الجمهورية الجزائرية
الديمقراطية الشعبية
REPUBLIQUE ALGERIENNE DEMOCRATIQUE ET POPULAIRE
وزارة التعليم العالي
والبحث العلمي
Ministère de l'Enseignement Supérieur et de la Recherche Scientifique
جامعة سعيدة – د. الطاهر مولاي –
Université Saïda – Dr. Tahar Moulay –
Faculté des Mathématiques, de l'Informatique et de Télécommunications

MEMOIRE

Présenté pour l'obtention du **Diplôme** de **MASTER en** Télécommunications

Spécialité : Systèmes des Télécommunications

Par : MAACHOU Souad
KEBIR Chahra

Design and Optimization of a DGS Patch Antenna Using ANN

Soutenu, le 19/06/ 2022, devant le jury composé de :

M. BOUHMIDI Rachid	MCA	Président
M. BOUDKHIL Abdelhakim	MCA	Rapporteur
M. CHETIOUI Mohammed	MCA	Examinateur

2024 / 2025

Acknowledgments

First and foremost, we thank Allah Almighty, who inspired us with patience, granted us strength, and guided us to complete this humble work.

We would like to express our heartfelt gratitude to our family, especially our parents, whose unwavering support and encouragement have been invaluable to us throughout this academic path.

We would like to thank our supervisor Dr. BOUDKHIL A for his supervision, availability, fruitful remarks and precious guidance during the realization of this project.

We also extend our thanks to the PhD student Senasli Lamia for her assistance in our work.

We also thank all the jury members Dr. Bouhmdi R and Dr. Chetioui M for agreeing to evaluate this modest work.

Finally, we thank all the teachers and managers of our Telecommunications Department at Saida University.

Dedication

I dedicate this humble work:

To my dear father, forever present in my heart who passed away before seeing the fruits of hisefforts and embracing this success.

To my role model and beloved, my dear mother, I owe everything I am today to your love, prayers, and countless sacrifices.

To my biggest supports, my sister Amal and my brothers Abdelhak and Kadirou, heartfelt thanks for your unwavering love and support.

To my friends Fatima, Khadidja and Chahra who made the path more joyful and less difficult, thank you for all the beautiful memories we created together.

To all my family, all my gratitude and love.

Souad

Dedication

I want to dedicate this work to:

My very dear mother, the source of affection and joy.

My adorable father, the symbol of patience and sacrifice.

My very dear sisters: Soumeya, Fatima, and my dear brother: Bouziane and Mohamed who have supported me.

Chahra

Table of Content

List of Figures

List of Tables

List of abbreviations

2D : Two Dimensional

3D : Three Dimensional

5G : Fifth Generation

AI : Artificial Intelligen**ce**

ANN : Artificial Neural Networks

ART : Adaptive Resonance Theory

BP : Backpropagation

BW : Bandwidth

CAD : Computer-Aided Design

CNN : Convolutional Neural Network

CPU : Central Processing Unit

DBN : Deep Belief Network

DGS : Defective Earth Structure

DMS : Defective Microstrip Structure

DNN : Deep Neural Network

ELU : Exponential Linear Unit

EM : Electromagnetic

FEM : Finite Element Method

GAs : Genetic Algorithms

GPU : Graphics Processing Unit

HFSS : High Frequency Structure Simulator

IOT : Internet Of Things

LSTM : Long Short-Term Memory

MAE : Mean Absolute Error

MIMO : Multiple Input Multiple Output

MLP : Multi-Layer Perceptron

MPP : Massively Parallel Processing

MSE : Mean Squared Error

NN : Neural Network

PSO : Particle Swarm Optimization

RBF : Radial Basis Function

ReLu : Rectified Linear Unit

RF : Radio Frequency

RL : Return Loss

RNN : recurrent neural networks

SGD : Stochastic Gradient Descent

SMP : Symmetric Multiprocessing

Tanh : Tangen Hyperbolic

TPU : Tensor Processing Unit

VHF : Very High Frequency

VSWR : Voltage Standing Wave Ratio

General Introduction

Recent advancements in Artificial Neural Networks (ANNs), have significantly impacted the field of antenna engineering. In patch antenna design, where electromagnetic behavior is governed by complex, nonlinear interactions among geometrical and material parameters, ANNs have demonstrated exceptional capability as predictive and optimization tools. Unlike traditional methods - such as parametric sweeps and full-wave electromagnetic (EM) simulations - which are often computationally intensive and time-consuming, ANN models can learn the underlying patterns from simulation or measurement data and generalize to unseen designs with remarkable efficiency.

Numerous studies have explored the use of ANNs for modeling and optimizing patch antennas. Early works primarily focused on simple feedforward networks trained to predict basic performance parameters such as resonant frequency, gain, and bandwidth. These models significantly reduced design time by enabling rapid estimation of antenna characteristics based on input design parameters. More recent approaches have incorporated deeper architectures and hybrid models, combining ANNs with evolutionary algorithms (like Genetic Algorithms or Particle Swarm Optimization) to enhance the inverse design process. Additionally, convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been explored for feature extraction from 2D/3D antenna geometries and for modeling dynamic or frequency-dependent behavior.

In this regards, this study aims to integrate ANNs with EM solvers in a closed-loop optimization, where the ANN acts as a surrogate model, accelerating convergence toward optimal solutions. This hybrid approach allows high fidelity with reduced computational cost, especially valuable in multi-objective optimization tasks involving efficiency, return loss, bandwidth, and radiation characteristics. The increasing availability of data and improvements in ANN training methods continue to expand the role of machine learning in antenna design, establishing ANN-based modeling as a state-of-the-art methodology for developing efficient, compact, and high-performance patch antennas.

Chapter 1

Patch Antenna Design

1.1. Introduction

The design of patch antennas was early proposed on 1953 by Deschamps [1], but it was not until 1970 that Howell and Muson [2] could be effectively implemented, thanks to the arrival of low-loss dielectrics on the market. Since then, the patch antennas have undergone numerous refinements and research efforts to overcome its many drawbacks. A printed radiating element, commonly referred to as a “patch” is a micro-strip that it is generally rectangular in shape. The structure consists of a ground plane and a dielectric substrate with one or more metallic features on its surface. Their distribution over a surface at the microscopic scale is also important, as are criteria such as lightness and cost. New requirements were reached with the expansion of communication methods in wireless communication systems. There is no doubt that these antennas are also very useful because they are cheap and space-saving [3].

1.2. Structure and Parameters

Patch antennas are the most important type of antennas used in wireless communications systems and find a broad application. These antennas first appeared in the 1950s, but the fully-fledged development took place in the 1970s. Printed antennas are evenly radiated parts of the planar structure. The patch antenna operates on the principle of generating electromagnetic waves due to oscillating electric currents in the metallic patch. The patch is placed on a dielectric material (substrate) above the ground plane. The “patch” functions to transmit and radiate the electromagnetic signal, while the “ground plane” provides a stable reference point to enhance the antenna’s overall efficiency by reflecting the waves and directing them effectively. The antenna is made by etching a printed circuit board. Owing to their design technology, they can be integrated as close as possible to electronic circuits while taking up minimal space and adapting to various surface types. It has the advantages of being lightweight, easy to manufacture, and easy to implement, in addition to being aerodynamic and low-cost. Patch antennas are used in many applications, starting from the VHF bands [3].

1.2.1. Description of the Structure

A patch antenna is a microstrip line with a particular shape. It performs two fundamental functions that define the general principle of an antenna, radiation (emission) and the reception of an electromagnetic wave. It consists of a [4]:

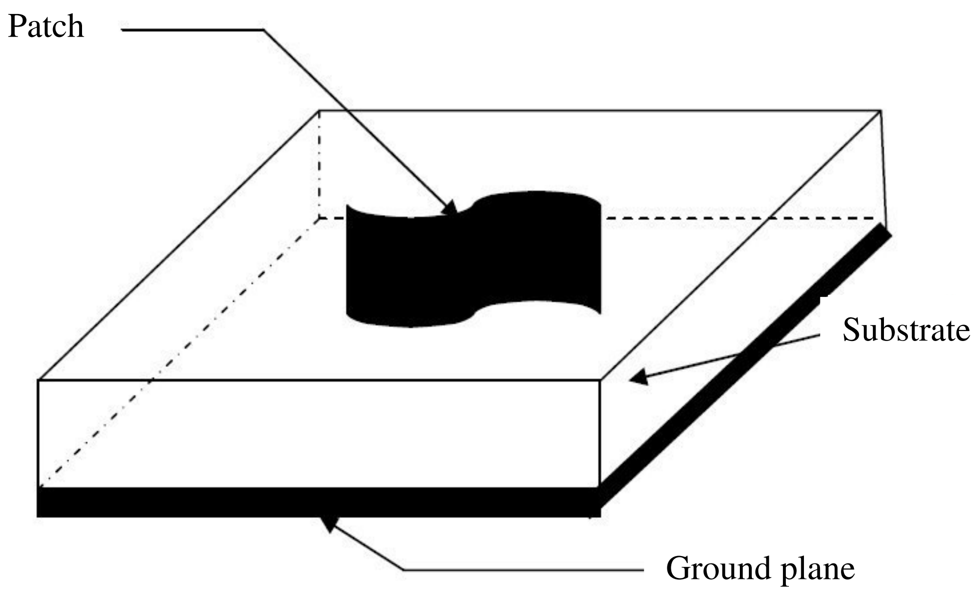


Figure 1.1- Presentation of a Patch Antenna Design

- ❖ **Ground plane**: is a conductive surface (copper) covering the bottom the lower part of the substrate. It is used to radiate the upper part of the substrate.

- **Dielectric substrate:** Made of an insulating material, generally thin compared to the wavelength, with a relative permittivity$(2.2 < \varepsilon_r < 12\ )$. This substrate is used to increase the power radiated by the antenna, reduce Joule losses, and improve antenna bandwidth. Sometimes it's preferable to use thick dielectric substrates with low permittivity for high efficiency and wide bandwidth.

- **Radiating element (patch/microstrip):** A metallic part (generally 17.5 to 35 microns thick for microwaves and 9 microns thick for millimeter waves) of variable shape and size depending on the application. It can have various geometries (circular, rectangular, triangular, etc.). It must be connected to the rest of the circuit by a transmission line (microstrip), which should be impedance-matched to the antenna and the rest of the circuit to avoid reflectionphenomenon.In practice, the rect Patch l the disk represent the most used forms of the radiating element. It consists of a part conductor which will radiate, the shape and dimensions determine the frequency operation of the antenna.

1.2.2. Main Parameters

- **Resonance Frequency:** It is the frequency at which the antenna exhibits a minimum amplitude of the reflection coefficient. It is given by the following relationship [5]:

$$f_r = \frac{c}{2\sqrt{\varepsilon_r}} \frac{1}{L + 2\Delta L}$$

c : Speed of light in vacuum $(\approx 3 \times 10^8 m/s)$

L: Length of the patch

ε_r: Relative permittivity

❖ **Bandwidth:** It refers to the range of frequencies over which the antenna performs efficiently, typically defined by the return loss or the reflection coefficient. The bandwidth of a patch antenna is generally narrow due to the compact size and relatively small frequency range within which the antenna resonates efficiently.

The bandwidth is determined by the quality factor (Q) of the antenna, which depends on the size of the patch, the dielectric constant of the material, and the feed method. For most standard patch designs, the bandwidth is typically around **1% to 5%** of the center frequency [6].

$$BW(\%) = \frac{f_H - f_L}{f_c} \times 100$$

f_H: highest frequency

f_L:lowest frequency

f_c:the central or resonant frequency

❖ **Return loss:** It measures how much of the signal is reflected back from the antenna due to impedance mismatches. A high return loss means that less power is reflected, and more is radiated by the antenna. The value of return loss greater than **-10 dB** is generally considered good because it means less than 10% of the signal is reflected back. Mathematically, return loss RL is related to the reflection coefficientS_{11} :

$$RL = -20\log|S_{11}|$$

S_{11}: Reflection coefficient

The impedance matching between the antenna and the transmission line (e.g., coaxial cable or microstrip line) is critical in minimizing return losses [7].

❖ **Gain:** The gain of an antenna is a measure of how well it focuses the radiated energy in a particular direction compared to an isotropic radiator (which radiates equally in all directions). Patch antennas typically have a gain of 6-9 dBi, which is relatively moderate compared to other types of antennas like parabolic dishes, but it's sufficient for many communication applications. This parameter is expressed by:

$$G(\theta,\phi) = 4\pi \; \frac{p(\theta,\phi)}{P_{isotropic}}$$

$p(\theta,\phi)$: Power radiated in a specific direction

$P_{isotropic}$: Power that would be radiated by an ideal isotropic antenna in that direction (uniform in all directions)

The gain depends on the:

- **Patch's size**: Larger patches generally provide higher gain.
- **Feed configuration:** Optimized feed designs can improve efficiency.
- **Quality of materials:** Low-loss materials improve radiation efficiency.

❖ **Characteristic Impedance:** The calculation of the characteristic impedance is not an easy task. From the transmission line theory, the relation between the velocity and per unit length inductance and capacitance is:

$$v = \frac{1}{\sqrt{LC}} = \frac{C}{\sqrt{\varepsilon_r}}$$

Using equation $Z_0 = \sqrt{\frac{L}{C}}$, the characteristic impedance can be expressed as:

$$Z_0 = \sqrt{\frac{L}{C}} = \frac{1}{vC} = \frac{\sqrt{\varepsilon_r}}{cC}$$

Thus, to *compute* the characteristic impedance, we just need to obtain the per unit length capacitance C once the effective permittivity is known. This approach makes a difficult task slightly easier. When the thickness of the metal strip can be neglected, it has been found that [8]:

- When $W/d < 1$, the characteristic impedance of the line is:

$$Z_0 = \frac{60}{\sqrt{\varepsilon_r}} \ln\left(\frac{8d}{W} + \frac{W}{4d}\right) > \frac{126}{\sqrt{\varepsilon_r}}$$

It decreases monotonically to $126/\sqrt{\varepsilon_r}$ asW/d increases to 1.

- When $W/d > 1$, the characteristic impedance of the line is:

$$Z_0 = \frac{120\pi}{\sqrt{\varepsilon_R}\left(\frac{W}{d} + 1.393 + 0.667\ln\left(\frac{W}{d} + 1.44\right)\right)} < \frac{126}{\sqrt{\varepsilon_r}}$$

It also decreases monotonically from $126/\sqrt{\varepsilon_r}$ as W/d increases. That is, the larger the ratio W/d , the smaller the characteristic impedance; also, the larger the permittivity, the smaller the characteristic impedance. Practical limitations exist on the range of impedances that can be manufactured. These limits depend on factors such as the dielectric constant, substrate height and manufacturing capability. In general, the thinnest line that can be etched routinely with a goodphotolithographic process is of the order of 0.1 mm. This then puts the upper bound of the impedance at [90–120]Ω. The lower bound is determined by the line width, which should not be comparable to a wavelength. The typical value of the characteristic impedance for industrial standard lines is 50 or 75 [8].

- **Radiation patterns:** The radiation pattern (or antenna pattern) of an antenna refers to a mathematical or graphical representation that describes how an antenna transmits or receives electromagnetic energy as a function of direction in space. It is generally expressed in 2D or 3D in the far-field domain, where the radiation characteristics are well defined. There are two principal planes:

- **The E-plane**: in the x-z plane ($\varphi = 0°$, elevation plane).
- **The H-plane**: in the x-y plane ($\theta = \frac{\pi}{2}$, azimuthal plane).

❖ In the case of a patch (or microstrip) antenna, which is a planar directional antenna mounted on a dielectric substrate, the radiation pattern presents a main lobe directedperpendicularly to the surface of the patch, with minimal radiation towards the back [9].

