

**REPUBLIC OF TURKEY
ERCIYES UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED
SCIENCES
DEPARTMENT OF ELECTRICAL & ELECTRONICS
ENGINEERING**

**CHANNEL ESTIMATION IN OFDM SYSTEM USING
NEURAL NETWORK COMBINED WITH ARTIFICIAL
BEE COLONY ALGORITHM**

**PREPARED BY
SIDRA MEO RAJPUT**

**SUPERVISED BY
Prof. Dr. Necmi TAŞPINAR**

MSc. Thesis

**July 2018
KAYSERİ**

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**July 2018
KAYSERİ**

SCIENTIFIC ETHICS CONFORMITY

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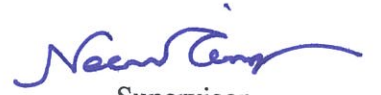
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SUITABILITY FOR INSTRUCTION GUIDE

The MSc. thesis entitled “Channel Estimation in OFDM System Using Neural Network Combined With Artificial Bee Colony Algorithm” has been prepared in accordance with Erciyes University Graduate School of Natural and Applied Sciences Institute Thesis Preparation and Writing Guide.



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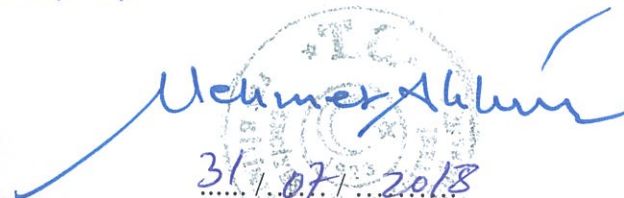


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APPROVAL:

That the acceptance of this thesis has been approved by the Institute Board with the decision number 2018/33-58 and the date of 31/07/2018



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Director of the Institute
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CHANNEL ESTIMATION IN OFDM SYSTEM USING NEURAL NETWORK COMBINED WITH ARTIFICIAL BEE COLONY ALGORITHM

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ABSTRACT

For many modern wireless and telecommunications systems, Orthogonal Frequency Division Multiplexing (OFDM) is being used as a modulation technique. OFDM has been adopted for the cellular telecommunications standard LTE / LTE-A, also it has been chosen by other standards including WiMAX, Wi-Fi and many more. In this study, a multi-layered perceptron based neural network has been trained with artificial bee colony (ABC) optimization algorithm for channel estimation of an OFDM system. The results of the algorithm (ABC-NN) are compared with conventional channel estimators such as Least Square (LS) and Minimum Mean Square Error (MMSE) and also with conventional back propagation neural network (BPNN). In this work, mean square error (MSE) and bit error rate (BER) have been used to evaluate the performance of ABC-NN. The simulation results show that channel estimation based on ABC-NN gives better performance as compared to LS algorithm and BP-NN without the need of channel statistics and noise information. Although MMSE algorithm performs better than ABC-NN for channel estimation of OFDM, ABC-NN is less complex and does not require prior channel state information.

Keywords: OFDM, Channel Estimation, Neural Network, Artificial Bee Colony

YAPAY ARI KOLONİSİ ALGORİMASI İLE BİRLEŞTİRİLMİŞ YAPAY SİNİR AĞI KULLANARAK OFDM SİSTEMİNDE KANAL KESTİRİMİ

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ÖZET

Dikgen Frekans Bölmeli çoğullama (OFDM: Orthogonal Frequency Division Multiplexing), çoğu modern kablosuz haberleşme sistemleri için modülasyon tekniği olarak kullanılmaktadır. OFDM, hücreli haberleşme standardı LTE / LTE-A'ya adapte edilmiştir. Ayrıca WiMAX, Wi-Fi ve daha fazlası dahil olmak üzere diğer standartlar tarafından da tercih edilmiştir. Bu çalışmada, OFDM sisteminde kanal kestirimi için, çok katmanlı algılayıcı tabanlı yapay sinir ağı, yapay arı kolonisi (ABC: Artificial bee colony) optimizasyon algoritması ile eğitilmiştir. Önerilen algoritmanın (ABC-NN) sonuçları, en küçük kareler (LS: Least Squares) ve en küçük ortalama karesel hata (MMSE) gibi geleneksel kanal kestiriciler ve ayrıca geleneksel geri yayılım yapay sinir ağı (BPNN: back propagation neural network) ile kıyaslanmıştır. Bu çalışmada, ABC-NN'nin performansını değerlendirmek için ortalama karesel hata (MSE: mean square error) ve bit hata oranı (BER: bit error rate) kullanılmıştır. Simülasyon sonuçları, ABC-NN'ye dayalı kanal kestiriminin, kanal istatistikleri ve gürültü bilgisine ihtiyaç duymaksızın, LS algoritması ve BP-NN'ye nazaran daha iyi performans sergilediğini göstermektedir. MMSE algoritması, OFDM kanal kestirimi için ABC-NN'den daha iyi performans göstermesine rağmen, ABC-NN daha az karmaşıktır ve kanal durum önbilgisine ihtiyaç duymamaktadır.

Anahtar Kelimeler: OFDM, Kanal Kestirimi, Sinir Ağı, Yapay Arı Kolonisi

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LIST OF ABBREVIATIONS

ABC	Artificial Bee Colony
ABC-NN	ABC algorithm with a multi-layered Perceptron's Neural Network
ANN	Artificial Neural Network
CIR	Channel Impulse Response
CSI	Channel State Information
DAB	Digital Audio Broadcasting
DFT	Discrete Fourier Transform
FDM	Frequency-Division Multiplexing
FFT	Fast Fourier Transform
ICI	Inter Carrier Interference
IFFT	Inverse Fast Fourier Transform
IFI	Inter Frame Interference
ISI	Inter Symbol Interference
LTE	Long Term Evolution
MLP	Multilayer Layer Perceptron
MMSE	Minimum Mean Square Error
OFDM	Orthogonal Frequency-Division Multiplexing
OFDM-IDMA	OFDM with Interleaving Division Multiple Access
QPSK	Quadrature Phase Shift Keying
RBF	Radial Basis Function

CHAPTER 1

INTRODUCTION

1.1. Background

Wireless communication dates back to 19th century when the radio was invented. Since that time, wireless communication has grown tremendously and now it is almost impossible to imagine our lives without wireless technologies. This technology has become integral part in today's world. For the transmission of information from one place to another, wireless communication has become the most essential resource. For more than a hundred years, we have been using radio waves and electrical signal for communication purpose [14].

Wireless communication is not confined to just a few applications; it has been used widely for several types of communications such as radio broadcast, microwaves communication, satellite communication, Bluetooth, Zigbee, Infrared communication and mobile communication (GSM, CDMA, OFDM etc), WiFi, Global positioning systems (GPS) etc. [15].

Due to increased demands of wireless communication applications and devices, the demand for advancement in technology has also grown rapidly [16]. In order to meet requirement of this growing industry enormous research has been conducted to provide the desired result. The process is still continued and research is still going on for the advancements in wireless technology and to provide high data rates for the current and upcoming technologies.

Starting from the use of telegraph for long distance communication in mid-19th century, several technologies have been developed so far to provide best services of their time. These technologies include GSM (Global System for Mobile communication), GPRS

(General Packet Radio Service), W-CDMA (Wide-band Code Division Multiple Access) also known as Universal Mobile Telecommunications System (UMTS), CDMA-2000, Time Division Synchronous Code Division Multiple Access (TD-SCDMA), High Speed Packet Access (HSPA) and Long Term Evaluation (LTE) [17].

Speedy escalation of high-speed internet, greater quality of audio and video demands have always insisted researchers to explore new options to meet user requirements of high data rates [15]. Day by day demands for high data rate is increasing and due to this, wireless systems now and in future need technologies, which are capable of fulfilling resource hungry technologies. OFDM and MIMO OFDM techniques are considered as promising selection for providing high rates for future applications [18].

Our concerns are not limited the demands of high-speed and superior quality, it also includes the fast growing number of wireless subscribers/devices. The subscribers of wireless services are increasing day by day and the demand for spectrum is becoming necessary. As high data rates are required to provide good Quality of Service for various types of services, there is a need for groundbreaking solutions to upgrade total efficiency [19].

