	9.85	8.89	6.49
Avg	1.26	4.07	2.91	2.82	3.32	1.53

4.3 Slotline

Slotline, can be said as a microstrip line which has medium radiation, support Q factor of about 100, impedance from 60 to 200. It is easy to mount chip in shunt mode and difficult to mount in series mode. Slotted lines are used for microwave measurements and consist of a movable probe inserted into a slot in a transmission line.

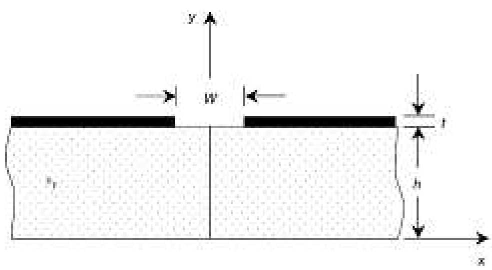
Slotline is a planar transmission line. A small narrow slot is etched out on one side of the dielectric substrate from ground plane metal surface. The other side will not have any metallic stuff.

This width 'W' determines the slotline characteristic impedance. The impedance increases with increase in W and is less sensitive to height of the substrate. It is a two conductor transmission line with major electric field component oriented across the slot. Hence it does not support TEM mode.

The Electromagnetic wave travels along the slotline which encounters substrate and air as medium for the transmission. Hence effective dielectric constant is equal to average of both eff = (r + 1) /2.

It is not a quasi-TEM line.

4.3.1 Schematic Diagram



4.3.2 Formula used

For $0.2 \leq W/d \leq 1.0$:

$$\lambda'/\lambda = 0.987 - 0.483 \log \varepsilon_r + W/d(0.111 - 0.0022\varepsilon_r) - (0.121 + 0.094W/d - 0.0032\varepsilon_r) \log (d/\lambda \times 10^2)$$

$$Z_0 = 113.19 - 53.55 \log \varepsilon_r + 1.25W/d(114.59 - 51.88 \log \varepsilon_r) + 20(W/d - 0.2)(1 - W/d) - [0.15 + 0.23 \log \varepsilon_r + W/d(-0.79 + 2.07 \log \varepsilon_r)] \cdot [(10.25 - 5 \log \varepsilon_r + W/d(2.1 - 1.42 \log \varepsilon_r) - d/\lambda \times 10^2)^2].$$

$$9.7 \leq \varepsilon_r \leq 20$$

$$0.02 \leq W/d \leq 1.0$$

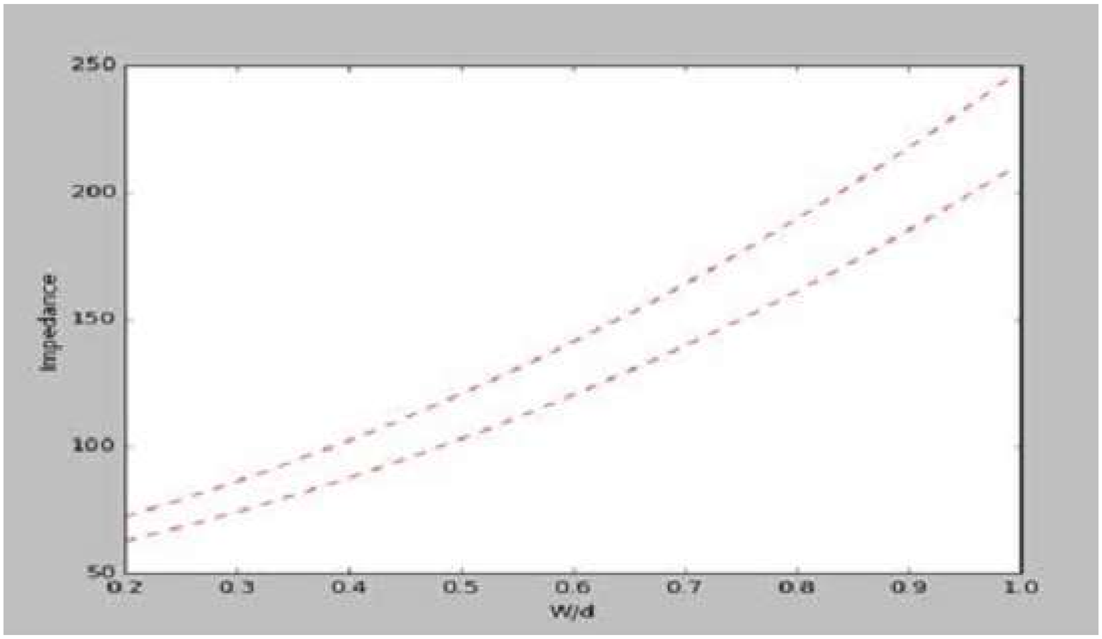
and

$$0.01 \leq d/\lambda \leq (d/\lambda)_0$$

where $(d/\lambda)_0$ is equal to the cutoff for the TE_{10} surface-wave mode on the slotline, and is given by

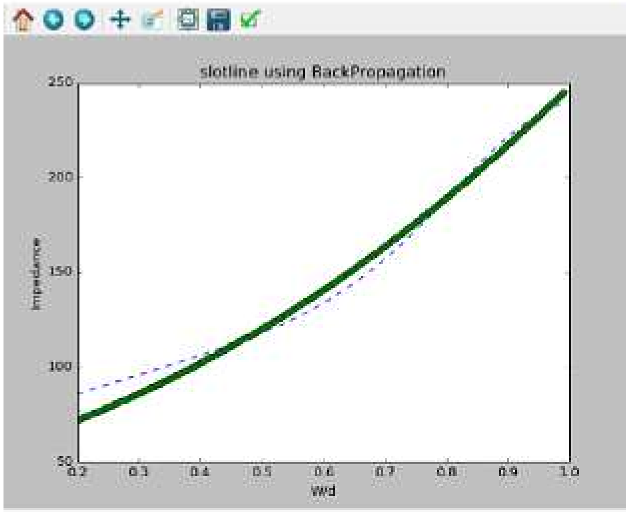
$$(d/\lambda)_0 = 0.25/\sqrt{\varepsilon_r - 1}.$$

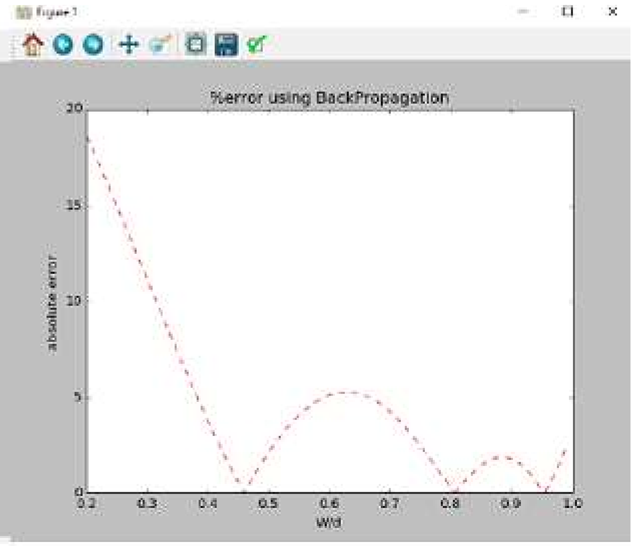
4.3.3 Graphical plot using formula method

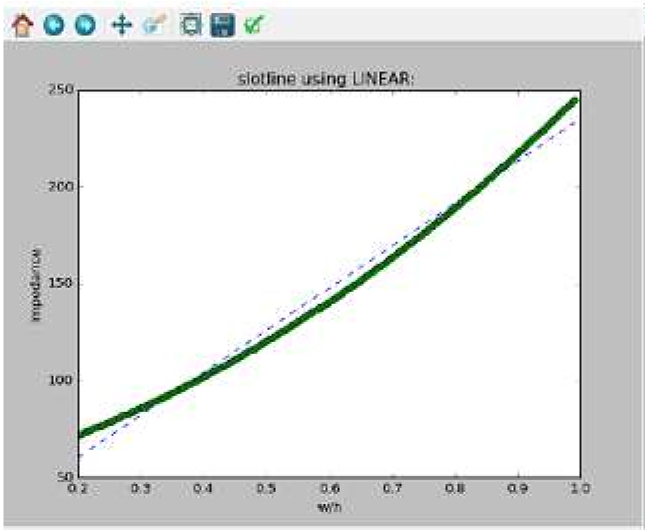


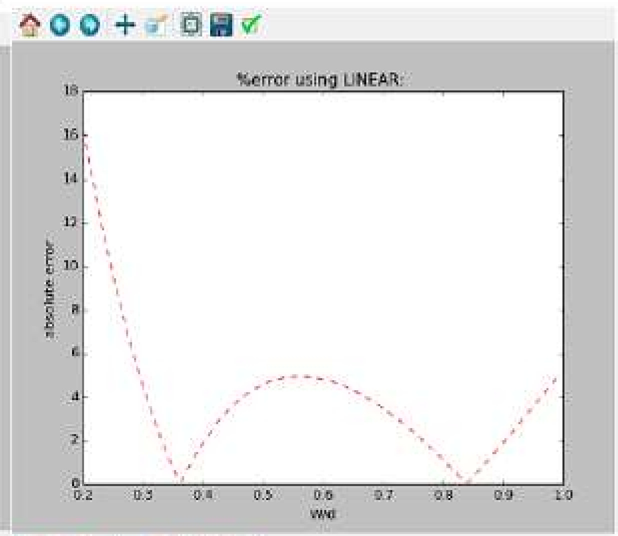
4.3.4 Graphical plots using different ANN methods

