**DOKUZ EYLÜL UNIVERSITY**

**GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES**

# MACHINE LEARNING BASED ANTENNA ARRAY BEAMFORMING

**by**

**Muhammed UĞUR KILIÇ**

**January, 2023**

**İZMİR**

# MACHINE LEARNING BASED ANTENNA ARRAY BEAMFORMING

**A Thesis Submitted to the**
**Graduate School of Natural And Applied Sciences of Dokuz Eylül University**
**In Partial Fulfillment of the Requirements for the Degree of Master of Science in**
**Electrical and Electronics Department**

**by**
**Muhammed UĞUR KILIÇ**

**January, 2023**
**İZMİR**

**M.Sc THESIS EXAMINATION RESULT FORM**

We have read the thesis entitled "**MACHINE LEARNING BASED ANTENNA ARRAY BEAMFORMING** " completed by **Muhammed UĞUR KILIÇ** under supervision of **Asst. Prof. Dr. Özgür Tamer** and we certify that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

.............................................................................

Asst. Prof. Dr. Özgür Tamer

Supervisor

.............................................................................

Doç. Dr. Hatice Doğan

Jury Member

.............................................................................

Prof. Dr. Mustafa Seçmen

Jury Member

Prof. Dr. Okan FISTIKOĞLU
Director
Graduate School of Natural and Applied Sciences

# ACKNOWLEDGEMENTS


My sincere thanks,

To my advisor, Mr Özgür Tamer, who guided me in my work,

To my family who made me come to this day and always supported me,

To my colleagues who supported me in my business life,

To my dear friends Mazlum Unay and Ulaş Yüksel who helped me in this work,

To my wife Burcu Mutlu Kılıç, who supported me in every difficulty and stood by me in all my moments.

Muhammed Uğur KILIÇ

## MACHINE LEARNING BASED ANTENNA ARRAY BEAMFORMING


## ABSTRACT

With the development of communication technologies, transmitting a wireless signal with maximum efficiency has gained importance. As the growing demand for mobile communications is constantly increasing, the need for better coverage, improved capacity, and higher transmission quality rises. Therefore, smart optimization methodologies such as beamforming has become more important. Beamforming is used to eliminate interference and improve the signal to noise ratio.

The present study focuses on estimating proper weights for beamforming of an array beamforming with the help of a neural network structure. Training set was created from different users located at different angles. Neural network classifies signal strength calculated for each user. Test user locations are selected randomly and according to these locations test steering vectors are created.Algorithm starts and creates classified signal strength and arrival angle outputs according to test steering vectors. It is aimed to provide better quality mobile network service for users in the concentrated region in cases that progress compared to the trained network.



**Keywords:** Beamforming, Neural Network, communication with neural network, mobile communications with beamforming, beamforming with neural network, machine learning.

# MAKİNE ÖĞRENMESİ TEMELLİ ANTEN DİZİSİ HÜZME YÖNLENDİRME


## ÖZ

İletişim teknolojilerinin gelişmesiyle birlikte kablosuz sinyalin maksimum verimle iletilmesi önem kazanmıştır. Mobil iletişim için artan talep sürekli arttıkça, daha iyi kapsama alanı, gelişmiş kapasite ve daha yüksek iletim kalitesi ihtiyacı da artmaktadır. Bu nedenle hüzme şekillendirme gibi akıllı optimizasyon metodolojileri daha önemli hale gelmiştir. Hüzmeleme ise paraziti ortadan kaldırmak ve sinyal-gürültü oranını iyileştirmek için kullanılmaktadır.

Bu çalışma, bir sinir ağı yapısı yardımıyla bir dizi hüzme şekillendirmenin hüzme şekillendirme için uygun ağırlıkları tahmin etmeye odaklanmaktadır. Farklı açılarda konumlanmış farklı kullanıcılardan eğitim seti oluşturulmuştur. Sinir ağı, her kullanıcı için hesaplanan sinyal gücünü ve açısını sınıflandırır. Test kullanıcı lokasyonları rastgele seçilir ve bu lokasyonlara göre test yönlendirme vektörleri oluşturulur. Algoritma test yönlendirme vektörlerine göre sınıflandırılmış sinyal gücü ve varış açısı çıktıları oluşturur.Eğitimli ağa göre ilerleme gösteren durumlarda, yoğunlaşan bölgedeki kullanıcılara daha kaliteli mobil ağ hizmeti sunulması amaçlanmaktadır.



**Anahtar kelimeler:** Hüzlemeleme, sinir ağı, sinir ağı ile haberleşme, hüzmeleme ile mobil haberleşme, sinir ağı ile hüzmeleme, makine öğrenmesi.

**CONTENTS**

**Page**

## LIST OF FIGURES

**Page**

## LIST OF TABLES

# CHAPTER ONE
# INTRODUCTION

Many techniques have been investigated for network communication. Especially with the requirements of mobile communication, improvements in signal quality have gained importance.As the increasing demand for mobile communication is constantly increasing, the need for better coverage, enhanced capacity and higher transmission quality also increases. Therefore, it is necessary to use the radio spectrum more efficiently. Smart antenna systems are capable of using the radio spectrum efficiently and promise an effective solution to existing wireless system problems while providing reliable and robust high-speed, high-data-rate transmission (P.Ioannides & Balanis, 2005). With the developments supported by artificial intelligence, users have reached a faster and higher quality communication.

User-oriented applications such as beamforming are included in such developments and in this thesis, artificial neural networks and beamforming are combined and examined.

## 1.1 Literature Survey

Beamforming is used to change the direction of signal for maximum efficiency and quality signal and decrease interference in communication system. In 1905, the German physicist and inventor Karl F. Braun presented the first public demonstration of beamforming. Braun built a phased array by placing three antennas so that radiation was amplified in one direction and reduced in another. (Braun, 1909).

Beamforming especially has gained more importance with the development of 4g and later with 5g. With the artificial neural network algorithm supported beamforming structure, user-oriented actions are taken at speeds far beyond human capacity and it is aimed to maximize the user experience.

When Warren McCulloch and Walter Pitts developed a computational model for neural networks based on threshold logic algorithms in 1943, the history of artificial neural networks (ANN) officially began. This method provided the path for the division of the research into two methods. One method emphasized biological processes, while the other concentrated on using neural networks to create artificial intelligence (Warren & Pitts, 1943).

The Hebbian learning theory was developed by D. O. Hebb in the late 1940s and is based on the brain plasticity mechanism. Unsupervised learning is hebbian learning.

Werbos' (1975) back-propagation method, which made it possible to train multi-layer networks in practice, was a major catalyst for the resurgence of interest in neural networks and learning. By adjusting the weights at each node, back-propagation sent the error term back up through the layers (Hebb, 1949).

Feed-forward neural networks and recurrent neural networks evolved between 2009 and 2012 in Eight worldwide contests in pattern recognition and machine learning were won by Schmidhuber's research team.

When it comes to today, the importance of machine learning has increased with the developments in the field of communication and it has started to take its place in the field of telecommunication. Some of the articles used in this field and applied in different telecommunication fields are as follows;

In May 24, 2019, beamforming neural network based on convolutional neural network (CNN) was proposed for minimizing power problem and achieving max SINR value.With MSE (mean square error) algorithm, weights are updated (Yongxu Zhu & Zheng, 2019).

In July 25, 2016, neural network is performed with using beamforming technique called mimimum variance distortionless response (MVDR). The trained NN can serve as an adaptive beamformer that enables a linear antenna array to orient the main lobe to a desired signal and inserts nulls into the corresponding interference signals in the presence of additional zero-average Gaussian noise (Zaharis, 2016).

In September, 2019, to overcome distortion on speech signal, convertional neural network beamformer is used to decrease non-linear distortion on speech signal to improve speech quality (Mizumachi, 2019).

In November, 2020, to improve Line of Sight (LOS) communication between receiver and transmitter sites , linear regression machine learning model was studied.The antenna array weights are pre-calculated for a number of beam directions and kept as a database. The signal weights are calculated from the arriving signal and given input data to a linear regression model and direction of arrival signal is predicted (Singh & Jayakumar, 2020).

In Dec, 2021, It is aimed to determine the precoder with the neural network by using the user's location.It allows to reduce or even eliminate the need for pilot symbols, depending on how the location is obtained(Le Magoarou & Crussière, 2021).

In article written by Maja Sarevska and Abdel-Badeeh M. Salem, the problem of Null-Steering beamforming using Neural Network (NN) approach for antenna array system are considered.The focus of antenna array signal processing is on DOA estimation and beamforming(Maja Sarevska, 2008).

In article written by Paramanand Sharma, A three-layer radial basis function neural network (RBFNN) is used, which treats the problem of calculating the weights of an adaptive array of antennas as a mapping problem.RBNN algorithm improves the array system performaence and signal steering mishmashes under non ideal conditions and gives best output SINR(Sharma, 2009).

In Dec,1998, neural network approach to problem finding weights of 1D (one dimensional) and 2D (two dimensional) adaptive arrays.With using using three-layer radial basis function neural networks (RBFNN), aiming to find optimum weights(El Zooghby & Georgiopoulos, 1998).

Article published in International Journal of Computer Applications in Nov,2015 by Adheed H. Sallomi,Sulaiman Ahmed, as we used in this thesis , this study focuses on the study that calculates the optimum weights on the adaptive beam using the elman neural network. In this study, Levenberg Marquardt (LM) algorithm and Resilient Backpropagation (Rprop) algorithms are used comparatively (Sallom & Ahmed, 2015).

In article written by Murat Güreken, the real-time target tracking issue is solved with a Neural Network (NN) based beamforming technique. The approach is used to two different types of arrays: circular and linear.SNR (Signal to Noise Ratio) value was calculated by calculating the direction of arrival angle (DOA) according to the GPS-based location of the users. Then, the error was calculated by running NN training according to the angle and SNR (Güreken, 2009).

## 1.2 Aim of The Study

In this project, it is aimed to form the signal to improve the user oriented signal level and quality by creating data for the learning mechanism by using receivers at different points. In the first case, the function defined to provide the best between the users whose location is known and the base station is used and the steering vectors are calculated. Afterwards, by training with this data with neural network structure, the system will aim to increase the user experience by shaping the signal according to the location information received from the system user, without using the function.

# CHAPTER TWO
# THEORETICAL BACKGROUND

## 2.1 Antenna Systems

A metallic object called an antenna is used to receive and/or transmit radio waves. Numerous distinct antenna types with unique characteristics are employed in radio systems for various applications. Antennas can be categorized in a number of ways. The following list of common antenna types;

### *2.1.1 Monopole Antenna Systems*

A monopole antenna is made out of a single conductor, typically positioned above the earth or another artificially conductive surface. The quarter-wave monopole is the most prevalent type, with the antenna being roughly one-fourth the radio waves' wavelength. Vertically polarized monopoles are employed for extensive coverage of a region since they have an omnidirectional radiation pattern (Bevelaqua, 2015).

Figure 2.1 VHF ground plane antenna (Wikipedia, 2012a)

Figure 2.2 Rubber ducky antenna on 446 MHz UHF(Wikipedia, 2012b)

### *2.1.2 Dipole Antenna Systems*

The dipole antenna's two poles or two conducting components are indicated by the name "di-pole." As can be seen, the fundamental antenna includes a two-conductor element. The dipole antenna is typically split in the middle, and these are typically on the same axis. (Basu, 2010).

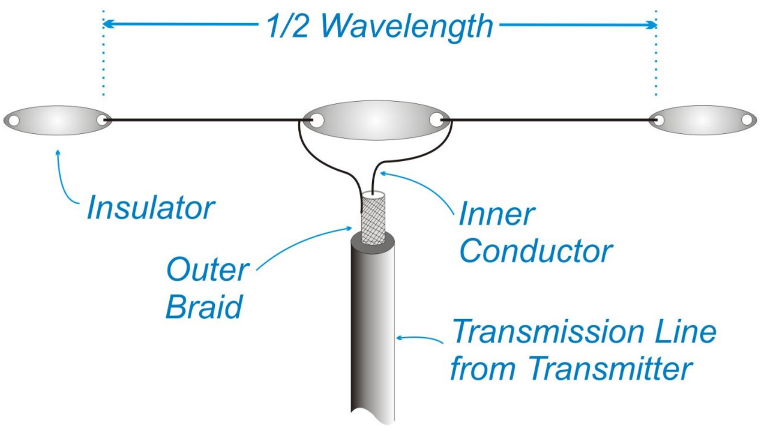


Figure 2.3 Basic Dipole Antenna(KONR, 2022)

## 2.2 Array Antenna Systems

Array antennas are made up of numerous antennas that operate as one compound antenna when combined.

Generalized mathematical expression of array factor of array antenna is as follows;

Antenna pattern=AFxSingle Element Pattern

$$AF = \sum_{n=1}^{N} I_n \times e^{j\times(n-1)\times(cos\varphi)} AF = 1 + I_1 e^{j\times(kd\cos\theta+\beta_1)} + I_2 e^{j\times(2kd\cos\theta+\beta_2} + ... \quad (2.1)$$

$$\varphi = kdcos\theta + \beta \quad (2.2)$$

if the array factor is multiplied by $e^{jx\varphi}$

$$(AF) \times e^{j\times(\varphi)} = 1 + I_1 e^{j\times(\varphi)} + I_2 e^{j\times k_2 \times 2\times(\varphi)} + ...I_1 e^{j\times k_1 \times N\times(\varphi)} \quad (2.3)$$

$$AF \times (e^j \times (\varphi) - 1) = (e^j \times N \times (\varphi) - 1) \quad (2.4)$$

$$AF = \frac{e^j \times N \times (\varphi) - 1}{e^j \times (\varphi) - 1} \quad (2.5)$$

Finally array factor becomes equation as follows;

$$AF = (e^{(j\times(N-1)\times\varphi)/2}) \times (\frac{(\sin\frac{N\times\varphi}{2})}{(\sin\frac{\varphi}{2})}) \quad (SeanV.Hum,\ 2021). \quad (2.6)$$

Types of Arrays:

Broadside: Maximum radiation at right angles to main axis of antenna(Amie Study Circle, 1994).

