A

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ON

SIGNAL RECOVERY IN UNDERWATER ACOUSTIC CHANNEL USING OPTIMIZATION TECHNIQUES

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by

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JAIPUR (RAJASTHAN) – 302017

Certificate

This is to certify that the dissertation report entitled **Signal Recovery in Underwater Acoustic Channel using Optimization Techniques** submitted by **Kamal Singh Khatak (2017PWC5117)**, in the partial fulfilment of the Degree Master of Technology in **Wireless and Optical Communication** of Malaviya National Institute of Technology, is the work completed by him under our supervision, and approved for submission during academic session 2018-2019.

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Declaration

I, Kamal Singh Khatak, declare that this Dissertation titled as "**Signal Recovery in Underwater Acoustic Channel using Optimization Techniques**" and the work presented in it is my own and that, to the best of my knowledge and belief.

I confirm that the major portion of the report except the refereed works, contains no material previously published nor present a material which to be substantial extent has been accepted or the award of any other degree by university or other institute of higher learning. Wherever I used data (Theories, results) from other sources, credit has been made to that source by citing them (to the best of my knowledge). Due care has been taken in writing this thesis, errors and omissions are regretted.

Date : **Kamal Singh Khatak**

Place : ID : 2017PWC5117

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Abstract

In this research, study of signal recovery in underwater acoustic communication using optimization techniques has been undertaken. As the nature of signals used to carry information in case of underwater channels is not radio, therefore acoustic signals for the design of underwater modem should be preferred. Radio signals comprising of EM waves get attenuated at very short distances due to the conductivity of sea water. The uncertainty of the underwater channel makes it very difficult to model a suitable channel for it. While modelling underwater channels, it is required to take these effects into consideration so that the system works with greater efficiency. Effects including frequency dependent propagation loss, low speed of sound propagation and severe multipath are the challenges while designing modem for underwater channels.

In this research underwater channel equalizer method is represented and we transmitted the signal to multiple block and at the receiver LMS adaptive equalizer and Genetic algorithm based equalizer are imported to get the optimized results. We will compare the results of error curves and bit error rate of resulted signal. The advantage of genetic algorithm over Least mean square algorithm is also be considered here. Further, in order to determine the reliability of the modern design, BER (bit error rate) analysis has been carried out. This system provides best trade-off between data rate and bit error rate for different kind of signals.

List of Abbreviation

2G	-	Second Generation
3G	-	Third Generation
AWGN	-	Additive White Gaussian Noise
DFE	-	Decision Feedback Equalizer
DFT	-	Discrete Fourier Transform
EM	-	Electromagnetic
FBF	-	Feed Backward Filter
FFF	-	Feed Forward Filter
GA	-	Genetic Algorithm
ISI	-	Inter Symbol Interference
LAN	-	Local Area Network
LMS	-	Least Mean Square
MLSE	-	Maximum Likelihood Sequence Detection
MSE	-	Minimum Square Error
M-PSK	-	M Array Phase Shift Keying
M-QAM	-	M Array Quadrature Amplitude Modulation
NLMS	-	Normalized Least Mean Square
OFDM	-	Orthogonal Frequency Division Multiplexing
PCA	-	Principal Component Analysis
PD	-	Potential Difference
pH	-	Potential of Hydrogen
PL	-	Path Loss
ppt	-	Parts Per Trillion
RF	-	Radio Frequency
RLS	-	Recursive Least Square

ULA	-	Uniform Linear Array
UWA	-	Under water Acoustic
VTRM	-	Virtual Time Reversal Mirror

List of Symbols

Kb/s	-	Kilobits per second
Km	-	Kilometres
Bps	-	Bits per second
m/s	-	Meter per second
w/m^2	-	Watt per square meter
m	-	meter
dB	-	Decibel
Hz	-	Hertz
MHz	-	Megahertz
^oC	-	Degree celcius
dB/Km	-	Decibel per kilometer

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CHAPTER 1
INTRODUCTION

Underwater acoustic communication and networking is very important both for commercial purposes and military purposes. To communicate effectively in water there are number of applications for marine operators, defense organizations, marine researchers/operators, oceanographers and off-shore oil industries, tactical surveillance etc. It is difficult to use radio signals to carry information signals throughout the underwater channels because of the short range of electromagnetic signals in underwater channels. Electromagnetic waves get easily absorbed by water and suffer from very high attenuation. And also low frequency signals demands for large height antennas and high power. Alternatively, acoustic waves provide the best possible choice of energy distribution to allow the data to propagate through underwater channels.

Acoustic communication is very complex in underwater and should be understood properly. A reflection on ocean boundaries and refraction under depth of ocean varies the speed of sound and sound propagates in multipath trajectories. Variability in ocean behaviour along with low sound speed in water induces the significant Doppler shifts. As a result the channel gets affected by time and frequency dispersions. These characteristics do not play a significant role in radio communication but because of these factors underwater acoustic communication is a major concern for people to get into it and force them to design better systems for underwater acoustic communications.

Underwater acoustic communication links are affected by noise from many different sources. Some of these sources are man-made and others are natural processes. For example seismic activities, turbulence, wave action, ship traffic etc. The time varying nature of underwater acoustic communication channel basically requires the use of channel re-training and tracking at the receiver section. Due to this communication overhead increases which make the signal transmission fast and give the results with high accuracy. The particular interest included here is to remove the noise and to reduce the error in communication process. Signal recovery is difficult for the receiver system if iterative process does not follow by such type of systems. In this work iterative algorithm such as least mean square algorithm and Genetic algorithm are applied this sets the channel equalization. The applied algorithms are optimized algorithm which gives the optimal solution for signal recovery.

1.1 Literature Survey

In this section the research work associated with underwater acoustic communication will be covered. Different techniques were used to transmit the signal under water. This section shows the progressive improvement in the field of underwater acoustic communication. The survey shows that how the speed and quality of transmission increased in underwater acoustic communication and how the signal recovered from different with different techniques used in underwater communication. Earlier, technique used for transmission was very simple and gives poor recovery of signal/data. In 1980s, establishment of the work related to underwater channels has been started and the people used very basic techniques. Now this field is explored well and day by day, new techniques are introduced to recover the signal from different noises which gives better speed and quality as well.

E. Lo et al. [1989] [1], this paper presented the instrumentation network model for underwater communication. The instrumentation network illustrated in this paper supports the investigation of characteristics of underwater acoustic wave propagation. The instrumentation network is consisting of a transmitter (to generate acoustic pulse data), submerged receiving transducer, a data storage and control computer. This was the basic four node network used for local area network (LAN) communication in underwater. The network design was very basic and based on the techniques used in 20^{th} century. This network is limited for communication over LAN (local area network) and not supports communication over wide area network. Data transfer rate was very small for this network and is in the range of few Kb/s.

D.Billon, B. Quellec [1994] [2], an analytical approach is designed to assess the performance of an acoustic communication system in this paper. And the approach is adaptive beam forming and equalizing. A generalized error data rate and SNR (Signal to Noise ratio) of digital transmission are conclude from steady state responses of adaptive equalizer and beam former. The digital modulation scheme used was based on M-PSK and M-QAM. This paper mainly focuses on the data rate. And have no dealing with noise compensation. Inter symbol interference encountered here because of multipath propagation and is not compensated here. The modulation technique provides lower bandwidth efficiency. Signal detection is complex and modulation techniques used are sensitive phase variations.

Bayan S. Sharif, Jeff Neasham et al. [1999] [3], at this time Doppler shift provides major challenge to designers of underwater communication. Carrier tracking and symbol synchronisation are affected by the shift induced by relative motion of the transmitter and receiver structure. A generic pre-processor is used in this paper to compensate Doppler Effect. This pre-processor system uses conventional equalization and beamforming structures. This technique is allowed only for the compensation of Doppler shifts. Others corrupted characteristics like Inter Symbol Interference (ISI), Multipath dispersive characteristics, Noise etc. can't be compensated by this method.

Zhang Xinhua, Zhang Anqing et al. [2000] [4], blind source separation technique is used to reconstruct the source signals of interest from the simulated mashed complex underwater signals. The multi path effect creates the oceanic ambient noise and signal distortion. The ideal method to overcome this issue is to accurately estimate the original source signals from a complex distorted signal. This paper presents the use of system model which is based on Principal component analysis. PCA is used to represent the multivariable data in compact form. This system model cannot remove the impulsive noise. This model provides the complex signal recovery and takes large computational time.

Jianguo Huang, Jing Sun et al. [2005] [5], in this paper OFDM is used which is the key technique of 21^{st} century. OFDM is the good technique which gives good performance against multipath interference, ability to combat the frequency selective fading and high frequency band efficiency. Before this time researcher focuses on short range underwater acoustic communication. But by this time, with the help of OFDM the researcher pays attention to medium range UWA communication (10 Km). With the help of guard time ISI removes easily in this technique. The data range studied was 4400bps at a range of 1.2 km. The OFDM technique provides signal having a noise like amplitude with a very large dynamic range, therefore it requires RF power amplifiers with a high peak to average power ratio. It is more sensitive to carrier frequency offset and drift than single carrier systems are due to leakage of the DFT.

Yin Jingwei, Wang Lei et al. [2008] [6], in this paper, VTRM is adopted for channel equalization which could be implemented numerically at the receiver using the channel estimation. The focusing effect and focusing gain is simulated in shallow water. At last, VTRM is applied in UWA multiuser communication with several modems sending information to one receiver at the same time. The results of simulation demonstrate that VTRM could mitigate ISI and separate each modem's information effectively. Therefore it is significant for realizing the UWA communication networks. This technique is limited to shallow water channels only and does not signal recovery solution. The increasing of the distance and carrier-frequency leads to larger transmission loss so that the available bandwidth is too limited (only several kHz).

Weijie Shen, Haixin Sun et al. [2009] [7], in this paper, blanking nonlinearity and clipping nonlinearity are applied in underwater acoustic DFT-SOFDM system. This method is widely used in practice since it is very simple to implement and provides an improvement in impulsive noise channels. The study was based on the experimental results in real underwater acoustic channel. To reduce the effect of impulse noise, the use of non-linear processing at the input of a DFT-SOFDM receiver has been proposed. The experimental results in shallow water show that the blanking nonlinearity provides better performance than the clipping nonlinearity. The system only removes the impulsive noise. It does not remove the noises or distortion from other sources. The system enables the DFT spreading. If impulse noise exceeds the certain threshold then it will be the system failure. This system not holds good result for single carrier signal because single carrier signal are highly sensitive to impulsive noises.

A. Radosevic, T.M. Duman et al. [2011] [8], this research is used to explore the feasibility of estimating or predicting an underwater acoustic channel impulse response one travel time ahead. The work here is motivated by the design of underwater acoustic communication systems that employs the adaptive modulation technique, whose performance depends upon the ability to predict the channel for few seconds in future. The possibility of predicting the channel here is based on experimental set up in shallow water off western coastal areas. And the key to enabling the prediction is decoupling if effects of motion induced phase off sets from slowly varying path gains. If the path gain variation are very fast and random then system fails to predict the channel.

Jeong-Woo Han, Chan-Ho Hwang et al. [2014] [9], in this paper, the underwater acoustic communication is presented using channel estimation based on data embedded pilot signalling. Channel estimation technique based on data embedded pilot transmits the data symbol and pilot symbol in the same time and the same frequency. The system with the data embedded channel estimation has a high spectral efficiency because of the simultaneous transmission of the pilot symbol and the data symbol. If delay spread is longer than the pilot symbol length then data demodulation will be difficult because equalizer has not optimized tap coefficients. This technique reduces the data rate.

Lixing Tang, Haixia Wu et al. [2017] [19], the paper puts forward a new method to optimize the pilot pattern and improve the performance of the channel estimation. The algorithm only generates fewer sets of the pilot placement as the original samples. The index of each pilot subcarrier location is refreshed by the operations. Pilot position indexes are generated. And after finding the minimum value the corresponding result gives the final value of pilot position. Calculation complexity is very high.

Research contribution: In this dissertation work optimized algorithms are applied to get signal recovery in underwater channels. The algorithms used in this research work are:

1) Least mean square algorithm

2) Genetic algorithm.

By looking at the complexity analysis of previous work it is mandatory to have simple system models for communication under water. The models which use the iterative process and give the optimized result are the need of today’s communication. The LMS algorithm and genetic algorithm are some of the algorithms which give the best fit solution by using the simple concepts inspired by nature. These algorithms are used because the concept used by these algorithms is channel equalization.

Channel equalization technique is used from last many years but it is the key for many communication processes either it is under water or it is in air. And system realization by using channel equalization as the backbone makes the system model very simple and fast. That’s why these techniques are used to implement to get the desired result and better signal recovery. The implementation process of these algorithms is discussed in later sections.

1.2 Motivation

As we know that most of the earth's surface (around 70%) is covered with water [22]. And communication underwater has many applications now days those are illustrated in previous section. Many communication systems are designed for underwater communication process. These communication systems provide better way of transmitting the signals inside water and these systems have good capability of signal recovery too. The motivation to do this work is to improve the system accuracy by iteration processes to recover the signal. In this report we will go for some optimized algorithms which give the optimal solution which fits best for the receiver design.

1.3 Aim of project

The aim of this project focuses on:

1) To design underwater acoustic communication channel by considering all parameters which can affects the underwater system.
2) To understand the concept of optimization techniques and their models.
3) To design the receiver model to get signal recovery in noisy environment with Channel equalization optimization technique.

1.4 Dissertation Report Layout

Chapter 1 describes the introduction of this report which covers basic knowledge of acoustic communication, Literature survey, motivation to do the work and aim of this project. Chapter 2 describes the fundamentals and characteristics of underwater channel. Chapter 3 gives the detailed explanation of channel equalization and optimization algorithms used. Chapter 4 represents the system model design and gives the simulation results. Finally chapter 5 describe the conclusion related to work and provides some future aspects.

CHAPTER 2

UNDER WATER ACOUSTIC THEORY

2.1 History

Underwater communication has been used by marine animals for last million of years. The science this communication process began in 1490, it was began with words of great Leonardo da Vinci "If you cause your ship to stop and place the head of a long tube in the water and place the outer extremity to your ear, you will hear ships at a great distance from you."

In 1687 Issac newton give his mathematical principles of Natural philosophy which covers the first mathematical treatment with sound. The next step was made by Chrales Sturm, a French mathematician and Daniel Colladon, a swiss physicist. In 1826, Jean Daniel Colladon, a physicist and Charles-Francois Sturn, a mathematician, performed an experiment, which is considered as the first research in the field of underwater communication [23]. The experiment was conducted in Geneva Lake, Switzerland where it was proved that sound propagates faster in water than in air. In the experiment, the church bell was used as the source of sound. One of them struck the church bell that was hanged under water instantly just after lightening gunpowder flash. The other person started the stop watch just after seeing the flash of the gunpowder and stopped it only after hearing the sound of church bell. The source and destination were kept at a distance of 10 miles and two different boats were used. They obtained with this experiment speed of sound in water as 1435 m/s. The result was near to accurate as the exact value of speed of sound in water is 1500 m/s. In 1877 Lord Rayleigh gives the theory of sound.

In 1919, the first scientific paper on underwater acoustics was published theoretically describing the refraction of sound waves produced by temperature and salinity gradients in the ocean. The range predictions of the paper were experimentally validated by propagation loss measurements.