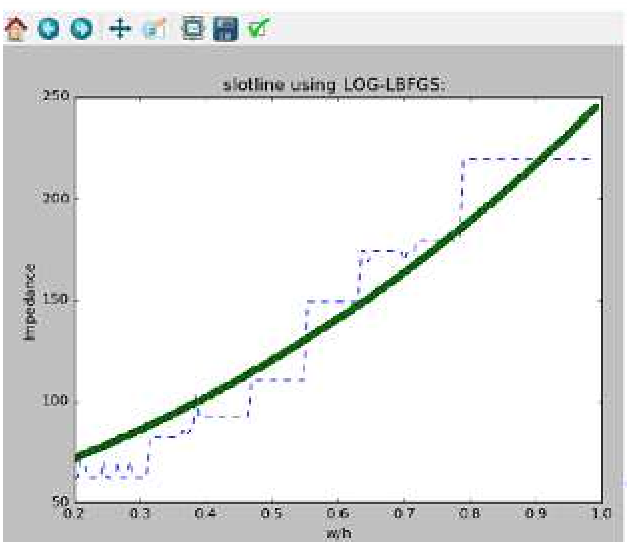
$\epsilon r = 16$ for all the plots using ANN
Dashed line implies Predicted Output
Dotted line implies Actual Output

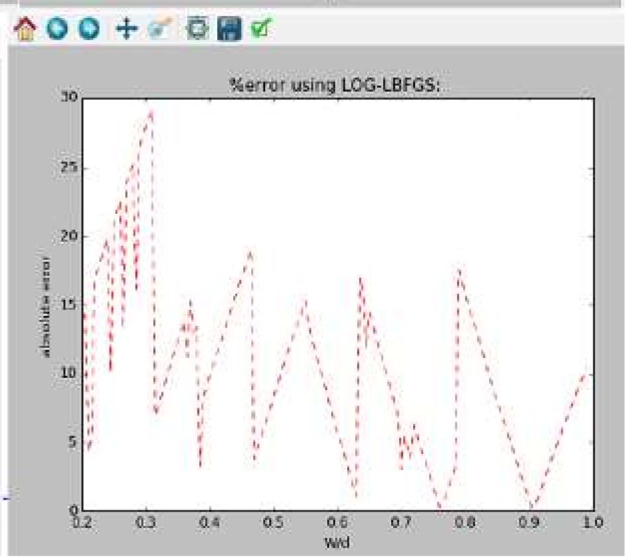


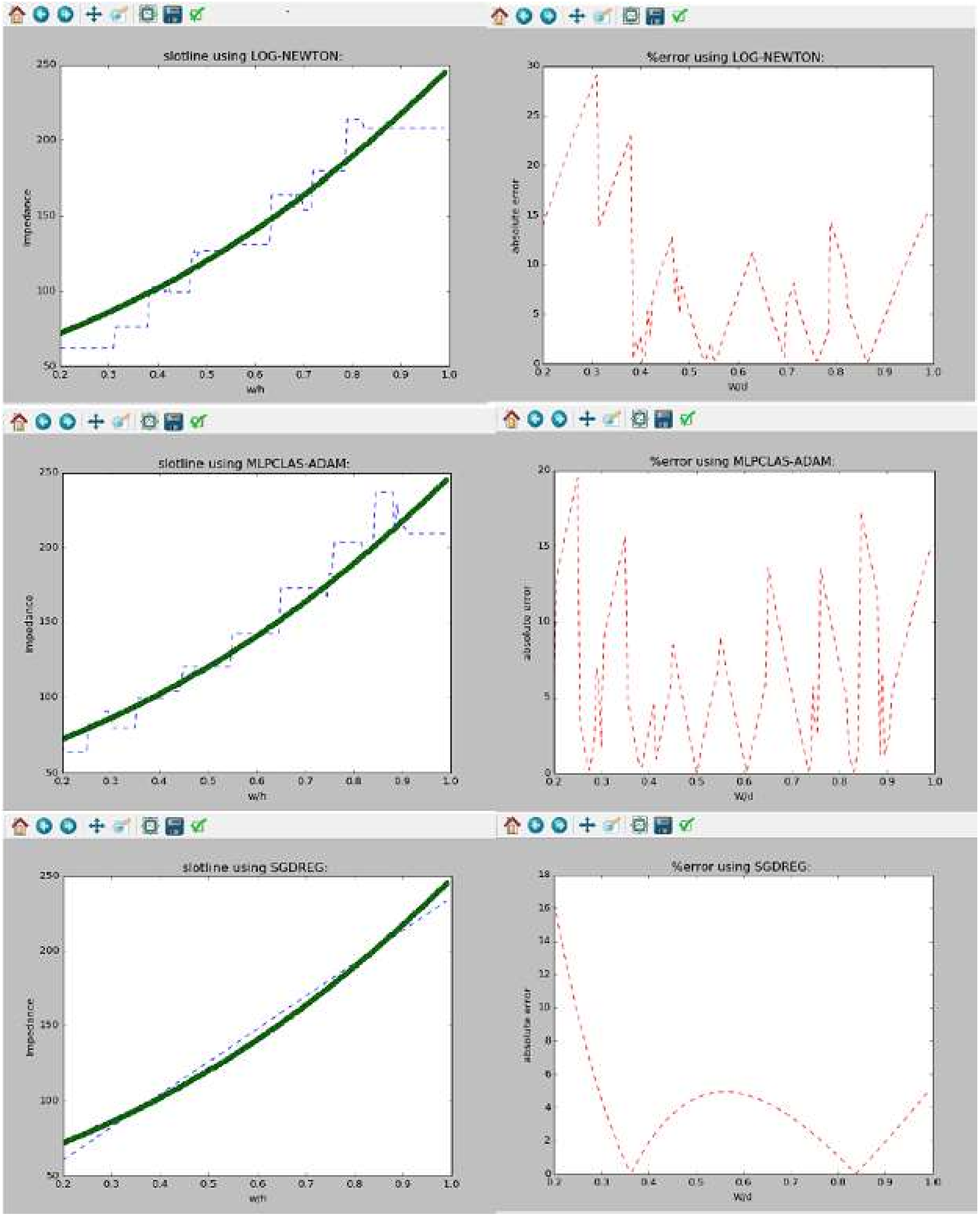











slotline using LOG-NEWTON:
impedance
w/h
%error using LOG-NEWTON:
absolute error
W/d
slotline using MLPCLAS-ADAM:
impedance
w/h
%error using MLPCLAS-ADAM:
absolute error
W/d
slotline using SGDREG:
impedance
w/h
%error using SGDREG:
absolute error
W/d

4.3.5 Predicted Impedance values for different ANN Algorithms

W/d	Impedance (actual)	SGD Regression	Linear Regression	Back Propagation	Logistic Regression
0.2	72.190	77.559	70.422	98.870	72.19
0.25	78.923	86.136	81.361	100.15	72.19
0.3	86.170	94.712	92.300	101.80	80.33
0.35	93.943	103.28	103.23	103.96	92.34
0.4	102.25	111.86	114.17	106.82	102.25
0.45	111.11	120.44	125.11	110.64	102.25
0.5	120.54	129.01	136.05	115.71	120.54
0.55	130.54	137.59	146.99	122.40	120.54
0.6	141.13	150.55	157.93	131.13	159.33
0.65	152.32	163.93	168.87	142.25	184.33
0.7	164.13	177.31	179.81	155.97	184.33
0.75	176.56	190.69	190.74	172.06	189.63
0.8	189.63	204.08	201.68	189.60	229.74
0.85	203.36	217.46	212.62	206.90	229.74
0.9	217.74	230.84	223.56	221.91	229.74
0.95	232.80	244.22	234.50	233.07	229.74

4.3.6 Error Tabulations for different ANN Algorithms

Error %	Back Propagation	Linear Regression	Log.Regr. LBFGS	Log.Regr. NEWTON	MLP Classifier	SGD Regression
max	18.5	16.3	19.07	19.07	19.55	6.3
avg	4.7	3.8	7.15	7.26	6.7	3.87

4.4 Co-Planar Waveguide(CPW)

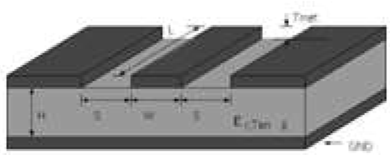
The Coplanar Waveguide is a planar transmission line, widely used for microwave Integrated Circuit design. Coplanar Waveguide consists of a conductor strip at the middle and two ground planes are located on either sides of centre conductor. All these lie in the same plane.

