VISVESVARAYA TECHNOLOGICAL UNIVERSITY

BELGAUM

A Project Report on

"IDENTIFICATION OF SPECTRUM HOLES USING ANN MODEL FOR COGNITIVE RADIO APPLICATIONS"

Submitted in partial fulfillment of the requirements for the award of the Degree of

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CERTIFICATE

Certified that the project work entitled "IDENTIFICATION OF SPECTRUM HOLES USING ANN MODEL FOR COGNITIVE RADIO APPLICATIONS" carried out by SALONI S VERNEKAR (1NT15EC143), SHALINI SRINIVAS (1NT15EC148), SUJAYANTH K VISHWAKARMA (1NT15EC158) and ARJUN PREETHAM M E (1NT15EC184), bonafide students of NITTE MEENAKSHI INSTITUTE OF TECHNOLOGY in partial fulfilment for the award of Bachelor of Engineering in ELECTRONICS AND COMMUNICATION of VISVESVARAYA TECHNOLOGICAL UNIVERSITY, Belgaum during the year 2018-2019. The project report has been approved as it satisfies the academic requirement in respect of the project work prescribed as per the autonomous scheme of NITTE MEENAKSHI INSTITUTE OF TECHNOLOGY for the said Degree.

Signature of the Guide	Signature of the HOD	Signature of the Principal
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ABSTRACT

In Cognitive Radio any user or transceiver has ability to sense best suitable channel, while channel is not in use. It means an unlicensed user can share the spectrum of a licensed user without any interference. Though, the spectrum sensing consumes a large amount of energy and it can reduce by applying various artificial intelligent methods for determining proper spectrum holes. It also increases the efficiency of Cognitive Radio Network.

ANN consists of number of neurons and they are interconnected by weighted links.The incoming signals are multiplied by the corresponding weights of the links and a bias term is added. All these terms now multiplied to form an input to next layers neuron, which is subjected to a nonlinear function i.e. activation function like sigmoid or hyperbolic.

Cognitive radio is now the relevant technology under development that enables one to utilize the spectrum more efficiently. Here we propose a new artificial neural network model that predicts the channel capacity of the received signal. This information is analyzed theoretically which is subsequently verified by a suitable simulation scheme for identifying possible white space in a given band.

ACKNOWLEDGEMENT

The satisfaction and euphoria that accompanies the successful completion of any project would be incomplete without the mention of people who made it possible and whose constant encouragement and guidance has been a source of inspiration throughout the course.

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DECLARATION

We the students of B.E. VIII Semester, SALONI S VERNEKAR (1NT14EC143), SHALINI SRINIVAS (1NT14EC148), SUJAYANTH K VISHWAKARMA (1NT14EC158) and ARJUN PREETHAM M E (1NT14EC184), studying at Nitte Meenakshi Institute of Technology, Bangalore, hereby declare that the final year project titled "Identification Of Spectrum Holes Using ANN Model For Cognitive Radio Application" submitted to the Department of Electronics and Communication Engineering, Nitte Meenakshi Institute of Technology, Bangalore, in partial fulfillment of Degree of Bachelor of Engineering is the original work conducted by us. The information and data given in the report is authentic to the best of our knowledge. We hereby declare that this final year report is not being submitted to any other university for the award of any other Degree, Diploma and Fellowship.

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CHAPTER 01

INTRODUCTION

Spectrum allocation (or frequency allocation) is the regulation and allocation of the electromagnetic spectrum into the radio frequency or commonly called RF bands. This allocation is usually done by governments in most countries across the world. Because radio propagation does not stop at national level, governments have sought to harmonize the allocation of RF bands and their standardization.

International Telecommunication Union

International Telecommunication Union (ITU) is the United Nations exclusive agency specifically for Information and Communication Technologies. Formed in the year 1865 to ease international connectivity in communications networks, ITU distributes radio spectrum and satellite orbits globally, develops the technical standards that ensures the networks and technologies seamlessly interconnected, and strives to improve access to Information and Communication technologies to underserved communities worldwide. Every time you make a phone call using mobile, access the Internet, send an email or browse you are benefitting from the work of ITU.

International Telecommunication Union:- Is committed to connecting everyone, everywhere irrespective of where they live or whatever their means. ITU protects and supports everyone's right to communicate effortlessly.

Cognitive Radio is the best solution for spectrum scarcity and spectrum under utilization over wireless communication channel.

Current radio systems are not able to identify the radio spectrum environment and operate in a specific frequency band using a specific spectrum access system. With the flourishing popularity and necessity of wireless devices, the radio spectrum is insufficient to provide the requirements for its complete utilization. The existing spectrum authorizing scheme is not able to oblige quickly growing demand in wireless communication due to the static spectrum allocation strategies. This allocation prompts increment in spectrum scarcity issue. Investigations of spectrum utilization indicate that not all the spectrum is used in space or time.

The study shows that in the current fixed spectrum allocation scheme some frequencies in the spectrum are not occupied or partially occupied and others are extremely used. These unoccupied frequencies have been termed as spectrum holes. A spectrum hole is a licensed frequency band that is being used for some time period in a specific area.

A technology is therefore needed which can sense and understand its local radio spectrum environment, to identify temporarily vacant spectrum and use, it has the potential to provide higher bandwidth services, increase spectrum efficiency and minimize the need for centralized spectrum management. This could be achieved by a radio that can make autonomous and rapid decisions about how it can access the spectrum. Cognitive radios have the potential to do this.

Cognitive radio (CR) technology is a propelled remote radio design which aims to expand spectrum utilization by distinguishing unused and under-used spectrum in burgeoning environments. Spectrum sensing is one of the key strategy for cognitive radio which detects the presence of primary client in authorized licensed frequency band utilizing dynamic spectrum assignment policies to utilize unused spectrum.

1.1 OBJECTIVES

The objectives of our project are as follows :

- The primary objective of this project is to maximize the decision accuracy under noisy conditions and its implementation. The conventional spectrum sensing has various limitations often leading to misinterpretations .
- ANN is the most feasible solution to achieve an optimal result. Levenberg-Marquardt is the fastest back propagation training algorithm.
- Implementation of neural network through LM Back propagation neural network.
- Real time data is collected from USRP B200 and the channel status is predicted using the already trained artificial neural network.

1.2 PROBLEM STATEMENT

Cognitive Radio empowers secondary users to use primary user's spectrum without any interference.

Spectrum Sensing is the important property of Cognitive Radio. Spectrum Sensing in Cognitive Radio is broadly classified into Co-operative and Non Co-operative Sensing.

Co-operative Spectrum Sensing requires the information of many other Cognitive Radio users to detect the presence of a primary user.

Non Co-operative Spectrum Sensing includes the Energy Detection, Cyclostationary and Matched filter Detection .

Energy Detection performs well if the noise at the receiver is known in prior. But the performance can be degraded by uncertainty in noise power .

The matched filter is used when the secondary user has a prior knowledge of the primary user signal. In cyclostationary feature detector it requires some parameters of the primary signal such as symbol rate and have high computational requirements.

Hence, a new approach of artificial neural network based spectrum sensing is proposed which senses the availability of a vacant channel in the primary users spectrum. Here, neural network is used because it is a smart, intelligent phenomenon with the capabilities to understand the environment, learn and adjust in real time operating parameter according to specific need of unlicensed user.

CHAPTER 02

LITERATURE SURVEY

2.1 Artificial Neural Network based spectrum recognition in cognitive radio by Rahul Singh and Sarita Kansal

In paper [1], a new approach of artificial neural network based spectrum sensing is put forward which can sense the availability of an unoccupied channel in the primary users spectrum and allocates it to secondary users. The primary objective of this paper is to implement through perceptron based neural network system to enhance the throughput. The throughput is evaluated and results shown using MATLAB

2.2 Identification of Spectrum Holes using ANN Model for Cognitive Radio Applications by Sandhya Pattnayak and R.Nandi.

In paper [2], a new technique is put forward to identify spectrum holes. A neural network model is designed to predict channel state information for spectrum sensing. Here the channel information is the channel capacity which is predicted from the Signal to Noise ratio of the channel scanned. The proposed ANN model predicts channel capacity and the output is used to compute and find whether channel is occupied or not.

2.3 ANN based Spectrum Sensing Technique for Cognitive Radio Applications by Sandhya Pattanayak and R.Nandi

In paper [4], a spectrum sensing technique for FM and wireless microphone signals in TV band is Proposed with the help of an ANN Model. The artificial neural network model is trained with the autocorrelation peaks of the signal in the given channel and this is used to identify if it as a white space or a primary signal. The efficiency in terms of false alarm rate and probability of detection is increased in this technique. This method involves less mathematical complexity in comparison to other recent spectrum sensing techniques

2.4 Spectrum Sensing in the Presence of Multiple Primary Users byLu Wei, Student Member, IEEE, and Olav Tirkkonen, Member, IEEE

In paper [6], multi-antenna cooperative spectrum sensing in cognitive radio networks is considered. An detector based Analyzer is used for spherical testing such environment. Based on the moments of the distributions involved, accurate and simple analytical equation for the key performance metrics of the detector is obtained. The false alarm, detection probabilities, the detection threshold and Receiver Operation Characteristics is available . Simulations are enabled to check the accuracy of the obtained results and compared with other detectors in realistic sensing situations.

2.5 Highway Construction Investment Risk Evaluation Using BP Neural Network Model by Li Ma and Yiming Chang

In paper [10], China's realities are considered and Delphi Method is used to establish in this article. An evaluation index system of highway construction project which includes investment risks consisting of 19 factors from 6 aspects including political, economic and natural environment, project management, construction technology and operational management was used. Owing to the non-linear characteristics of the risk factors, the neural network tool box of MATLAB software was adopted to build a 19 * 12 * 1 BP neural network evaluation model. Finally, this model was applied in investment risk evaluation; the results show that BP neural network model can be used as a practical effective investment risk evaluation method of highway construction project.

2.6 Artificial Neural Network Based Spectrum Sensing Method for Cognitive Radio by Yu-Jie Tang, Qin-Yu Zhang, and Wei Lin

In paper [12], spectrum sensing method using artificial neural network (ANN) is proposed. Here, a detailed analysis of the proposed scheme is appropriated to detect the signals under low signal-to-noise ratio (SNR) environment and has reliable performance. In this paper, simulations also show that the discussed method outperforms over previous approaches in noisy environment while sensing the spectrum for CR systems.

2.7 A Neural Network Based Spectrum Prediction Scheme for Cognitive Radio by Vamsi Krishna Tumuluru, Ping Wang and Dusit Niyato

In this paper [13], a reliable prediction scheme is proposed. The unlicensed users willsense only those channels which are predicted to be vacant. Byachieving a low probability of error in predicting the vacant channels, the spectrum utilization can also be improvised. Since the traffic characteristics of most licensed user systems encounteredin real life are not known a priori, a design of the spectrum predictor using the neural network is modelled. A multilayer perceptron (MLP), which does not require a prior knowledge of the traffic characteristics of the licensed user systems is implemented.

CHAPTER 03

COGNITIVE RADIO

3.1 INTRODUCTION TO COGNITIVE RADIO

Cognitive Radios has been viewed as a smart device that can efficiently use the bandwidth of a spectrum. It has advanced as an assuring solution that will alleviate the continuous conflict between exponential spectrum demand and spectrum underutilization.CR is the amalgamation of software defined radio (SDR) and intelligent signal processing (ISP).CR implies intelligent signal processing (ISP) at the physical layer of a wireless system, i.e. the layer that performs functions such as communications resource management, access to the communications medium, etc.It is based on Software Defined Radio (SDR) technology and are an end result of a multi-disciplinary effort including wireless communication, digital communication, system engineering and artificial intelligence.

A cognitive radio spontaneously identifies unoccupied channels in wireless communication system and accordingly modifies its transmission and reception parameters so that more wireless communications may run contemporaneously in a given spectrum at a given geographical location and time. Cognitive radio alters its transmission and reception characteristics conforming to the environment surrounding it.

Cognitive Radios learns from the environment and adjusts its interior states to statistical variations in the incoming RF stimuli by making corresponding changes in certain operating parameters in real time. In general the cognitive radio may be expected to look at parameters such as channel occupancy, free channels, the type of data to be transmitted and the modulation types that may be used. It must also look at the regulatory requirements. In some instances it may be necessary to use a software defined radio, so that it can reconfigure itself to meet and achieve the optimal transmission technology for a given set of parameters.

It follows OOPDAL Loop : Observe, Orient, Plan, Decide, Act, Learn.

The hindrance faced in making Cognitive Radio a machine with the ability to automatically take decisions on its situational awareness.

3.2 CHARACTERISTICS OF COGNITIVE RADIO

The characteristics of cognitive radio include:

3.2.1 Cognitive Capabilities

Cognitive capability refers to the ability of radio to do sniffing or sensing information from its environment and perform real time interaction with it. The cognitive capability can be explained with the help of three characteristics which are: Spectrum Sensing, Spectrum Analysis and Spectrum Decision. The spectrum sensing performs the task of monitoring and detecting of spectrum holes. The spectrum analysis will estimate the characteristic of detecting spectrum hole. For spectrum decision, the appropriate spectrum is selected by determining the parameters like data rate and transmission mode.

3.2.2 Cognitive Radio Reconfigurability

Reconfigurability refers to the capability of the radio which allows the cognitive radio to adjust its parameters like link, operating frequency, modulation and transmission power at run time without any alterations in the hardware components. In other words Reconfigurability of Cognitive Radio is Software Defined Radio. By doing that we dynamically change all the layers of communication as seen in Fig 3.1 below. Depending on their spectrum availability we can use different technologies with the same hardware.

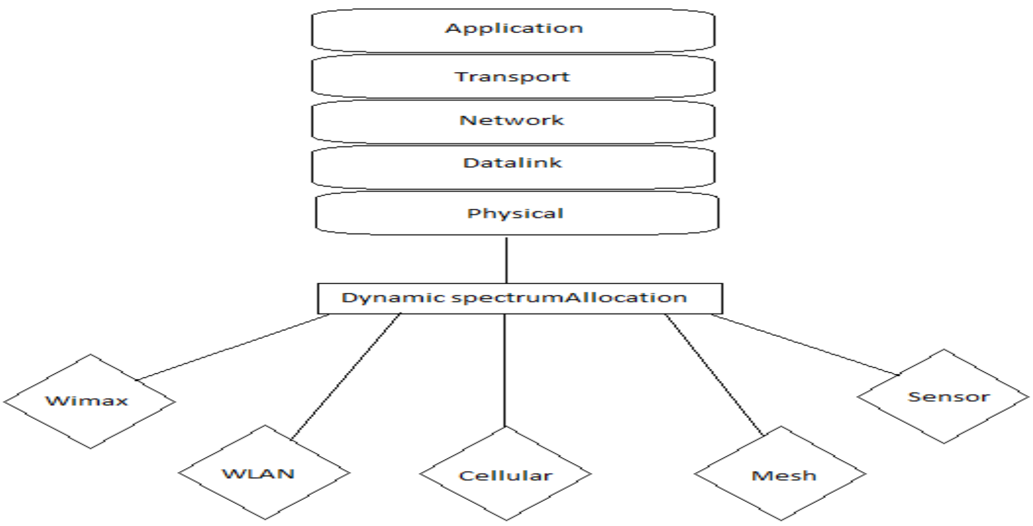


Fig 3.1 Dynamic changes in all Layers

3.3 Spectrum Sensing

The ultimate goal of the cognitive radio is to get the best available spectrum through Cognitive Capability and Reconfigurability as mentioned above. Since there is lack of spectrum, the most important challenge is to serve the licensed spectrum without intervening with the transmission of other licensed users as illustrated in Fig 3.2.The cognitive radio enables the usage of temporally vacant spectrum, which is mentioned as spectrum hole or white space. If this band is further used by a licensed user, the cognitive radio jumps to another spectrum hole or remains in the same band, amending its transmission power level or modulation scheme to avoid interference

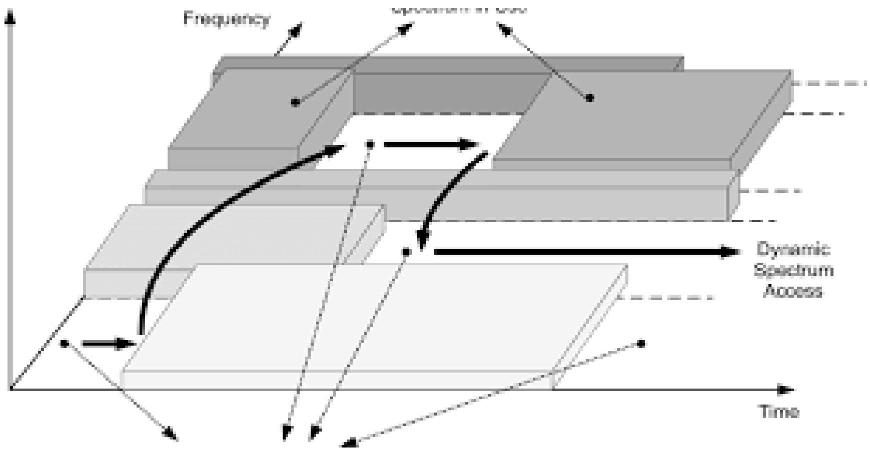


Fig 3.2 Spectrum hole concept

The cognitive capability of a cognitive radio permits real time interaction with its environment to determine suitable communication parameters and adapt to the dynamic radio environment.

