ANALYSIS OF FSS PROTOTYPE USING DEEP NEURAL NETWORK AND ITS SYNTHESIS IMPLEMENTING EVOLUTIONARY ALGORITHM

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CERTIFICATE OF RECOMMENDATION

This is to certify that the thesis entitled "***ANALYSIS OF FSS PROTOTYPE USING DEEP NEURAL NETWORK AND ITS SYNTHESIS IMPLEMENTING EVOLUTIONARY ALGORITHM***" submitted by **CHAMELI MITRA *(University Registration No: 160204 of 2021-2022)*** under my guidance and supervision and be accepted in partial fulfilment of the requirement for awarding the degree of "***MASTER OF ENGINEERING IN ELECTRONICS AND TELE-COMMUNICATION ENGINEERING***" of Jadavpur University. The research results presented in this thesis have not been included in any other paper submitted for the award of any degree to any other Institute or University.

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DECLARATION OF ORIGINALITY AND COMPLIANCE OF ACADEMIC ETHICS

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Thesis Title

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Date: 12.6.23

Chameli Mitra

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- Motivation of my work
- Novel aspects

Preface

FSS

A **metamaterial** is any material engineered to have a property that is not found in naturally occurring materials. They are made from assemblies of multiple elements fashioned from composite materials such as metals and plastics. These materials are usually arranged in repeating patterns, at scales that are smaller than the wavelengths of the phenomena they influence. Metamaterials derive their properties not from the properties of the base materials, but from their newly designed structures. Their precise shape, geometry, size, orientation and arrangement gives them their smart properties capable of manipulating electromagnetic waves: by blocking, absorbing, enhancing, or bending waves, to achieve benefits that go beyond what is possible with conventional materials. [1]

Metasurfaces are broadly defined as planar metamaterials with subwavelength thickness and they can be easily fabricated while using lithography and nano-printing techniques. Both metamaterials and metasurfaces are rapidly growing research directions, and with their use, spatially varying EM or optical responses can be achieved at will, with scattering phase, amplitude, and polarization. Through a good selection of materials and design, the ultra-thin structure of MSs can considerably suppress the detrimental and undesirable losses in the wave propagation direction. When considering the polarization response, all metasurfaces can be categorized based on the operating principle of array element, i.e their functionalities on frequency selective surfaces (FSS), high impedance surfaces, perfect absorbers, reflecting surfaces, etc. Since, in order to tailor the frequency selectiveness in transmission/reflection characteristics, only electrical polarization may be sufficient. From the theory of antenna and microwave engineering, these surfaces are made by planar and periodic arrays of metallic patches or strips with different shapes. The patch is of negligible thickness as compared to the wavelength, although it is large enough in contrast to the metal's skin depth. Consequently, such a structure can impeccably be estimated as a minuscule thin array of perfect conducting resonant elements. This approximation is also applicable to the complementary FSSs structures i.e apertures. However, aperture-type FSSs face a limitation when the area of the cavity/aperture becomes equal to the unit cell (a wire-mesh type) [2,3]. Square and hexagonal wire-mesh unit cells have typically been used and are also termed as the capacitive grid. The existence of the resonating size of array element causes the emergence of side lobes in the transmitted and reflected fields, which are the defining features of FSSs. However, as compared to the FSSs, the resonating element and unit cell of metasurface is relatively much smaller than the wavelength and it helps to eliminate the grating lobes in the frequency response. Therefore, FSSs in the Tgerahertz domain are usually termed as metasurfaces.

As early as 1947 George Sinclair, the founder of the Ohio State University Antenna Laboratory (which later became the ElectroScience Laboratory), realized that antennas placed on aircraft represented significant scatterers. Ed Kennaugh led much of the subsequent research on control of the radar cross section of antennas. This was initiated by a white paper on the "Echoing Area of Antennas" in 1961. One of the concepts introduced for this task was that of **frequency selective surfaces**, which became the major topic under investigation and which has continued to the present.

Traditionally, frequency selective surfaces (FSSs) comprising structures with periodicity in two dimensions have important applications as spatial filters in microwave and optics. Due to the manufacturing process, they are usually in the form of printed patches on a dielectric substrate or apertures in a conducting screen. The advent of powerful commercial simulation tools allows effective FSS designs with more flexibility. Exploitation of transmission and reflection information obtained from FSS also paves the way for better antenna designs.[1,15]

ANN

The idea of neural networks began unsurprisingly as a model of how neurons in the brain function, termed ‘connectionism’ and used connected circuits to simulate intelligent behaviour .In 1943, portrayed with a simple electrical circuit by neurophysiologist Warren McCulloch and mathematician Walter Pitts. Donald Hebb took the idea further in his book, The Organization of Behaviour (1949), proposing that neural pathways strengthen over each successive use, especially between neurons that tend to fire at the same time thus beginning the long journey towards quantifying the complex processes of the brain.

Two major concepts that are precursers to Neural Networks are:
1) ‘Threshold Logic’ — converting continuous input to discrete output
2) ‘Hebbian Learning’ — a model of learning based on neural plasticity, proposed by Donald Hebb in his book “The Organization of Behaviour” often summarized by the phrase: “Cells that fire together, wire together.”
both proposed in the 1940’s. In 1950s, as researchers began trying to translate these networks onto computational systems, the first Hebbian network was successfully implemented at MIT in 1954.

Around this time, Frank Rosenblatt, a psychologist at Cornell, was working on understanding the comparatively simpler decision systems present in the eye of a fly, which underlie and determine its flee response. In an attempt to understand and quantify this process, he proposed the idea of a Perceptron in 1958, calling it Mark I Perceptron. It was a system with a simple input output relationship, modeled on a *McCulloch-Pitts* neuron, proposed in 1943 by Warren S. McCulloch, a neuroscientist, and Walter Pitts, a logician to explain the complex decision processes in a brain using a linear threshold gate. A McCulloch-Pitts neuron takes in inputs, takes a weighted sum and returns ‘0’ if the result is below threshold and ‘1’ otherwise.

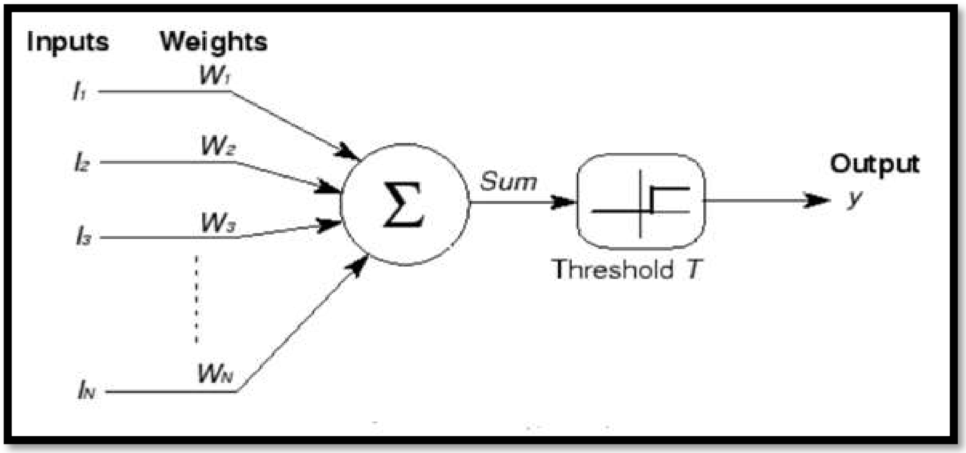


Fig. 1.1 A McCulloch-Pitts neuron

The beauty of Mark I Perceptron lay in the fact that its weights would be ‘learnt’ through successively passed inputs, while minimizing the difference between desired and actual output.

A major drawback? This perceptron could only learn to separate linearly separable classes, making the simple but non-linear exclusive-or circuit an insurmountable barrier**.**

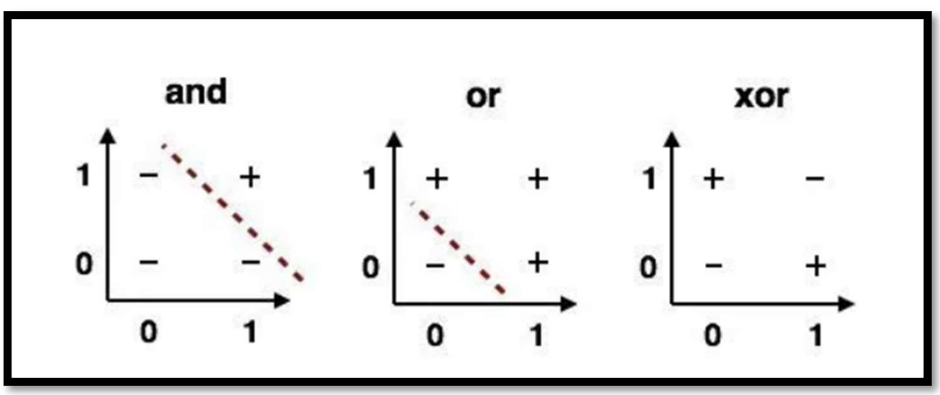


Fig. 1.2 Graphs showing the linear and non-linearly separable classes

Despite the messy and somewhat dis-satisfactory advent of the use of Machine Learning to quantify decision systems apart from the brain, today’s artificial neural networks are nothing more than several layers of these perceptrons.

What is periodic surface?

A periodic surface is basically an assembly of identical elements arranged in a one or two-dimensional infinite array. An example is shown in Fig. 1, where simple "dipoles" loaded at their centers with a load impedance Z_L have been arranged in a rectangular array with inter-element spacings D_x, and D_z.

FSS is a periodic surface with identical two-dimensional arrays of elements arranged on a dielectric substrate. An incoming plane wave will either be transmitted (passband) or reflected back (stopband), completely or partially, depending on the nature of array element. This occurs when the frequency of electromagnetic (EM) wave matches with the resonant frequency of the FSS elements. Therefore, an FSS is capable of passing or blocking the EM waves of certain range of frequencies in the free space; consequently, identified as spatial filters. Nowadays, FSSs have been studied comprehensively and huge growth is perceived in the field of its designing and implementation for different practical applications at frequency ranges of microwave to optical.

Fundamentally, any periodic array can be excited in two ways: by an incident plane wave $\overline{E_\iota}$, as shown in Fig. 1.3 top (passive array), or by individual generators connected to each element, as shown in Fig. 1.3 bottom (active array). In the latter case, the voltage generators must have the same amplitude and a linear phase variation across the active array in order for it to qualify as a periodic surface. (This constraint produces one or more radiated plane waves.) In the passive array case (Fig. 1.1 top), the incident plane wave will be partly transmitted in the forward direction ($\overline{E_t}$) and partly reflected in the specular direction ($\overline{E_r}$). Under resonant condition and for no grating lobes (see Section 1.9) the amplitude of the reflected signal may equal E_i while E‘ = 0. It is customary to define the specular reflection coefficient as $\overline{E_\iota}$ E_r

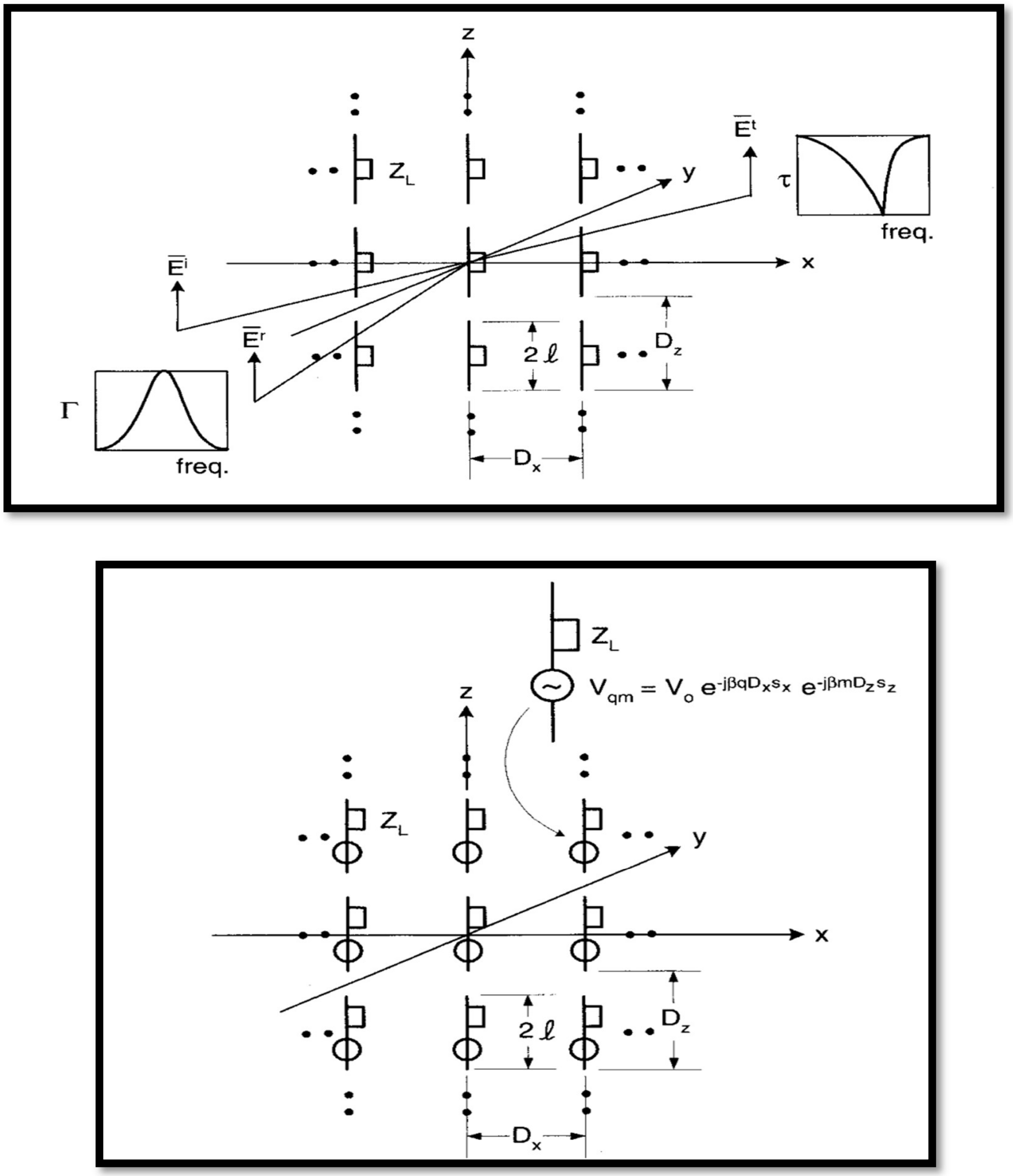


Fig. 1.3 Periodic structure of electric conductors (dipoles) with load impedances Z_L. Top: Passive case. The structure is excited by an incident plane wave $\vec{E}i$ which is being partly reflected in the specular direction ($\vec{E}r$) and partly transmitted in the forward direction ($\vec{E}t$). Bottom: Active case. Each element is excited by individual generators with the same amplitude and each has a linear phase variation across the aperture as shown. (s_x and s_z denote the directional cosines along the x- and z-axes, respectively).[1]

What is FSS?

Frequency Selective Surface is a robustly studied topic of electromagnetic (EM) science, which are two-dimensional periodic structures having planar metallic array

elements (patch or apertures) on a dielectric substrate, exhibiting transmission and reflection at certain resonant frequency.Frequency-selective surfaces (FSSs) have been studied over the past five decades . They have evolved from simple designs to the complex geometries known today. This evolution has been mainly driven by the increasingly stringent performance requirements of recent applications. Progress on frequency-selective surfaces has also been motivated by the significant improvements in analysis methods, computational power, and fabrication technology. The frequency selective surfaces (FSS) are periodic structures in either one, two dimensions (i.e. singly or doubly periodic structures) which, as the name suggests, perform a filter operation. Thus, depending on their physical construction, material and geometry, they are divided into low-pass, high-pass, band-pass and band-stop filters.