In coplanar waveguide, EM energy is concentrated within the dielectric. The leakage of the Electromagnetic energy in the air can be controlled by having substrate height (h) twice that of the width (S). The coplanar waveguide supports quasi TEM mode at low frequencies while it supports TE mode at high frequencies.

The gap in the coplanar waveguide is usually very small and supports electric fields primarily concentrated in the dielectric. With little fringing field in the air space, the coplanar waveguide exhibits low dispersion. In order to concentrate the fields in the substrate area and to minimize radiation, the dielectric substrate thickness is usually set equal to about twice the gap width.

CPW has a zero cut-off frequency (suitable for wideband), but its low order propagation mode is indicated with Quasi-TEM because it is not a real TEM mode. At higher frequencies, the field becomes less-TEM, and more TE in nature. The CPW magnetic field is elliptically polarized.

4.4.1 Schematic Diagram



4.4.2 Formula used

$$\varepsilon_{\text{eff}} = 1 + \frac{\varepsilon_r - 1}{2}\frac{K(k')}{K(k)}\frac{K(k_1)}{K(k_1')}$$

$$Z_o = \frac{30\pi}{\sqrt{\varepsilon_{\text{eff}}}}\frac{K(k')}{K(k)}$$

$$k = \frac{a}{b}$$

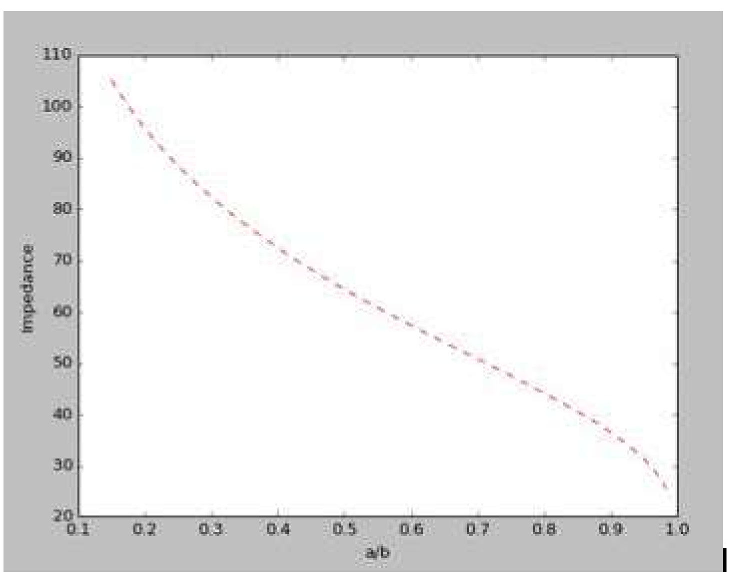
$$k' = \sqrt{1-k^2}$$

$$k_1 = \frac{\sinh(\pi a/2h)}{\sinh(\pi b/2h)}$$

$$k_1' = \sqrt{1-k_1^2}$$

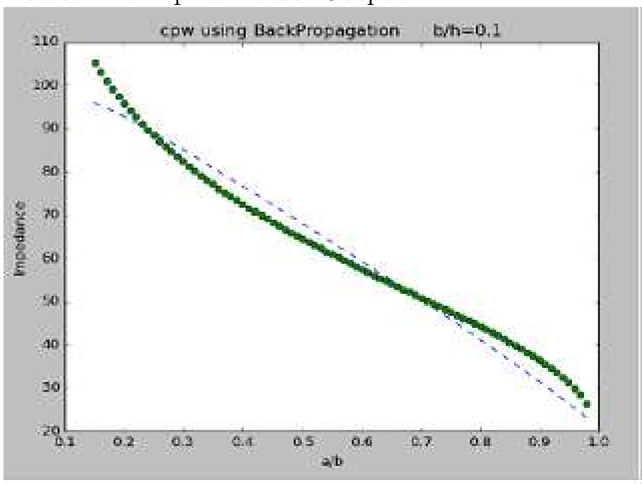
$$\frac{K(k)}{K(k')} = \begin{cases} \dfrac{\pi}{\ln\left(2\dfrac{1+\sqrt{k'}}{1-\sqrt{k'}}\right)}, & 0 \leq k \leq 0.707 \\[2ex] \dfrac{1}{\pi}\ln\left(2\dfrac{1+\sqrt{k}}{1-\sqrt{k}}\right), & 0.707 \leq k \leq 1 \end{cases}$$

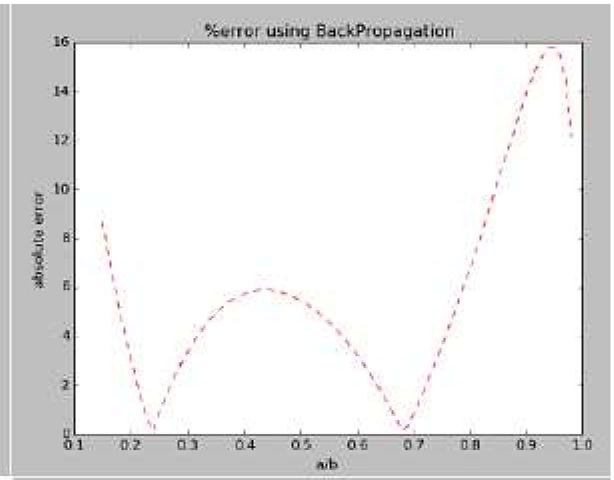
4.4.3 Graphical plot using formula method

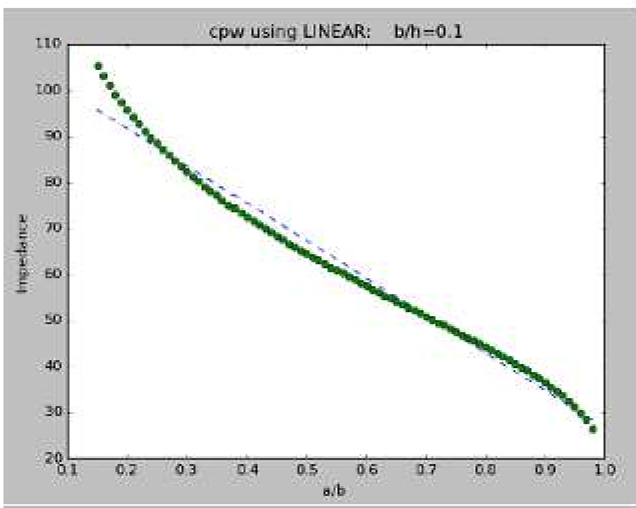


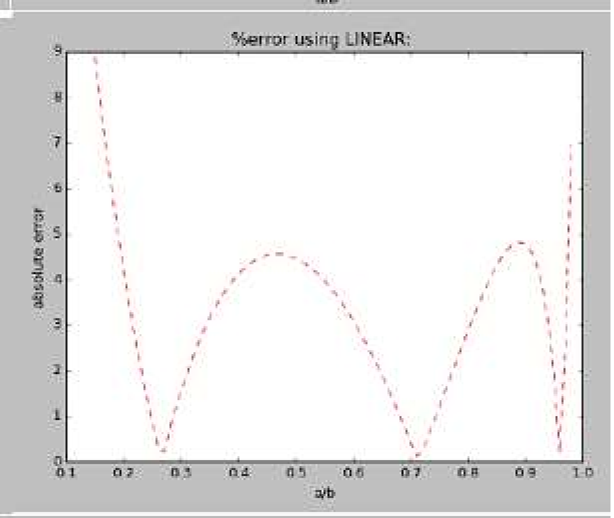
4.4.4 Graphical plots using different ANN methods