In addition, the demand for lower cost, higher data rates, increased throughput and vast coverage etc. has created congestion in the available spectrum for mobile networks [20]. In such circumstances, Multiple-Input Multiple-Output (MIMO) technology seems promising to meet spectrum demands by proposing improved spectral efficiency [21]. MIMO systems are categorized by various antenna elements at the transceiver and these systems have shown potential increase in capacity multi path environments [22].

1.2. Wireless communication system

A classic wireless communication system consists for transmitter, channel and receiver as shown is Figure 1.1. Transmitter mainly contains five blocks including source encoder, encryption, channel encoding, modulation and multiplexing. After being processed at these blocks, input signal is transmitted via wireless channel. Similarly, typical receiver for wireless device also consists of five blocks. i.e. source decoding, decryption, channel decoding, demodulation and de-multiplexing [1].

Wireless channel is open space which serves as transmission medium for the signal. Open space is full of buildings, trees, rain drops, mountains etc. in outdoor environment or other objects such as walls, furniture etc. in indoor environment. Presence of these objects and environmental conditions makes the wireless channel hard to predict and variable in nature. Such environmental conditions and unpredictable nature increase the chances of distortion, interference, noise and scattering effects on the transmitted signal. Fig. 1.2 shows a multi path channel where signal is affected by several objects [23].

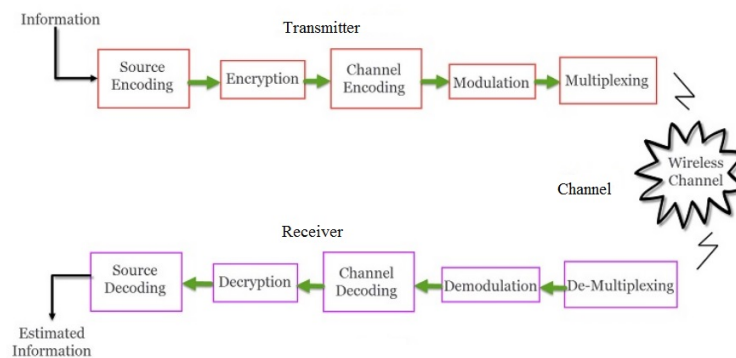


Figure 1.1. A typical wireless communication system [1].

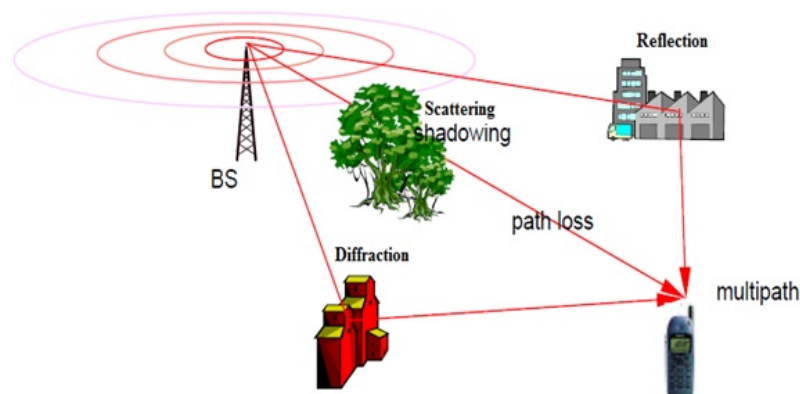


Figure 1.2. Multi-path propagation for wireless signal [2].

1.2.1. Effect of multi-path environment and its mitigation

The major issue caused by multi-path propagation of transmitted signal is inter-Symbol Interference (ISI). ISI is the distortion of signal that occurs due to interference of one symbol with the following symbols making them blur together which effects the decision at receiver. As the signal passes through wireless medium, it takes up multiple paths to reach the receiver, also the signal is reflected by large buildings on its way or refracted

through tress etc. all these cause ISI. For that reason, it is important to eliminate the effects of ISI from the signal [24].

Of age technologies, such GSM and CDMA were relying on single carrier transmission. Single carrier system has a problem of ISI due to frequency selective nature of wireless channel. The problem of ISI can be resolved with the help of multi-carrier system, which divides the channel into several narrow-band channels. Therefore, most of the problems, which exist in single carrier systems, can be avoided by using multiple parallel carriers for transmission of data and increased the throughput of the system [25]. Due to this reason and several other reasons researchers have pushed their focus and efforts towards multi carrier systems.

In multi-carrier system, the bandwidth of channel is divided into many narrow individual (small) sub-carriers and the frequency response of each sub-carrier is flat because every sub-carrier takes up a small portion of the original channel bandwidth [26]. The sum of the output of all the sub-carriers constitutes the overall throughput of a system. Consequently, in a multi-carrier system, the data rate for each sub-carrier is only a portion of that in a simple single carrier system with equal output. This feature provides us the opportunity to design a system which supports high data rates as well as maintain longer symbol durations [26].

OFDM is a multi-carrier modulation technique, which divides signal bandwidth into many narrow sub-carriers before transmitting the data. Parallel sub channels in OFDM increase the symbol duration and thereby reduce or eliminate the ISI which is caused due to multipath environments [27]. Currently, OFDM is the most widely used solution for high-speed applications of wireless communication in outdoor and indoor environment. OFDM uses non-overlapping adjacent channel and permits multiple carriers for transmitting different symbols [27].

In wireless environment, every transmission scheme be it single carrier system or multiple carrier system require channel estimation to access channel state information (CSI) of the system. CSI is needed to remove the effects of wireless channel on received signal, these effect are caused due to tall buildings, mountains etc. [28].

Commonly, channel estimation practices covers of two kinds of technique, which consist of blind channel and pilot based estimation [29]. We will discuss these techniques in next chapter. There are various channel estimation methods that can be utilize with above discussed channel estimation practices. These include as least square (LS) algorithm and minimum mean square error (MMSE) algorithm etc. LS algorithm is somewhat simple and uncomplicated to implement but it does not perform well for time varying and fast fading channel. On the contrary, MMSE algorithm performs superior than LS algorithm but at the same time it is far more complex to use for any system [30].

Not only these conventional algorithms are being used for channel estimation but also advance algorithms based on neural networks as well as artificial optimization algorithms are being developed and used for this purpose. Artificial Neural Network (ANN) can be used as a tool for problems such as pattern classification and prediction problems. ANN has variety of application including character recognition and financial problems [31]. Moreover, ANN can also be used in wireless communication. Predominantly, for problems like channel estimation in OFDM wireless channels ANNs have gained vast interest these days [32].

1.3. Motivation

Our motivation in this thesis is to contribute to robustness of OFDM system's channel estimation using artificial bee colony (ABC) algorithm. Therefore, in this thesis we have used a channel estimation technique using multi-layered perceptron neural network combined with artificial bee colony algorithm.

As discussed above ANN and optimization, algorithms are gaining interest for channel estimation in OFDM and research is being carried out in this direction, we have conducted a detailed literature review to express the importance of our work in this field.

1.4. Literature Review

The first OFDM scheme was introduced in 1966 by Robert W.Chang in his research on the synthesis of band-limited orthogonal signals for multi-channel data transmission, later in 1970 he patented his work [33]. The idea behind OFDM was to split frequency selective

channel into multiple parallel sub channels [34] [35].

Later, many researchers, investigated the performance of parallel transmission. Initially, orthogonality in OFDM systems was not easy to maintain, it required complicated circuitry and high cost for hardware [36]. This problem was resolved in 1971 with the use of Discrete Fourier Transform (DFT) for modulation and demodulation of baseband signal at the receiver [37]. Use of DFT considerably reduced the cost of implementing OFDM system [33].

Another big step to overcome the problem of achieving orthogonality was accomplished in 1980, when cyclic extension was introduced by Ruiz and Peled [38]. In their method, they had replaced the OFDM null guard with cyclic prefix, which mitigated the effect of ISI but at the same time affected the data rate.

As the data is transmitted in blocks in OFDM, two methods are used to identify channel use of pilot tone within each block or insertion of training sequence among successive blocks. These training sequences can be used to obtain channel impulse response in time domain or by use of pilot symbols in frequency domain [39].