The duties required for adaptive operation in open spectrum are shown in Fig 3.3 which is referred to as the cognitive cycle.

The three important steps of the cognitive cycle, shown in Fig 3.3 are as follows:

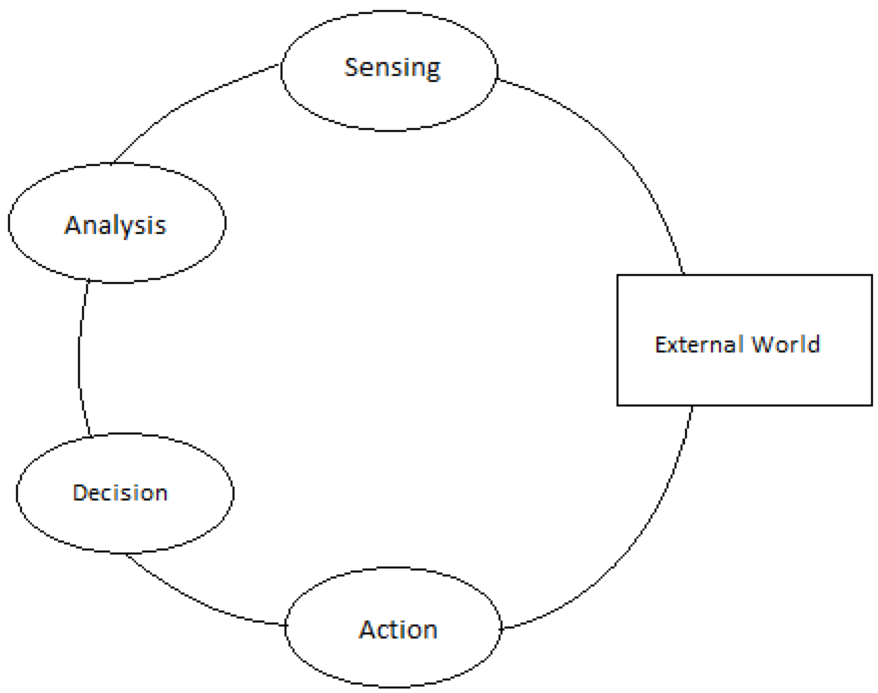


Fig 3.3 Cognitive Cycle

3.3.1 Spectrum sensing

A cognitive radio perceives the radio environment and finds the available spectrum band, the information related to its parameters and detects spectrum holes.

3.3.2 Spectrum analysis

The study of the spectrum holes that are observed through spectrum sensing and their characteristics are estimated.

3.3.3 Spectrum decision

Cognitive radio first decides its capabilities like the data rate, the transmission mode, and the bandwidth of the transmission. Next, the suitable spectrum band selection is made from the spectrum holes decided during spectrum sensing. Once the operating spectrum band is determined, the communication can be executed over this spectrum band. However, since the radio environment varies from one timeline to another, the cognitive radio should familiar with the changes in the radio environment.

If some primary user wants to transmit on the spectrum band, which is in usage of cognitive radio then the spectrum mobility function is invoked to ensure a seamless transmission. Any environmental change during the transmission such as primary user appearance, user mobility, or traffic variation can trigger this adjustment.

3.4 The Cognitive Radio Architecture

Existing wireless network architectures enrols diversity in terms of spectrum policies and communication technologies . Moreover, some amount of the radio spectrum is licensed for different technologies and some bands remain unlicensed called Industrial Scientific Medical (ISM) band. A clear elucidation of Cognitive Radio Network architecture is required for the development of communication protocols.

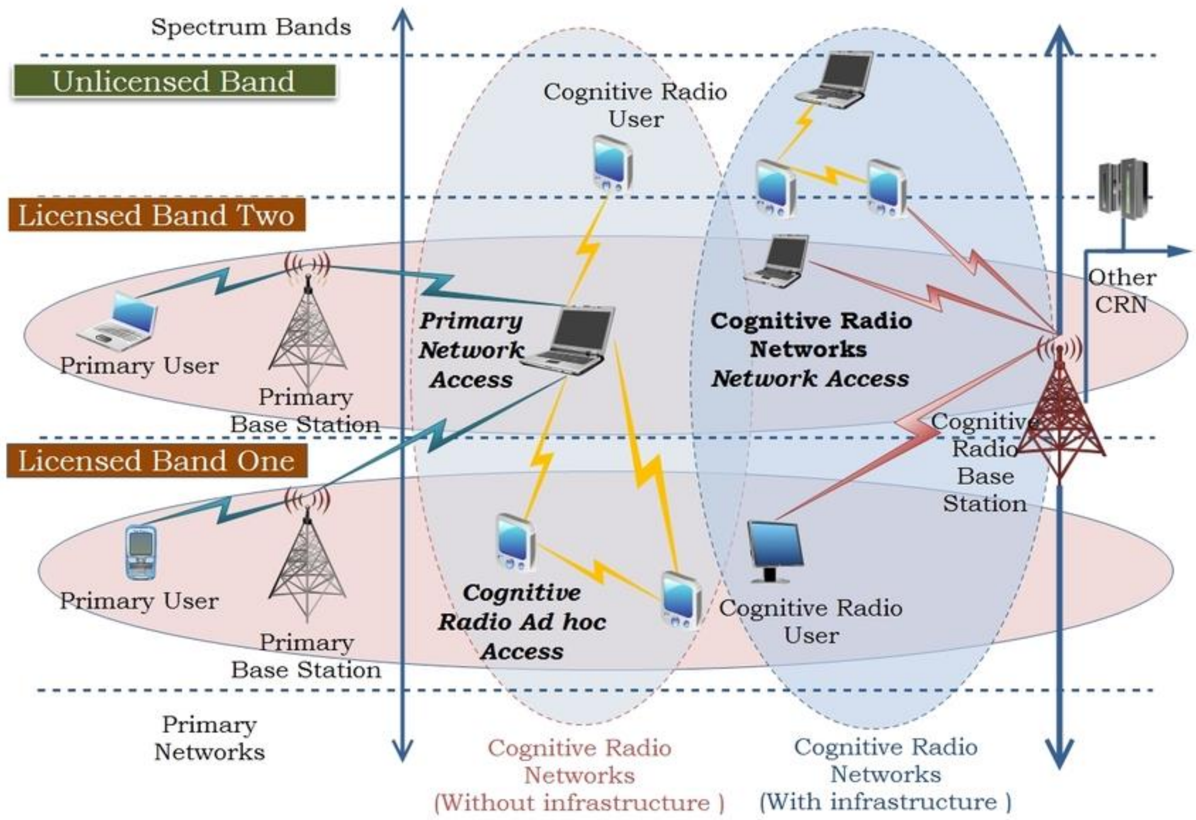


Fig 3.4 Cognitive Radio Network Architecture

The constituents of the Cognitive Radio network architecture, as shown in Fig 3.4 can be categorized into two groups which is the primary network and the Cognitive Radio network. The basic elements of the primary and the CR network are defined as follows:

3.4.1 Primary network

A network with entitlement for a specific radio spectrum band is called primary network. Few of the primary network are common cellular network, WiMAX, CDMA and TV broadcast networks. The constituents of the primary network are given below.

3.4.2 Primary user

A user of primary network which has a permit to operate in a certain spectrum band. Primary user has access to the network via base station. All of its services and operations are controlled by base station. Therefore, it should not be affected by any unlicensed user. Therefore, primary users do not need any alteration for coexistence with Cognitive Radio base-stations and Cognitive Radio users.

3.4.3 Primary base-station

A predeterminedinfrastructure network component for a specific technology with licensed band is called Primary base station. Example is when base station transceiver system (BTS) in a cellular system and BTS in WiMAX. Primary base station does not have capability for coexisting with Cognitive Radio Network, therefore, the primary base station require some alterations such as the need to have both licensed and Cognitive Radio protocols present for the primary network access of Cognitive Radio users.

3.4.4 Cognitive Radio network

A network where the spectrum access is allowed only in expedient manner and does not have license to operate in a desired band is called Cognitive Radio Network. It can be deployed both as an infrastructure network and an ad hoc network as shown in Fig 3.4

The components of a CR network are as follows.

1. Cognitive Radio user

Cognitive Radio user and secondary user has no spectrum license for its operation so some of the additional functionality is required to share the licensed spectrum band.

2. Cognitive Radio base-station

Cognitive radio base station or secondary base station is a predetermined infrastructure component that provides single hop connection to Cognitive Radio users without any license of radio spectrum. Cognitive Radio users can access the other networks with the help of this connection.

3.5 Applications of Cognitive Radios

Cognitive Radio Networks can be applied in many cases few are listed below :

3.5.1 Leased network

Primary network may provide a leased network by allowing cognitive radio user to access its licensed spectrum in an expedient manner without causing harm to the communication of the primary user.

3.5.2 Cognitive mesh network

For providing broadband connectivity wireless mesh networks are in boom as a cost effective technology. However mesh networks require higher capacity to meet the immediate requirements of the applications that demand higher throughput. Since the cognitive radio technology enables the access to larger amount of spectrum, therefore cognitive radio networks will be a greater choice to meet the requirements of mesh networks.

3.5.3 Emergency network

Cognitive Radio Networks can be put into practice for Public safety and emergency networks. In the case of natural disasters, when primary networks are temporarily disable their spectrum band can be used by Cognitive Radio users. Cognitive Radio networks can communicate on available spectrum band in ad hoc mode without the necessity for an infrastructure and by maintaining communication priority and response time.

3.5.4 Military network

The Cognitive Radio networks can be used in military radio environment. Cognitive Radio networks can enable the military radios to choose arbitrary intermediate frequency bandwidth, modulation schemes, and coding schemes, adapting to the variable radio environment of battlefield.

CHAPTER 04

SENSING TECHNIQUES

4.1Classification of Techniques

Spectrum sensing is the main challenge to the Cognitive Radios. In the spectrum sensing there is a necessity to find spectrum holes in the radio environment for Cognitive Radio users. However, it is not easy for Cognitive Radio to have a direct computation of channel between primary transmitter and receiver. A CR can not do both, transmission and detection of the radio environment simultaneously, thus, we need a spectrum sensing technique that takes less time for sensing the radio environment. The different spectrum sensing techniques have been classified in the following three categories.

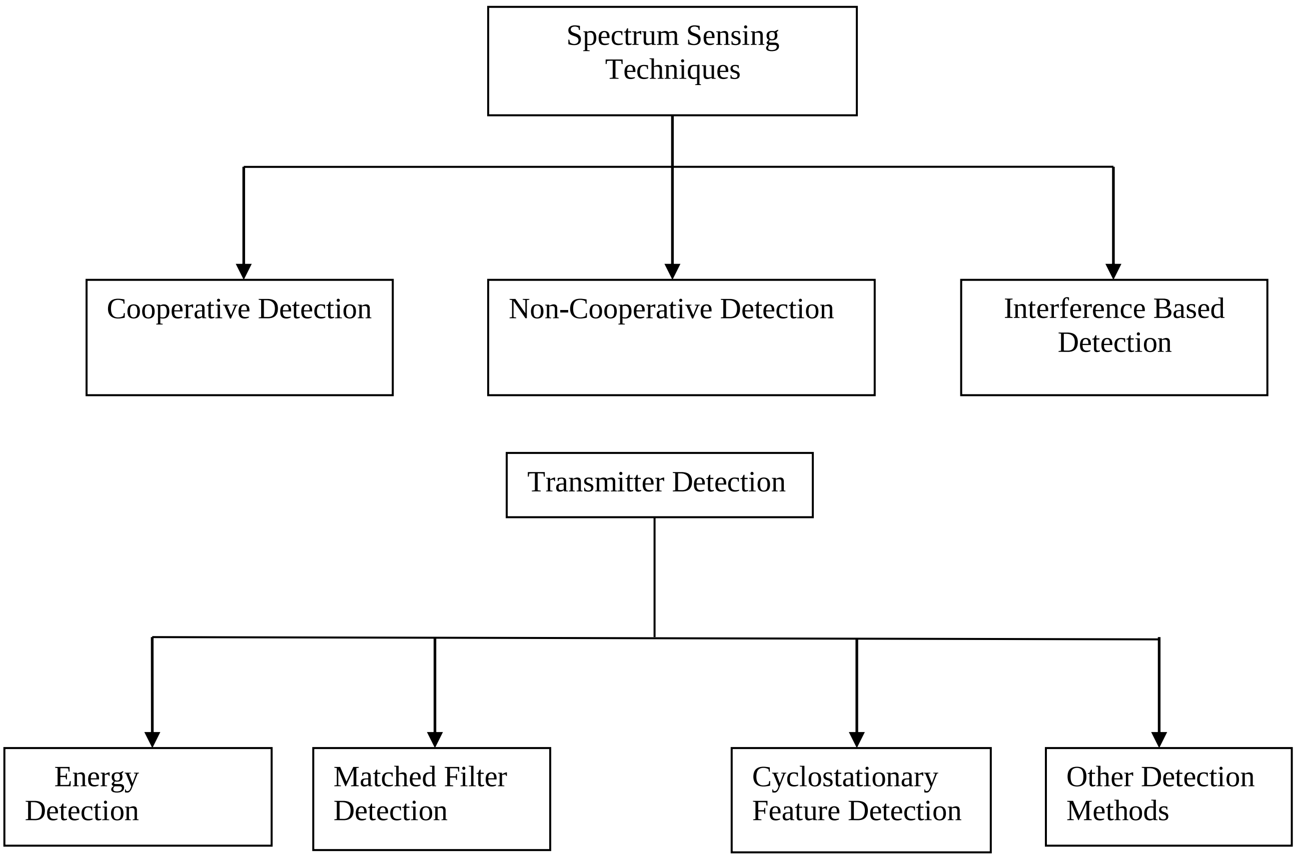


Fig 4.1 Classification of Spectrum sensing

1. Matched Filter Detection

A matched filter is a linear filter designed to provide maximum signal-to noise ratio at its output for a given transmitted waveform. Fig 4.2 shows the block diagram of matched filter. The signal received by CR is given as input to matched filter which is

$$r(t) = s(t) + n(t).$$

The matched filter convolutes the r (t) with h (t) where h (t) = s (T-t + τ). Finally the output of matched filter is compared with a threshold λ to decide whether the primary user is present or not.