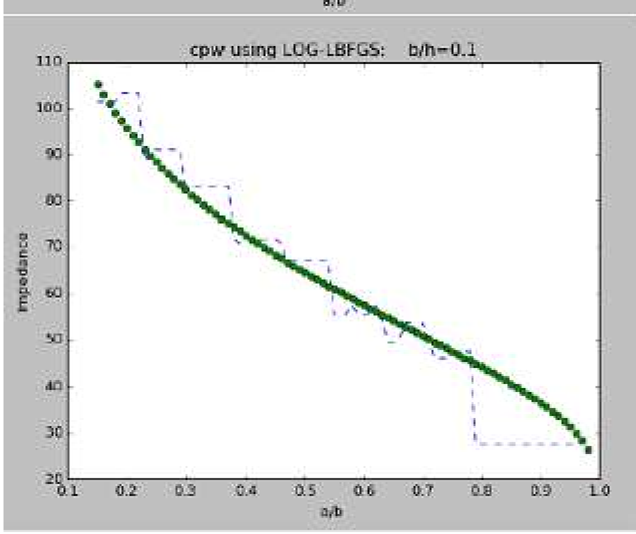
$\epsilon r = 6$ for all the plots using ANN
Dashed line implies Predicted Output
Dotted line implies Actual Output

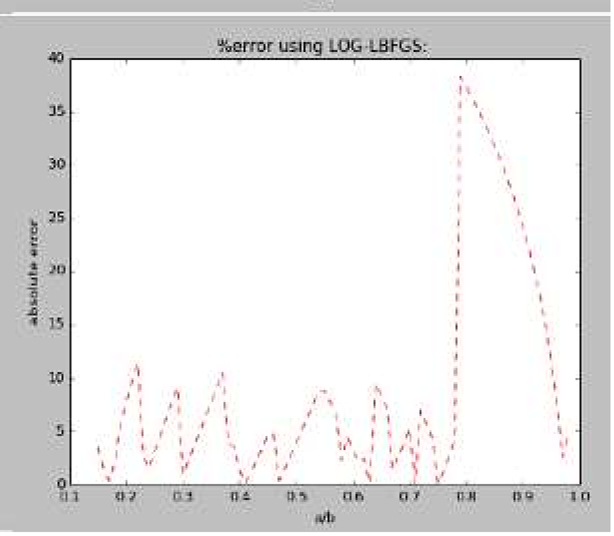


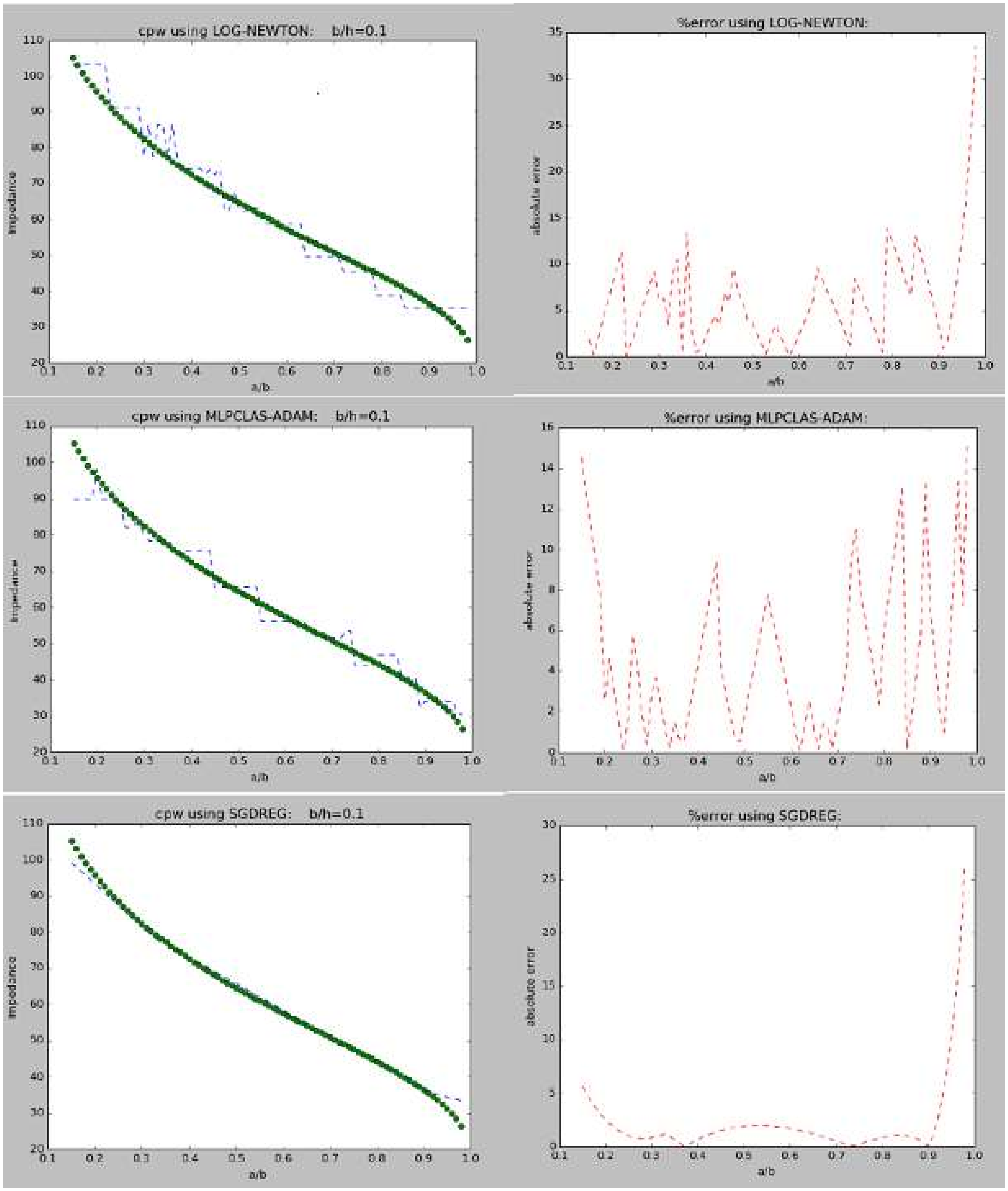











cpw using LOG-NEWTON: b/h=0.1
impedance
a/b
%error using LOG-NEWTON:
absolute error
a/b
cpw using MLPCLAS-ADAM: b/h=0.1
impedance
a/b
%error using MLPCLAS-ADAM:
absolute error
a/b
cpw using SGDREG: b/h=0.1
impedance
a/b
%error using SGDREG:
absolute error
a/b

4.4.5 Predicted Impedance values for different ANN Algorithms

a/b	Impedance (actual)	SGD Regression	Linear Regression	Back Propagation	Logistic Regression
0.2	95.797	89.401	87.771	92.76	99.23
0.25	88.451	83.547	83.704	88.97	87.15
0.3	82.368	77.693	79.636	84.87	82.36
0.35	77.138	72.628	75.568	80.58	73.39
0.4	72.515	68.987	71.501	76.24	68.33
0.45	68.335	65.345	67.433	71.92	69.96
0.5	64.486	61.703	63.365	67.64	58.12
0.55	60.882	58.062	59.298	63.40	54.79
0.6	57.452	54.420	55.230	59.18	54.79
0.65	54.136	50.779	51.162	54.94	45.59
0.7	50.874	47.137	47.095	50.62	45.59
0.75	47.600	43.496	43.027	46.20	41.38
0.8	44.232	39.854	38.960	41.62	34.69
0.85	40.638	36.213	34.892	36.85	31.35
0.9	36.572	32.571	30.824	31.86	31.35
0.95	31.358	29.978	26.757	26.63	31.35

4.4.6 Error Tabulations for different ANN Algorithms

Error %	Back Propagation	Linear Regression	Log.Regr. LBFGS	Log.Regr. NEWTON	MLP Classifier	SGD Regression
Max	15.83	8.87	38.33	33.53	15.10	26.37
Avg	5.74	3.11	9.19	6.04	4.66	2.16

4.5 Co-Planar Strip

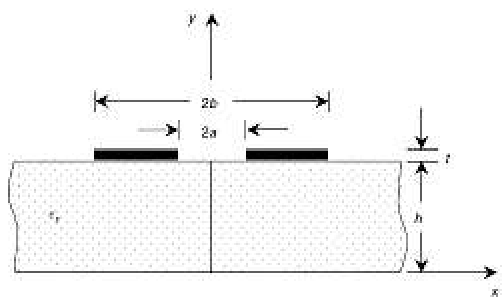
Coplanar strips (CPS), employ two parallel strips on the same side of a dielectric substrate. This structure is also useful for RF and microwave ICs, especially balanced circuits due to its inherent balanced nature. The CPS structure allows easy connections for series and shunt solid state devices. Its effective dielectric constant and characteristic impedance for zero strip thickness can be evaluated using the following closed-form equations derived from a conformal-mapping method.