2.2 Fundamentals of Underwater acoustic communication

There are many important physical quantities that are described to get the basic knowledge of acoustic communication field [24]. Acoustic pressure, acoustic intensity, acoustic impedance are some basic properties of sound waves that are described below.

2.2.1 Sound

It is generated due to the vibrations in any object and these vibrations get through the physical medium surrounding it. The propagation of the vibrations is due to the oscillations in the particles of any medium in the same direction as that of the wave propagation. That's why these waves are known as longitudinal waves. We can check the behaviour of wave propagation in sound on the basis of listed facts.

1. A complicated relationship between density and pressure of the medium. This relationship helps to find out the speed of sound in medium by the effect of temperature on it.
2. The behaviour of sound waves is also affected by the motion of the medium itself. If our medium is in moving condition, then absolute speed of sound waves can be increase or decrease. And the absolute speed also depends on direction in which the medium is moving.
3. Sound wave behaviour is also depends on the viscosity of medium. The rate at which attenuation in sound takes place determines by the viscosity.

2.2.2 Acoustic pressure

The acoustic pressure (P) for any given plane wave can be determined by the given equation 2.1.

$$P = \rho_0 cv = \rho c 2\pi f \xi \qquad (2.1)$$

$$\text{Where, } \xi = v/2\pi f$$

ρ_0 shows the density of fluid, c represents the sound wave propagation speed and v is the velocity of particle. Quantity P can be taken similar to potential difference (PD) in case of electrical circuits. $\rho_0 c$ is known as the specific impedance and acts similar to intrinsic impedance in case of electromagnetic.

2.2.3 Acoustic intensity

The power carried by sound waves or acoustic waves per unit area in a perpendicular direction to that area is known as the acoustic intensity. Acoustic intensity is also named as the sound level intensity. The unit for acoustic intensity is watt per square meter (w/m^2). Sound intensity is not the same physical quantity as sound pressure. Hearing is directly sensitive to sound pressure which is related to sound intensity. In consumer audio electronics, the level differences are called "intensity" differences, but sound intensity is a specifically defined quantity and cannot be sensed by a simple microphone. The rate at which sound energy passes through a unit area held perpendicular to the direction of propagation of sound waves is called intensity of sound. Mathematical representation of acoustic intensity is shown by equation 2.2.

$$I = Pv \tag{2.2}$$

It is also known as the acoustic power density generated by source.

2.2.4 Acoustic impedance

Impedance of acoustic wave is defined by the following equation:

$$Z = P/U \tag{2.3}$$

Where, U represents the acoustic volume flow. Here, Z is the function in terms of frequency having both real and imaginary parts.

2.2.5 Sound speed variation

Sound speed in water depends upon various parameters like temperature, pressure and salinity. Variation of these parameters with respect to depth is shown in figure 2.1 below.

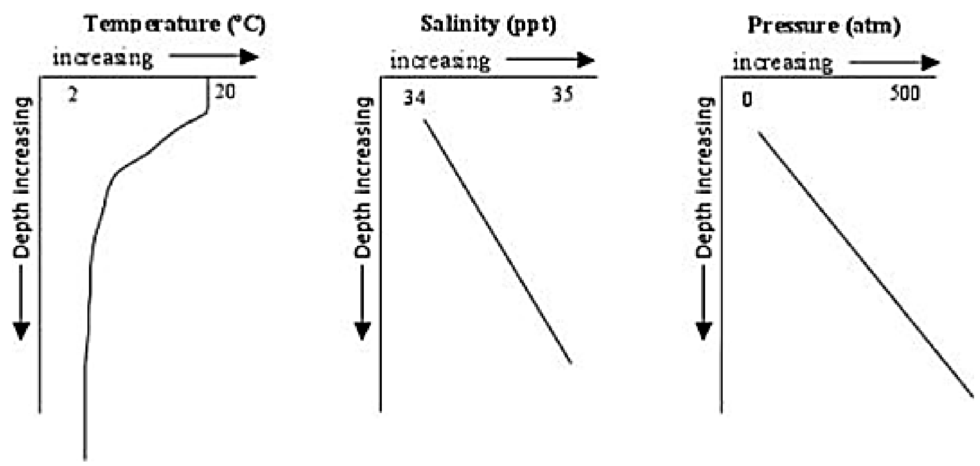


Figure 2.1: Variation of sound parameter

The variation of sound in water as function of depth is shown in figure 2.2. It shows that up-to 1000 m, speed of sound decreases from 1500m/s to 1490 m/s after that it again starts increasing and reaches maximum.

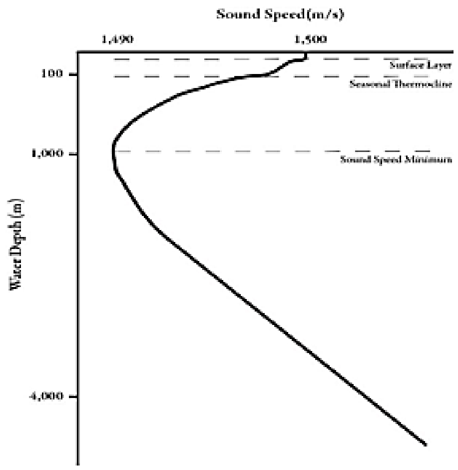


Figure 2.2: Variation of sound speed with depth

2.3 Underwater channel characteristics

The performance of underwater sound propagation is very much affected by the physical and chemical properties of the underwater channel [25]. Due to several effects like absorption and spreading, the underwater acoustic signal will suffer attenuation which degrades the performance of communication system. Due to the geometry of underwater channel, there is very high probabilities that the signals propagating underwater will suffer fading due to multipath propagation which again will result in inter symbol interference (ISI) at the receiver.

2.3.1 Spreading Loss

The main reason for spreading loss is the ever rising area covered by the equal amount of signal energy as the wave front shifts away from the source [26]. Mathematically, it is given by the equation 2.4 as:

$$\mathrm{PL_{spreading}}(\mathrm{r}) = \mathrm{k} \times 10\log(\mathrm{r})\ \ (\mathrm{dB}) \tag{2.4}$$

Where r denotes the range (in meters) and k represents the spreading loss.

When the medium in which the signal is propagating is unbounded then the value of k is taken as 2 while if the medium is bounded then value of k is taken as 1. As we can see, the spreading loss has a logarithmic relation with range hence at short distance spreading loss has a very high impact on the signal.

2.3.2 Dispersive channel characteristics

As we know that the received power is fluctuated by fading. In addition to that, the transmitted pulse shape is affected by channel having multipath propagation. As transmitted signal's components take the different paths at different time intervals to reach the receiver because of this, number of replicas is generated at the receiver end for the same signal. If these pulses can not be resolved, then effect of this multipath produces the pulse broadening which leads to inter symbol interference in communication process. The effect of inter symbol interference on transmitted signal (pulse) is shown in figure 2.3 below. Here a Gaussian pulse having width of (σ_d = 14.14) is transmitted across a wireless channel. And the dispersive nature of this wireless channel provides the sense that if a narrow pulse is sends across the channel, depending on the nature of reflection, diffusion, refraction or scattering the obtained multiple pulses may be spread out more and more. Due to this fact, the pulses arrived at the receiver can easily be overlapped and causes the pulse broadening which is shown in given figure below. If receiver is moving at speed of v then also dispersive behaviour comes into action due to Doppler Effect. This motion introduces a Doppler shift in the received signal frequency. The expression for this frequency shift is given by equation 2.5 as:

$$f_{Dmax} = f_c(v/c) \tag{2.5}$$

Where, c is nothing but the speed of sound.

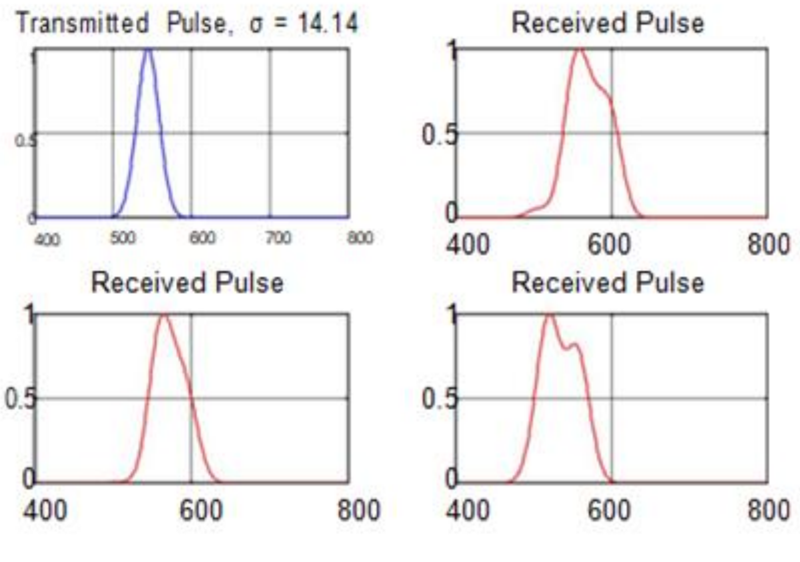


Figure 2.3: Pulse broadening in transmission due to Doppler Effect

2.3.3 Absorption Loss

Because of relaxation and viscous friction of molecules within a medium, there are energy losses which can be in the form of heat when an acoustic wave propagates in it. These losses are known as absorption losses. Mathematically, it is given by the equation 2.6 as:

$$\mathrm{PL}_{\mathrm{absorption}}(\mathrm{r};\mathrm{f}) = 10\log\big(\mathrm{a}(\mathrm{f})\big) \times \mathrm{r}\ \ (\mathrm{dB}) \tag{2.6}$$

Here, α tells about the absorption coefficient which is frequency dependent. For a specified range, relation of absorption variation with frequency is linear. The sound wave absorption in sea water is due to the viscosity, ionic relaxation of several constituents of sea water like sulphate of magnesium and boric acid and their relaxation time. At frequencies above 100 KHz, the effect of viscosity is more as compared to others. The ionic relaxation effect of magnesium affects the mid frequency ranges from 10 kHz to 100 kHz and the effects of boric acid are more prominent at lower frequencies below 10 kHz. Generally absorption loss increases with increasing frequency and decreases with increasing depth. Many empirical formulas have been made which takes into account salinity, frequency, temperature, pH and depth of sea water, in order to give the relationship between absorption coefficient and these factors. One of these empirical formula is the Thorp's expression. It is valid for frequencies starting from 100 Hz to 1 MHz and considers sea water with salinity of 35 ppt, pH as 8 and temperature 4 degree Celsius. The Thorp's expression is given by the equation 2.7 as:

$$\alpha(\mathrm{f}) = \frac{0.11\mathrm{f}^2}{1+\mathrm{f}^2} + \frac{44\mathrm{f}^2}{4100+\mathrm{f}^2} + 275 \times 10^{-4}\mathrm{f}^2 + 0.0033\ (\mathrm{dB/km}) \tag{2.7}$$

The graph showing the variation of absorption coefficient w.r.t. frequency is given below in figure 2.4. The value of absorption coefficient can be seen varying with change in frequency, depth and temperature [27].

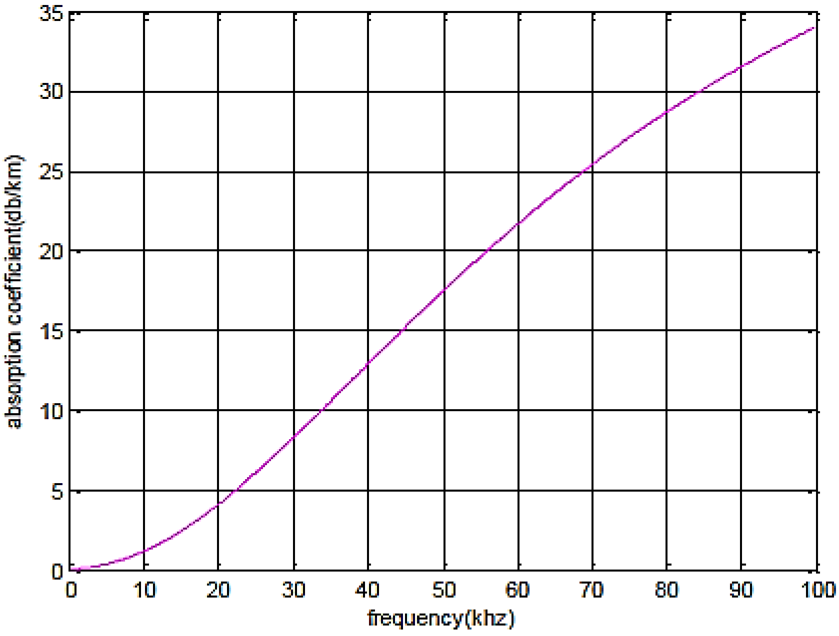


Figure 2.4: Variation of absorption coefficient

2.3.4 Multipath

Multipath propagation is the most prominent problem in case of underwater communication. This problem is due to the reception of different replicas of transmitted signal at different instant of time as they travel through different paths which have different delays and attenuations. This leads to the ISI. In order to combat the effect of ISI, several diversity techniques have been recommended or we can also use OFDM in order to achieve better performance in case of multipath fading channels. In underwater environment, signal suffers several reflections and refractions at the surface and bottom of the water body. These reflections and refractions lead to multipath propagation of the transmitted wave. At the receiver, the different replicas are received at different instances of time with different delays and attenuations and causes ISI. These effects are more prominent in shallow water environments. Figure 2.5 shows the multipath propagation due to direct path and indirect path.

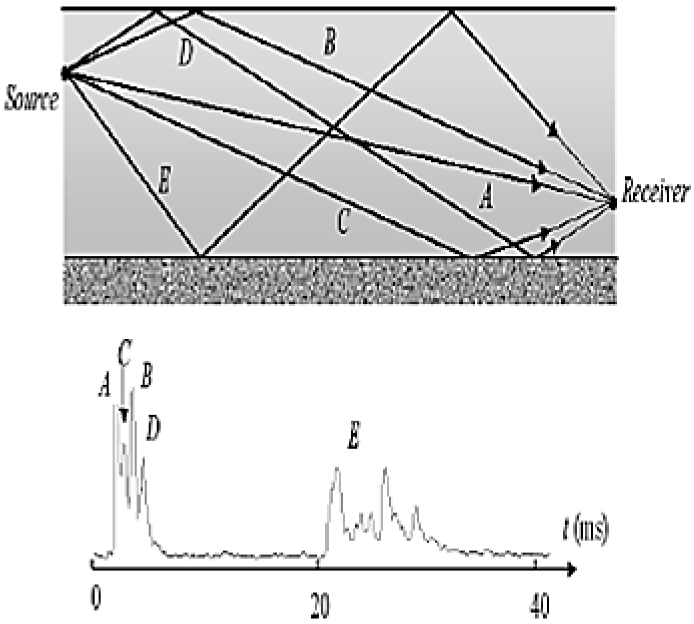


Figure 2.5: Multipath trajectories in UWA communication

2.3.5 Coherence Time/Bandwidth of Channel

The coherence time and the coherence bandwidth of channel are two more parameters in addition to Doppler spread and delay spread (B_d, T_m) those are used to characterize fading and multipath channels. Coherence time is the time interval over which the characteristics of channel changes by very little amount and is given by equation 2.8 as:

$$T_c = 1/Bd \tag{2.8}$$

Similar to the coherence time, coherence bandwidth is the bandwidth over which the characteristics (magnitude $\alpha(t)$ and phase ($\phi(t)$) of channel are highly correlated to each other. All the frequency components of a signal within this bandwidth range will fade simultaneously. This coherence bandwidth is formulated by the equation 2.9 as the reciprocal T_m:

$$B_c = 1/T_m \tag{2.9}$$

2.3.6 Multipath spread factor of channel

Spread factor of channel is the product of Doppler spread and multipath spread (T_mB_d). If T_mB_d product is less than 1 then channel is said to be under spread. And vice versa, if T_mB_d product is greater than 1 then channel is said to be over spread. Generally, if channel is over spread (i.e. large time variations $T_m >> T_c$) then the estimation of the carrier phase of channel can be very difficult. And it happens due to any of the large multipath spread and Doppler spread or both of them. And if the channel is under spread (i.e. slower time variations $T_c >> T_m$) then the estimation of the carrier phase of channel is obtained with good precision.