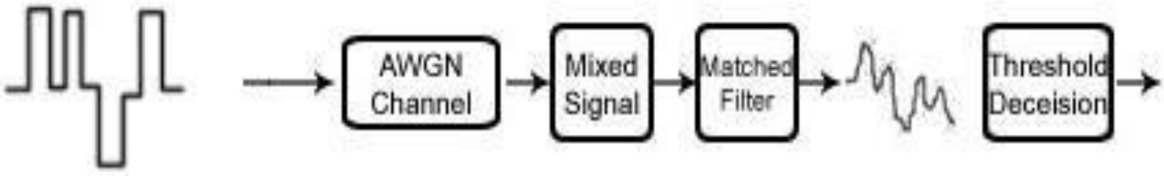


Fig 4.2 Block Diagram of Matched Filter

A Matched filter is an ideal detector in an AWGN channel if the waveform of the primary user is formerly known by Cognitive radio. It means that Cognitive radio should have the understanding about the waveform of primary user such as modulation type and order, the pulse shape and the packet format.If the

CognitiveRadio does not have this type of earlier information then it is difficult to detect the presence of primary user. We can use Matched Filter Detection because in most of the communication networks we can achieve this coherency by initiating pilots, preambles, synchronization word or spreading codes in the waveform of primary users. But there are disadvantages in matched filter because each Cognitive radio should have the information of all the primary users present in the radio environment. The advantage of a matched filter is that it takes lesser time for high processing gain. Although,the major drawback of Matched Filter is that a CR would need a dedicated receiver for every primary user class.

2. Energy Detection

If Cognitive radio does not have adequate information about primary user's waveform, then the matched filter is not the optimal choice. Hence, if it is conscious of the power of the random Gaussian noise, then energy detector is optimal.The input band pass filter selects a center frequency fs and bandwidth of interest. The filter is followed by a squaring device to calculate the received energy then the integrator ascertains the observation interval, T.

Finally, the output of the integrator, Y is analyzed with a threshold, λ to decide whether primary user is present or not.

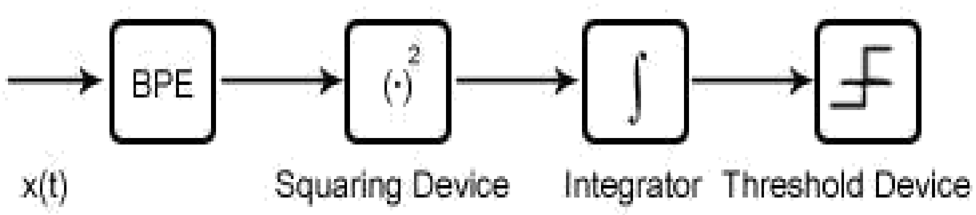


Fig 4.3 Block Diagram of Energy Detector

In a non fading environment where h is amplitude gain of the channel, probability of detection Pd and probability of false alarm Pf are given by following formulas :

$$Pd = P(Y > \lambda / H1)$$

$$Pf = P(Y > \lambda / H\,0)$$

Where Y is the SNR, m = TW is the (observation/sensing) time bandwidth product Γ (.) and Γ (.,.) are complete and incomplete gamma functions, Qmis the generalized Marcum Q-function.

In a fading environment h is the amplitude gain of the channel that changes due to the shadowing or fading effect which makes the SNR variable. Pf is the same as that of non fading case because Pf is non-dependent of SNR. Pd gives the probability of detection conditioned on instantaneous SNR. In this case average probability of detection may be derived by averaging over fading statistics:

$$Pd = \int_x \sqrt{\,}\, Q_m \left(\sqrt{2Y}, \lambda\right) f_\gamma(x)\,dx$$

Where f γ (x) is the probability distribution function of the SNR under fading. A low value of Pd suggests an absence of primary user with high probability; it means that the Cognitive Radio user can use that spectrum. A high value of Pf shows minimal use of spectrum.It is suggested that in a radio spectrum environment, different Cognitive Radio users need to coordinate in order to detect the presence or absence of the primary user.

In such a situation, comprehensive model relating different parameters such as detection probability, number and spatial distribution of spectrum sensors and more importantly propagation characteristics are yet to be discovered. One of the main problems of energy detection is that performance is more prone to uncertainty in noise power. It cannot differentiate between signal power and noise power rather it just indicates the absence or presence of the primary user.

3. Cyclostationary Feature Detection

Modulated signals are usually dualed with sine wave carriers, pulse trains, repeating spreading, hopping sequences, or cyclic prefixes, which often builds up periodicity in the signal. Even though the data is stationary random process, these modulated signals are characterized as Cyclostationary, since their statistics, mean and autocorrelation, exhibits periodicity. These features are by analyzing a spectral correlation function In order so that the receiver can implement parameters like pulse timing, carrier phase etc, it is required for the periodicity is contributed for signal format. This periodicity can be implemented for the detection of random signals with a specific type of modulation with the noise and other modulated signals.

Recent efforts on research has exploited the Cyclostationary feature of signal as method for classification, which has been found to be far greater than the simple energy detection and match filtering. As discussed, a matched filter is a coherent detector which requires earlier knowledge about primary user’s wave whereas energy detector as a non coherent detection that does not require any kind of prior information about the primary user’s waveform. Although energy detector is faster to implement, it is highly vulnerable to in band interference and changing noise levels and cannot distinguish between signal power and noise power.

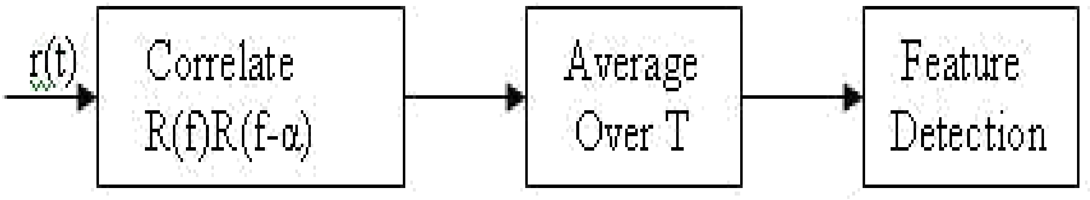


Fig 4.4 Block Diagram of Cyclostationary Feature Detector

Application of spectrum correlation function for Cyclostationary feature detection is illustrated in Fig 4.4. Detected characteristics are the number of signals, modulation types, symbol rates and the presence or absence of interferers. If the correlation factor is more than the threshold then it implies the presence of a primary user in radio environment. Although it accomplishes a better work than energy detector because it can distinguish between signal power and noise power, it is arithmetically very complex that requires more processing time, which generally affects the performance of Cognitive radio.Signal processing techniques encourages the need to understand other feature detection techniques that can improvise sensing detection and recognize the different modulation types and the different type of signals in low SNR environments.

4.2 Cooperative Vs Non Cooperative

The detection functioning can be classified into two main branches, Non cooperative and cooperative. In non cooperative detection cognitive radio user can detect the presence of a primary transmitter by its own inspection and analysis while not depending on the other cognitive radio users. While in Cooperative detection the information from many other cognitive radio users are united to detect the presence of a primary user. Moreover, Cooperative behavior helps to vanquish the multi path fading and shadowing effect that will enhance its usability. There are two methods for the implementation of cooperative detection that is centralized and distributed. In Centralized Cooperative detection mechanism the base station is responsible for getting all details from other cognitive radio users to detect the primary user. Whereas in distributed mechanism cognitive radio interchange messages between each other to get the aspired objective. In comparison to the non cooperative, the cooperative detection provides more precise performance at the cost of additional operations but it still lacks about the information about the location of the primary user receiver

CHAPTER 05

USRP B200

5.1 Overview

The USRP-B200 ensures a fully integrated, single board, Universal Software Radio Peripheral platform with a continuous frequency coverage from 70 MHz to 6 GHz. Designed specifically for a low cost for economical experimentation, it unites a integrated direct conversion transmitter receiver providing up to 56MHz of real time bandwidth, an open and highly efficient reprogrammable Spartan6 FPGA, and rapid and convenient bus powered Super speed USB 3.0 connectivity Full support for the USRP Hardware Driver software permits the user to instantly begin configuring with GNU Radio and provides seamless transition code from the B200 for higher performance. An enclosure accessory kit allows users of green PCB devices to assemble a protective steel case.

Experiment with the USRP B200 across a wide range of applications such as : FM radio and Television broadcast, cellular, GPS, Wi-Fi, ISM etc. Users can instantly begin prototyping in GNU-Radio and participate in the open source Software Defined Radio community. The USRP Driver software allows efficient code reuse from existing designs, affinity towards open source applications like HDSDR and Open BTS, and an improved path to industry ready USRP systems to meet application requirements.

5.2 B200 System Architecture

The integration of Radio Frequency front ended on the USRP B200 is designed with the new Analog Devices AD9364, a single chip direct conversion transmitter-receiver and digital base band processor, capable of streaming up to 56 MHz of real time Radio Frequency bandwidth. The B200 uses one signal chain of the AD9364 allows it to be bus powered and reducing software and hardware design complexity. Onboard signal processing and control of the AD9364 is achieved by a Spartan6 XC6SLX75 FPGA connected to a host PC using Super Speed USB 3.0. The USRP B200 real time system throughput is bench marked at 61.44MS/s quadrature provides full 56 MHz of instantaneous RF bandwidth to the host computer for additional processing using GNU Radio Software Defined Radio design environment.

Fig 5.1 USRP B200

5.3 Features

- The integrated USRP device with continuous RF coverage from 70 MHz –6 GHz
- Full duplex fast operation with up to 56 MHz of real time bandwidth
- Fast and convenient bus powered connectivity using Super Speed USB 3.0
- GNU Radio and Open BTS support through the open-source USRP Hardware Driver
- Open and reconfigurable Spartan 6 XC6SLX75 FPGA with free Xilinx tools (for advanced users)
- Early prototyping platform for the Analog Devices AD9364 RFIC, a fully integrated direct conversion transceiver with mixed signal baseband
- Steel encapsulation accessory kit available for green PCB devices

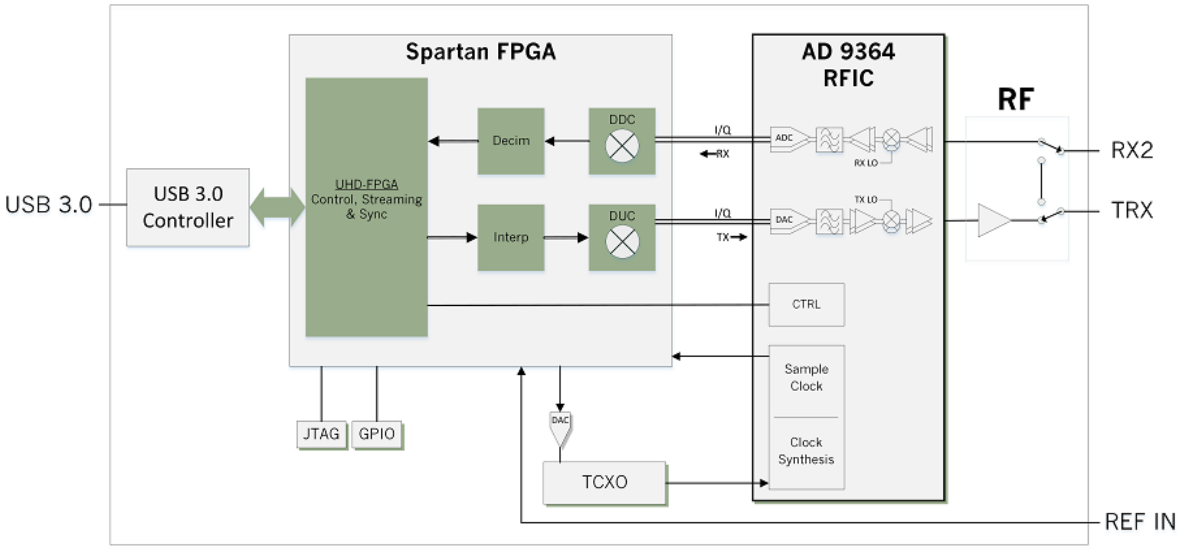


Fig 5.2 Architecture of B200

- Hardware Capabilities:
  - Integrated RF frontend (70 MHz - 6 GHz)
  - External PPS reference input
  - External 10 MHz reference input
  - Configurable clock rate
  - Variable analog bandwidth (200 kHz - 56 MHz)
  - GPIO header
  - [B200/B210] Internal GPSDO option (see **Internal GPSDO Application Notes (USRP-B2x0 Models)** for details)
  - [B210/B200mini] JTAG Connector
  - [B210] MICTOR Debug Connector
- FPGA Capabilities:
  - Timed commands in FPGA
  - Timed sampling in FPGA

5.4 FM Broadcast Receiver With USPR B200

The block diagram given in fig 5.3 illustrates FM receiver with the USRP B200. The log periodic antenna connected to the USRP B200 is used to receiver live FM signals. The antenna is connected to the USRP B200 which is interfaced with MATLAB Simulink. The FM demodulator in the Simulink has built in code blocks to perform successful reception. The speaker receives the live FM audio. The scope helps to display the received signal.

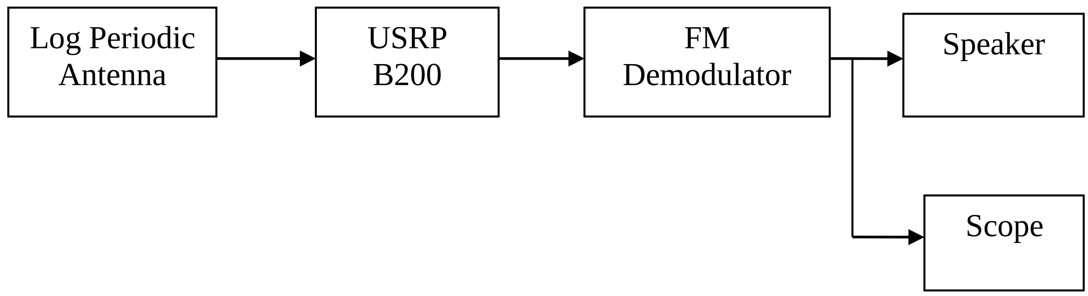


Fig 5.3 Block diagram of USRP using Simulink

Log Periodic Antenna :-The antenna used with the USRP B200 is the log-periodic antenna, which is also called a log-periodic aerial or log-periodic array ,this is a multi-element, directional antenna developed to work over a wide range of frequencies. It was first invented by Dwight Isbell and Raymond DuHamel in the year 1958.

The log-periodic antenna is the log-periodic dipole array or LPDA, which is most commonly used. The LPDA has a of number of half-wave dipole driven elements of slowly increasing length, each having a pair of metal rods. The dipoles are scaled close together in a straight line, which is in parallel to the feed line with alternating phase. Electrically, it simulates a series of two or three-element Yagi antennas connecting it together, each set tuned to a different frequency.

LPDA antennas looks similar to Yagi antennas, in that they both consist of dipole rod elements scaled in a line along a support boom, but they perform in different ways. Adding elements to a Yagi increases its gainor directionality ,while adding elements to a LPDA enhances its frequency response and bandwidth.

The most useful application of a LPDAs is in rooftop terrestrial television antennas, as they must have large bandwidth to cover the wide television bands of approximately 54–88 and 174–216 MHz in the VHF and 470–890 MHz in the UHF and also have high gain.

CHAPTER 06

ARTIFICIAL NEURAL NETWORK

6.1 Introduction To Artificial Neural Network

Artificial Neural Network (ANN)is similar to the biological basic units (cells) of the human brain. It consists of a number of interconnected processors called as neurons. Each connection, is like synapses in the human brain, which can transmit a signal from one artificial neuron to another neuron. The signal received by the artificial neuron will be processed and then, that signal is sent to connected artificial neurons.