Coplanar-strip (CPS) waveguides are widely used in high-speed digital and microwave/millimeter wave integrated circuits. They have the same advantages as ordinary coplanar waveguides, including possible shunt and series connection of microwave components, achieving the desired impedance regardless of the thickness of the substrate.

If the cross-sectional dimensions are chosen properly, these lines provide lower substrate losses since the currents induced in the substrate may be partially cancelled, thus reducing the losses in the substrate. A CPS with a ground plane on the backside of the substrate, where the strips are excited differentially, that is, if the strips have equal but opposite potentials relative to the ground plane offers similar advantages.

CPS is inherently balanced, i.e., the currents in the strips are opposite but equal and have similar distributions across the strips. Due to the balanced nature, the lines are less sensitive to induced noises and are widely used in low-noise amplifiers, oscillators, etc.

4.5.1 Schematic Diagram



4.5.2 Formula used

$$\varepsilon_{\text{eff}} = 1 + \frac{\varepsilon_r - 1}{2}\frac{K(k')}{K(k)}\frac{K(k_1)}{K(k_1')}$$

$$Z_o = \frac{120\pi}{\sqrt{\varepsilon_{\text{eff}}}}\frac{K(k)}{K(k')}$$

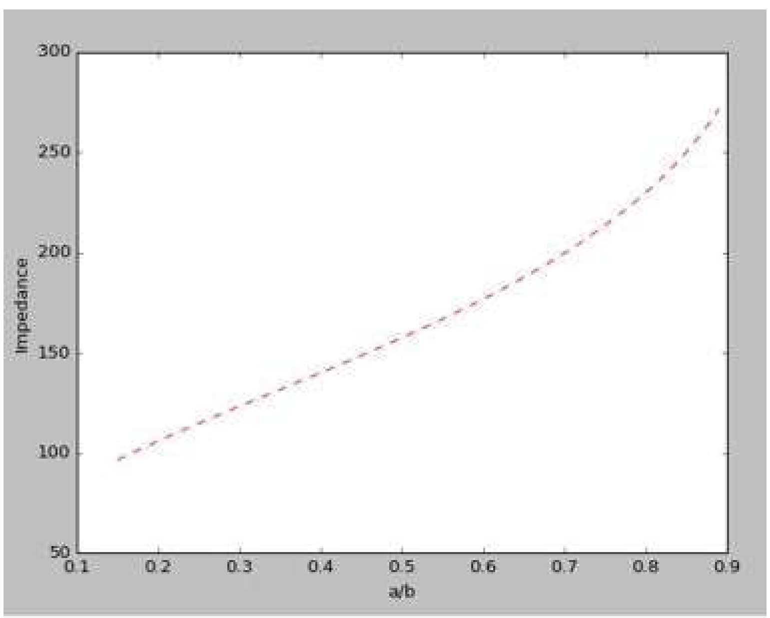
$$k = \frac{a}{b}$$

$$k' = \sqrt{1-k^2}$$

$$k_1 = \frac{\sinh(\pi a/2h)}{\sinh(\pi b/2h)}$$

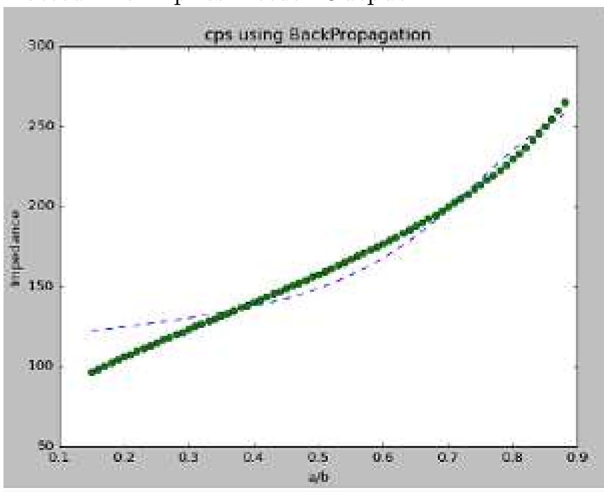
$$k_1' = \sqrt{1-k_1^2}$$

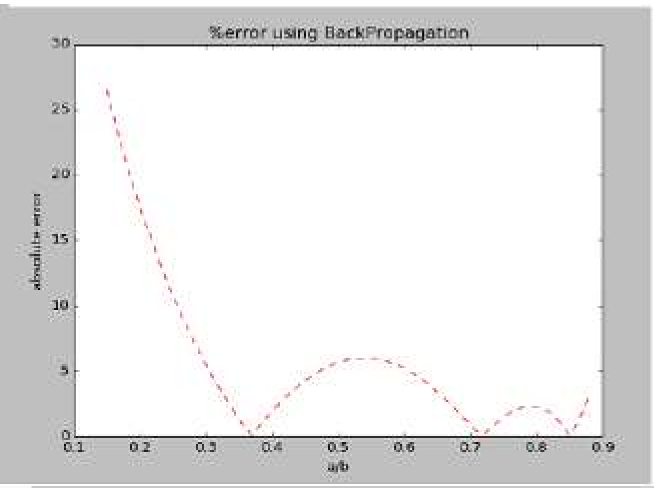
4.5.3 Graphical plot using formula method

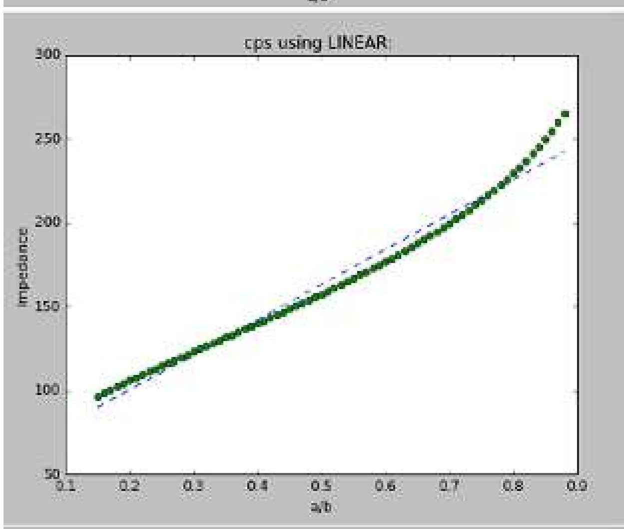


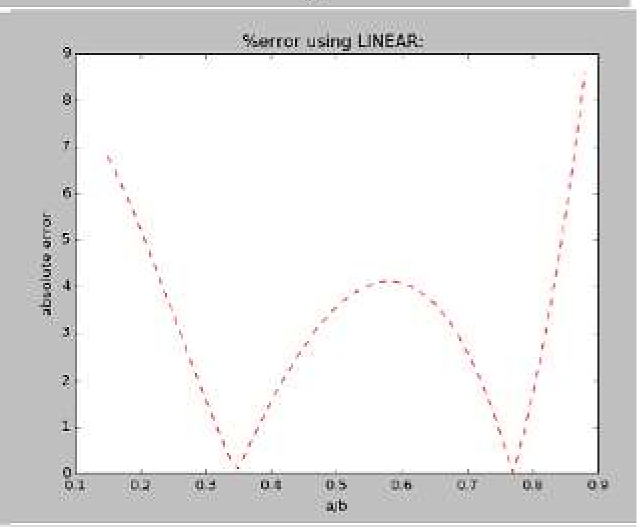
4.5.4 Graphical plots using different ANN methods

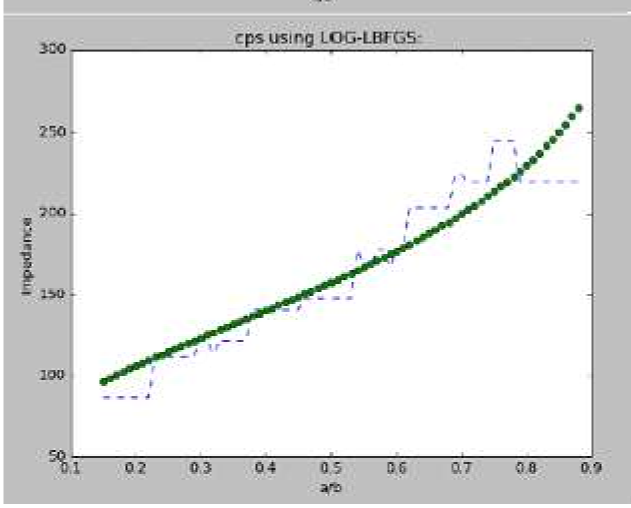
$\epsilon r = 6$ for all the plots using ANN
Dashed line implies Predicted Output
Dotted line implies Actual Output