2.3.7 Path Loss

Path loss is the total loss incurred due to absorption and spreading loss. It is reduction in the power density of a signal when it travels through any medium. The expression for the path loss is given by the equation 2.10 as:

$$\text{Path Loss}(\mathrm{r}, \mathrm{d}, \mathrm{t}, \mathrm{f}) = \mathrm{k} * 10 \log(\mathrm{r}) + \mathrm{a}(\mathrm{f}, \mathrm{t}, \mathrm{d}).\mathrm{r}.10^{-3} \ \ (\mathrm{dB}) \qquad (2.10)$$

2.3.8 Propagation delay and Noise

Because of slow speed of acoustic waves in underwater channel, there are propagation delays which get added to the transmitted signal [28] [29]. As we compare underwater communication with radio communication, we will find that delays introduced in underwater communication will be very large as the speed of sound in water is around 1500 m/s while the speed of EM waves in open air is considered as 3×10^8 m/s. Due to large propagation delays, it is not desirable to apply feedback techniques to combat channel impairments. The typical values of propagation delays in underwater channels are considered in several seconds. Its value is much higher than the propagation delay in case of radio communication which is around several microseconds.

There are generally four noise components which are considered for underwater channel [28]. There, we can find thermal noise ($N_{th}(f)$) which is always present in the communication system and is generally considered as Additive White Gaussian Noise (AWGN). There is noise due to the movement of waves which is known as wave noise ($N_w(f)$) and it makes the medium unstable and varying in time. Due to the movement of the ships and other floating vessels, there is movement of water which again creates noise in the underwater environment. This kind of noise is known as Shipping noise (NS (f)). One more type of noise is present which is known as turbulence noise ($N_T(f)$) due to the natural causes line turbulences caused due to storms and rain. The sum of all these noise components can give the total noise present in the system.

2.3.9 Doppler shift

When sound waves are propagating through a channel then a relative motion of the receiver or transmitter or moving medium can change their frequency. This change in the carrier frequency of signal and the time domain is termed as Doppler shift. The Doppler frequency shift can be expressed by the equation 2.11 [30] as:

$$f_p = f_c(v + c)/c \quad (2.11)$$

Here c is the speed of sound, f_c is the frequency of transmitted signal which is known as carrier frequency.

Doppler Effect is one of the most prominent factor which leads to the signal distortion in communication theory [30]. As the speed of sound waves is much lower as compared to the speed of EM waves, this factor becomes more important in underwater acoustic communication. Doppler Effect is due to the relative motion between transmitter and receiver [31] [32]. This will influence in signal in two ways. One is the effect on the pulse width of the signal i.e. either it will get stretched or compressed. Another one is the change in the frequency of the signal by some offset value. This is due to the compression or expansion of the signal in time domain. For short ranges, the Doppler Effect has no relevant effect on underwater communication. The figure 2.6 given below shows the Doppler Effect.

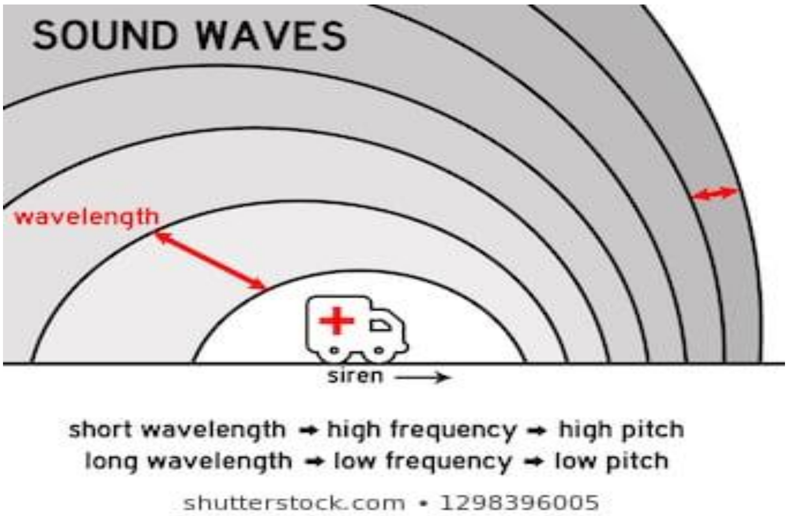


Figure 2.6: Doppler Effect

2.3.10 Channel Bandwidth

Absorption coefficient is the main limiting factor which put a restriction on the maximum desirable frequency used in the underwater system. The attenuation suffered by a signal of frequency *f*, propagating in an underwater channel over a distance *d* can be given by equation 2.12 as:

$$A(l, f) = d^k * a(f)^d \tag{2.12}$$

	Range	Bandwidth
Very long Distance	1000 (Km)	<1 (KHz)
Long Distance	10-100(Km)	2.5(KHz)
Medium Distance	**1-10 (Km)**	**10(**KHz**)**
Short Distance	0.1-1(Km)	20-50(KHz)
Very Short Distance	<0.1(Km)	>100(KHz)

Table 2.1: Limitations of range and bandwidth

Where, *k* is the spreading factor and its value is taken as 1.5 and and *a(f)* is the absorption coefficient. Higher is the value of frequency, greater is the attenuation.

This is the reason why there is a trade-off between the maximum frequency or channel bandwidth used and the attenuation which can be tolerated. This problem also puts a restriction on the maximum channel bandwidth and the range of communication. This limitation has been appended in table 2.1.

2.3.11 Large scale and small scale variations

In designing of acoustic channel it is necessary to understand the physical aspects of propagation of acoustic waves as well as the effects of random channel variations. Channel variations are of two types and these are classified into small scale channel variations and large scale channel variations. Small scale channel variations occur for short span (parts of second) of time and also these variations occur over short displacements. For small scale variations the environmental conditions and system geometry do not too much, while large scale variations takes place due to location uncertainty and variable environmental conditions.

The time-invariant and deterministic model of an acoustic channel is that of a multipath channel having an additional low pass filter. Energy absorption for low pass filter is high for higher acoustic frequencies. Attenuation in signal takes place with increase in distance, according to the energy spreading law. Given Figure 2.7 illustrates this effect.

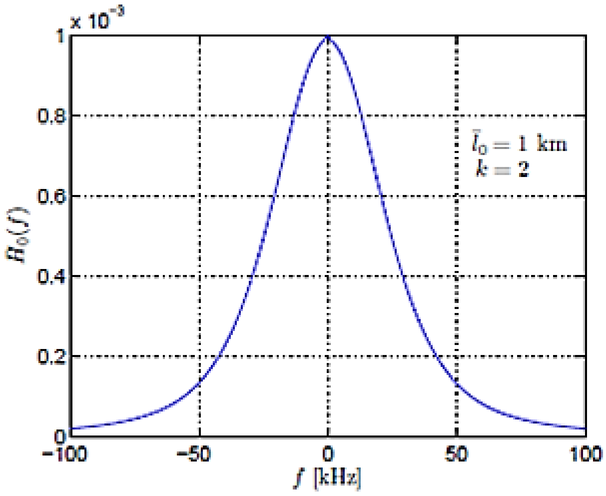


Figure 2.7: Transfer fn. corresponding to a single path having length of 1 km

For a multipath channel, all the paths are assumed to have same reference transfer function only but with a different delay and gain [34]. To determine the nominal delay (τ_p) and nominal path gain (h_p) Nominal channel geometry can be used as shown in figure 2.8.

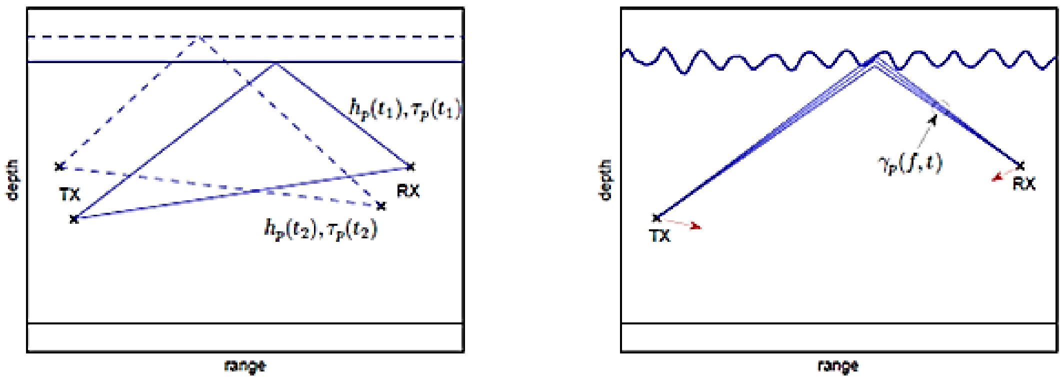


Figure 2.8: Large scale and small scale variations in underwater acoustic communication

CHAPTER 3

CHANNEL EQUALIZATION AND OPTIMIZED ALGORITHMS

3.1 Channel Equalizer

Equalization is the technique to improve the received signal quality and link performance over small scale time and distances. Equalization compensates for inter symbol interference (ISI) which is created by multiple paths in time dispersive channels [35]. An equalizer within a receiver compensates for the average range of expected channel amplitude and delay characteristics. Equalizer is mostly adaptive because channel is mostly unknown and time varying. In telecommunication, equalization is the reversal of distortion incurred by a signal transmitted through a channel. Equalizers are used to render the frequency response for instance of a telephone line flat from end-to-end. Sometimes equalization is also used with diversity and channel coding. And combinely all these three techniques give better received signal quality. But in this section we will focus mainly on concept of equalization and techniques associated with equalization.

Early telephone systems used equalization to correct for the reduced level of high frequencies in long cables, typically using Zobel networks [36]. These kinds of equalizers can also be used to produce a circuit with a wider bandwidth than the standard telephone band of 300 Hz to 3.4 kHz. This was particularly useful for broadcasters who needed "music" quality, not "telephone" quality on landlines carrying program material. It is necessary to remove or cancel any loading coils in the line before equalization can be successful. Equalization was also applied to correct the response of the transducers, for example, a particular micro-phone might be more sensitive to low frequency sounds than to high frequency sounds, so an equalizer would be used to increase the volume of the higher frequencies (boost), and reduce the volume of the low frequency sounds (cut). Similar approach was also used in television lines with two important additional complications. The first of these is that the television signal is a wide bandwidth covering many more octaves than an audio signal. A television equalizer consequently typically requires more filter sections than an audio equalizer. To keep this manageable, television equalizer sections were often combined into a single network using ladder topology to form a Cauer equalizer. The second issue is that phase equalization is essential for an analog television signal. Without it dispersion causes the loss of integrity of the original wave shape and is seen as smearing of what were originally sharp edges in the picture.

The above mentioned equalization techniques are for analog telecommunications [36]. Later on more impressive techniques were introduced for digital telecommunication as well. Some of the digital equalizer types are Linear equalizer, Decision feedback equalizer, Blind equalizer, Adaptive equalizer, Viterbi equalizer etc.

3.2 Fundamentals of Equalization

Inter symbol interference (ISI) caused by multipath in bandlimited (frequency selective) time dispersive channels distorts the transmitted signal, causing bit errors at the receiver. ISI has been recognized as the major obstacle to high speed data transmission over mobile radio channels. Equalization is a technique to remove ISI basically. In radio channels, a variety of adaptive equalizers can be used to cancel interference while providing diversity. The basic block diagram for use of equalizer is shown in figure 3.1 below.

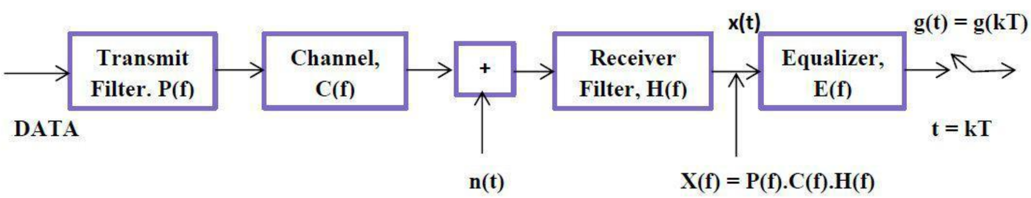


Figure 3.1: Block diagram of Equalizer

In Figure it is shown that Equalizer is used at the output of receiver. Equalizer acts as inverse filter at the receiver side having transfer function inverse as that of channel. We can classify the equalizers as shown below.

3.2.1 Linear equalizer

In this equalizer, the current and past values of the received signal are linearly weighted by the filter coefficient and summed to produce the output as shown in figure 3.2. If the delays and the tap gains are analog, the continuous output of the equalizer is sampled at the symbol rate and the samples are applied to the decision device. The implementation is, however carried out in the digital domain where the samples of the received signal stored in a shift register.

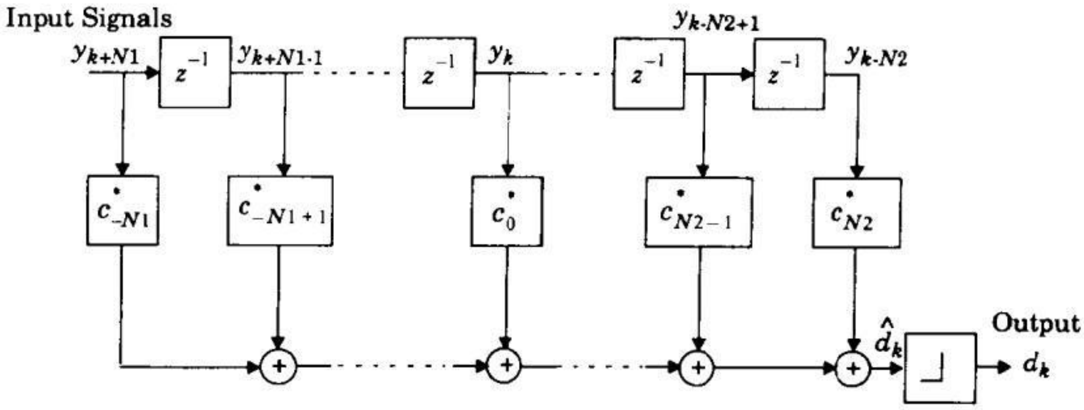


Figure 3.2: Linear Transversal Equalizer

The minimum mean squared error $E[e(n)^2]$ that a linear transversal equalizer can achieve is given by equation 3.1

$$E[|e(n)|^2] = \frac{T}{2\pi}\int_{\frac{-\pi}{T}}^{\frac{\pi}{T}} \frac{N_0 dw}{|F(\exp(iwt))|^2 + N_0} \qquad (3.1)$$

where F (exp(iwt)) is the frequency response of the channel and N_0 is the noise power spectral density.