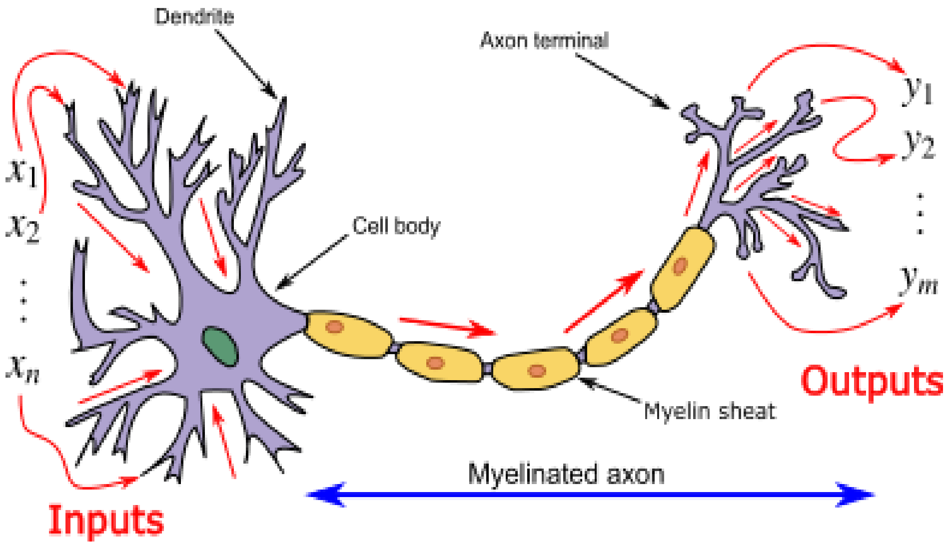


Fig 6.1 Neuron diagram

The working of artificial neuron is like working of biological neuron with inputs and outputs. The neural network performs useful computations by learning process. The neural network is formed by connecting the output of neurons to the input of other neuron by forming directed and weighted graph. The interneuron connection strength which is known as synaptic weights. These weights are used to store the learned knowledge.

6.1.1 MODEL OF A NEURON

A neuron is a information processing unit that is the basic operation of a neural network .The below mentioned block diagram of Fig 6.2 shows the model of neuron .

The basic elements of neural model are as follows:

1. A set of synapses also called as connecting links ,which are characterized by its own weight. A signal X_j at the input of synapse connected to neuron k is multiplied by the synaptic weight Wkj. It is necessary to make a noteof the manner in which the subscripts of the synaptic weight Wkj are to be written. The first subscript is Wkj which refers to the neuron in question, and the second subscript refers to the input end of the synapse to which the weight is referred to. Unlike the weight of a synapse in the brain, the synaptic weight of an artificial neuron may lie in arrange that includes positive as well as negative values.

2. An adder that will help summing up the input signals, weighted by the respective synaptic strengths of the neuron the operations described here constitute a linear combiner.

3. An activation function for limiting the amplitude of the output in a neuron. The activation function is also referred to as a squashing function, in that it squashes the permissible amplitude range of the output signal to some finite values.

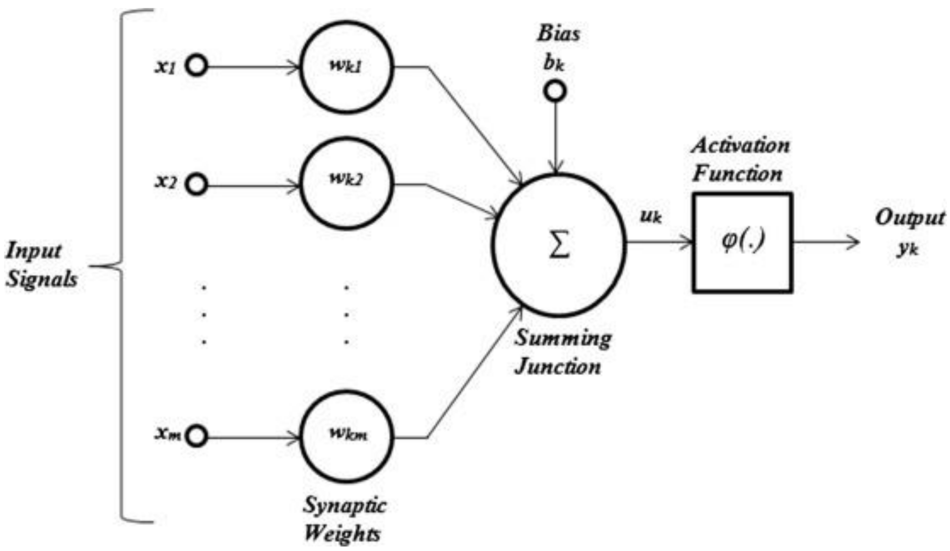


Fig 6.2 Model of Neuron

The neural model of Fig. 6.2 also includes an externally applied bias, denoted by bk. The bias bk here has the effect of increasing or lowering the net input of the activation function, depending on whether it is negative or positive, respectively. In mathematical terms, we may describe the neuron k depicted in Fig 6.2 by writing the pair of equations:

$$\text{Here } U_k = \sum_{j=1}^{m} w_{kj} x_j$$

and

$$y_k = u_k + b_k$$

6.1.2 Definition of Activation Function

An Activation function decides, when a neuron should be activate or not by calculating weighted sum and further it will add bias with it. The purpose of the activation function is to introduce non-linearity into the output of a neuron.

6.2 VARIANTS OF ACTIVATION FUNCTION

1) Linear Function :-

- **Equation :** It has the equation similar to that of a straight line i.e. **y = ax**
- No matter how many number of layers considered, if all are linear in nature, then the final activation function of last layer is linear function of the input of first layer.
- **Range :** -inf to +inf
- **Uses :** It is used at just one place i.e. output layer.
- **Issues :** If we will differentiate linear function to bring non-linearity, result will no more depend on input "x" and function will become constant, it won't introduce any ground-breaking behavior to our algorithm.

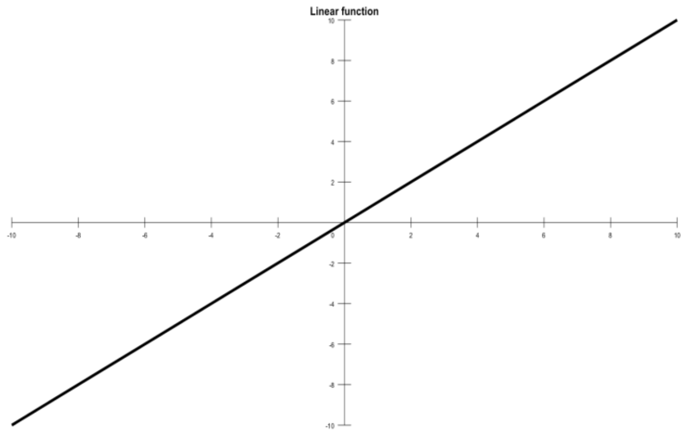


Fig 6.3 Linear function Graph

2) Sigmoid Function :-

- This is a function which is plotted as **'S'** shaped graph.
- **Equation :** $A = 1/(1 + e^{-x})$
- **Nature :** Non-linear in nature. We find that X values lies between -2 to 2, Y values are very steep. The meaning is that, small changes in x would also bring about large changes in the value of Y.
- **Value Range :** 0 to 1
- **Uses :** It used in output layer of a binary classification, where result is either 0 or 1, as value for sigmoid function lies between 0 and 1 only so, result can be predicted easily to be 1 if value is greater than 0 and 0.5 otherwise.

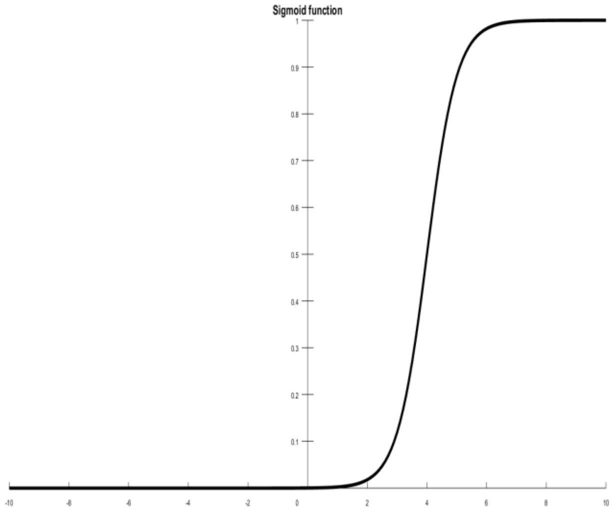


Fig 6.4 Sigmoid function Graph

3) Tanh Function :-

- The activation function will work almost always better than sigmoid function is Tanh function also knows as **Tangent Hyperbolic function**. This is actually mathematical shifted version of the sigmoid function. They are similar and can be derived from each other.
- **Equation :-**f(x) = tanh(x) = 2/(1 + e^{-2x}) - 1ORtanh(x) = 2 * sigmoid(2x) - 1
- **Value Range :-** -1 to +1.
- **Nature :-** non-linear
- **Uses :-** It is used in hidden layers of a neural network as it's values lies between **-1 to 1** hence the mean for the hidden layer comes out be 0 or very close to it, hence helps in centering the data by bringing mean close to 0. It probably makes learning for the next layer much easier.

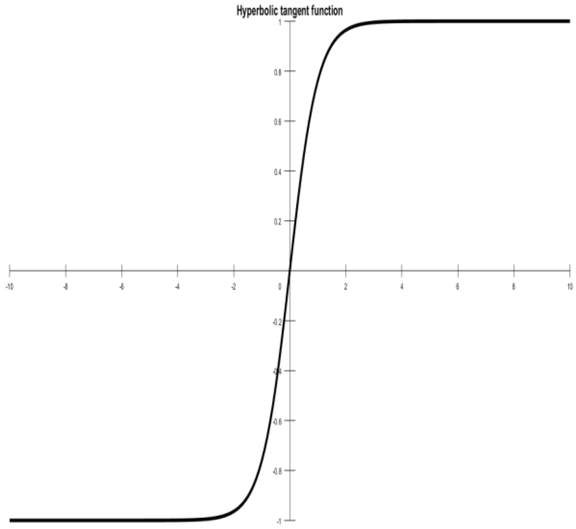


Fig 6.5 Tanh function Graph

4). RELU:-

- Rectified linear unit is the most widely used activation function. Basically implemented in hidden layers of Neural network.
- **Equation :-** ***A(x) = max(0,x)***. It gives an output x if x is positive and 0 if negative.
- **Value Range :-** [0, inf]
- **Nature :-** non-linear, which means we can smoothly back propagate the errors and have multiple layers of neurons being activated by the help of this activation function.
- **Uses :-** ReLu is less computationally expensive than tanh and sigmoid because it involves very easy mathematical operations. Only a few neurons are activated making the network sparse making it efficient and easy for computation.

RELU learns much faster than sigmoid function and Tanh function in all possible ways.

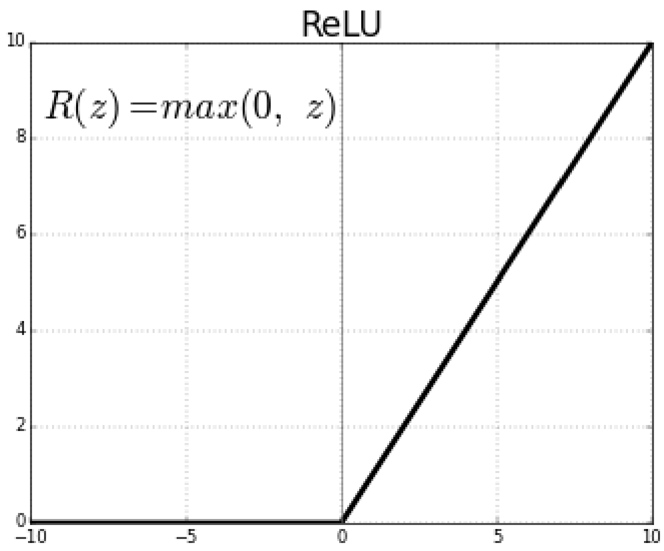


Fig 6.6 REUL function graph

5). Softmax Function :-

- The softmax function is a type of sigmoid function but is handy when we are trying to handle classification problems.
- **Nature :-** non-linear
- **Uses :-** Multiple classes are tried to be handled. The softmax function would squeeze the outputs for each class between 0 and 1 and would also divide by the sum of the outputs.
- **Output:-** The softmax function is ideally used in the output layer of the classifier where we are actually trying to attain the probabilities to define the class of each input.

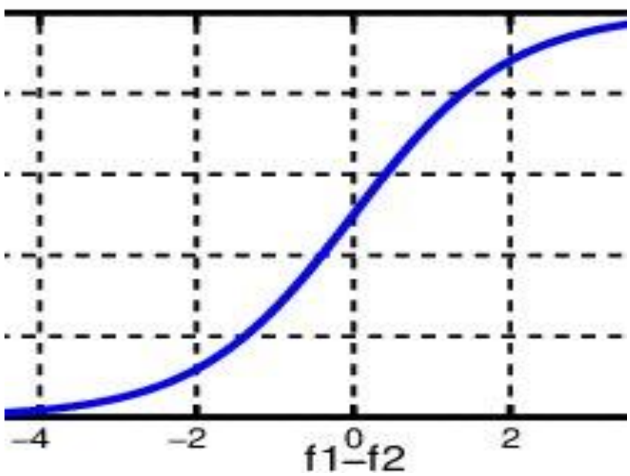


Fig 6.7 softmax function Graph

6.3 ARCHITECTURE OF NEURAL NETWORK

There are 3 types of network architecture :

1. Single Layer Network
2. MultiLayer Network
3. Recurrent Network

1. Single-Layer Network

Single Layer network is the simplest form of layered network is shown in Fig 6.8 given below . The shaded nodes on the left are the input layer. The input layer neurons here are only to pass and distribute the inputs and perform no computation. Therefore the only true layer of neurons is the one on the right. Each of the inputs x1,x2,x3…xn is connected to every artificial neuron in the output layer through the connection weight. Since every value of outputs y1,y2,…yn is calculated from the same set of input values, each output is varied based on the connection weights.

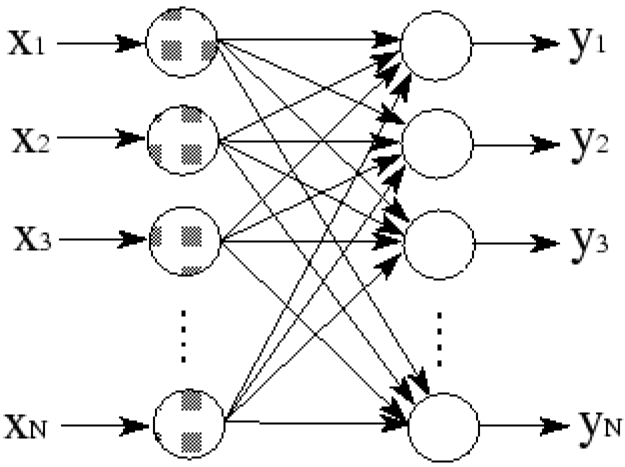


Fig 6.8 Single layer Network

2.Multilayer Network

Multilayer Network is a complex structure of neural network below in fig 6.9 shows the multilayer neural network which distinguishes itself from the single-layer network by having one or more hidden layers.