Equivalent circuit theory can provide useful physical insight, provide interpolation of transmission and reflection coefficients as a function of frequency and also provide methods of synthesis. This is because the response of an equivalent circuit is by definition a realizable function of frequency and there exists a well-established body of theory on the use of equivalent circuits in control theory, filter theory and circuit synthesis . It may also be used in RAM design for the same reasons. However, for all but the simplest circuits, equivalent circuits are not generally unique and it may be necessary to switch between topologies depending on some external parameter if the LCR values are to remain all positive. Thus, one equivalent circuit may be good for a range of angles of incidence (with capacitors, inductors and resistors that change value with angle of incidence) but may need to be switched to another representation outside of this range.

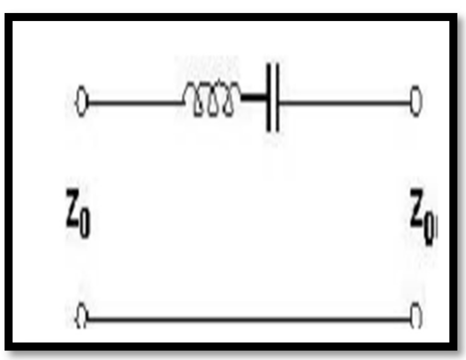


Fig. 1.4 Simplest equivalent circuit representations of a band pass FSS in free space corresponding to a slot structure for one polarization and incidence angle.[1,15]

What is ANN?

The history of Artificial Neural Networks (ANN) began with Warren McCulloch and Walter Pitts (1943) who created a computational model for neural networks based on algorithms called threshold logic. This model paved the way for research to split into two approaches. One approach focused on biological processes while the other focused on the application of neural networks to artificial intelligence. This work led to work on nerve networks and their link to finite automata.

Artificial Neural Net models have been studied for many years in the hope of achieving human-like performance in the fields of speech and image recognition. These models are composed of many nonlinear computational elements operating in parallel and arranged in patterns reminiscent of biological neural nets. Computational elements or nodes are connected via weights that are typically adapted during use to improve performance.[16]

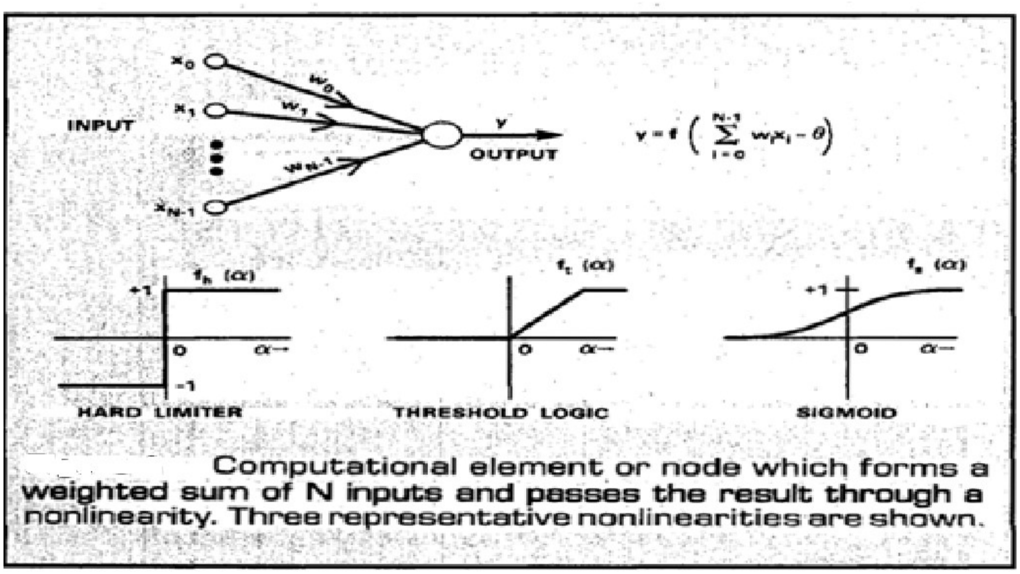
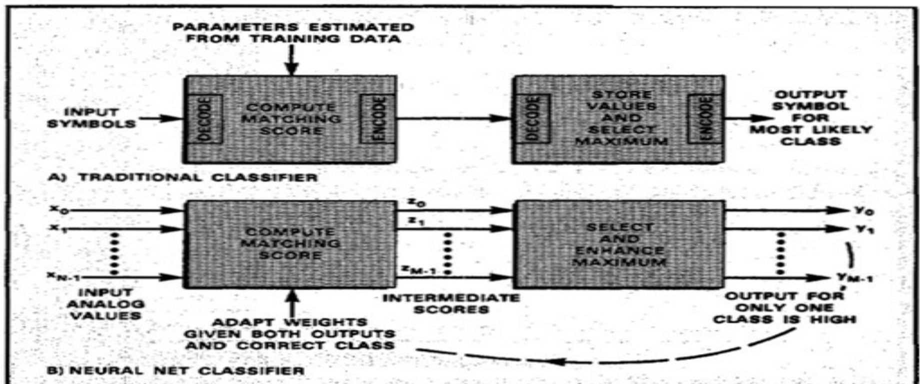


Fig. 1.5 Artificial Neural Net (ANN) Model



Block diagrams of traditional (A) and neural net (B) classifiers. Inputs and outputs of the traditional classifier are passed serially and internal computations are performed sequentially. In addition, parameters are typically estimated from training data and then held constant. Inputs and outputs to the neural net classifier are in parallel and internal computations are performed in parallel. Internal parameters or weights are typically adapted or trained during use using the output values and labels specifying the correct class.

Fig. 1.6 Block Diagrams of traditional and neural net classifiers

What is DNN?

The history of deep learning can be traced back to 1943, when Walter Pitts and Warren McCulloch created a computer model based on the neural networks of the human brain. They used a combination of algorithms and mathematics they called “threshold logic” to mimic the thought process.

The adjective "deep" in deep learning refers to the use of multiple layers in the network. Early work showed that a linear perceptron cannot be a universal classifier, but that a network with a nonpolynomial activation function with one hidden layer of unbounded width can. Deep learning is a modern variation that is concerned with an unbounded number of layers of bounded size, which permits practical application and optimized implementation, while retaining theoretical universality under mild conditions. In deep learning the layers are also permitted to be heterogeneous and to deviate widely from biologically informed connectionist models, for the sake of efficiency, trainability and understandability.
Deep neural networks are generally interpreted in terms of the universal approximation theorem or probabilistic inference. The classic universal approximation theorem concerns the

capacity of feedforward neural networks with a single hidden layer of finite size to approximate continuous functions. In 1989, the first proof was published by George Cybenko for sigmoid activation functions and was generalised to feed-forward multi-layer architectures in 1991 by Kurt Hornik. Recent work also showed that universal approximation also holds for non-bounded activation functions such as the rectified linear unit. [8]

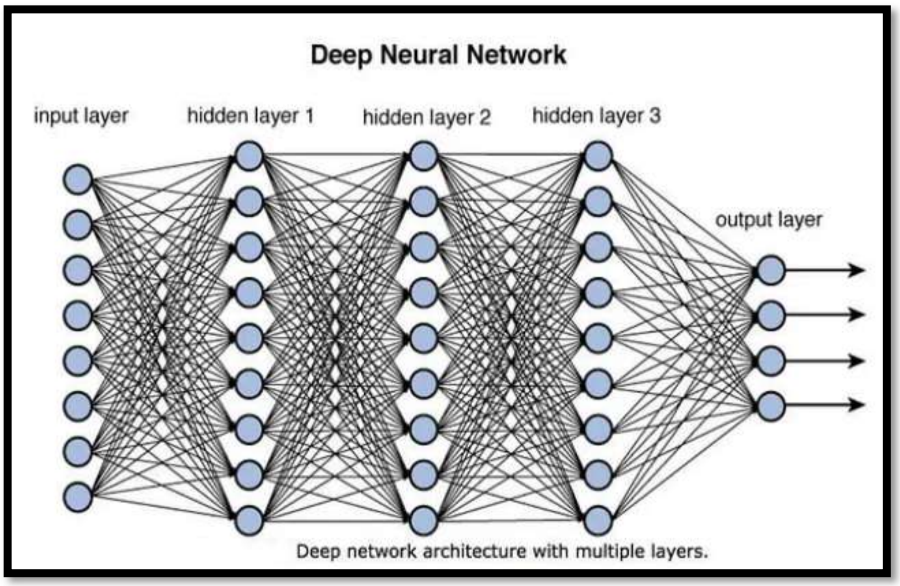


Fig. 1.7 Representation of Deep Neural Network with multiple layers

Basic Difference between ANN and DNN

Artificial neural networks (ANNs) were inspired by information processing and distributed communication nodes in biological systems. ANNs have various differences from biological brains. Specifically, artificial neural networks tend to be static and symbolic, while the biological brain of most living organisms is dynamic (plastic) and analog.

Deep learning is a modern variation that is concerned with an unbounded number of layers of bounded size, which permits practical application and optimized implementation, while retaining theoretical universality under mild conditions. In deep learning the layers are also permitted to be heterogeneous and to deviate widely from biologically informed connectionist models, for the sake of efficiency, trainability and understandability.

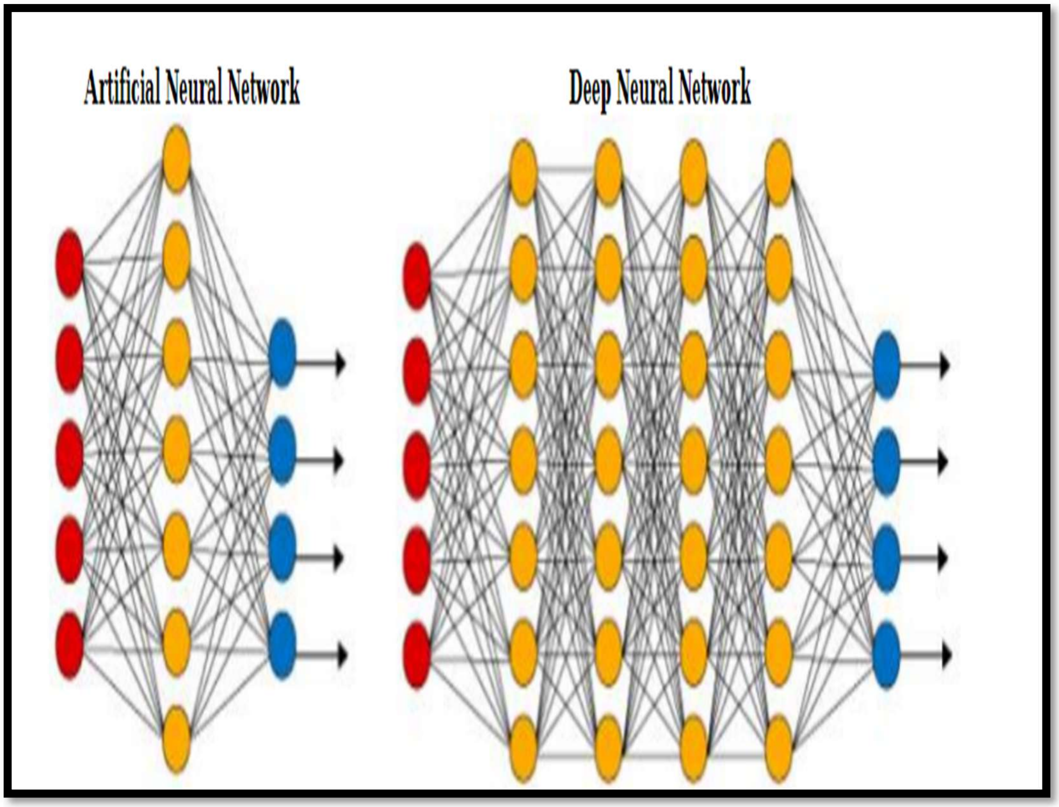


Fig. 1.8 Difference between ANN and DNN on the basis of architecture

Therefore the basic difference between ANN and DNN lies in the fact that ANN consists of one or two hidden layers to process data while DNN mainly contains multiple layers between the input and output layers.

Motivation of my work

Implementation of neural network to model a frequency selective surface prototype can serve as an excellent alternative for four main situations:

1. When closed-form solutions do not exist ,and trial-and-error methods are the main approaches to tackle the problem at hand;
2. When an application requires real-time performance;
3. When faster convergence rates are required in the optimization of large systems;
4. When enough measured data exist to train an Neural Network for prediction purposes, especially when no analytical tools exist.

The utility of FSS prototype lies in the significant reduction in the complexity and ambiguity to obtain dimensions of a structure for a specific frequency and bandwidth.

Novel Aspects

The novelty of my work has been discussed below:

- Implementation of Neural Network in determining the frequency and bandwidth will reduce the tedious job of determining them by trial and error method.
- Determining the dimensions of the structure, just from the frequency and bandwidth of operation will reduce time and complexity.
- The mean square error will reduce with multiple layer and multiple neurons in each layer yielding an accurate result which is difficult to obtain using circuits.

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Chapter 2

LITERATURE SURVEY

Introduction

Metamaterial

The core concept of metamaterial design is to craft materials by using artificially designed and fabricated structural units to achieve the desired properties and functionalities. These structural units—the constituent artificial 'atoms' and 'molecules' of the metamaterial—can be tailored in shape and size, the lattice constant and interatomic interaction can be artificially tuned, and 'defects' can be designed and placed at desired locations.

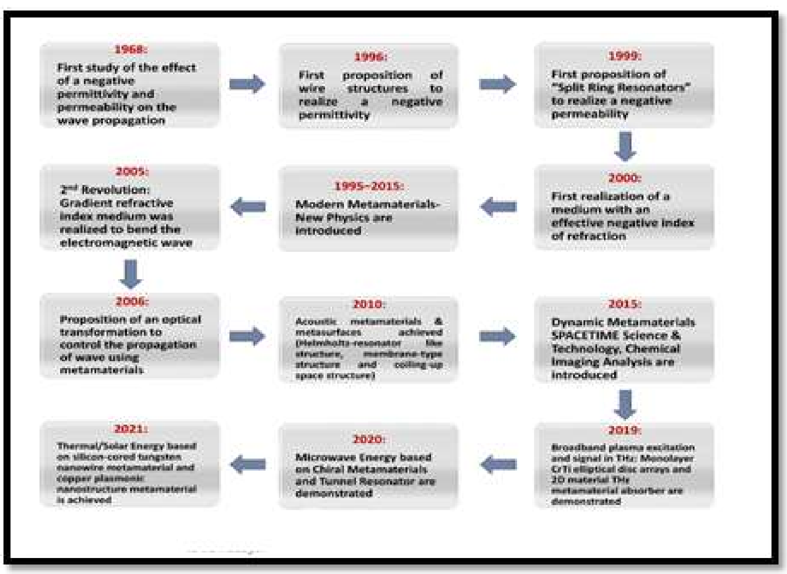

Fig. 2.1 Schematic depicting the evolution of metamaterials

KEY HIGHLIGHTS

- Introduction
  - Metamaterial
  - Neural Network
- Previously Reported Work
  - Brief Review on Negative Materials
  - Comparison between FSS and metamaterial
  - Applications of Metamaterials
  - Applications of FSS
  - Synthesis of FSS Using Generic Algorithm by Equivalent circuit Method

Neural Network

The term "**Artificial Neural Network**" is derived from Biological neural networks that develop the structure of a human brain. Similar to the human brain that has neurons interconnected to one another, artificial neural networks also have neurons that are interconnected to one another in various layers of the networks. These neurons are known as nodes.