3.2.2 Non-Linear Equalizer

Nonlinear equalizers are used in many applications where the channel distortion is too severe for a linear equalizer to handle, and are commonplace in practical wireless system [37]. Linear equalizers do not perform well on channels which have deep spectral nulls in the pass band. In an attempt to compensate for the distortion, the linear equalizer places too much gain in the vicinity of the spectral null, thereby enhancing the noise present in those frequencies.

Three very effective nonlinear methods have been developed which offer improvements over linear equalization techniques and are used in most 2G and 3G systems. All these are described one by one below.

1. **Decision Feedback Equalizer**

The basic idea behind decision feedback equalization is that once an information symbol has been detected and decided upon, the ISI that it induces on future symbols can be estimated and subtracted out before detection of subsequent symbols. The DFE can be realized in either the direct transversal form or as a lattice filter. It consists of a feed forward filter (FFF) and a feedback filter (FBF) [38]. The FBF is driven by decisions on the output of the detector, and its coefficients can be adjusted to cancel the ISI on the current symbol from past detected symbols

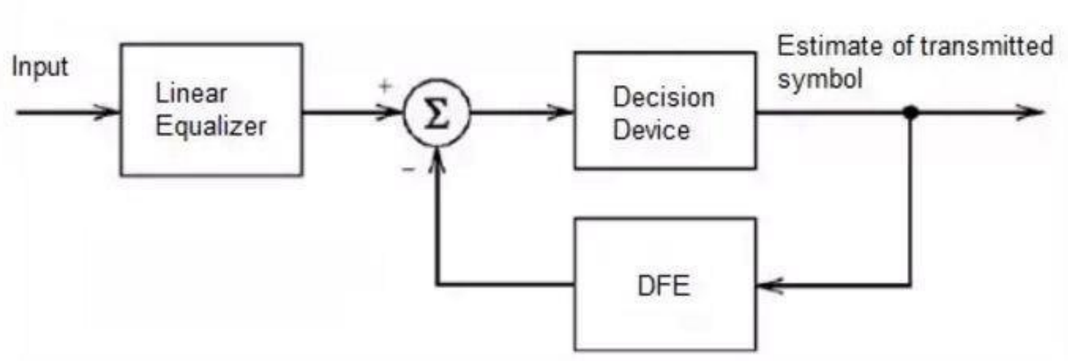


Figure 3.3: Decision feedback equalizer (DFE)

A decision feedback equalizer (DFE) is a filter that uses feedback of detected symbols to produce an estimate of the channel output. The DFE is fed with detected symbols and produces an output which typically is subtracted from the output of the linear equalizer as shown in figure 3.3. As in the case of linear equalizers the DFE consists of a real FIR filter, if the transmitted symbols are real or a complex FIR filter if the symbols are complex. Since the DFE can only estimate the post-cursors, typically it needs to be used in combination with a linear equalizer.

During the steady-state operation, the DFE contains an estimate of the impulse response of the channel or of the convolution of the channel with the linear equalizer, if a linear equalizer is used as well. Since the DFE copies the channel output and the DFE output is subtracted from the incoming signal, it can compensate for severe amplitude distortion without increasing the noise in the highly distorted frequency bands.

2. **Maximum Likelihood Sequence Estimation (MLSE) Equalizer**

To remove the limitations of MSE-based equalizers researchers investigates the optimum nonlinear structures. And these equalizers use various forms of classical maximum likelihood receiver structure. These equalizers use various forms of the classical maximum likelihood receiver structure. Using a channel impulse response simulator within the algorithm, the MLSE tests all possible data sequences (rather than decoding each received symbol by itself), and chooses the data sequence with the maximum probability as the output [39]. An MLSE usually has a large computational requirement, especially when the delay spread of the channel is large. Using the MLSE as an equalizer was first proposed by Forney in which he set up a basic MLSE estimator structure and implemented it with the Viterbi algorithm. The MLSE can be viewed as a problem in estimating the state of a discrete-time finite state machine, which in this case happens to be the radio channel with coefficients f_k and with a channel state which at any instant of time is estimated by the receiver based on the L most recent input samples. Thus the channel has M^L states, where M is the size of the symbol alphabet of the modulation. The Viterbi algorithm then tracks the state of the channel by the paths through the trellis and gives at stage k a rank ordering of the M^L most probable sequences terminating in the most recent L symbols [39]. The structure of MLSE with an adaptive matched filter is shown in figure 3.4.

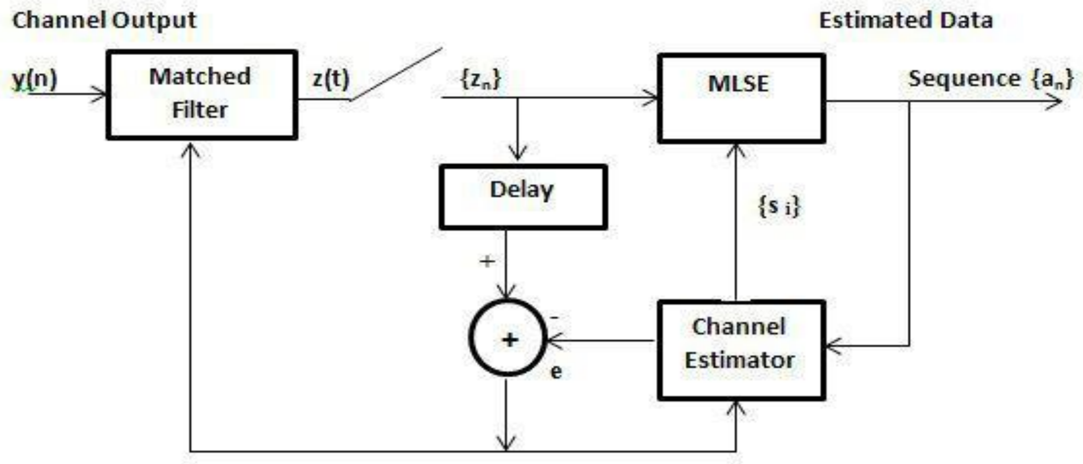


Figure 3.4: Structure of MLSE with an adaptive matched filter

3.2.3 Adaptive Equalizer

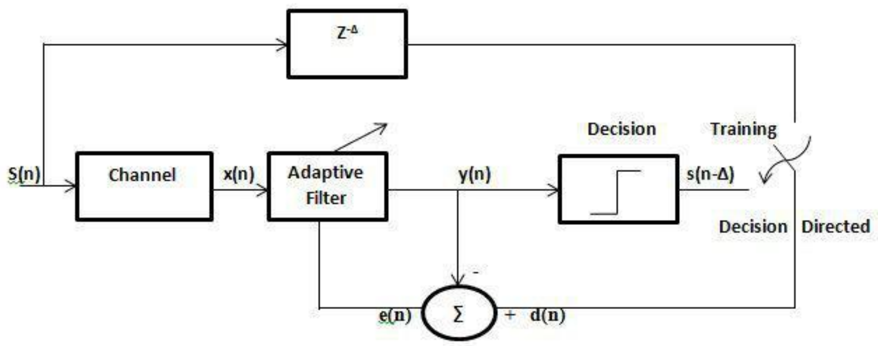


Figure 3.5: Adaptive channel equalization system

A variety of adaptive equalizers can be used to cancel interference while providing diversity. Since the mobile fading channel is random and time varying, equalizers must track the time varying characteristics of the mobile channel and thus are called Adaptive equalizers. The purpose of adaptive channel equalization is to compensate for signal distortion in a communication channel. Communication systems transmit a signal from one point to another across a communication channel, such as an electrical wire, a fiber-optic cable, or a wireless radio link. During the transmission process, the signal that contains information might become distorted. A basic adaptive channel equalization model is shown in figure 3.5. To compensate for this distortion, you can apply an adaptive filter to the communication channel. The adaptive filter works as an adaptive channel equalizer. Adaptive equalization has two modes.

1. Training

2. Decision directed mode

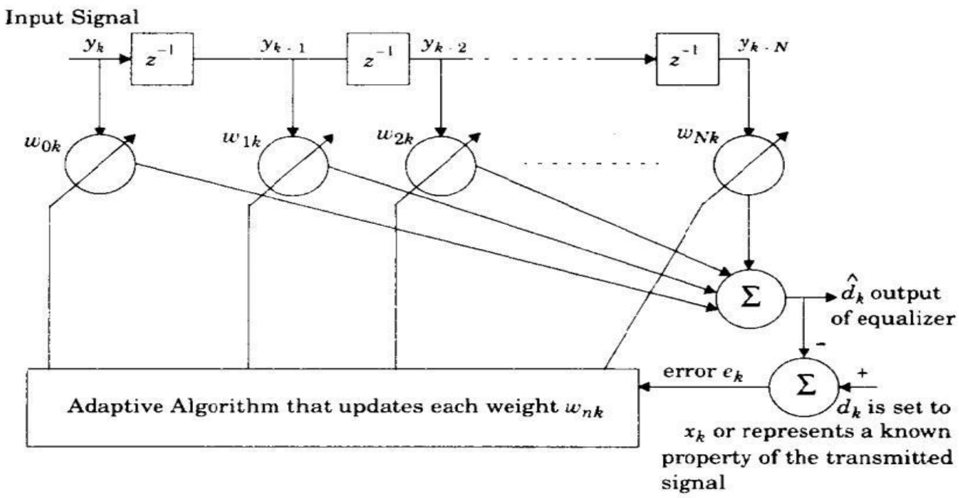


Figure 3.6: A basic linear equalizer during training

Since an adaptive equalizer compensates for an unknown and time varying channel, it requires a specific algorithm to update the equalizer coefficients and track the channel variations. Equalizer during training is shown in the figure 3.6. A wide range of algorithms exist to adapt the filter coefficients. The development of adaptive algorithms is a complex undertaking, and it is beyond the scope of this text to delve into great detail on how this is done. This section describes some practical issues regarding equalizer algorithm design, and outlines three of the basic algorithms for adaptive equalization. Though the algorithms detailed in this section are derived for the linear transversal equalizer.

The performance of an algorithm is determined by various factors.

1. Rate of convergence
2. Misadjustment
3. Computational complexity
4. Numerical properties

3.2.4 Blind Channel Equalizer

Blind equalization is a digital signal processing technique in which the transmitted signal is inferred (equalized) from the received signal, while making use only of the transmitted signal statistics. Hence, the use of the word blind in the name.

Blind equalization is essentially blind deconvolution applied to digital communications. Nonetheless, the emphasis in blind equalization is on online estimation of the equalization filter, which is the inverse of the channel impulse response, rather than the estimation of the channel impulse response itself [39]. This is due to blind deconvolution common mode of usage in digital communications systems, as a mean to extract the continuously transmitted signal from the received signal, with the channel impulse response being of secondary intrinsic importance. The estimated equalizer is then convolved with the received signal to yield an estimation of the transmitted signal

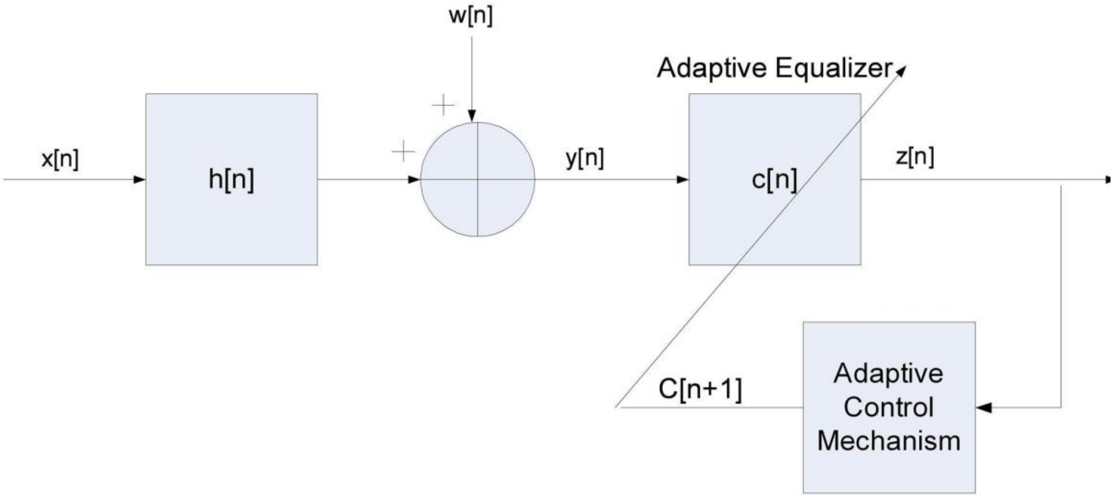


Figure 3.7: Blind Channel equalizer

The field of blind channel equalization has been existence for a little over twenty years. Research during this time has centred on developing new algorithms and formulating a theoretical justification for these algorithms. Blind channel equalization is also known as a self-recovering equalization. The model for blind channel equalizer is shown in figure 3.7. The objective of blind equalization is to recover the unknown input sequence to the unknown channel based solely on the probabilistic and statistical properties of the input sequence.

3.3 Optimization Algorithm

In optimization of a design, the design objective could be simply to minimize the cost of production or to maximize the efficiency of production. An optimization algorithm is a procedure which is executed iteratively by comparing various solutions till an optimum or a satisfactory solution is found. With the advent of computers, optimization has become a part of computer-aided design activities. There are two distinct types of optimization algorithms widely used today.

a) Deterministic algorithms: They use specific rules for moving one solution to other. These algorithms are in use to suite some times and have been successfully applied for many engineering design problems.
b) Stochastic algorithms: The stochastic algorithms are in nature with probabilistic translation rules. These are gaining popularity due to certain properties which deterministic algorithms do not have.

3.3.1 Design implementation for optimized algorithm:

A naive optimal design is achieved by comparing a few (limited up to ten or so) alternative solutions created by using a priori problem knowledge. In this method feasibility of each design solution is first investigated. Thereafter an estimate of underlying objective (cost, profit, etc.) of each solution is compared and best solution is adopted. It is impossible to apply single formulation procedure for all engineering design problems, since the objective in a design problem and associated therefore, design parameters vary product to product different techniques are used in 4 different problems. Purpose of formulation is to create a mathematical model of the optimal design problem, which then can be solved using an optimization algorithm. Figure 3.8 below shows an outline of the steps usually involved in an optimal design formulation.