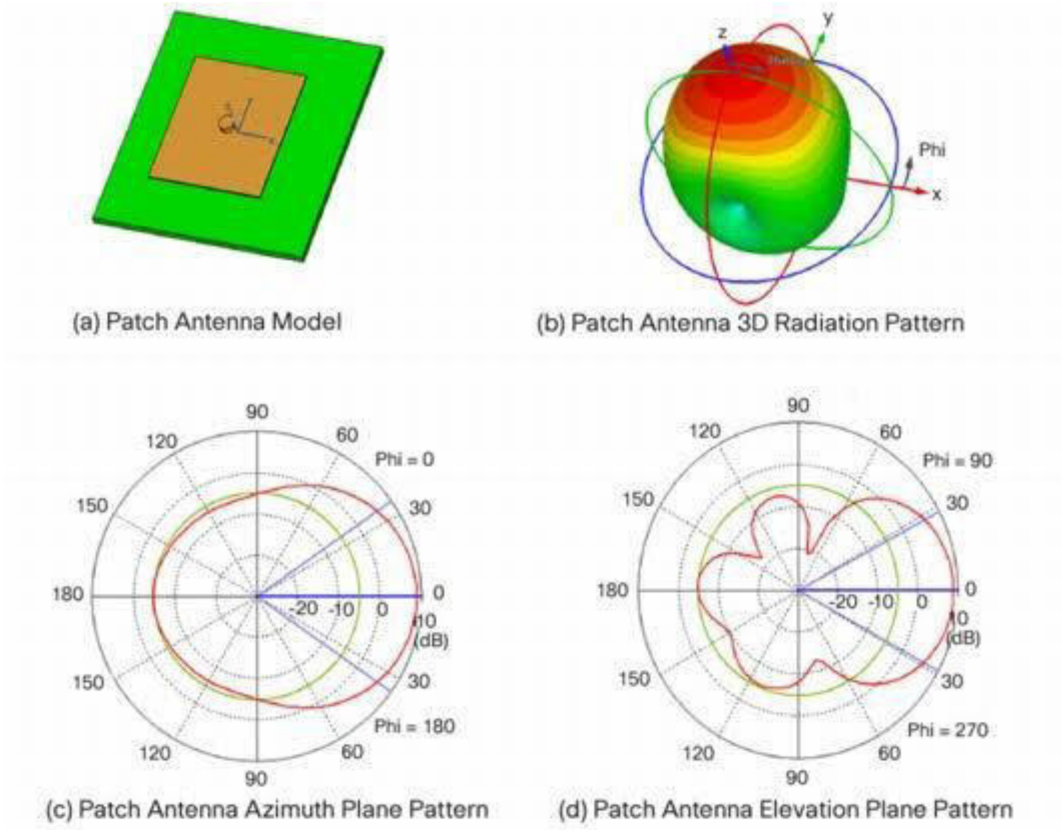


Figure 1.2 - 3D and Polar Radiation Pattern of a Patch Antenna

1.3. Feeding Methods for Patch Antennas

There are many configurations that can be used to feed microstrip antennas. The four most popular are:

1.3.1. Microstrip Line Feed

The microstrip line feed is also a conducting strip, usually of much smaller width compared to the patch. This method of feeding is very widely used because it is easy to fabricate, simple to match by controlling theinset position and rather simple to model. However, as the substrate thickness increases, surface waves and spurious feed radiation increase, which for practical designs limitthe bandwidth (typically 2–5%) [3].

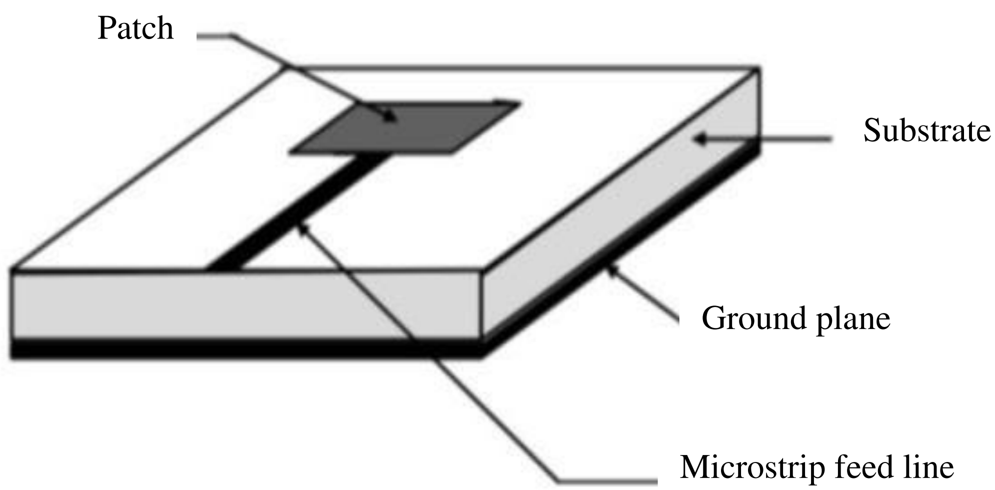


Figure 1.3 - Microstrip Line Feed

1.3.2 Coaxial Probe

Coaxial feed or probe feed is a very common technique used for feeding Microstrip patch antennas. As seen from Figure 1.4, the inner conductor of the coaxial connector extends through the dielectric and is soldered to the radiating patch, while the outer conductor is connected to the ground plane. The main advantage of this type of feeding scheme is that the feed can be placed at any desired location inside the patch in order to match with its input impedance. This feed method is easy to fabricate, cheap, effective and has low spurious radiation. However, its major disadvantage is that it provides narrow bandwidth and is difficult to model since a hole has to be drilled in the substrate and the connector protrudes outside the ground plane [10].

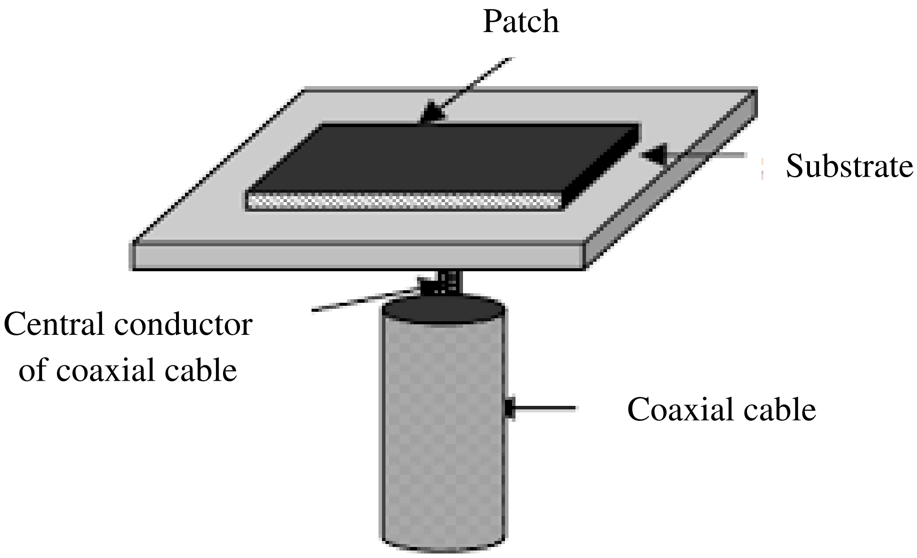


Figure 1.4 - Coaxial Probe

1.3.3. Proximity Coupling

This type of feed technique is also called as the electromagnetic coupling scheme. As shown in Figure 1.5, two dielectric substrates are used such that the feed line is between the two substrates and the radiating patch is on top of the upper substrate. The main advantage of this feed technique is that it eliminates spurious feed radiation and provides very high bandwidth (as high as 13%), due to overall increase in the thickness of the microstrip patch antenna. The major disadvantage of this feed scheme is that it is difficult to fabricate because of the two dielectric layers, which need proper alignment. Also, there is an increase in the overall thickness of the antenna [11].

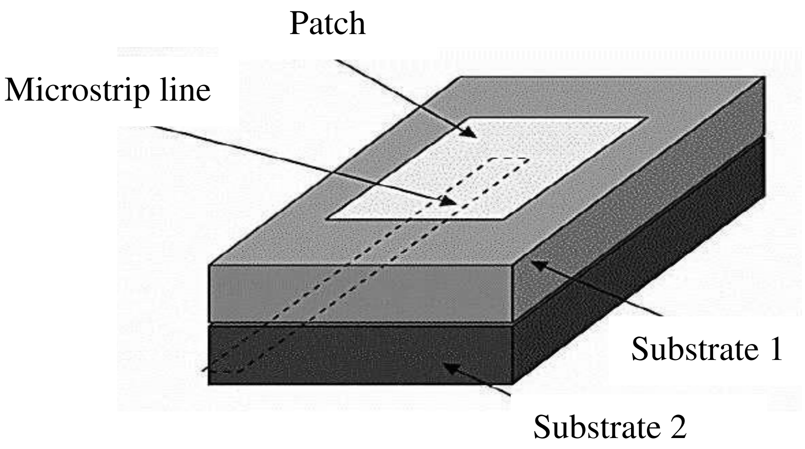


Figure 1.5 - Proximity Coupled Feed

1.3.4 Aperture Coupled

In this type of feed technique, the radiating patch and the microstrip feed line are separated by theground plane as shown in Figure 1.6. Coupling between the patch and the feed line is made through aslot or an aperture in the ground plane.The coupling aperture is carefully designed to be centered beneath the patch to ensure a symmetrical configuration, thereby reducing cross-polarization effects.The amount of coupling from the feed line to the patch is determined by the shape, size and location of the aperture. Since the ground planeseparates the patch and the feed line, spurious radiation is minimized.This type of coupling gives wider bandwidth. However, its major disadvantage is that it is difficult to fabricate due to multiple layers, which also increases the antenna thickness [12].

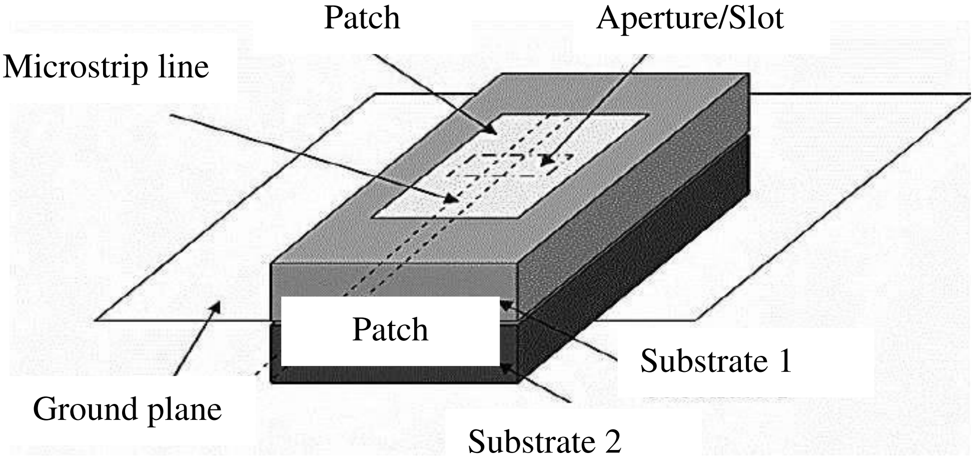


Figure 1.6 - Aperture Feed

1.4. Types of Patch Antennas

There are a large number of shapes of microstrip patch antennas; they have been designed to match specific characteristics. Some of the common types are shown in Figure 1.7, for millimeter wave frequencies, the most common types are rectangular, square, and circular patches.

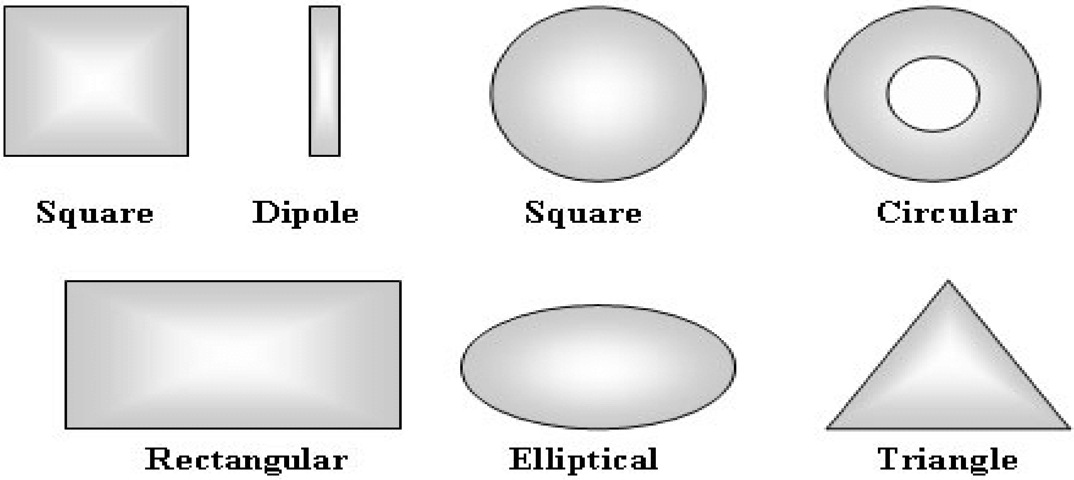


Figure 1.7 - The Most Common Shapes of Patch Antenna Designs

The choice of the substrate is also important, we have to consider the temperature, humanity, and other environmental ranges of operating. Thickness of the substrate h has a big effect on the resonant frequency and bandwidth BW of the antenna. Bandwidth of the microstrip antenna will increase with increasing substrate thickness but with limits, otherwise the antenna will stop resonating [13].

1.5. Advances and Limitations in Patch Antenna Designs

1.5.1. State of the Art

Patch antennas have gained significant attention in recent decades because of their small size, ease of manufacture, and multiple uses in several fields such as wireless networks, radar, mobile phone systems, 5G devices, and others. This interest has prompted many researchers to conduct in-depth studies on antenna designs with the aim of improving their performance in terms of bandwidth, gain, miniaturization and efficiency. Among the proposed designs are the following:

- **Single-band and multi-band antennas:** Traditional single-band antennas have been replaced by dual or multi-band designs to operate over several frequency bands simultaneously [14].
- **Miniaturized and low-profile antennas:** Miniaturization techniques such as short pins, meandered lines, and slots have been employed to reduce the size of the patch antenna [15].
- **Wearable and flexible antennas:** wearable antennas using textile substrates have emerged as a key solution for body area networks and smart clothing [16].

❖ **Reconfigurable antennas:** Reconfigurable patch antennas use electronic switches like PIN diodes and varactors to alter frequency, bandwidth or polarization [17].

Several achievements have been achieved in the field of patch antennas, represented by the application of artificial intelligence techniques such as genetic algorithms and machine learning have been applied to optimize antenna parameters and improve its performance [18].

The use of electromagnetic band blocking structure techniques and metamaterials also contributed to enhance bandwidth and gain[12]. In addition, patch antennas have proven to be highly effective in 5G and millimeter wave applications due to their ability to achieve strong performance [19].

However, microstrip antennas also have some limitations compared to conventional microwave antennas:

- ✓ Narrow bandwidth and associated tolerance problems.
- ✓ Somewhat lower gain (-6 dB).
- ✓ Large ohmic loss in the feed structure of arrays.
- ✓ Most microstrip antenna radiate into half-space.
- ✓ Complex feed structures required for high-performance arrays.
- ✓ Polarization purity in difficult to achieve.
- ✓ Poor end fire radiation, except tapered slot antennas.
- ✓ Extraneous radiation from feeds and junctions.
- ✓ Lower power handling capability (-100 W).
- ✓ Excitation of surface waves.

1.5.2. DMS and DGS Techniques for Patch Antenna Designs

❖ **The Defective Microstrip Structure (DMS):** The defect is corrected by applying a uniform or non-uniform, periodic or non-periodic pattern to the structure of the microstrip. Regarding microstrip antennas, the patch (radiating element) is etched. Two methods can be used to repair the defect: either by filling the slot on the surface of the printed part, or by cutting the slot at the boundaries of the part. Defects are recorded on the patch surface during slot loading and can take various shapes, such as bent slots. Or square slots [20].