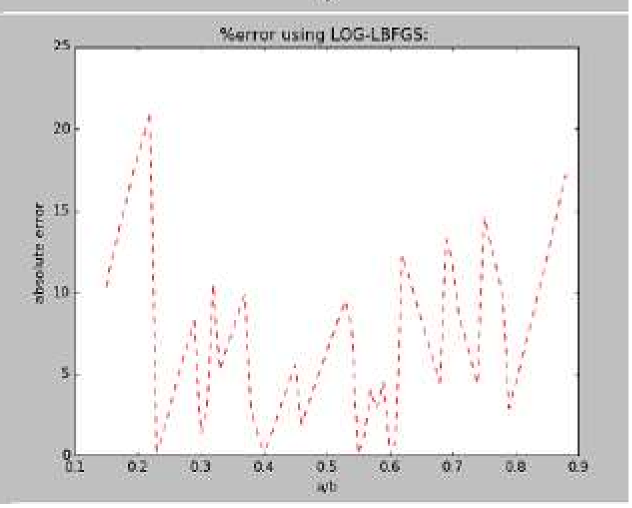


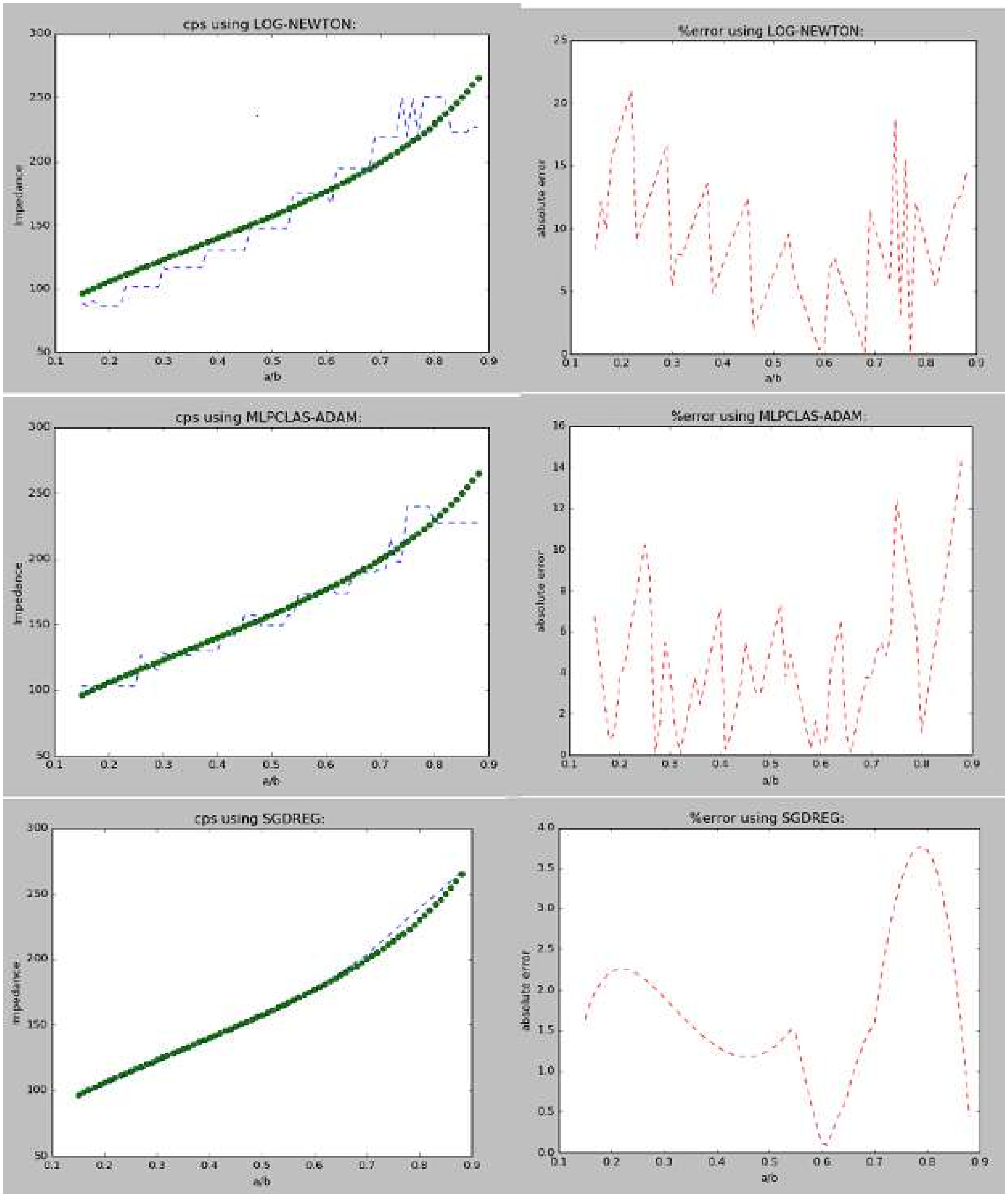











cps using LOG-NEWTON:
Impedance
a/b
%error using LOG-NEWTON:
absolute error
a/b
cps using MLPCLAS-ADAM:
Impedance
a/b
%error using MLPCLAS-ADAM:
absolute error
a/b
cps using SGDREG:
Impedance
a/b
%error using SGDREG:
absolute error
a/b

4.5.5 Predicted Impedance values for different ANN Algorithms

a/b	Impedance (actual)	SGD Regression	Linear Regression	Back Propagation	Logistic Regression
0.2	106.071	110.511	110.512	123.260	96.61
0.25	114.887	120.961	120.963	126.144	121.69
0.3	123.380	131.410	131.415	129.389	131.75
0.35	131.752	141.860	141.867	133.206	131.75
0.4	140.159	152.310	152.318	137.892	150.48
0.45	148.737	162.761	162.770	143.859	150.48
0.5	157.620	173.211	173.221	151.639	157.62
0.55	166.957	183.662	183.673	161.861	187.76
0.6	176.929	194.113	194.125	175.105	187.76
0.65	187.769	204.564	204.576	191.584	213.54
0.7	199.810	215.015	215.028	210.606	229.8
0.75	213.549	225.466	225.480	230.124	254.9
0.8	229.808	235.917	235.931	247.107	229.8
0.85	250.121	246.368	246.383	259.159	229.8

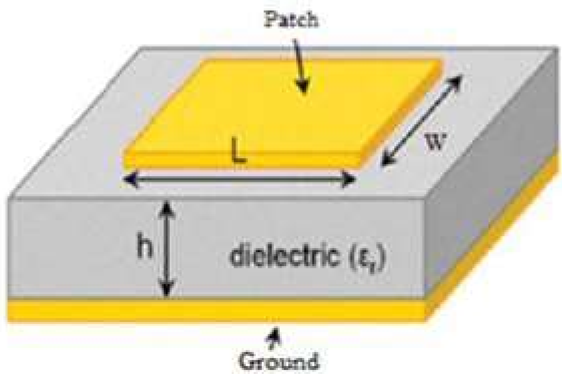
4.5.6 Error Tabulations for different ANN Algorithms

Error %	Back Propagation	Linear Regression	Log.Regr. LBFGS	Log.Regr. NEWTON	MLP Classifier	SGD Regression
Max	26.51	8.60	20.01	21.01	14.38	3.77
Avg	5.58	3.13	7.50	8.80	4.58	1.76

4.6 Microstrip Patch Antenna

The patch dimensions of rectangular microstrip antennas are usually designed so that its pattern maximum is normal to the patch. Because of their narrow bandwidths and effectively operation in the vicinity of resonant frequency, the choice of the patch dimensions giving the specified resonant frequency is very important [8]. The rectangular microstrip antennas are made of a rectangular patch with dimensions of width (W), length (L) over a ground plane with a substrate thickness h and dielectric constants (er). Dielectric constants are generally used in the range 2.2 ¡ er ¡ 12. But, the most desirable are the dielectric constants at the lower end of this range together with the thick substrates, because they give larger bandwidth and better efficiency