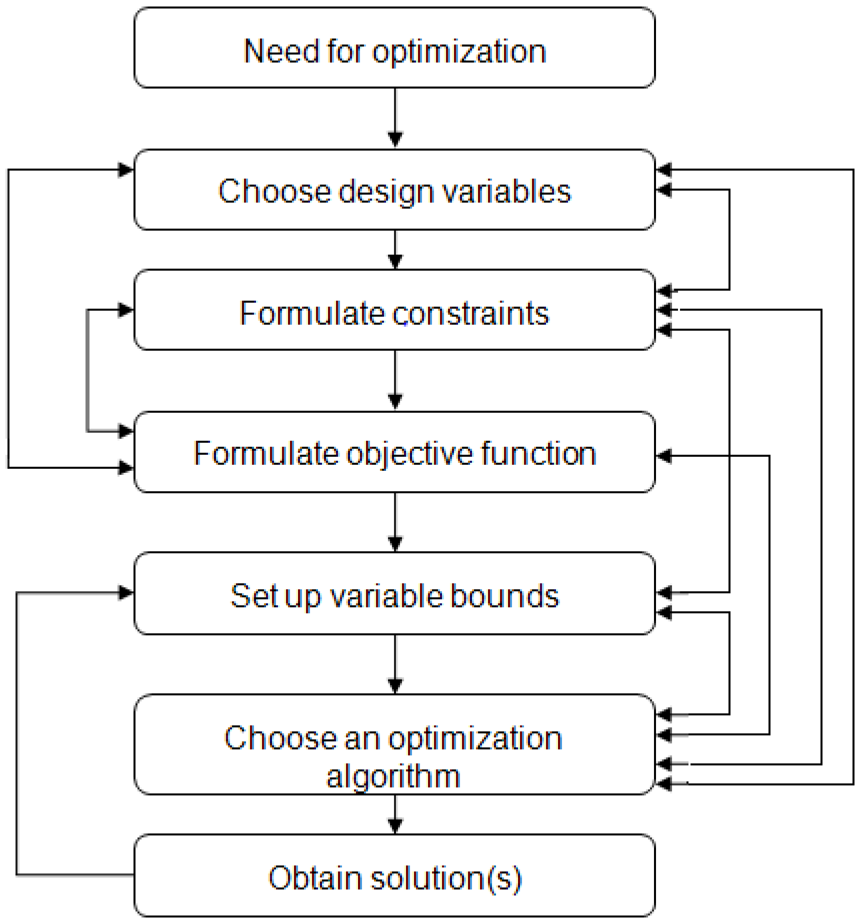


Figure 3.8: A flow chart for the optimally designed procedure

Design Variables: The formulation of an optimization problem begins with identifying the underlying design variables, which are primarily varied during the optimization process. A design problem usually involves many design parameters, of which some are highly sensitive to the proper working of the design. These parameters are called design variables in the parlance of optimization procedures. Other (not so important) design parameters usually remain fixed or vary in relation to the design variables. The first thumb rule of the formulation of an optimization problem is to choose as few design variables as possible. The outcome of that optimization procedure may indicate whether to include more design variables in a revised formulation or to replace some previously considered design variables with new design variables.

Constraints: The constraints represent some functional relationships among the design variables and other design parameters satisfying certain physical phenomenon and certain resource limitations. The nature and number of constraints to be included in the formulation depend on the user. Constraints may have exact mathematical expressions or not. For example, maximum stress is a constraint of a structure. If a structure has regular shape they have an exact mathematical relation of maximum stress with dimensions. But incase irregular shape, finite element simulation software may be necessary to compute the maximum stress. The following two types of constraints emerge from most considerations: 1. Inequality type constraints. 2. Equality type constraints.

Objective functions: The next task in the formulation procedure is to find the objective function in terms of the design variables and other problem parameters. The common engineering objectives involve minimization of overall cost of manufacturing or minimization of overall weight of a component or maximization of total life of a product or others. Although most of the objectives can be quantified (expressed in mathematical form), there are some objectives (such as aesthetic aspect of a design, ride characteristics of a car suspension design and reliability of a design) that may not be possible to formulate mathematically. In such a case an approximating mathematical expression is used.

Variable bounds: The final task of the formulation procedure is to set the minimum and the maximum bounds on each design variable. Certain optimization algorithms do not require this information. In these problems, the constraints completely surround the feasible region. Other problems require the search algorithm with in these bounds. In general, all N design variables are restricted to lie within the minimum and the maximum bounds.

Optimized algorithms: For the sake of clarity, the optimization algorithms are classified into a number of groups, which are now briefly discussed.

(a) Single-variable optimization algorithms: These algorithms are classified into two categories

i. Direct methods

ii. Gradient based methods

Direct methods do not use any derivative information of the objective function; only objective function values are used to guide the search process. However, gradient-based methods use derivative information (first and/ or second order) to guide the search process. Although engineering optimization problems usually contain more than one variable, single-variable optimization algorithms are mainly used as unidirectional search methods in multivariable optimization algorithms.

(b) Multi- variable optimization algorithms: These algorithms demonstrate how the search for the optimum point progresses in multiple dimensions. Depending on whether the gradient information is used or not used, these algorithms are also classified into direct and gradient-based techniques.

(c) Constrained optimization algorithms: These algorithms use the single variable and multivariable optimization algorithms repeatedly and simultaneously maintain the search effort inside the feasible search region. These algorithms are mostly used in engineering optimization problems.

(d) Specialized optimization algorithms: Two of these algorithms integer programming and geometric programming are often used in engineering design problems. Integer programming methods can solve optimization problems with integer design variables. Geometric programming methods solve optimization problems with objective functions and constraints written in a special form.

(e) Non-traditional optimization algorithms: There are two algorithms which are nontraditional, these are:

1) Genetic algorithms

2) Simulated annealing

The algorithms used in this report are least mean square algorithm and genetic algorithm those are described in later sections below.

3.4 Applied Algorithms

3.4.1 Least mean square Algorithm:

The Least Mean Square (LMS) algorithm, introduced by Widrow and Hoff in 1959 is an adaptive algorithm, which uses a gradient-based method of steepest decent. LMS algorithm uses the estimates of the gradient vector from the available data. LMS incorporates an iterative procedure that makes successive corrections to the weight vector in the direction of the negative of the gradient vector which eventually leads to the minimum mean square error [40]. Compared to other algorithms LMS algorithm is relatively simple. It does not require correlation function calculation nor does it require matrix inversions.

3.4.1.1 LMS algorithm and adaptive arrays

Consider a Uniform Linear Array (ULA) with N isotropic elements, which forms the integral part of the adaptive beam forming system as shown in the figure 3.9 below. The output of the antenna array x(t) is given by equation 3.2 as:

$$x(t) = s(t)a(\theta_0) + \sum_{i=1}^{N_u} u_i(t)a(\theta_i) + n(t) \tag{3.2}$$

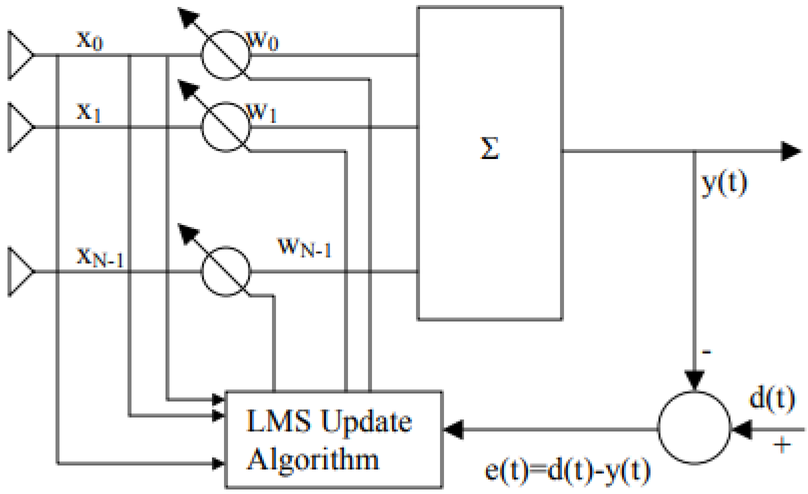


Figure 3.9: LMS adaptive beamforming network

s(t) denotes the desired signal arriving at angle θ_0 and $u_i(t)$ denotes interfering signals arriving at angle of incidences θ_i respectively. $a(\theta_0)$ and $a(\theta_i)$ represents the steering vectors for the desired signal and interfering signals respectively. Therefore it is required to construct the desired signal from the received signal amid the interfering signal and additional noise n(t).

As shown above the outputs of the individual sensors are linearly combined after being scaled using corresponding weights such that the antenna array pattern is optimized to have maximum possible gain in the direction of the desired signal and nulls in the direction of the interferers. The weights here will be computed using LMS algorithm based on Minimum Squared Error (MSE) criterion. Therefore the spatial filtering problem involves estimation of signal s(t) from the received signal x(t) (i.e. the array output) by minimizing the error between the reference signal , which closely matches or has some extent of correlation with the desired signal estimate and the beamformer output y(t) (equal to Wx(t)). This is a classical Weiner filtering problem for which the solution can be iteratively found using the LMS algorithm.

3.4.1.2 LMS algorithm formulation

(All the signals are represented by their sample values)

From the method of steepest descent, the weight vector equation is given by the equation 3.3 as:

$$w(n+1) = w(n) + \frac{1}{2}\mu[-\nabla(E\{e^2(n)\})] \tag{3.3}$$

Where μ is the step-size parameter and controls the convergence characteristics of the LMS algorithm; $e^2(n)$ is the mean square error between the beamformer output y(n) and the reference signal which is given by equation 3.4.

$$e^2(n) = \left[d^*(n) - w^h x(n)\right]^2 \tag{3.4}$$

The gradient vector in the above weight update equation can be computed as

$$\nabla_w(E\{e^2(n)\}) = -2r + 2Rw(n) \tag{3.5}$$

In the method of steepest descent the biggest problem is the computation involved in finding the values r and R matrices in real time. The LMS algorithm on the other hand simplifies this by using the instantaneous values of covariance matrices r and R instead of their actual values i.e.

$$R(n) = x(n)x^h(n) \tag{3.6}$$

$$r(n) = d^*(n)x(n) \tag{3.7}$$

Therefore the weight update can be given by the equation 3.8,

$$\begin{aligned} w(n+1) &= w(n) + \mu x(n)\left[d^*(n) - x^h(n)w(n)\right] \\ &= w(n) + \mu x(n)e^*(n) \end{aligned} \tag{3.8}$$

The LMS algorithm is initiated with an arbitrary value w(0) for the weight vector at n=0. The successive corrections of the weight vector eventually leads to the minimum value of the mean squared error.

Therefore the LMS algorithm can be summarized in the following equations;

$$\text{Output, } y(n) = w^h x(n) \tag{3.9}$$

$$\text{Error, } e(n) = d^*(n) - y(n) \tag{3.10}$$

$$\text{Weight, } w(n+1) = w(n) + \mu x(n)e^*(n) \tag{3.11}$$

3.4.1.3 Convergences and stability of LMS algorithm

The LMS algorithm initiated with some arbitrary value for the weight vector is seen to converge and stay stable for

$$0 < \mu < 1/\lambda_{max} \tag{3.12}$$

Where λ_{max} is the maximum eigen value of the correlation matrix R. The convergence of the algorithm is inversely proportional to the eigenvalue spread of the correlation matrix R. When the eigenvalues of 'R' are widespread, convergence may be slow. The eigenvalue spread of the correlation matrix is estimated by computing the ratio of the largest eigenvalue to the smallest eigenvalue of the matrix. If μ is chosen to be very small then the algorithm converges very slowly. A large value of μ may lead to a faster convergence but may be less stable around the minimum value. One of the literatures [will provide reference number here] also provides an upper bound for μ based on several approximations as $\mu <= 1/(3\mathrm{trace}(R))$.

The LMS algorithm is most commonly used adaptive algorithm because of its simplicity and a reasonable performance. Since it is an iterative algorithm it can be used in a highly time-varying signal environment. It has a stable and robust performance against different signal conditions. However it may not have a really fast convergence speed compared other complicated algorithms like the Recursive Least Square (RLS). It converges with slow speeds when the environment yields a correlation matrix R possessing a large eigen spread. Usually traffic conditions are not static, the user and interferer locations and the signal environment are varying with time, in which case the weights will not have enough time to converge when adapted at an identical rate. That is,μ the step-size needs to be varied in accordance with the varying traffic conditions. There are several variants of the LMS algorithm that deal with the shortcomings of its basic form. The Normalized LMS (NLMS) introduces a variable adaptation rate. It improves the convergence speed in a non-static environment. In another version, the Newton LMS, the weight update equation includes whitening in order to achieve a single mode of convergence. For long adaptation processes the Block LMS is used to make the LMS faster. In block LMS, the input signal is divided into blocks and weights are updated blockwise. A simple version of LMS is called the Sign LMS. It uses the sign of the error to update the weights. Also, LMS is not a blind algorithm i.e. it requires a priori information for the reference signal. A Pseudo code for LMS Algorithm:

Input: Binary Sequence x

Output: Recovered Binary Sequence y

---

a(1,N) ← Underwater channel weights

w(1,2N+2) ← Weights of Equalizer

```
        d = [zeros (1,N+1)    x]
        buffer 1 = zeros (1,N)
        buffer 2 = w
        count = 0
        noise = sqrt (10^-SNR/10)*(rand(1,N)-0.5)
        for  i=1:n
step 1:    |    buffer (2,N) = buffer (1,N-1)
step 2:    |    y1= buffer1*a’
step 3:    |    y2= y1 + noise
step 4:    |    buffer2 (2, 2N+2) = buffer2 (1, 2N+1)
step 5:    |    y = buffer2*w’
step 6:    |    error (i) = y (i) – d (i)
sstep7:    |    w = w + 2*µ*buffer2*e
        end
        SNR = 0:2:30
        for  h = 1: length (SNR)
           |    noise = sqrt (10^-SNR(h)/10)*(rand(1,n)-0.5)
           |    for i = 1: n
           |       |    Repeat steps 1 to 5
           |       |    if  y (i) ~= d(i)
           |       |       |    count = count + 1
           |       |    end
           |    end
           |    errorcount (1, i) = count
        end
        ber = log10 (errorcount/n)
                plot (ber, SNR)
```

3.4.2 Genetic Algorithm

Genetic algorithms are a type of optimization algorithm, meaning they are used to find the optimal solution(s) to a given computational problem that maximizes or minimizes a particular function. Genetic algorithms represent one branch of the field of study called evolutionary computation, in that they imitate the biological processes of reproduction and natural selection to solve for the ‘fittest’ solutions [41].

Its Principal is “Select the best, Discard the rest”. For example giraffes have long neck. So Giraffes with slightly longer necks could feed on leaves of higher branches when all lower ones had been eaten off. They had a better chance of survival. Favorable characteristic propagated through generations of giraffes. Favorable characteristic propagated through generations of giraffes. This longer necks may have due to the effect of mutation initially. So, giraffe (Survival of the best or fittest) is one of the examples of genetic algorithm.

The fitness function is the function that the algorithm is trying to optimize. The word “fitness” is taken from evolutionary theory. It is used here because the fitness function tests and quantifies how ‘fit’ each potential solution is. The fitness function is one of the most pivotal parts of the algorithm, so it is discussed in more detail at the end of this section [42]. The term chromosome refers to a numerical value or values that represent a candidate solution to the problem that the genetic algorithm is trying to solve. Each candidate solution is encoded as an array of parameter values, a process that is also found in other optimization algorithms.

An important concept of GAs is the notion of population. Unlike traditional search methods, genetic algorithms rely on a population of candidate solutions. The population size, which is usually a user-specified parameter, is one of the important factors affecting the scalability and performance of genetic algorithms. For example, small population sizes might lead to premature 98 SASTRY, GOLDBERG AND KENDALL convergence and yield substandard solutions. On the other hand, large population sizes lead to unnecessary expenditure of valuable computational time.

3.4.2.1 Steps of Genetic Algorithm

Once the problem is encoded in a chromosomal manner and a fitness measure for discriminating good solutions from bad ones has been chosen, we can start to evolve solutions to the search problem using the following steps:

1. Initialization: The initial population of candidate solutions is usually generated randomly across the search space. However, domain-specific knowledge or other information can be easily incorporated.

2. Evaluation: Once the population is initialized or an offspring population is created, the fitness values of the candidate solutions are evaluated.

3. Selection: Selection allocates more copies of those solutions with higher fitness values and thus imposes the survival-of-the-fittest mechanism on the candidate solutions. The main idea of selection is to prefer better solutions to worse ones, and many selection procedures have been proposed to accomplish this idea, including roulette-wheel selection, stochastic universal selection, ranking selection and tournament selection, some of which are described in the next section.