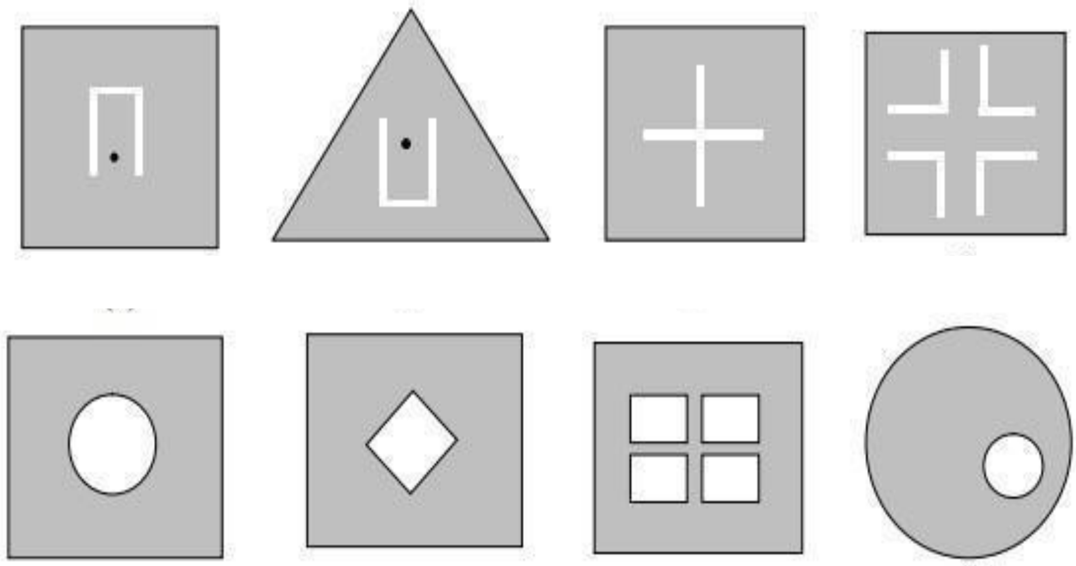


Figure 1.8 - Types of DMS Slot Load

In the slot loading technique, imperfections are eliminated at the boundaries of the radiating element, as shown in Figure 1.8, where the current flow is determined by the length of the part and the depths of the slot.

❖ **Defective Earth Structure (DGS):** The Defective Ground Structure (DGS) is a method used in the design of antennas and microwave circuits. This technique involves creating patterns or specific structures on the ground plane adjacent to the antenna or circuit, with the aim of modifying or interfering with the electromagnetic properties of the structure. The Defective Ground Structure (DGS) is primarily used to improve the performance of antennas and circuits by mitigating undesirable effects such as spurious resonances, unwanted couplings, losses, and electromagnetic interference. By modifying the structure of the adjacent ground, DGS can alter the propagation properties of electromagnetic waves, thereby optimizing the performance of the antenna or circuit in terms of bandwidth, directivity, gain and rejection of unwanted frequencies [20].

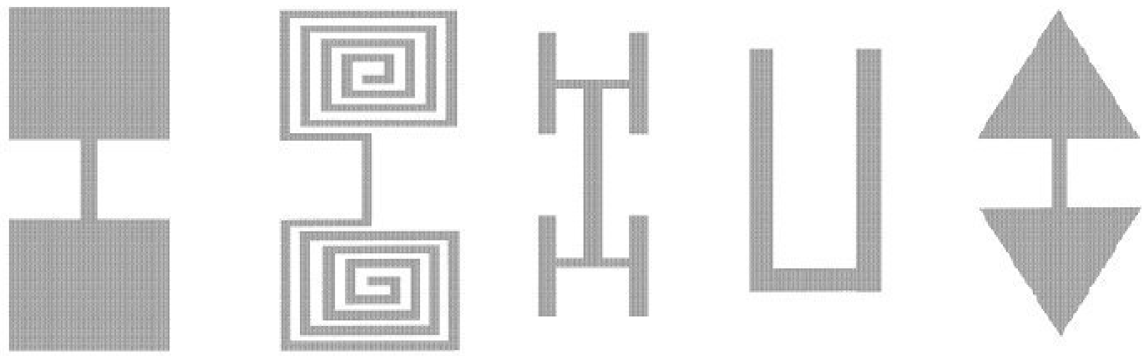


Figure 1.9 - Different Forms of DGS

1.6. Conclusion

Patch antennas represent a significant advancement in the field of wireless communications thanks to their compact, cost-effective, and easily integrated design. Despite some limitations such as low bandwidth or moderate gain, their numerous advantages make them an ideal solution for many applications, particularly in modern telecommunications systems. Their continued evolution and ongoing research suggest promising improvements to meet the growing needs for performance and miniaturization.

Chapter 2

ANN-Based Modeling

2.1. Introduction

In recent decades, Artificial Intelligence (AI) [21] has made significant strides in solving complex problems that were once thought to be the exclusive domain of human intelligence. Among the various subfields of AI, Artificial Neural Networks (ANNs) [22] have emerged as one of the most powerful and versatile tools for tasks involving pattern recognition, classification, prediction, and decision-making. Inspired by the structure and functioning of the human brain, ANNs are computational models composed of interconnected processing units called neurons. These networks are capable of learning from data, identifying intricate patterns, and improving their performance over time through training. Their ability to generalize from examples has made them essential in a wide range of applications, from image and speech recognition to medical diagnosis, financial forecasting, and autonomous systems. The objective of this chapter is to explore the fundamental principles of artificial neural networks, analyze their architectures, and examine their practical applications. Special emphasis is placed on understanding how ANNs optimize the performance of patch antennas and how recent ANN advancements have significantly enhanced their capabilities.

2.2. Fundamentals of Artificial Neural Networks

2.2.1. Principles of Artificial Neural Networks

These are the basic elements of a neural network, they are mathematical models inspired by the structure and behavior of biological neurons. They are composed of interconnected units called formal or artificial neurons capable of performing certain specific and well-defined functions. Neural networks allow to approach non-linear relationships with significant degrees of complexity. The input cells are intended to collect the information that is transformed by the hidden cells up to the output cells (figure 2-1) [22]:

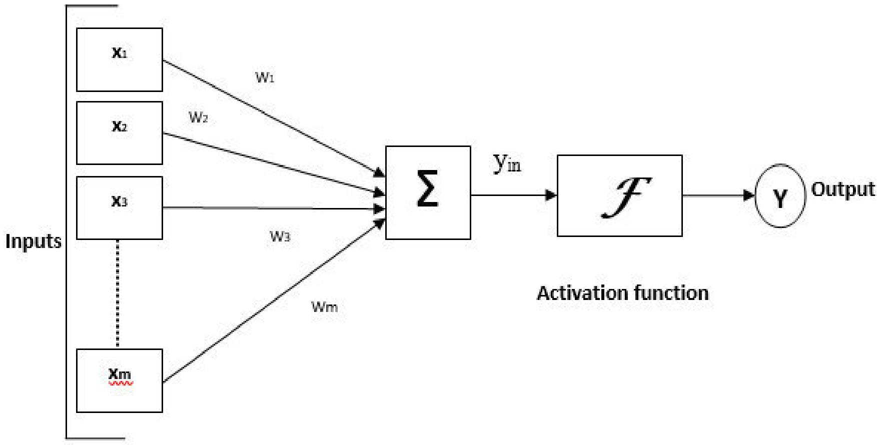
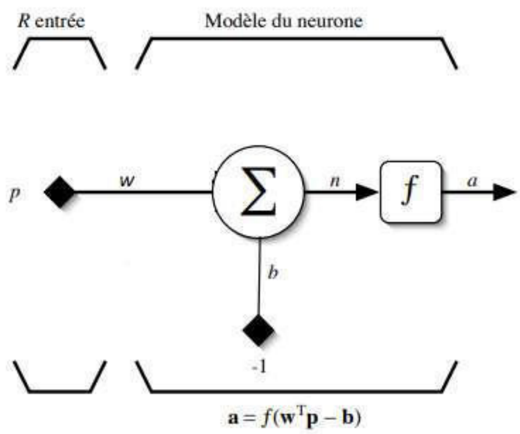


Figure 2.1 – Basic Artificial Neural Network Model

The weighting coefficients are called synaptic weights. In the behavior of these neurons, two phases are distinguished: the first is the calculation of the weighted sum of the inputs, while the second is the application of a transfer function that calculates the value of the neuron's state from this sum.

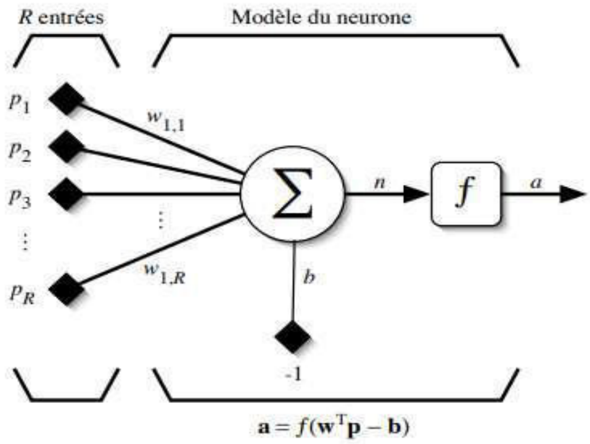
2.2.2. Neuron Entries in Artificial Neural Networks

❖ **Neurons to enter simply:** The output depends on the chosen transfer function. The bias is almost similar to the weight, except that it has a constant input value equal to 1. However, it can be omitted depending on the conditions chosen by the user. Note that w and b are adjustable scalar parameters of the neuron. Typically, the transfer function f is chosen by the user and



the parameters w and b are adjusted by learning laws to adapt the input/output neuron to a specific goal [23].

- **Neurons with multiple inputs:** Typically, a neuron has more than one input, as shown in the figure. The result n is then transformed by a transfer function f that produces the neuron's output a. This output corresponds to a weighted sum of the weights and inputs minus what is called the bias b of the neuron. The result n of the weighted sum is called the activation level of the neuron. The bias b is also called the activation threshold of the neuron. When the activation level exceeds the bias, the neuron is considered active. While the activation level reaches or exceeds threshold b, then the argument of *f* becomes positive (or null). Otherwise, it is negative. The weight of an artificial neuron therefore represents the efficiency of a synaptic connection. A negative weight inhibits an input, while a positive weight accentuates it [24].



2.2. Structure of Artificial Neuron Networks

Neural network architecture defines its structure including number of hidden layers, number of hidden nodes and number of output nodes:

- **Layers of neural networks:** As the brain is a gigantic network of neurons, the neural network is a network of nodes. A variety of neural networks can be created depending on how the nodes are connected. One of the most commonly used types of neural networks uses a layered structure of nodes, as illustrated in figure 2.2. The neural network has evolved from a simple architecture to an increasingly complex structure. Originally, the pioneers of neural networks had a simple architecture with only input and output layers, called single-layer neural networks.

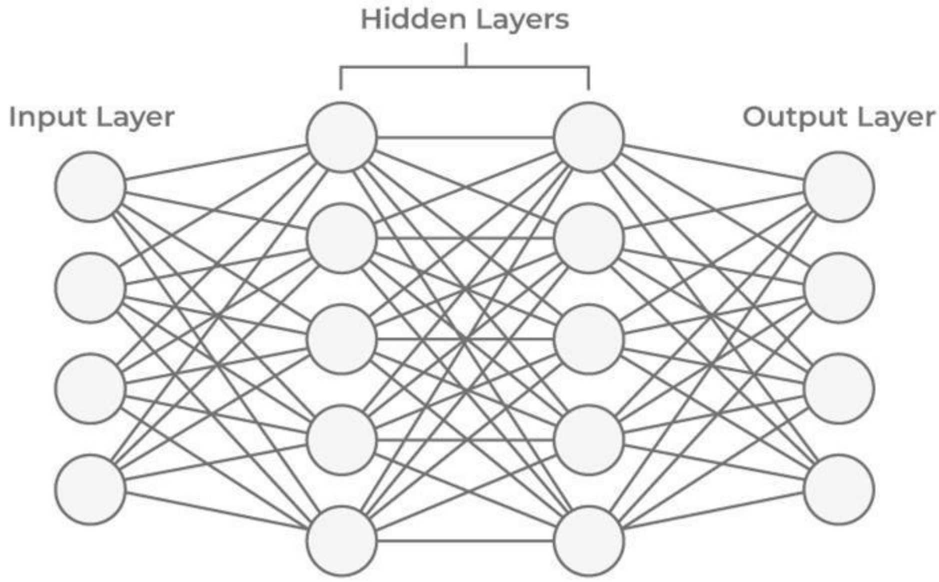
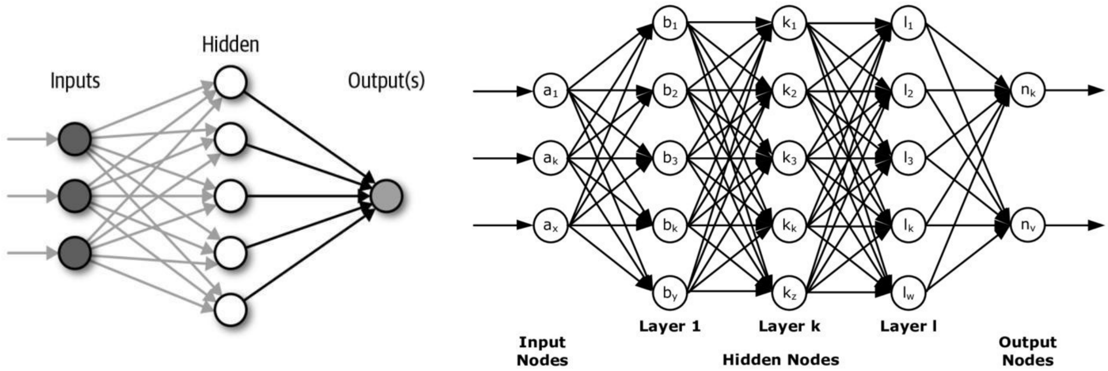


Figure 2.2 – Structure of Artificial Neural Network

❖ **A layered node structure:** The group of square nodes in figure 2.2 is called the input layer. The nodes in the input layer simply act as the passage that transmits the input signals to the following nodes. Therefore, they do not calculate the weighted sum and the activation function. This is why they are indicated by squares and distinguished from the other circular nodes. In contrast, the group of nodes farthest to the right is called the output layer. The output of these nodes becomes the final result of the neural network. The layers between the input layer and the output layer are called hidden layers. They are given this name because they are not accessible from outside the neural network.

When hidden layers are added to a single-layer network, it produces a multilayer neural network. Therefore, the multilayer neural network consists of an input layer, one or more hidden layers, and an output layer. A neural network with a single hidden layer is called a shallow neural network or a vanilla neural network. A multilayer neural network that contains two or more hidden layers is called a deep neural network. Most of the contemporary neural networks used in practical applications are deep neural networks [25].

The neuron network began as a single-layer neural network and evolved into a shallow neural network, followed by deep neural networks. Deep neural networks were not seriously highlighted until the mid-2000s, after two decades since the development of shallow neural networks. Therefore, for a long time, the multilayer neural network meant only the single hidden layer neural network. When the need to distinguish multiple hidden layers arose, a distinct name was given to deep neural networks (figure 2.3).