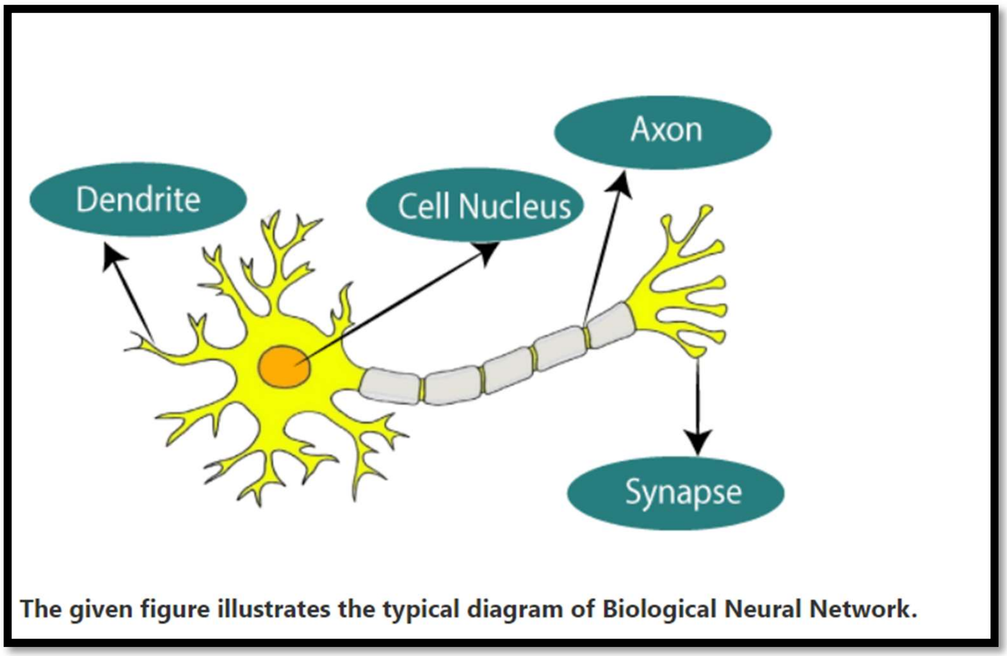

Fig. 2.2 Biological Neural Network

Previously Reported Work

Brief Review on Negative Materials

The dielectric constant ε and the magnetic permeability μ are the fundamental characteristic quantities which determine the propagation of electromagnetic waves in matter. This is due to the fact that they are the only parameters of the substance that appear in the dispersion equation

$$\left|\frac{\omega^2}{c^2}\epsilon_{il}\mu_{lj} - k^2\delta_{ij} + k_i k_j\right| = 0 \quad (1)$$

Which gives the connection between the frequency ω of a monochromatic wave and its wave vector k.

In the case of an isotropic substance ,Eq(1) takes a simpler form:

$$k^2 = \frac{\omega^2}{C^2}n^2 \quad (2)$$

Here n^2 is the square of the index of refraction of the substance , and is given by

$$n^2 = \epsilon\mu \quad (3)$$

If we do not take losses into account and regard n, ϵ and μ as real numbers,it can be seen from (2) and (3) that a simultaneous change of the signs of ϵ and μ has no effect on these relations.

This situation can be interpreted in various ways:

1) We may admit that the properties of a substance are actually not affected by a simultaneous change of the signs of ϵ and μ.
2) It might be that for ϵ and μ to be simultaneously negative contradicts some fundamental laws of nature, and therefore no substance with $\epsilon<0$ and $\mu<0$ can exist.

Finally , it could be admitted that substances with negative ϵ and μ have some properties different from those of substances with positive ϵ and μ.

As we shall see in what follows, the final case is the one that is realized.

Comparison Between FSS and Metamaterial

FSS and metamaterials show properties which can be used to manipulate the wave fronts. Usually structures are designed using metamaterials and FSS to work in electromagnetic spectrum. Amplitude, frequency and phase of the electromagnetic waves can be manipulated by metamaterials. Metamaterials show properties that are not usually found in nature. FSS is an assembly of identical planar structures which behave as an EM filter. FSS are frequency selective in nature. Different design and orientation of both FSS and metamaterials gives different properties and phenomena’s. The main difference between FSS and metamaterials arise from the structure of FSS and elements of metamaterials. The selection of FSS and metamaterials depends upon the type of applications such as reflection or transmission in a particular frequency range or absorption in a particular frequency range.

Frequency selective surfaces or FSS are planar periodic structures that repeats either in one dimension or in two dimensions. It consists of elements which are called unit cells that repeats in a uniform manner. The size, shape and the spacing between the elements determine the resonance of FSS structures. They can reflect transmit or absorb the electromagnetic radiations that are incident on them. The resonance also depends on the angle of incidence and polarization. The dielectric which is used to support the FSS structures also affect the resonance. There are mainly two types of FSS which are the slot type and patch type FSS.

Properties which are not seen naturally can be obtained by using metamaterials. Metamaterials enables people to construct devices that can manipulate wave fronts. Thus, desired properties can be obtained. Properties like negative refraction (negative permeability and permittivity) can be obtained. Perfect lens and invisibility cloaking are the major advantages of metamaterials. Metamaterials are three dimensional materials that have negligible layer thickness.

FSS are two dimensional structures. The slot type and patch type FSS shows different resonance characteristics. The slot type FSS shows the opposite resonance of its complementary patch type FSS. the patch type FSS act as a low pass filter while its complementary slot type act as a high pass filter. when both effects are combined it gives a flat response. FSS act as a band pass or band stop filter depending on the shape of elements. Different shapes of element give different resonance. The figure below represents the **Patch and Slot type FSS** respectively.

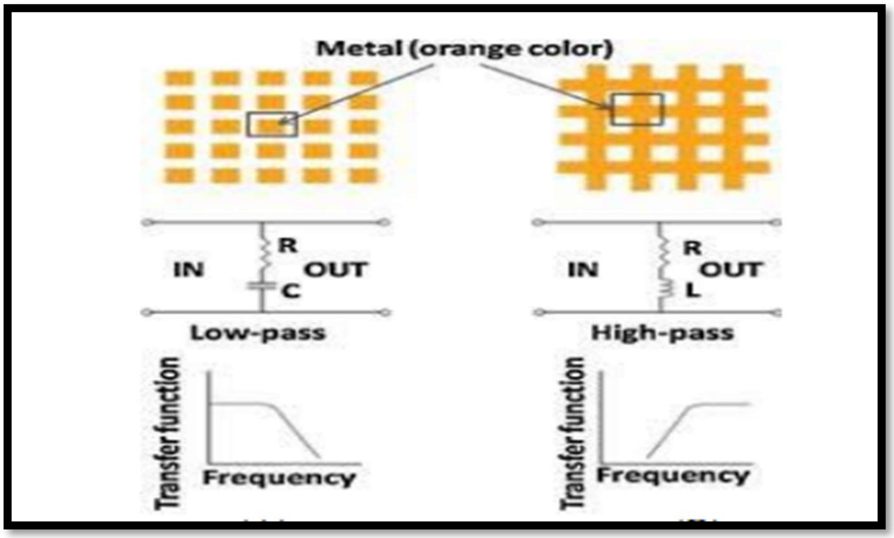

Fig. 2.3 Patch and slot type FSS

Metamaterials are three dimensional periodic structures composed of structures called unit cell. Unit cell is combination of split ring resonators (SRR) and wire structure. An array of unit cell is used to create a metasurface. The figure represents the combination of thin wires and SRR. SRR has two concentric metallic rings, with gap in each ring. Gap between inner and outer ring acts as capacitor. The rings act as inductor. This results in LC resonant circuit.

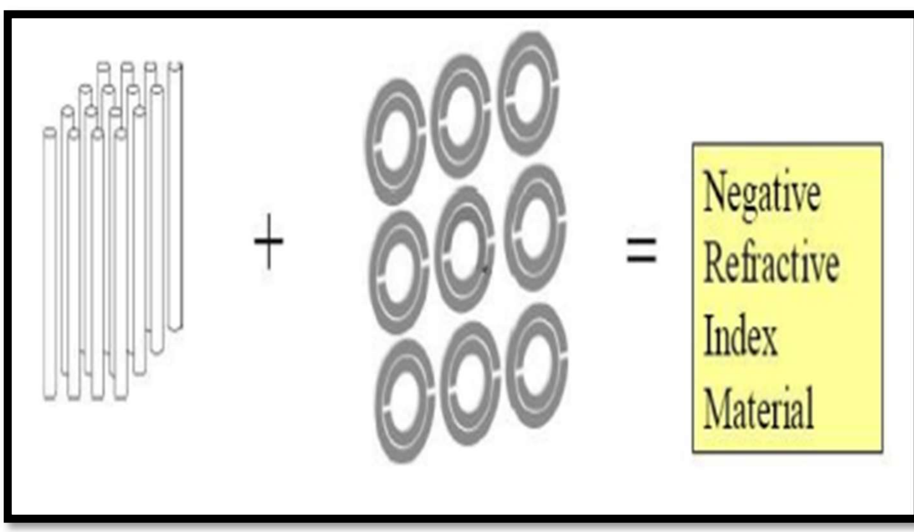

Fig. 2.3 Combination of thin wires and SRR

A new technique using neural networks to efficiently design microstrip circuits has been studied. A full-wave analysis is employed to rigorously characterize a microstrip circuit, which results in a finite set of pairs of input and output parameter vectors. The neurons, arranged **as** a three-layer network, are used to learn the mappings from input to output and then give accurate approximations for the output vectors at any arbitrary input. It is emphasized that a three-layer neural network is capable of performing any mapping if the right connections among the neurons can be made.[6]

Neural networks have recently been introduced to the microwave area as a fast and flexible vehicle to microwave modeling, simulation and optimization. A novel neural network structure, is knowledge-based neural network (KBNN), where microwave empirical or semi analytical information is incorporated into the internal structure of neural networks. The microwave knowledge complements the capability of learning and generalization of neural networks by providing additional information which may not be adequately represented in a limited set of training data. Such knowledge becomes even more valuable when the neural model is used to extrapolate beyond training data region. A new training scheme employing gradient based l_2 optimization technique is developed to train the KBNN model. [7]

Full-wave EM analysis is employed to characterize MMIC components. Structures for simulation are chosen using design of experiments (DOE) methodology. EM-ANN models are then trained using physical parameters as inputs and S-parameters as outputs. Once trained, the EM-ANN models are inserted into a commercial microwave circuit simulator where they provide results approaching the accuracy of the EM simulation tool used for characterization of the MMIC components without increasing the analysis time significantly. The proposed technique is capable of providing simulation models for MMIC components where models do not exist or are not accurate over the desired region of operation.[8]

Another approach to microwave circuit analysis and Optimization featuring neural network models at either device or circuit levels. At the device level, the neural network represents a physics oriented FET model yet without the need to solve device physics equations repeatedly during optimization. At the circuit level, the neural network speeds up optimization by replacing repeated circuit simulations. Compared to existing polynomial or table look up models used in analysis and optimization, the approach has the potential to handle high-dimensional and highly nonlinear problems.[9]

The trend of using accurate models such as physics based FET models, coupled with the demand for yield optimization results in a computationally challenging task. At the device level, the neural network represents a physics-oriented FET model yet without the need to solve device physics equations repeatedly during optimization. At the circuit level, the neural network speeds up optimization by replacing repeated circuit simulations. This method is faster than direct optimization of original device and circuit models.

Applications of Metamaterials

The main applications of metamaterials include invisibility cloaking, phase compensation, negative refraction. Cloaking is achieved by guiding the electromagnetic waves around an object thus making the object inside invisible. Figure 4 shows the invisibility cloaking. Phase compensation is achieved by passing wave through double positive surface (DSP) and then through double negative surface (DNG).DSP has positive phase shift while DNG has negative phase shift. This gives zero phase difference. Metamaterial are also used for manufacturing antennas with enhanced power reduced size and high directivity. They are also used in absorber, sound filters and sensors for variety of applications. The figure illustrates Cloaking.

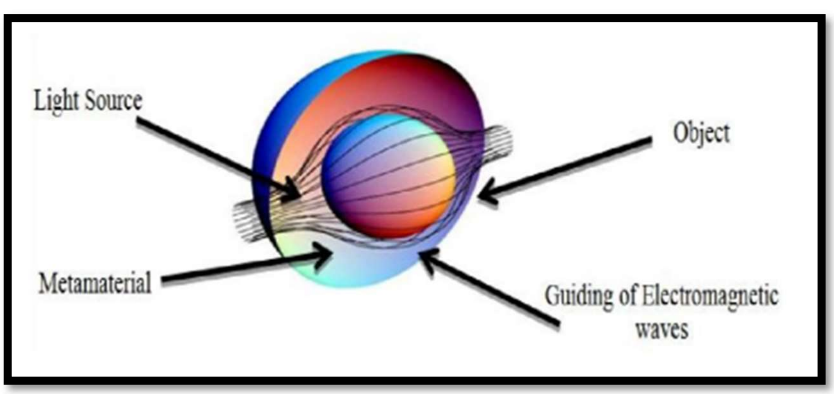

Fig. 2.4 Illustration of cloaking

Applications of FSS

There are different fields of FSS application. Mainly its application comes in design of antenna. FSS helps in operating antenna's in their desired frequency range by selectively trans mitting or reflecting the electromagnetic waves by using the frequency selectivity property of FSS. FSS are used in radomes, which are structures used to protect satellites or stations. The FSS structures on radomes reflect all the undesired frequencies and only pass the desired frequency. Another major application is in stealth technology which is used to make aircrafts or warships less visible to the radar signal by reducing the radar cross sectional area of the aircraft. FSS are usually used at the front door of microwave oven for preventing the harmful waves from coming out of the oven but the same time allowing visible light to go into the oven.[3]

Frequency Selective Surfaces has been synthesized using Generic Algorithm by the application of equivalent circuit method. The designed FSS arrays used square loops and quasi-square open loops. This technique quite useful but efficiency gets reduced when a negligible mean square error is required. It is then the utility of Neural Network comes into action where we can modify the number of hidden layers and neurons easily to get the desired mean square error.[5]

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Chapter 3

UTILITY OF METAMATERIALS

KEY HIGHLIGHTS

- As an alternative of Lens.
- Historical Origins

As an alternative of lens

Metamaterials are a new class of artificial compound materials, which exhibit exceptional properties not found in naturally occurring materials. To Understand the motivation behind introducing Metamaterials, we need to focus on the basic working principle of Lens.

When light is incident on the glass, it is bent by the shape of the glass so that on other side ,light converges at a point.

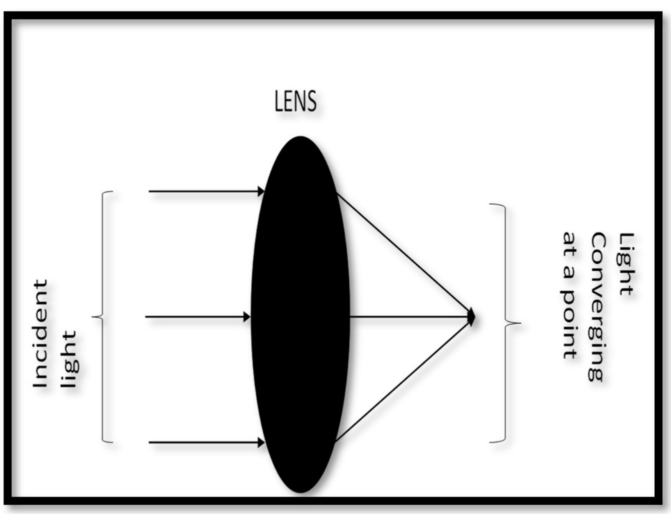


Fig. 3.1 Representation of Lens property (in terms of light)

From the perspective of how wave travels, there is an alternate view of how lenses work.

