FINAL THESIS REPORT

TITLE: CALCULATION OF FSS PARAMETERS USING MACHINE LEARNING WITH HFSS SIMULATION DATA

UNDER THE SUPERVISION OF
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TABLE OF CONTENTS

PREFACE

Frequency Selective Surfaces (FSS) are defined as thin repetitive surfaces that act as spatial filters for the electromagnetic waves passing through them. FSS are most commonly used in the radio frequency region of EM waves and find a lot of application in fabrication of radomes. A radome (radar dome) is a protective structure that helps in protecting radar antennas from harsh environments. A good radome is constructed in such a way that minimally absorbs the ER waves transmitted or received by the radio antenna, effectively transparent to the ER waves in the operating range of the antenna.

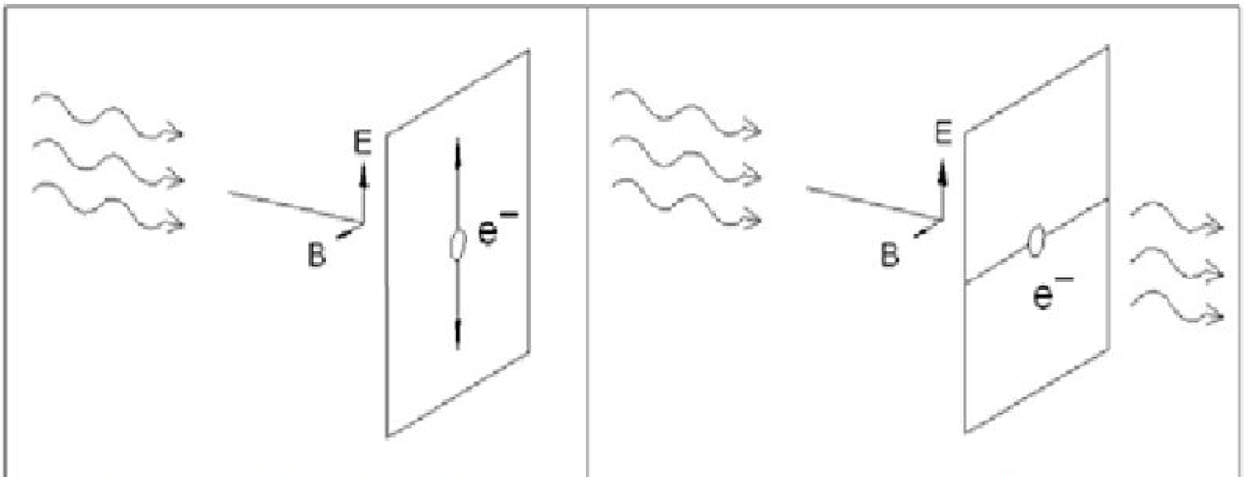
OBJECTIVE

The objective of this study is to understand FSS parameters that govern the response to EM waves and predict their values to get a desired response. Such a study can facilitate fabrication of FSS for the transmissive Radome application. As the objective is not an easy one and demands for the requirement of heavy mathematical analysis of the electromagnetic theory. Hence, to meet the objective, machine learning is used as a helping tool. To use a supervised machine learning model, a dataset is required for training, validation and testing of the model. To produce such a dataset, a few already fabricated FSS structures can be tested for their response to radio waves using radio frequency sensors. Since FSS structures can be easily simulated using HFSS simulation software, in this study, the dataset is created using simulations instead of actual FSS structures and radio frequency sensors.

FREQUENCY SELECTIVE SURFACE

FSS consists of carefully tailored, periodically arranged metallic patches which can be freestanding or over some specific substrate. These metallic patches act as inductors and capacitors, as a result of acceleration, deceleration and accumulation of free electrons in these. The combination of inductance and capacitance results in the LC filter for the incident EM wave. The characteristic of this filter depends on the physical parameters of the metallic patches, and in turn decides the transmission and/ or reflection characteristics of the EM waves, and hence the signal along with it. The value of L and C is sophisticatedly dependent on the dimensions of the patches as well as their orientation with respect to incident EM waves.

Interaction of incident EM waves with free electrons in the metallic patches leads to motion of electrons in the direction depending on polarization of the incident wave. This motion of free electrons makes the metallic patch to act as circuit elements and hence affects the frequency response of FSS. The concept of metallic stripes working as inductors and capacitors is supported by the concept of free electrons oscillating due to the effect of electric field associated with electromagnetic waves, which is further explained below with the help of diagram.



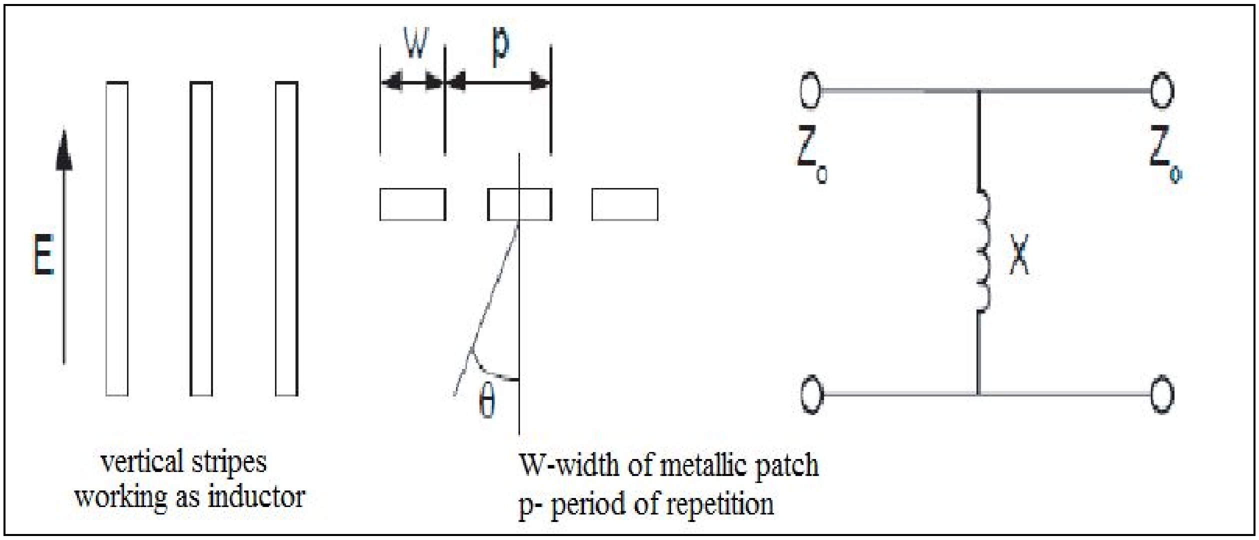
(a) oscillating electron due to effect of electric field EM wave reproducing induction effect

(b) bound electron unable to oscillate, works as accumulated charge resulting in capacitance

MODELLING EQUIVALENT ELECTRONIC CIRCUIT

Implementing circuitry design provides us the freedom and flexibility to design and also includes loss mechanism due to induction and capacitance. Absorption can be made sensitive to a particular frequency or can also be tuned by varying inductance and capacitance of the circuit. Research in the field of materials towards their property of absorbing microwaves and dependence on their characteristics is under trial. For the appropriate calculations of the impedance due to a FSS, various approximations are used. To analyze the properties of a FSS model, we create its equivalent circuit model and then compare its transmission characteristics with experimental results.