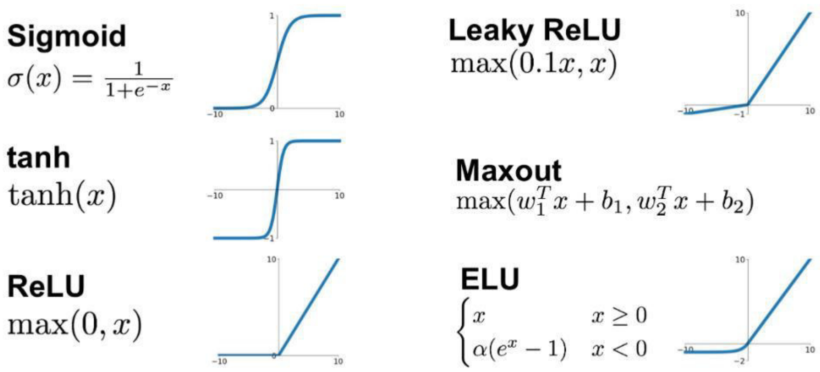
(a) **(b)**

Figure 2.3 – Artificial Neural Network Depend on the Architecture of the Layers, (a) Machine Model, (b) Deep Model

Machine learning models and deep learning models differ primarily in their architectural complexity and application scope. Traditional machine learning models, often referred to as shallow ANNs, typically consist of one or two hidden layers and are well-suited for relatively simple tasks with structured and lower-dimensional data. These models are faster to train, require less computational power, and offer better interpretability, making them practical for straightforward prediction or classification problems. In contrast, deep learning models, or deep ANNs, feature multiple hidden layers that allow them to learn hierarchical and highly abstract representations of data. This deep architecture makes them particularly powerful for solving complex, nonlinear problems such as image processing, speech recognition, or advanced electromagnetic modeling in antenna design. However, deep models demand large datasets, significant computational resources, and careful regularization to prevent overfitting, and they are generally more difficult to interpret.

Whenever we learn something, our brain stores knowledge, the computer uses memory to store information. Although they both store information, their mechanisms are very different. The computer stores information in a specific memory location, while the brain modifies the association of neurons. The neuron itself has no storage capacity; it only transmits signals from one neuron to another. The brain is a gigantic network of these neurons, and the association of neurons forms specific information. The neural network imitates the mechanism of the brain. As the brain is composed of connections of many neurons, the neural network is built with node connections, which are elements that correspond to the neurons in the brain. The neural network mimics the association of neurons, which is the most important mechanism of the brain, using the weight value.

❖ **Activation function**: Activation functions are mathematical formula that determines the output of a processing node. Each unit takes its net input and applies an activation function to it. Non linear functions have been used as activation functions such as logistic, tanh etc. Each function has its strengths and is chosen based on the problem type, network depth, and performance needs. The purpose of the transfer function is to prevent output from reaching very large value which can paralyze neural networks and thereby inhibit training. Transfer functions such as sigmoid are commonly used [26].



Sigmoid: Maps input to a range between 0 and 1. Useful for binary classification but can suffer from vanishing gradients.

Tanh (Hyperbolic Tangent): Outputs values between -1 and 1. It centers data but also faces vanishing gradient issues for deep networks.

ReLU (Rectified Linear Unit): Outputs zero for negative inputs and linear for positive ones. It is computationally efficient and helps mitigate vanishing gradients, making it popular in deep learning.

Leaky ReLU: A variation of ReLU that allows a small gradient for negative inputs, reducing the risk of "dying neurons".

Softmax: Converts outputs into probabilities that sum to one, commonly used in the final layer of classification networks with multiple classes.

ELU (Exponential Linear Unit): Similar to Leaky ReLU but with smoother output transitions for negative values, improving learning in some cases.

Figure 2.4 – Different Activation Function for ANN

2.3. Architectures of Artificial Neural Networks

A neural network architecture (RNA) [27] is a set of formal neurons linked in layers and functioning in parallel. They have the ability to store empirical knowledge and make it available for use. According to the chosen interconnection logic, neural networks are distinguished into two major groups: feed forward networks (static) and recurrent networks (dynamic), as shown in figure 2.5 which illustrates the synoptic diagram of the two respective types of networks.

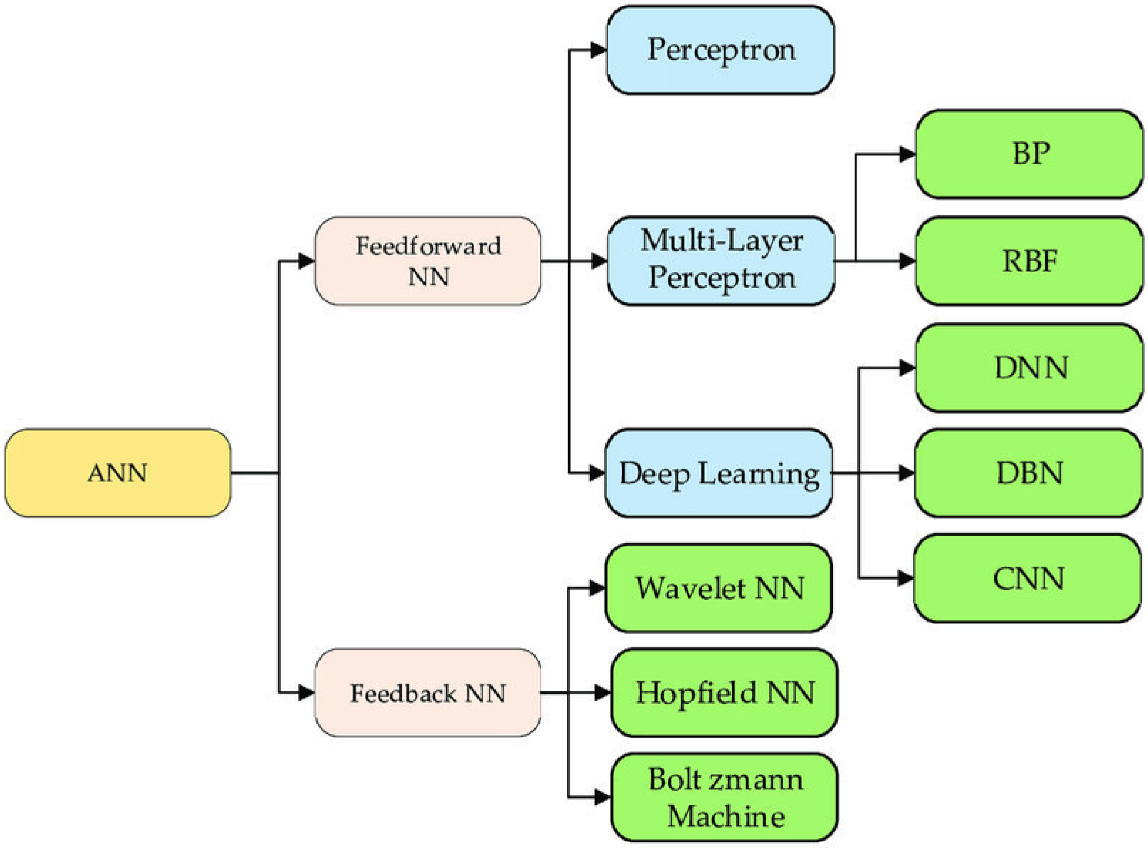


Figure 2.5 - Network Architecture Taxonomy

Network Architecture Taxonomy classifies neural networks based on their structure and connectivity. Broadly, networks are divided into:

❖ **Feedforward Networks (Non-recurrent):** Information flows in one direction — from input to output — without cycles. Examples include:

- **Single-layer Perceptron:** Basic model for simple classification tasks.
- **Multilayer Perceptron (MLP):** Has one or more hidden layers, capable of modeling complex relationships.
- **Radial Basis Function Networks (RBF):** Use radial basis functions as activation functions, ideal for interpolation and approximation tasks.

❖ **Feedback Networks (Recurrent Networks / With loops):** Networks where connections form directed cycles, allowing them to maintain a "memory" of previous inputs. Examples include:

- **Hopfield Networks:** Used for associative memory and optimization problems.
- **Self-Organizing Maps (Kohonen Maps):** Unsupervised learning models for clustering and visualization.
- **Adaptive Resonance Theory (ART) Networks:** Designed for pattern recognition, capable of learning new patterns without forgetting old ones.

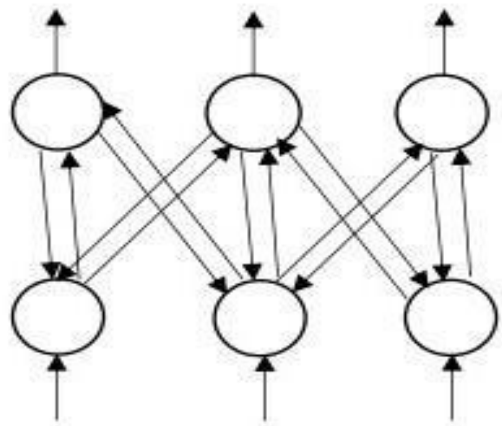
Feedforward architectures are generally used for static pattern recognition, while recurrent ones are suited for dynamic problems like sequence prediction and time-series analysis.

2.3.1. Non-looped neural networks (Static)

An un-looped neural network performs one (or more) algebraic functions of its inputs, by composition of the functions performed by each of its neurons [28]. This network is represented graphically by a set of neurons connected to each other. In such a network, the flow of information flows from the entrances to the exits without "going back". The neurons that perform the final composition calculation function neurons are the output neurons, those that perform intermediate calculations are the hidden neurons. The only constraint on the graph of the connections of a non-neural network loop, is that it does not contain a cycle, so one can imagine a wide variety of topologies for these networks. For example, layers of neurons can be formed by prohibiting any connection between neurons in the same layer and also connections between neurons in the same layer. The majority of applications for neurons bring into play its layered networks. The most popular class of non-layered loops are called Multilayer Perceptrons or MLP in which the hidden layers use a multi-layer threshold or sigmoid.

2.3.2. Looped neural networks (Dynamics)

Also called "recurrent networks" [29], these are networks in which there is a return in Back of Information. This is the most general architecture for a neural network, whose graph of connections is cyclic: in this type of network when you move in the direction of the connections, it is possible to find at least one path that returns to its starting point. The exit of a neuron from the network can therefore be a function of itself; this is obviously not the case appropriate only if the notion of time is explicitly taken into account. At each connection of a looped neuron is attached an integer multiple delay of the chosen unit of time. Looped networks have less memory in the sense that their response, to an input, is independent of the previous state of the network. In other words, the recurring or feedback are dynamic systems.



2.3.3. Multi-Layer Perceptron (MLP)

The most popular form of neural network architecture is MLP as shown in figure 2.6 [25]. There are some of the features of MLP listed as follow:

- ✓ It consists of any number of inputs.
- ✓ It has one or more hidden layers with any number of units.
- ✓ Input layers consist of linear combination functions.
- ✓ Hidden layers consist of sigmoid activation functions.
- ✓ Output layer consist of any activation function It has connections between the input layer and rest hidden layer, between hidden layers and between hidden layer and the output layer.
- ✓ It is an extended Perceptron, with one or more layers hidden between the input and output layers.
- ✓ Due to its extended structure, a Multi-Layer Perceptron can solve any logical operation, including the XOR problem. type Feedforward

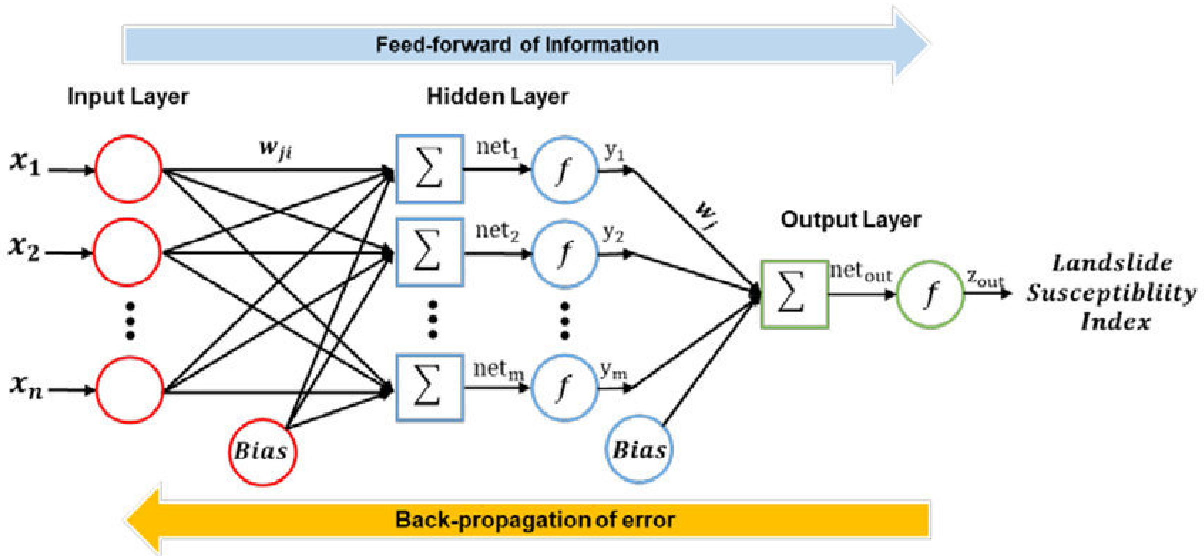


Figure 2.6 - MLP Architecture

The architecture of an MLP is straightforward yet powerful. Its layered structure-with an input layer, one or more hidden layers applying non-linear transformations, and an output layer- allows it to approximate complex functions. The fully connected nature and the training process via backpropagation are key components that enable MLP to learn from data effectively [25].

2.3.4. Convolutional Neural Network (CNN)

The Convolutional Neural Network (CNN) [29] is a specialized deep learning architecture designed to process data with a grid-like topology, such as images. Its architecture is typically composed of several key layers and components that work together to extract and learn hierarchical features. CNNs have a come a long way in recent years. CNNs have been really beneficial for the field of deep learning for computer vision and image processing. In this article, we will be analyzing the common architectures of CNN.