As discussed in previous section, channel estimation is required to assess the impact of channel on received signal and pilot tones are used for this purpose. The transmitted signal can be accurately recovered, if the receiver is capable of correctly estimating channel state. Coleri et.al [40] have studied the arrangement of pilot insertion for channel estimation of OFDM system.

Ozdemir and Arslan [25] has presented a detailed overview of several channel estimation methods which can be used for OFDM. They have also discussed the advantages, disadvantages and the relation of existing techniques for channel estimation. Zaier and Bouallegue [41] have investigated the performance of four classic channel estimation techniques. They have compared the results of LS, MMSE, Linear MMSE (LMMSE) and Lr-LMMSE algorithms. In [42] Hsieh and Wei have studied the comb-type pilot sub-channel organization for OFDM system channel estimation.

Several researchers have studied various method for channel estimation and they have also proposed techniques to improve those methods. Until now, LS and MMSE algorithms

have been used for channel estimation several times. In [43], authors have compared LS and MMSE in terms of their performance and complexity in OFDM systems. In [43] it is shown that, due to previous knowledge of channel covariance and noise variance, performance of MMSE algorithm is better than LS algorithm but at the same time need of prior knowledge makes MMSE algorithm more complex. In [44], LMS and LS algorithms are investigated for channel estimation OFDM system.

In recent years, not only classical methods such as LS and MMSE algorithms have been used for channel estimation but other techniques have also been used such as neural networks and artificial optimization algorithms. Several combinations of evolutionary algorithm (EAs) and neural networks have been studied and developed such as NN trained with Genetic algorithm (GA), NN with Particle Swarm Optimization (PSO) etc.

In [45], authors have used artificial optimization algorithm i.e. GA for the OFDM channel estimation and they have compared the results with neural network. They have trained NN with GA and compared the results with simple NN and conventional channel estimation methods.

Neural networks have gained interest in many fields because of their learning ability and helping to model complex relationships between inputs and outputs. These networks are being used for image processing, forecasting of sales and economy, character recognition etc. It is also being utilize for estimation of frequency response of wireless channel. In [46], authors have used Radial Basis Function (RBF) neural network for the estimation of channel coefficient in OFDM system. They have shown that their proposed algorithm doesn't need any prior information about channel state and performs better than LS algorithm. They have also used other training algorithm for neural network in their study.

Şimşir and Taşpınar have done great contribution to channel estimation for Orthogonal Frequency Division Multiplexing-Interleave Division Multiple Access (OFDM-IDMA) systems, they have published several research papers in this regard. In [12], they have proposed an algorithm, which uses Levenberg-Marquardt neural network algorithm OFDM-IDMA systems channel estimation. They have compared their results with traditional pilot tones based algorithms of channel estimation. They have demonstrated channel estimation based on computer simulation can provide better performance than

that of conventional methods. The advantages of their algorithm are better performance with lesser complexity. They have also extended their work for multiuser systems. Moreover, they have discussed that how the performance of these methods vary depending on the number of users.

In another their paper [47], they have studied the effect of pilot tone placement on working of channel estimation. The optimization and proper position of pilot tone plays significant role for lessening errors in estimation process. In [48], authors have presented a method for optimization of pilot tones and improving the working of traditional Least Square method. They call it Grey Wolf Optimizer (GWO), it is been developed for OFDM-IDMA system's channel estimation. They have also compared it with other optimization algorithms such as Particle Swarm Optimization (PSO) and Genetic Algorithm(GA) and it is less complex than those PSO and GA optimization methods.

Researches have not only used Levenberg-Marquardt algorithm for channel estimation of frequency response, they also used a combination of fuzzy logic and ANN i.e. neuro fuzzy to improve the performance of estimation methods. In [48], authors have developed an estimator for OFDM-IDMA system; this estimator uses adaptive neuro fuzzy inference system (ANFIS). In order to evaluate the performance of their proposed method, authors have compared the results with five distinct methods including MMSE, LS, and the multilayered perceptron (MLP) method using three different training methods such as Levenberg-Marquardt (MLP-LM), backpropagation algorithm (MLP-BP), and radial basis function neural network (RBFNN). Their ANFIS based estimator performs better than LS, MLP-LM, RBFNN and MLP-BP techniques. MMSE algorithm performs better than other techniques but it is computationally complex and requires channel state information.

Fine-tuning of pilot position for reducing the estimation error has been a huge issue for multi-carrier systems such as OFDM. Authors in [49] have used PSO optimization technique to enhance the performance of LS algorithm by adjusting pilot location. They have shown that adjusting the pilot tone placement offers greater performance in comparison with other pilot placement techniques. They have also shown that there is a direct impact of pilot location on working of LS algorithm, which is used OFDM-IDMA

system's channel estimation.

Şimşir and Taşpınar have not only used PSO algorithm for OFDM-IDMA system, they have also used Firefly Algorithm (FA) to observe the effects of pilot design for OFDM-IDMA systems. According to them performance of channel estimation algorithm and the location of pilot tone hold a strong relationship. In [50], they have proposed pilot tone location optimization method based on firefly algorithm. For fitness function, they have utilized the higher bound of MSE, in optimization process. Their method performs better than conventional processes of channel estimation and pilot tone placement.

In [51], they have used Harmony Search (HS) method and optimized the distribution of pilot pattern for enhancing the LS estimator for OFDM-IDMA system. Moreover, Seyman and Taşpınar [52] used PSO algorithm for the organization of pilot tones for channel estimation in MIMO OFDM.

The remaining of this thesis is arranged as follows, Section II explains OFDM system model and channel estimation methods in detail. Section III discusses artificial neural network in combination with ABC algorithm, then Section IV presents simulation results of the NN-ABC comparing with conventional methods and NN. Finally, section V provides conclusion of this research work.

CHAPTER 2

OFDM SYSTEM MODEL AND CHANNEL ESTIMATION METHODS

2.1. Background of OFDM

OFDM technology was developed in the 1960s and 1970s in order to minimize interference among adjacent channels in frequency domain and to attain better data transmission in channel prone to interference and signal corruption due to conventional modulation schemes. This technology was first introduced in 1966 by Chang who used to work at Bell Labs. Later, Ebert and Weinstein in 1971 improved in OFDM technology by introducing guard bands for enhanced orthogonality in transmission channels to avoid effects of multipath propagation [39].

Currently, all over the world OFDM is of great interest in research laboratories and universities. OFDM is used in wireless communication systems to provide high-speed transmission of data in outdoor and indoor environment, including wireless LAN (IEEE 802.11a, IEEE 802.11n, IEEE 802.11g, IEEE 802.11ad and IEEE 802.11ac). It is also used in high performance LANs type 2 (HIPERLAN/2), WiMAX, 3GPP LTE and LTE advance standards for mobile phone communication, advanced narrow-band as well as broadband power line communications, Li-Fi communication, asymmetric digital subscriber line (ADSL), ultra wideband communication (UWB). Moreover, OFDM is used in radio and digital television broadcast services such as digital audio broadcasting (DAB) [53].

OFDM technology is a special case of frequency-division multiplexing (FDM). FDM is a multiplexing scheme that allows combination of numerous signals for transmission on a single communications channel. Each signal is allocated a unique frequency range called subcarriers/sub-channels. These channels are non-overlapping and multiple users

can operate simultaneously by using different channels of the frequency domain. FDM only works properly if frequency carriers are not overlapping. Thus, the communication link must have sufficient bandwidth in order to carry the extensive range of frequencies [3]. Fig. 2.1 shows an FDM system, here each channel operates at a different carrier frequency.

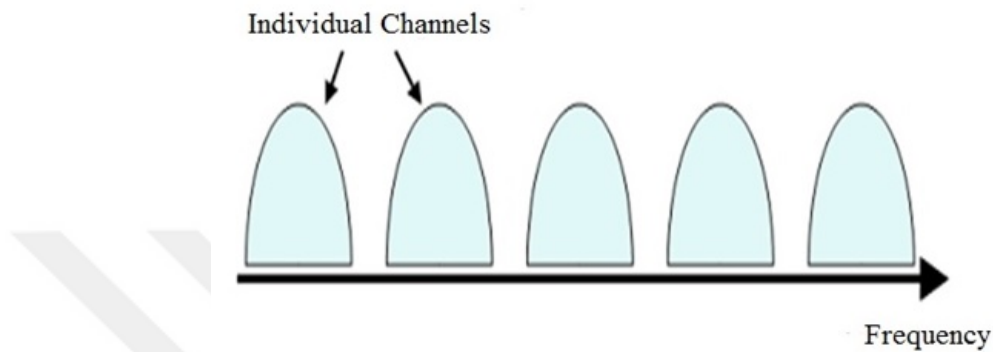


Figure 2.1. FDM channels [3].