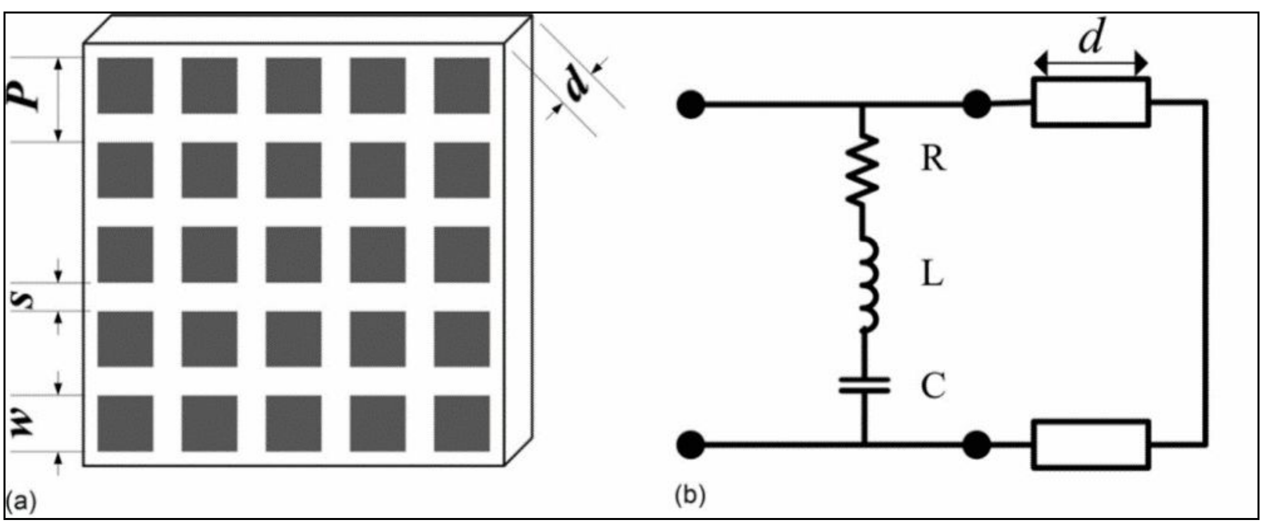
The following figure represents the working of metallic patch parallel to electric field as inductor; similarly, the patch perpendicular to electric field will work as capacitor. The equivalent circuit method includes calculation of impedance of FSS which must be a resistive, inductive and capacitive equivalent of the structure.



For a three dimensional FSS, calculation of all the values of impedances will be dependent on the shape and size of the unit cell. Total impedance of the structure will be the parallel addition of individual impedance of FSS and equivalent impedance at some distance d. This can be represented as follows:

$$\frac{1}{Z_S} = \frac{1}{Z_d} + \frac{1}{Z_{FSS}}$$

Equivalent circuit of three dimensional FSS can be presented by the following figure:



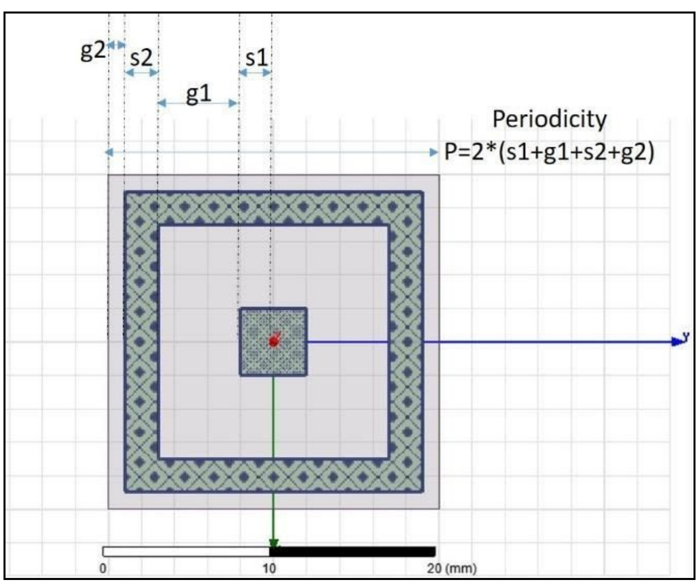
By using the above process we can get the idea of basic structure that is required for the fabrication of FSS for a certain frequency. But this structure needs to be optimized further because in practical scenarios there are various other factors affecting the working of the FSS. For that the simulation is required. Going for simulation directly can be very long a tedious job as will be a result of various guess values to be simulated with a possibility of not even reaching the solution ever. While just calculation without simulation does not assure the correct result. Hence we need to follow both methods, one after another.

To minimize the calculative approach for all the possibly required applications in various frequencies, in this study machine learning will be used along with the simulations to reach the desired FSS design.

MACHINE LEARNING APPROACH

The objective is to train a machine learning model to predict the dimensions g1, g2, s1 and s2 which define the capacitor and inductor values in an equivalent filter circuit. The training data is obtained using simulations that produce transmission coefficients for frequencies in a given range.

Below given is the structure for FSS radome design:



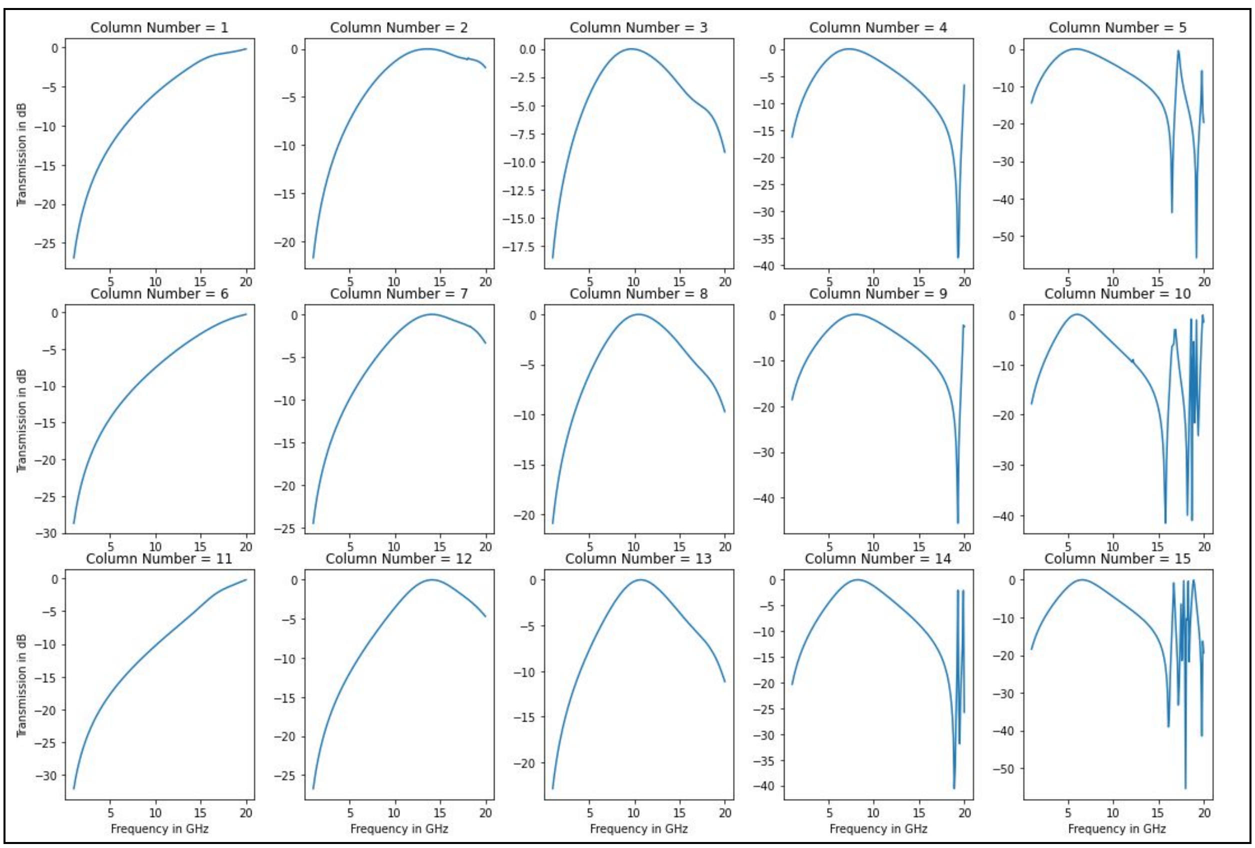
HFSS SIMULATION DATA

FSS structures with 600 combinations of g1, g2, s1, s2 having following characteristics were simulated through HFSS

- g1 is in the range 0 to 10 mm and increments by 2mm.
- g2 is in the range 0 to 2 mm and increments by 0.5mm.
- s1 is in the range 1 to 5 mm and increments by 1mm.
- s2 is in the range 0.5 to 2 mm and increments by 0.5mm.

The output of the simulations was a CSV file containing all the structures and transmission coefficients for frequencies from 1 GHz to 20 GHz with an increment of 0.1 GHz i.e 191 frequency values for all 600 combinations of g1, g2, s1 and s2 .

Here are transmission coefficients vs frequencies graphs for some of these structures:



DETAILS OF THE MACHINE LEARNING CODE

IMPLEMENTATION

The machine learning code used in this study is implemented on the programming language python 3.6 making use of a number of useful python libraries. Following are the python dependencies of the ML code :

- **Numpy**: For dealing with multi dimensional data matrices.
- **Pandas**: For using important data structures like DataFrame
- **Matplotlib**: For plotting and displaying graphs
- **Tensorflow**: For implementing Neural Networks
- **Sklearn**: For additional support

For managing the code smoothly **Jupyter Notebook**, a development application and **Anaconda** for managing the python libraries are also used.

DATA CLEANING

- This study deals with the FSS designs producing a high transmission coefficient of **-0.45 dB** for a frequency range between 1 to 20 GHz so all the designs not showing such characteristics inside this frequency range are eliminated from the dataset.
- Only the starting and ending points of the frequency range for which a particular design shows a transmission coefficient higher than -0.45 dB, also known as frequency cutoffs, are pertinent to modeling the relationship and, hence isolated for further processing.
- Since one design can produce multiple pairs of cutoff frequencies, all the pairs may also be included. But including more than one cutoff pair is not useful for training because the MLP architecture can only model a relationship that has a fixed number of frequency cutoff pairs for every FSS design. So, in this study, for every design only the first frequency cutoff pair is included.

DATA SCALING

All the inputs and outputs are bought in the range of (-1, 1) by using the following mean normalization formula:

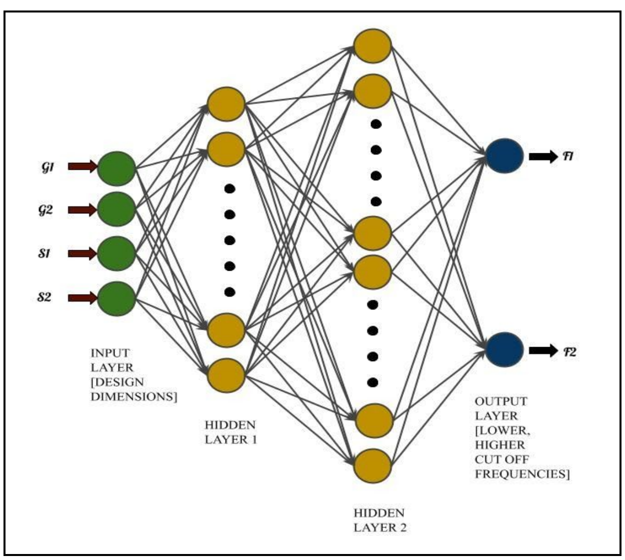
$$x = \frac{x' - \mu}{x'_{max} - x'_{min}}$$

Data scaling plays an important role in machine learning as unscaled input variables can lead to **SLOW** and **UNSTABLE** learning while unscaled output variables can lead to **EXPLODING GRADIENTS** causing the learning process to fail. Since, the range of tanh is also (-1, 1), scaling of outputs allows tanh to be used as an activation function in the output layer which helps in achieving convergence easily.