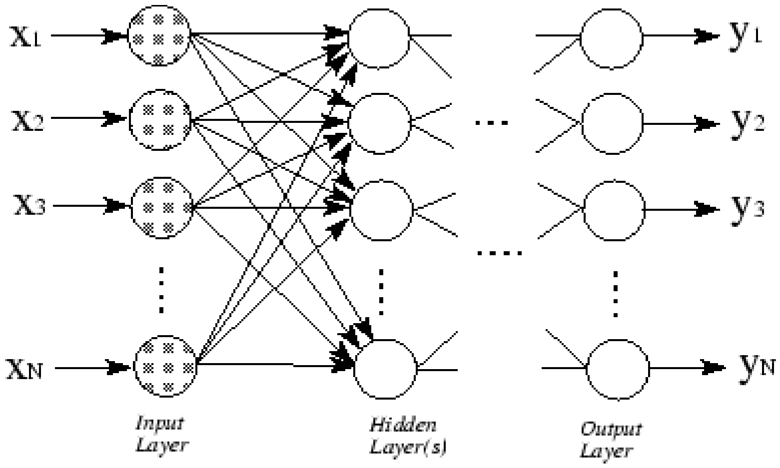


Fig 6.9 Multilayer Network

Multilayer network can also viewed as cascading of groups of single-layer networks. The three layers are explained below.

Input Layer :- This layer is meant to accepts input features. It provides information of the outside world to the network, no computation is performed at this layer, nodes here just pass on the information to the hidden layer.

Hidden Layer :- Nodes of this layer will not be exposed to the outer world, but they are the part of the abstraction provided by any of neural network. Hidden layer performs all sort of computation with the help of the features entered through the input layer and transfer the result to the output layer.

Output Layer :- This layer will bring up the information learned by the network to the outer world.

3. Recurrent Network

A recurrent neural network differentiates itself from a feed forward neural network in that it has at least one feedback loop. This network may consist of a single layer of neurons with each neuron feeding its output signal back to the inputs of all the other neurons, as illustrated in the architectural graph in Fig.6.10. In recurrent network each node in a layer is connected with a directed connection to every other node in the next successive layer. Each node has a time-varying real-valued activation. Each connection has a modifiable real-valued weight. Nodes here are the input nodes which receives data from outside the network and the output nodes yields result.

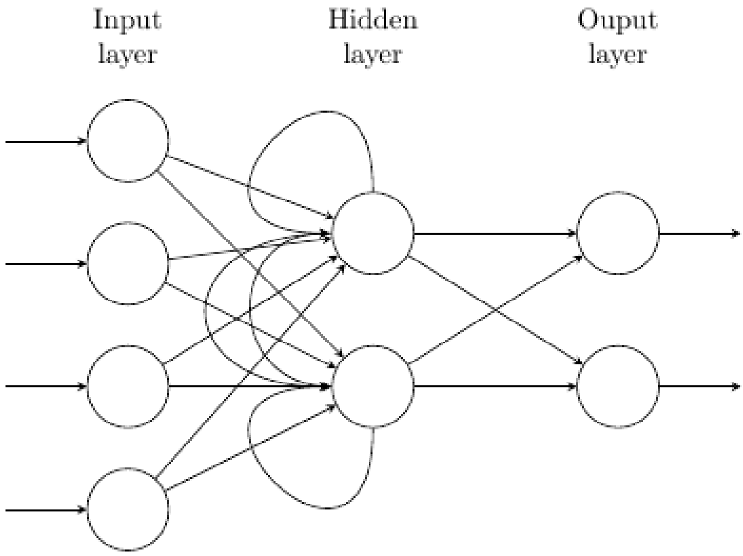


Fig 6.10 Recurrent Network

The presence of feedback loops in the recurrent structure has a major impact on the learning capability of the network and on its performance. Moreover, the feedback loops involve the use of particular branches composed of unit-time delay elements, which result in a nonlinear dynamic behavior, assuming that the neural network contains nonlinear units.

6.4 How neural networks learn

Artificial Neural Network obtain knowledge by learning. The learning process is a mathematical logic or algorithm which improves the network's performance and training time. There are different learning strategies and are as follows:-

- **Supervised learning:-**In this the supervised learning is a learning in which we teach or train the ANN using data which is well labeled that means some data is already tagged with correct answer. The ANN is provided with new set of examples so that supervised learning algorithm analyses the training data and produces an correct outcome from labeled data. The learning rule is then used to adjust the weights and biases of the network in order to move the network outputs closer to the targets.

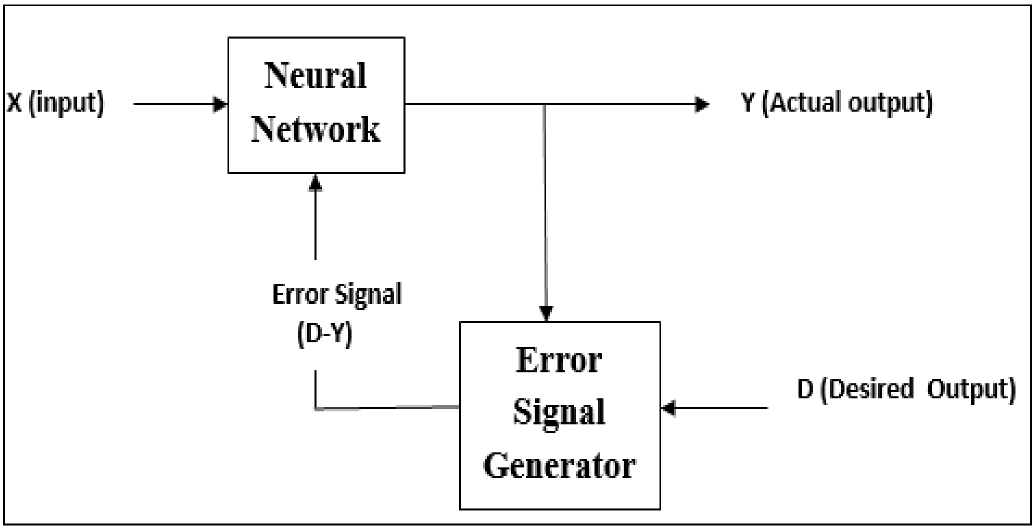


Fig 6.11 Supervised Learning

- **Unsupervised learning:-** In this type of learning is done without the supervision of a teacher. This learning process is independent. During the training of ANN under unsupervised learning, the input vectors of similar type are combined to form clusters. A new input pattern is applied, for the neural network to give an output response indicating the class to which input pattern belongs. In this, there would be no feedback from the environment as to what should be the desired output and whether it is incorrect or correct. Therefore, this type of learning the network itself must discover the patterns, features from the input data and the relation for the input data over the output. The biases and weights are modified in response to network inputs only.

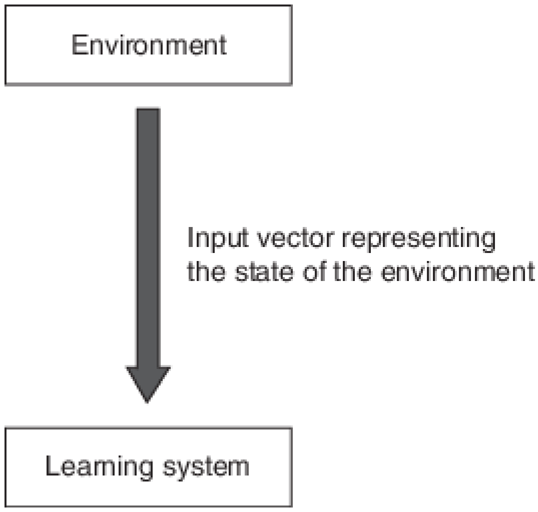


Fig 6.12 Unsupervised Learning

- **Reinforced learning:-** Reinforcement learning is considered as one of three machine learning paradigms, alongside supervised learning and unsupervised learning. This differs from supervised learning in that labeled output or input pairs need not be presented, and sub-optimal actions need not be explicitly corrected. Instead the focus is finding a balance between exploration and exploitation knowledge. In this algorithm, the neural network is reinforced for positive results, and punished for a negative result, forcing the neural network to learn over given time.

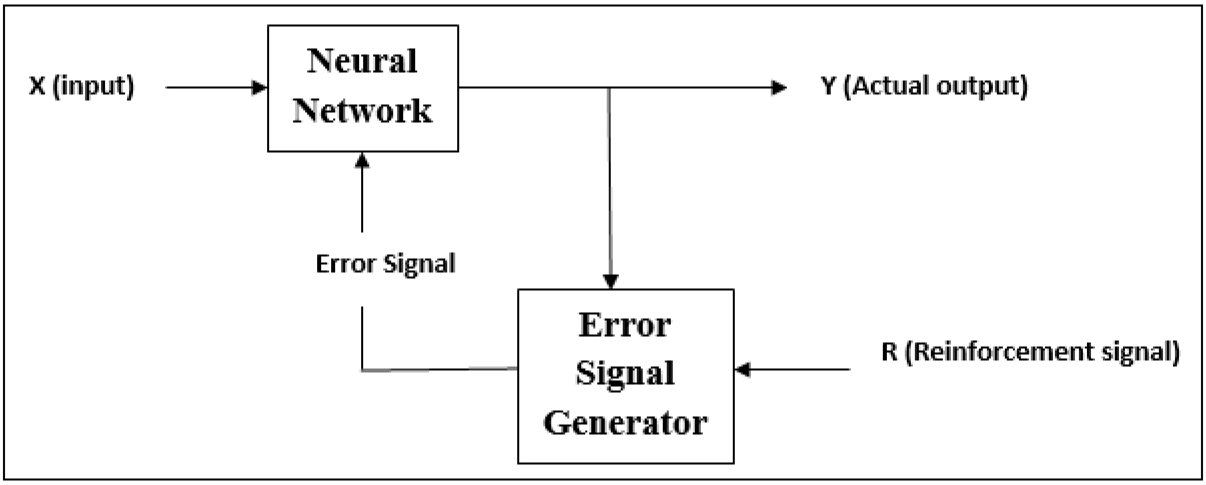


Fig 6.13 Reinforced Learning

6.5 Training an Artificial Neural Network

An algorithm called training algorithm finds a decision function that updates the weights of the network. There are many variations of the training algorithms. Here algorithms update the network weights and biases to map correctly arbitrary inputs to outputs.

The training algorithms were collected into five group:-

1. Gradient Descent

2. Conjugate Gradient

3. Quasi-Newton

4. Resilient Back propagation

5. Levenberg-Marquardt algorithms.

1. Gradient Descent Algorithms(GDAs):

BP learning algorithms provide needed and desired weights. The standard BP algorithm is gradient descent back propagation is the batch steepest descent training algorithm and aims to decline network error as rapidly as possible. In GD, the weights will changed in proportion to negative of an error derivate on each weight.

2. Resilient Back propagation(RP):

Resilient Back propagation is a heuristic learning algorithm that improved the convergence speed by using the only sign of the derivative, not magnitude of the derivative of the error function for the weight update. This reduces the number of learning steps and other adaptive parameters, according to GDAs, and it computes local learning scheme easily when compared .

$\Delta xk = -sign\ (\ \Delta Ek\ \Delta xk\ )\ \Delta k$

Δxk is used to denote the changes of current weights vector, ΔEk is used to denote error function E at k, and the Δk is used to denote the increase in biases.

3. Conjugate Gradient Algorithms (CGAs):

Conjugate gradient algorithms (CGAs), which can be evaluated as one class of optimization methods which are much more efficient than GDAs having a low memory requirement and providing fast convergence. However, it tends to be unstable in large-scale problems occasionally as it does. Also, CGAs are practical for minimizing functions of very many variables since the storing of any matrices is not necessary .The whole CGAs work by searching in steepest descent direction which is negative of the gradient.

4. Quasi-Newton Algorithms (QNAs):

They are similar in fast optimization to CGAs and can be considered as the basic local method using second-order information. The computation cost of the algorithms is too expensive, dense, and complex when compared to CGAs. The weights are updated according to the Newton method described. This method is based on Newton method, but it does not require calculation of second derivatives so that it is called Quasi-Newton (or secant) methods.

$xk+1 = xk - Hk -1gk$

Hk is the Hessian matrixof the performance index at current values of the weights and biases.

5. Levenberg-Marquardt Algorithm (LM):

This is agreed as a standard technique for solving nonlinear least squares problems. This occurs as a combination of gradient descent and Gauss-Newton method. LM adaptive behavior according to the distance of solution so that it can be guaranteed the solution in many cases. When BP is gradient descent, the algorithm is far from the solution and it is quite slow in some case. Thereby, in the case that BP is Gauss-Newton, the algorithm is close to correct one. In LM, the computation of the approximate Hessian is done slightly, and the gradient is computed in the manner as said

$H = J^*T^*J(10)\ g = J^*Te$

where J and e indicate the Jacobin matrix and a vector of network errors, respectively. LM algorithm uses this approximation in the manner such as Newton. LM equation is given by,

$X_{k+1} = X_k - [J*T*J + \mu*I] -1\ J * T$ e.

6.6 Explanation of feed forward LM back propagation network

This neural network is the feed-forward back propagation neural network with supervised learning. The structure of layered feed forward neural networks is considered and each of these networks consists of a set of inputs and one or more layers of neurons. Inputs are connected to neurons in the first layer with the exception of the special input X_0, representing the bias of each neuron, which is connected to all neurons in the network. Neurons in one layer are connected to all neurons in the successive layers. The last layer is called an output layer. Any layers that precede the output layer are called hidden layers. The set of inputs is sometimes referred to as an input layer. Levenberg-Marquardt algorithm gives the best performance when compared to any other back propagation algorithm.

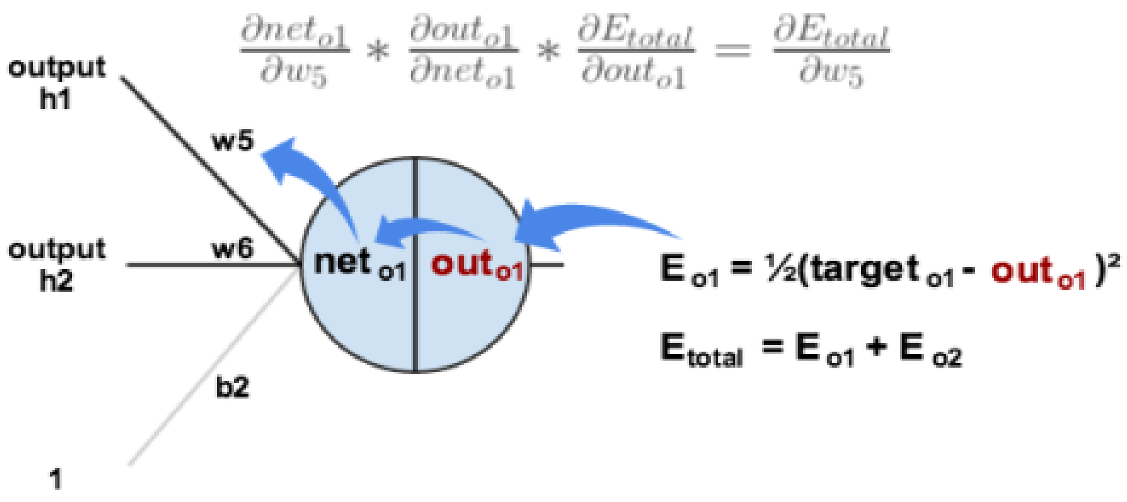


Fig 6.14 Basic back propagation artificial neuron

6.6.1 Levenberg - Marquardt Algorithm

Levenberg – Marquardt algorithm is specifically designed to minimize sum-of-square error functions of the form

$E = ½* \sum k(e_k)^2 = 1/2||e||^2$

Where e_k is the error in the k^{th} pattern and e is a vector with element e_k. If the difference between the pervious weight vector and the new weight vector is small, the error vector can be expanded to first order by means of a Taylor series.