FDM technology requires enormous bandwidth with successful transmission of signal without adjacent channel interference and we all know that bandwidth is a limited resource. To resolve the issue of enormous bandwidth needs, Orthogonal Frequency-Division Multiplexing (OFDM) was introduced. OFDM is a multi-carrier modulation technique, which divides signal bandwidth into many narrow sub-carriers before transmitting the data. These sub-carriers are precisely orthogonal to each other and thus overlap without interfering one another. Consequently, OFDM systems maximize spectral efficiency without causing adjacent channel interference. In addition, parallel sub-channels in OFDM increase the symbol duration and thereby reduce or eliminate the inter-symbol interference (ISI) which is caused due to multi-path environments [4].

OFDM technology has changed the concept of bandwidth utilization in communication. OFDM system's frequency domain is shown in Fig. 2.2. In this Fig., it is shown that for each individual channel there are seven sub-carriers. OFDM allows greater data throughput than with an FDM system because increase in channel bandwidth increases the symbol rate [4].

Conventionally, FDM uses filters at the receiver to separate sub-carriers. Thus, guard bands are inserted between the sub-carriers to separate the sub channels efficiently.

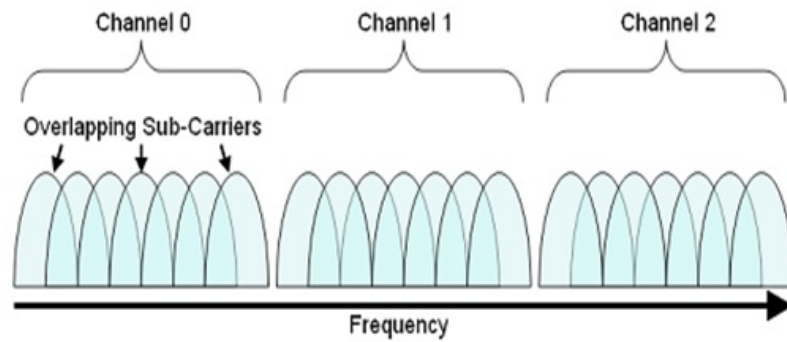


Figure 2.2. OFDM channels [4].

However, OFDM makes the sub-carriers mathematically orthogonal, which enables OFDM receivers to separate the sub-carriers using FFT and exclude the use of guard bands [5].

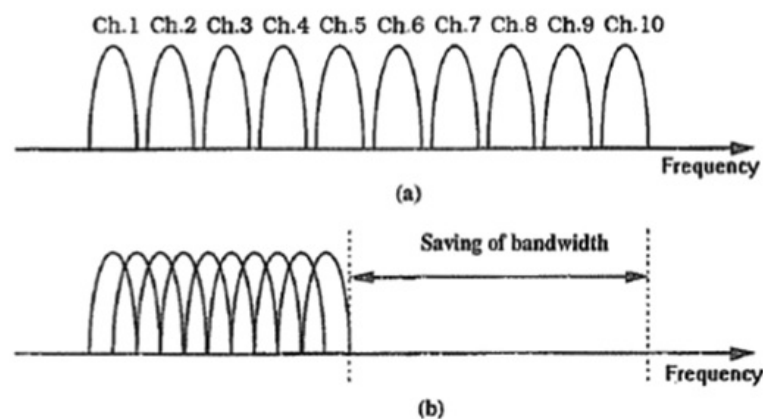


Figure 2.3. Comparison FDM and OFDM Channels [5].

Fig. 2.3 shows comparison of conventional FDM channels and Orthogonal FDM channels. Part (a) of Fig. 2.3 shows that in FDM technology all channels operate separately and none of them is overlapped over one another. On the other hand part (b) of Fig. 2.3 shows that all 10 channels are overlapping each other in orthogonal fashion there by avoiding the interference to each other. Fig. 2.3(b) also shows that significant amount of bandwidth is saved by using orthogonality in sub-carriers.

Mathematically, orthogonal sub-carriers have been a revolution for OFDM because it allows OFDM receivers to isolate the sub-carriers using FFT eliminating the use of guard bands. Fig. 2.3 shows overlapping OFDM sub-carriers making full use of the spectrum [6].

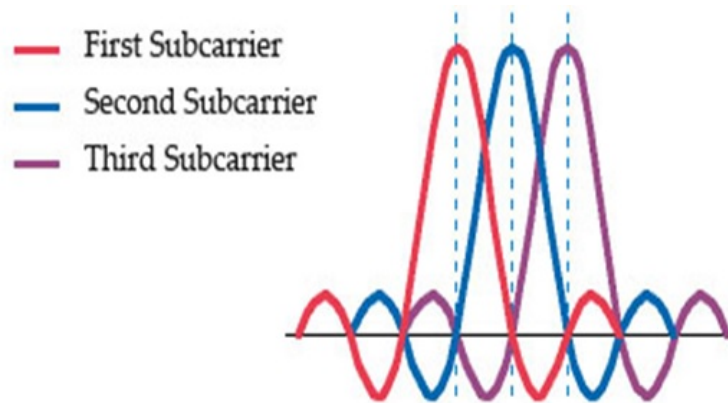


Figure 2.4. Overlapping OFDM sub-carriers [6].

The maximum power of each sub-carrier corresponds directly with the minimum power of each adjacent channel thus each sub-carrier in OFDM overlap without interfering with other sub-carriers. Fig 2.4 represents the frequency domain of an OFDM system graphically. Here we can see that the power in all the other sub-carriers is zero at the peak of each sub-carrier [6].

The leading advantage of OFDM scheme over single-carrier schemes is its capability to handle extreme channel conditions such as attenuation of high frequencies in wire, fading due to multi-path and narrow-band interference, without need of complex equalization filters [54]. The other advantages are of FDM system are listed below:

(i) **Spectrum efficiency:**

Overlapping sub-carriers provide high spectral efficiency and wiser use of spectrum.

(ii) **Resilience to selective fading:**

OFDM is resilient to frequency selective fading as the channel is divided into several small sub-carriers that are affected independently as flat fading sub channels.

(iii) **Simple digital realization:**

In OFDM, digital realization is easy by use of FFT operations.

(iv) **Resilient to ISI:**

OFDM is resilient to ISI and inter frame interference (IFI) due to low data rate on individual sub-channels and use of cyclic prefix.

(v) **Less complex receiver:**

Low complexity receivers can be employed as ISI and ICI are eliminated with use of adequately large guard interval.

(vi) **Symbol recovery:**

In OFDM, lost symbols (because of frequency selective channel) can be recovered by the use of suitable interleaving and channel coding.

(vii) **Resilience to interference:**

OFDM offers satisfactory guard against impulsive parasitic noise and co-channel interference.

(viii) **Several modulation schemes:**

OFDM is capable of using many different modulation schemes on each sub-channel depending on the communication environments of individual sub-channel.

The negatives of OFDM are listed below [55]:

(i) **High PAPR:**

An OFDM signal has comparatively high large dynamic range/ peak to average power ratio and amplitude variation like noise, this effect the efficiency of RF amplifier. The amplifiers should be linear and need to accommodate the large amplitude variations due to these factors the amplifier cannot function at high efficiency level. OFDM requires high peak-to-average power ratio (PAPR) for RF power amplifiers to sidestep performance degradation.

(ii) **Sensitive to carrier offset and drift to carrier off set and drift:**

As compared to single carrier systems, OFDM is sensitive to drift and carrier frequency offset which results due to leakage of the DFT.

(iii) **Loss of spectral efficiency:**

OFDM may have poor spectral efficiency because of the addition of a guard interval.

(iv) **Synchronization issues:**

OFDM is sensitive to carrier frequency offset and drift. Thus, correct time and frequency synchronization is required.