End-fire: Maximum radiation along the main axis of antenna

Parasitic: Some elements not connected to source. They re-radiate power from other elements.

Phased: All elements connected to source. This type is used for in this thesis.

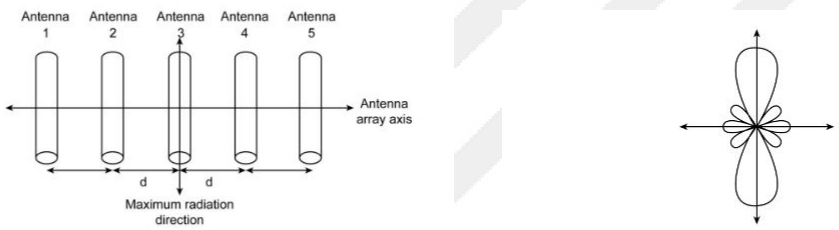


Figure 2.4 Broad Antenna Array and Radiation

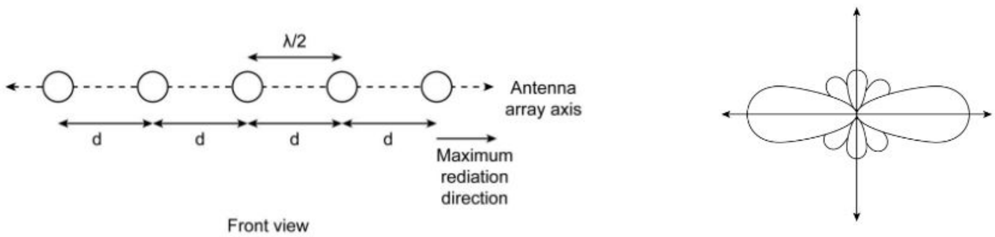


Figure 2.5 Endfire Antenna Array and Radiation

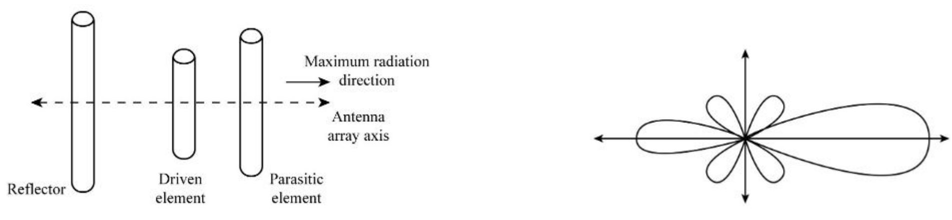


Figure 2.6 Parasitic Antenna Array and Radiation (Electronics Desk, 2012)

.

For broadside antenna main lobe at at =0 or at=180

For endfire antenna main lobe at at =90,

The maximum value of the array occurs when

$$\varphi = kdcos\theta + \beta = 0 \tag{2.7}$$

Normalized array function of broadside antenna $\beta = 0$;

$$AF = \frac{1}{N} \times \frac{(\sin \frac{N \times \varphi}{2})}{(\sin \frac{\varphi}{2})} \tag{2.8}$$

Normalized array function of endfire antenna $\beta = \pm kd$;

$$\varphi = kd \times (\cos\theta \pm 1) \tag{2.9}$$

$$AF = \frac{1}{N} \times \frac{(\sin \frac{N \times \varphi}{2})}{(\sin \frac{\varphi}{2})} \tag{2.10}$$

Formulations among antenna types vary according to the arrangement of antenna elements. The difference between the maximum radiation angle varies according to the differences between the phase angles. The general antenna array formulation is the same for all antenna types, regardless of the array.

### *2.2.1 Phased Array Antenna Systems*

Multiple emitters/receivers are found in phased array antennas, which are utilized for beamforming in RF applications, particularly high frequency ones. There are three common uses for WiFi, chirped radar, and 5G. (Cadence, 2021). By altering the phase difference between the signal transmitted to each transmitter in the array, a phased array antenna enables beamforming. This eliminates the need for the antenna to be physically moved in order to regulate and steer the radiation pattern to a target (Torres-Rosario, 2005).

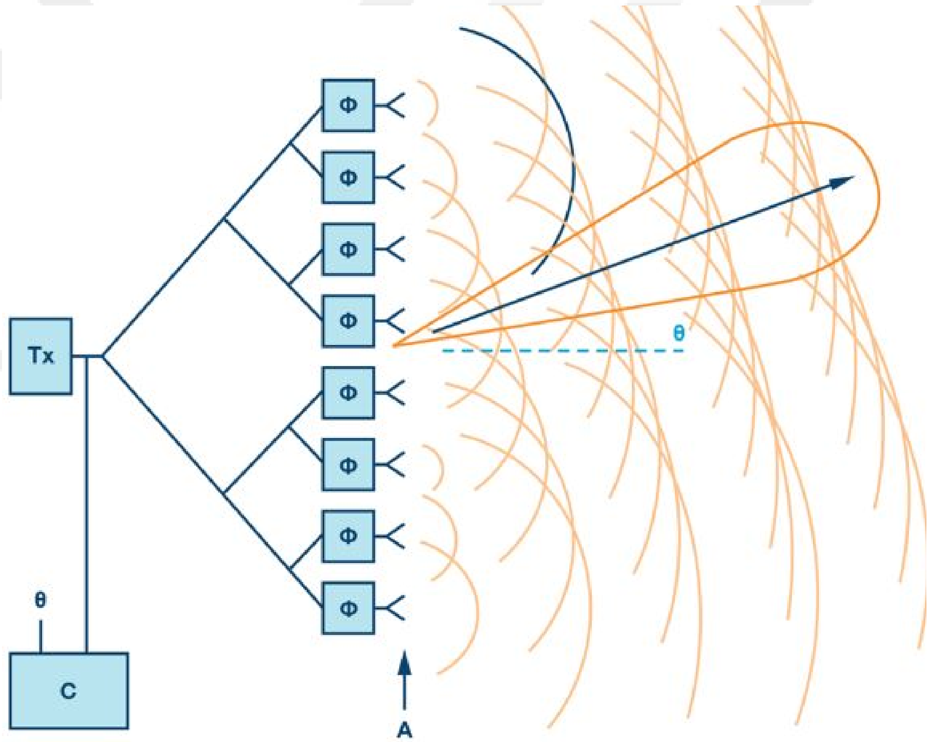


Figure 2.7 Phased Array Antenna(Mailloux, 1992)

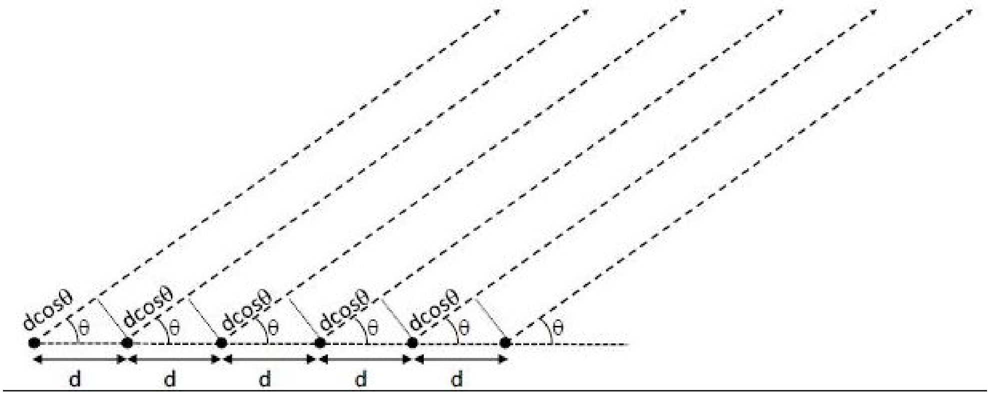


Figure 2.8 A Phased Array System (Tougaw, 2018)

The array factor takes into account array characteristics like the separation between elements and the progressive phase difference between each element.

$$AF = \sum_{n=1}^{N} e^{j\times(n-1)\times(kdcos\theta+\beta)} \tag{2.11}$$

where, N are the number of elements,  is the ongoing phase shift between each antenna element, d is the distance between each element in the array, A is the input signal or element factor and s is steering vector.

$$s(t) = [s0(t), s1(t).......sm(t)] = \begin{pmatrix} e^{j\times\theta 0} \\ e^{j\times\theta 1} \\ \vdots \\ e^{j\times\theta .m} \end{pmatrix} \tag{2.12}$$

#### 2.2.1.1 Uniform Line Array

A group of sensor components that are uniformly spaced along a line constitute a uniform linear array. A dipole antenna that can send and receive electromagnetic waves is the most popular kind of sensor. It is thought that plane waves of electromagnetic waves are how they reach the array. This indicates that the transmitter and receiver are separated by a significant distance. The spacing 'd' between array elements must be less than or equal to half the wavelength (Ahmed, 2018).

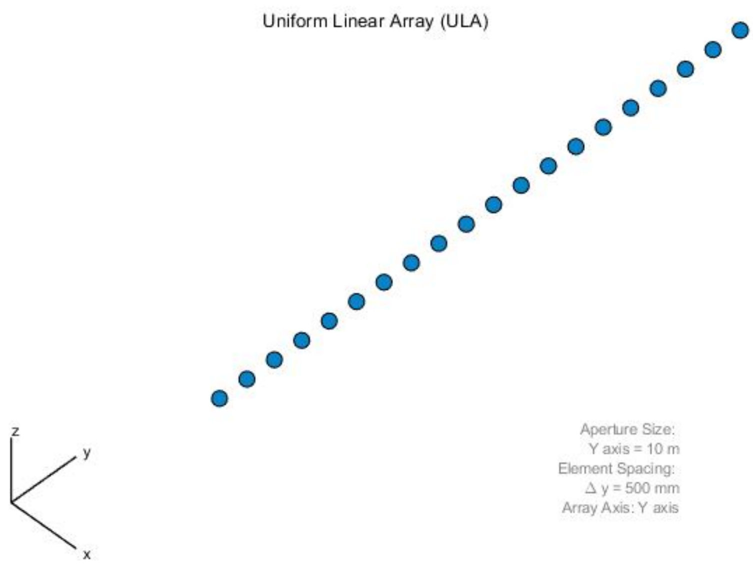


Figure 2.9 Uniform Line Array

#### 2.2.1.2 *Uniform Planar Array*

An effective way for improving the performance of wireless communication systems is antenna array signal processing. Uniform planar array antenna type is more stable for beamforming than line array antenna because of it enables shape signal two coordinate.

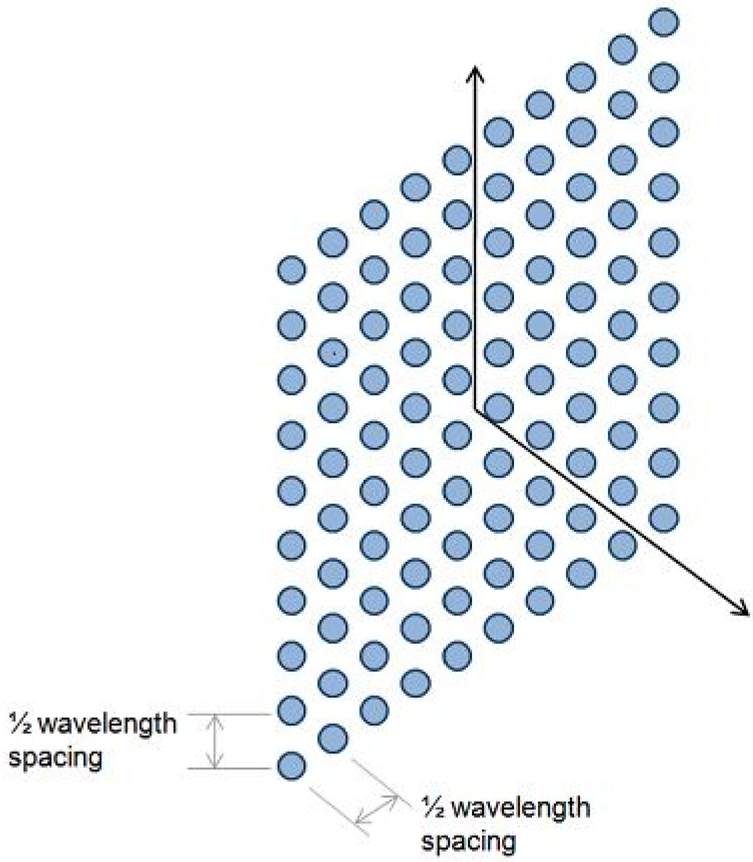


Figure 2.10 Uniform Planar Array

## 2.3 Smart Antenna System

Smart antennas, often referred to as adaptive array antennas or multiple antennas, are antenna arrays with strong and sophisticated signal processing algorithms that are used to generate beamforming vectors that track and position the antenna beam on the moving user or target (Prasanthi, 2022).