MULTI LAYERED PERCEPTRON ARCHITECTURE

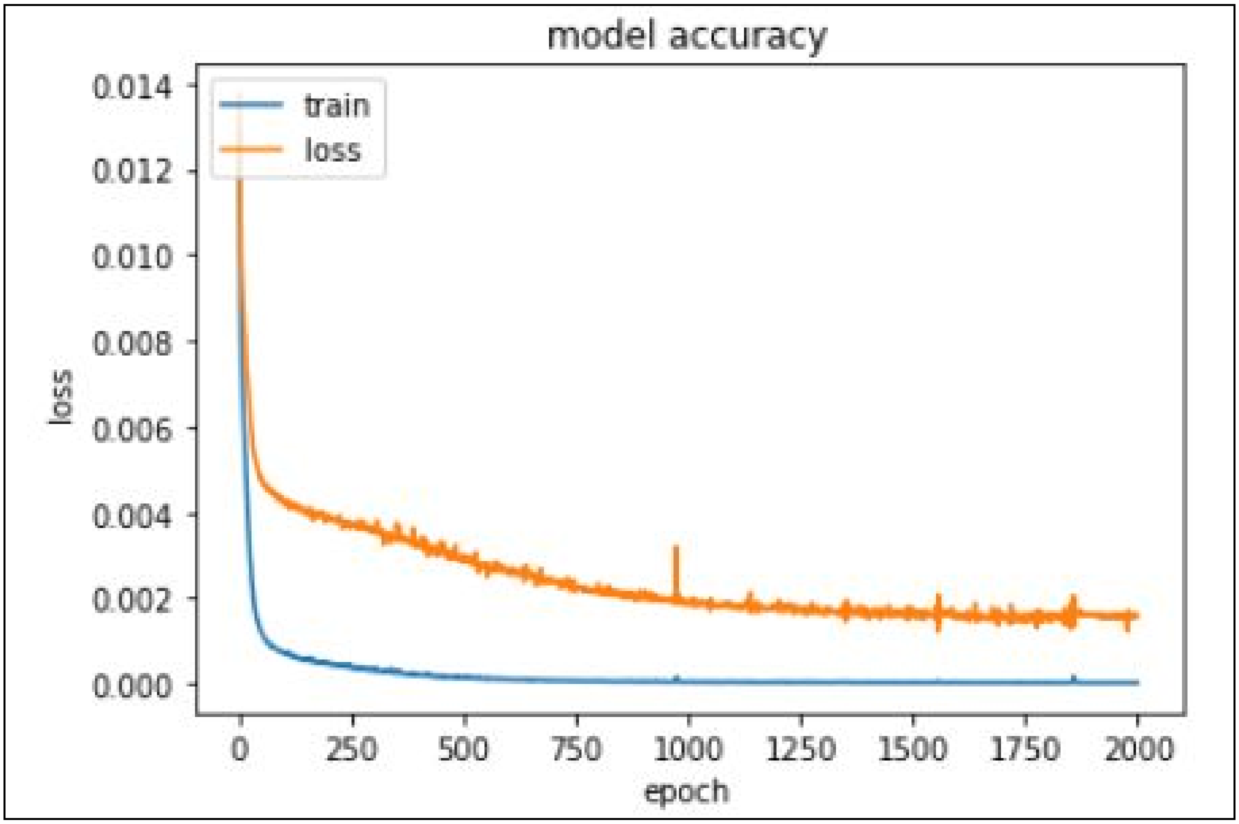
To model the relationship between FSS dimensions and cutoff frequencies a multi-layered perceptron design is used with following features:

- **INPUT LAYER => 4 NEURONS** [4 inputs dimensions]
- **FIRST HIDDEN LAYER => 8 NEURONS**
- **SECOND HIDDEN LAYER => 32 NEURONS**
- **OUTPUT LAYER => 2 NEURONS** [2 cutoff frequencies]



- The hidden layers implement the **RECTIFIED LINEAR ACTIVATION** function which because of its infinite range of all positive numbers, helps avoid **EASY SATURATION** of gradients.
- To capture **NON-LINEARITIES** in the relationship while avoiding saturation of the gradients the output layer uses the **HYPERBOLIC TANGENT ACTIVATION** function.
- The number of perceptrons in each layer is in powers of 2 because that helps the GPU to take advantage of optimizations related to efficiencies in working with powers of two.
- Number of hidden layers and the number of neurons per layer are taken such that the most optimum accuracy in the final solution can be achieved.
- The data is divided into training, validation and test data in the ratio **3:1:1**. Such a ratio is chosen so that a large amount of data is available for training the model but enough still remains to evaluate the accuracy of the model.
- **LOGARITHMIC HYPERBOLIC COSINE** loss function is used in this study because it is similar to 'mean squared error loss' for small values of input, but tends towards $abs(x) - log(2)$ for large values of input, which helps ignore occasional wildly incorrect predictions.
- **ADAM** optimizing algorithm is used for this model because it combines the best properties of the AdaGrad and RMSProp algorithms to provide an optimization algorithm that can handle sparse gradients on noisy problems. Hyperparameters for adam used in this model are as follows:
    - Learning Rate (α) = 0.001
    - Exponential Decay Rate for first moment (β_1) = 0.9
    - Exponential Decay Rate for second moment (β_2) = 0.999
    - Epsilon (ε) = 1e - 08
- A total of **2000** epochs are used to train the MLP because any number more than that would lead to overfitting.

Learning curve for the ML model is as follows:



Loss function used to calculate loss in this graph is log-cosh and the loss is calculated on outputs that are scaled using the mean normalization method.

FREQUENCY LOOKUP TABLE

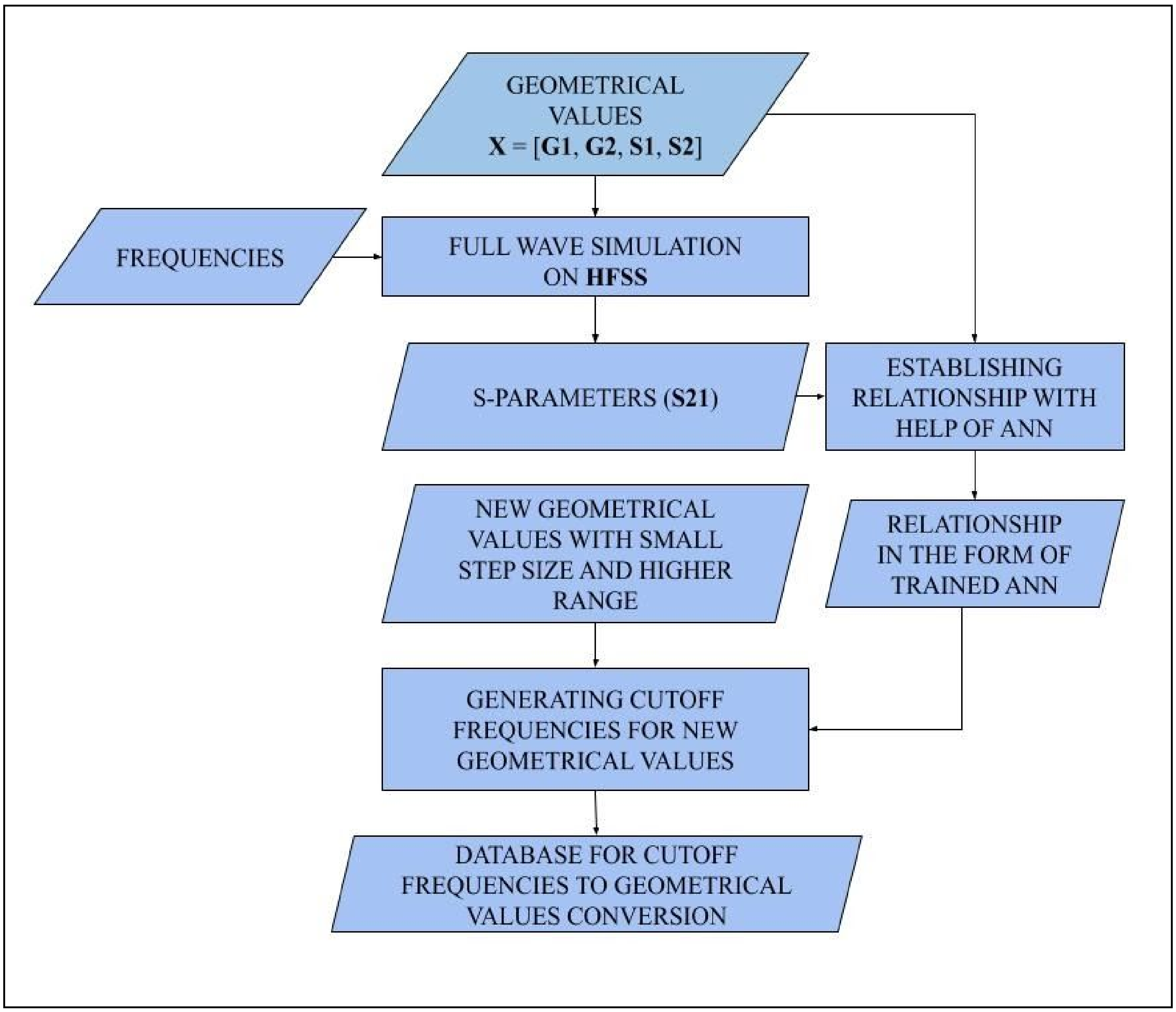
- The reason for making a lookup table is three fold:
    - The relation from cutoff to dimension is hard to capture because it is highly convoluted. Modeling such a relation will be computationally expensive and prone to inferior accuracy.
    - The Lookup table can accommodate all the possible combinations of dimensions with a very small step size and higher range compared to the input data and still remain feasible.