OFDM has achieved a noteworthy existence in the wireless marketplace. The blend of high spectral efficiency, resilience to interference because of multi-path effects and high data capacity is a proof that OFDM is ideal for the high data applications.

2.2. Orthogonal Frequency Division Multiplexing (OFDM) Systems

Let say we want to send data sequence using OFDM. The first designing parameter in OFDM transmitter is to choose number of sub-carriers needed to send data. Let us consider that we have N sub-carriers and each sub-carrier is orthogonal to each other in terms of frequency. Based on the number of sub-carriers, we need to convert serial data stream into N parallel streams. Serial to parallel converter translates serial input sequence in to N parallel outputs indexed from 0 to $N - 1$.

Now, each stream is individually modulated using BPSK, QPSK or QAM. Once the parallel data is digitally modulated into required modulation format pilot tone is interested. After that, inverse Fourier transform is carried out to translate the signal from frequency domain signal $X_i(k)$ to time domain $x_i(n)$ as shown in Eq. (2.1) and then these parallel streams are converted back to serial streams for transmission [45].

$$x_i(n) = 1/N \sum_{k=0}^{N-1} X_i(k) e^{2\pi i k n / N}, n = 0, 1, \dots, N - 1 \quad (2.1)$$

where $X_i(k)$ is the i th OFDM symbol in k th sub-channel, N signifies the number of sub-channels and $x_i(n)$ is the i th OFDM symbol in n th symbol period. After IFFT, these parallel streams are converted back to serial streams for transmission.

Before transmission, guard interval is added to the signal to avoid ISI and to maintain orthogonality of sub-carriers so that each sub-carrier can be completely and easily separated at receiver. For guard interval, cyclic prefix is used which is aperiodic extension of the signal itself. After adding guard interval the total symbol duration T_{total} becomes the sum of useful symbol duration T and guard interval T_g i.e $T_{total} = T + T_g$. The time domain samples of the signal $x_g(n)$ after guard interval is as follows:

$$x_g(n) = \begin{cases} x_i(n + N), & n = N_g \text{ to } -1 \\ x_i(n), & n = 0 \text{ to } N - 1 \end{cases}$$

where N_g is the number of samples in $x_g(n)$.

Finally, the resultant OFDM signal is sent to channel for transmission as shown in Fig. 2.5.

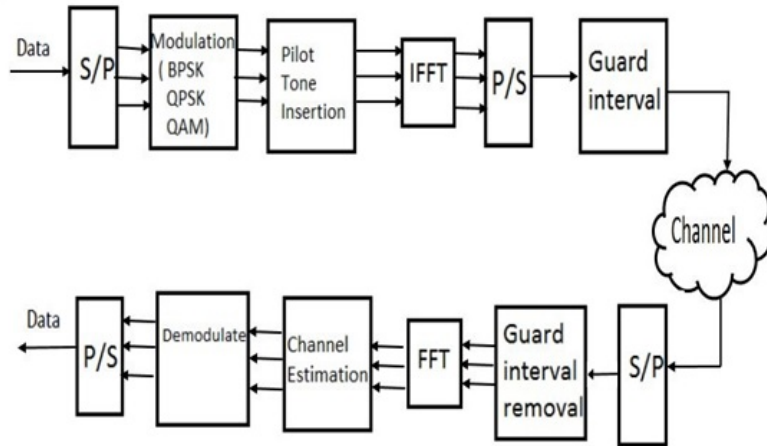


Figure 2.5. System model for OFDM signal [7].

The signal received after propagation through channel is given as:

$$y_g(n) = x_g(n) \otimes h_i(n) + w_i(n) \quad (2.2)$$

where $h_i(n)$ provides the impulse response of channel and $w_i(n)$ represents the white Gaussian noise which is always present in the channel. The channel impulse response $h_i(n)$ is given as:

$$h_i(n) = \sum_{p=0}^{P-1} \alpha_p \delta(n - \tau_p) \quad (2.3)$$

where P is number of propagation paths and p is the individual path. α_p and τ_p are the path gain and delay of p th path respectively.

When the signal is received, first of all the guard interval is removed and received signal is separated from guard band as follows:

$$y_g(n) - N_g \leq n \leq N - 1,$$

$$y_i(n) = y_g(n + N_g) = 0, \dots, N - 1 \quad (2.4)$$

The received signal $y_i(n)$ is then translated to parallel streams of data. Now data is converted back to frequency domain by taking FFT of the parallel signal streams as follows:

$$X_i(k) = \sum_{n=0}^{N-1} x_i(n) e^{2\pi i kn/N} \quad (2.5)$$

where $k = 0, 1, \dots, N - 1$.

After FFT, the process of channel estimation is implemented and channel frequency responses is obtained with the help of pilot tone which was passed through channel and exposed to frequency selective multipath fading. Later, data is converted to serial stream and demodulated to extract the transmitted data sequence. The received signal after demodulation is represented as:

$$Y_i(k) = X_i(k)H_i(k) + W_i(k) \quad (2.6)$$

2.3. Channel Estimation Methods

In wireless communication, transmitted signal passes through a radio channel before reaching to receivers therefore, estimation of the effect of the channel on the transmitted information is required to recover the signal [28]. Wireless channels cause ISI because of multi-path fading. In order to remove effects of channel from the received signal, receiver need to have information of the Channel Impulse Response (CIR), which is generally calculated by channel estimator.

Commonly, channel estimation practices covers of two kinds of technique, which consist of blind channel and pilot based estimation. In blind channel estimation, statistical properties of received signal are used to estimate channel coefficients and there is no need to insert a pilot signal or preamble [56]. Apparently, blind channel estimation is prone to overhead issues connected to training signals and efficiently use available bandwidth. However, the performance of blind channel estimation method is normally not better

than pilot based channel estimation methods, as it needs substantial number of received symbols for obtaining statistical properties of channel [29]. Blind channel requires large memory and it is unable to track fast channel variations. Thus, in most of the current wireless communication systems, non-blind channel estimation is used [57, 58].

In pilot based channel estimation method a training sequence is inserted at the start of transmission this sequence comprises of pilot (known data symbols) and provides initial channel estimation parameters [40]. This training sequence is used for channel estimation at the receiver. The pilot symbols allows frequent channel estimation in multi-path fading channel and for this reason pilot assisted transmissions are commonly used in existing wireless communication systems. If high number of pilot symbols are used, accuracy of channel estimation can be improved but it leads to decreased transmission rate due to more pilot symbols in place of data symbols. For that reason, system should be designed to balance between high transmission rate and accurate channel estimation [59].

The pilot based channel estimation method is further classified in block-type pilot channel estimation and comb-type channel estimation [8]. In block-type, the pilot tone is inserted in all sub-channels of OFDM symbols in a specified period. Block-type pilot channel estimation was developed based on assumption of slow fading channel. The second type was introduced to meet the requirements of equalization where channel changes are uniform from one OFDM block to another OFDM block. Thus, in comb-type, the pilot tone is inserted into certain sub-channels of OFDM symbols where interpolation is required to estimate the conditions of data sub-channels [60, 61]. Fig. 2.6 shows the two types of pilot sequence organization for OFDM channel estimation. In this research, we have used block type pilot sequence.

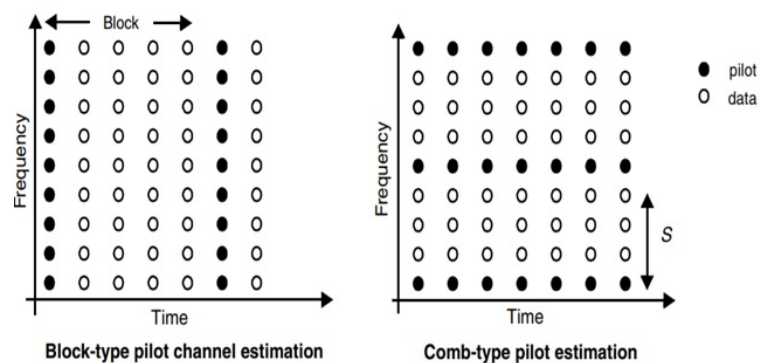


Figure 2.6. Type of pilot sequence organization for OFDM channel estimation [8].