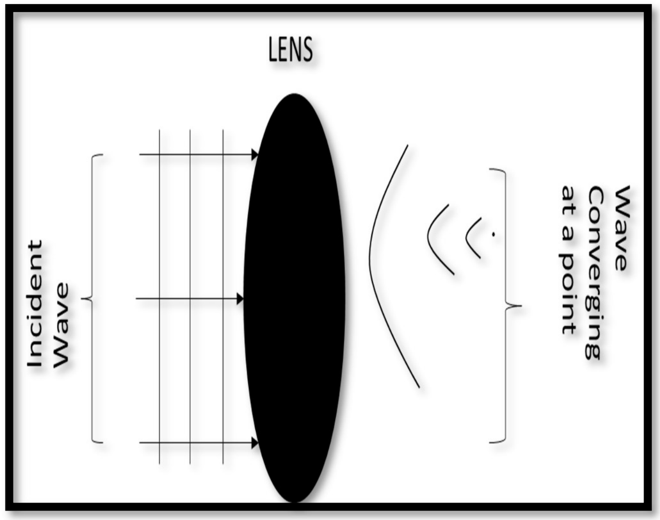


Fig. 3.2 Representation of Lens property (in terms of wave)

The Wavefront of the light wave travelling in this direction hits the lens. In the middle of the lens light slows down since lens is thicker and on the edges of the lens ,where the lens is thinner ,light slows down less. The shape of the wavefront after coming out of the lens becomes curved and creates a converging Wavefront ,also creating a focus at a point.

Conventional Lens works because of their specific shape. The incident light wave slows down at the middle where the material is thickest and slows down the least at the edges where the material is thinnest. This creates a converging wavefront in an image.

Lenses are expensive and complicated because we are stuck with the material properties like glass.

The only way we can create spatially varying light propagation is with the shape of the lens and the shape of the lens has to be controlled very precisely in optical devices.

But what if we are no longer stuck with material properties that are fixed ?

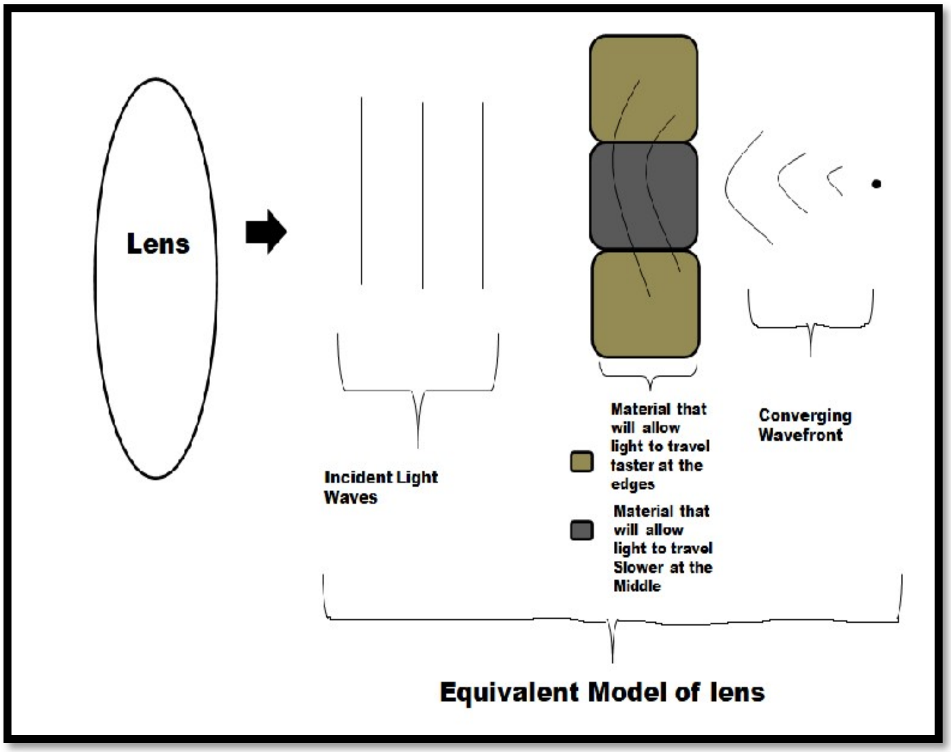


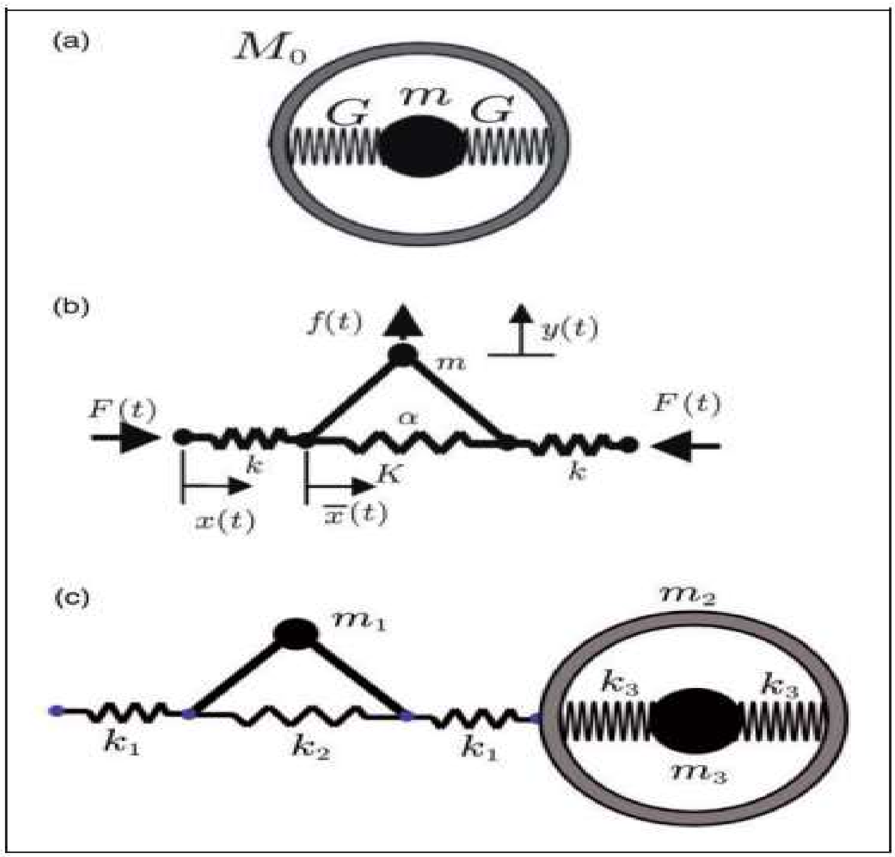
Fig. 3.3 Equivalent model of lens

If we have more flexibility in the material properties then we could imagine creating lens that have much simpler shape .We simply need material properties in the middle of the lens in order to slow down the light waves and allow the light waves to travel faster at the edges.

If we have the ability to do that we could create a lens which does exactly the same thing i.e creating a converging wavefront ,with much simpler shape which will be easier to fabricate.

This is the basic idea of controlling light waves with Metamaterials. [2]

The metamaterials have spatial alternation in boundary conditions or phases of the constituent components or geometry. The usual arrangement of these materials is based on components that are periodically and regularly embedded in the base environment. AMs can have a negative modulus of elasticity, negative density, or anisotropic mass. These capabilities caused metamaterials to be in high demand and provided an unprecedented way to manipulate wave propagation and vibration. In AMs, the embedded components are generally called resonators. Transitional and rotational resonators are two common types of resonators found in metamaterials, which can effectively change density and elasticity. Unlike conventional materials, the resultant properties are a function of frequency, mass, and elastic components, which leads to achieving negative properties at a specific frequency range. There are double-negative metamaterial systems, which exhibit negative refractive index and are created by combining two resonators. That essentially stems from having group and phase velocities with opposite signs. The double-negative metamaterial is usually referred to as the left-handed AMs or the negative indicator material. Here is an overview of the materials with effective negative mass, negative elasticity, and double-negative material.



Effective negative mass, negative modulus, and doubly negative material.

Fig. 3.4 Overview of materials with different property

Historical Origins

The first work on a periodic one-dimensional (1D) lattice is the result of Newton's attempt to derive the formula for the velocity of sound in air. One can speculate that because of lack of knowledge of differential calculus, a natural approach would have consisted in discretizing the continuous media supporting the propagation of sound into a series of lumped masses connected by a lumped spring. This process, which is illustrated in Fig. 3.5, leads to a periodic system, which is known to have a more complex wave behavior than the original continuous system.

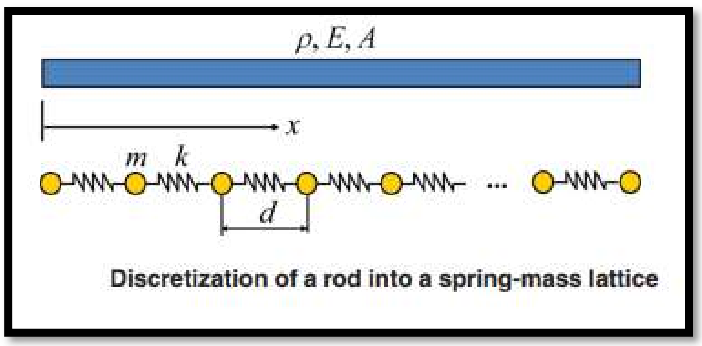


Fig. 3.5 Process of discretization of a rod into a spring-mass lattice

The same system was later investigated by John Bernoulli and his son Daniel, who, in a series of studies starting in 1727, demonstrated that a system of N masses is characterized by N modes of vibration and associated frequencies, and essentially formulated the principle of superposition. Subsequent studies included the estimation of the velocity of wave propagation along one axis of a cubic lattice structure as a function of wavelength. These efforts have led to the first instance of observation of wave dispersion from the estimation of the phase velocity's dependency on frequency.

The realization of phononic crystals in different forms, e.g., bulk, semi-infinite surfaces, plates, beams, has opened up a range of opportunities for realistic applications in engineering and applied physics. The concept of a bandgap naturally lends itself to applications involving vibration and acoustic filtering and control. For example, vibration isolation [5,6] or minimization [7,8], as well as noise isolation and control , may be realized with profound effectiveness. Similarly, nondestructive testing of materials for defects may be conducted by utilizing phononic crystal phase-surface characteristics for the emission of probing “wave beams” .

Utilization as sensors for the determination of liquid properties has been yet another application for phononic crystals . The underlying concept is based on introducing a line defect that acts as a slit cavity, which in itself is also part of the fluidic system. The cavity mode causes a distinct transmission peak within the bandgap of the phononic crystal where the frequency of maximum transmission depends on the speed of sound of the confined liquid. In other work involving microfluidics, Cooper et al. have demonstrated a simple interface between a piezoelectric surface acoustic wave device and a disposable microfluidic chip, patterned with a phononic crystal structure. They have illustrated that microfluidic manipulation, such as centrifugation of blood, may be performed on a disposable phononic chip. Employment of phononic crystals for mass sensing has also been demonstrated, e.g., Nardi et al. used a hypersonic surface phononic crystal to realize ultrahigh sensitivity mass sensing at operational acoustic frequencies that exceed 100 GHz .e causes a distinct transmission peak.

Another active line of applied research is concerned with wave collimation and refraction. The interest here has been primarily in acoustics, although the ideas are also applicable to elastic waves. The function of sound collimation has been studied by Chen et al. , Espinosa et al. , Christensen et al. , and Shi et al. . Refraction and focusing of sound waves have been a major topic due to the potential significant impact on the fields of subsurface imaging and NDE. Phononic crystals can be used to induce two types of refractions: positive and negative. Positive refraction is carried out by shaping the phononic crystal boundaries in order to refract an incoming wave . The realization of negative refraction on the other hand is more subtle as it is based on tuning the phononic crystal to exhibit opposite phase and group velocity signs at the frequency of interest . Use of phononic crystals for focusing has also been realized using nonlinear solitary waves generated in an array of precompressed metallic beads .

Another intriguing application of phononic crystals is wave rectification, whereby a device is designed to allow acoustic or elastic waves to travel along one direction but not in the opposite direction. This principle promises to be of great benefit for vibration mitigation but also could be used as a building block in acoustic/ elastic logic gates in analogy to electronics. While not yet perfectly implemented, some promising approaches have been proposed. For example, Liang and coworkers utilized 1D layered phononic crystals composed of two segments, a linear segment to filter an incoming wave and a nonlinear segment to enable energy to transfer to a different mode at a slightly different frequency . Nonlinearity was used once again, now in the context of bifurcation phenomenon within a linear chain of precompressed beads, to generate a rectification effect . Two-dimensional linear phononic crystals were employed as well to realize an acoustic diode, but with a mechanism based on diffraction and modal conversion at bandgap edges . A major challenge that is yet to be tackled is to achieve rectification in a perfectly asymmetric fashion, without alteration of frequencies and along a straight line and a broad frequency band.[9]

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Chapter 4

Analysis of wave propagation in an anisotropic medium

KEY HIGHLIGHTS

- Dispersion equation
- Significance of the relation between frequency and wave vector
- What is a Tensor?
- Analysis of Wave Propagation
- Significance of Left handed and right handed substances

Dispersion equation

The dielectric constant ε and the magnetic permeability μ are the fundamental characteristic quantities which determine the propagation of electromagnetic waves in matter. This is due to the fact that they are the only parameters of the substance that appear in the **dispersion equation**

$$\left|\frac{\omega^2}{c^2}\epsilon_{il}\mu_{lj} - k^2\delta_{ij} + k_i k_j\right| = 0 \quad \text{.............................(1)}$$

Which gives the connection between the frequency ω of a monochromatic wave and its wave vector k.

Significance of the relation between frequency and wave vector

In the case of an isotropic substance ,Eq(1) takes a simpler form:

$$k^2 = \frac{\omega^2}{c^2}n^2 \quad \text{...(2)}$$

Here n^2 is the square of the index of refraction of the substance , and is given by

$n^2 = \epsilon\mu$ ....(3)

If we do not take losses into account and regard n, ϵ and μ as real numbers,it can be seen from (2) and (3) that a simultaneous change of the signs of ϵ and μ has no effect on these relations.[2]

This situation can be interpreted in various ways:

3) We may admit that the properties of a substance are actually not affected by a simultaneous change of the signs of ϵ and μ.
4) It might be that for ϵ and μ to be simultaneously negative contradicts some fundamental laws of nature, and therefore no substance with ϵ<0 and μ<0 can exist.

Finally , it could be admitted that substances with negative ϵ and μ have some properties different from those of substances with positive ϵ and μ.

As we shall see in what follows, the final case is the one that is realized. [2]

Gauss' law $\vec{\nabla} \cdot \vec{D} = \rho$,in a dielectric (ρ=0) can be written as $i\vec{k} \cdot \vec{D} = o$ implying the propagation direction $\hat{k}$ is orthogonal to the displacement vector $\vec{D}$.

But the Poynting vector $\vec{\boldsymbol{S}} = \vec{\boldsymbol{E}} \times \vec{\boldsymbol{H}}$ which gives the direction of energy flow is orthogonal to the electric field $\vec{E}$, not the displacement vector.

Thus energy does not flow in the direction of the wave's propagation if the polarization of the wave ($\hat{E}$) is not an eigen-vector of the material's dielectric tensor .

Charges in a material are the source of polarization. They are bound to neighboring nuclei like masses on springs. In an anisotropic material the stiffness of the springs is different depending on the orientation. The wells of the electrostatic potential that the charges sit in are not symmetric and therefore the material response (material polarization) is not necessarily in the direction of the driving field.

What is a Tensor?

A **tensor** is an algebraic object that describes a multilinear relationship between sets of algebraic objects related to a vector space.