- The database can be filled with the custom range of dimension, hence giving control over the dimensions of FSS designs that the lookup table outputs corresponding to any pair of cutoff frequencies.

- A total of 41,62,091 combinations of dimensions are generated and fed into a trained MLP so that they can be mapped with cutoff frequencies and stored inside a lookup table.
- This lookup table is used to find an entry having minimum average absolute error for the frequencies provided by the user. One important benefit of using such a technique is that multiple entries can have same errors implying that multiple designs can give the similar results hence giving the user the freedom to select the best suited one.

FLOW DIAGRAM

Following flow diagram visually depicts the sequence of steps followed in this study to create a lookup table that can give dimensions of FSS for any desired cutoff frequency pairs.



RESULTS

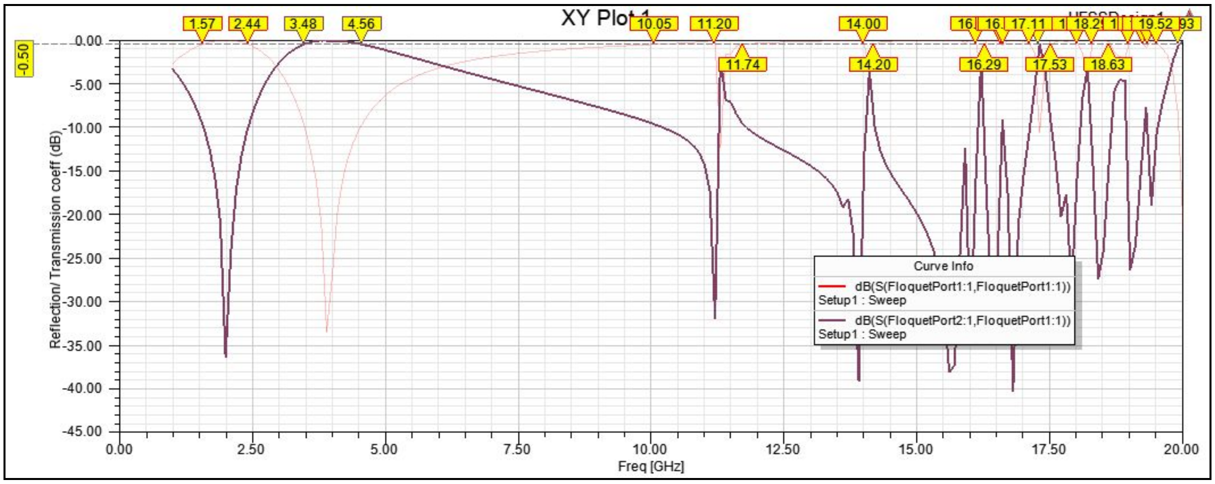
The neural network was tested for a few cutoff frequency pairs. The dimensions obtained for those frequency pairs were then simulated and the actual cutoff frequencies were recorded. Following table presents the dimensions obtained from the neural network and the actual cutoff frequency pairs for those dimensions.

User defined cut-off frequencies (in GHz)		Dimensions (in mm) obtained by using trained model				Results obtained			
						Simulation result cut-off frequencies (in GHz)		Absolute Error	
Lower cutoff frequency	Upper Cutoff frequency	G1	G2	S1	S2	Lower cutoff freq	Upper cutoff freq	Lower cutoff	Upper cutoff
2	4	02.00	00.20	07.05	00.10	3.48	4.56	1.48	0.56
3	5	10.75	01.60	07.05	02.05	3.51	5.41	0.51	0.41
6	8	10.00	00.50	03.00	02.00	5.66	7.90	0.34	0.10
8	10	03.75	00.70	03.45	02.65	7.77	8.84	0.23	1.16
10	12	02.00	01.50	03.00	01.50	9.68	12.12	0.32	0.12
12	14	03.25	01.60	01.85	02.65	11.55	14.15	0.45	0.15
14	16	02.75	02.90	01.45	02.95	13.00	15.23	1.00	0.77
16	18	00.75	03.00	01.85	01.00	14.94	17.63	1.06	0.37
8	12	04.00	00.50	03.00	00.50	7.79	11.99	0.21	0.01
6	14	11.25	00.00	00.25	00.10	6.13	13.16	0.13	0.84
8	18	06.00	00.00	01.00	00.50	9.76	18.23	1.76	0.23

Absolute Error has been calculated by taking simulation frequency as reference value, in both lower and upper cutoff frequency cases.