The two main groups of smart antennas differ in the following ways in terms of transmitting strategy options;

**Switched beam**: A finite number of fixed, predefined patterns or combining strategies.

**Adaptive array**: An infinite number of patterns (scenario-based) that are adjusted in real time.

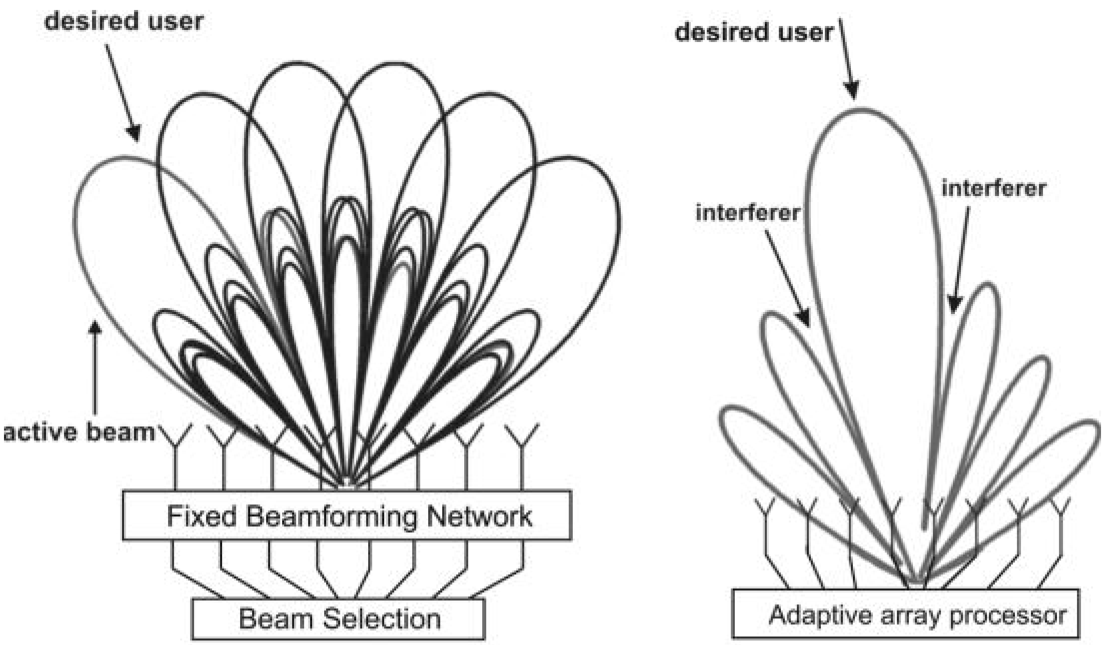


Figure 2.11 Switched and Adaptive Array System (K. A. Gotsis & Sahalos, 2019)

## 2.4 Beamforming

A general method for controlling a the beam of antenna is beamforming. By combining the phases of the signals traveling in the desired direction and canceling out the pattern traveling in the sidelobe direction, beamforming produces the radiation pattern of the antenna array. The received signal is optimized by adjusting the phases and amplitudes (Sharma, 2009). For mmWave communication, beamforming is a very helpful approach. Since mmWave antenna systems often have small antenna patterns with significant attenuation, beamforming helps mmWave communications because multi-element antennas with active beamforming may boost gain and direct the beam toward a receiver to provide the best signal quality (Kappes, 2019).Beamforming also enables mmWave signal to have a longer range and higher throughput.

When creating an array, numerous factors must be taken into account. In array designs, variables including array geometry, element spacing, element lattice structure, and element tapering are frequently used. Before the final design is executed, it is also critical to define the impacts of mutual coupling. After the array architecture has been configured initially, architectural partitioning may be repeatedly assessed against the system performance objectives. In systems using millimeter waves, the array's surface area decreases according to wavelength size. An antenna array created for millimeter wave frequencies, for instance, can be up to 100 times smaller than one created for microwave frequencies. You can attain a high beamforming gain by constructing an array with more antenna components. As beams are directed in a certain direction, the highly directional beam helps to mitigate the increasing path loss at higher frequencies of operation (Mathworks, 2020).

There are three types of beamforming seperated each other by physical elements and connections;

*Analog beamforming* sends same signal to each antenna element and controlling the phase of each transmitted signal.

*Digital beamforming* uses various signals for each antenna. It needs the carrier frequency of the processed signal to be upconverted after a crossover RF chain that comprises digital-to-analog (D/A) converters, mixers, and power amplifiers since it regulates the phase and amplitude of the signal (Ali & Nordin, 2017).

*Hybrid beamforming* mixes digital and analog beamforming, which means that part of the beamforming is done digitally in the baseband and portion is done by analog RF beamformers (Kim, 2013).

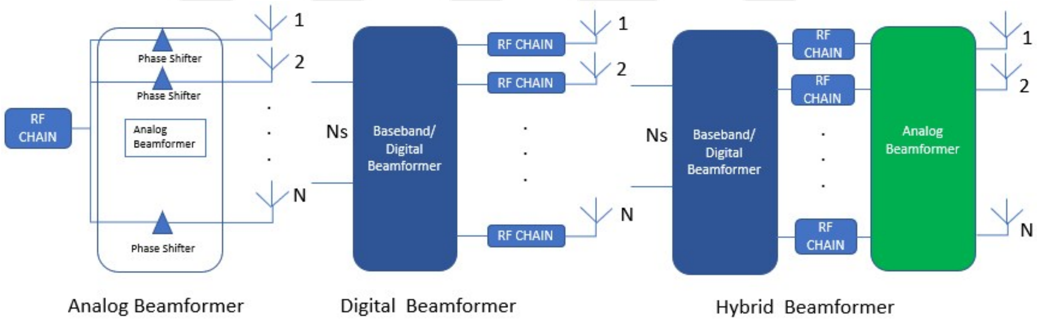


Figure 2.12 Beamforming Types (Wondie & Steinbrunn, 2020).

## 2.5 Machine Learning

An application or branch of artificial intelligence is machine learning. A system may learn itself, without being explicitly coded, and improve with time thanks to machine learning.

Understanding data structure and fitting it into models that people can use and comprehend is the goal of machine learning. The majority of jobs in machine learning may be divided into broad groups. These categories define how learning occurs, and supervised learning and unsupervised learning are two of the most popular machine learning techniques (Pedamkar, 2022).

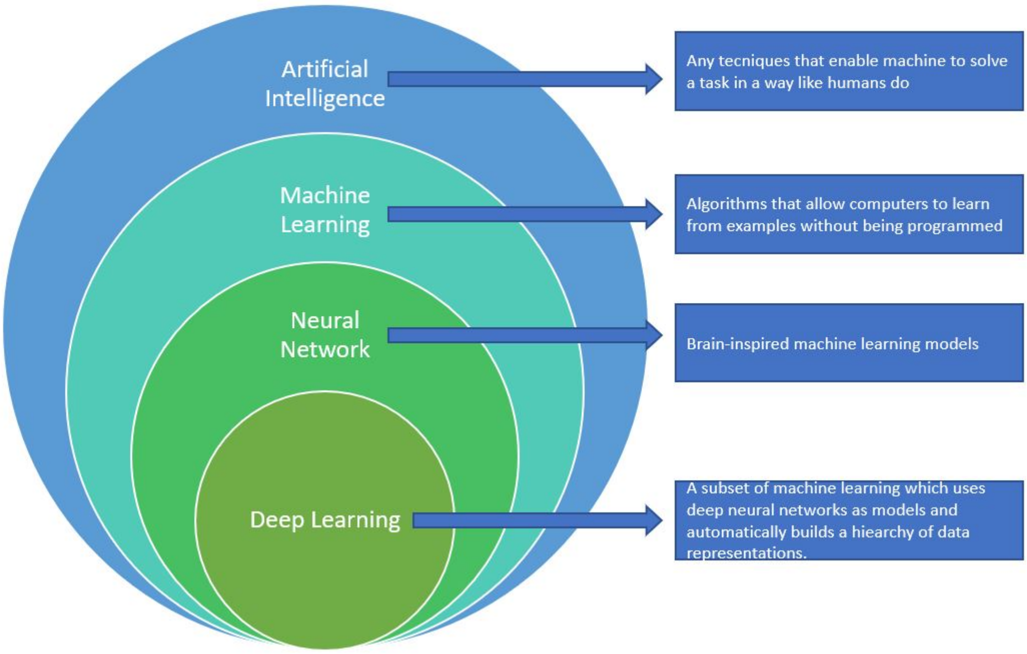


Figure 2.13 Artificial Intelligence and its sub-branches

## 2.6 Neural Network

Neural network has been investigated by scientist in a diverse range of disciplines including computer science, psychology, biology, organic chemistry and telecommunication industry which we analyse and implement (Xu Y. & C., 2021). An technique used for machine learning that models data using graphs of Artificial Neurons, a mathematical model that "mimics how a neuron in the brain operates," is known as a neural network. The program is designed to mimic the functioning of a biological brain network. By reducing the discrepancy between the expected result and the actual result, it seeks to identify patterns between the input attributes and the anticipated output. Every neuron functions like a perceptron.The perceptron, a fundamental neural network building component, is one of the oldest supervised training techniques. Figure below that will help us understand better (Sharma, 2009).

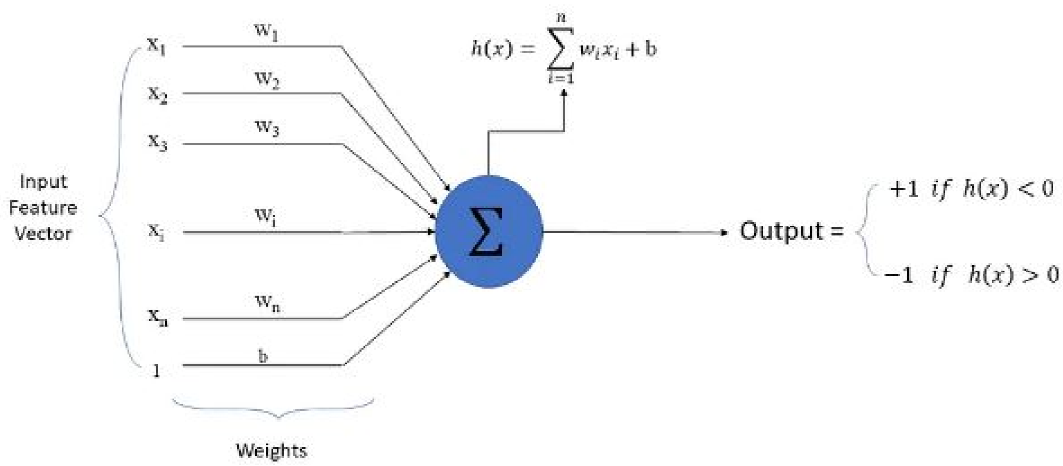


Figure 2.14 Block Model OF Perceptron (Sharma, 2009).

There are three important types of neural network are used to improve performance of models;

### 2.6.1 Feedforward Neural Network

A collection of many neurons are found in each layer of an feedforward neural network. Because the inputs are typically evaluated in the forward direction.

Counting the number of inputs, outputs, hidden neurons, and hidden layers is part of defining an FNN design (Facundo Bre & Fachinott, 2018).A simple FNN is shown below;

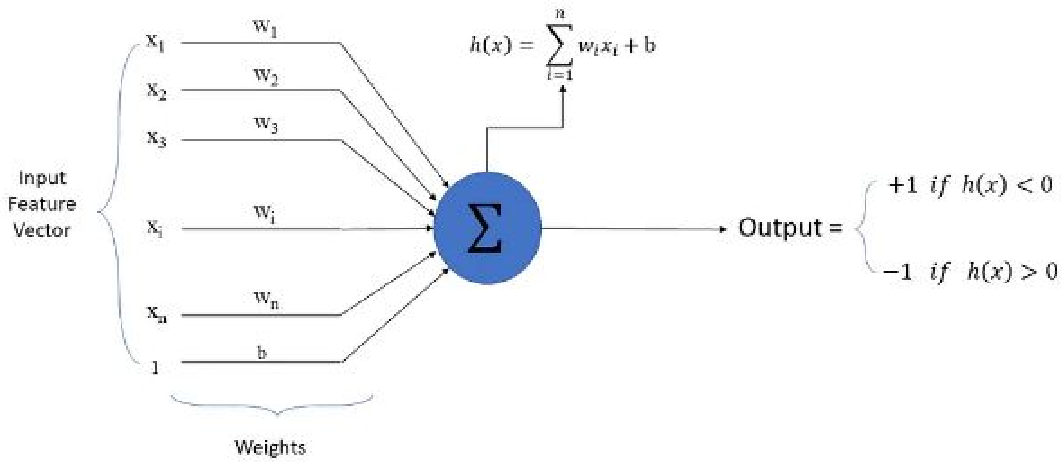


Figure 2.15 Feedforward neural network architecture (Sharma, 2009).

### *2.6.2 Convolution Neural Networks*

One of the most popular deep neural networks is Convolutional Neural Network. Its name is derived from the linear convolution process between matrices in mathematics. The reduction of ANN's parameter count is CNNs' most advantageous feature. Convolutional, non-linear, pooling, and fully-connected layers are among the many layers that make up CNN. Image, video, and speech recognition are all made possible by CNN (S. Albawi & Al-Zawi, 2017).