$e(j+1) = e(j) + \partial e_k / \partial w_I (w(j+1) - w(j))$

The error function can be expressed as

$E = 1/2 \| e(j) + \partial e_k / \partial w_I (w(j+1) - w(j))^2 \|$

Minimizing the error function with respect to the new weight vector is given by

$W(j+1) = w(j) - (Z^T Z)^{-1} Z^T e(j)$

Where $(Z)_{kI} = \partial_{ek} / \partial_{wI}$

As the Hessian for the sum ofsquare error function is

$(H)_{Ij} = \partial^2 E / \partial_{wI} \partial_{wj} = \sum \{ (\partial_{ek} / \partial_{wI}) (\partial_{ek} / \partial_{wI}) + e_k \partial^2 e_k / \partial_{wI} \partial_{wj} \}$

Neglecting the second term the Hessian can be written as follows

$H = Z^T Z$

Updating of the weights therefore involves the inverse Hessian or an approximation for nonlinear networks. The Hessian is relatively easy to compute, since it is based on first order derivatives with respect to the network weights that are easily accommodated by backpropagation. Although the updating formula can be applied iteratively to minimize the error function, this may result in a large step size. In the Levenberg-Marquardt algorithm, the error function is minimized as the step size is kept small in order to ensure the validity of the linear approximation. This is accomplished by using a modified error function of the form.

$E = 1/2\|e(j) + \partial_{ek} / \partial_{wI} * (w(j+1) - w(j))^2 + \lambda \| w(j+1) - w(j))\|^2 + \lambda \|w(j+1) - w(j)\|^2$

where λ is a parameter of the step size. Minimizing the modified error with respect to w(j+1) given by,

$w(j+1) = w(j) - (Z^T Z + \lambda I)^{-1} Z^T e(j)$

very large values of λ amount to standard gradient descent, as very small values λ of amount to the Newton method.

6.7 Advantages and Disadvantages of Artificial Neural Network

1. Artificial Neural Network has the ability for learning and modeling non-linear and complex relationships, this is really important because in real-life, many of the relationships between outputs and inputs are non-linear as well as complex.

2. Artificial Neural Network can generalize after it learns from the initial inputs and their relationships, it can take information from unseen relationships on unseen data as well, thus making the model generalize and predict on unseen data set.

3. Unlike many other prediction techniques, this Artificial Neural Network does not impose any restrictions on the input variables. In addition to this, many studies have shown that Artificial Neural Network can better model heteroskedasticity that is data with high volatility and non-constant variance, given its ability to learns hidden relationships in the data without imposing any fixed relationships in the data. Hence this is something very useful in financial time series forecasting (e.g. stock prices) where data volatility is very high.

6.8 Application Of Artificial Neural Network

1. **Image Processing and Character recognition:** This given ANNs ability is to take in a lot of inputs, process them to infer hidden as well as non-linear, complex relationships, They play a huge role in character and image recognition. Character recognition like handwriting has lot of applications in bank fraud detection and even national security assessments. Image processing is an newly growing field with varity of applications from facial recognition in social media, cancer detention in medicine to satellite imagery processing for defense usage and agricultural purpose. The research on ANN now has given the way for deep neural networks that forms the basis of "deep learning" and which has now opened up all the exciting and transformational innovations in computer vision, speech recognition, natural language processing famous examples being self-driving cars of all time.

2. Forecasting: This type of application is required extensively in everyday business decisions (e.g. sales, financial allocation between products, capacity utilization), in monetary policy and economic, in finance and stock market. Majorly, forecasting problems are complex, for example, predicting stock prices is a complex problem with a lot of underlying factors (some known, some unseen). Typical forecasting models throw up limitations in terms of taking into account these complex, non-linear relationships. ANN application when applied in the right way, can provide easy alternative, given its ability to model and extract unseen features and relationships. Also, unlike these traditional models, ANN doesn't impose any restriction on input and left over distributions.

A lot of research is going on in the field of ANN ,recent advances Recurrent Neural Networks for fore casting and in the usage of LSTM.

ANNs are powerful models that have a huge range of applications in the fields of medicine, security, banking/finance as well as government, agriculture and defense.

CHAPTER 07

7.1 Introduction to MATLAB and Neural Network Tool Box

MATLAB, is short for Matrix Laboratory. It is a programming package specifically designed for quick and easy scientific calculations and input/output. It has hundreds of built-in functions for a wide variety of computations and many toolboxes designed for specific research disciplines, including statistics, optimization, solution of partial differential equations, data analysis.

With tools and functions for managing large data sets, MATLAB offers specialized toolboxes for working with machine learning, neural networks, deep learning, computer vision, and automated driving. MATLAB helps to create and visualize models, and deploy models to servers and embedded devices.

7.1.1 Work flow to design Neural Network

Each neural network development typically follows these steps:

- Access and preparation of our data
- Creating the neural network
- Configuring the network’s inputs and outputs
- Tuning the network parameters the weights and biases to optimize performance
- Training the network
- Validating the network’s results
- Integrating the network into a production system

7.2 Code Generation and Deployment

Using Deep Learning Toolbox with MATLAB Coder, GPU Coder, and MATLAB Compiler, We can deploy trained networks to embedded systems, or integrate them with a wide range of production environments. We can use MATLAB Coder to generate C and C++ code for our trained network, which enables us to simulate a trained network on PC hardware and then deploy the network to embedded systems. We can use MATLAB Compiler and MATLAB Compiler SDK to deploy trained networks as C/C++ shared libraries, Microsoft.

7.2.1 Simulink Support

Deep Learning Toolbox provides a set of blocks for building neural networks in Simulink. All blocks are compatible with Simulink Coder. These blocks are divided into four libraries:

1. Transfer function blocks, takes a net input vector and generate a corresponding output vector

2. Net input function blocks, takes any number of weighted input vectors, weight-layer output vectors, and bias vectors, and return a net input vector

3. Weight function blocks, which apply a neuron's weight vector to an input vector (or a layer output vector) to get a weighted input value for a neuron

4. Data pre-processing blocks, which map input and output data into the ranges best suited for the neural network to handle directly.

Alternatively, we can create and train your networks in the MATLAB environment and automatically generate network simulation blocks for use with Simulink. This approach also enables us to view your networks graphically

CHAPTER 08

IMPLEMENTATION

The block diagram for the project is given in the figure 8.1,signals from 1 to n are given to the modulators where it is multiplied with a carrier signal. The n signals are multiplexed and passed through a single communication channel. At the receiver end, the signal is demultiplexed and given to band pass filters (BPF) depending on the number of input signals. The band pass filters are tuned to a particular frequency. The SNR of each channel is obtained. These SNR values are used to calculate the channel capacity. A dataset of 52 values of SNR and Channel capacity is used to train the ANN model. The neural network predict channel capacity for new sets of SNR . This channel capacity can be used to determine the presence of a spectrum hole

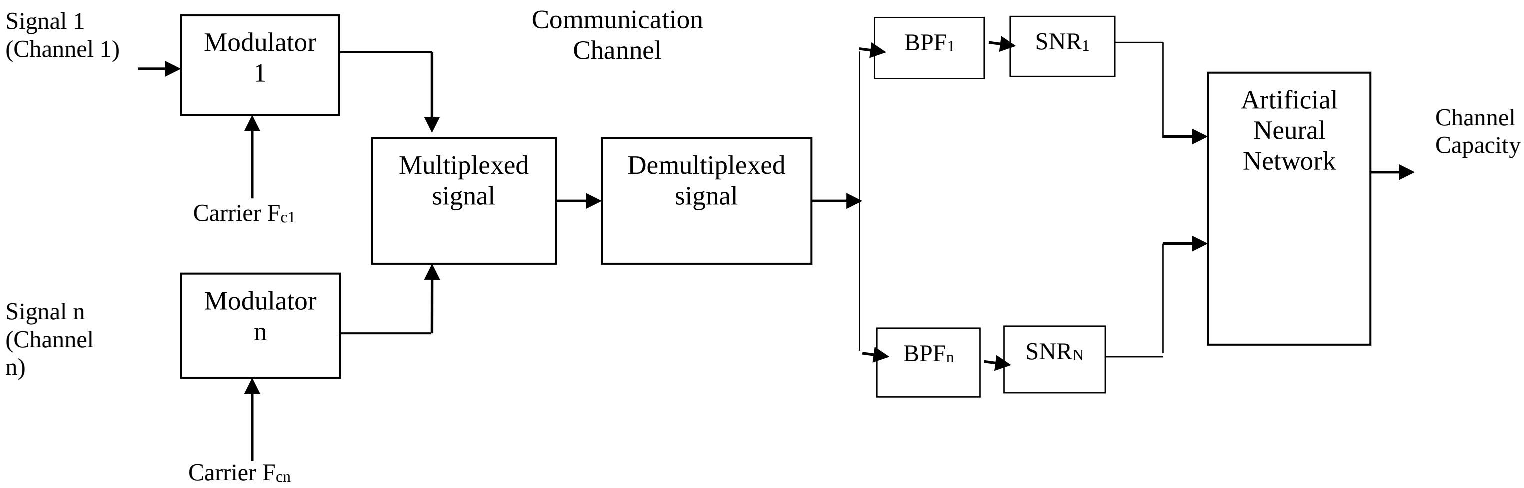


Fig 8.1 Block diagram of the project

Data Set Generation

In the proposed model, Frequency division multiplexing system is used for Seven primary users. It is based on sharing the available bandwidth of a communication channel among the signal to be transmitted.. Each baseband data signal of the primary user is amplitude modulated with the carrier signal of assigned frequency of each user.

The modulated signal is added together in a linear mixer. The linear mixer is different from a normal mixer. In linear mixer the sum and difference of frequency components are not produced but only algebraic addition of modulated signals will take place. Thereafter channel assignment is done and transmitted onto the channel. Additive White Gaussian Noise

(AWGN) is added in the channel to the multiplexed signal.

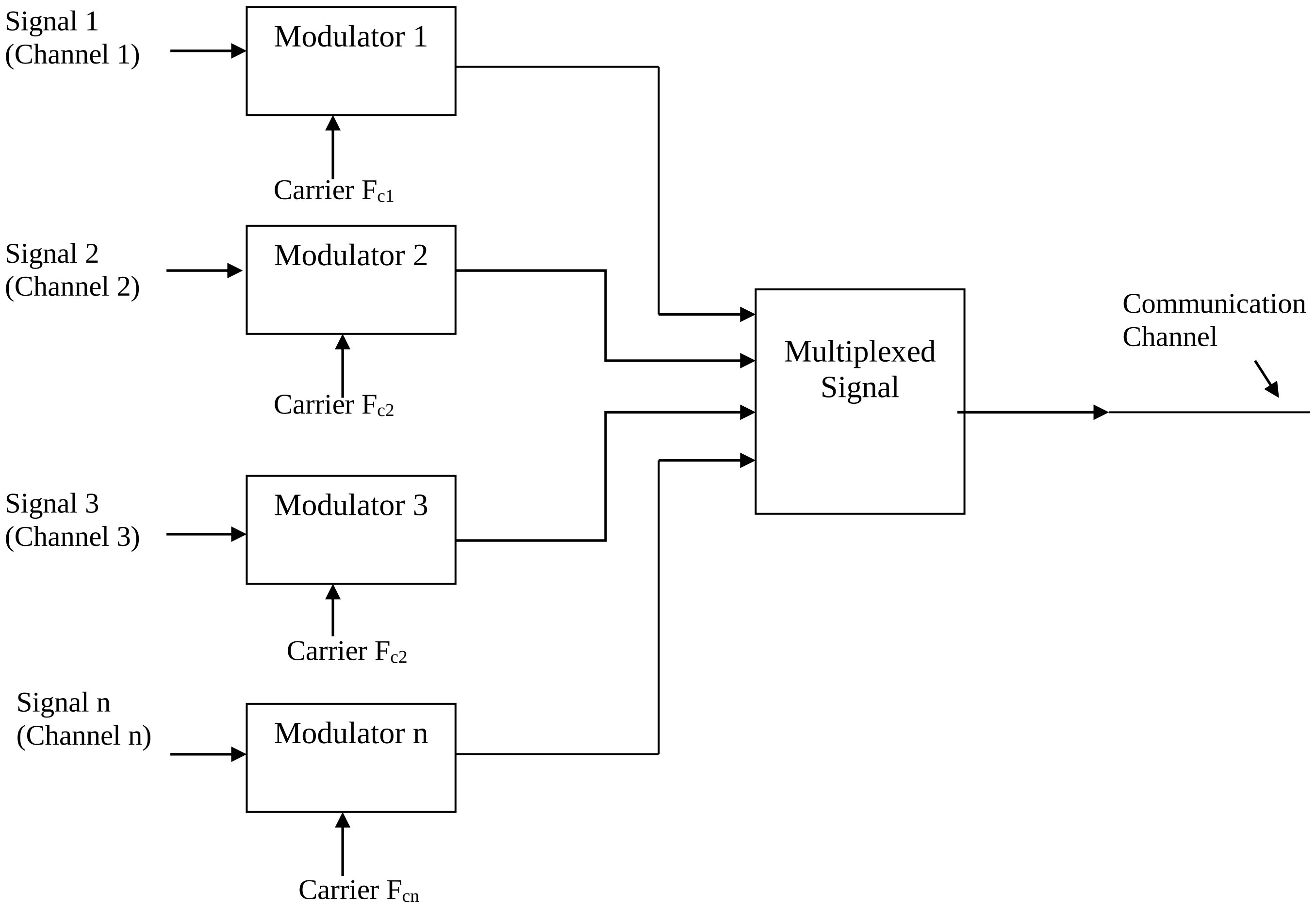


Fig 8.2 Transmitter side

Spectrum in FDM

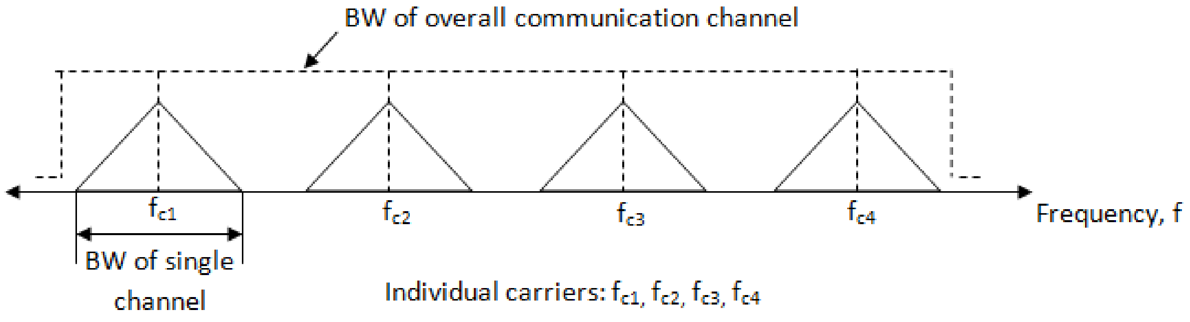


Fig 8.3 Spectrum of the Multiplexed Signal

At the reception side, The multiplexed signal is applied to group of band pass filter. Each band pass filter has a center frequency corresponding to each primary user. The output obtained from band pass filter is considered to determine Signal to Noise (SNR).

Firstly, Channel capacity of each signal is calculated theoretically. Power of the each received signals is also calculated theoretically.