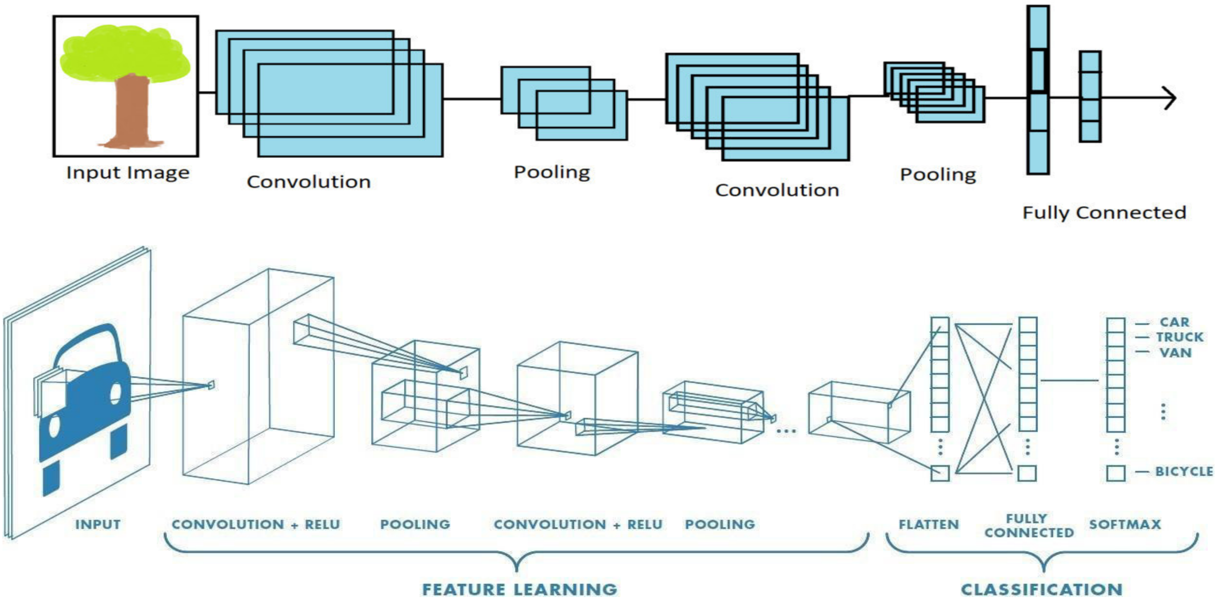
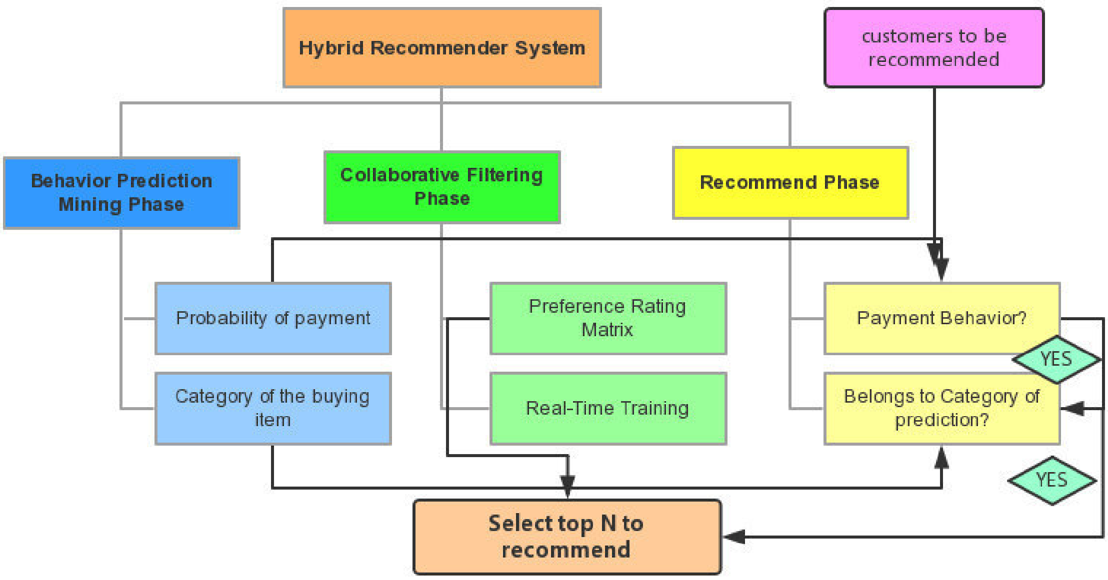


Figure 2.7 - Architecture of Convolution Neural Networks

- **Classic network architecture of convolution neural networks:** It typically follows a structured sequence of layers designed to automatically and adaptively learn spatial hierarchies of features from input images:
  - **Input Layer:** Receives raw pixel data (e.g., an image of size 32×32×3 for a color image).
  - **Convolutional Layers:** Apply multiple filters (kernels) to the input to extract feature maps such as edges, textures, and patterns. Each filter slides over the input image to create an activation map.
  - **Activation Function (typically ReLU**): Introduces non-linearity after each convolution operation to help the network learn complex patterns.
  - **Pooling Layers (Subsampling/Downsampling):** Reduce the spatial dimensions (width and height) of the feature maps while retaining the most important information. Common methods include Max Pooling and Average Pooling.
  - **Fully Connected (Dense) Layers:** After several convolutional and pooling layers, the high-level reasoning in the neural network is done via fully connected layers. These layers connect every neuron from the previous layer to the next.
  - **Output Layer:** Produces the final prediction, usually through a Softmax activation (for classification tasks) or another suitable function.

2.3.5. Hybrid Models

A Hybrid Architecture [26] refers to a system that combines different types of systems, such as connecting multiple SMP machines using a high-speed interconnect or linking small MPP machines that share memory. The choice of a hybrid architecture depends on the specific application's requirements and concurrency needs. Hybrid models in the context of artificial intelligence and machine learning refer to approaches that combine two or more different modeling techniques or paradigms to leverage the strengths of each. These models are designed to address the limitations inherent in any single method by integrating complementary methods. Many organizations need a hybrid approach to analytics, automation, and services because their data is hosted both on-premises and in the cloud. Organizations often extend on-premises data solutions to the cloud. some common aspects and examples of hybrid architecture in AI as shown in figure 2.8 :



Data collection: Simulation and measurement -based dataset generation

Data preprocessing: Normalization - Features selection - Augmentation

Training process: Choosing hyper-parameters - Loss function –Optimizers

Validation techniques: Cross validation - Test dataset - Performance evaluation

Figure 2.8 - Architecture of the Hybrid Model

Optimizers play a vital role in the performance and efficiency of neural networks. The selection of an appropriate optimizer depends on several factors including dataset characteristics, model complexity, convergence speed, and generalization ability. While traditional methods such as SGD remain useful, modern alternatives like Adam, AdamW, and Lookahead have become standard in many deep learning applications.

2.4. Validation Techniques for Artificial Neural Network Models

Validation is a critical process in training artificial neural networks to ensure that the model generalizes well to unseen data. While training focuses on minimizing the loss function on the training dataset, validation assesses the model's performance on a separate dataset that is not used for training. This helps prevent overfitting and guides the selection of hyper-parameters.

❖ **Hold-Out Validation:** This is the simplest method, where the original dataset is split into:

- Training set (e.g., 70–80%)
- Validation set (e.g., 10–15%)
- Test set (e.g., 10–15%)

The model is trained on the training set, and its performance is monitored on the validation set. After training, final performance is reported on the test set.

- Pros: Fast and simple
- Cons: May lead to high variance depending on the data split

❖ **K-Fold Cross-Validation:** The dataset is divided into K equally sized folds. The model is trained K times, each time using a different fold for validation and the remaining K−1 folds for training. The average validation performance across all folds is reported.

- Pros: More reliable estimate of performance
- Cons: Computationally intensive

❖ **Stratified K-Fold Cross-Validation:** A variant of K-Fold that ensures each fold maintains the same class distribution as the entire dataset. It is particularly useful for imbalanced classification problems.

- Pros: Balanced evaluation
- Cons: Slightly more complex implementation

❖ **Leave-One-Out Cross-Validation:** A special case of K-Fold where K = number of samples. Each sample is used once as validation, and the rest for training.

- Pros: Makes full use of the data
- Cons: Extremely computationally expensive for large datasets

❖ **Time-Series Split:** For time-dependent data (e.g., financial, weather, sensor data), data must be split chronologically to preserve temporal order. Typically, the training set precedes the validation set in time.

- Pros: Respects time dependencies
- Cons: Can lead to limited validation size

❖ **Nested Cross-Validation:** Used for both model selection and evaluation, especially when tuning hyper-parameters. An inner loop is used for hyperparameter tuning, while an outer loop evaluates generalization performance.

- Pros: Reduces bias in model selection
- Cons: Computationally expensive.

2.5. Advantages of ANN over Conventional Modeling Methods

- **Learning ability:** One of the main advantages of ANNs is their ability to learn and adapt to new situations. They can be trained on large datasets and learn patterns that are not easily discernible by humans.
- **Non-Linear Relationships:** ANNs are capable of learning non-linear relationships between inputs and outputs, making them useful in a wide
- They can also be adapted to handle different types of data and perform different types of tasks.range of applications such as image and speech recognition.
- **Fault tolerance:** ANNs are also able to tolerate faults, meaning that they can still function correctly even if some of the neurons in the network are damaged or destroyed.
- **Handles missing data:** Another advantage of artificial neural networks is that they remain functional despite noise or errors in data. This makes them suitable in situations with noisy, incomplete, or corrupted data.
- **Parallel processing:** Another advantage of ANNs is their ability to perform many calculations simultaneously, which allows them to process large amounts of data quickly and efficiently.
- **Generalization ability:** ANNs can generalize from examples they have seen during training and apply their learning to new data. This means that they can make accurate predictions even on data they have not seen before
- **Uses large datasets:** Artificial neural networks can learn and generalize from large amounts of data. They can be trained using large datasets and this allows them to make predictions and decisions based on patterns.

2.6. Conclusion

A neural network is an artificial representation of the human brain that attempts to simulate the learning process. The term "artificial" means that neural networks are implemented in computer programs that are able to handle the large number of calculations required during the learning process. Artificial neural networks (ANNs), like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process, connections that exist between the neurons. This is true of ANNs as well, they are composed of layers of interconnected processing units – neurons- that transform input data through a series of weighted connections and activation functions. The ability of ANNs to approximate complex, nonlinear functions makes them powerful tools for modeling, prediction, classification, and optimization tasks.

Chapter 3

ANN-Based Modeling for DGS Patch Antenna Design

3.1. Introduction

In antenna design, engineers often face challenges involving multi-variable optimization, where numerous geometrical and electrical parameters influence the antenna's performance. Parameters such as resonant frequency, bandwidth, gain, efficiency, return loss, and radiation pattern must all be carefully considered. Traditional design methods typically involve full-wave electromagnetic (EM) simulations, parametric sweeps, and manual tuning processes that can be both time-consuming and computationally intensive. ANNs offer a promising alternative by acting as surrogate models or predictive engines that can learn the input-output relationships from previously simulated or measured antenna data. Once trained, an ANN can rapidly predict performance metrics based on input design parameters, or inversely, determine suitable design parameters to achieve target specifications. This greatly accelerates the design process and reduces the computational cost [23].

3.2. ANN Relevance in Antenna Designs

Artificial Neural Networks (ANNs) have emerged as powerful tools in the field of antenna design, offering efficient alternatives to traditional simulation-based approaches. Antenna design is inherently a complex, nonlinear, and multi-parametric problem, involving a wide range of variables such as geometry, materials, frequency response, bandwidth, gain, and radiation patterns. Traditional methods like full-wave electromagnetic simulations, while accurate, are often computationally expensive and time-consuming, especially when multiple design iterations are required.

ANNs address these challenges by learning the intricate relationships between input design parameters and output performance metrics from existing simulation or measurement data. Once trained, an ANN model can predict antenna characteristics (like resonant frequency or return loss) or suggest optimal design parameters with high speed and accuracy. This not only reduces the need for repeated simulations but also enables rapid optimization, real-time analysis, and intelligent design exploration. In modern antenna engineering — especially for complex structures such as microstrip patch antennas, MIMO systems, or antennas for 5G and IoT applications — ANNs enhance the design process by enabling inverse design, tolerance analysis, and performance prediction under various conditions. They can also be integrated with evolutionary algorithms or electromagnetic solvers to create hybrid optimization frameworks [29].

3.3. State of Art of ANN-Based Modeling for Patch Antenna Designs

The design of microstrip patch antennas is a complex and multi-objective optimization problem that involves numerous parameters such as geometry, substrate properties, and operating frequency. Traditional design methods rely heavily on full-wave electromagnetic (EM) simulations, which, although accurate, are often computationally intensive and time-consuming, especially when exploring large design spaces or performing inverse designs. To overcome these limitations, Artificial Neural Networks (ANNs) [30-31] have emerged as efficient surrogate models capable of learning the nonlinear relationships between antenna design parameters and performance metrics such as resonant frequency, return loss, bandwidth, and radiation efficiency.

Early research in this domain, such as that by Patnaik et al. (2000), demonstrated the use of feedforward ANNs to predict the resonant frequency and bandwidth of rectangular patch antennas with reasonable accuracy. Subsequent works expanded the scope to include multi-output models and hybrid approaches combining ANN with optimization algorithms like Genetic Algorithms (GAs) and Particle Swarm Optimization (PSO). These hybrid methods further improved the design accuracy and computational efficiency. Das et al. (2013) presented an ANN-based approach for modeling the input impedance and return loss, showing excellent generalization capability across a wide design space. Recent studies have also explored the use of deep neural networks (DNNs) for more complex antenna structures and multi-layer configurations.

More advanced architectures, including Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, are now being applied to extract spatial and temporal features from high-dimensional design data. These models are often integrated into closed-loop frameworks with EM simulators, where the ANN serves as a fast surrogate model that accelerates convergence during optimization. The work of Abdelrahman et al. (2021) offers a comprehensive review of hybrid machine learning approaches in antenna design, emphasizing the growing role of ANN in reducing simulation cost, enhancing prediction accuracy, and enabling real-time design feedback. Overall, ANN-based modeling is becoming a cornerstone methodology for modern patch antenna design, particularly in the development of compact, high-performance antennas for 5G, IoT, and wearable applications.

3.4. Patch Antenna EM Design

3.4.1. Designing Tools

Various software tools are used in this study. Below is a concise presentation of each, along with its role in the modeling task:

- **HFSS:** It is 3D high-frequency electromagnetic simulation software developed by ANSYS. It is based on the finite element method (FEM) to solve Maxwell's equations. It enables precise analysis of complex structures such as antennas, waveguides, and RF/microwave components, by providing key results including scattering parameters (S), impedances, reflectance factors (VSWR), and the spatial distribution of electromagnetic fields.
  HFSS is used for designing an initial structure of a rectangular patch antenna and extracting its EM response. It allows defining parameters and varying them during simulation to understand the antenna response’s behavior and extract the needed data set. One of the advantages of HFSS is its ability to directly provide the return loss parameter (S_{11}), the voltage standing wave rate (VSWR) and impedance parameters (Z) as a function of frequency.
- **Python and Google Co-Lab:** It is an open-source programming language known for its simplicity, readability, and extensive scientific libraries, such as NumPy, Pandas, TensorFlow, and Keras. It is used to develop the ANN to allow data processing and antenna modeling. It is mainly employed to train and evaluate the applied machine learning model**.** Google Co-Lab, is a also a free platform offered by Google that allows users to write and execute Python code directly in their web

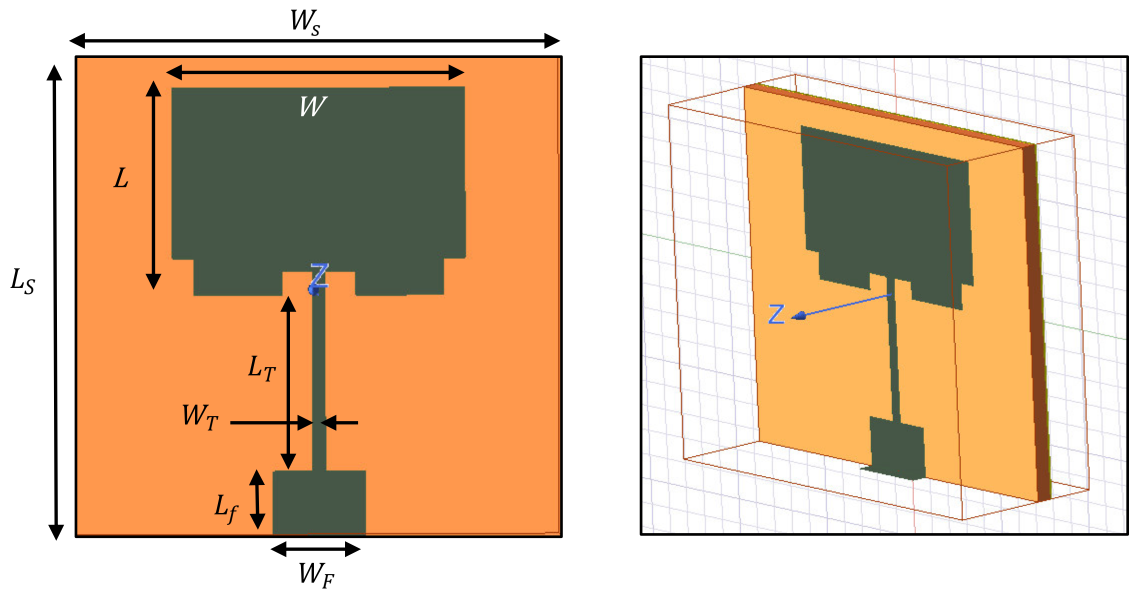
browser. It enables the execution of Jupyter notebooks without the need to worry about hardware specifications or software installations. This tool is particularly useful in the fields of artificial intelligence, data processing and machine learning. It allows easy access to computing resources (CPU, GPU, TPU) as well as libraries commonly used for developing, training and evaluating models, including artificial neural networks.