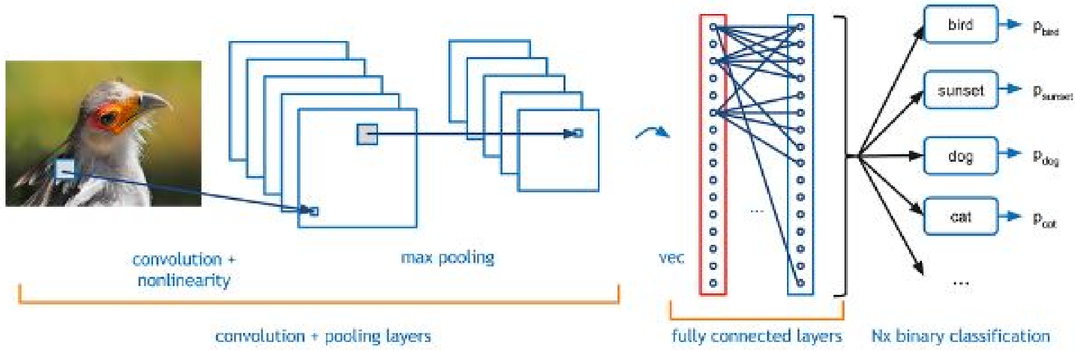


Figure 2.16 CNN Architecture (Shahid, 2019).

### *2.6.3 Recurrent Neural Network*

A recurrent link to the input of a recurrent neural network improves in estimating the layer's result. Each output element in an RNN is handled as a function of earlier output elements (Zaremba Wojciech & Oriol, 2014).

RNN results from a looping restriction on the hidden layer of an ANN.

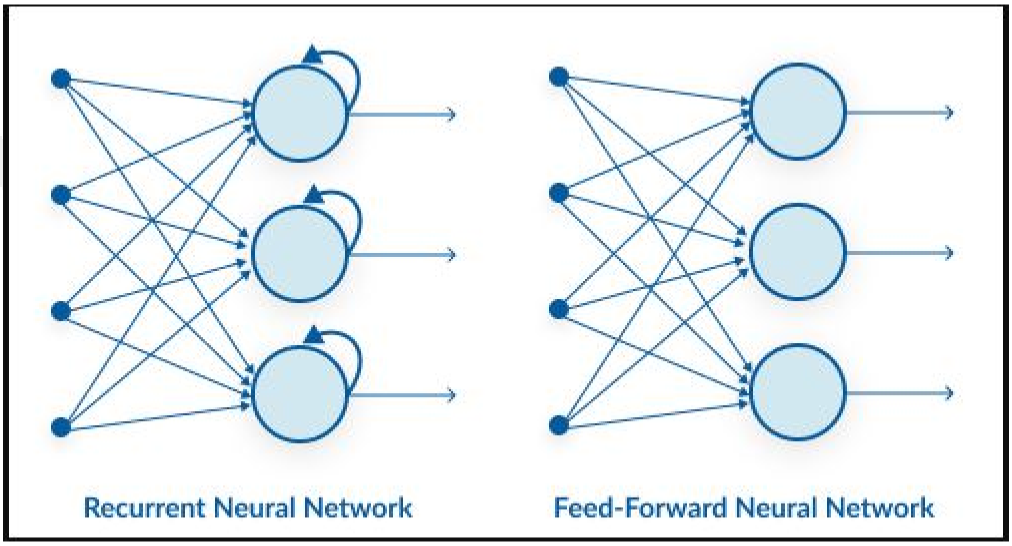


Figure 2.17 Basic RNN structure vs ANN structure (Pai, 2020).

Neural network types have some differences. Some of the main ones are listed in the table below.

Table 2.1 Neural Network Types Comparison.

| | FNN | RNN | CNN |
|---|---|---|---|
| Data | Tabular Data | Sequence Data (Time Series,Text,Audio) | Image Data |
| Recurrent Connections | No | Yes | No |
| Parameter Sharing | No | Yes | Yes |
| Spatial Relationship | No | No | Yes |

Many training algorithms have been proposed for RNN also called feedback neural;

*Elman Neural Network*, the first type of neural network employed in this study, is made up of several models of neuronal cells that are organized in accordance with predetermined criteria. Elman's 1990 research on the backpropagation (BP) neural network led to the development of a straightforward RNN known as the Elman neural network. (D. E. Rumelhart & Williams, 1986). Comparing to traditional neural networks, ENN has additional inputs from the hidden layer, which forms a new layer-the context layer (Guanghua Ren & Zeng, 2018).

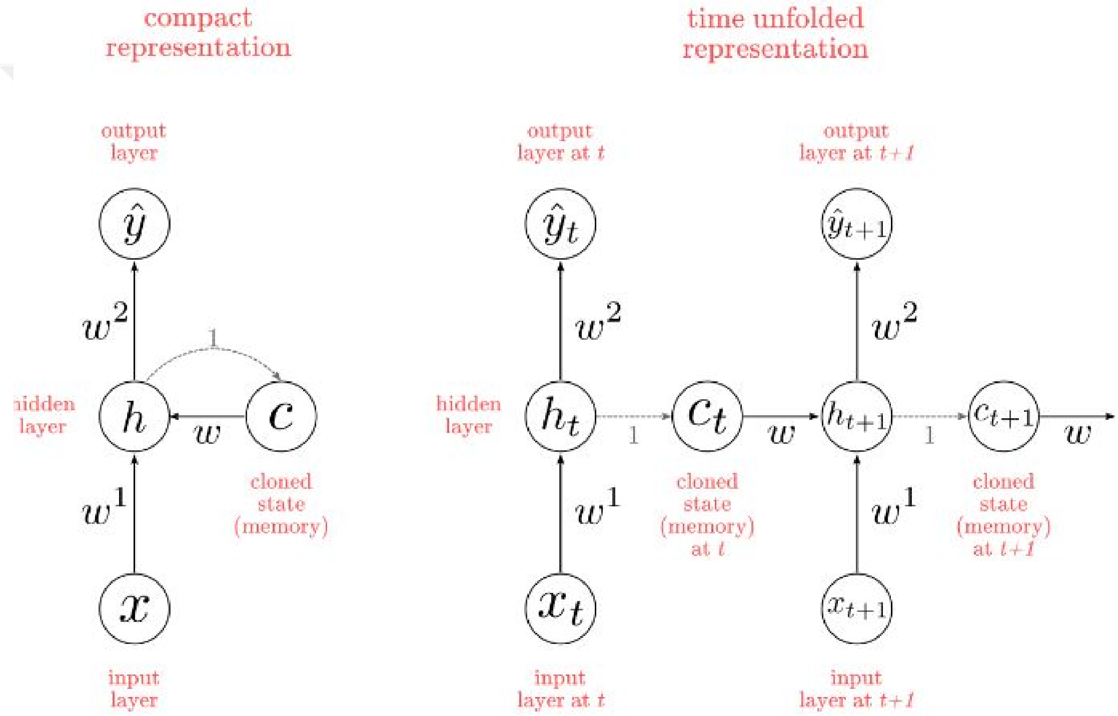


Figure 2.18 Elman neural network (Caceres, 2020).

*Jordan networks* and Elman networks are related. Instead of the hidden nodes, the context units are provided from the output layer. Context units in the Jordan network are also called state layers. They have a recurring bond with themselves (Cruse, 2006).

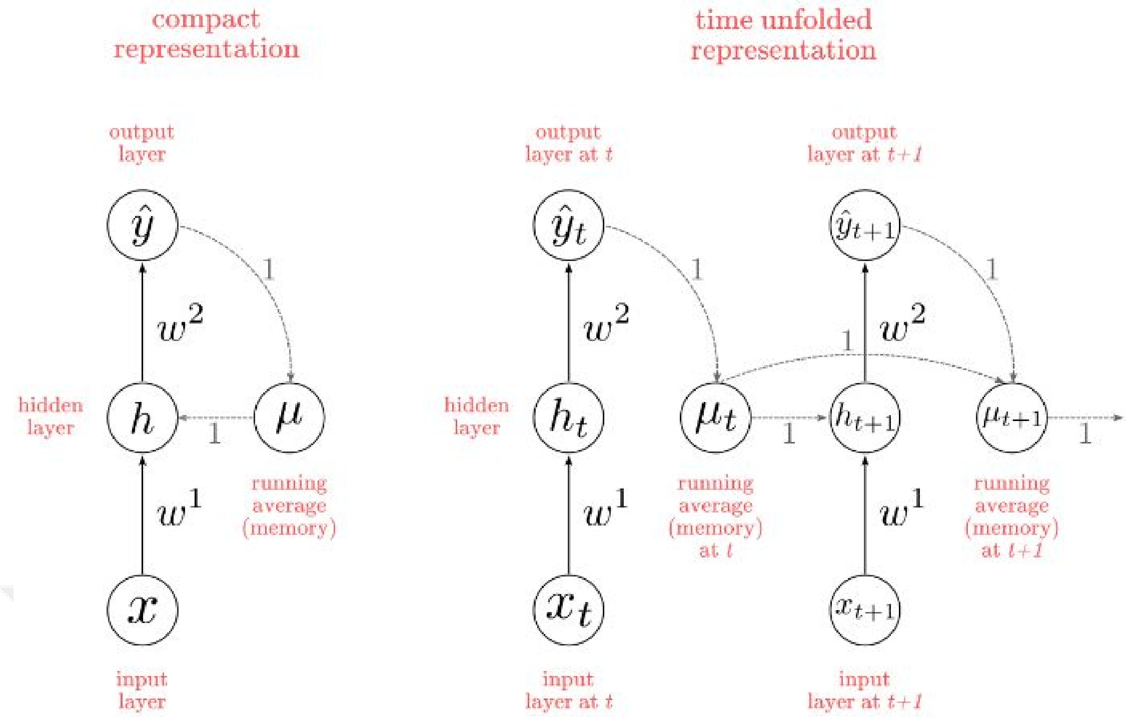

Figure 2.19 Jordan Network (Caceres, 2020).

*Recurrent neural networks* are recursive artificial neural networks with a certain structure that of a linear chain.

*A recurrent multilayer sensor network (RMLP)* network consists of cascading subnets, each containing multiple layers of nodes. Each of these subnets must feed forward, except for the last layer, which may have feedback links. Each of these subnets is connected only by feed-forward links (Tutschku, 1995).

*The Hopfield network* is an RNN in which all the links between the layers have equal dimensions. It requires static inputs and is therefore not a generic RNN because it does not handle pattern sequence(Hopfield, 1982).

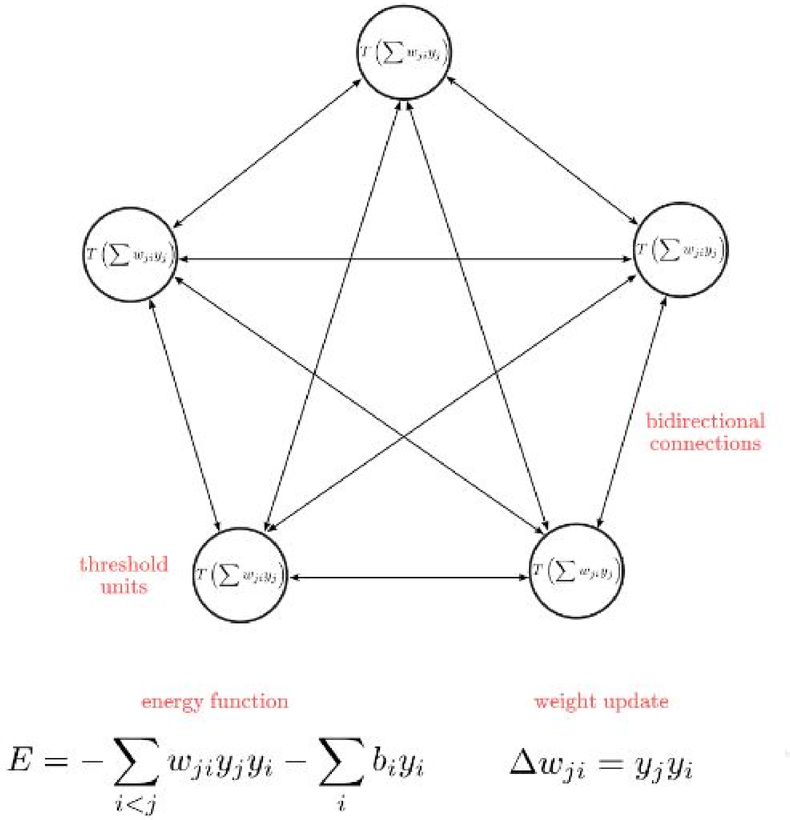


Figure 2.20 Hopfield Network (Caceres, 2020).

In this project, to maximize the response to training data, neural networks algorithms alter the amplitude and phase shift of the system's structure. The reduction of the discrepancy between output data and target data is the aim of neural network training. Coefficients are adjusted iteratively until a user-defined threshold is met.

## 2.7 Mathematical Model Of The Project

It simulates an antenna array with a homogeneous linear array of 16 elements. It is expected that a wave guidance will strike each element of the array parallel and at the same angle because of the far field geometry of the array, with each element's signal having a different phase delay. The m-dimensional output of a linear antenna array with m elements is as follows mentioned before in phased array antenna;

$$X(t) = As(t) + n(t) \tag{2.13}$$

The array factor takes into account array factors such as the phase difference between each element and the distance between elements.

$$AF = \sum_{n=1}^{N} e^{j\times(n-1)\times(kdcos\theta+\beta)} \tag{2.14}$$

where N denotes the number of antenna elements, is the progressive phase shift between each antenna element, d denotes the inter-element distance between each element in the array, A denotes the input signal or element factor, and s denotes the steering vector.

$$s(t) = [s0(t), s1(t).......sm(t)] = \begin{pmatrix} e^{j\times\theta 0} \\ e^{j\times\theta 1} \\ \vdots \\ e^{j\times\theta .m} \end{pmatrix} \tag{2.15}$$

Q is called the angle vector or arrival angle vector from receiver sites.Arrival angles coming from all receiver sites are changes and steering vector weights ( phase angles) are updated. In this way, the output signal is formed to the locations of the users. n(t) is additional noise. Signal strength, returned as in dBm for each receiver sites.

$$SS = 10log10(P/1MW) \tag{2.16}$$

P is the power of the signal on the receiver side coming from transmitter.