4. Recombination: Recombination combines parts of two or more parental solutions to create new, possibly better solutions (i.e. offspring). There are many ways of accomplishing this (some of which are discussed in the next section), and competent performance depends on a properly designed recombination mechanism. The offspring under recombination will not be identical to any particular parent and will instead combine parental traits in a novel manner (Goldberg, 2002).

5. Mutation: While recombination operates on two or more parental chromosomes, mutation locally but randomly modifies a solution. Again, there are many variations of mutation, but it usually involves one or more changes being made to an individual's trait or traits. In other words, mutation performs a random walk in the vicinity of a candidate solution.

6. Replacement: The offspring population created by selection, recombination, and mutation replaces the original parental population. Many replacement techniques such as elitist replacement, generation-wise replacement and steady-state replacement methods are used in GAs.

7. Repeat steps 2–6 until a terminating condition is met.

3.4.2.2 Code of Genetic Algorithm

A simple code for genetic is given below, which is explaining the main process of this algorithm

```
function genti ()

{

        Initialize population;

        Calculate fitness function;

        While (fitness value! = termination criteria)
```

```
    {
        Selection;
        Crossover;
        Mutation;
        Calculate fitness function;
    }
}
```

3.4.2.3 Operators in Genetic Algorithm

Selection, Recombination and Mutation are some of the operators those are commonly used in Genetic algorithm and are listed below [41] [42].

1) **Selection operator-** Selection procedures can be broadly classified into two classes as follows.

   Fitness Proportionate Selection: This includes methods such as roulette-wheel selection and stochastic universal selection. In roulette-wheel selection, each individual in the population is assigned a roulette wheel slot sized in proportion to its fitness. Figure of roulette-wheel selection is shown below. That is, in the biased roulette wheel, good solutions have a larger slot size than the less fit solutions. The roulette wheel is spun to obtain a reproduction candidate The roulette wheel selection scheme can be implemented as follows:

   1. Evaluate the fitness, f_i , of each individual in the population.

   2. Compute the probability (slot size), p_i , of selecting each member of the population: $pi = fi/(f_1+f_2+\ldots\ldots.+f_n)$, where n is the population size.

   3. Calculate the cumulative probability, q_i , for each individual: $q_i = p_1+p_2+...+p_i$.

   4. Generate a uniform random number, $r \in (0, 1]$.

   5. If $r < q1$ then select the first chromosome, X_1, else select the individual X_i such that $q_{i-1} < r \leq q_i$.

   6. Repeat steps 4–5 n times to create n candidates in the mating pool.

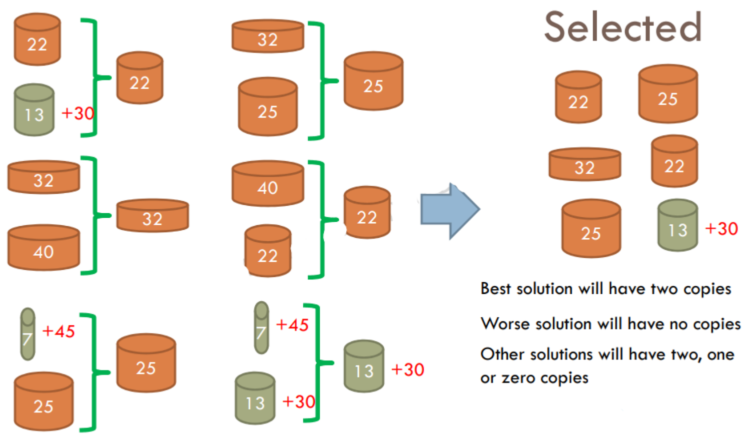


Figure 3.10: Tournament Selection method

Ordinal Selection: This includes methods such as tournament selection and truncation selection. In tournament selection, s chromosomes are chosen at random (either with or without replacement) and entered into a tournament against each other. The fittest individual in the group of k chromosomes wins the tournament and is selected as the parent. The most widely used value of s is 2. Using this selection scheme, n tournaments are required to choose n individuals. In truncation selection, the top $(1/s)^{th}$ of the individuals get s copies each in the mating pool.

Chrom #	Fitness	% of RW	EC	AC
1	50	26.88	1.61	2
2	6	3.47	0.19	0
3	36	20.81	1.16	1
4	30	17.34	0.97	1
5	36	20.81	1.16	1
6	28	16.18	0.90	1
	186	100.00	6	6

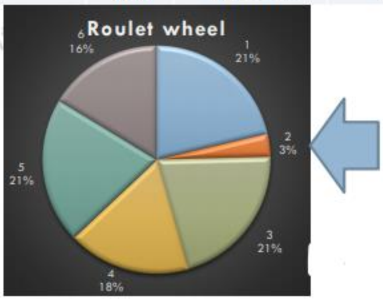


Figure 3.11: Roulette-wheel Method

2) **Recombination (Crossover) operator:** After selection, individuals from the mating pool are recombined (or crossed over) to create new, hopefully better,

offspring. In the GA literature, many crossover methods have been designed and some of them are described in this section. Many of the recombination operators used in the literature are problem-specific and in this section we will introduce a few generic (problem independent) crossover operators. It should be noted that while for hard search problems, many of the following operators are not scalable; they are very useful as a first option. Recently, however, researchers have achieved significant success in designing scalable recombination operators that adapt linkage. In most recombination operators, two individuals are randomly selected and are recombined with a probability p_c, called the crossover probability as shown by figure 3.12 and 3.13. That is, a uniform random number, r, is generated and if $r \leq p_c$, the two randomly selected individuals undergo recombination. Otherwise, that is, if $r > p_c$, the two offspring are simply copies of their parents. The value of p_c can either be set experimentally, or can be set based on schema-theorem principles.

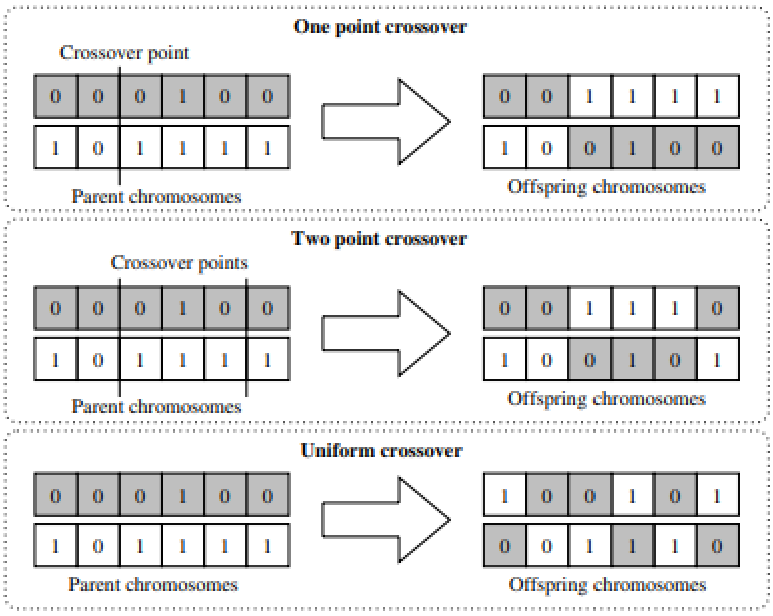


Figure 3.12: One-point, two-point, and uniform crossover methods

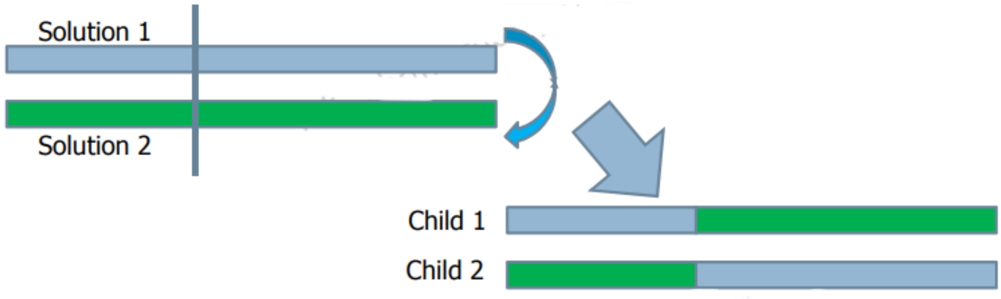


Figure 3.13: Crossover of two solutions crossover

3) **Mutation Operators**: If we use a crossover operator, such as one-point crossover, we may get better and better chromosomes but the problem is, if the two parents (or worse, the entire population) has the same allele at a given gene then one-point crossover will not change that. In other words, that gene will have the same allele forever. Mutation is designed to overcome this problem in order to add diversity to the population and ensure that it is possible to explore the entire search space. In evolutionary strategies, mutation is the primary variation/search operator. Unlike evolutionary strategies, mutation is often the secondary operator in GAs, performed with a low probability. One of the most common mutations is the bit-flip mutation shown in figure 3.14. In bitwise mutation, each bit in a binary string is changed (a 0 is converted to 1, and vice versa) with a certain probability, pm, known as the mutation probability. As mentioned earlier, mutation performs a random walk in the vicinity of the individual. Other mutation operators, such as problem-specific ones, can also be developed and are often used in the literature.

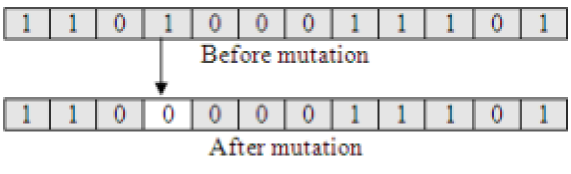


Figure 3.14: Illustration of Mutation operator

4) **Replacement**: Once the new offspring solutions are created using crossover and mutation, we need to introduce them into the parental population. There are many ways we can approach this. Bear in mind that the parent chromosomes have already been selected according to their fitness, so we are hoping that the children (which include parents which did not undergo

crossover) are among the fittest in the population and so we would hope that the population will gradually, on average, increase its fitness. Some of the most common replacement techniques are outlined below.

Delete-all: This technique deletes all the members of the current population and replaces them with the same number of chromosomes that have just been created. This is probably the most common technique and will be the technique of choice for most people due to its relative ease of implementation. It is also parameter-free, which is not the case for some other methods.

Steady-state: This technique deletes n old members and replaces them with n new members. The number to delete and replace, n, at any one time is a parameter to this deletion technique. Another consideration for this technique is deciding which members to delete from the current population. Do you delete the worst individuals, pick them at random or delete the chromosomes that you used as parents? Again, this is a parameter to this technique.

Steady-state-no-duplicates: This is the same as the steady-state technique but the algorithm checks that no duplicate chromosomes are added to the population. This adds to the computational overhead but can mean that more of the search space is explored. A Pseudo code for Genetic Algorithm:

Input: Binary Sequence x

Output: Recovered Binary Sequence y

---

a(1,N) ← Underwater channel weights

w(1,2N+2) ← Weights of Equalizer

d = [zeros (1,N+1)   x]

buffer 1 = zeros (1,N)

buffer 2 = w

count = 0

noise = sqrt (10^-SNR/10)*(rand(1,N)-0.5)

for i=1:n

Step 1: buffer (2,N) = buffer (1,N-1)

Step 2: y_1= buffer1*a’

Step 3: y_2= y_1 + noise

Step 4: buffer2 (2, 2N+2) = buffer2 (1, 2N+1)

Step 5: y = buffer2*w’

```
Step 6:        error (i) = y (i) – d (i)
Step7:         function genti ()
               {
                       Initialize population;
                       Calculate fitness function;
                       While (fitness value! = termination criteria)
                       {
                               Selection;
                               Crossover;
                               Mutation;
                               Calculate fitness function;
                       }
               }
       end
       SNR = 0:2:30
       for  h = 1: length (SNR)
               noise = sqrt (10^-SNR(h)/10)*(rand(1,n)-0.5)
               for i = 1: n
                 |     Repeat steps 1 to 5
                 |     if  y (i) ~= d(i)
                 |       |     count = count + 1
                 |     end
               end
               errorcount (1, i) = count
       end
       ber = log10 (errorcount/n)
       plot (ber, SNR)
```

CHAPTER 4

PROPOSED WORK AND SIMULATION RESULTS

4.1 Acoustic channel model

In this section description and discussion of acoustic channel model is given. Acoustic channel model is designed with the help of channel equalization technique. As shown in figure 4.1 the input is fed to the acoustic channel. Acoustic channel is consisting of weights or taps those are assigned with all possible parameters of underwater acoustic communication. The noise and output of the channel are combined together to generate a mixed signal. This signal is fed to the equalizer which trains and tests the channel with the iterative procedure and applied algorithms gives the optimized solution.

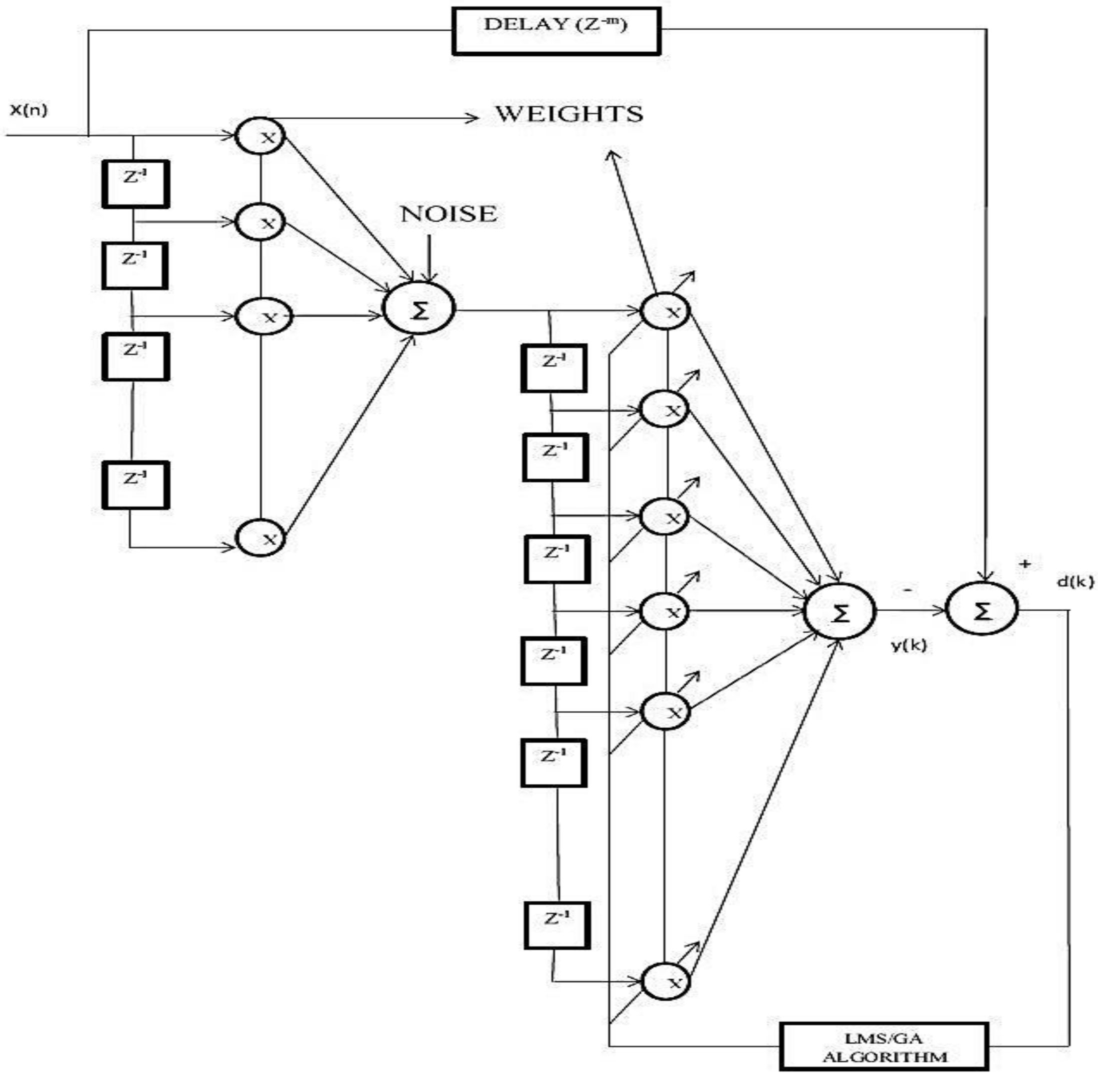


Figure 4.1: Acoustic channel equalizer model

To understand the concept that how channel optimization algorithm works a flow chart is given in figure 4.2 which describes the optimization procedure.