3.4.2. Initial Patch Antenna Design

The explored patch antenna [32] is of a rectangular shape. It has been designed using HFSS to meet the specifications defined as follows:

- ✓ A dielectric substrate of Rogers RT/duroid 6002 having a permittivity $\varepsilon_r = 2.49$, a thickness $h = 0.32\ mm$ and a tangent loss $\delta = 0.001$
- ✓ A direct microstrip feed line that is assumed to be 50Ohms.
- ✓ A wide frequency range from 60 to 66 GHz.
- ✓ An implemented patch and ground plane using copper.
- ✓ An overall size of 7.91×7.2 mm^2 for the proposed antenna.

Figure 3-1 illustrates the initial antenna structure obtained by using matching technique that involves inserting notches at the corners of the rectangular patch to achieve the target goal for the desired frequency. Initial antenna dimensions are summarized in table 3-1. The initial patch antenna EM response is displayed in figure 3.2 that is of -24dB of return loss and 1,13 of voltage standing wave rate at the resonance frequency which is equals to 60.66GHz.

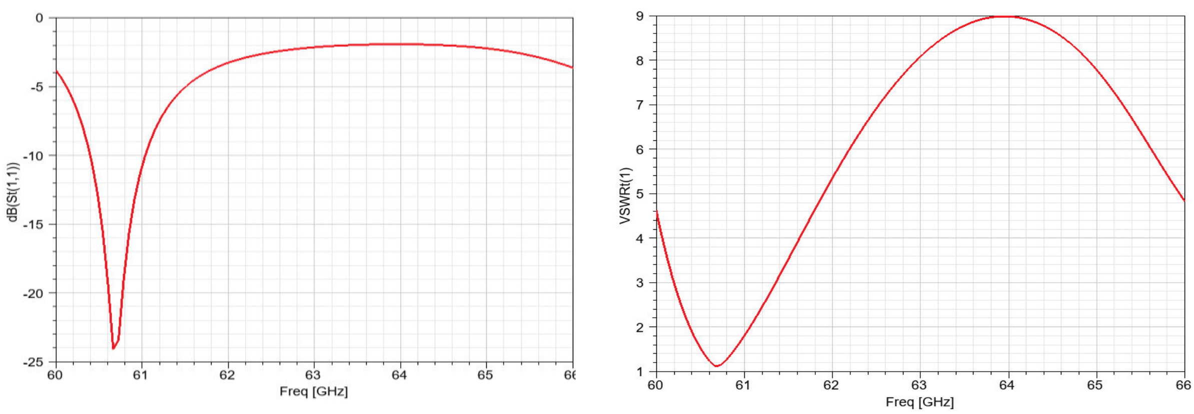


(a) (b)

Figure 3.1 - Initial patch antenna design, (a) 2D / (b) 3D view in HFSS

Table 3.1 - Geometric dimensions of the initial patch antenna design

Parameters		**Value (mm)**
Ground plane	Width (W_g)	7.91
	Length (L_g)	7.2
Substrate	Width (W_S)	7.91
	Length (L_S)	7.2
Patch	Width (W)	4.73
	Length (L)	3.055
Transformer	Width (W_T)	0.2
	Length (L_T)	2.5
Feedline	Width (W_F)	1.5
	Length (L_F)	1



(a) (b)

Figure 3.2 – Initial patch antenna EM response, (a) return loss (S_{11}), (b) voltage standing wave rate (VSWR)

3.4.3. DGS Implementation to the Patch Antenna Design

Defected Ground Structure (DGS) technique has been introduced to enhance the electromagnetic performance. This method involves creating a specific slot in the ground plane, which alters the propagation characteristics of electromagnetic waves and reduces unwanted effects such as surface waves, spurious resonances, and undesirable coupling. In this design, a π-shaped slot has been modeled in the ground plane using HFSS, known for its ability to improve impedance matching and reduce losses.

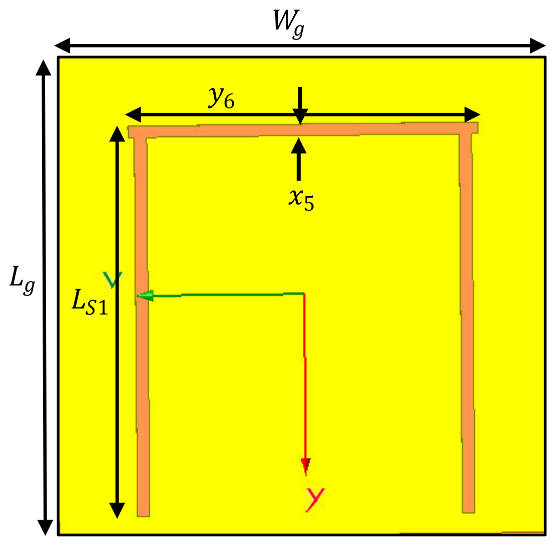
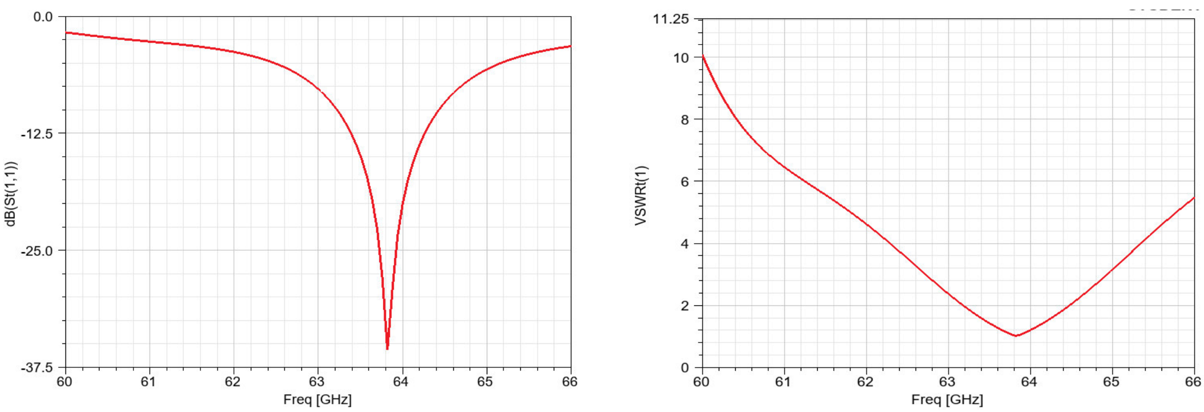


Figure 3.3 – Implemented DGS geometry



(a) **(b)**

Figure 3.4 – DGS patch antenna EM response, (a) return loss (S_{11}), (b) voltage standing wave rate (VSWR)

It is clearly shown that the antenna achieves a good reflection level of approximately -35.60dB and good voltage standing wave rate of 1.03 at 63.81GHz due to the good impedance matching.

3.5. ANN-Based Modeling for Patch Antenna Design

3.5.1. Data Collection

Upon finalizing, the antenna design stage, a data collection process has been initiated as a crucial step for building a training dataset for subsequent modeling using ANN. This phase involved defining the input variables of the antenna, performing multiple simulations through parametric sweep techniques using HFSS and extracting the necessary data including the reflection coefficient (real and imaginary parts).

The input variables primarily consisted of the geometrical characteristics of both patch and DGS, in addition to operating frequency. These variables were chosen due to their direct impact on the electromagnetic behavior of the antenna. Each parameter was assigned a variation range and a number of sweep points (count) to ensure the generation of diverse and sufficient data. The table 3.2 below summarizes the selected parameters, their respective variation ranges, and the number of values used in each sweep:

Table 3.2 - Input parameters for data collection

Dimensions	Bottom	Top	Count
Freq (GHz)	60	66	100
L_{s1} (mm)	5.4	5.9	6
X_3 (mm)	0.32	0.37	6
X_5 (mm)	0.175	0.17505	6
Y_6 (mm)	5.5	6	6

HFSS automatically ran a series of simulations, where different sets of geometric parameters were applied in each run. For each simulation, the antenna's response was extracted in the form of the reflection coefficient. The output data included both its real and imaginary parts which will later serve as output values for training the ANN model. After completing all simulations, the antenna's performance is analyzed by evaluating the variation of the reflection coefficient across the frequency range from 60GHz to 66GHz. This parameter is essential for assessing impedance matching and identifying the resonance frequency.

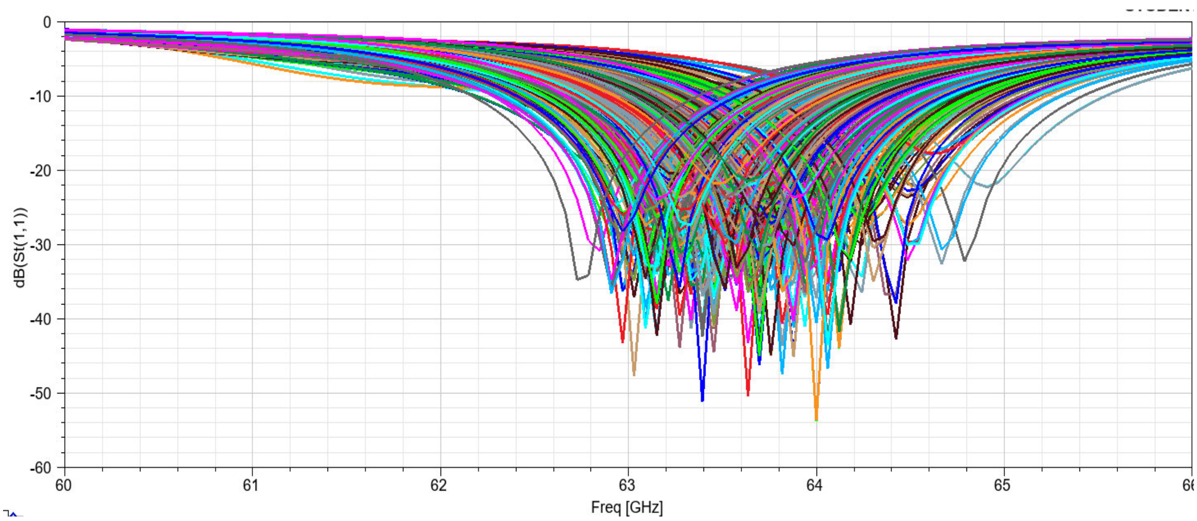


Figure 3.5 - Representation of reflection coefficient sweeps as a function of resonance frequency

Upon completing the simulations and collecting the results, the data was organized and stored directly using HFSS. This dataset includes all input variables for each simulation, along with the corresponding output results represented by the real and imaginary parts of the reflection coefficient. This dataset plays a key role in training and validating ANN model, which is designed to predict the antenna's electromagnetic behavior based on its geometrical configuration and operating frequency.

3.5.2. ANN Model

A neural network architecture is chosen in a way that suits the design problem solving according to collected data characteristics by considering the number of layers, the types of activation function and the connectivity schemes based on the complexity of the problem and the available computing resources. In this study, the develop ANN model is illustrated by the figure 3.6 below:

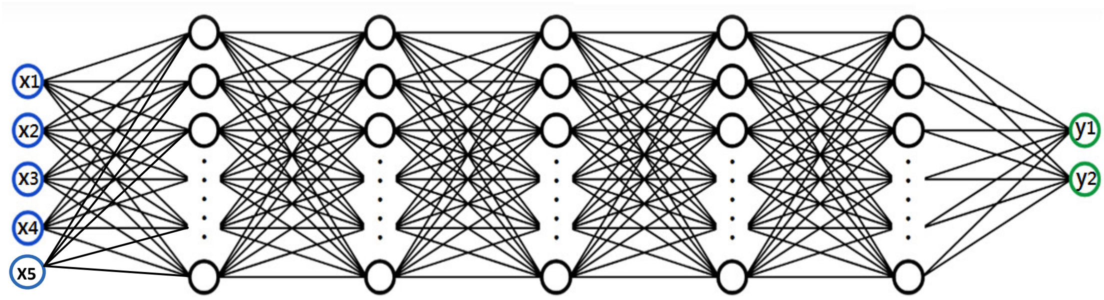


Figure 3.6 – developed ANN topology

Inputs are the geometric DGS parameters including (L_{s1}, x_3, x_5, y_6) in addition to the operating frequency. Lets $x = [x_1, x_2, x_3, x_4, x_5]$ represent the vector of the model's inputs, and lets $y = [y_1, y_2]$ represent the vector of the model's outputs. The vector y contains the real and imaginary parts of the S_{11} parameters. Five hidden layers were used with ReLU and sigmoid activation functios as shows the figure 3.7:

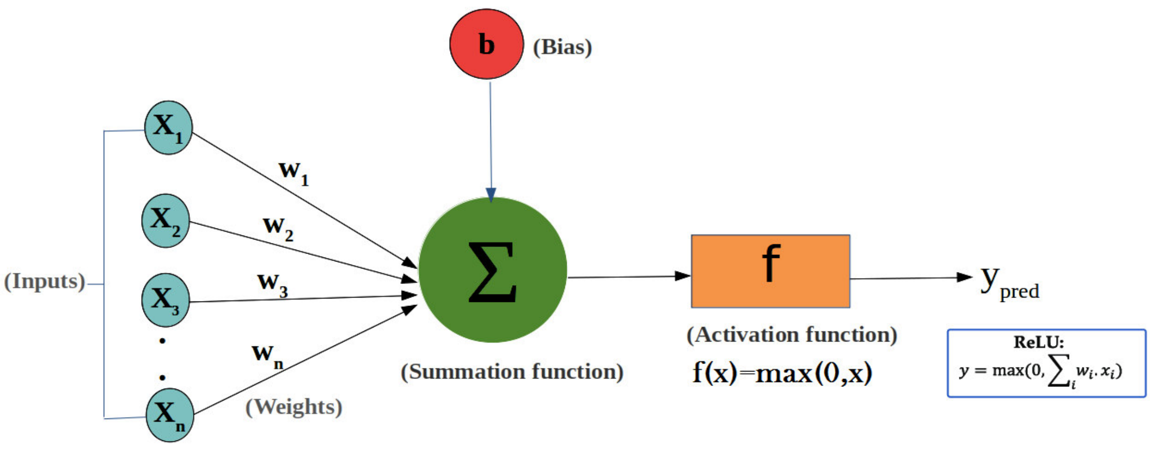


Figure 3.7 – Developed ANN model of a single neuron

The network initializes the weights (*w*) and biases (*b*) randomly for each neuron in the network, then it takes the input data and propagates it forward through the layers to calculate the final output. The input layer consists of 5 neurons, each representing one input feature, each neuron in the input layer multiplies its corresponding input value with its weight and sums them up with the bias term.

The ReLU activation function is then applied to the weighted sum, which sets negative values to 0 and keeps positive values unchanged. Similarly, the above steps are repeated for each neuron in each hidden layer, propagating the inputs forward through the network. The network compares the predicted outputs with the desired outputs and calculates the loss or error. This can be done using a suitable loss function, such as mean squared error (MSE) or cross-entropy loss.

Backpropagation is the process of updating the weights and biases to minimize the loss, the network calculates the gradients of the loss with respect to the weights and biases using the chain rule of calculus, these gradients indicate how much each weight and bias contributes to the overall loss, and they are used to update the weights and biases in the opposite direction of the gradient, thereby reducing the loss. The weights and biases are updated using an optimization algorithm, such as stochastic gradient descent (SGD), multiplied by a learning rate to control the step size of the updates.

3.5.3. Training Stage

Training the ANN model involves the process of iteratively presenting the training dataset to the model, calculating the loss, and updating the model's internal parameters to minimize prediction errors. Steps involved in training are:

- **Define the training process and the loss function:** The number of epochs (iterations) is specified. An appropriate loss function is chosen to measure the discrepancy between the model's predicted outputs and the true outputs in the training dataset.
- **Select an optimizer:** An optimization algorithm is selected to update the model's parameters based on the calculated loss.
- **Training loop:** The training dataset is iterated for the specified number of epochs. In each epoch, present the input samples to the model and obtain the predicted outputs. Compare the predicted outputs with the true outputs and calculate the loss using the chosen loss function.
- **Backpropagation and parameter update:** A backpropagation is performed to calculate the gradients of the loss with respect to the model's parameters. The optimizer updates the model's parameters accordingly, using the gradients and the chosen optimization algorithm.
- **Monitor training progress:** During training, monitor and log metrics such as loss, accuracy, or other relevant evaluation metrics on the training set. This allowed to assess the model's performance and detect any potential issues.
- **Validation set evaluation:** The model's performance is periodically evaluated on a separate validation dataset to assess its generalization capabilities and prevent overfitting.
- **Hyperparameter tuning:** Different hyperparameter values such as learning rate, batch size and/or regularization techniques are experimented to find the best combination that maximizes the model's performance on the validation set.