### *2.7.1 Multi Layer Neural Network*

Network has more than one neurons,each neurons connected to next layer multiple neuron.

#### *2.7.1.1 Training Step*

- Firstly, random users angle and signal strength or quality is taken an stored in angle and signal strength vector.
- Steering vector is created by angle vector.
- Input data is angle or signal strength of users.
- The weights are phase angle=0 and steering vector is equal to 1 for all elements.
- After that phase angles are updated for each user.
- Error from each neuron output ;

$$e_j = |Y_j - Z| \tag{2.17}$$

- Adjust weights from each output using gradient descent method;

$$W_j = W_j - 1 + r \times e_j \times Y_j \times f^{-1} X \tag{2.18}$$

  (r=learning rate)

- Adjust weights from each output using Levenberg Marquardt method;

$$W_k + 1 = W_k - |J \times J^T + u \times I|^{-1} J^T \times e \tag{2.19}$$

  (J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors)

- Finally , test data is sent to network and classify output.

### *2.7.2 Flowchart of The Training Algorithm*

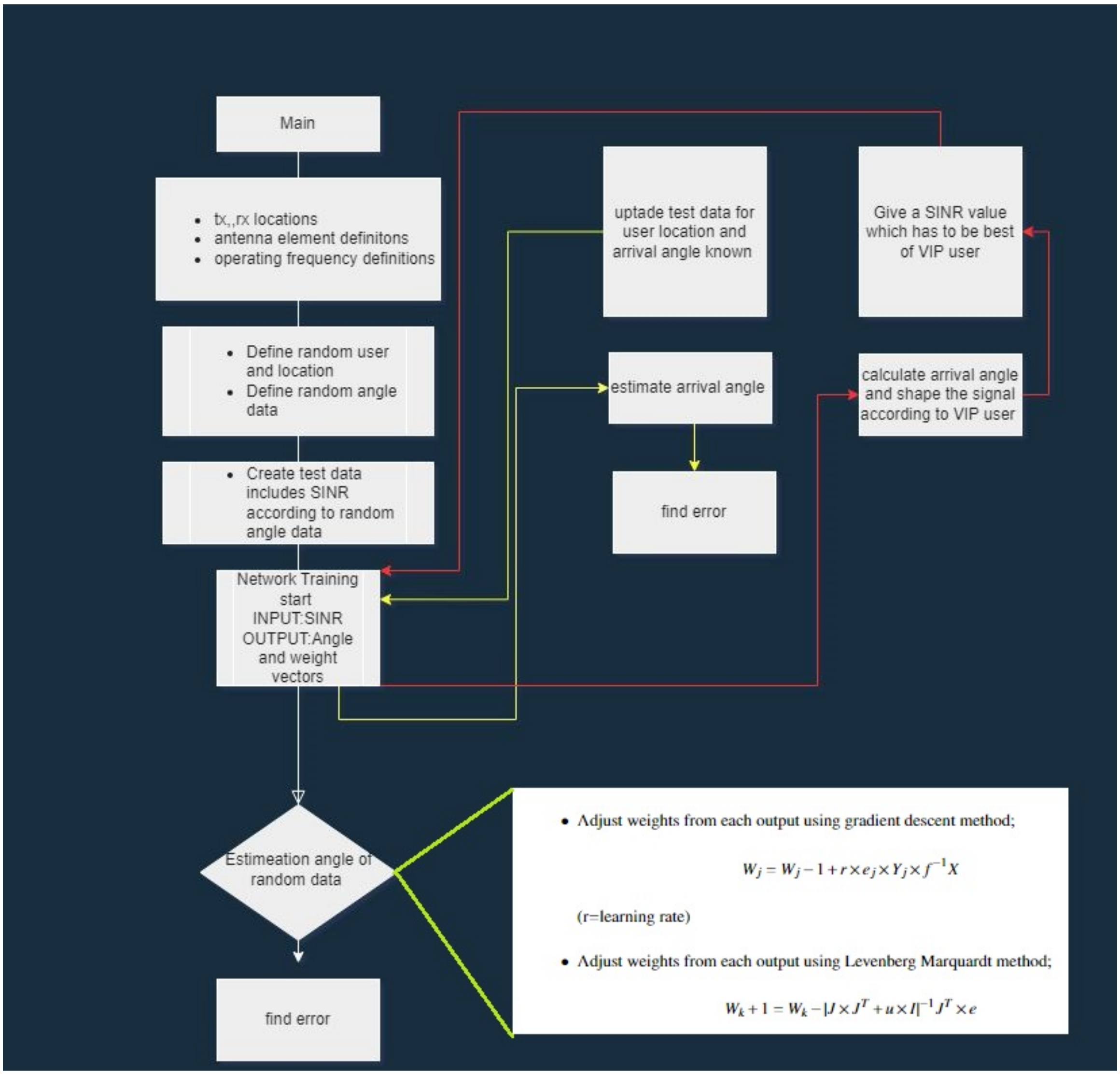


Figure 2.21 Flowchart of The Training Algorithm

# CHAPTER THREE

# APPLICATIONS AND RESULTS

In this section , the method for beamforming and neural network systems having different algorithm , results from the different user locating different place will be shown. For each beamform creating for each user are shown step by step, finally training and test datas will be evaluated.

Firstly, we begin by creating transmitter or base station site with Matlab.We define transmitter location, frequency and antenna type shown below in table;

Table 3.1 Base Station Parameters Definition

| Base Station Physical Values | |
|---|---|
| Antenna Element | Dipole Crossed |
| Power (W) | 40 |
| Location | Izmir/Buca |
| Lattitude-Longitude | 38.3888 27.1806 |
| Operating Frequency | 2.1 Ghz |

Then, the angle of arrival according to the locations of the receivers and the steering vector with this angle are calculated. Each receiver creates its own steering vector or array factor. This data is then defined in an MxN sized matrix to be used for the neural network algorithm. Each column has steering vector values specified for individual users.

M:Number of element N:Number of receiver

Firstly, defining transmitter site to represent a base station operating 2.1 Ghz with 40 watt of power. Location of base station is chosen as Buca/Izmir.

In below, base station can be shown with Site Viewer on matlab;

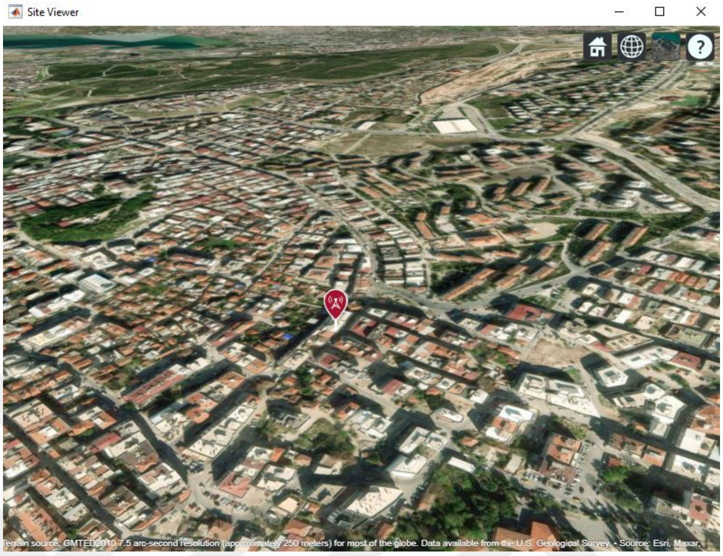


Figure 3.1 Base Station in site viewer

Then, after determining the antenna type and array type of the base station, the beam pattern before beamforming (it varies according to the antenna type) is as follows;

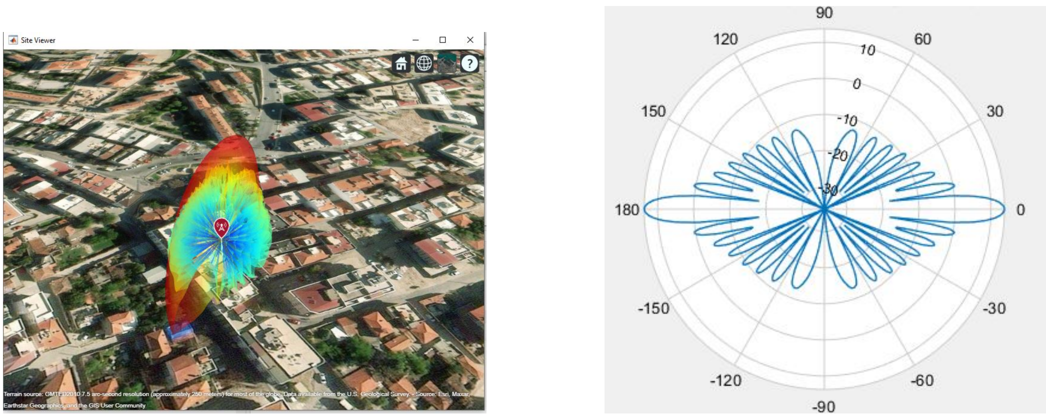


Figure 3.2 Beam Pattern and Azimuth Plot without Beamforming

Then, 1000 different locations are determined to be used in training by the recipient. The angle and signal levels between the transmitter and receiver were calculated using a separate link for each user. The link established between the first user and the base station is as follows;

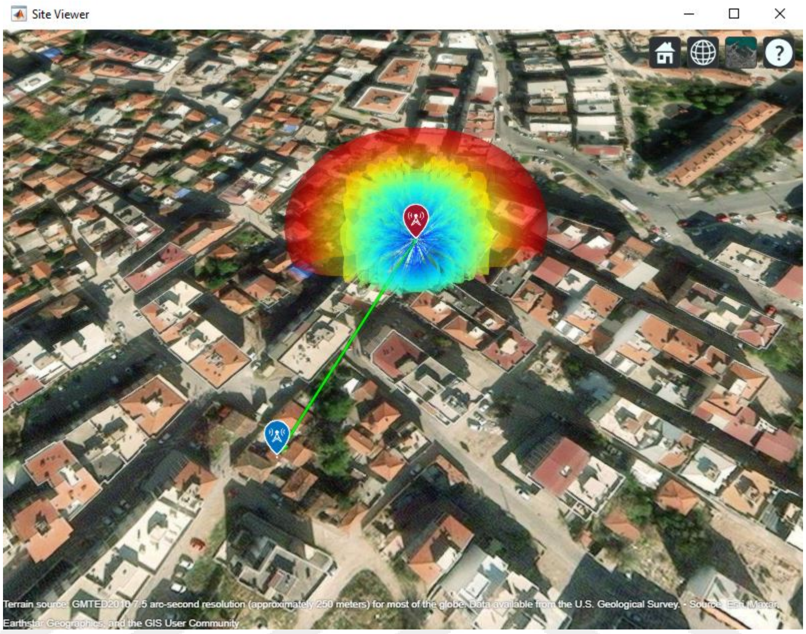


Figure 3.3 Receiver Site

## 3.1 Beamforming Architecture

Thanks to the steering vectors created for each user the output signal is formed and basic beamforming is applied. A different phase angle value is applied to each antenna element according to the arrival angle value and the beam is formed. The basic beamforming structure applied in this project is as follows;

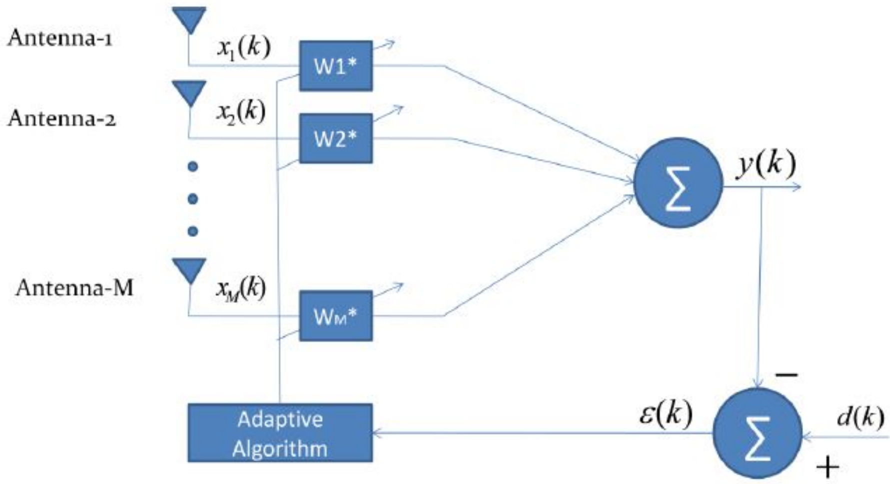


Figure 3.4 Beamforming Block Diagram()

After taking first angle of user between base station and creating new form of signal using beamforming technique mentioned above for first user to achieve maximum signal strength as follows;