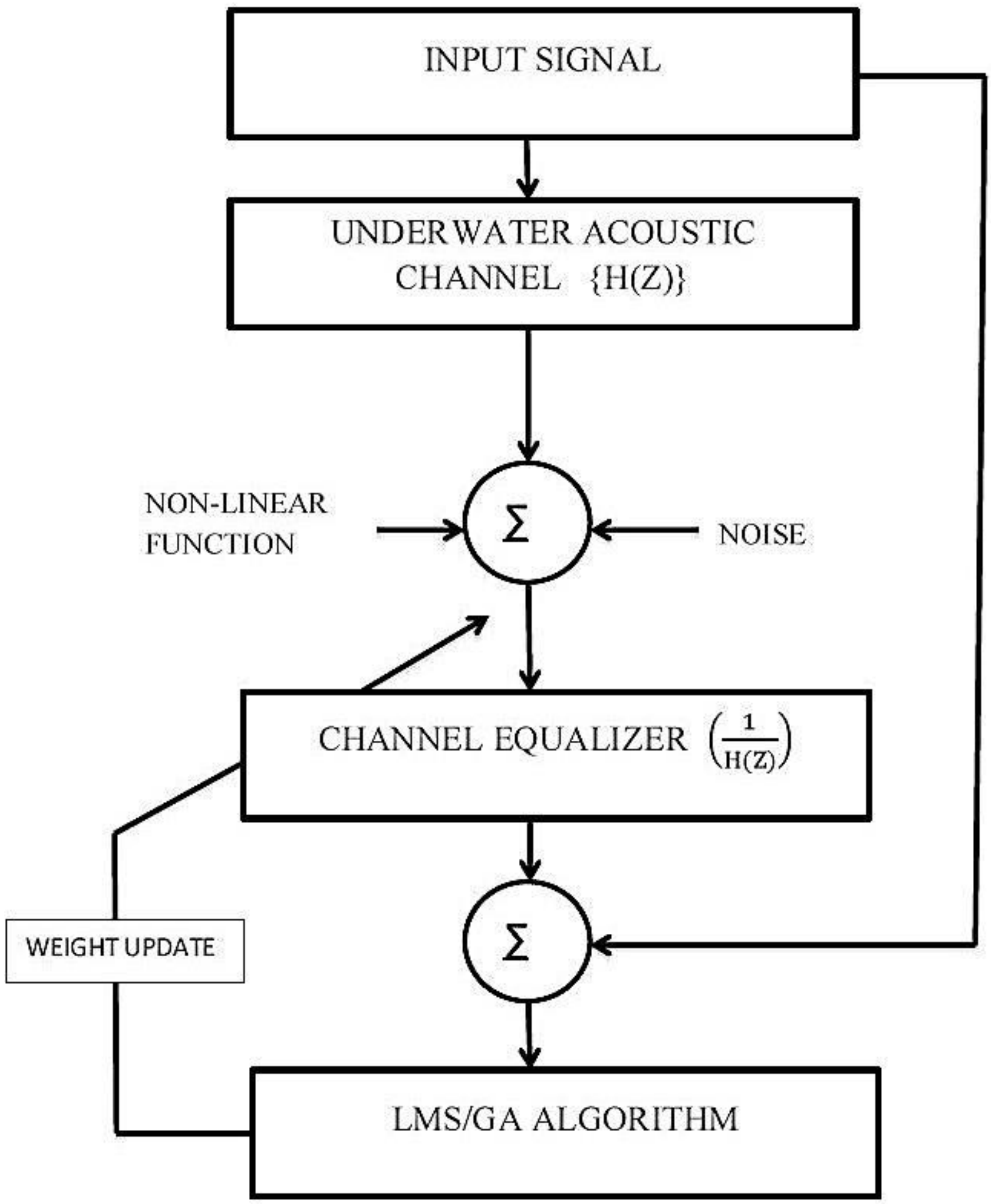


Figure 4.2: Flow chart of optimization process

Channel equalization algorithm applies the weight update equations which matches with the weights of channel to give best possible identification of channel response. Channel equalizer performs the inverse operation of channel transfer function. After getting perfect matching with the weights of inpurt channel the error curve is studied which should be decreased with the non linear fashion.

4.2 Channel Simulator Algorithm

Large scale channel variations are resulting in different path gains and different time delays. Whereas small scale channel variations results in scattering coefficients mainly. Where, $\gamma_p(f, t)$, p = 0, 1, 2,3. . . shows scattering coefficients, and $\tau_p(t) = \tau_{p0} - a_p t$ shows path delays which varies in time according to the Doppler scaling factors a_p. Scattering coefficients are designed as complex-valued Gaussian processes, whose statistical properties (frequency and correlation in time) are determined. A channel simulator algorithm is provided to simulate a proper channel model by considering all the possible parameters. After simulation nominal channel geometry and channel gain results take place those are shown in figure 4.3 and 4.4.

Step1. Initialization set $\bar{h}_p, \bar{\tau}_p, \sigma^2_{\delta p}, B_{\delta p}$

Step2. For realizing each large scale processes do

Step3. Set h_p , τ_p

Step4. For realizing small-scale process on $t \in T_n$

Step5. for p = 1, …

Step6. $\gamma_p(f,t) = \frac{1}{h_p}\sum_i h_{p,i} e^{-j2\pi f \delta \tau_{p,t}(t)}$

Step7. $\tilde{\gamma}_p(f,t) = \gamma_p(f,t) e^{j2\pi a_p f t}$

Step8. $H(t,f) = \widetilde{H}_0(f) \sum_p h_p \gamma_p(t,f) e^{-j2\pi f \tau_p}$

Step9. $\widetilde{G}(t) = \frac{1}{B}\int_{f_0}^{f_0+B} |H(t,f)|^2 df$

Step10. $G = E_{\tilde{\gamma}}\{\widetilde{G}(t)\}$

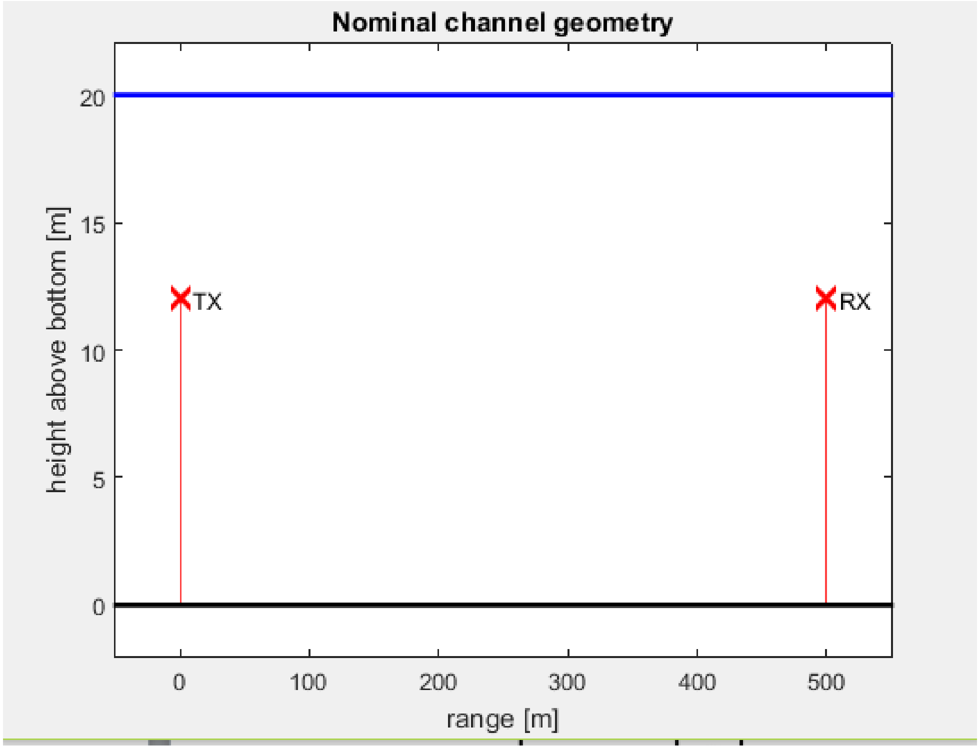


Figure 4.3: Channel geometry

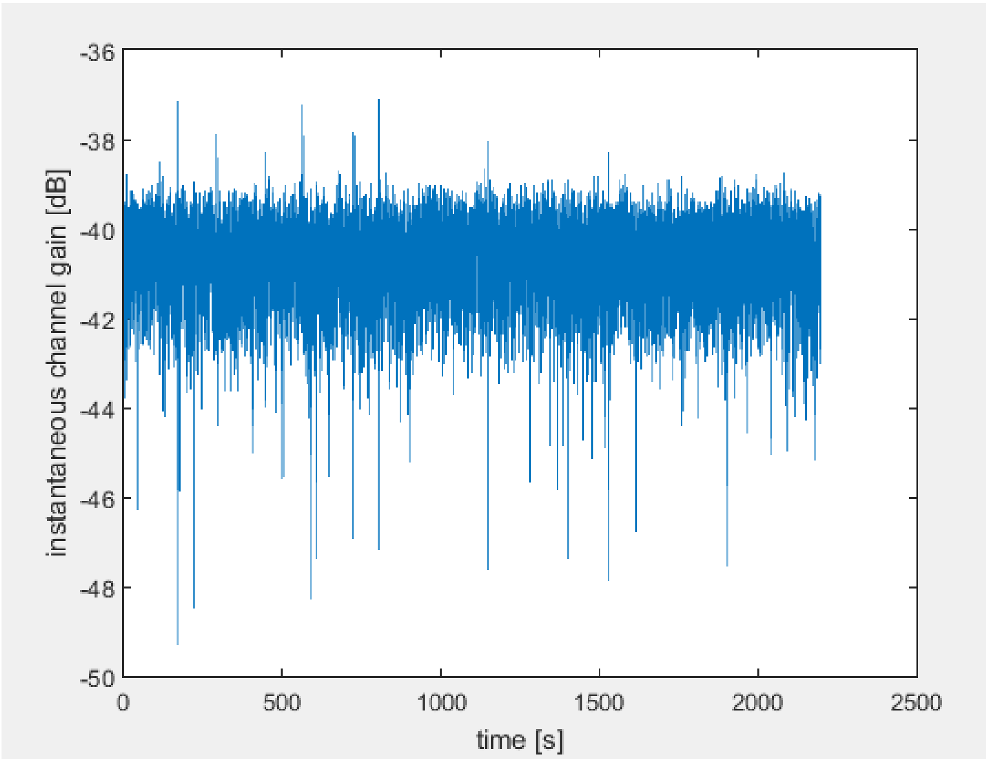


Figure 4.4: Channel gain

4.3 System training and testing

Large variations in under water acoustic communication channel leads to the channel retraining and testing again and again to give the optimized result which fits best in designing of receiver. A system is trained by providing a set of data to the input of equalizer. System will process this data and gives the best fit solution. It will save the results of data recovery in its memory and apply the same methodology in testing part. In testing the system processes the new data with the help of given data which is saved in system memory.

Training: Training part includes underwater acoustic channel (represented as FIR filter) which includes N parameters, channel equalizer having weights (W=2N+2), a delay unit (delay=N+1), optimization algorithms and nonlinearity. The input binary signal is given to our acoustic channel and at channel output noise gets introduced which results in corrupted/ distorted signal. So to reduce the noise an equalizer channel having taps of 2N+2 is designed and its weights are updated in such a way that the noise gets reduced by using various optimization techniques. The output of the channel equalizer is compared with delayed version of input signal. When our signal passes through channel then it takes time of N delay unit. And after this by passing through the channel it goes through the equalizer which further adds one delay unit. So the total delay at the output of equalizer is N+1 and to compare this equalizer output with the input we use a delay of N+1 unit. Now the error is generated by subtracting the equalizer output with the delayed input and goes into the optimization unit. The optimization techniques are used to reduce the error. In each iteration the error is reduced by updating the weights so we train our system by updating the weights of equalizer and thereby reducing the error. In his work we use LMS and GA algorithms to train our system. Figure 4.5 shows the training part of equalizer used.

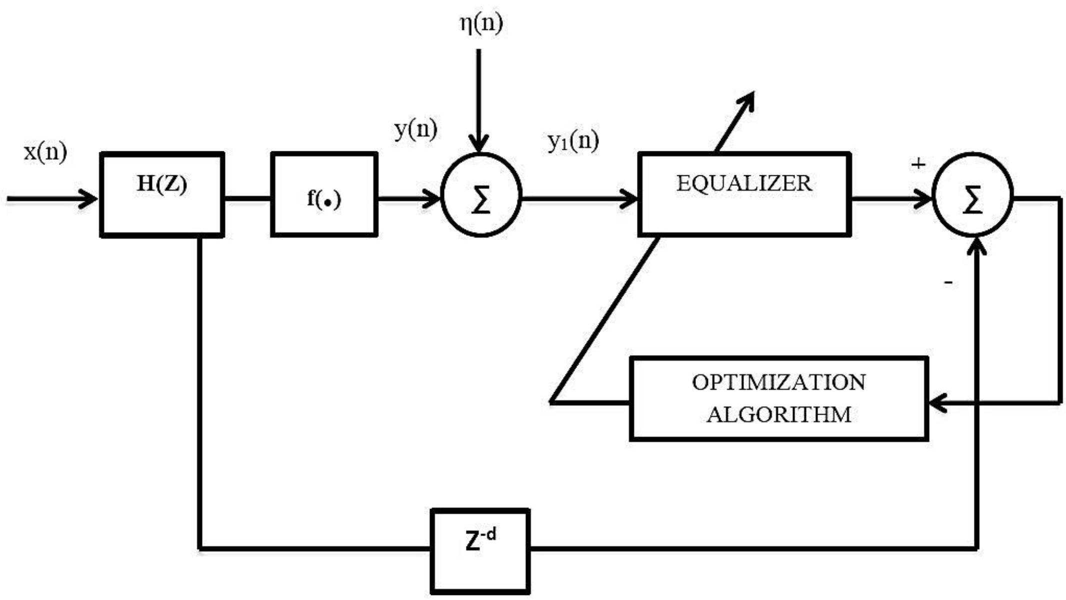


Figure 4.5: Training part of the equalizer

Testing: Testing part includes acoustic channel, nonlinearity, channel equalizer and decision device. In this section there is no need of optimization technique as the system is already trained. So now we only need to test the new signal and recover the same signal back after passing through this channel model. As our system is already trained therefore we can now pass new data through acoustic channel and test our equalizer by studying the error count rate. If the error count rate decreases then it means our system was properly trained. Figure 4.6 below shows the testing section of equalizer.