The permittivity tensor relates the electric flux density to the electric field

$$D_{i=} \in ijE_j$$

Or in matrix form,

$$\begin{pmatrix} D_x \\ D_y \\ D_z \end{pmatrix} = \begin{pmatrix} \epsilon_{xx} & \epsilon_{xy} & \epsilon_{xz} \\ \epsilon_{yx} & \epsilon_{yy} & \epsilon_{yz} \\ \epsilon_{zx} & \epsilon_{zy} & \epsilon_{zz} \end{pmatrix} \begin{pmatrix} E_x \\ E_y \\ E_z \end{pmatrix}$$

When we consider 2-D(surface) version of metamaterial i.e metasurface, the tensor becomes **Dyadic ,** in matrix form ,

$$\begin{pmatrix} D_x \\ D_y \\ D_z \end{pmatrix} = \frac{1}{\epsilon_0} \begin{pmatrix} \epsilon_x & 0 & 0 \\ 0 & \epsilon_y & 0 \\ 0 & 0 & \epsilon_z \end{pmatrix} \begin{pmatrix} E_x \\ E_y \\ E_z \end{pmatrix}$$

$$\begin{pmatrix} D_x \\ D_y \\ D_z \end{pmatrix} = \begin{pmatrix} k_x & 0 & 0 \\ 0 & k_y & 0 \\ 0 & 0 & k_z \end{pmatrix} \begin{pmatrix} E_x \\ E_y \\ E_z \end{pmatrix}$$ where $\frac{\epsilon_x}{\epsilon_0} = k_x$ (Dielectric Constant)

Analysis of Wave Propagation

Fields of Plane Wave is expressed as: $\overrightarrow{\boldsymbol{E}} = \overrightarrow{\boldsymbol{E_0}} \boldsymbol{e}^{i(\omega t - \vec{k} \cdot \vec{r})}$ $\overrightarrow{\boldsymbol{H}} = \overrightarrow{\boldsymbol{H_0}} \boldsymbol{e}^{i(\omega t - \vec{k} \cdot \vec{r})}$

By Maxwell’s equations we know,

$$\vec{\nabla} x \vec{E} = -\frac{\partial \vec{B}}{\partial t}$$

$$\frac{\partial E_z}{\partial y} = -ik_y E z_0 e^{-i(k_x x + k_y y + k_z z - wt)} = -ik_y Ez$$

Consider the x-component of $\vec{\nabla}x\vec{E} = \frac{\partial E_z}{\partial y} - \frac{\partial Ey}{\partial y} = -(\ ik_y Ez - ik_z Ey) =-\ i(\ \vec{k}x\vec{E})_x$

Taking all 3 components we get,

$$\boldsymbol{\vec{\nabla}x\vec{E} = -\ i(\ \vec{k}x\vec{E})}$$

$$\frac{\partial \vec{\mathrm{B}}}{\partial \mathrm{t}} = \frac{\partial}{\partial \mathrm{t}}\left(\hat{\mathrm{i}}\mathrm{B_x} + \hat{\mathrm{j}}\mathrm{B_y} + \hat{\mathrm{k}}\mathrm{B_z}\right)$$

$$\frac{\partial \vec{B}_x}{\partial t} = i\omega B_{x_0} e^{i\left(\omega t - \left(k_x x + k_y y + k_z z\right)\right)}$$

$$= i\omega B_x$$

Therefore ,this term

$$\boldsymbol{\frac{\partial \vec{B}}{\partial t} = i\omega \vec{B}}$$

Then by,

$$\vec{\nabla}x\vec{E} = -\frac{\partial \vec{B}}{\partial t}$$

$$\vec{k} \times \vec{E} = \omega \vec{B}$$

$$\vec{k} \times \vec{E} = \ \omega \mu_0 \vec{H}$$

$$\vec{H} = \frac{\vec{k} \times \vec{E}}{\omega \mu_0} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (a)$$

Another Maxwell equation states,

$$\vec{\nabla}x\vec{H} = \frac{\partial \vec{D}}{\partial t}$$

$$\vec{\nabla}x\vec{H} = \mathrm{i}(\ \vec{k}x\vec{H})$$

$$\frac{\partial \vec{\mathrm{D}}}{\partial \mathrm{t}} = -\mathrm{i}\omega\vec{\mathrm{D}}$$

$$\vec{k} \times \vec{H} = -\omega \vec{D}$$

$$\vec{D} = -\frac{\vec{k} \times \vec{H}}{\omega} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(b)$$

Combining (a) and (b) we can write,

$$\vec{D} = -\frac{1}{\omega}\vec{k} \times \left(\frac{1}{\omega\mu_0}\vec{k} \times \vec{E}\right) = -\frac{1}{\omega^2\mu_0}\,\vec{k} \times \vec{k} \times \vec{E}$$

$$\vec{k} \times \vec{k} \times \vec{E} = -\omega^2\mu_0\vec{D}$$

Therefore Generalized Wave Equation for $\vec{E}$ and $\vec{H}$ fields are:

$\underline{\boldsymbol{\vec{k} \times \vec{k} \times \vec{E} = -\omega^2 \mu \in \vec{E}}}$……………………………….(c)

$\underline{\boldsymbol{\vec{k} \times \vec{k} \times \vec{E} = -\omega^2 \mu \in \vec{H}}}$………………………………….(d)

Using (c) and applying vector properties we can write

$(\vec{k} \cdot \vec{E})\vec{k}$ - $(\vec{k} \cdot \vec{k})\vec{\mathrm{E}} = -\omega^2\mu \in \vec{\mathrm{E}}$

$k^2(\hat{k} \cdot \vec{E})\hat{k} - k^2\vec{E} = -\omega^2\mu \in \vec{\mathrm{E}}$

$k^2(\hat{k} \cdot \vec{E})\hat{k} - k^2\vec{E} = -\omega^2\mu_0\epsilon_0\bar{\bar{\epsilon}}_r\,\vec{\mathrm{E}}$ For Anisotropic medium, $\mu = \mu_0$, $\in = \epsilon_0\bar{\bar{\epsilon}}$

$= -\frac{\omega^2}{c^2}\bar{\bar{\epsilon}}_r\vec{\mathrm{E}}$ Since $\frac{1}{c^2} = \mu_0\epsilon_0$,

$\vec{k} = \frac{\omega}{c}\eta_\omega\,\hat{k}$

$= -\frac{k^2}{\eta_\omega^2}\bar{\bar{\epsilon}}_r\vec{\mathrm{E}}$

Finally the expression becomes,

$(\hat{k} \cdot \vec{E})\hat{k} - \vec{E} = -\frac{1}{\eta_\omega^2}\bar{\bar{\epsilon}}_r\vec{\mathrm{E}}$

Consider x-component writing $\bar{\bar{\epsilon}}_r = k_x$

$(k_x x + k_y y + k_z z)\, k_x$ - E_x = - $\frac{1}{\eta_\omega^2} k_x\, E_x$

$(\frac{1}{\eta_\omega^2} k_x + \ k_x^2 - 1)\ E_x + \ k_y k_x E_y + k_z k_x E_z$ =0

For y and z components, considering normalization: $k_x^2 + \ k_y^2 + \ k_z^2 = 1$

$k_y k_x E_x + (\frac{1}{\eta_\omega^2} k_y - \ k_x^2 - k_z^2)\ E_y + k_z k_y E_z$ =0

$k_z k_x E_x + \ k_z k_y E_y + (\frac{1}{\eta_\omega^2} k_z - \ k_x^2 - k_y^2)\ E_z$ =0

Set of 3 simultaneous equations then forms the matrix equation :

$$\begin{pmatrix} \frac{1}{\eta_\omega^2} k_x - \ k_y^2 - k_z^2 & k_y k_x & k_z k_x \\ k_y k_x & \frac{1}{\eta_\omega^2} k_y - \ k_x^2 - k_z^2 & k_y k_z \\ k_z k_x & k_y k_x & \frac{1}{\eta_\omega^2} k_z - \ k_x^2 - k_y^2 \end{pmatrix} \begin{pmatrix} E_x \\ E_y \\ E_z \end{pmatrix} = 0$$

For a given propagation direction i.e for a given $k_y, k_x\ k_z$:

- The determinant yields the possible values of η_ω as the eigen values.
- Each eigen value constitutes respective eigen vector namely E_x , E_y, E_z.

Eigen Value Equation

- The determinant equation leads to a cubic equation in η_ω^2 .
- The coefficient of η_ω^6 term vanishes.
- Thus yields a quadratic equation in η_ω^2.

The quadratic equation in η_ω^2:

- 2 roots : $\eta_{\omega 1}$ and $\eta_{\omega 2}$
- Two refractive indices seen by the waves in two polarization directions

Significance of Left handed and right handed substances

To ascertain the electromagnetic laws essentially connected with the sign of ∈ and μ , we must turn to those relations in which ∈ and μ appear separately, and not in the form of their product.

These relations are primarily the Maxwell Equations and the constitutive relations:

$\vec{\nabla} x \vec{E} = -\frac{\partial \vec{B}}{\partial t}$ ……………………………………………………(1)

$\vec{\nabla} x \vec{H} = \frac{\partial \vec{D}}{\partial t}$ …………………………………………………………(2)

$\vec{B} = \mu \vec{H}$ ………………………………………………………..(3)

$\vec{D} = \epsilon \vec{E}$ ………………………..……………………………………(4)

For a plane monochromatic wave ,in which all quantities are proportional to $e^{i(kz-\omega t)}$ the expressions (1)…(4) reduce to

$\vec{k} \times \vec{E} = \frac{\omega}{c} \mu \vec{H}$ ……………………………………………………(5)

$\vec{k} \times \vec{H} = -\frac{\omega}{c} \epsilon \vec{E}$ …………………..………………………..……(6)

<u>**It can be seen at once from these equations that if ∈ >0 and μ > 0 then E,H and k form a right-handed triplet of vectors , and if ∈ <0 and μ < 0 they are a left-handed set.**</u>

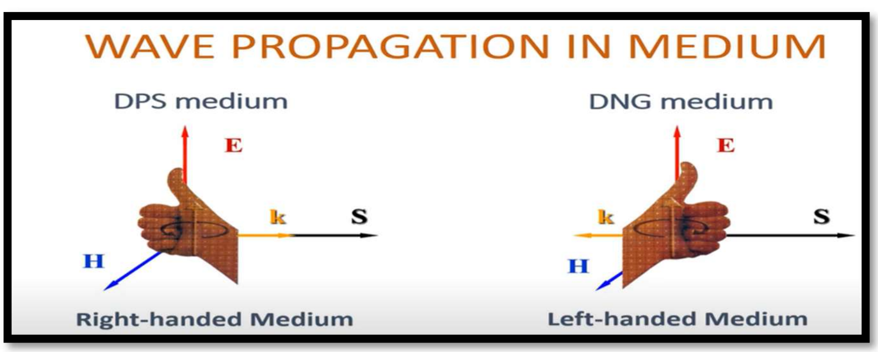

Fig. 4.1 Wave propagation in medium

If we introduce direction cosines for the vectors E, H and k and denote them by $\alpha_i, \beta_i, \gamma_i$ respectively, then a wave propagated in a given medium will be characterized by the matrix

$$G = \begin{pmatrix} \alpha_1 & \alpha_2 & \alpha_3 \\ \beta_1 & \beta_2 & \beta_3 \\ \gamma_1 & \gamma_2 & \gamma_3 \end{pmatrix} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(7)$$

The determinant of this matrix is equal to +1 if the vectors E ,H , and k are a right- handed set, and -1 if this set is left-handed. Denoting this determinant by P, we can say that P characterizes the "right-ness" of the given medium.

The medium is "right-handed" if P = +1 and "left-handed" if P = -1. The elements of the matrix (7) satisfy the relation $G_{ik} = P\, A_{ik}$

Here A_{ik} is the algebraic complement of the element G_{ik} . Furthermore the elements of G are ortho-normal.

The energy flux carried by the wave is determined by the Poynting vector S, which is given by

$$\vec{S} = \frac{c}{4\pi}\, \vec{E} \times \vec{H} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(8)$$

According to (8) the vector S always form a right-handed set with the vectors E and H.

<u>Accordingly , for right-handed substances S and k are in the same direction , and for left-handed substances they are in opposite direction.</u>

<u>Since the vector k is in the direction of the phase velocity, it is clear that left-handed substances are substances with a so-called negative group velocity ,which occurs in particular in anisotropic substances or when there is spatial dispersion . In what follows we shall for brevity use the term "*left-handed substance*", keeping in mind that this term is equivalent to the term "*Substance with negative group velocity*" .</u>

As a consequence of the fact that in left-handed substances the phase velocity is opposite to the energy flux:

- In left-handed substances there will be a **reversed Doppler effect**.
- The **Vavilov-Cerenkov effect will also be reversed**, just like Doppler effect.

Also ,the refraction of a ray at the boundary between two media with different Rightnesses: [1]

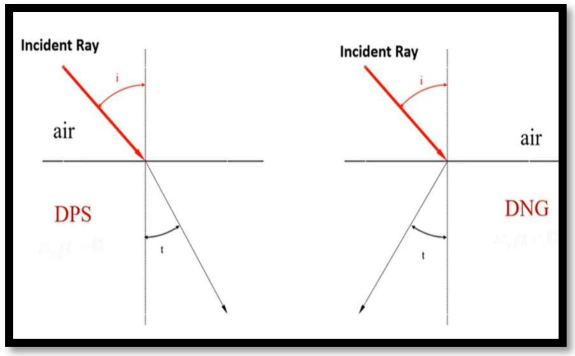

Fig. 4.2 Representation of rays at the boundary in different medium

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Chapter 5

WHY NEURAL NETWORK ?

KEY HIGHLIGHTS

- Utility of Neural Network
- Why DNN?
- Algorithm for neural network selection

Utility of Neural Network

Implementation of neural network to model a frequency selective surface prototype can serve as an excellent alternative for four main situations:

5. When closed-form solutions do not exist ,and trial-and-error methods are the main approaches to tackle the problem at hand;
6. When an application requires real-time performance;
7. When faster convergence rates are required in the optimization of large systems;
8. When enough measured data exist to train an Neural Network for prediction purposes, especially when no analytical tools exist. [1]

Why DNN ?

Artificial neural networks (ANNs) were inspired by information processing and distributed communication nodes in biological systems. ANNs have various differences from biological brains. Specifically, artificial neural networks tend to be static and symbolic, while the biological brain of most living organisms is dynamic (plastic) and analog.

Deep learning is a modern variation that is concerned with an unbounded number of layers of bounded size, which permits practical application and optimized implementation, while retaining theoretical universality under mild conditions. In deep learning the layers are also permitted to be heterogeneous and to deviate widely from biologically informed connectionist models, for the sake of efficiency, trainability and understandability.

Therefore the basic difference between ANN and DNN lies in the fact that ANN consists of one or two hidden layers to process data while DNN mainly contains multiple layers between the input and output layers. [2]

Algorithm for neural network selection

The type of neural network has been chosen by following the steps:

1. The number of neurons in the hidden layer (for ANN(Artificial Neural Network) ,only one hidden layer is used) has been varied to get the minimum square error (1%).
2. After multiple trials , the required result is not obtained. Then the number of hidden layer is varied which is nothing but DNN(Deep Neural Network).
3. Then for accuracy purpose, the number of neurons in each hidden layers among the multiple hidden layers used for computation has been varied to obtain the desired minimum square error.