,

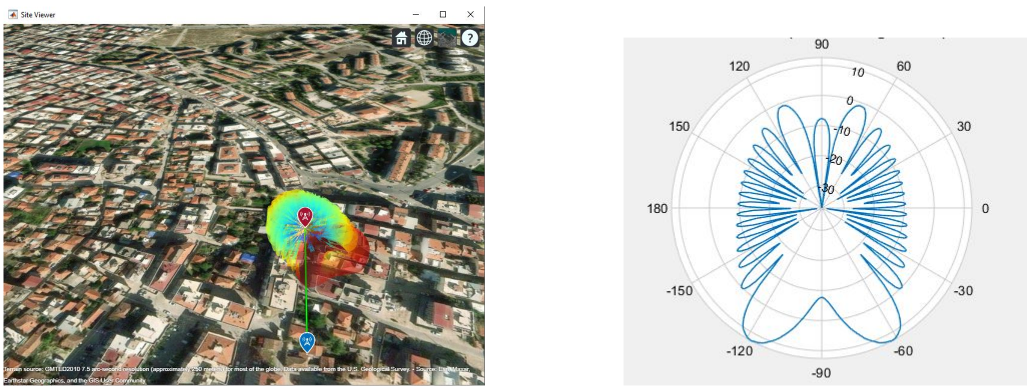


Figure 3.5 Beam Pattern and Azimuth Plot for First Beamforming

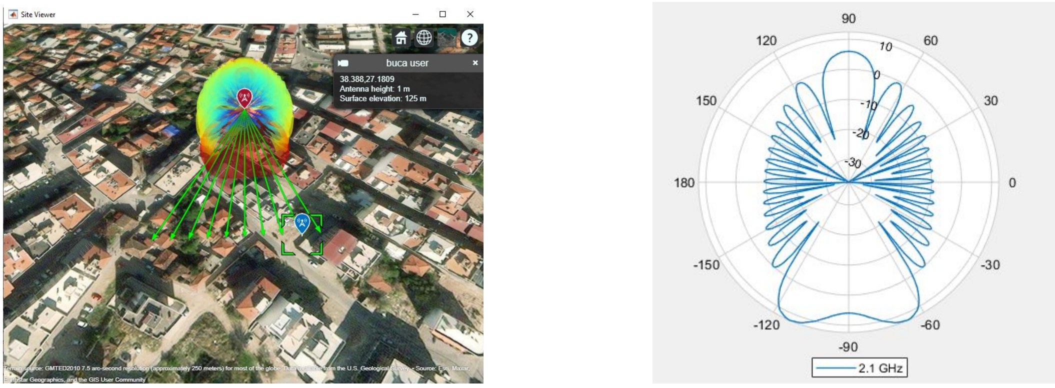


Figure 3.6 Beam Pattern and Azimuth Plot for 9th Beamforming

## 3.2 Neural Network Architecture

Data set taken before from each user for neural network training is used.Neural network uses signal strength or signal quality and arrival angle received with base station to predict the best beamforming vector at the each receiver site. With the test steering vector data, best signal strength are calculated for each user.

Firstly in classification method, neural network training outputs according to each range using the classification method for the outputs, estimating the signal level and angle for each test user and placing them in a certain range.

Secondly, it is aimed to estimate the angles of the users in different locations according to the base station from which they receive service by using the signal quality. In this context, the system was trained by using 10000 signal quality as input and angle values according to the base station as output. Then, 10000 different user information with known signal quality is given as input to the trained system. The system estimated the angle between it and the base station according to the signal quality of each user as output. The error was calculated by comparing these angle values with the required angle values.

The results obtained using different algorithms including different types of neural networks, which were mentioned earlier in section 2, will be observed and the results related to the beamforming architecture will be examined.

### 3.3 Results

Firstly, the test angle values were studied with Elman network by using the angle values between the receiver and the base station. Relevant values were classified with 30 degrees difference between -180 and 180 degree angle values and approximate results were estimated by Elman network algorithm. Afterwards, the learning rate values were changed from the training options and the value that would give the optimum result was found. The best value for the Elman network was chosen as 0.5. The training values determined for Elman network are as follow;

Table 3.2 Elman Neural Network Training Options

| | Epoch | Learning Rate | Error Goal | Hidden Layer |
|---|---|---|---|---|
| Elman Neural Network | 10000 | 0.05 | 0.0005 | Two |

Classification options are shown below;

```
for j=1:1:10000
    if -180>=ang(:,j)&&  -150<ang(:,j)
        target3(:,j)=h;
    elseif -150>=ang(:,j)&&  -120<ang(:,j)
       target3(:,j)=x;
    elseif -120>=ang(:,j)&&  -90<ang(:,j)
       target3(:,j)=b;
    elseif -90>=ang(:,j)&&  -60<ang(:,j)
        target3(:,j)=c;
    elseif -60>=ang(:,j)&&  -30<ang(:,j)
        target3(:,j)=d;
        elseif -30>=ang(:,j)&&  0<ang(:,j)
        target3(:,j)=e;
    elseif 0>=ang(:,j)&&  30<ang(:,j)
        target3(:,j)=o;
    elseif 30>=ang(:,j)&&  60<ang(:,j)
        target3(:,j)=p;
    elseif 60>=ang(:,j)&& 90<ang(:,j)
       target3(:,j)=r;
    elseif 90>=ang(:,j)&&  120<ang(:,j)
            target3(:,j)=s;
    elseif 120>=ang(:,j)&&  150<ang(:,j)
        target3(:,j)=t;
    elseif 150>=ang(:,j)&& 180<ang(:,j)
        target3(:,j)=k;
    end
end
```

Figure 3.7 Classification Values for Angle Estimation

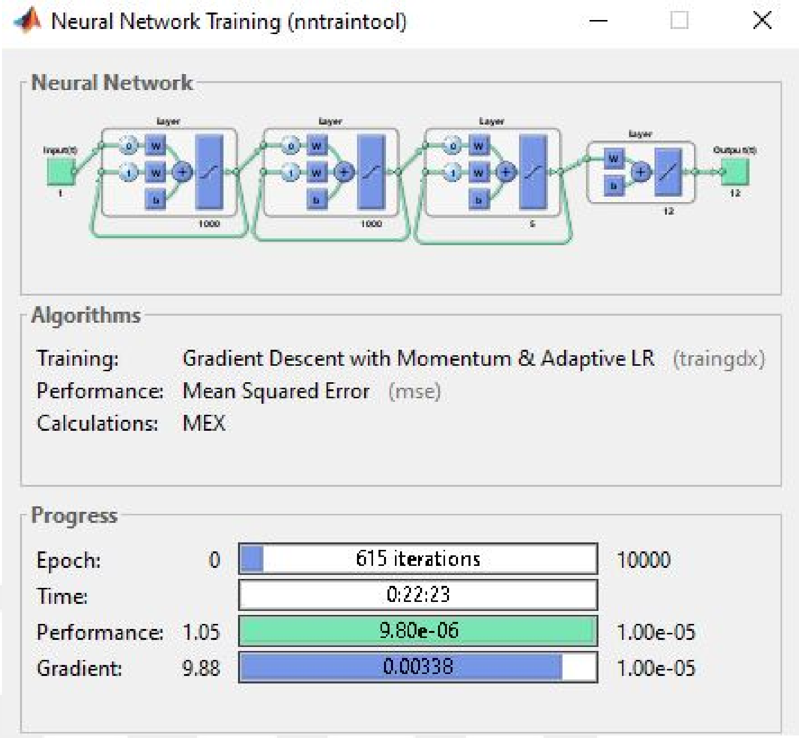


Figure 3.8 Elman Neural Network Training

After training , estimation values are assigned 1xN vector. N is equal to 1000 which is test user number. For first and 17th user, estimations are true and it is shown below;

Table 3.3 Original & Estimation Arrival Angle Value for 1st & 17th Users

| **Training Output First User** | | **Original Value** |
|---|---|---|
| -0.1920 | | angtest(1,1)= -124.0048 |
| 0.8541 | | |
| 0.1911 | | |
| 0.2088 | | |
| -0.7105 | | |
| 0.8697 | | |
| 0.0137 | | |
| 0.3127 | | |
| -1.5021 | | |
| -0.7649 | | |
| -0.6816 | | |
| -0.2052 | | |

| **Training Output 17th User** | | **Original Value** |
|---|---|---|
| -0.0451 | | angtest(:,17)= 117.6860 |
| -0.0328 | | |
| -0.2873 | | |
| 0.0301 | | |
| 0.0268 | | |
| -0.2572 | | |
| -0.2018 | | |
| -0.1927 | | |
| -0.1181 | | |
| 0.3468 | | |
| -0.0080 | | |
| 0.0338 | | |

The training values determined for feedforward network are as follow;

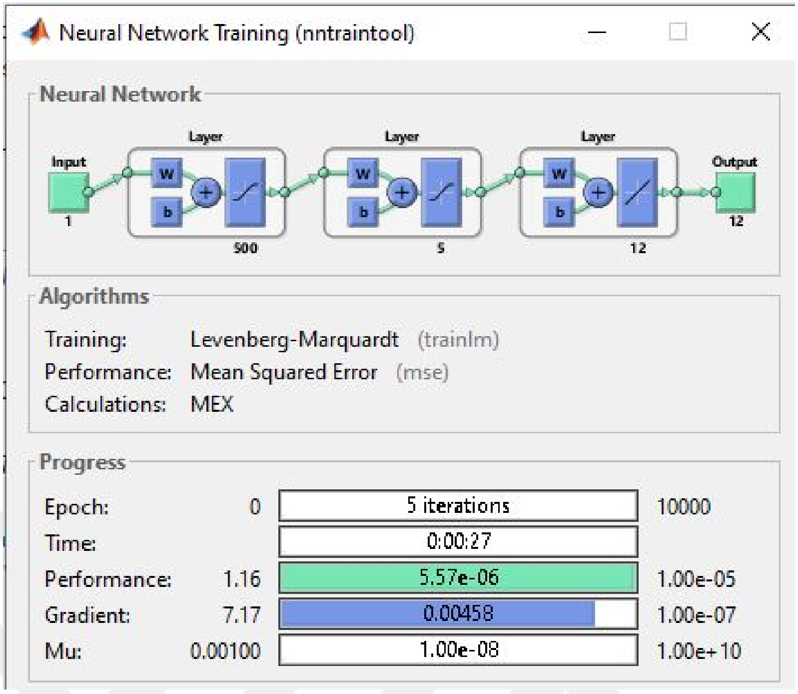


Figure 3.9 Feedforward Neural Network Training

Table 3.4 Original & Estimation Arrival Angle Value for 1st & 17th Users

| Training Output First User | | Original Value |
|---|---|---|
| 0.0215 | | angtest(1,1)= -124.0048 |
| -0.0166 | | |
| 0.0025 | | |
| 0.0067 | | |
| -0.0035 | | |
| 0.0062 | | |
| -0.0190 | | |
| 0.0097 | | |
| 0.0252 | | |
| 0.0407 | | |
| -0.0277 | | |
| 0.0078 | | |

| Training Output 17th User | | Original Value |
|---|---|---|
| 0.0051 | | angtest(:,17)= 117.6860 |
| 0.0003 | | |
| -0.0088 | | |
| 0.0084 | | |
| -0.0066 | | |
| 0.0086 | | |
| -0.0015 | | |
| -0.0039 | | |
| -0.0041 | | |
| 0.0049 | | |
| -0.0090 | | |
| 0.0026 | | |

As a second study, unlike the classification method, instead of classifying the output, it produces a single output according to the target value defined according to the angle value from the system trained according to the signal quality. Error was calculated by comparing these outputs with the required angle. Results determined for the angle values found in the ranges <-45,45> and <-90,90> and corresponding measurements accordingly.

- The training values determined for Feedforward Neural Network are as follow;

  Levenberg Marquardt is used as backpropagation train function. In this way, training output gives faster results. In Figure 3.10 and 3.11 show the results of regression value and Figure 3.16 and 3.17 show the results of Error Graph for feedforward neural network. Values in the range <-90,90> give better results because they contain values in a larger area.

- The training values determined for Elman network are as follow;

  It works slower than the feedforward neural network and Bayezian Regulation is used as the train function. It is slower than the Levenberg-Marquardt backpropagation train function, but provides improved output accuracy when working with large challenging data. In Figure 3.12 and 3.13 show the results of regression value and Figure 3.18 and 3.19 show the results of Error Graph for elman neural network. Also better than feedforward neural network results.

- The training values determined for Fitting Neural Network are as follow;

  In fitting neural network has a two-layer feed-forward network to train to solve data fitting problems. Levenberg-Marquardt is used as backpropagation train function. Compared to feedforward and Elman neural network training algorithms, its accuracy rate is lower and it reaches results with less trials than other training algorithms. In Figure 3.14 and 3.15 show the results of regression value and Figure 3.20 and 3.21 show the results of Error Graph for fitting neural network. Fitting neural network has lower prediction accuracy than Elman and feedforward neural network training algorithms.