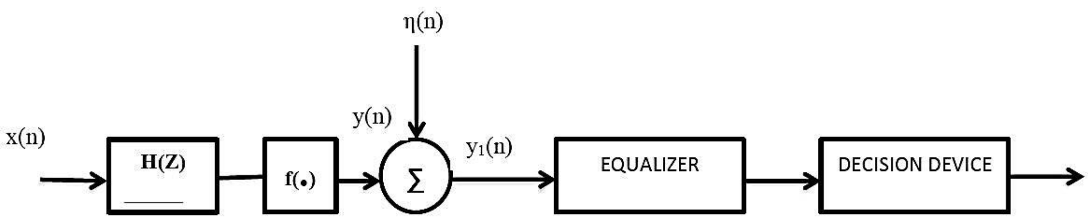


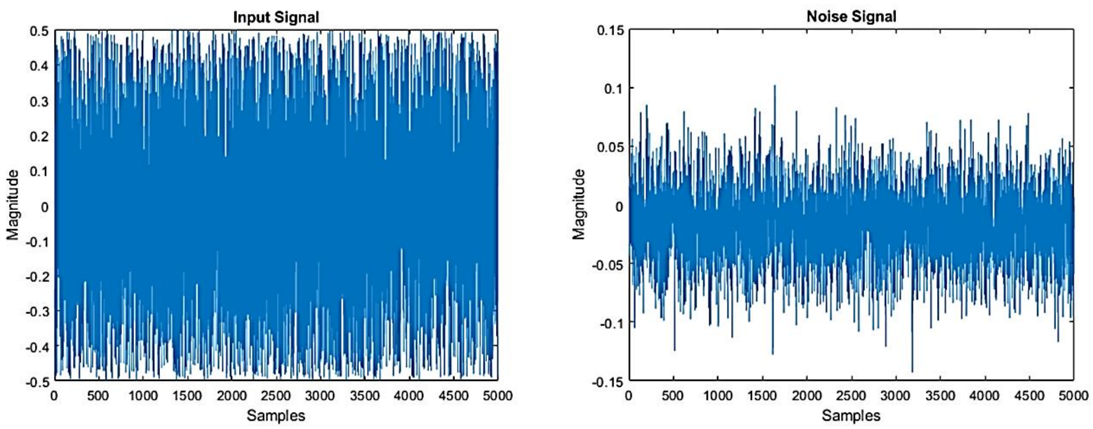
Figure 4.6: Testing part of Channel equalizer

4.4 Simulation Results

The results for under water acoustic linear/nonlinear channel using LMS and GA are shown below.

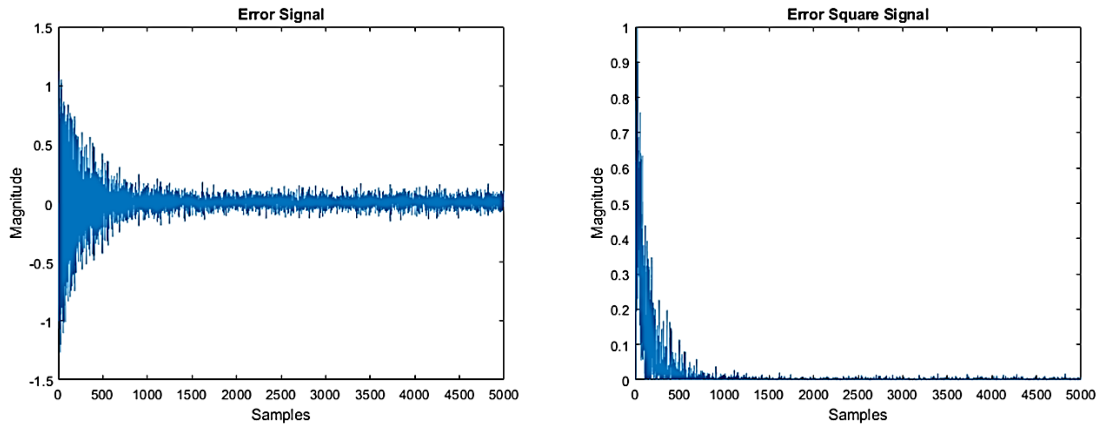
4.4.1 Simulation results of Underwater Linear channel Equalizer using LMS

In this work parameters those are affecting the underwater acoustic channel are taken into consideration. So FIR channel having of taps equal to the channel parameters are considered. A channel equalizer of 2N+2 taps is designed and delay unit is consisting of N+1 taps where N is the number of system parameters. Now samples are taken for a given input which passes through the channel shown in figure 4.7 (a) and this input signal is converted into binary form. Now these binary bits are passed through the channel one by one. Figure 4.8 (a) shows that the trained system reduces error approximately to zero. Figure 4.9 shows the decrease in error count, so as SNR increases the number of error bits decreases. In this work we trained our system at SNR of 30 dB. And testing is applied for SNRs of 0 to 30 dB. From the simulation results it is clear that as SNR increase BER (Bit error rate) decreases BER decreases from -6 dB to -34dB as shown in figure 4.10.



(a) (b)

Figure 4.7: (a) Input data sequence (b) Noise signal



(a) (b)

Figure 4.8: (a) Error signal results (b) Error square signal results

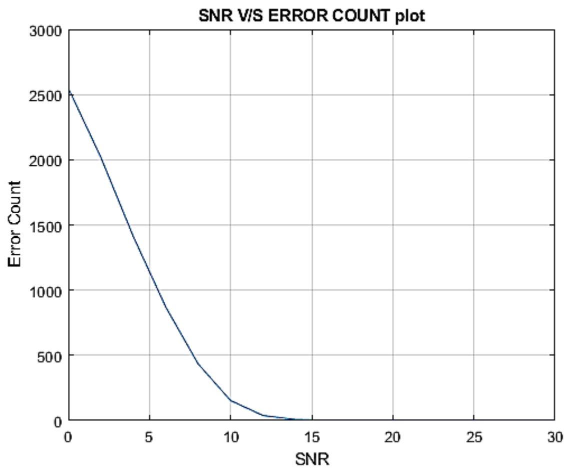


Figure 4.9: SNR v/s error count plot

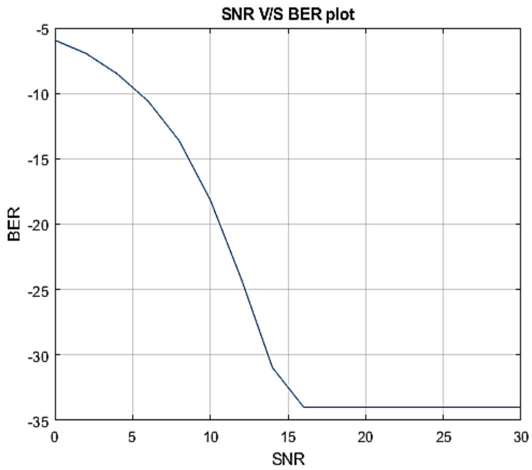
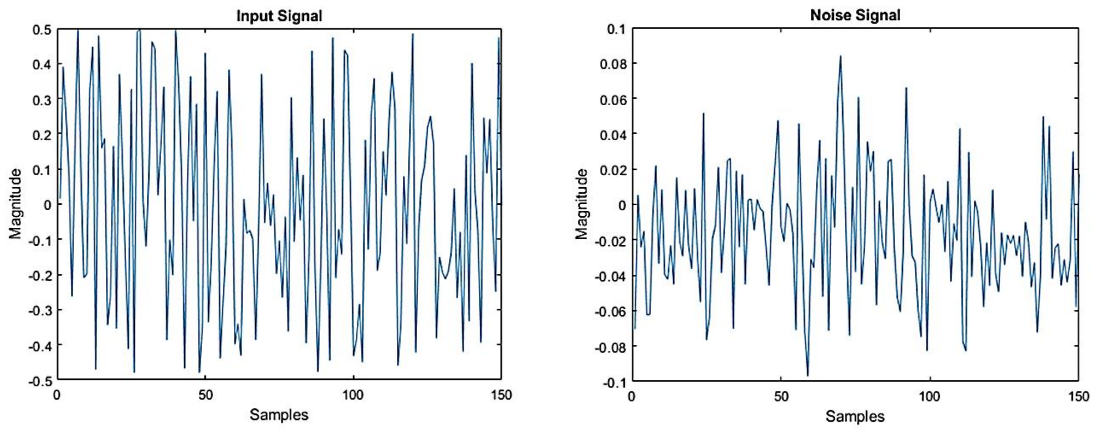


Figure 4.10: SNR v/s BER plot

4.4.2 Simulation results of Underwater Non-Linear channel Equalizer using GA

The communication process in GA remains same as that of LMS algorithm. Figure 4.11 shows the input data sequence and noise introduced in system model. Error count reduces to zero as shown in figure 4.12. The simulation result shows that BER decreases from -6 dB to -44 dB. The no. of iterations used are 150 for genetic algorithm.



(a) (b)

Figure 4.11: (a) Input data sequence (b) Noise Signal

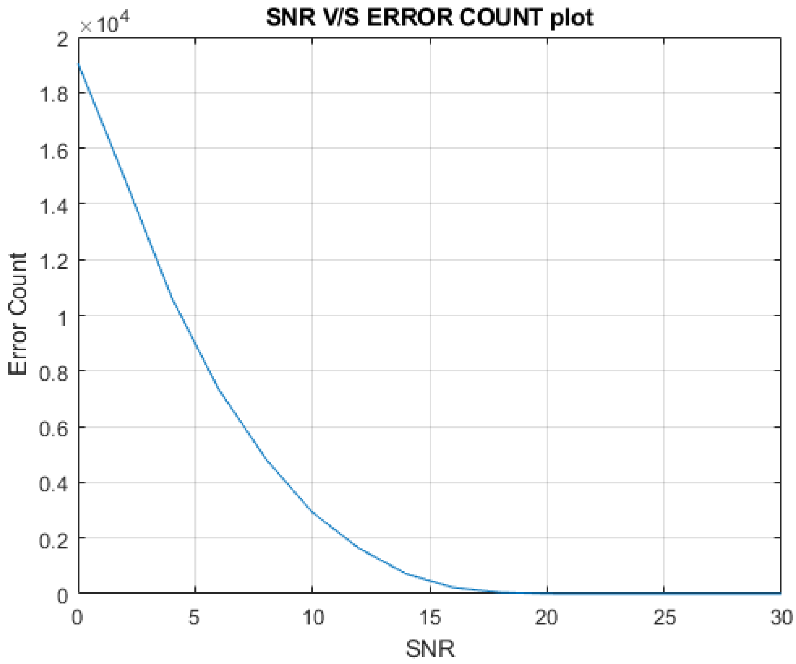


Figure 4.12: SNR v/s Error count plot

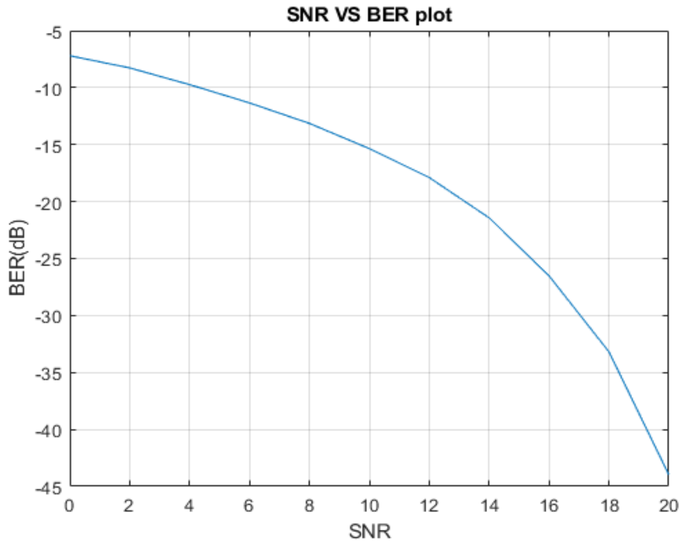


Figure 4.13: SNR V/S BER plot

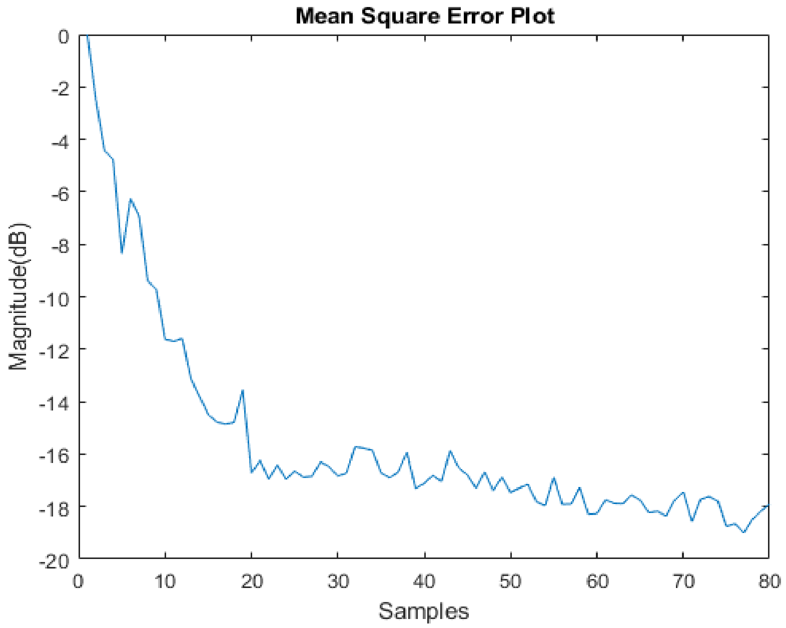


Figure 4.14: Mean square error plot

CHAPTER 5

CONCLUSION AND FUTURE WORK

In this paper we presented an underwater acoustic channel equalizer method, in this method, we transmitted the signal to multiple block and at the receiver LMS adaptive equalizer and Genetic algorithm based equalizer are imported to get the optimized results. Simulation results show that error count decreases with the increase in signal to noise ratio. And Bit error rate also decrease with the increase in Signal to noise ratio. In LMS algorithm number of iterations used is high as compared to genetic algorithm. Least mean square error uses around 5000 iterations because system requires retraining again and again. Genetic algorithms require around 150 iterations to give the optimized results. The BER decreases from -6 dB to -34 dB on logarithmic scale in Least mean square while it is decreasing from -6 dB to -44 dB in genetic algorithm. Comparative analysis shows that genetic algorithm provides better results as compared to Least mean square algorithm. One more advantage which is studied in this analysis is that genetic algorithms holds good for nonlinear functions as well.

There are many nature inspired algorithms which holds good for channel equalization. So in future these algorithms can also be introduced in this research analysis. Communication over multiple channels can also be optimized in future. Variety of applications is present for underwater acoustic communication and each application faces some different type of problems. So by removing the problem with optimization technique to get accurate results will be one of the better future perspectives. Variety of noises is present in underwater channels. So by designing the system models for these types of noises by applying the optimized algorithm can one of be the future aspect.

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