As shown in Fig. 2.6 that in block-type pilot based estimation there is periodical transmission of OFDM channel estimation symbols and all sub-channels are used as pilots. The goal is to estimate the condition of wireless channel using pilot signal and received signal, with or without having information of channel statistics. The receiver uses the state of estimated channel and decode the received signal.

There are various channel estimation methods which can be utilize with above discussed channel estimation practices. These include as Least square (LS) Algorithm and Minimum mean square error (MMSE) Algorithm etc. LS algorithm is somewhat simple and uncomplicated to implement but it does not perform well for time varying and fast fading channel. On the contrary, MMSE algorithm performs superior than LS algorithm but at the same time it is far more complex to use for any system.

Until now LS and MMSE algorithms have been used for channel estimation several times. In [43], authors have compared LS and MMSE in terms of their performance and complexity in OFDM systems. In [43], it is shown that, due to previous knowledge of channel covariance and noise variance, performance of MMSE algorithm is better than LS algorithm but at the same time need of prior knowledge makes MMSE algorithm more complex. In [44], LMS and LS algorithm are investigated for channel estimation in OFDM system. In recent years, not only classical methods such as LS and MMSE algorithms have been used for channel estimation but other techniques have also been used such as neural networks and artificial optimization algorithms. In [12], Şimşir and taşpınar have studied neural networks for channel estimation of OFDM-IDMA system. In [45], authors have used artificial optimization algorithm i.e. genetic algorithm combined with neural networks for the OFDM channel estimation and they have compared the results with neural network.

2.3.1. Least Square Algorithm

The least square algorithm is used to approximate the solution of the system or set of equations where unknowns are less than the number of equations. The meaning of the term "Least square" is that the overall solution minimizes the sum of the squares of errors in the results of every single equation. The LS channel estimation method is used to

estimate channel H' in such a way that the cost function is minimized [12, 62].

$$F(H') = (y - xH')^H(y - xH') \quad (2.7)$$

Where x represents the transmitted signal and y represents the received signal. In order to find out the minimum value of function, the first derivative of the function should be set equal to zero. Thus, the derivative of cost function with respect to H' must be set to zero.

$$\partial F(H')/\partial H' = -2(x^H y)^* + 2(x^H x H')^* = 0 \quad (2.8)$$

Then we get $x^H x H' = x^H y$, and if we modify this equation we can get the solution for least Square channel estimation as follows:

$$H'_{LS} = (x^H x)^{-1} x^H y = x^{-1} y \quad (2.9)$$

Hence, for each sub-carrier the least square channel estimator H'_{LS} is written as follows:

$$H'_{LS}(k) = y(k)/x(k) \quad (2.10)$$

where $k = 0, 1, 2, \dots, N - 1$.

Although LS algorithm is relatively easy to implement and does not require any prior knowledge of channel conditions but its performance is poor for time-varying channels and it has high mean square error. The algorithm that can handle deficiencies of LS algorithm is MMSE algorithm.

2.3.2. Minimum Mean-Square-Error (MMSE) Method

Minimize the expected or mean value of the square of the error is referred as Minimum Mean-Square-Error (MMSE). In signal processing as well as statistics, a minimum mean square error (MMSE) estimator is used as a measure of estimator quality. As shown in Fig. 2.7, the Mean Square Error (MSE) of the channel estimate H' is given as:

$$F(H') = E\{\|e\|^2\}$$

$$F(H') = E\{\|H - H'\|^2\} \quad (2.11)$$

The MMSE algorithm finds an estimate in terms w in such a way that MSE in above Eq. (2.11) is minimized.

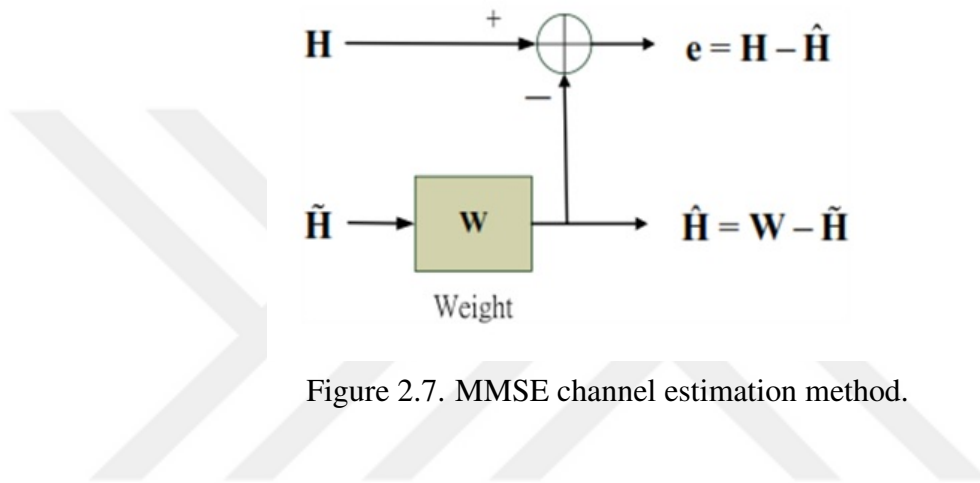


Figure 2.7. MMSE channel estimation method.

According to orthogonality principle the estimation error $e = H - H'$ is orthogonal to \tilde{H} ,

$$E\{e\tilde{H}^H\} = E\{(H - H')\tilde{H}^H\}$$

$$E\{e\tilde{H}^H\} = E\{(H)\tilde{H}^H - WE\}\tilde{H}^H\}$$

$$E\{e\tilde{H}^H\} = R_{H\tilde{H}} - R_{\tilde{H}\tilde{H}} \quad (2.12)$$

where $R_{H\tilde{H}}$ is the cross correlation N by N matrix of H and \tilde{H} matrices.

Matrix W can be obtained from Eq. (2.12) as follows:

$$H' = W\tilde{H} = R_{H\tilde{H}} * R_{\tilde{H}\tilde{H}}^{-1} * \tilde{H}$$

$$H' = W\tilde{H} = R_{H\tilde{H}}(R_{HH} + \partial_z^2/\partial_x^2)^{-1}\tilde{H} \quad (2.13)$$

From the Eq. (2.13) , we can clearly see that MMSE is computationally complex and it is difficult to deal with matrix inversion, but it's performance is very good, and it always outperforms LS algorithm.



CHAPTER 3

ARTIFICIAL NEURAL NETWORK COMBINED WITH ABC ALGORITHM

3.1. Artificial Neural Networks

Neural networks are nothing more than decent function approximators we give an input vector to a trained network, it performs a sequence of operations, and produces an output. Neural network is trained to estimate an unknown function. For training purpose, a collection of data points called as training set is given to the network. The network learns from training data set and simplifies it to make future interpretations [63].

An Artificial Neural Network (ANN) is composed interconnected processing elements called neurons and the connections between them are called weights. ANN are inspired by biological neurons, these networks perform their simulations same as human brains and replicate learning process like human being [64]. ANN perform tasks such as classification, clustering, pattern recognition etc. The similarity between ANN and human brain can be explained in two ways:

- (i) Like human brain NN also gain knowledge by learning.
- (ii) The knowledge/learning of neural network is stored in inter-neuron connection strengths is called synaptic weights.

Artificial Neural Network uses diverse types of training algorithms for adjusting weights in each iteration to get the desired output for a specified input. Neural networks have wide-ranging applications to real world problems and there are several types neural networks employed for different applications in many fields. Some application industries of ANN are; telecommunications, character recognition, image processing, forecasting,

marketing, retail and sales, insurance, banking and finance etc. [65, 66].

Before detail discussion of artificial neural network, let us first understand the actual working and information processing of neurons in human brain. A human brain is made up a billions of cells called neurons, these neurons are shown in Fig. 3.1. The dendrites (input part) receive the outside signal; this signal goes to neuron, which is responsible for processing of received signal. After processing, the signal is transformed to output signal, which is then transmitted to other neuron via axon in the form of electrical signal. The dendrites of next neuron receives this signal via synapse and based on the strength of the signal, the neuron accepts or rejects the signal [9].