### 3.3.1 Graph of Results

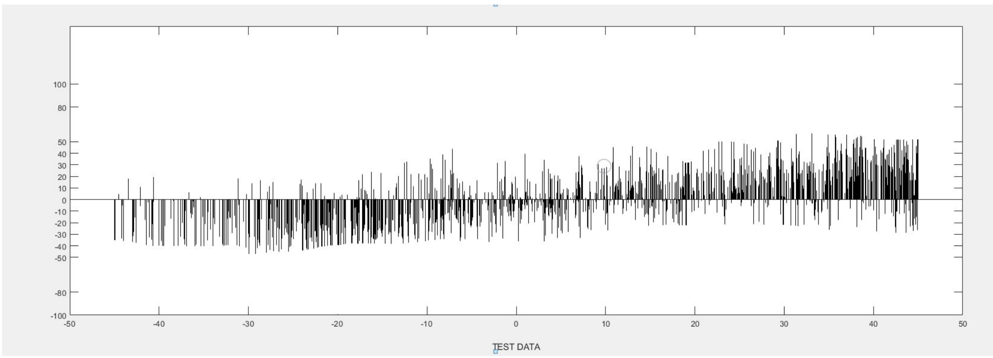


Figure 3.10 Error Graph Feedforward Neural Network for interval <-45,45>

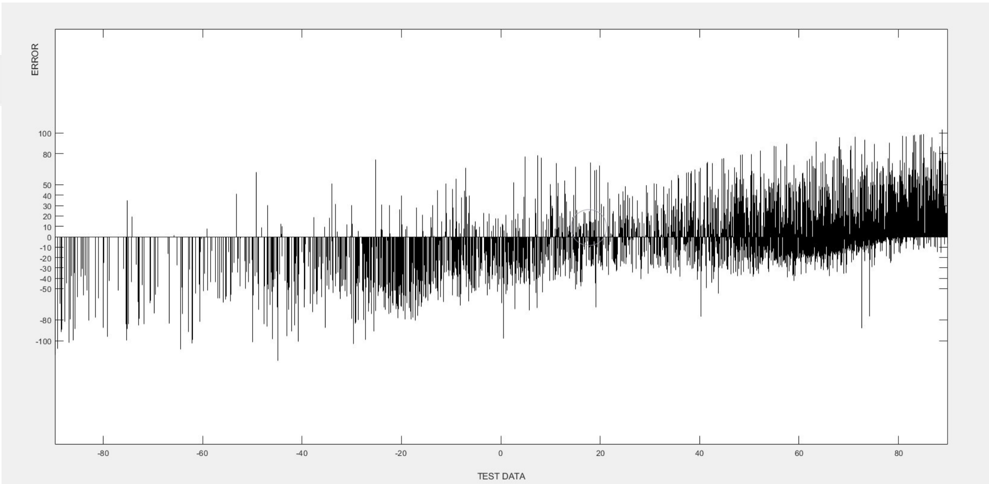


Figure 3.11 Error Graph Feedforward Neural Network for interval <-90,90>

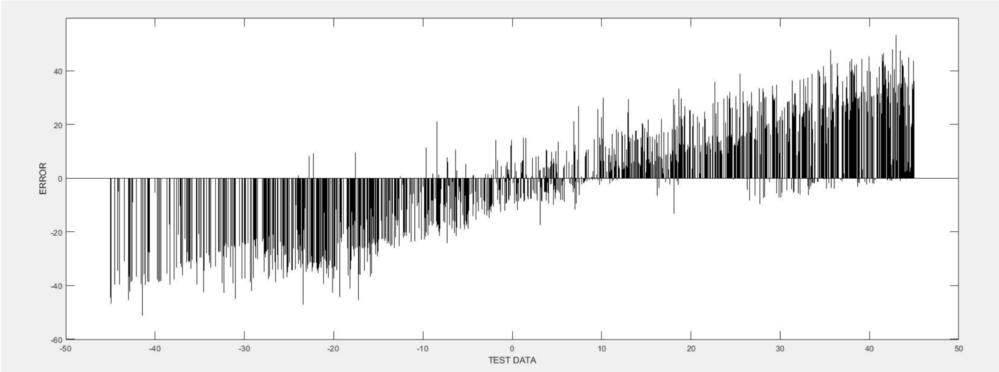


Figure 3.12 Error Graph Elman Neural Network for interval <-45,45>

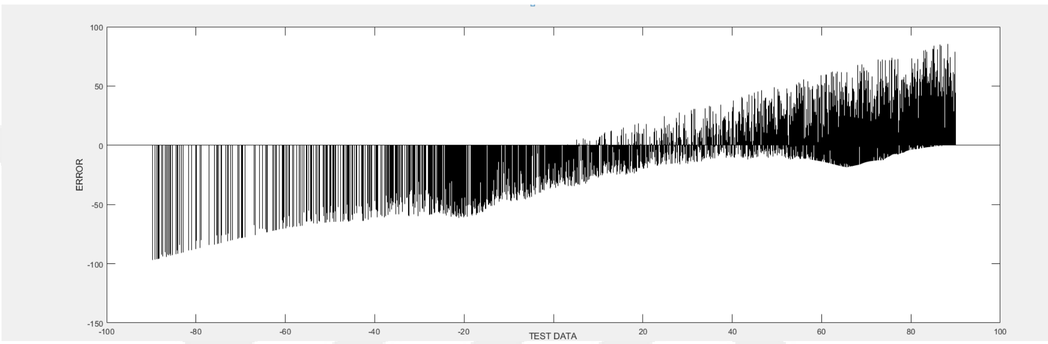


Figure 3.13 Error Graph Elman Neural Network for interval <-90,90>

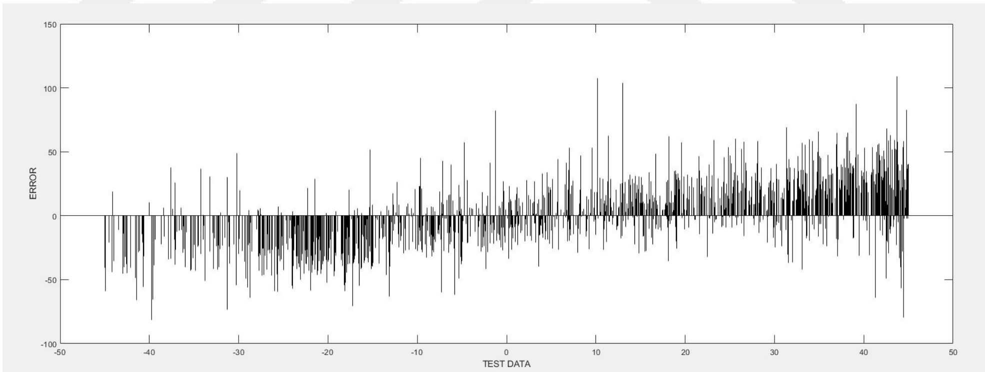


Figure 3.14 Error Graph Fitting Neural Network for interval <-45,45>

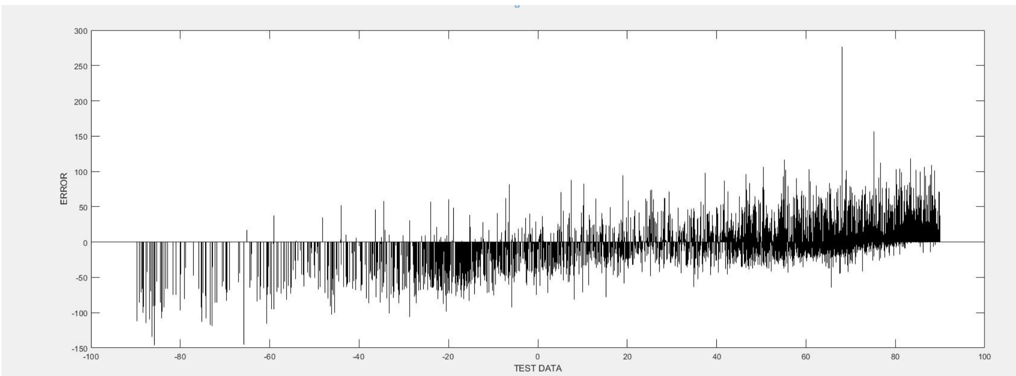


Figure 3.15 Error Graph Fitting Neural Network for interval <-90,90>

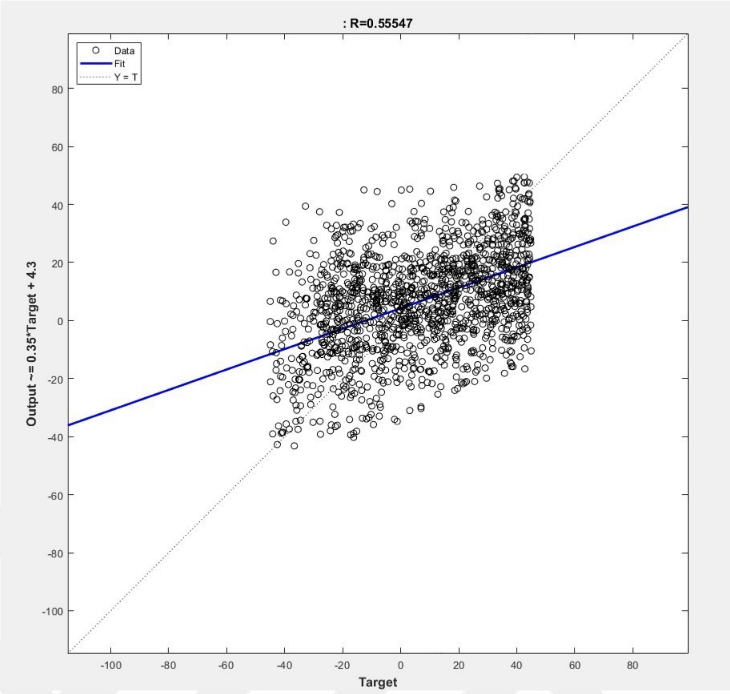


Figure 3.16 Regression Output Feedforward Neural Network for <-45,45>

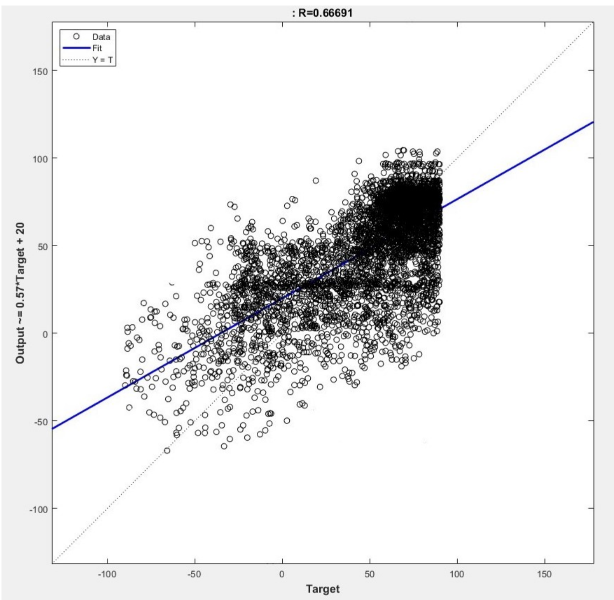


Figure 3.17 Regression Output Feedforward Neural Network for <-90,90>

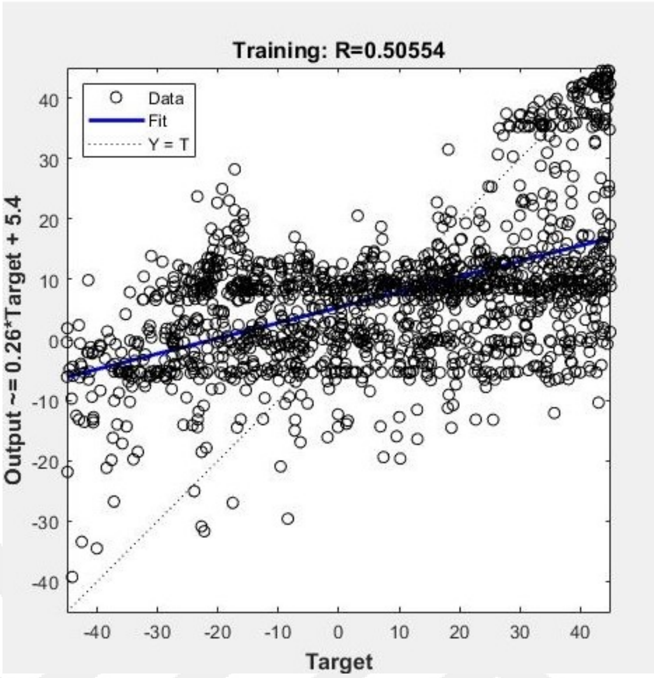

Figure 3.18 Regression Output Elman Neural Network for <-45,45>

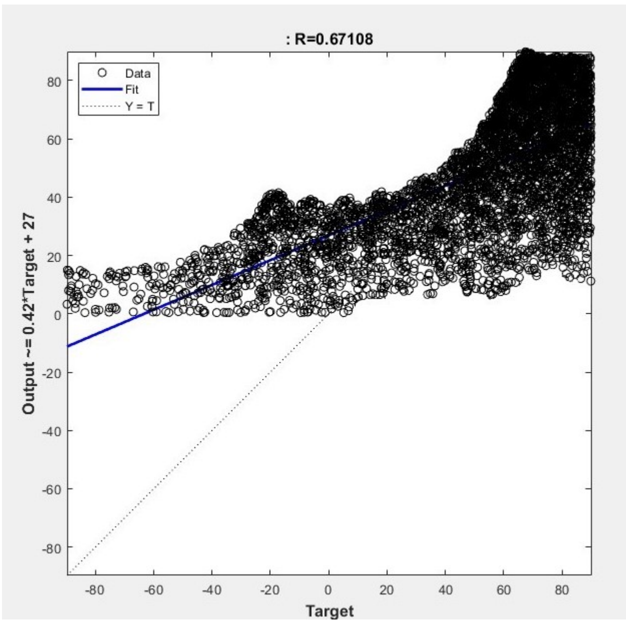

Figure 3.19 Regression Output Elman Neural Network for <-90,90>

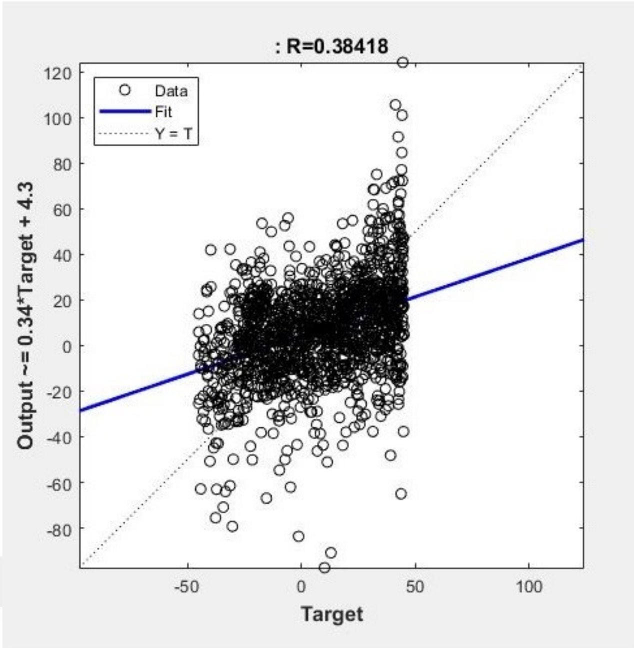


Figure 3.20 Regression Output Fitting Neural Network for <-45,45>

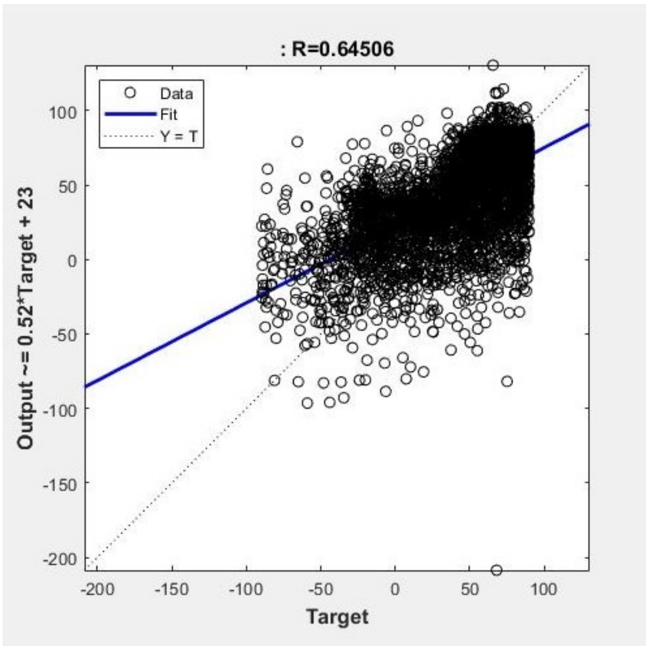


Figure 3.21 Regression Output Fitting Neural Network for <-90,90>

### *3.3.2 Challenges and Solutions*

The reaction of the system to any random signal will be as follows: The system is expected to produce 2 outputs for the user according to the incoming data. These outputs are at the same distance from the base station but at different angle values. The system measures the SINR on the user again with a 10 degree change, determines its direction according to the improvement or worsening condition, and shapes the signal according to the angle at the relevant limit value in the neural Network. In this way, the problem is eliminated with an additional short-term measurement in the Beamforming algorithm for different users at the same distance and with the same SINR value.

## 3.4 Comparison

Consequently, the time in seconds between epochs is faster in elman neural network and slower in feedforward neural network. However, while more epochs are required for elman neural network, it gives more accurate results. Feed forward gives results with a much lower epoch number. Feed forward results were less reliable than elman neural network in our study, but more data sets are required and it would be useful to work with longer epoch numbers. Since working with the same hidden layer and number of neurons requires a long time for feedforward neural network, the study was done with less hidden layers and neurons. When the whole training period is considered, It was seen that the fitting neural network algorithm was not suitable for this study and elman neural network gives better results in longer periods. Better learning rate must be determined for neural network.

According to all training algorithms, the results obtained in the range of <-90,90> have a higher accuracy rate. The biggest reason for this is that the separation of users is easier in a wider area. The results may be more accurate if it is studied only for users with an angle of incidence greater than zero.

# CHAPTER FOUR
# CONCLUSION

In this paper, by using the neural network structure, the signal level and arrival angle are calculated according to the location of the users, and it is aimed to provide maximum quality service for a base station and to improve user satisfaction. The feedforward, elman and fitting neural network algorithms were examined comparatively.

As a result, Elman neural network training algorithm with Bayesian Regulation as a training fuction gives better results in accordance with our thesis purpose. The results obtained with the feedforward network algorithm and the Levenberg-Marguardt training method gives less accurate results, and the elman neural network will be used in further studies.

The studies conducted in (Sallom & Ahmed, 2015) and (Güreken, 2009) are similar to the approaches in our thesis, but they differ in method. In both studies, the error calculation was made according to the desired and trained angle values obtained by the neural network study for the location of the user. In our study, as a more complex structure, the neural network algorithm was used in order to estimate the angle of arrival according to the signal levels received from the users and also to estimate the current location of the user.

In (Maja Sarevska, 2008), the blind beamforming study was analyzed and a weight estimation was made by running the neural network for the user whose location is unknown. Similarly, in our thesis, the arrival angle and signal level were determined according to the location of the users at first, but the angle estimation was made according to the signal level in the training part. In this respect, the two studies are similar, and the radial basis neural network, which is an artificial neural network, was used as the neural network algorithm, like the elman neural network we use.

In (Yugo M. Kuno & Madhu, 2019) by using neural network and beamforming together, the traditional beamforming structure was compared and it was aimed to send a more specific signal to the target user, that is to give service, by reducing the side lobe and noises of the NN. The training data includes interfering and target signal direction, ramdom amplitudes and phases and additive noise. In this way, it is aimed to obtain a better quality signal by learning the noise shape and direction of arrival. The minimum variable distortionless resporse bemformer (MVDR) and capon beamformer are used to transmit signal to the target user in the maximum possible way. This thesis is different from the techniques and purpose we use, but in further studies, it is possible to provide a higher quality service by estimating the location of use with neural network by combining this study and the techniques we use.

In (Mizumachi, 2019), showing similar aspects with the previous study, but aimed to use this study together with beamforming and deep neural network structure in order to reduce the noise on the speech signal and to obtain a quality speech signal. In this study, a different training algorithm than ours is used, and by combining it with our study in future studies, both the location of the user can be quickly determined and a very high quality service can be provided by reducing the unwanted noise on the speech signal by giving a quality signal.

In (Singh & Jayakumar, 2020), RMSE (Root Mean Square Error) was used as a value indicating how much difference there is between target and calculated values. The linear regression model was used as the neural network model. Linear regression is a machine learning model and is a useful method for mapping inputs and outputs. In our thesis, the neural network structure, which is one of the sub-branches of machine learning, has been examined. Both studies differ in this respect and are similar in terms of method and purpose. Both studies make angle estimation as a result of the training algorithm.