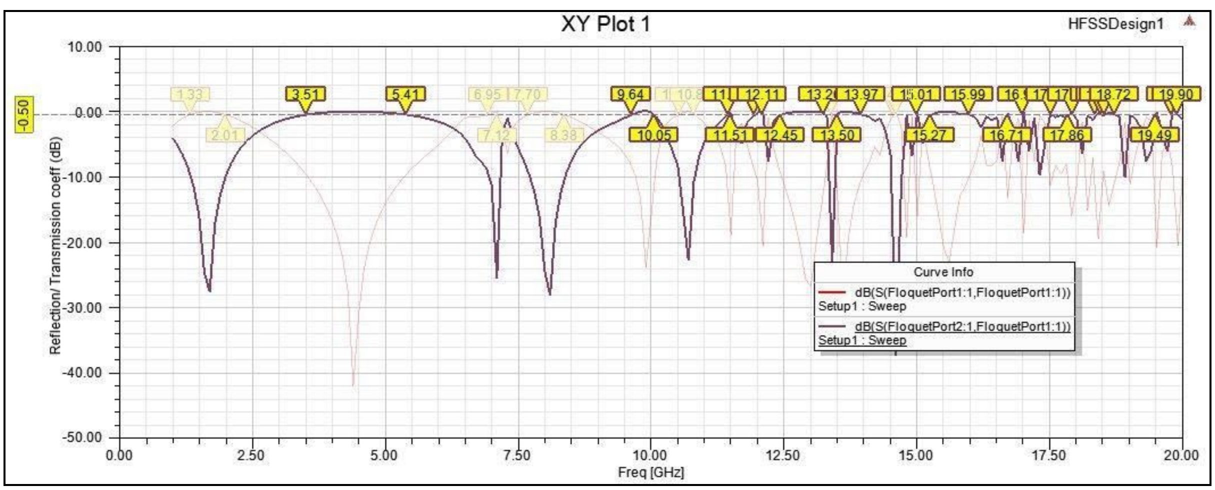
Following are the graphs obtained from simulating the dimensions obtained from the neural network.

Test for user defined cutoff frequency range from 2 GHz to 4 GHz:



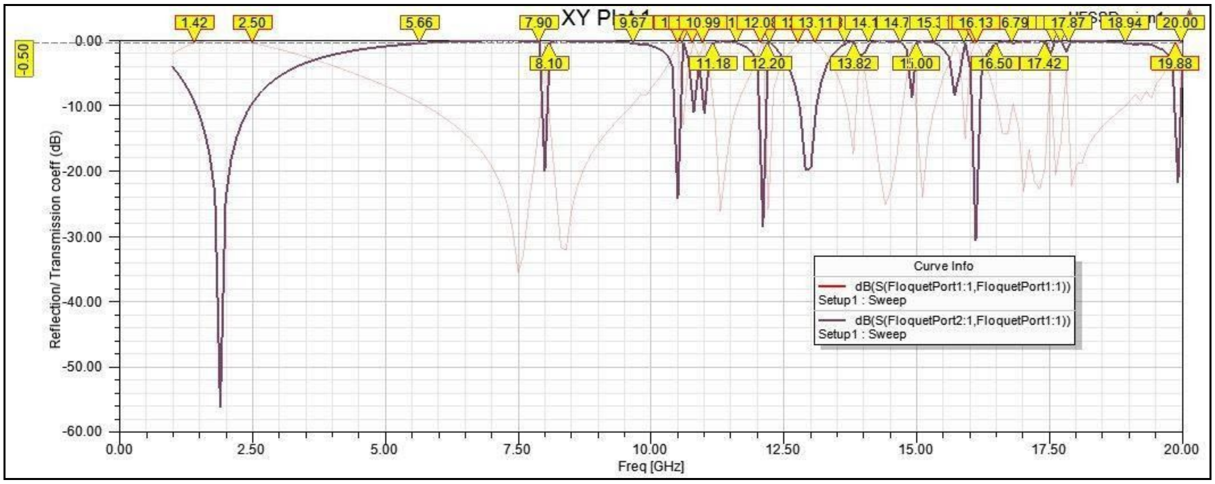
The cut off frequency obtained is from **3.48 GHz** to **4.56 GHz**.

Test for user defined cutoff frequency range from 3 GHz to 5 GHz:



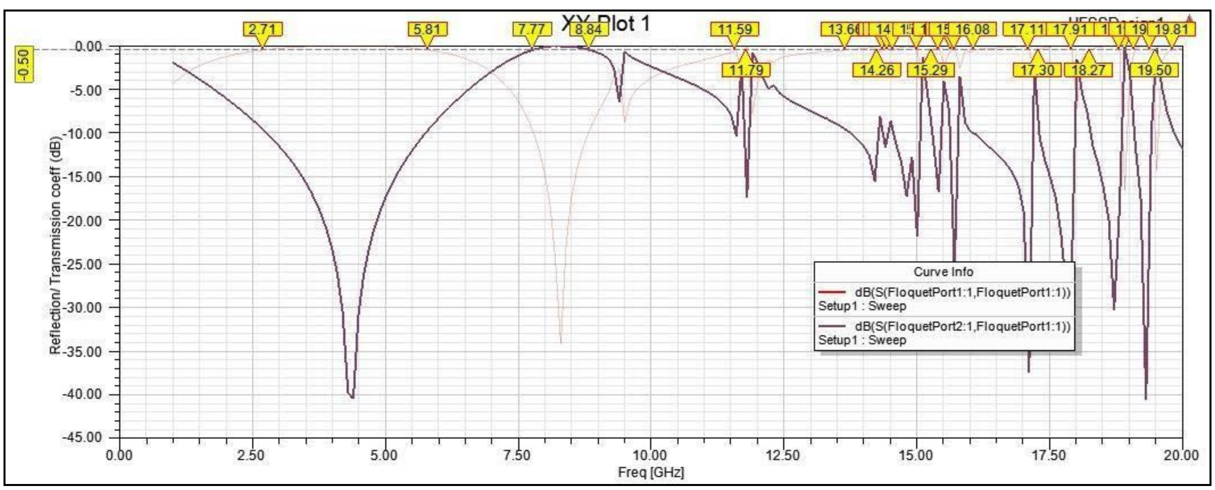
The cut off frequency obtained is from **3.51 GHz** to **5.41 GHz**.

Test for user defined cutoff frequency range from 6 GHz to 8 GHz:



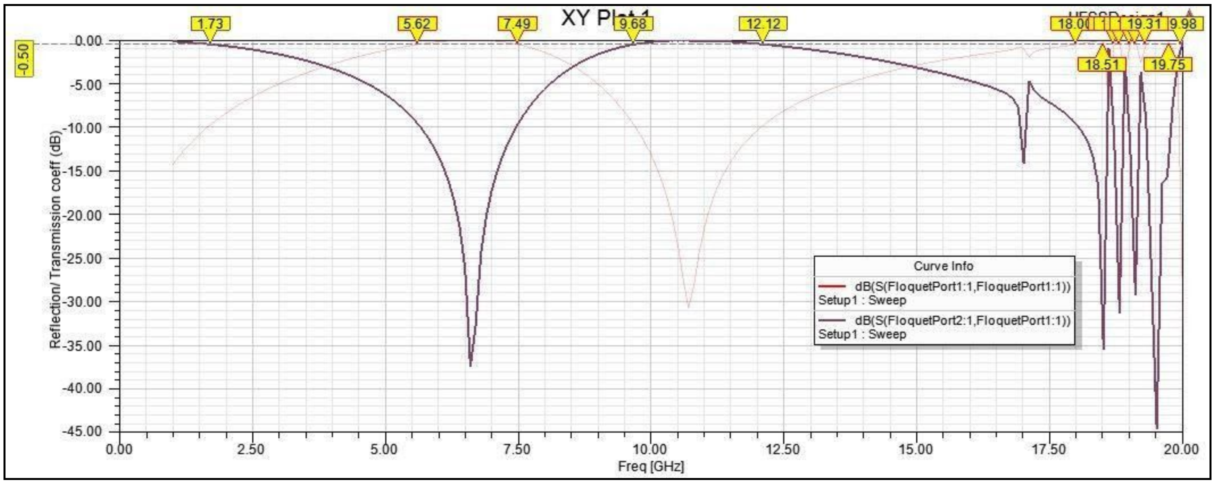
The cut off frequency obtained is from **5.66 GHz** to **7.90 GHz**.