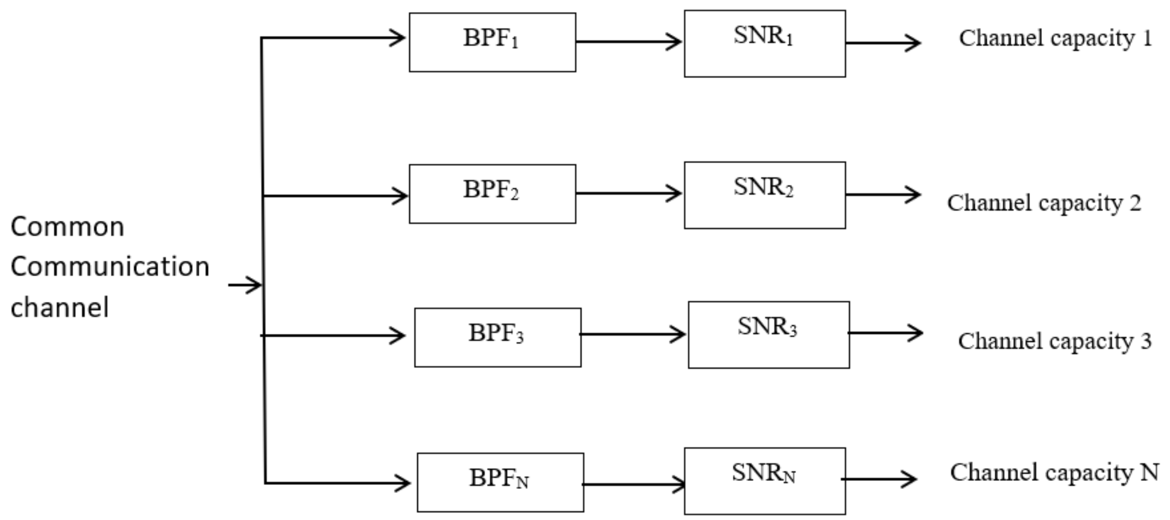


Fig 8.4 Reception side

These power of the signals and channel capacity values are used as training dataset.

Prediction using Artificial Neural Network

Feed forward LM back propagation neural network is trained with 52 each values of average of signals and SNR values as the input of the ANN and channel capacity and power of the signals as output of the ANN.

Neural network is trained to predict channel capacity and power of the signal by setting threshold to conclude the presence of primary user.

If the channel capacity value is above the hard threshold value, then the particular user is absent. otherwise present.

If the power of the each signal is above the hard threshold value, then the particular user is present. otherwise absent.

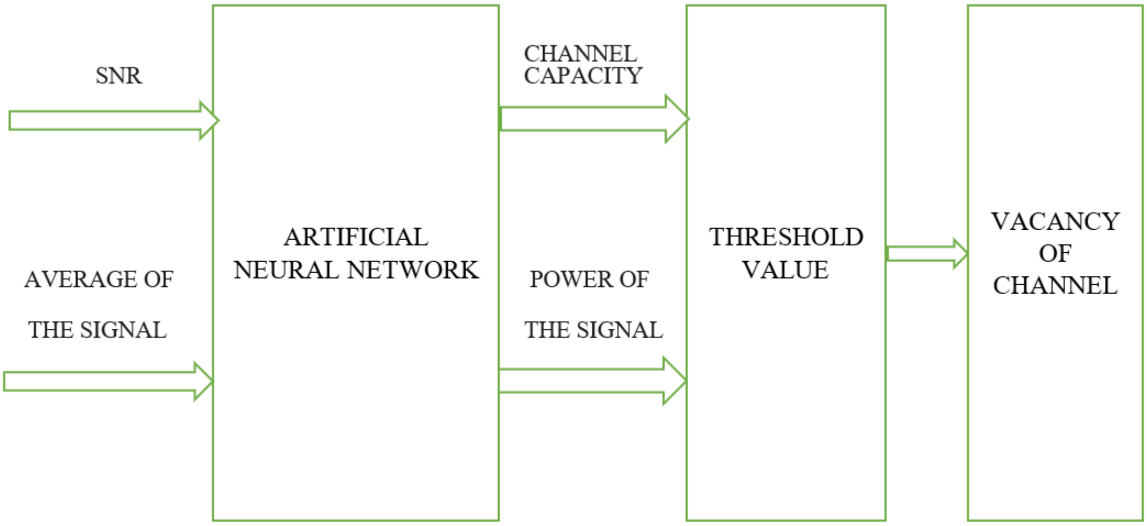


Fig 8.5 ANN Prediction Model

Live FM signal reception using USRP B200 SDR

Furthermore, USRP B200 SDR board is used as FM receiver in MATLAB simulation. Different FM station is tuned to receive station signal. SNR values are collected using scope block in MATLAB SIMULINK. These SNR values of different stations are given as input to ANN to predict their presence.

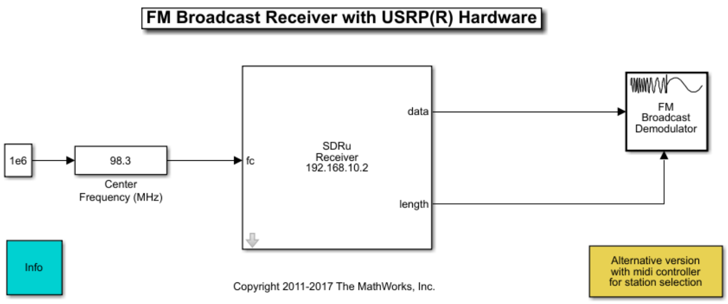
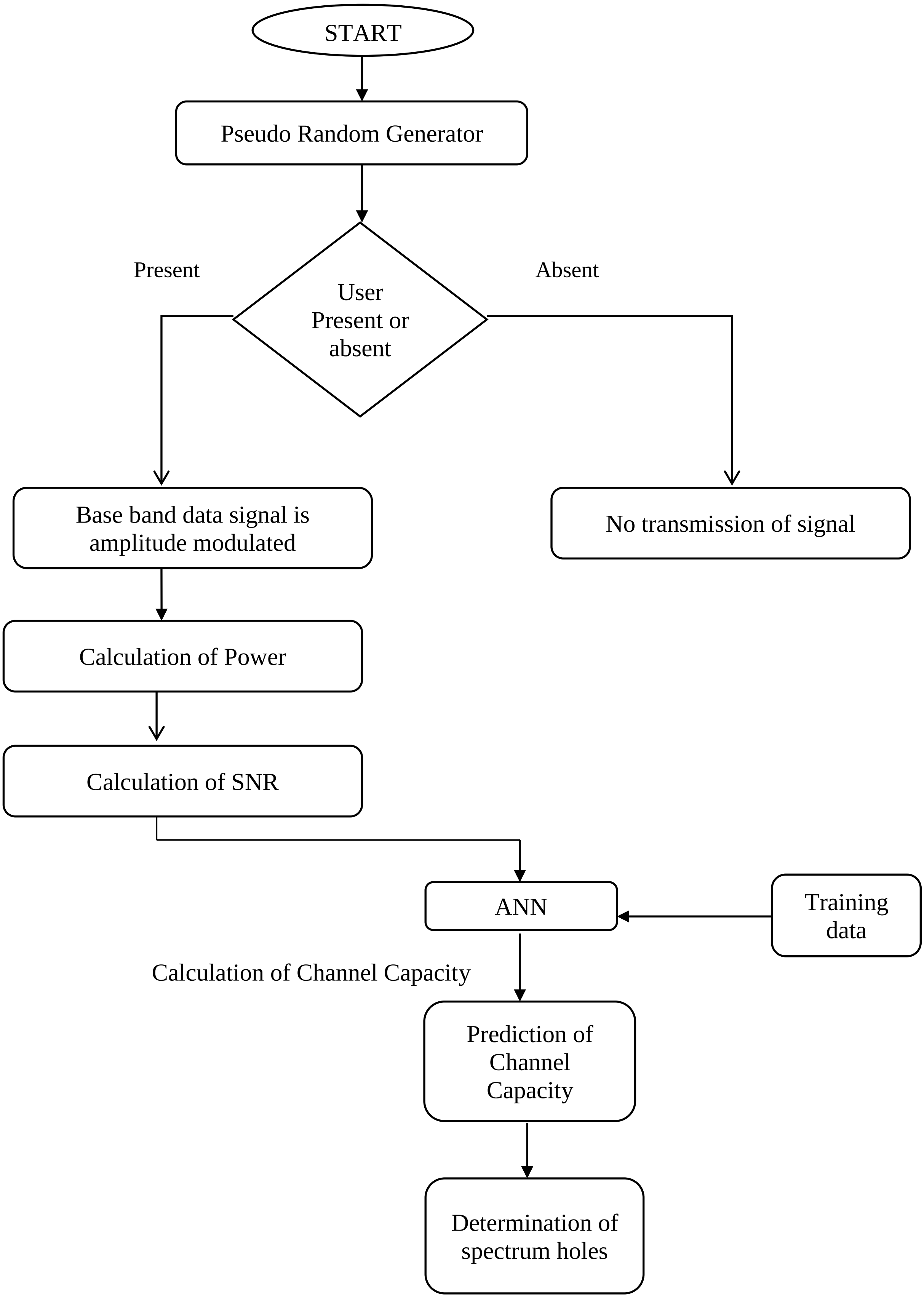


Fig 8.6 Simulink block

FLOW DIAGRAM



CHAPTER 09

RESULTS

9.1 PROCEDURE AND OUTPUT

- In our project, we have considered seven user who are randomly made active or inactive using MATLAB 'randn' function. The status of each user is displayed as shown in the figure8.1.

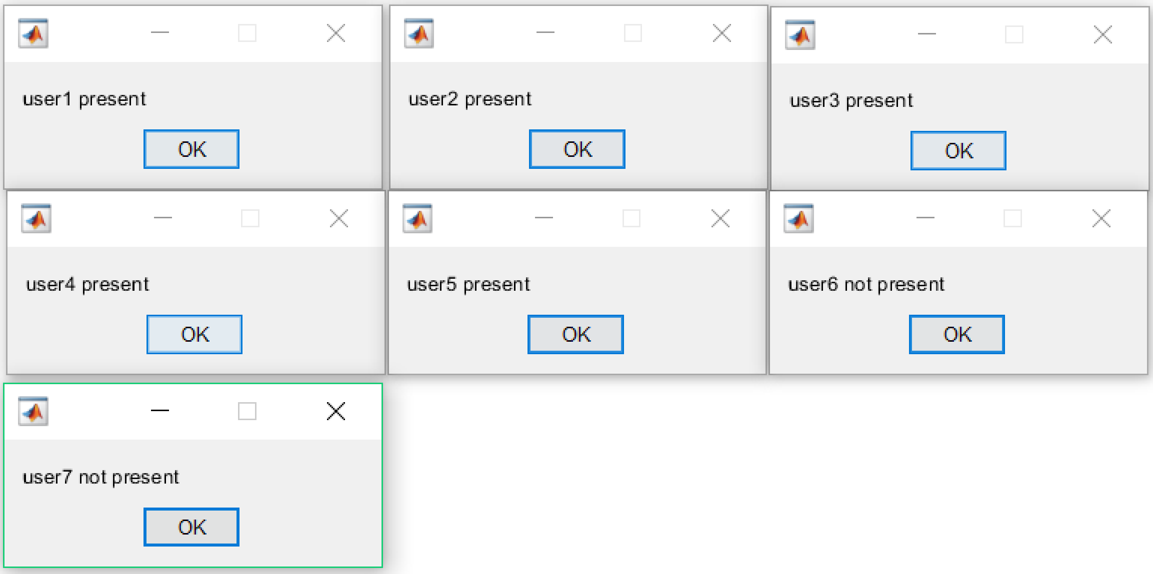


Fig 9.1 Display of user status

- Power spectrum density [power vs frequency] graph is obtained for the received multiplexed signal for the considered seven users in the fig 8.2.

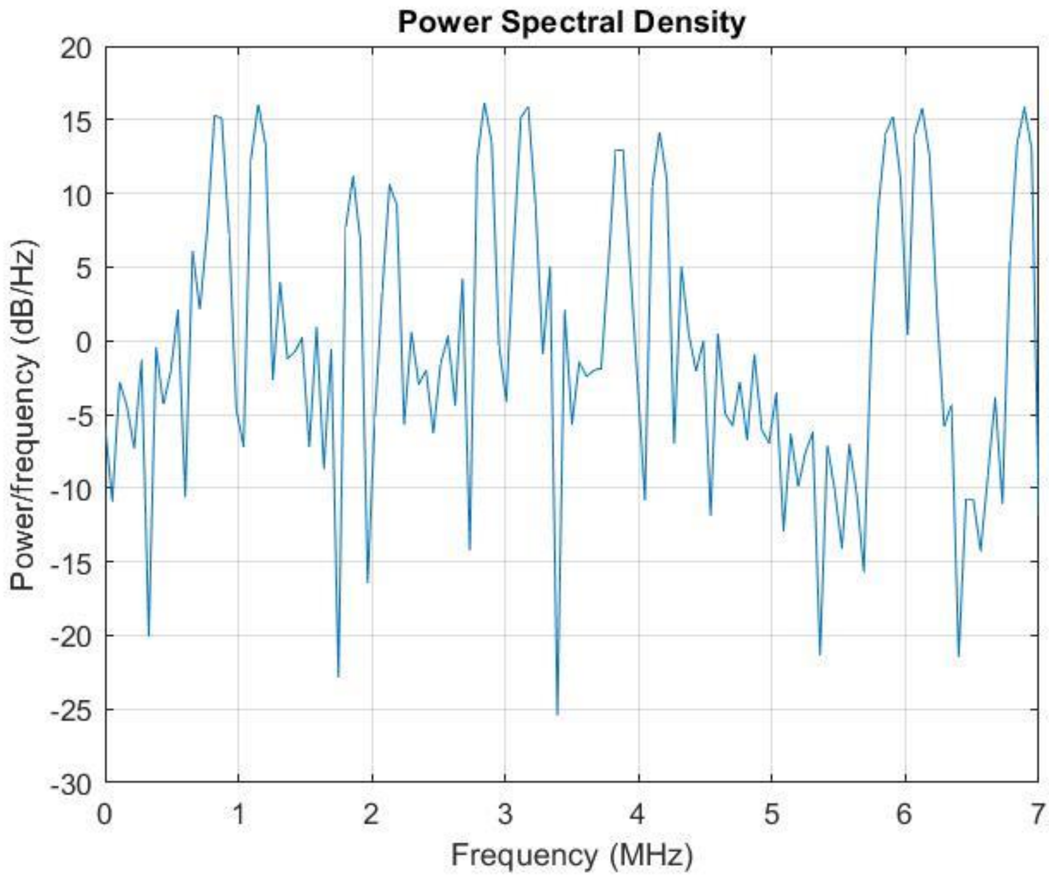
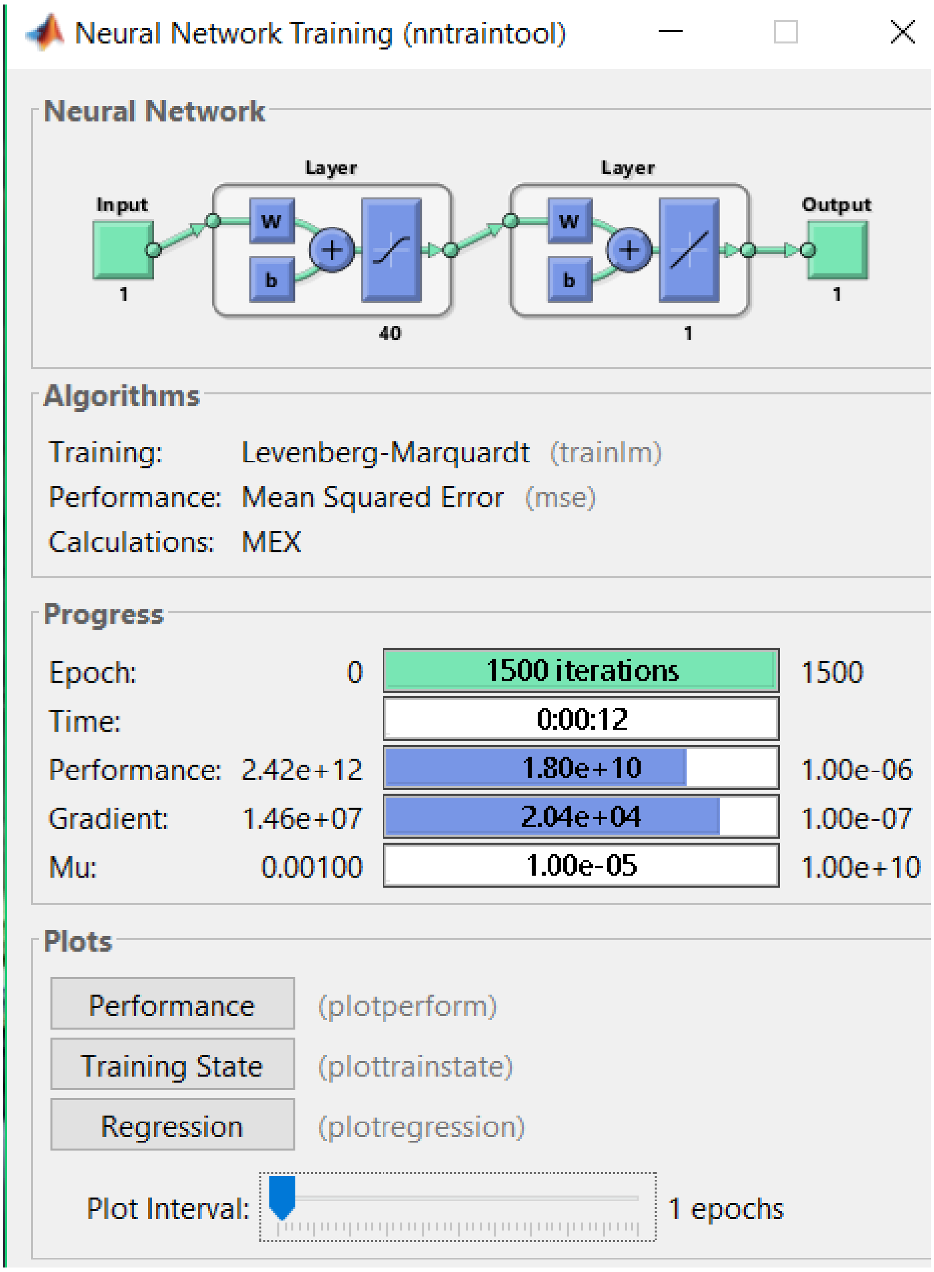