As a further study of this thesis, beamforming will be made according to the user density and the coverage will be directed to the region where the user is dense. With machine learning, the hours of these user densities will be determined and beamforming will be run before the user density.

## REFERENCES


Ahmed, Y. (January 21,2018). *Fundamentals of a uniform linear array (ula)*. https://www.raymaps.com.

Ali, E. I., & Nordin, R. (2017). Beamforming techniques for massive mimo systems in 5g: overview, classification, and trends for future research. *Frontiers Inf Technology Electronic Eng*, 18, 753–772.

Amie Study Circle (1994). *Antenna arrays*. Radar Antenna Engineering. https://amiestudycircle.com.

Basu, D. (2010). *Dictionary of Pure and Applied Physics 2nd ed.* Florida: CRC Press.

Bevelaqua, P. (15 June 2015). *Monopole antenna*. https://www.antenna-theory.com/antennas/monopole.php.

Braun, K. F. (1909). Nobel lecture: Electrical oscillations and wireless telegraphy. *Nobel Media AB 2013*.

Caceres, P. (2020). *The recurrent neural network*. https://pabloinsente.github.io.

Cadence (2021). *Phased array antennas*. https://resources.system-analysis.cadence.com/.

Cruse, H. (2006). Neural networks as cybernetic systems. *Brains, Minds Media*, 146–148.

D. E. Rumelhart, G. E. H., & Williams, R. J. (1986). Learning representations by back-propagating error. *Nature*, 323(6088),533–536.

El Zooghby, G. C., & Georgiopoulos, M. (1998). Antenna array beamforming using neural network. *IEEE Transactions on Antennas and Propagation*, 46, 1891–1892.

Electronics Desk (2012). *Types of antenna arrays*. https://electronicsdesk.com.

Facundo Bre, J. M. G., & Fachinott, V. D. (2018). Prediction of wind pressure coefficients on building surfaces using artificial neural networks. *International Conference on Engineering and Technology (ICET)*, *158*, 1429–1441.

Guanghua Ren, Yuting Cao, S. W. T. H., & Zeng, Z. (2018). A modified elman neural network with a new learning rate scheme. *Neurocomputing*, 286, 11–18.

Güreken, M. (2009). Neural network based beamforming for linear and cylindrical array applications. *Middle East Technical University*, 1–5.

Hebb, D. O. (1949). *The Organization of Behavior*. New York: The Orwell Press.

Hopfield, J. J. (1982). Neural networks and physical systems with emergent collective computational abilities. *Proceedings of the National Academy of Sciences of the United States of America*, 79(8),2554–2558.

K. A. Gotsis, K. S., & Sahalos, J. N. (2019). On the direction of arrival (doa) estimation for a switched-beam antenna system using neural networks. *IEEE Transactions on Antennas and Propagation*, 57(5),1399–1411.

Kappes, M. (2019). All-digital antennas for mmwave systems. *Microwave Journal*, 1–5.

Kim, C., K. T. S. J. (2013). Multi-beam transmission diversity with hybrid beamforming for mimo-ofdm systems. *IEEE Globecom Workshops*, 61–65.

KONR, B. (2022). *Dipole antenna*. https://www.hamradioschool.com.

Le Magoarou, Luc, Y. T. P. S., & Crussière, M. (2021). Deep learning for location based beamforming with nlos channels. *Arxiv*, 1–5.

Mailloux, R. J. (1992). Antenna array architecture. *Proceedings of the IEEE*, 80(1),163–172.

Maja Sarevska, A.-B. M. S. (2008). Antenna array beamforming using neural network. *International Journal of Electronics and Communication Engineering*, 2(12),2923 – 2927.

Mathworks (2020). White paper-hybrid beamforming for massive mimo phased array systems.

Mizumachi, M. (2019). Neural network-based broadband beamformer with less distortion. *International Congress on Acoustics*, 1–5.

Pai, A. (2020). *Cnn vs. rnn vs. ann – analyzing 3 types of neural networks in deep learning*. https://www.analyticsvidhya.com.

Pedamkar, P. (2022). *Machine learning vs neural network*. https://www.educba.com.

P.Ioannides, & Balanis, C. (2005). Uniform circular arrays for smart antennas. *IEEE Antennas and Propagation Magazine*, 47(4),192 – 206.

Prasanthi, T. D. (2022). Adaptive array antennas. *International Journal of Multidisciplinary Educational Research*, 1–5.

S. Albawi, T. A. M., & Al-Zawi, S. (2017). Understanding of a convolutional neural network. *International Conference on Engineering and Technology (ICET)*, 1–6.

Sallom, A. H., & Ahmed, S. (2015). Elman recurrent neural network application in adaptive beamforming of smart antenna system. *International Journal of Computer Applications*, 129(11), 38–43.

Sean V. Hum (2006-2021). *Ece422 - radio and microwave wireless systems*. Class Notes. https://www.waves.utoronto.ca/prof/svhum/ece422.html.

Shahid, M. (2019). *Convolutional neural network*. https://towardsdatascience.com/.

Sharma, P. (2009). Neural network based robust adaptive beamforming for smart antenna system.

Singh, A. J., & Jayakumar, M. (2020). Machine learning based digital beamforming for line-of-sight optimization in satcom on the move technology. *2020 4th International Conference on Electronics, Communication and Aerospace Technology (ICECA)*, 422–427.

Torres-Rosario, J. A. (2005). Implementation of a phased array antenna using digital beamforming.

Tougaw, D. (2018). *Applied Electromagnetic Field Theory*. Valparaiso: Valparaiso University.

Tutschku, K. (1995). Recurrent multilayer perceptrons for identification and control: The road to applications. *Univ. Würzburg, Germany, ser. Research Report Series*, 8–15.

Warren, M., & Pitts, W. (1943). A logical calculus of ideas immanent in nervous activity. *Bulletin of Mathematical Biophysics*, 5, 115–133.

Wikipedia (2012a). *Antenna types*. from https://en.wikipedia.org/wiki/Antenna_types.

Wikipedia (2012b). *Antenna types*. from https://en.wikipedia.org/wiki/Whip_antenna.

Wondie, T. K. E. Y., & Steinbrunn, J. (2020). Massive mimo, mmwave and mmwave-massive mimo communications: Performance assessment with beamforming techniques. *Research Square*, 17–22.

Xu Y., Liu X., C. X., & C., H. (Oct,2021). Artificial intelligence: A powerful paradigm for scientific research. *Innovation (Camb)*.

Yongxu Zhu, Jun Zhang;Jiangzhou Wang, A. P. P. W. X., & Zheng, G. (2019). Deep learning based beamforming neural networks in downlink miso systems. *2019 IEEE International Conference on Communications Workshops*, 1–5.

Yugo M. Kuno, B. M., & Madhu, N. (2019). A neural network approach to broadband beamforming. *Proceedings of the 23rd International Congress on Acoustics*, 6961–6968.

Zaharis, Z. D. (2016). Implementation of antenna array beamforming by using a novel neural network structure. *2016 International Conference on Telecommunications and Multimedia*, 1–5.

Zaremba Wojciech, S. I., & Oriol, V. (2014). Recurrent neural network regularization. *ArXiv*, abs/1409.2329.