Test for user defined cutoff frequency range from 8 GHz to 10 GHz:



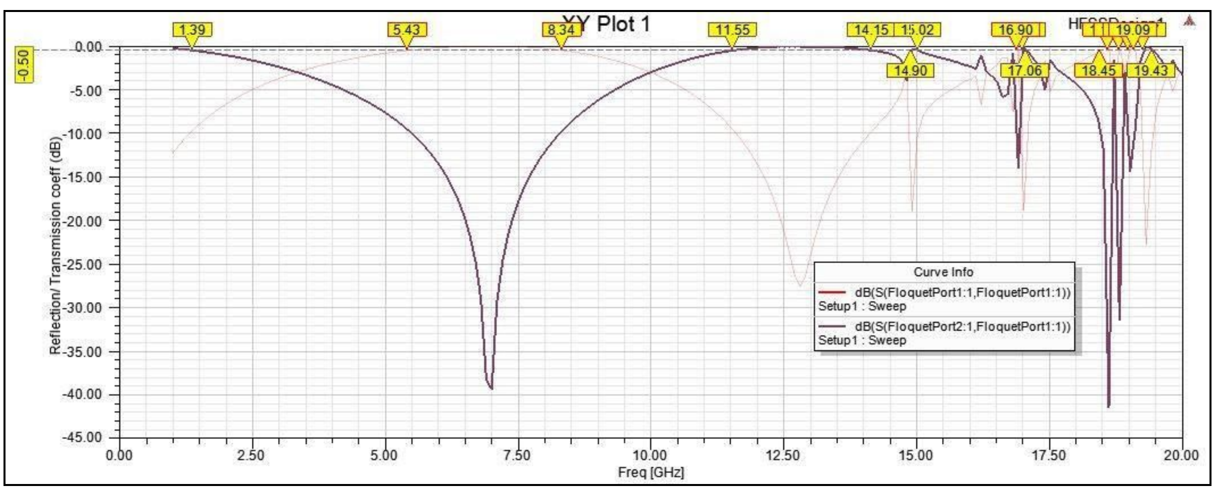
The cut off frequency obtained is from **7.77 GHz** to **8.84 GHz**.

Test for user defined cutoff frequency range from 10 GHz to 12 GHz:



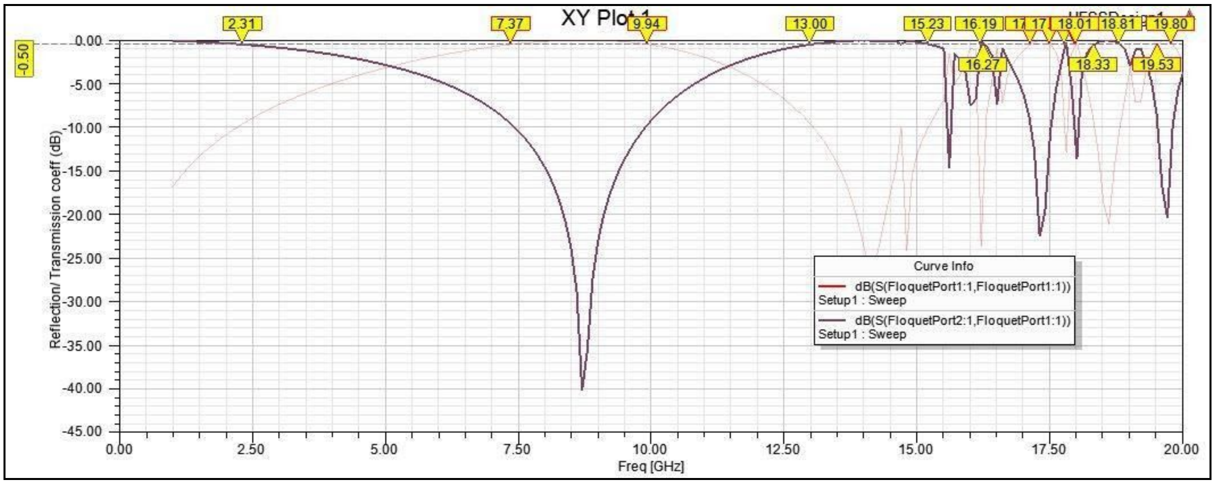
The cut off frequency obtained is from **9.68 GHz** to **12.12 GHz**.

Test for user defined cutoff frequency range from 12 GHz to 14 GHz:



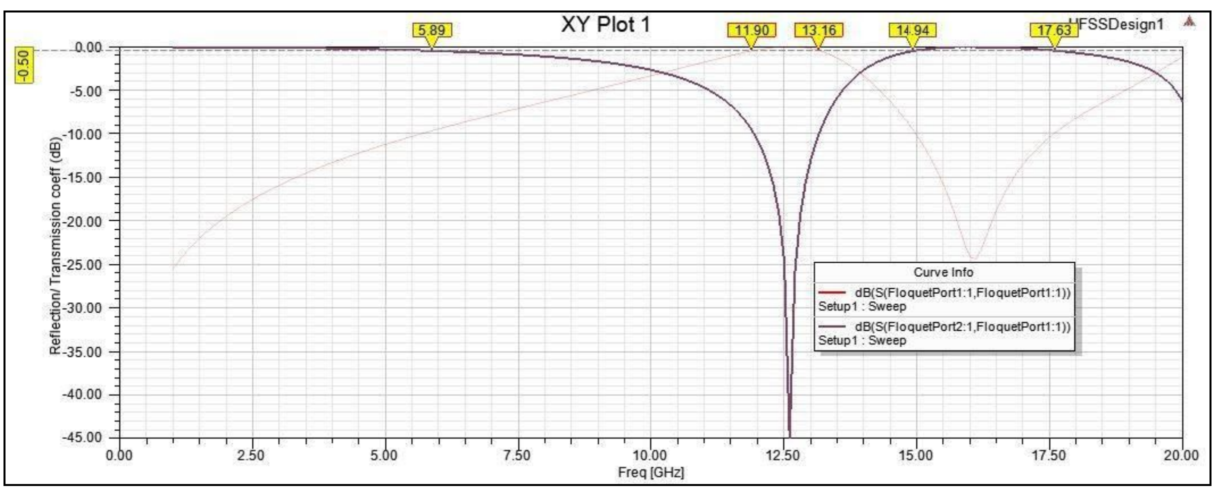
The cut off frequency obtained is from **11.55 GHz** to **14.15 GHz**.