Fig 9.2 Power Spectral Density graph

- The implemented ANN model has three layers as shown in fig 9.3.
  - No of neurons in input layer = 1
  - No of hidden layer = 1
  - No of hidden neuron = 40
  - Activation function in hidden layer is Tan sigmoid
  - No of neurons in output layer = 1
  - Activation function in output layer is Linear transfer



- The performance of the trained ANN model is given by mean square error vs epochs graph in the figure 8.5.Here, the set goal is reached for 218 epochs.

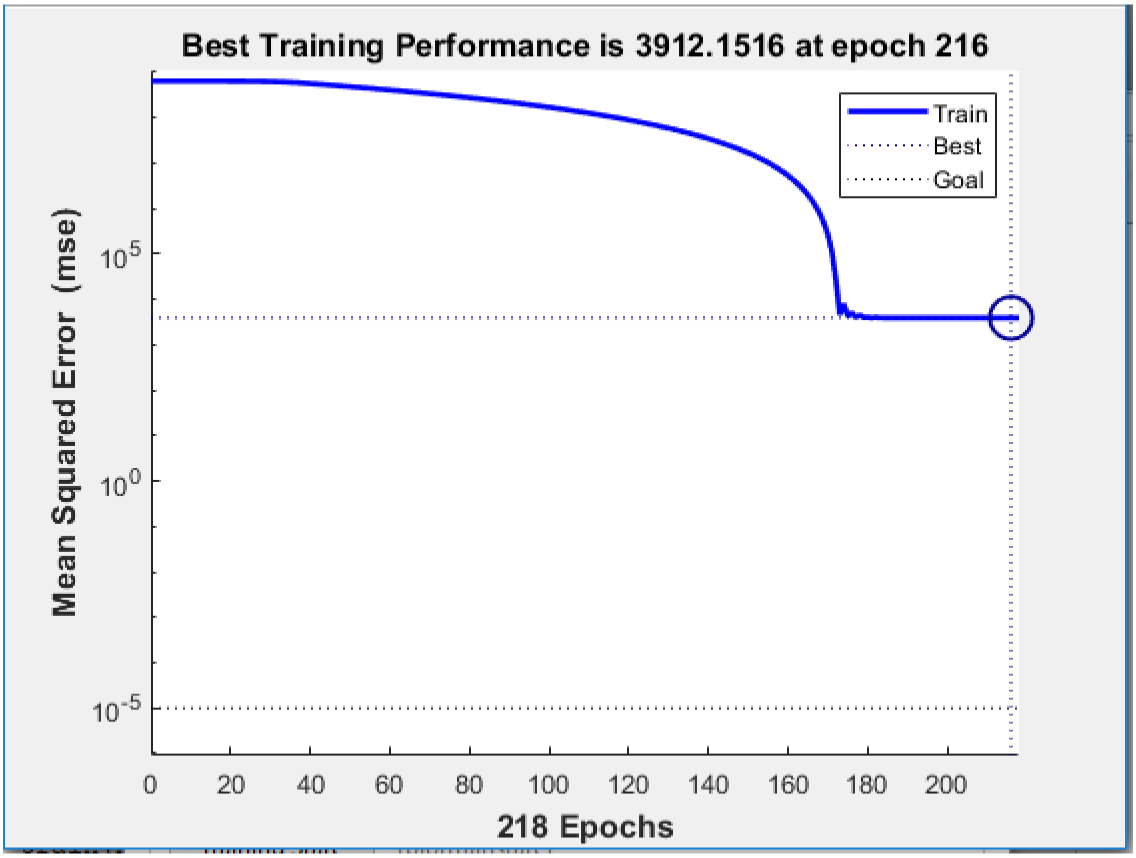


Fig 8.5 ANN Performance graph

- The figure8.6 shows the Neural Network Training Regression which is the graph of Target values vs output values. The graph shows, the target values fed for training ANN model and the output of the ANN model. This is the regression graph obtained for the best fit.

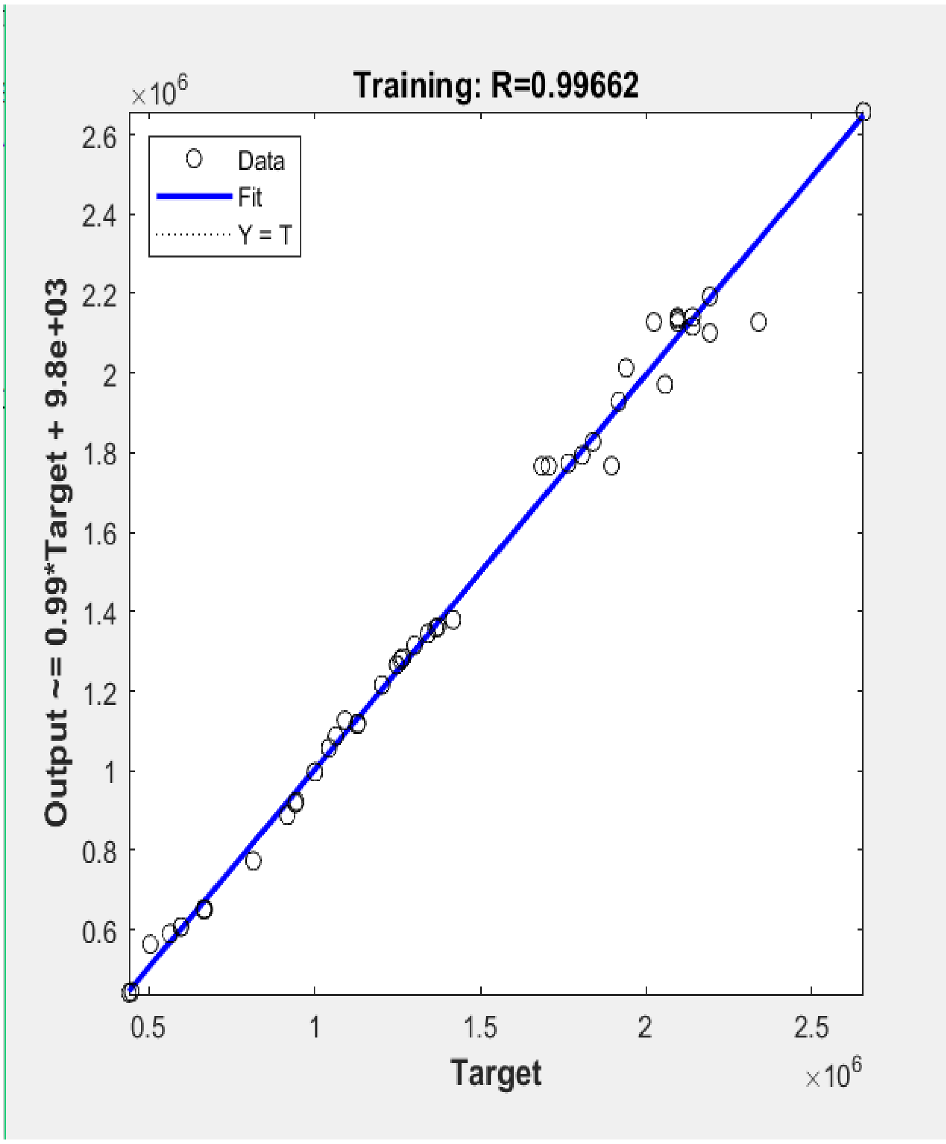
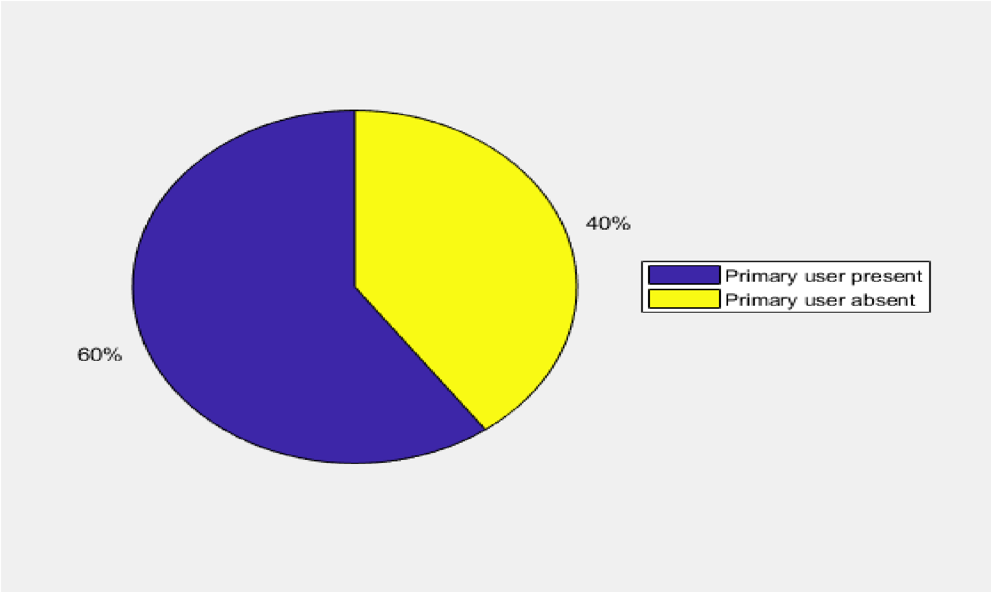


Fig 8.6 ANN Regression Graph

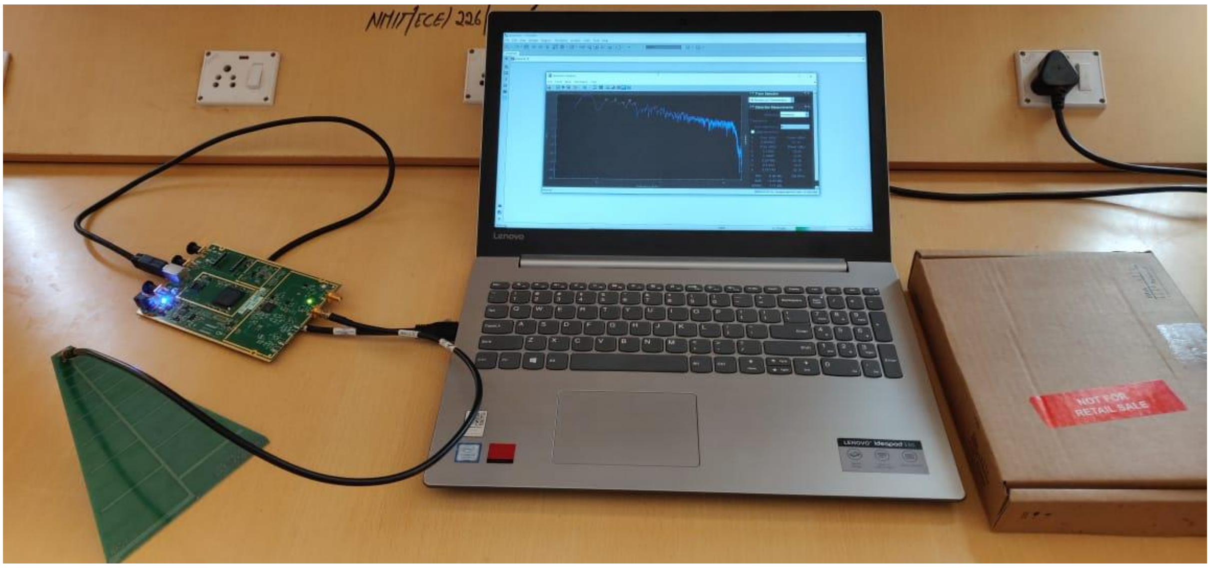
- The figure 8.7 is the pie chart showing the percentage of active users and inactive users.



Radio technology	F_{start} in Mhz	F_{center} in Mhz	F_{stop} in Mhz	Signal BW Mhz	SNR	CC using USRP (Mbps)	CC using ANN (Mbps)	Error
FM Broadcast	105.8	106	106.2	0.2	26.8	0.946	0.934	0.012
FM Broadcast	88.8	89	89.2	0.2	28.6	0.982	0.949	0.033
FM Broadcast	98.1	98.3	98.5	0.2	3.19	0.377	0.384	-0.007
FM Broadcast	93.3	93.5	93.7	0.2	1.79	0.259	0.313	-0.054

Table 8.1 Comparison of ANN Output and USRP B200 Output for FM Broadcasting channels

USRP B200 is used to get live FM Broadcasting signals of four stations; two allocated and two non allocated stations. The channel capacity for these stations are theoretically calculated and also predicted using the trained ANN model. These channel capacity values are tabulated in the above table 8.1.The error between the practical and theoretical values are also tabulated.



USRP B200 is interfaced with Simulink by referring fig 8.7. Code Blocks are available for the same . The SNR values obtained are used to calculate channel capacity and the results are tabulated in table 8.1

CHAPTER 10

CONCLUSION AND FUTURE SCOPE

In this project, we propose an Artificial Neural Network model which predicts the channel capacity. This channel state information is analyzed by determining the bandwidth for identifying the spectrum holes. It is observed that channel capacity predicted by the ANN model can be considered as a decision making parameter to declare channel occupancy status. The analysis made from the graphs show that a channel, which is not transmitting, would have low channel capacity. Hence we can identify white spaces in a particular geographical location.

Also, USRP B200 is used to obtain real time Signal To Noise ratio for FM channels to determine Channel Capacity using Artificial Neural Network to estimate user status.

In this simulation we have successfully analyzed the performance of two neural network that is feed forward Neural Network where feed forward based spectrum sensing algorithm in cognitive radio network shows better performance.

FUTURE SCOPE

- To obtain real-time data beyond ISM bands and dynamically predict spectrum holes using ANN model.
- To install this Cognitive Radio System in either base station or user's device.
- Enhancement in Cognitive Radio for emergency and public safety applications.
- To incorporate the effect of correlation in the design of the user-group assignment that selects the users with minimum correlation to sense in each group for performance enhancement.

CHAPTER 11

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