4.6.1 Schematic Diagram



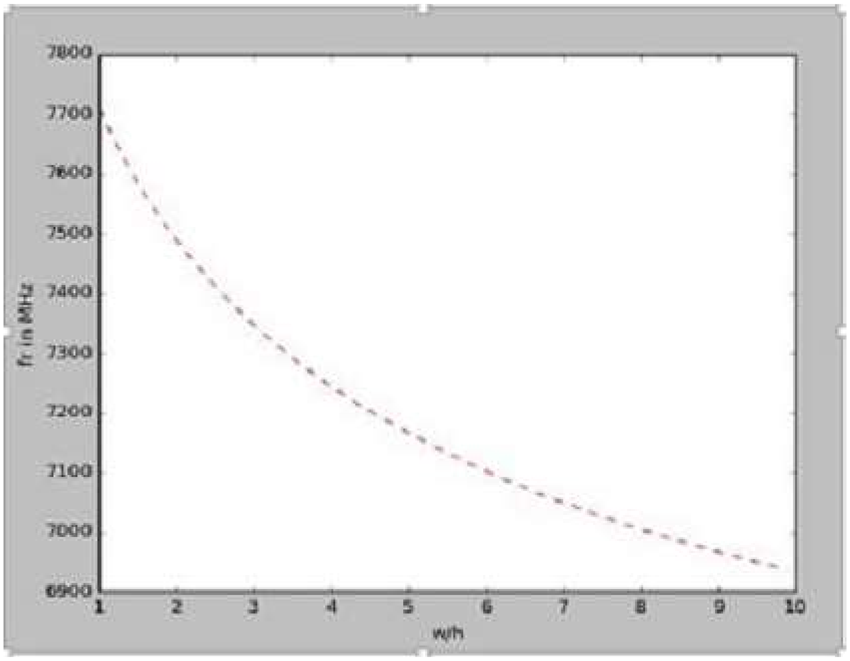
4.6.2 Formula used

$$\varepsilon eff = \frac{\varepsilon r + 1}{2} + \frac{\varepsilon r - 1}{2}\left[1 + 12\frac{h}{w}\right]^{-\frac{1}{2}}$$

$$\Delta L = 0.412h\,\frac{(\varepsilon\mathrm{eff} + 0.3)(\frac{\mathrm{W}}{\mathrm{h}} + 0.264)}{(\varepsilon\mathrm{eff} - 0.258)(\frac{\mathrm{W}}{\mathrm{h}} + 0.8)}$$

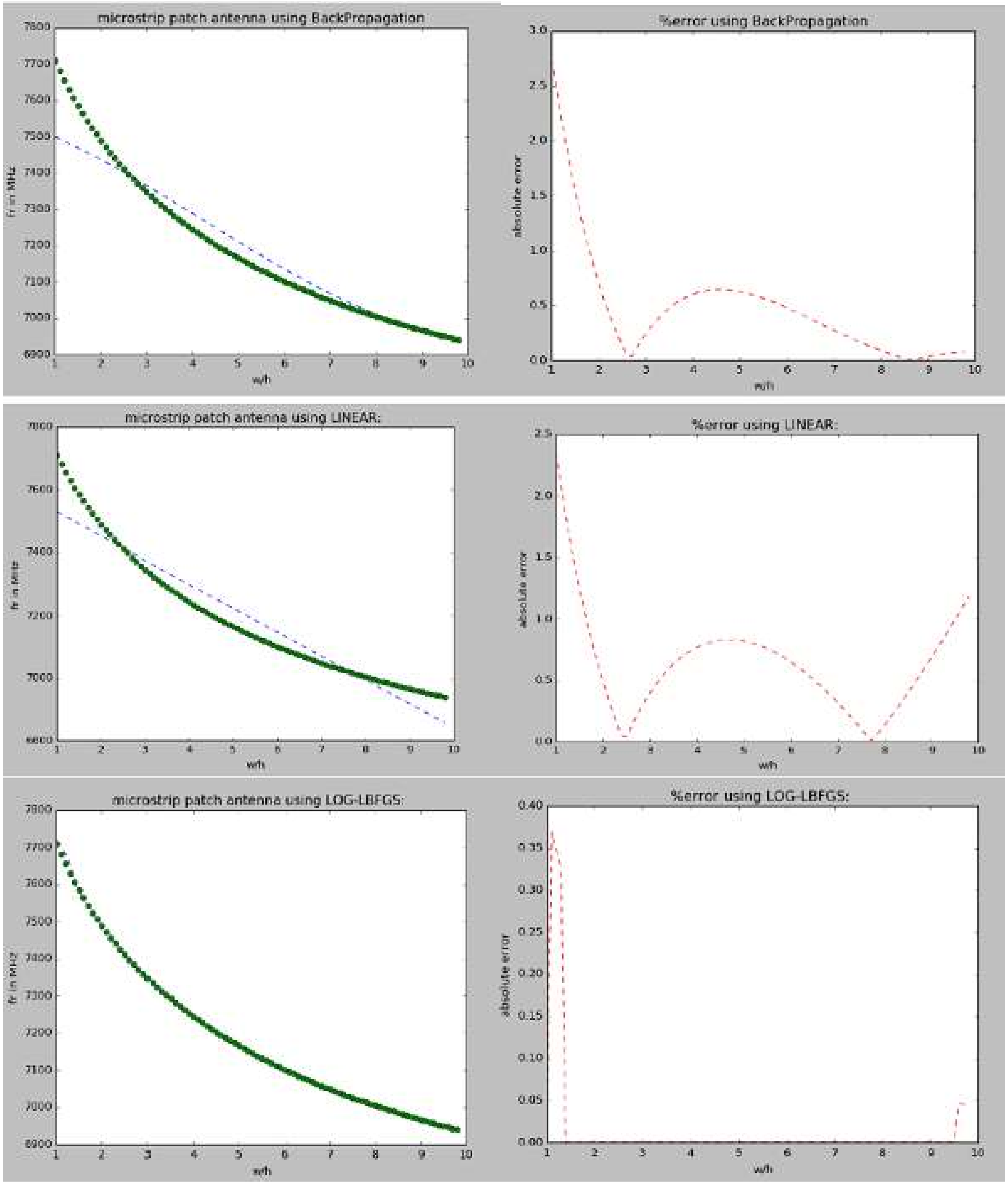
$$fr = \frac{c}{2\sqrt{\varepsilon}eff\,(L + 2\Delta L)}$$

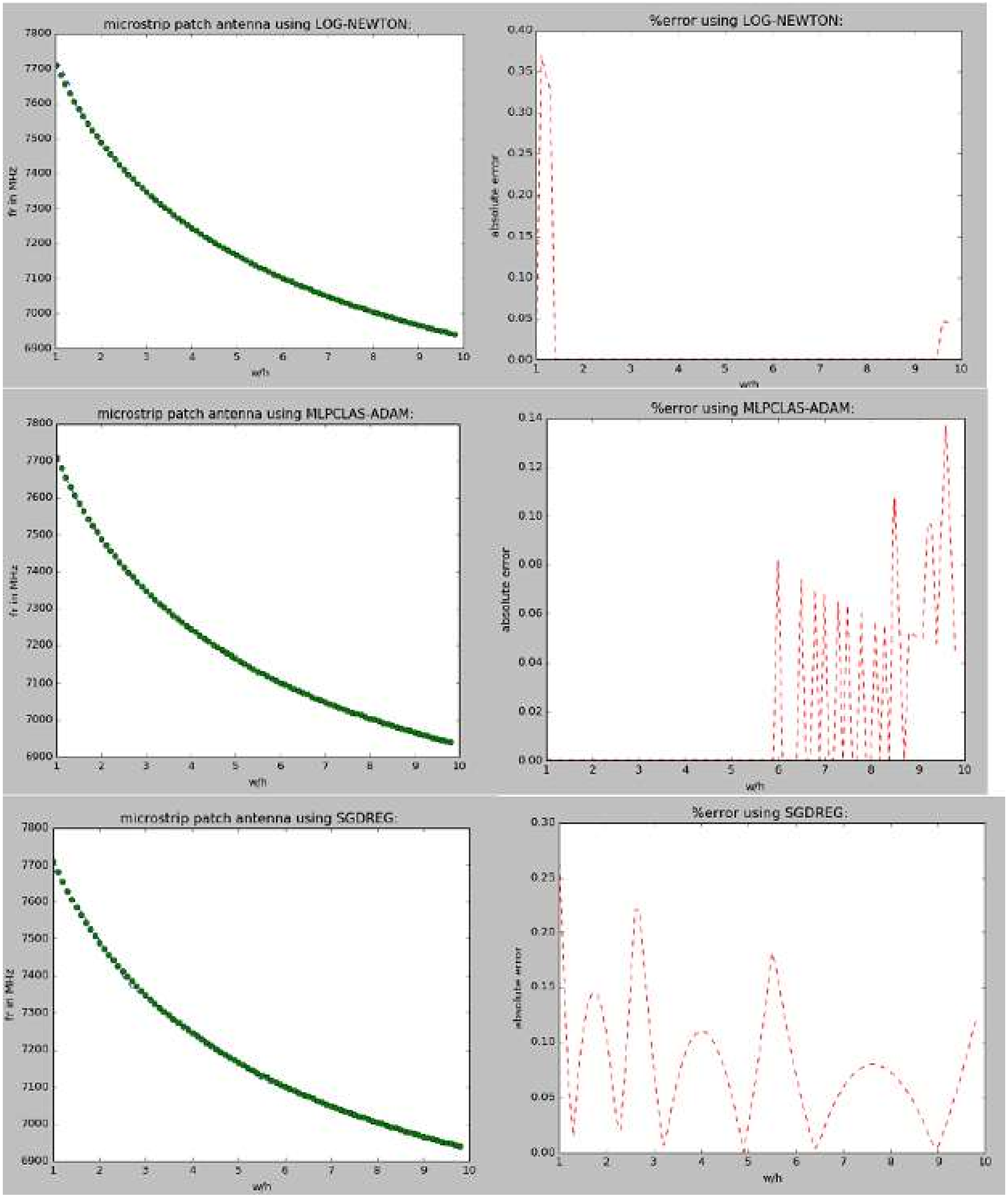
4.6.3 Graphical plot using formula method