Test for user defined cutoff frequency range from 14 GHz to 16 GHz:



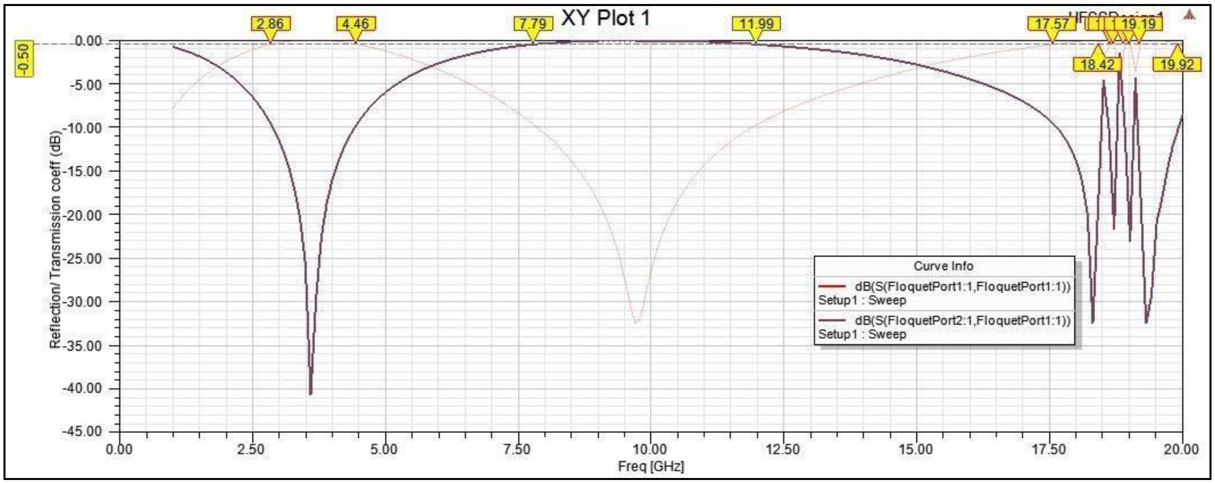
The cut off frequency obtained is from **13 GHz** to **15.23 GHz**.

Test for user defined cutoff frequency range from 16 GHz to 18 GHz:



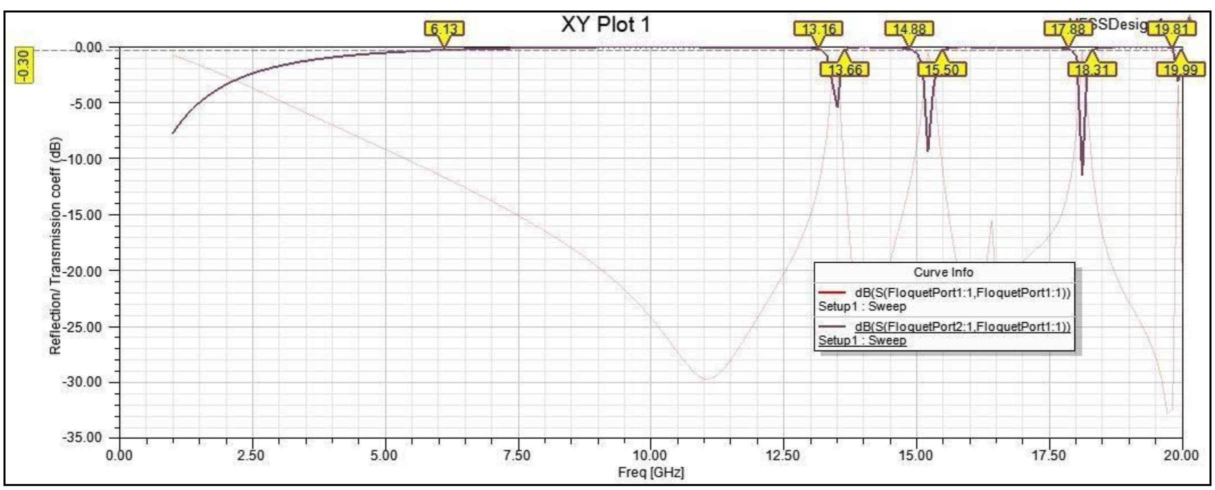
The cut off frequency obtained is from **14.94 GHz** to **17.63 GHz**.

Test for user defined cutoff frequency range from 8 GHz to 12 GHz:



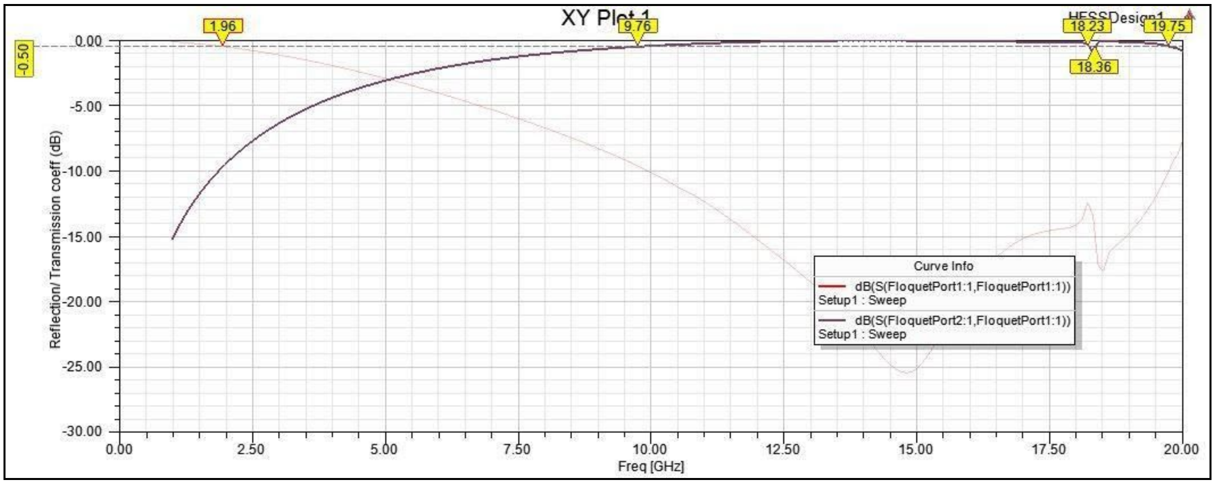
The cut off frequency obtained is from **7.79 GHz** to **11.99 GHz**.

Test for user defined cutoff frequency range from 6 GHz to 14 GHz:



The cut off frequency obtained is from **6.13 GHz** to **13.16 GHz**.

Test for user defined cutoff frequency range from 8 GHz to 18 GHz:



The cut off frequency obtained is from **9.76 GHz** to **18.23 GHz**.

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