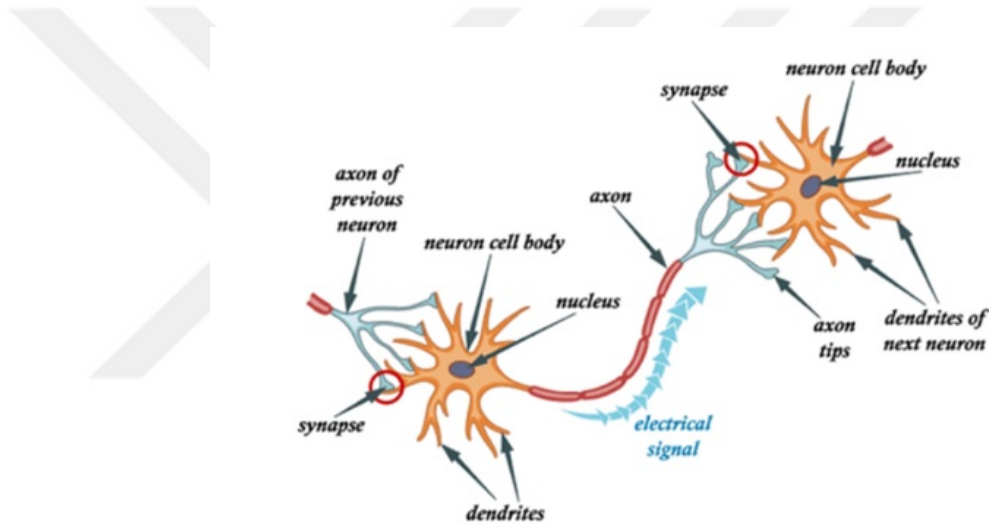


Figure 3.1. Working of neurons in human brain [9].

If compare this human brain analogy with ANN, a simple ANN consists of three layers i.e. input layer, hidden layer and output layer as shown in Fig. 3.2. Each circle represents a neuron which accepts input, process that input, produce an output based on input and passes on the output to other neuron. When the output is passed to the other neuron, it is multiplied by a weight. Next neuron accept the new value as its input. The input artificial neural network serves a purpose of dendrites and the output serves as axon of a human brain [9] [67].

Every single neuron in human brain is connected to 1000 more neurons and these neurons can switch in one millisecond which is very slow as compared to switching of 10 nanoseconds in computer. Despite being slower than computer processing, neurons in human brain are capable of making quick complex decisions. One of the reason for

this fast performance could be parallel processing of biological neurons. Therefore, new developed neural network algorithms are expected to perform parallel operations [68,69].

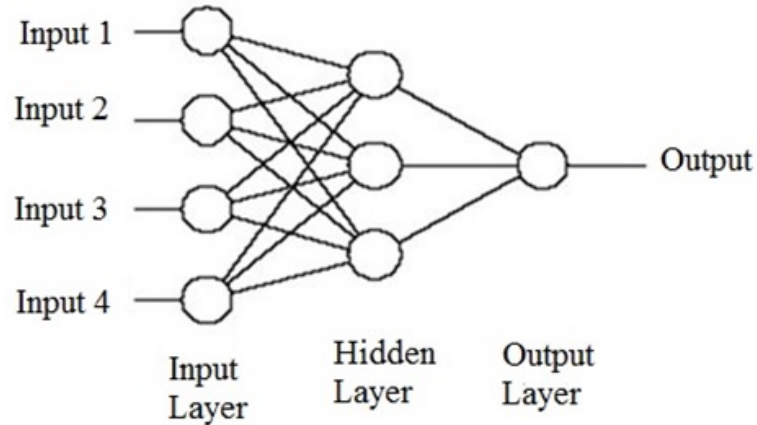


Figure 3.2. Basic artificial neural network architecture [9].

Neural networks are classically arranged in layers. These layers are composed of many interconnected 'nodes' which comprises of an 'activation function'. Data is feed to the network through the 'input layer', which is connected to one or more 'hidden layers'. The actual processing is done at hidden layer through a system of weighted 'connections'. The hidden layers is then connected to an 'output layer', it sends the processed output to output layer as shown in the Fig. 3.2 [9].

3.1.1. Neural Network Architectures

There is an extensive list of architectures that have been used so far for implementation of neural network and every design has its own advantages and disadvantages. Some of the types of popular artificial neural network architectures are listed below [70]:

- (i) Radial Basis Function Network,
- (ii) Multilayer perceptron,
- (iii) Recurrent Neural Network,
- (iv) Hopfield Network,
- (v) Boltzman Machine etc.

The most commonly used neural networks are Multi Layer Perceptron (MLP) and Radial Basis Function (RBF) networks. In this thesis, we have used multi layer perceptron's. Fig. 3.3 shows architecture of MLP network.

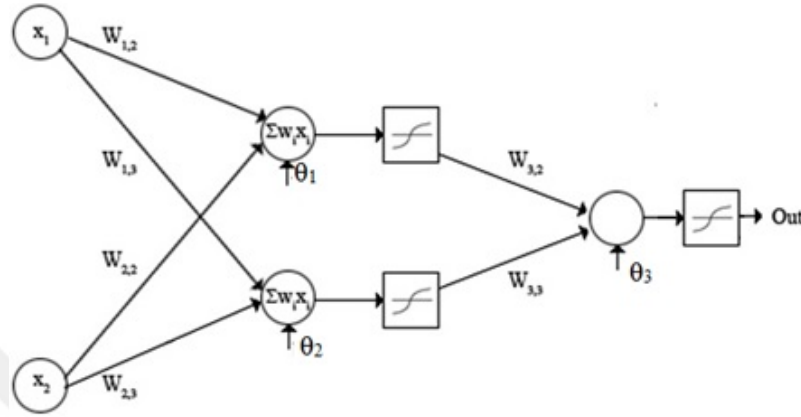


Figure 3.3. Architecture of multi layer perceptron's network [10].

MLPs consist of multiple layers including input layer, several hidden layers, and output layers which are connected to each other via neurons. The processing unit in neural network works in two stages: weighted summation and non-linear function, this permits the ANN to realize a learning stage of the problem to be solved. Each value of an input value x_i is linked with its synaptic weights w_{ji} as shown in Fig.3.4. Additionally, the summation function also takes an additional input value ϕ_i having weight value 1, which is called as bias or threshold for the neuron. The summation function is performed as follows:

$$n_i = \sum_{j=1}^k w_{ji}x_i + \phi_i \quad (3.1)$$

The sum of the products n_i is passed to the next stage to accomplish the activation function g , which produces the output of the neuron, and find out the performance of the neural network. For mathematical convenience, the most commonly used activation function g are hyperbolic tangent (tanh) or a sigmoid function. Hyperbolic tangent is defined as follows:

$$\tanh = \frac{1 - e^{-x}}{1 + e^{-x}} \quad (3.2)$$

Thus, the output of node is:

$$y_i = g_i = g\left(\sum_{j=1}^k w_{ji}x_j + \phi_i\right) \quad (3.3)$$

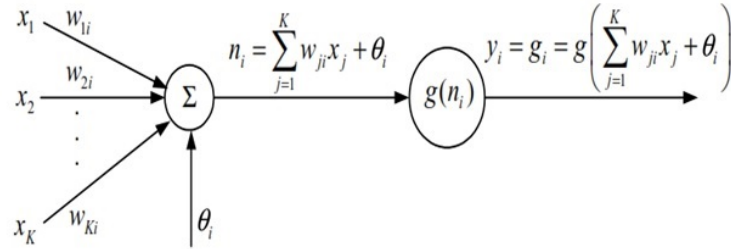


Figure 3.4. Single node of a MLP network [11].

MLP network is formed by connecting several nodes altogether in parallel and series fashion as shown in Fig. 3.5.