4.6.4 Graphical plots using different ANN methods

$\epsilon r = 6$ for all the plots using ANN
Dashed line implies Predicted Output
Dotted line implies Actual Output




microstrip patch antenna using LOG-NEWTON:
fr in MHz
w/h
%error using LOG-NEWTON:
absolute error
w/h
microstrip patch antenna using MLPCLAS-ADAM:
fr in MHz
w/h
%error using MLPCLAS-ADAM:
absolute error
w/h
microstrip patch antenna using SGDREG:
fr in MHz
w/h
%error using SGDREG:
absolute error
w/h

4.6.5 Predicted Frequency values for different ANN Algorithms

w/h	Fr in MHz (actual)	SGD Regression	Linear Regression	Back Propagation	Logistic Regression
1	7710.557	7692.914	7529.473	7423.486	7710.55
1.5	7585.017	7593.029	7491.309	7404.791	7585.01
2	7489.211	7493.143	7453.145	7384.815	7489.21
2.5	7411.944	7397.386	7414.982	7363.487	7411.94
3	7347.491	7348.007	7376.818	7340.736	7347.49
3.5	7292.474	7298.629	7338.654	7316.491	7292.47
4	7244.707	7251.310	7300.490	7290.679	7244.7
4.5	7202.688	7204.505	7262.326	7263.229	7202.68
5	7165.336	7157.707	7224.162	7234.072	7165.33
5.5	7131.843	7123.447	7185.999	7203.139	7131.84
6	7101.594	7100.492	7147.835	7170.364	7101.59
6.5	7074.102	7077.537	7109.671	7135.687	7074.1
7	7048.982	7054.582	7071.507	7099.047	7048.98
7.5	7025.921	7031.627	7033.343	7060.392	7025.92
8	7004.661	7008.672	6995.180	7019.674	7004.66
8.5	6984.987	6985.717	6957.016	6976.851	6984.98
9	6966.719	6962.762	6918.852	6931.889	6966.71
9.5	6949.706	6939.807	6880.688	6884.762	6949.7

4.6.6 Error Tabulations for different ANN Algorithms

Error %	Back Propagation	Linear Regression	Log.Regr. LBFGS	Log.Regr. NEWTON	MLP Classifier	SGD Regression
Max	2.74	2.34	0.36	0.36	0.13	0.27
Avg	0.48	0.63	0.01	0.03	0.02	0.07

Chapter 5

Summary and Conclusion

5.1 Result

5.1.1 Number of samples Vs. Error, Training time

Number of Iterations = 1000

Training Samples	Training Time(sec)	Max. Error	Avg. Error
50	2.3171	5.3877	1.1901
100	4.7014	4.9802	1.1056
200	10.2239	3.2034	1.1349

5.1.2 Number of iterations Vs. Error, Training time

Number of samples = 100

No. of iterations	Training time (sec)	Max. Error	Avg. Error
100	0.4856	14.1003	9.9315
1000	4.6585	5.2516	1.4858
10000	51.7350	2.0861	0.9876

Through our analysis and results, we deduced that increasing the number of iterations helped the network predict the characteristics more accurately with lesser error percentages. Also increasing number of samples helps the cause, but increasing it beyond a certain level did not affect the error percentage significantly. In addition, the negative effect of increasing the samples is an exponential increase in the training time of ANN.

Increasing the number of iterations also increases the training time by a small factor but the error percentage is largely reduced. Another goal was to find, which algorithm worked the best for all the transmission lines we chose. We found that each transmission line worked best with different algorithms, though SGD gave average results for most.

5.1.3 Comparison of Algorithms

Planar Transmission Line	ANN Algorithm with minimum average error %	ANN Algorithm with maximum average error %
Microstrip	Logistic Reg.–LBFGS, Newton	Linear Regression
Stripline	Backpropagation	Linear Regression
Slotline	Linear Regression	Logistic Regression - Newton
CPW	SGD Regression	Logistic Regression - LBFGS
CPS	SGD Regression	Logistic Regression - Newton
Microstrip Patch Antenna	Logistic Regression - LBFGS	Linear Regression

From the above table it is clear that there is no one best method that is effective for all the Transmission Lines. The performance of the algorithm depends on the distribution of output characteristics against the input parameters of the line. For instance, Linear regression proved effective for Slotline because the characteristic curve is almost linear.

5.2 Conclusion

This thesis addressed efficient neural modeling methods for predicting transmission line characteristics. The existing ANN models for transmission lines are done using toolboxes in MATLAB or other Simulation softwares. Most of these softwares are not portable and are too heavy. In our project, we used PYTHON to model our Neural Networks. Python is portable and can be converted to a web-application which is a major advantage. The Artificial neural network was trained for predicting characteristics of Transmission Lines, which have been presented. In this paper our methods of synthesis and analysis of artificial neural network have been described, as can be seen from our simulation results which have been compared with graphs plotted with actual formula results. The error percentage curve is the proof of this result. The errors were found to be tolerable for most algorithms used for the transmission lines.

Thus the artificial neural network models given in this paper can also be used for many engineering purposes and applications because the results obtained using the models are very close to the theoretical values.

5.2.1 Scope of Improvement

Research on K-Nearest neighbor algorithms (KNN) to compare them with ANN algorithms used in this project would be useful to evaluate the best method for microwave transmission lines. Since Python was used in training the network, a real time web-application can be designed where users can interact with the application and design Transmission Line models as per requirement. Another milestone in this area would be to incorporate the microwave oriented features and techniques of the neural technology on real time applications. Neural networks with their unparalleled speed advantage, and their ability to learn and generalize wide variety of problems, promise to be one of the most powerful vehicles helping microwave design.

Chapter 6

References

6.0.1 Books

[1] K.C.Gupta and Ramesh Garg, *Microstrip Lines and Slotlines*

[2] Cam Nguyen, *Analysis Methods for RF, Microwave, and Millimeter-Wave Planar Transmission Line Structures*, Texas A and M University

[3] William J. Getsinger, *An Introduction To Microwave Transmission Lines*

6.0.2 Reports

[1] Peter Robrish, *"An Analytic Algorithm for Unbalanced stripline Impedance".*

[2] Ramesh Garg AND K. C. Gupta, *"Expressions for Wavelength and Impedance of a Slotline".*

[3] Bablu Kumar Singh, *"Design of Rectangular Microstrip Patch Antenna based on Artificial Neural Network Algorithm,"* Jodhpur Institute of Engineering and Technology

[4] S.Gevorgian, H.Berg, H.Jacobsson, and T.Lewin, *"Application Notes Of Basic Parameters Of Coplanar-Strip Waveguides On Multilayer Dielectric/Semiconductor Substrates".*

[5] M. Naser-Moghaddasi, Pouya Derakhshan Barjoei, Alireza Naghsh, *"A Heuristic Artificial Neural Network for Analyzing and synthesizing Rectangular Microstrip Antenna".*