Flowchart

Reason for selecting Deep Neural Network (DNN) approach to meet our specific criteria has been shown with the help of flowchart:

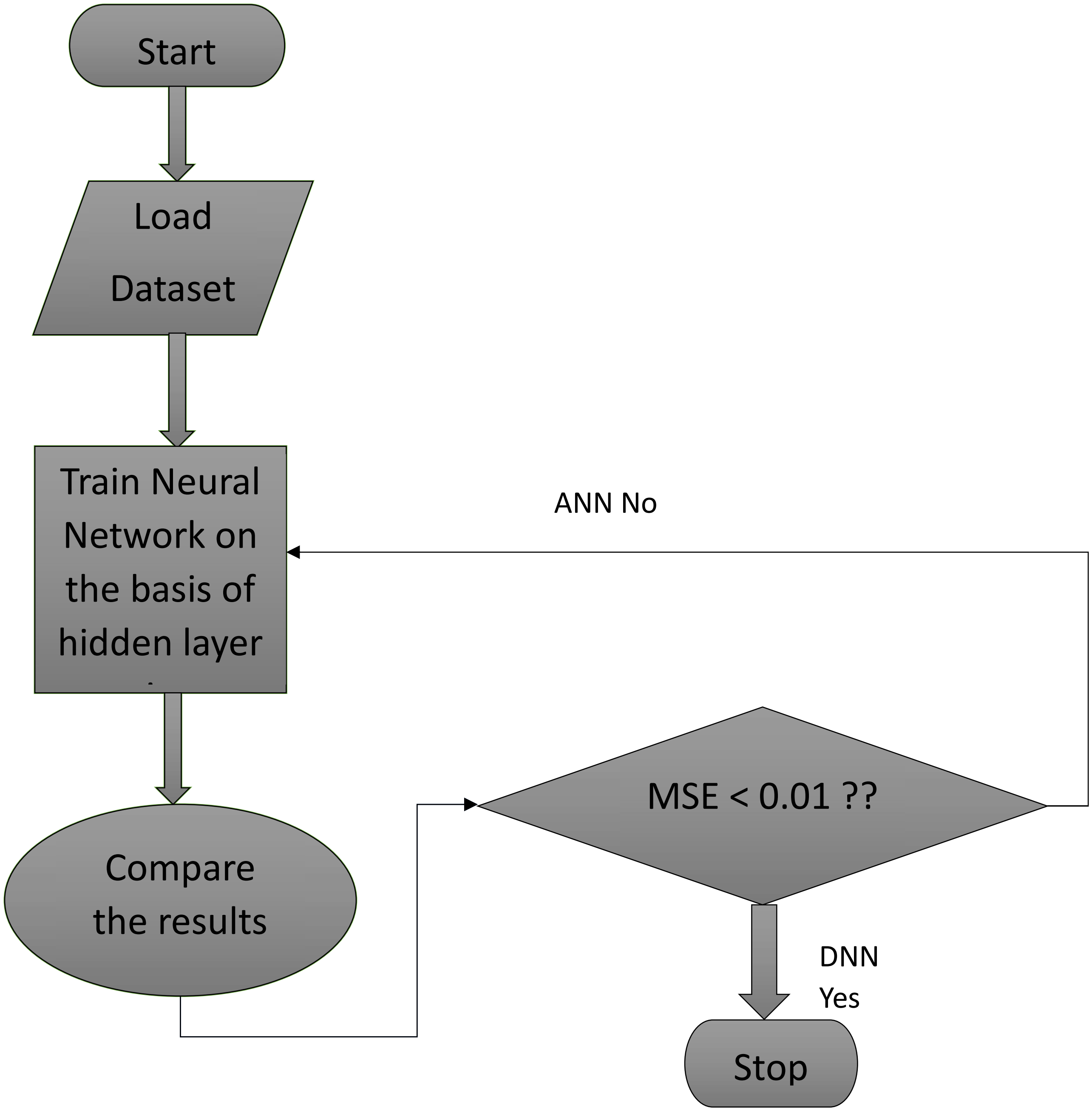

Fig. 5.1 Flowchart

Results

The data obtained after training the DNN has been shown below. Regression value (R) Should be close to unity for best result.

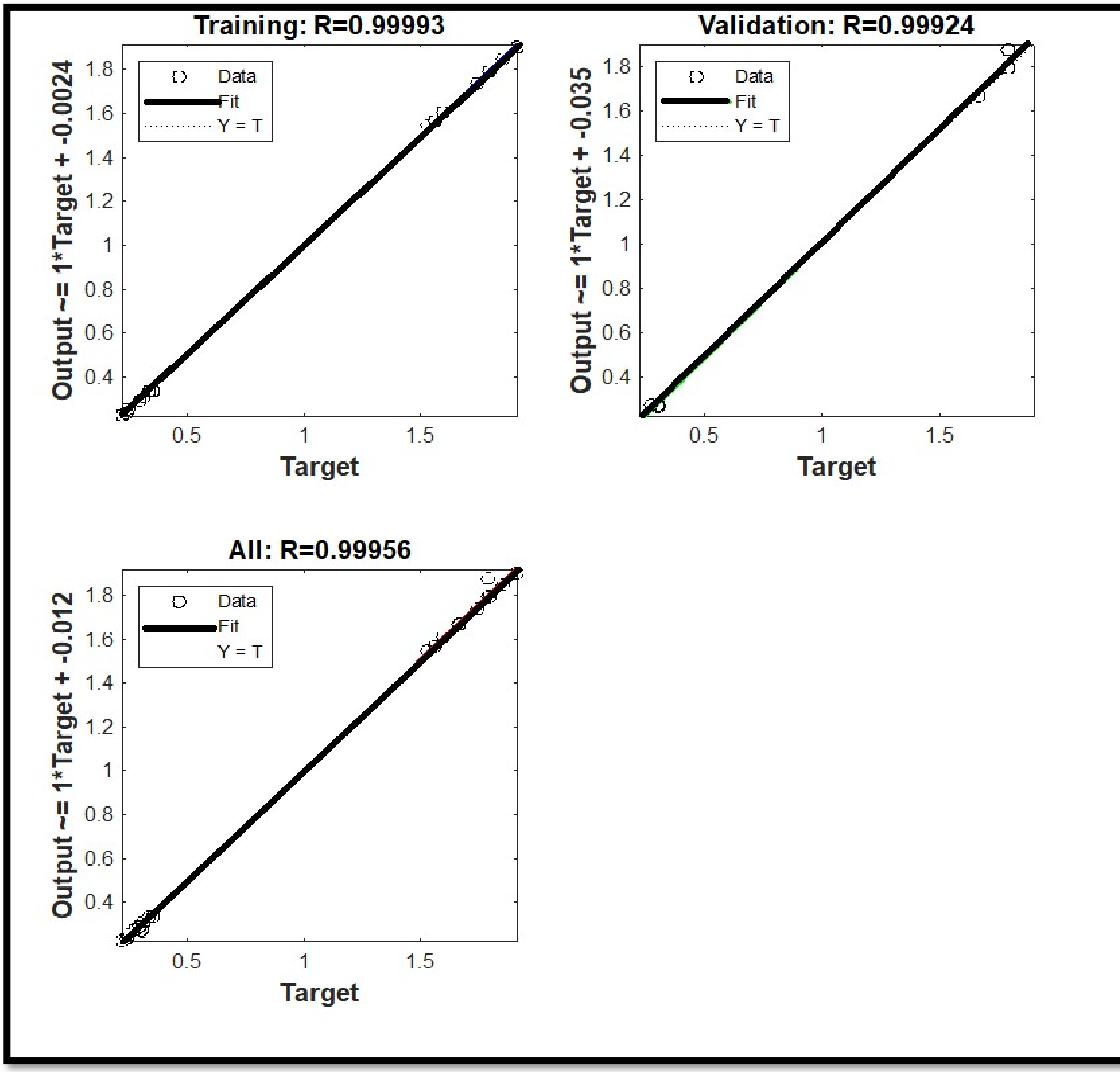

Fig. 5.2 Plots showing regression values

As discussed earlier, the goal is to reduce minimum square error (i.e upto 1%) which is achieved as shown below.

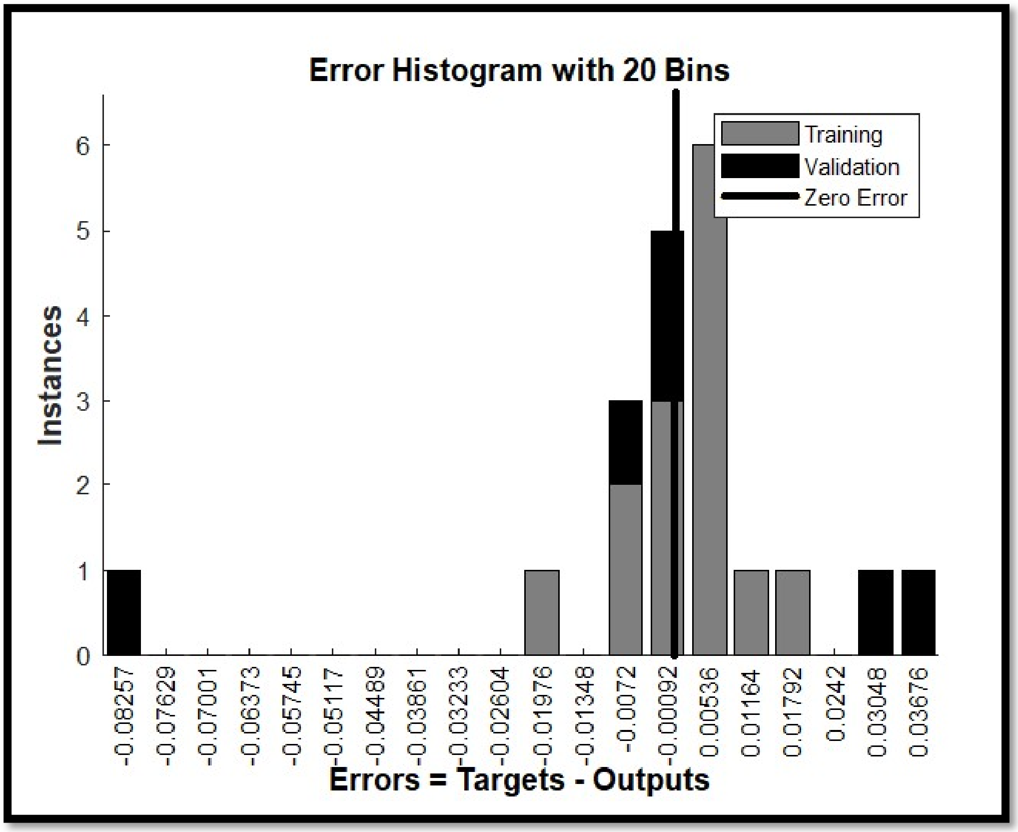

Fig. 5.3 Graph showing the error value

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Chapter 6

Analysis of FSS Prototype through Deep Neural Network approach

KEY HIGHLIGHTS

- Problem Statement
- Proposed Structure
- Neural Model
- Result

Problem Statement

Freestanding FSSs are periodic arrays of metallic patch or aperture elements characterized by the total reflection (patches) or transmission (apertures) in the neighbourhood of the element resonance. In this work, a feed forward ANN is applied to synthesize FSS freestanding structures. The trained ANN is used in the design of FSS at some microwave bands. ANN model implemented exhibits an extrapolation performance in regions where there is little or no knowledge of structure responses.

Proposed Structure

The considered structure is composed of a periodic array of patch elements freestanding. The proposed FSS structure is shown below where ‘P’ represents the length of the patch, ‘L’ represents the length of the substrate and ‘g’ represents the periodicity.

Universal approximation theorem implies that neural networks with appropriate activation functions can approximate any nonlinear function with minimum error. The most common way of setting number of layers to 1 is inspired by the universal approximation theorem. But universal approximation theorem does not assert that a single hidden layer is the optimal solution which is responsible to predict the output accurately in terms of learning time (number of epochs), execution convenience (number of hidden neurons), ability to generalize (performance of the neural network with non-trained data).

Pictorial Representation

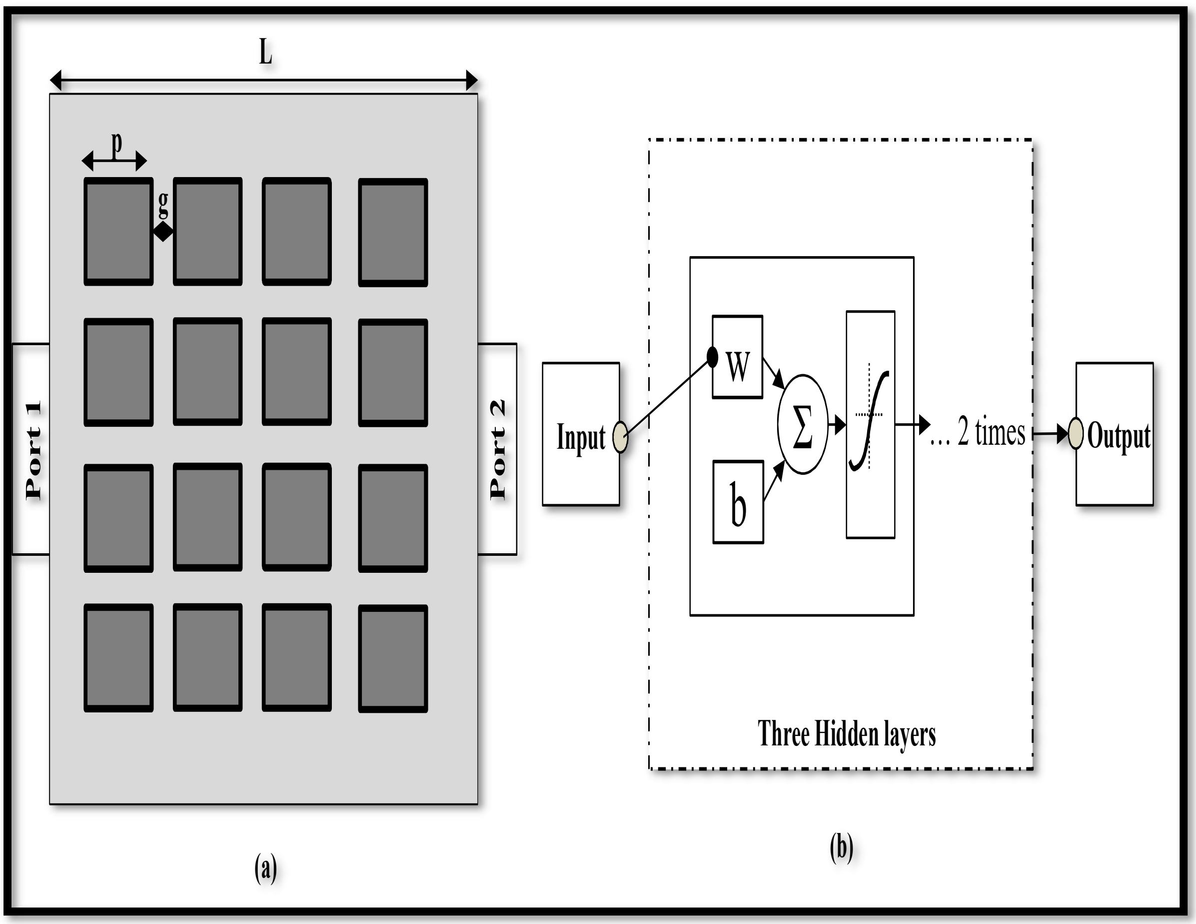
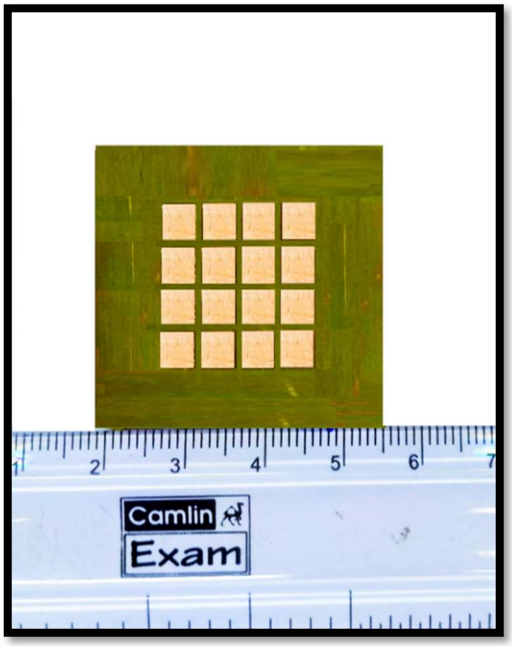


Fig. 6.1 Representation of proposed work

Fabricated Structure along with the designed Network



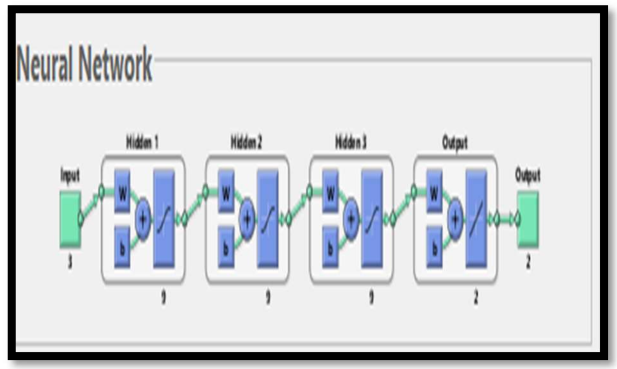


Fig. 6.2 Representation of proposed work done

[Note: The above fabrication has been done two times; one with the figure as shown and another with bigger dimension (almost 200 mm square substrate) for taking the measurements in our lab.]