- **Iterate and refine:** Based on the evaluation results, the model is refined to adjust hyperparameters, introduce regularization techniques and/or modify the network architecture as necessary.
- **Test set evaluation:** Finally, the model's performance is assessed on a separate test dataset that was not used during training or validation. Relevant metrics are evaluated to gauge the model's generalization capabilities.

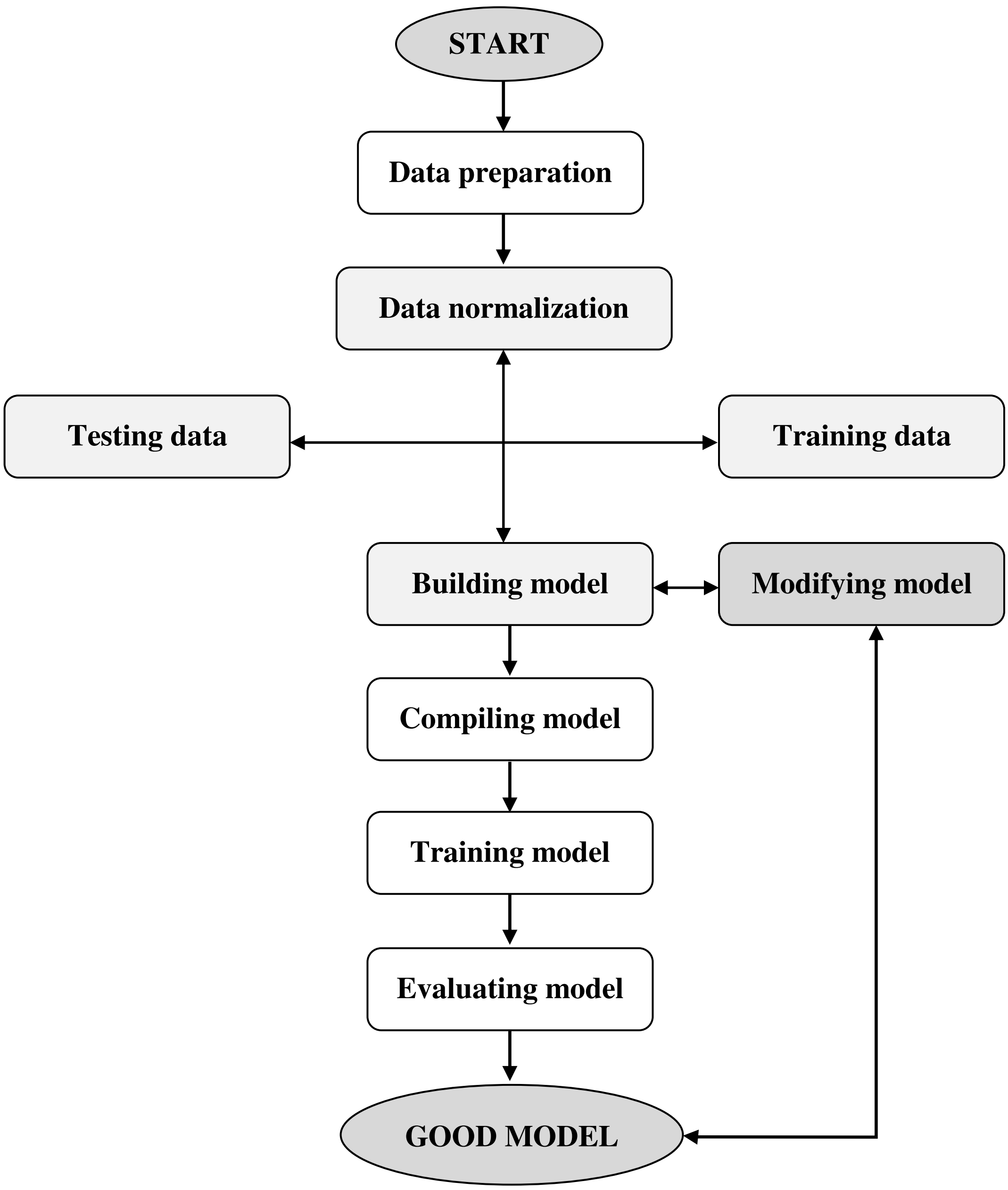


Figure 3.8 - Overall development process diagram of the developed ANN model

A python simulation script is used to train the ANN model training because it allows customizing various aspects of the network, facilitating a deeper understanding of neural networks and their applications. The general process of the developed ANN model parametric model based python is illustrated by figure 3.8 above.

❖ **Step 1- Data preparation:** Starting with collecting the data and preprocessing it.

	Ls1	x3	x5	y6	Freq	Re(s11)	Im(s11)
0	5.4	0.32	0.17500	5.5	60.000000	-0.589368	0.607050
1	5.4	0.32	0.17500	5.5	60.060606	-0.572109	0.613097
2	5.4	0.32	0.17500	5.5	60.121212	-0.554684	0.618300
3	5.4	0.32	0.17500	5.5	60.181818	-0.537146	0.622637
4	5.4	0.32	0.17500	5.5	60.242424	-0.519555	0.626087
...	...	...	...	...	...	...	...
129695	5.9	0.37	0.17505	6.0	65.757576	-0.597119	0.443108
129696	5.9	0.37	0.17505	6.0	65.818182	-0.591530	0.454572
129697	5.9	0.37	0.17505	6.0	65.878788	-0.585703	0.465731
129698	5.9	0.37	0.17505	6.0	65.939394	-0.579652	0.476592
129699	5.9	0.37	0.17505	6.0	66.000000	-0.573391	0.487158

129700 rows × 7 columns

❖ **Step 2 - Normalization and standardization:** Normalizing features involves adjusting all features to a common scale, which improves the accuracy of ANN detection.

❖ **Step 3 – Training and testing model:** This line trains the model using the training features (***x* train**) and training labels (***y* train**). The training is performed for 100 epochs, where an epoch represents a complete pass through the entire training dataset.

Figure 3.9 - Training and testing dataset split

❖ **Step 4 - Implementation of ANN model:** Use the trained model to predict S-parameters for new geometric configurations.

```
# Build regression ANN model
model = tf.keras.Sequential([
    tf.keras.layers.Dense(256, activation='sigmoid',input_shape=(5,)),
    tf.keras.layers.Dense(512, activation='relu'),
     tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dense(64, activation='relu'),
     tf.keras.layers.Dense(512, activation='relu'),
     tf.keras.layers.Dense(128, activation='relu'),
     tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dense(2) # Output a single continuous value
])

# Compile model
model.compile(optimizer='adam', loss='mse', metrics=['mae'])

# Train the model
model.fit(X_train, y_train, epochs=100, verbose=1)
```

Table 3.3 - Make prediction

Iteration	**Real of S_{11}**	**Imaginary of S_{11}**
Real value	-0.12325997	-0.11197192
Predicted value	-0.14129093	-0.1114959
Real value	-0.42618481	-0.07313558
Predicted value	-0.42236537	-0.05730164
Real value	-0.47033788	-0.04204915
Predicted value	-0.47152174	-0.0215576

❖ **Step 5 – Test evaluation:** In this case the mean square error on the error metric is chosen to evaluate the developed ANN model. The mean square error metric calculate the average magnitude of the errors between the actual and predicted values : $MSE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_{ai} - Y_{pi}\right|^2$

```
# model.evaluate returns a list of metrics when multiple are specified
evaluation_results = model.evaluate(X_test, y_test)

# Access the individual loss and metric values from the list
test_loss = evaluation_results[0]
test_mae = evaluation_results[1]

print(f'Test loss:{test_loss:.6f}')
print(f'Train loss:{test_mae:.6f}') # Also print the MAE for clarity
```

3.6. Results and Discussion

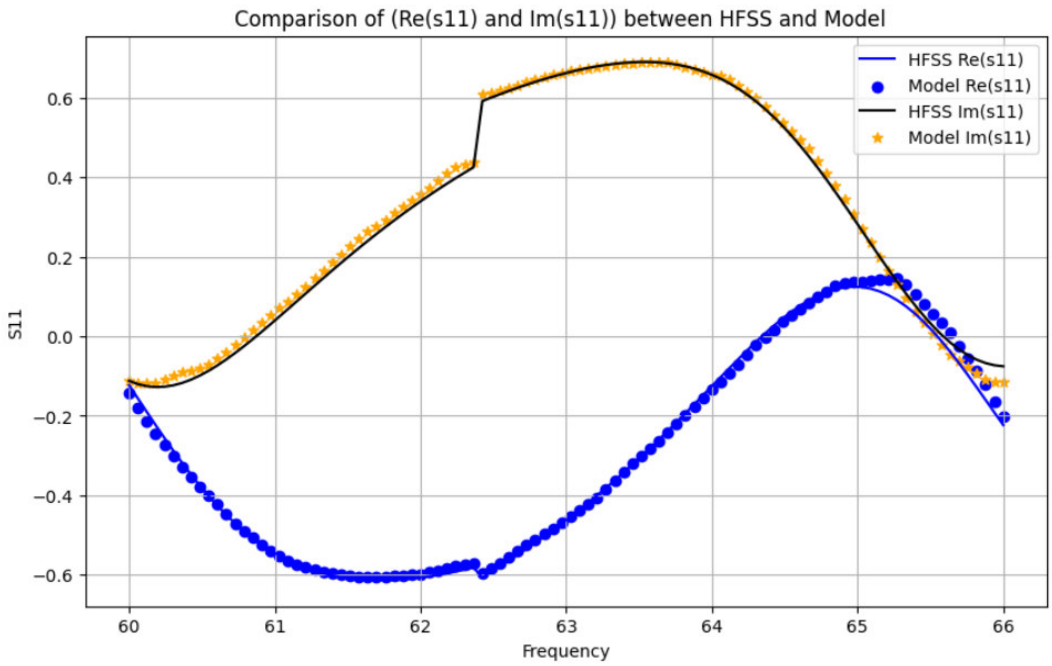


Figure 3.10 - Comparison of S_{11} parameter between simulated and predicted values

From figure 3.10, it is clearly observed that a successful alignment of both real and imaginary values of S_{11} parameter as provided by the HFSS and predicted by the developed ANN model is obtained. This comparison has been made using a data test by X_Test = [5.8 0.36 0.17504 5.9] that falls in the range of 0 to 100 at the first simulation .

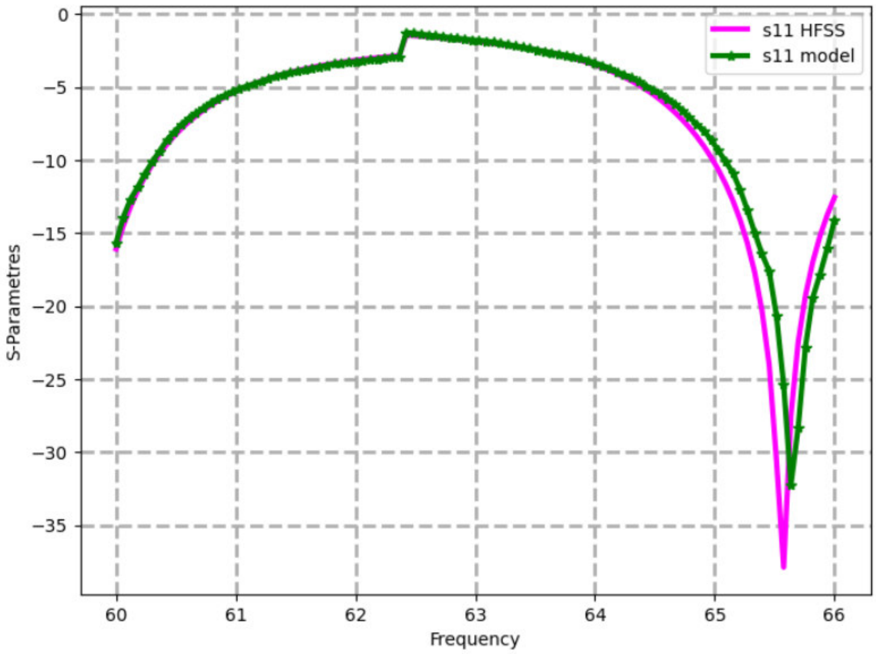


Figure 3.11 – Comparison of S_{11} magnitude between simulated and predicted values

The magnitude of S_{11} parameter is also plotted as function of frequency for both the true values and the predicted values of the selected data (figure 3.11). The figure compares the magnitude values of a data set with the predicted values from a model. The data test of X_Test = [5.8 0.36 0.17505 5.9] falls in the range of 600 to 700. From the assumption that the output results are almost good. The predicted values closely align with the magnitude values of the data set, indicating accurate predictions.

The phase of S_{11} parameter built by the ANN model (figure 3.12) closely match the target simulated values, demonstrating a high level of accuracy in the simulation of X_Test = [5.8 0.36 0.17505 5.9] which is from data test between 1600 and 1700 that builds confidence in the model's predictive ability.