Neural Model

Significance of neural network in electromagnetics comes into play for variety of situations. One such problem is the requirement of estimating desired frequency response of the corresponding FSS. FSSs are periodic arrays of metallic patches which are used to modify the incidence characteristics of incident wave on it. There are other related problems like the requirement of real-time performance of any system due to certain input parameters. A deep neural network (DNN) can serve the purpose of an excellent tool for microwave modelling and also to predict the output in a negligible computation time.

The basic concepts used in DNNs are:

Synapses: The connecting links between two neurons each of which is characterized by a specific weight .

Adder: The input signals are summed after being weighted by the respective synapses of the neuron.

Type of Activation Function: This is used to introduce non-linearity into the output of a neuron to avoid overloading. A particular activation function is chosen based on the nature of the problem. Different activation function can be chosen at each hidden layer consisting of several neurons or nodes. The choice of "*tanSigmoid*" activation function in the first and second hidden layers provides the optimized result in terms of best modelling accuracy [1].

Backpropagation

The most widely held algorithm for updating Neural Network correcting weights during the training phase is known as backpropagation. Multilayer Perception (MLP) networks were used in ANN algorithm. MLP neural networks are the easiest ANN models, and for that reason most commonly used [1], [2].Further, MLPNNs are trained through the standard back propagation algorithm .Three layer Perceptron has generally three layers, named as, an input layer, a hidden or intermediate layer and an output layer. The neurons of input layer allocate the input values to the hidden layer(s) neurons[3].

Each neuron of hidden layer j adds up its input values x_j after assigning weight to them and thus strengthens the individual connections w_{ji} as of the input layer and calculates its output value y_i as a mathematical function f of the addition:

$y_i = f(\sum w_{ij} x_j)$ ………………..(1)

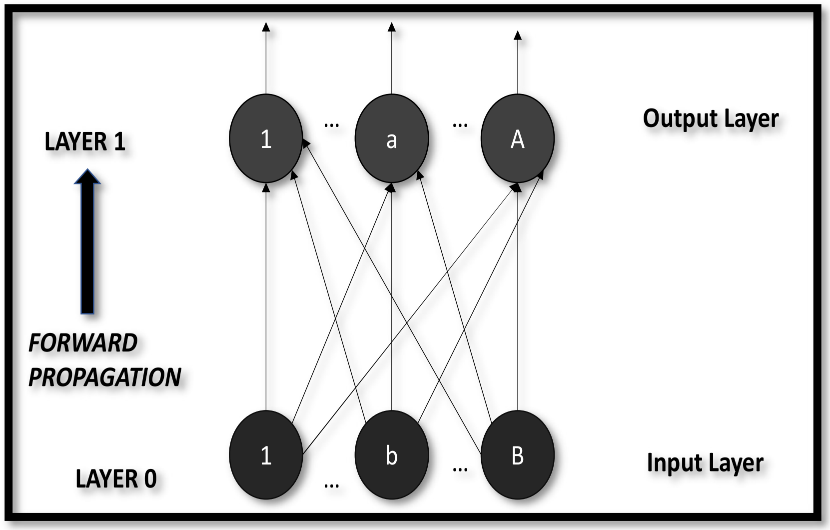


Fig. 6.3 Single layer Feed-Forward Neural Network (Single Layer Perceptron)

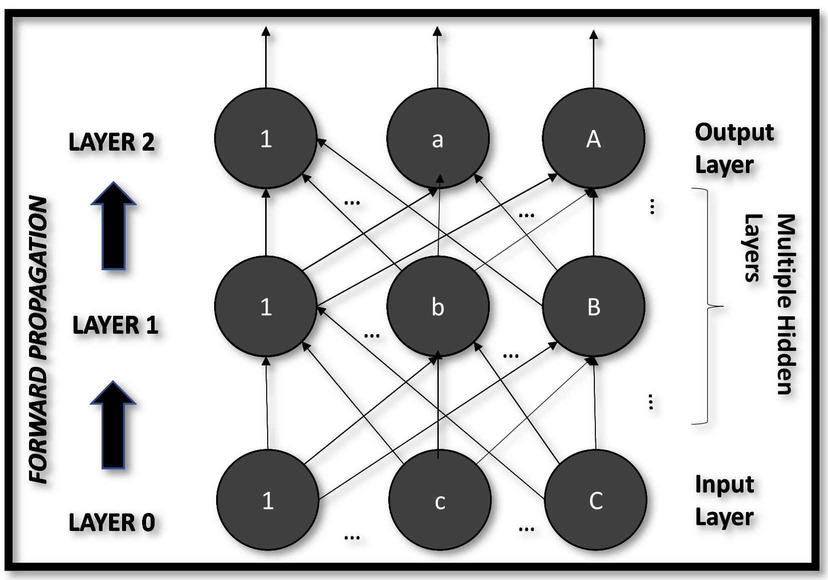


Fig. 6.4 Multilayer Feed-Forward Neural Network (DNN)

where f notation used to represent a hyperbolic or sigmoid tangent function. In the same way neurons of output layer are formed. Training an ANN involves the adjustment of weights of the network by means of a learning algorithm. Here, the back propagation learning algorithm [10] is used which is also called the gradient descent algorithm that provides the modification in $w_{ij(k)}$ in the form of weighted connection among neurons i and j in this way:

$\Delta w_{ij(k)} = \alpha\delta_i x_j + \mu\Delta w_{ij} (k - 1)$…………….(2)

where α denotes the learning coefficient, x_j represent the input value, μ is designated as the momentum coefficient and belongs to a term depending on whether neuron is a hidden neuron or a output neuron [4] [5][6].

Result

In this work, physical attributes of FSS are successfully modeled to predict its output in terms of frequency and bandwidth. The learning parameters are set empirically and the mean square error is found to be ~ 1% as depicted in Table I. This is achieved by varying hidden nodes and also varying the number of neurons in each hidden layer. The necessary computation has been done using *Levenberg - Marquardt training algorithm* . The most essential parameters required for every application based on FSS can be obtained efficiently using this approach.

TABLE I. ANALYSIS OF THE RESULTS .

Normalized Target value		**Normalized Predicted Value**		**Mean Square Error**	
Frequency (GHz)	***Bandwidth (GHz)***	***Frequency (GHz)***	***Bandwidth (GHz)***	***Frequency (GHz)***	***Bandwidth (GHz)***
1.5982	0.2480	1.6102	0.261	0.012	0.013
1.6654	0.2745	1.6774	0.2855	0.012	0.011
1.7433	0.2961	1.7573	0.3081	0.014	0.012
1.7938	0.3131	1.7828	0.3001	0.011	0.013

Table I Table showing the analysis of the results obtained

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Chapter 7

SYNTHESIS OF FREQUENCY SELECTIVE SURFACES USING DIFFERENTIAL EVOLUTION ALGORITHM ALONG WITH NEURAL NETWORK

KEY HIGHLIGHTS

- Introduction
- Problem Statement
- Differential Evolution Strategy
- Flowchart
- Results

Introduction

Differential Evolution (**DE**) is a evolutionary computation method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. Such methods are commonly known as metaheuristics as they make few or no assumptions about the problem being optimized and can search very large spaces of candidate solutions. However, metaheuristics such as DE do not guarantee an optimal solution is ever found.

DE is used for multidimensional real-valued functions but does not use the gradient of the problem being optimized, which means DE does not require the optimization problem to be differentiable, as is required by classic optimization methods such as gradient descent and quasi-newton methods. DE can therefore also be used on optimization problems that are not even continuous, are noisy, change over time, etc.[1]

DE optimizes a problem by maintaining a population of candidate solutions and creating new candidate solutions by combining existing ones according to its simple formulae, and then keeping whichever candidate solution has the best score or fitness on the optimization problem at hand. In this way, the optimization problem is treated as a black box that merely provides a measure of quality given a candidate solution and the gradient is therefore not needed.[2][3]

Problem Statement

The aim is to find a set of parameters that minimizes or maximizes a certain cost function. In this work, the problem is to find a set of physical dimensions for a frequency selective surface (FSS) that force it to have some desired properties. The frequency chosen for-the study is between 1GHz and 20GHz.

Differential Evolution Strategy

Similar to all evolutionary optimization algorithms, DES also operates on a population with N_{pop}, individuals. Each individual of the solution vector is composed of N_{par} optimization parameters. The initial population is created with random values chosen from within the given boundaries:

$$X_{i,j}^{p} = X_j^{min} + R_j \times (X_j^{max} - X_j^{min}),\ j = 1,2,\ldots, N_{par} \qquad (1)$$

where R_j is a random number, uniformly distributed between 0 and 1, and X_j^{min} and X_j^{max} denote the minimum and maximum permissible values of the j^{th} parameter, respectively.

After initialization, the algorithm evolves to the genetic evolution loop by mutation, crossover and selection operator in sequence. Mutation operation is the key procedure in DES. The difference vector is created as:

$$X^{M,i} = X^{n,opt} + P_{mut} (X^{n,p1} - X^{n,p2}), \quad i \neq p1 \text{ and } i \neq p2 \qquad (2)$$

where the superscript M denotes mating pool, $X^{n,opt}$ represent the best individual. $\{X^{n,p1}, X^{n,p2}\}$ are the two randomly chosen individual at generation n. They are different from each other and also different from $X^{n,opt}$, P_{mut} is usually in the range of [0.4,1] that controls mutation operation Crossover is the next operation in which a trial vector $X^{c,i}$ is formed, where

$$(X^{c,i})_j = \begin{cases} \left(X^{M,i}\right)_j, & \gamma \leq P_{cross} \\ \left(X^{n,i}\right)_j, & otherwise \end{cases}$$

where the superscript c denotes children population, γ is a real random number in the range of [0,1] and P_{cross} is the probability of a real-valued crossover factor. Finally, the selection operation is to produce better offspring. Each child competes with its parent, and survives only if its fitness is better. The next round of genetic evolution then begins.

Flowchart

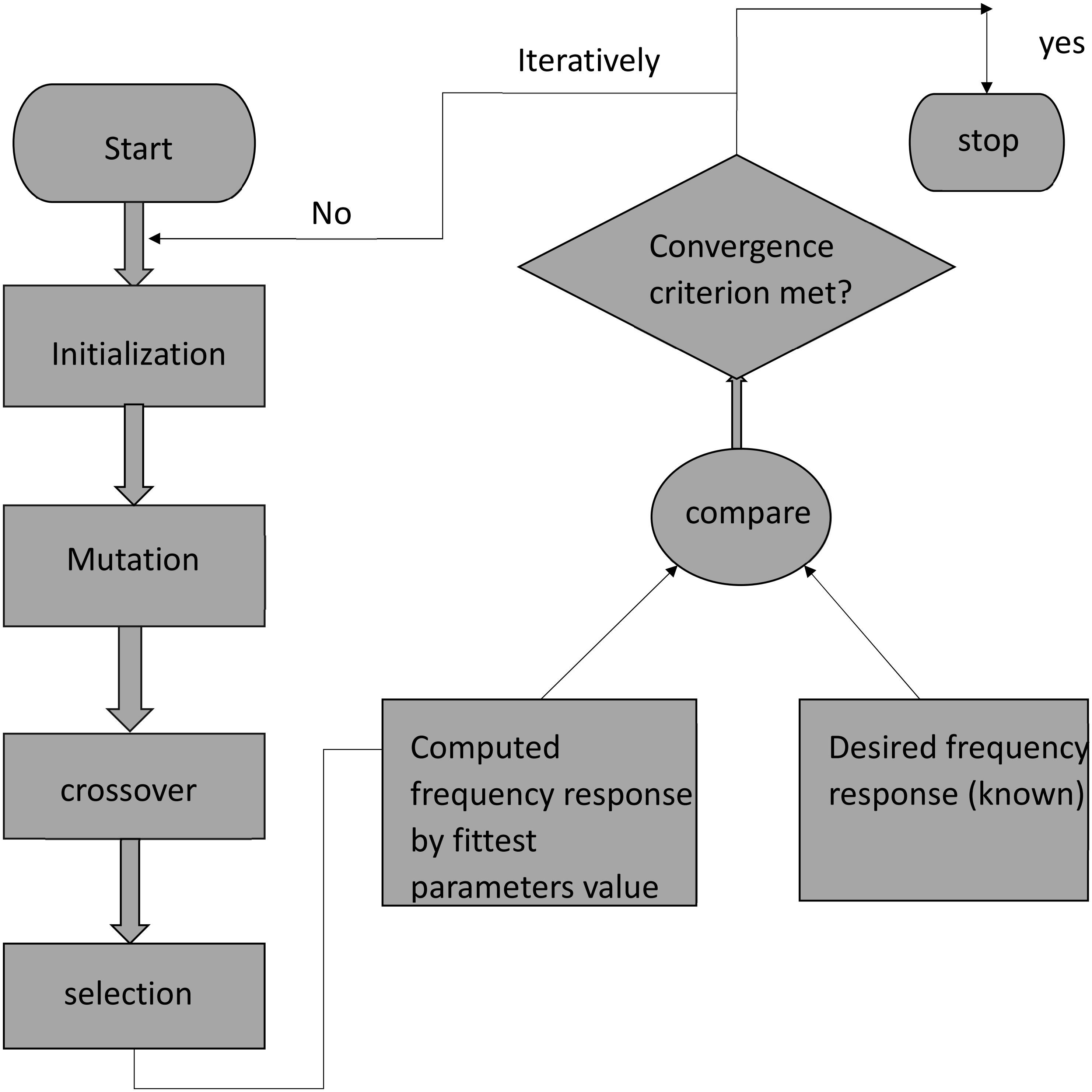

Fig. 7.1 Flowchart

Results

Here, the differential evolution strategy (DES), an efficient optimization method, is introduced to solve the computationally intensive FSS design problem. The DES has already been successfully demonstrated in a variety of applications and has shown to outperform other known global optimization methods on a number of synthetic problems because of its good convergence properties.

The DES parameters used were ,Population size : 6. The search parameters of DES were set to be P_{cross} = 0.8 .

The optimized parameters i.e ,**substrate length, patch length and periodicity** are obtained after 100 iterations.

The Convergence curve of Differential Evolution Algorithm (DE) has been shown below.

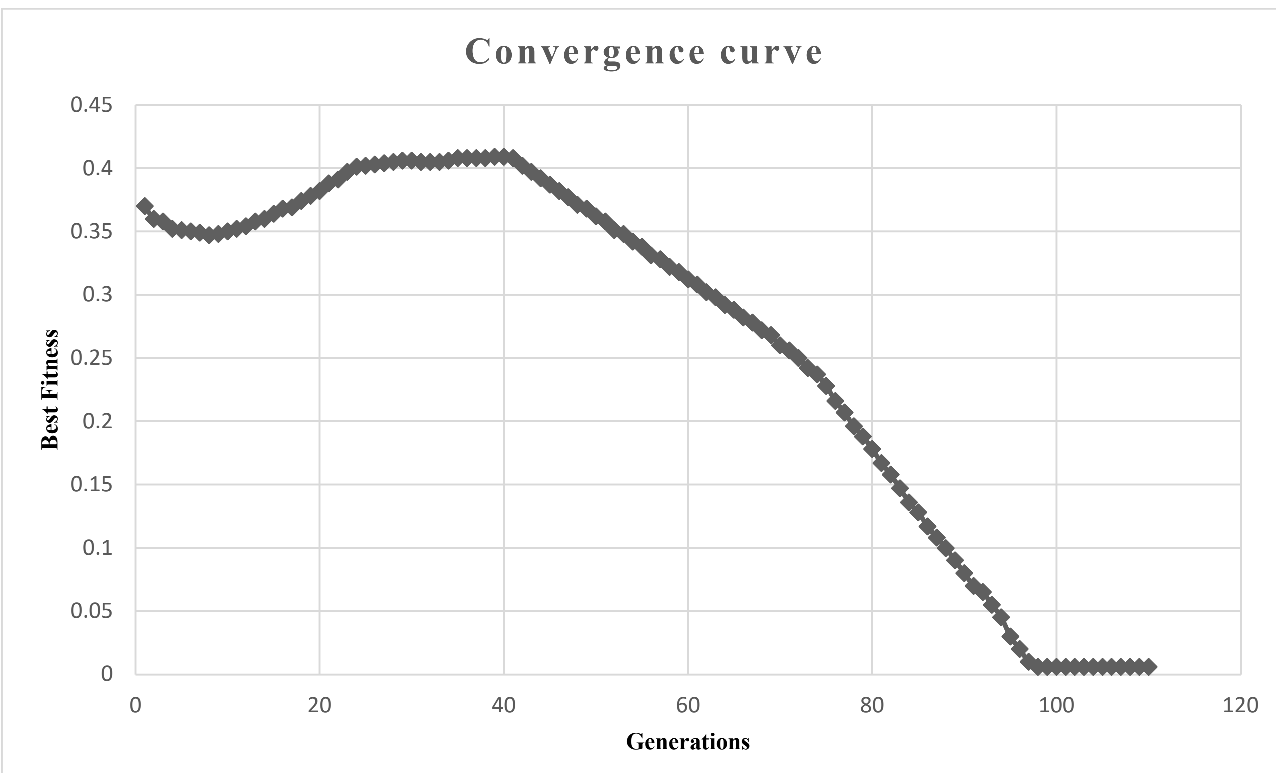

Fig. 7.2 Convergence Curve

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Chapter 8

RESULT ANALYSIS

The analysis of various plots regarding the fabricated structure has been done. The surface has been kept at a far field ($2D^2/\lambda$) where D is the linear dimension of the antenna used for measurement.

Firstly the reflection coefficient has been checked without the FSS as shown:

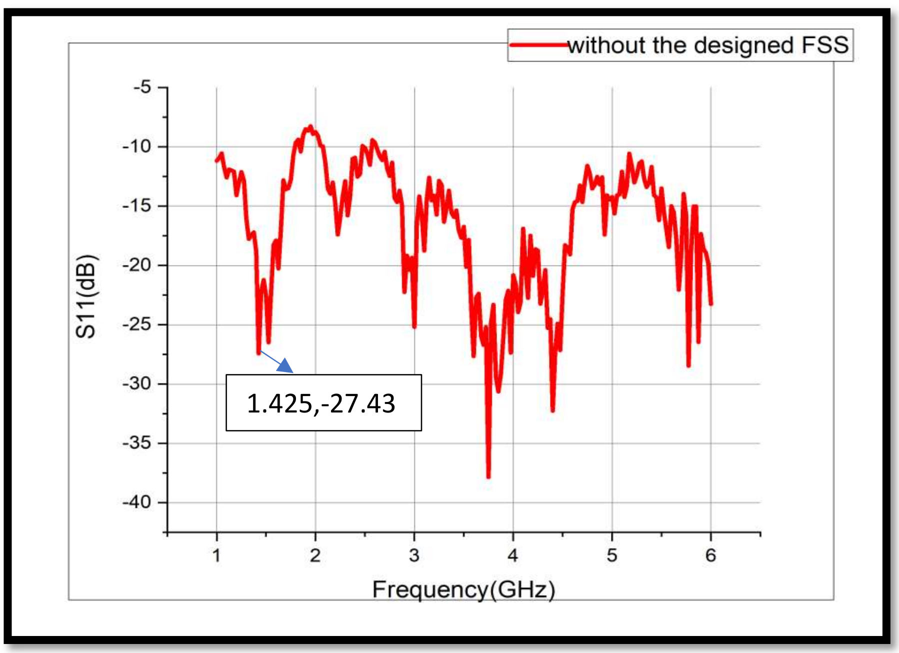

Fig. 8.1 Plot of Reflection Coefficient characteristics without the designed FSS

Next the reflection coefficient has been checked with FSS as shown:

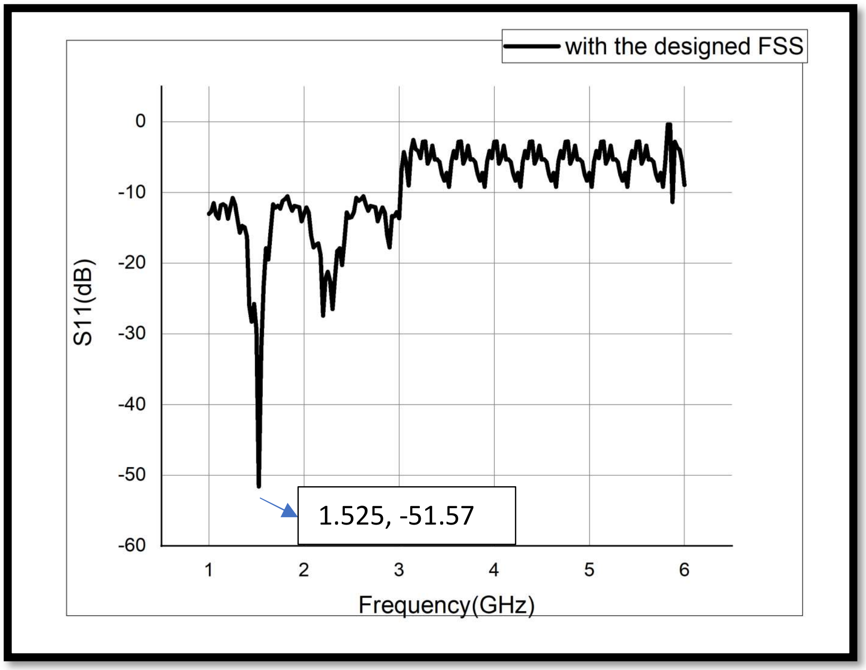

Fig. 8.2 Plot of Reflection Coefficient characteristics with the designed FSS

The transmission coefficient characteristics with the designed FSS :

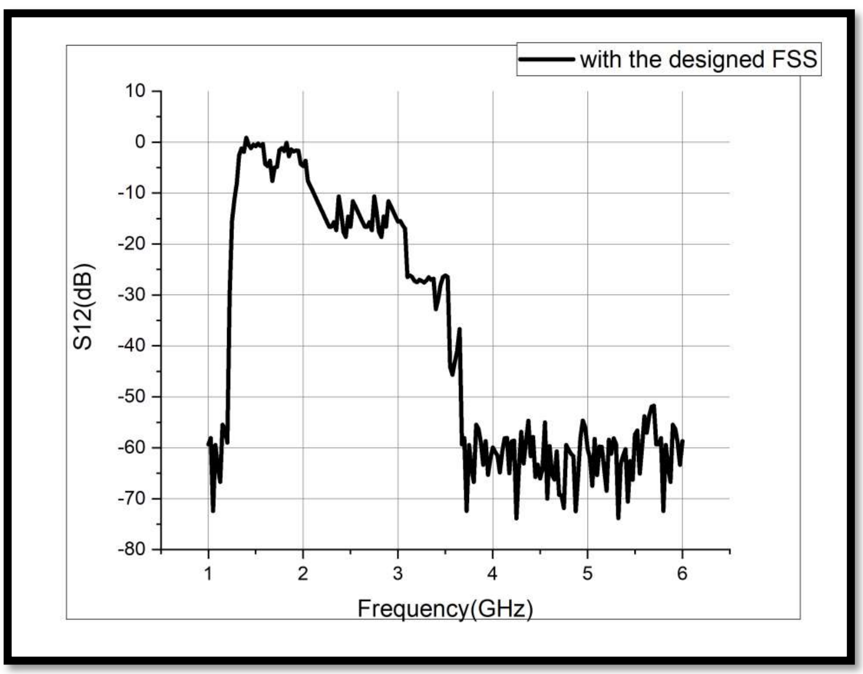

Fig. 8.3 Plot of Transmission Coefficient characteristics with the designed FSS

The results obtained after simulating the structure using MATLAB and CST software :

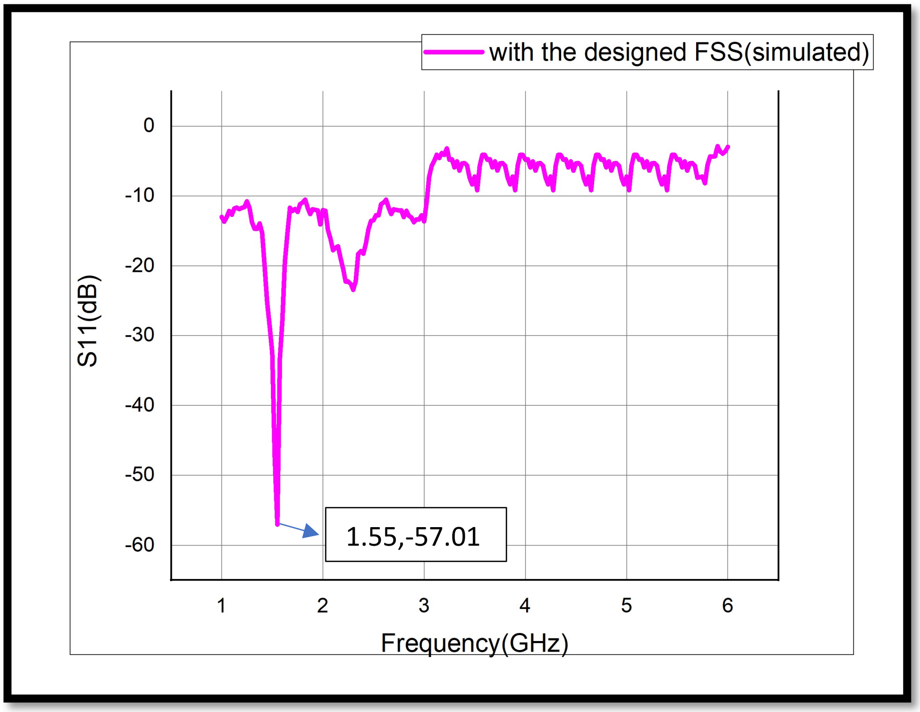

Fig. 8.4 Plot of Reflection Coefficient characteristics with the designed FSS(simulated)

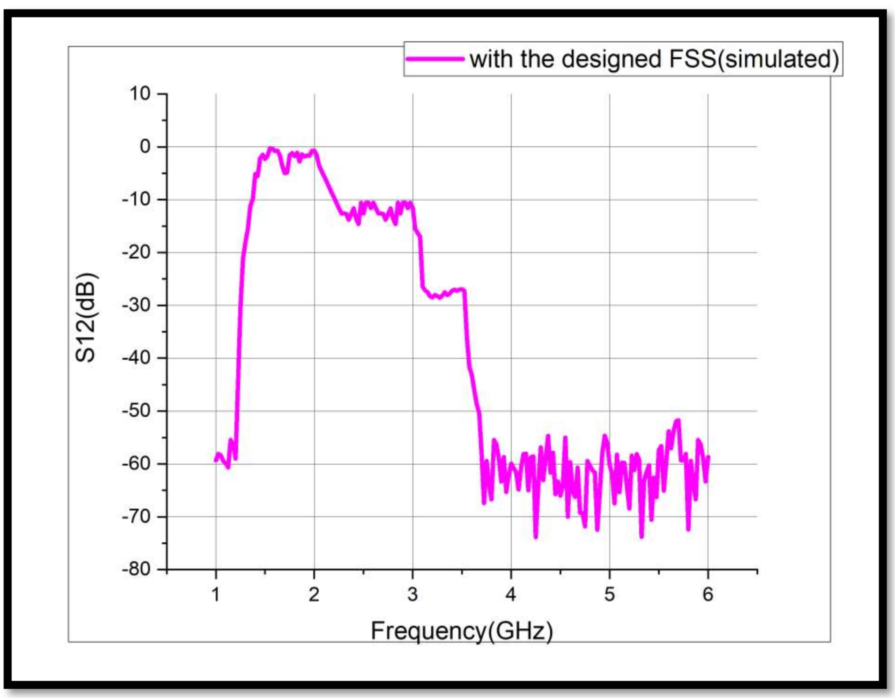

Fig. 8.5 Plot of Transmission Coefficient characteristics with the designed FSS(simulated)

From the above comparison we can conclude the following important points regarding the insertion of the designed FSS:

- At 1.525 GHz, the reflection coefficient decreases which results in maximum radiation at this frequency.
- The directivity is increased at the particular frequency(1.525 GHz).
- There is a shift in the resonance frequency after insertion of FSS.

  <u>Thus it can be applied where there is a need to switch the resonant frequency as per requirement as in ELECTRONIC WARFARE.</u>

The comparison between the simulated and measured result(fabricated structure) clearly shows that the error is negligible (i.e the shift in the resonant frequency from 1.55 GHz(simulated) to 1.525 GHz(measured)) which is around 0.025.

[Note: The results shown here is the data observed in our lab using the fabricated structure with square substrate of 200mm length along with 4x4 square patches of 20mm length on it]

Chapter 9

CONCLUSION

KEY HIGHLIGHTS

- Overall Summary of the Thesis
- Chapter-wise Analysis

Overall Summary of the thesis

Periodic structures are providing promising avenues for new and ongoing research, as well as a strong potential for transition of many concepts and fundamental studies to fully developed industrial technologies. The field is experiencing continued growth in research activities as demonstrated by the increasing number of symposia, workshops, and conferences.

Metamaterials are becoming a new and, of course, an interesting field of research for many scientists in different areas of science such as physics, engineering, mathematics, etc. Metamaterials have many types with additional features and applications, and their extraordinary properties cause them to be utilized in various fields and disciplines.

Neural networks recently gained attention as fast and flexible vehicles to microwave modeling, simulation, and optimization. After learning and abstracting from microwave data, through a process called training, neural network models are used during microwave design to provide instant answers to the task learned. Appropriate neural network structure and suitable training algorithm are two of the major issues in developing neural network models for microwave applications. Together, they decide amount of training data required, accuracy that could possibly be achieved, and more importantly developmental cost of neural models.

Neural network technology is an emerging technology in the microwave area for microwave modeling, simulation, optimization, and design. The efficient development of an accurate neural model requires a proper neural network structure and suitable training algorithms, two important aspects in successful applications of neural networks in solving microwave design problems. This work presented a review of the current status of this area.

Neural networks have a very promising future in the microwave design area. Benefits of applying neural network technology can be potentially achieved at all levels of microwave design from device, components, to circuits and systems, and from modeling, simulation, to optimization and synthesis. From the research point of view, future work in structures and training algorithms will shift from demonstration of basic significance of the neural network technology to addressing challenges from real microwave applications.

In many practical cases, training data from simulation-measurement contains accidental but large errors due to convergence difficulties in simulators or equipment limits that may happen when data generation goes to extreme points in the parameter space. Existing training algorithms can be susceptible to such large errors, and consequently the neural model obtained is not reliable. Robust algorithms automatically dealing with such cases need to be developed, avoiding manual debugging for clues of model inaccuracy.

My work mainly focuses to implement neural network in modelling a frequency selective surface prototype to eliminate the drawback that closed form solution do not exist.

Chapter-wise Analysis

Chapter 1 introduces with the major topics that will be used in the entire work. It emphasizes on the key concepts that need to be understood in order to successfully complete the work. Motivation and the novel aspects has been discussed in the later part of the chapter.

Chapter 2 summarizes a large number of papers or research articles to get a broader aspect to work on the related field.

Chapter 3 highlights the physics behind the significance of metamaterials, the reason behind its demand in various applications.

Chapter 4 discusses a detailed analysis of wave propagation in an anisotropic medium using mathematical derivation. Last part outlines the significance of left and right handed material .

Chapter 5 emphasizes on the importance of Neural Network and how it has been implemented to get the desired result.

Chapter 6 features the analysis of the FSS prototype using Deep Neural Network to get the minimum error between the actual and desired output.

Chapter 7 stresses on the synthesis of the FSS prototype using Evolutionary Algorithm applying the same Neural Network.

Chapter 8 focusses on the utility of the designed FSS by analysing its functionalities using different plots.

Chapter 9 summarises the entire work with analysing each and every chapter.