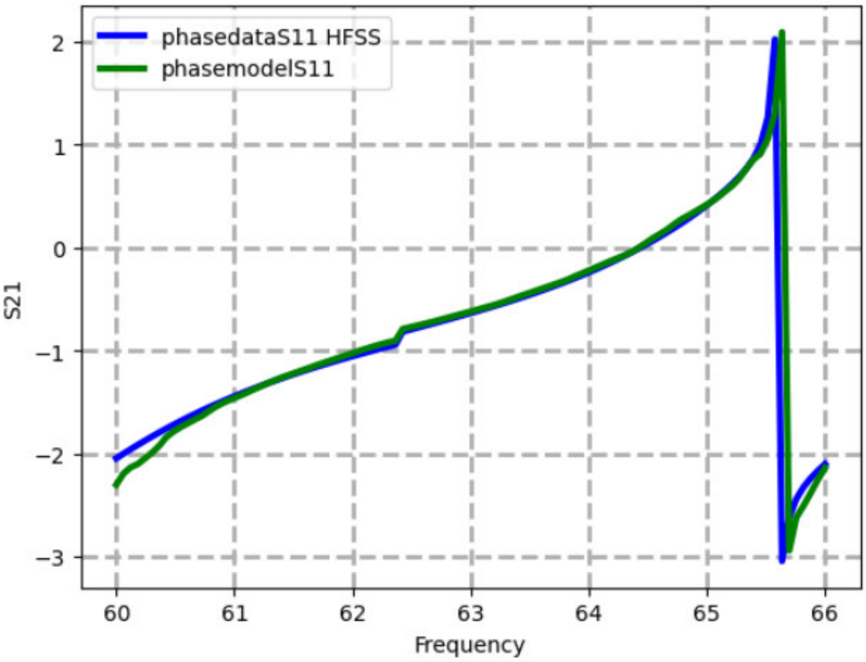


Figure 3.12 – Comparison of S_{11} phase between simulated and predicted values

```
Epoch 83/100
3243/3243 ━━━━━━━━━━━━━━━━━━━━ 22s 7ms/step - loss: 6.0178e-04 - mae: 0.0160
Epoch 84/100
3243/3243 ━━━━━━━━━━━━━━━━━━━━ 24s 7ms/step - loss: 5.9403e-04 - mae: 0.0159
Epoch 85/100
3243/3243 ━━━━━━━━━━━━━━━━━━━━ 40s 7ms/step - loss: 6.0313e-04 - mae: 0.0162
Epoch 86/100
3243/3243 ━━━━━━━━━━━━━━━━━━━━ 40s 7ms/step - loss: 5.8788e-04 - mae: 0.0158
Epoch 87/100
3243/3243 ━━━━━━━━━━━━━━━━━━━━ 24s 7ms/step - loss: 5.9586e-04 - mae: 0.0158
Epoch 88/100
3243/3243 ━━━━━━━━━━━━━━━━━━━━ 41s 7ms/step - loss: 5.9823e-04 - mae: 0.0160
Epoch 89/100
3243/3243 ━━━━━━━━━━━━━━━━━━━━ 41s 7ms/step - loss: 5.9082e-04 - mae: 0.0158
Epoch 90/100
3243/3243 ━━━━━━━━━━━━━━━━━━━━ 24s 7ms/step - loss: 5.9283e-04 - mae: 0.0159
Epoch 91/100
3243/3243 ━━━━━━━━━━━━━━━━━━━━ 41s 7ms/step - loss: 5.8553e-04 - mae: 0.0158
Epoch 92/100
3243/3243 ━━━━━━━━━━━━━━━━━━━━ 41s 7ms/step - loss: 5.9819e-04 - mae: 0.0159
Epoch 93/100
3243/3243 ━━━━━━━━━━━━━━━━━━━━ 41s 7ms/step - loss: 5.8512e-04 - mae: 0.0157
Epoch 94/100
3243/3243 ━━━━━━━━━━━━━━━━━━━━ 23s 7ms/step - loss: 5.9201e-04 - mae: 0.0157
Epoch 95/100
3243/3243 ━━━━━━━━━━━━━━━━━━━━ 23s 7ms/step - loss: 5.7929e-04 - mae: 0.0157
Epoch 96/100
3243/3243 ━━━━━━━━━━━━━━━━━━━━ 24s 8ms/step - loss: 5.9366e-04 - mae: 0.0158
Epoch 97/100
3243/3243 ━━━━━━━━━━━━━━━━━━━━ 41s 8ms/step - loss: 5.8625e-04 - mae: 0.0157
Epoch 98/100
3243/3243 ━━━━━━━━━━━━━━━━━━━━ 24s 7ms/step - loss: 5.8814e-04 - mae: 0.0157
Epoch 99/100
3243/3243 ━━━━━━━━━━━━━━━━━━━━ 23s 7ms/step - loss: 5.8362e-04 - mae: 0.0156
Epoch 100/100
3243/3243 ━━━━━━━━━━━━━━━━━━━━ 24s 8ms/step - loss: 5.7938e-04 - mae: 0.0156
811/811 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.0053 - mae: 0.0503
Mean Absolute Error on Test Set: 0.05
```

Figure 3.13 – Test results (mean absolute error metric)

Foundational steps have been required to build effective ANN model, from data preprocessing to training, testing, evaluating then deployment. The developed ANN model presents an efficient tool in designing the explored DGS patch antenna. A specific synthesis is defined as the forward side and then analysis as the reverse side of the problem. Therefore, using the geometric DGS dimensions at the output of the synthesis network can predict the response of the patch antenna which are the real and imaginary parts of S_{11} with high accuracy and very low MAE (figure 3.13).

3.7. ANN-based Patch Antenna Advantages

The use of ANNs in the design and analysis of patch antennas is becoming increasingly popular due to their ability to model complex and nonlinear relationships. Main advantages of using ANN in antenna design can be summarized as follows [14]:

- **Fast and accurate design optimization**: Reduce the time and computational cost which is involved in traditional design methods like full-wave EM simulations. Provide quick predictions of antenna parameters (e.g., resonant frequency, gain, bandwidth) based on geometric and material inputs.
- **Inverse design capabilities**: Enable inverse modeling, where desired antenna performance metrics (e.g., bandwidth, frequency) are given, and the ANN predicts the optimal design parameters.
- **Nonlinear function approximation:** Model the "complex, nonlinear behavior" of patch antennas that may not be easily described by analytical equations.
- **Multi-objective optimization**: Simultaneously optimize several performance metrics (e.g., bandwidth, gain, return loss) using ANN models in conjunction with optimization algorithms like GA or PSO.

- ❖ **Adaptive and Intelligent Design:** Allow for self-learning and adaptability in design processes. Improve performance with iterative learning.
- ❖ **Efficient parametric studies:** Rapidly explore the effect of varying parameters (e.g., substrate thickness, dielectric constant, patch dimensions) on antenna performance.
- ❖ **Integration with CAD tools**: Serve as a surrogate model in design software to accelerate the optimization loop within electromagnetic solvers.

3.8. Conclusion

Engineers frequently encounter complex multi-variable optimization problems in antenna design, where numerous geometric and electrical parameters significantly affect performance. Key factors such as resonant frequency, bandwidth, gain, efficiency, return loss, and radiation pattern must be meticulously evaluated. Conventional design approaches rely heavily on full-wave electromagnetic (EM) simulations, parametric analyses, and manual tuning, which are often both time-consuming and computationally demanding. Artificial Neural Networks (ANNs) present a compelling alternative by serving as surrogate models capable of learning the relationships between design inputs and performance outputs from prior simulations or experimental data. Once trained, ANNs can swiftly predict performance metrics from given design parameters or inversely determine optimal design configurations to meet specific targets. This significantly streamlines the design workflow and minimizes computational overhead.

General Conclusion

This study has demonstrated the potential of leveraging artificial intelligence particularly artificial neural networks (ANNs)to model and optimize a patch antenna incorporating a Defected Ground Structure (DGS). The primary objective was to highlight how AI techniques can be utilized to enhance antenna performance while significantly reducing design costs and development time.

We began by conducting a comprehensive analysis of the electromagnetic characteristics of patch antennas, with a specific focus on the role of DGS in improving performance metrics. This investigation underscored key challenges in antenna design, including miniaturization, bandwidth enhancement, and the optimization of operational parameters.

Subsequently, we examined the fundamental concepts of artificial neural networks, detailing their structure, operating principles, and the various architectural types both static and dynamic. This theoretical foundation was essential to support their application in the field of electromagnetic modeling.

The final phase of this work presented a practical implementation of ANN for the modeling and optimization of a 64GHz DGS patch antenna. Using a dataset generated through electromagnetic simulations, we trained an ANN capable of accurately predicting critical performance parameters such as resonance frequency, bandwidth, and gain based on geometric inputs.

The results validated the ANN’s capacity to reduce design time and effectively optimize antenna parameters, all while maintaining a high level of predictive accuracy. These findings confirm the relevance of integrating ANN as intelligent tools in antenna design processes. Looking forward, several avenues for further research can be identified:

- ❖ Expanding the training dataset to encompass a wider variety of antenna geometries and frequency bands;
- ❖ Investigating alternative AI methodologies, such as convolutional neural networks or evolutionary algorithms;
- ❖ Conducting experimental validation of the proposed configurations to reinforce the credibility of the simulation-based results.

Finally, this study demonstrates that the incorporation of ANN into the antenna design process that offers a fast, effective, and cost-efficient approach. Future work aiming at broadening the learning scope, applying advanced AI architectures, and validating results experimentally could further enhance the robustness and applicability of this methodology.

References

References

1- A. B. Constantine, «Antenna theory: analysis and design», MICROSTRIP ANTENNAS, third Ed. John wiley sons, 2005.

2- J. Bahl and P. E. Bharton, «Microstrip antennas »,Dedham, MA: Artech House, 1980.

3- Barkat Ouarda « Etude et synthèse des caractéristiques de réseaux d'antennes imprimées supraconductrices dans la bande millimétrique » ,Thèse de doctorat de l'université Mentouri Constantine décembre 2009.

4- Pozar, David M, «Microwave Engineering»,FourthEd. John Wiley & Sons, 2011.

5- Yi . Huang , K. Boyle «ANTENNAS FROM THEORY TO PRACTICE»,first Ed. John Wiley & Sons,2008.

6- A. Achit , and C. Hamza , « Conception et réalisation d'un nouveau système d'antennes MIMO pour le standard 5G»Mémoire de Master del'université Akli Mohand Oulhadj Bouira 2023.

7- S. K. Dash and S. R. Khuntia, Fundamentals of electromagnetic theory. 2011.

8- D. M. Pozar and B. Kaufman, «Increasing the bandwidth of a microstrip antenna by proximity coupling»,Electron. Lett., vol. 23, no. 8, pp. 368–369, 1987.

9- V. Rathi, G. Kumar, and K. P. Ray, « Improved coupling for aperture coupled microstrip antennas», IEEE Trans. Antennas Propag., vol. 44, no. 8, pp. 1196–1198, 1996.

10- J. D. Kraus. R. J. Marhefka, « Antenna for all application »,3rd Ed., McGraw-Hill,2002.

11- A.A. Kishk, «Modern Antenna Designs for Wireless Systems», IEEE Antennas and Propagation Magazine, vol.52, no.3,2010.

12- R. Garg ,P.Bhartia, I. Bahl and A. Ittipiboon ,«Microstrip Antenna Design Handbook»,Artech House,2000.

13- A. Bhardwaj, K. Singh, «Wearable Antennas for Body Area Networks: A Review », Microwave Review, vol. 25, no. 1, 2019.

14- I. Elfergani,«Reconfigurable Patch Antennas for Modern Wireless Systems», Springer, 2018.

15- S. Singh, «AI-driven Patch Antenna Optimization Techniques», Procedia Computer Science, vol. 167, pp. 2315-2322, 2020.

16- K. Jha, G. Singh,«Broadband Microstrip Antennas for 5G Applications», IEEE Access, vol. 8, pp. 163123-163132, 2020.

17- R. Ahmed Serier , Y. Louzri ,‟ Optimisation et Conception d'une Antenne Miniatur pour les Applications 5G, Intégrant les Techniques DMS et DGS», Mémoire de Master. Blida

18-AN Introduction To Artificial Neural Network, Harsh Kukreja1, Bharath N1, Siddesh C S1 , Kuldeep S2, Department Of Electrical & Electronics Engineering, School Of Engineering & Technology, Jain, University, Bangalor.

19-Artificial Neural Networks - Prof. Crescenzio Gallo Basic concepts

20-Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research, S.Agatonovic-Kustrin *,R. Beresford,School of Pharmacy, University of Otago, PO Box 913, Dunedin, New Zealand

21-Data Processing Using Artificial Neural Networks, Written By Wesam Salah Alaloul and Abdul Hannan Quresh.

22- Artificial Neural Networks Basic concepts Prof. Crescenzio Gallo, Étude et simulation des performances d'une antenne micro-rubans á base des réseaux de neurones (cas d'une antenne rectangulaire).

23- Deep Learning Goodfellow, I., Bengio, Y., & Courville, A. (2016).. MIT Press.

24- Artificial Neural Networks: An Introduction De Kevin L. Priddy, Paul E. Keller

25- Artificial Neural Networks: An Introduction, De Kevin L. Priddy, Paul E. Kelle, Chollet, F. (2018). Deep Learning with Python. Manning Publications.

26- Neural Networks and Deep Learning. Nielsen, M. (2015).

27- Hybrid Recommender System Based On Personal Behavior Mining, Articel: hybrid work mode lbycarolyn Heinze

28- Hands-On Machine Learning with Scikit-Learn, Géron, A. (2019)., Keras, and tensorflow. O'Reilly Media.

29- Advantages and Disadvantages of Artificial Neural Networks, Posted on May 24, 2024 by Alex Ivankov

30- Artificial neural network based design of microstrip antennas, Patnaik, L. M., & Mishra, R. K. (2004), IEEE Xplore / sciencedirect / Springer.

31- Design and Analysis of Microstrip Patch Antennas Using Artificial Neural Network, Vivek Singh Kushwah and Geetam Singh Tomar, Published: 15 November 2017, DOI: 10.5772/intechopen.69522.

32- L. G. Ayalew and F. M. Asmare, "Design and optimization of pi-slotted dual-band rectangular microstrip patch antenna using surface response methodology for 5G applications", Heliyon, Vol. 8, pp. 1-14, Nov 2022.

Summary

Patch antennas are essential components in wireless communication systems, supporting various applications. They are easily implemented using planar technology, consisting of a microstrip patch on the top and a grounded substrate on the bottom. Designing patch antennas still faces limitations and requires effective techniques to achieve high electromagnetic (EM) responses. Artificial Neural Network (ANN) modeling is a powerful technique for optimizing patch antenna performances. By learning complex relationships between design parameters and performance metrics, ANN models can predict antenna characteristics with high accuracy. This approach reduces computational costs compared to traditional simulation methods and enables rapid design optimization for improved efficiency, bandwidth, and radiation performance. In this regard, this study aims to develop efficient patch antenna designs using accurate ANN modeling, combined with an EM simulator as a realistic environment for effective optimization procedures.

Key words: Wireless communications, Patch Antennas, EM-Response, Return Loss, ANN Modeling.

ملخص

تُعد الهوائيات المرقّعة من المكوّنات الأساسية في أنظمة الاتصالات اللاسلكية، حيث تدعم مجموعة واسعة من التطبيقات. ويمكن تنفيذها بسهولة باستخدام تقنية مستوية، وتتكوّن من رقعة ميكروشريطية في الأعلى وطبقة أرضية على الجانب السفلي من الركيزة. ورغم بساطتها، لا تزال عملية تصميم هذه الهوائيات تواجه بعض القيود، مما يتطلب استخدام تقنيات فعّالة لتحقيق استجابات كهرومغناطيسية عالية. ويُعتبر نمذجة الشبكات العصبية الاصطناعية تقنية قوية لتحسين أداء الهوائيات المرقّعة، حيث تُمكّن هذه النماذج من تعلّم العلاقات المعقدة بين معلمات التصميم ومؤشرات الأداء، وبالتالي التنبؤ بخصائص الهوائي بدقة عالية. وتُساهم هذه المقاربة في تقليل الكلفة الحسابية مقارنةً بالطرق التقليدية المعتمدة على المحاكاة، كما تتيح تحسين التصميم بسرعة من أجل رفع الكفاءة، وتوسيع عرض النطاق، وتحسين أداء الإشعاع. وفي هذا السياق، تهدف هذه الدراسة إلى تطوير تصاميم فعالة لهوائيات مرقّعة باستخدام نمذجة دقيقة للشبكات العصبية الاصطناعية، وذلك بالاعتماد على محاكي كهرومغناطيسي كمحيط واقعي لتطبيق إجراءات تحسين فعّالة.

الكلمات المفتاحية: الاتصالات اللاسلكية، الهوائيات المرقعة، الاستجابة الكهرومغناطيسية، فقدان الانعكاس، نمذجة الشبكات العصبية الاصطناعية.

Résumé

Les antennes patch sont des composants essentiels dans les systèmes de communication sans fil, soutenant une variété d’applications. Elles sont facilement réalisables grâce à la technologie planaire, consistant en une plaque micro-ruban sur la face supérieure et un substrat relié à la masse en dessous. Cependant, la conception des antennes patch reste limitée par certains défis et nécessite des techniques efficaces pour obtenir de bonnes performances électromagnétiques (EM). La modélisation par réseaux de neurones artificiels (RNA) représente une méthode puissante pour optimiser les performances des antennes patch. En apprenant les relations complexes entre les paramètres de conception et les indicateurs de performance, les modèles RNA permettent de prédire avec une grande précision les caractéristiques de l’antenne. Cette approche permet de réduire les coûts de calcul par rapport aux méthodes classiques de simulation, tout en accélérant le processus d’optimisation pour améliorer l’efficacité, la bande passante et les performances de rayonnement. Dans ce cadre, cette étude vise à développer des conceptions d’antennes patch efficaces en utilisant une modélisation RNA précise, combinée à un simulateur électromagnétique servant d’environnement réaliste pour des procédures d’optimisation performantes.

Mots clés : Communications sans fil, antennes patch, réponse électromagnétique, perte de retour, modélisation par réseaux de neurones artificiels.