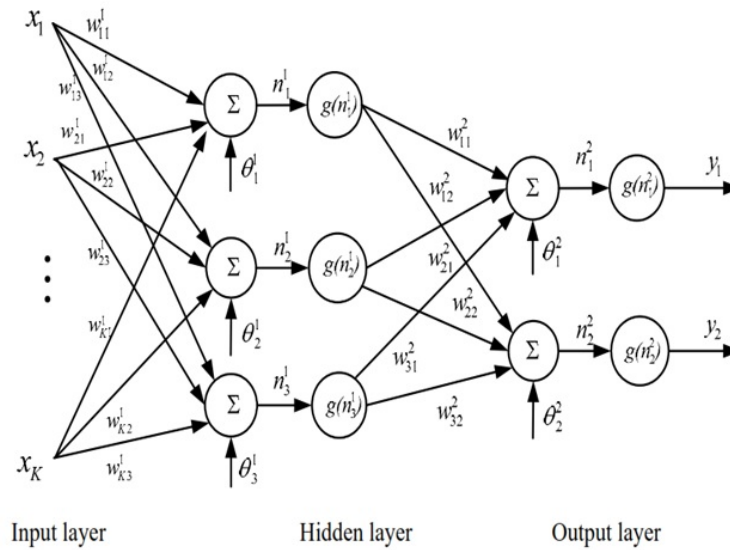


Figure 3.5. MLP network with one hidden layer [11].

The output y_i of the MLP network is:

$$y_i = g_i = g\left[\sum_{j=1}^3 w_{ji}^2 g(n_j^1) + \phi_i^2\right] = g_i = g\left[\sum_{j=1}^3 w_{ji}^2 g\left(\sum_{k=1}^K w_{kj}^1 x_k^1 + \phi_j^1\right) + \phi_i^2\right] \quad (3.4)$$

For any given task, the procedure is as follows. First the structure of the MLP network is fixed i.e. the number of neurons (nodes) and the number of hidden layers are chosen.

Also, the type of activation functions for each layer are selected at this stage, the unknown network parameters which needs to be estimated are the weights and biases (w_{ji}, ϕ_i).

3.1.2. Neural Network Training Algorithms

There is a long list of algorithms which have been used so far for training of NN and every method has its own pros and cons. The most famous are back-propagation and Levenberg-Marquardt algorithms. Back-propagation is a gradient based algorithm, which has many variants. Levenberg-Marquardt is usually more efficient, but needs more computer memory. In gradient descent algorithm if the target output is different from the actual output, the error or difference is calculated. After that algorithm makes changes to the weights in such a way the error is minimize. On the other hand, in back propagation training algorithm, the error is propagated back to input layer from layer through the hidden layer and then weights are updated [71].

These classic learning algorithms have deficiency, they usually converge to a local minimum instead of converging to the desired global minimum. Furthermore. the architecture and transfer function used in their design can influence the ANN's performance. Consequently, the learning algorithm can be trapped in a minimum far away from the best solution [45, 72].

Most commonly used NN training method involve derivative based algorithms such as gradient descent to minimize the learning error. As discussed earlier, derivative based algorithms sometimes have a problem of getting stuck in a possible local minima, also in order to find global minima the algorithm is needed to run exponential times [72]. On the other hand, heuristic algorithms such as Genetic Algorithm (GA), Artificial Bee Colony (ABC) algorithms are global search methods which can be used to find near optimal solutions mostly and also to avoid local minima problem.

Nowadays, these heuristic methods are in highlights for training of NN due to their ability to search all search spaces. However, these algorithm have some disadvantages as well, best results cannot be achieved from these methods in first attempt and many trails have to be made to obtain the desired results [73]. In this thesis, ABC algorithm has been used for training of NN and based on available data set of real and imaginary inputs, the structure

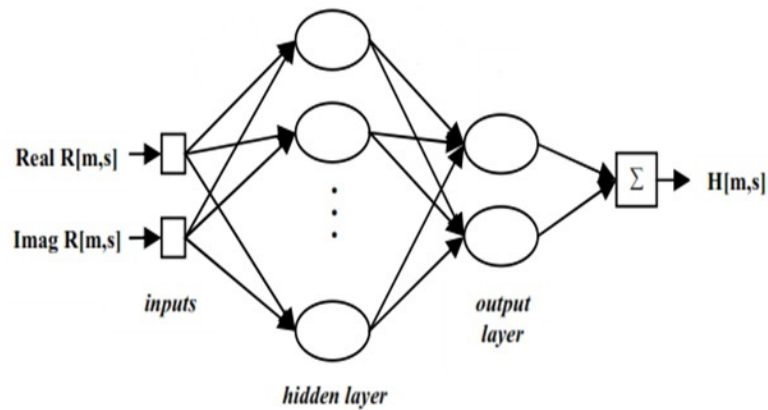


Figure 3.6. Structure of neural network [12].

of NN is shown in Fig. 3.6.

3.2. Artificial Bee Colony Algorithm

There is a need of optimization in many field including management, engineering and economy. Thus, well-organized and proficient algorithms are always needed to handle complex optimization problems of the real world. For last many years, few swarm intelligence based algorithms have been introduced which are inspired by organized behaviors of fishes, birds and insects. Some of these algorithms are listed below [74]:

- (i) Ant colony optimization (ACO).
- (ii) Artificial bee colony (ABC).
- (iii) Particle swarm optimization (PSO).

Studies show that performance of ABC algorithm is significantly better than other swarm intelligence based algorithms [75]. After its development, this algorithm has been used to solve different types of problems. In this thesis, we have used ABC algorithm for training of NN.

ABC algorithm is a swarm based intelligent algorithm inspired by foraging behavior of bees. This algorithm was introduced by Karaboga in 2005, and its working principle is similar to bees. Honey bees are assigned specified tasks to maximize the amount of

nectar (food) in a hive [76]. There are three types of honeybees in this algorithm which accomplish their task by cooperation. The three types are:

- (i) Employed bees,
- (ii) Onlooker bees,
- (iii) Scout bees.

In ABC algorithm, food sources (nectar) represents solutions x_i and the three types of bees i.e. search for the best solution. Each bee has a unique search characteristic

- (i) The employed bees are associated with specific food source.
- (ii) The onlooker (unemployed) bees observe the movement of employed bees in the hive to choose the rich sources depending on the information taken from employed bees.
- (iii) Scout bees search for undiscovered sources randomly [77].

From the view of a meta-heuristic, a population of solutions refers to the undiscovered food sources and the optimization task corresponds to finding the most beneficial source by exploiting the unique forage attributes of the employed bees and unemployed bees (onlooker and scout bees). Each type of bee is represented as a phase in the algorithm [13].

- Initialization Phase: The population of food sources is initialized using Eq. (3.5):

$$x_{ij} = x_j^{min} + rand(0, 1)(x_j^{max} - x_j^{min}) \quad (3.5)$$

where $i = 1, 2, \dots, n$, $n =$ food source and $j =$ index.

- Employed bee phase: For each solution, bees search for new solution having more nectar amount in the neighborhood using Eq. (3.6) and make a greedy selection between Eq. (3.5) and Eq. (3.6). If the new solution is better than previous solution, it is kept in the memory and old one is discarded.

$$x'_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \quad (3.6)$$

where $k \in [1, n]$ and $i \neq k$.

- Onlooker bee phase: At this phase, bees observe the dance of the employed bee to learn locations of food source and the quality of nectar, also the size of the food source. The onlooker bee select a food source probabilistically depending on the amount of nectar as displayed by employed bee, probabilistic selection uses the probability values p_i given by Eq. (3.7).

$$p_i = \frac{fitness_i}{\sum_{i=1}^n fitness_i} \quad (3.7)$$

where $fitness_i$ is the fitness value of solution i , and again greedy selection is made same as in employed bee phase.

- Scout bees phase: When some of the solutions/ food sources are abandoned new solutions are searched by scout bees randomly.

$$x_m = l_i + rand(0, 1) * (u_i - l_i) \quad (3.8)$$

where u_i and l_i are upper and lower bound of the solution space respectively.

Here best solution is memorized and the process is continued.

The Pseudo code for ABC algorithm comprises of twelve steps and it is given below. In addition the flowchart is shown in Fig. 3.7.

1. Initialize the population of solutions x_i ,
2. Evaluate the population x_i ,
3. **for** cycle = 1 to maximum cycle number (MCN) do
4. Produce fresh solutions v_i for the employed bees by using Eq. (3.6) and evaluate them,
5. Apply the greedy selection process,
6. Calculate the probability values p_i for the solution x_i by Eq. (3.7),
7. Produce the fresh solutions v_i for the onlookers from the solutions x_i selected depending on p and evaluate them,

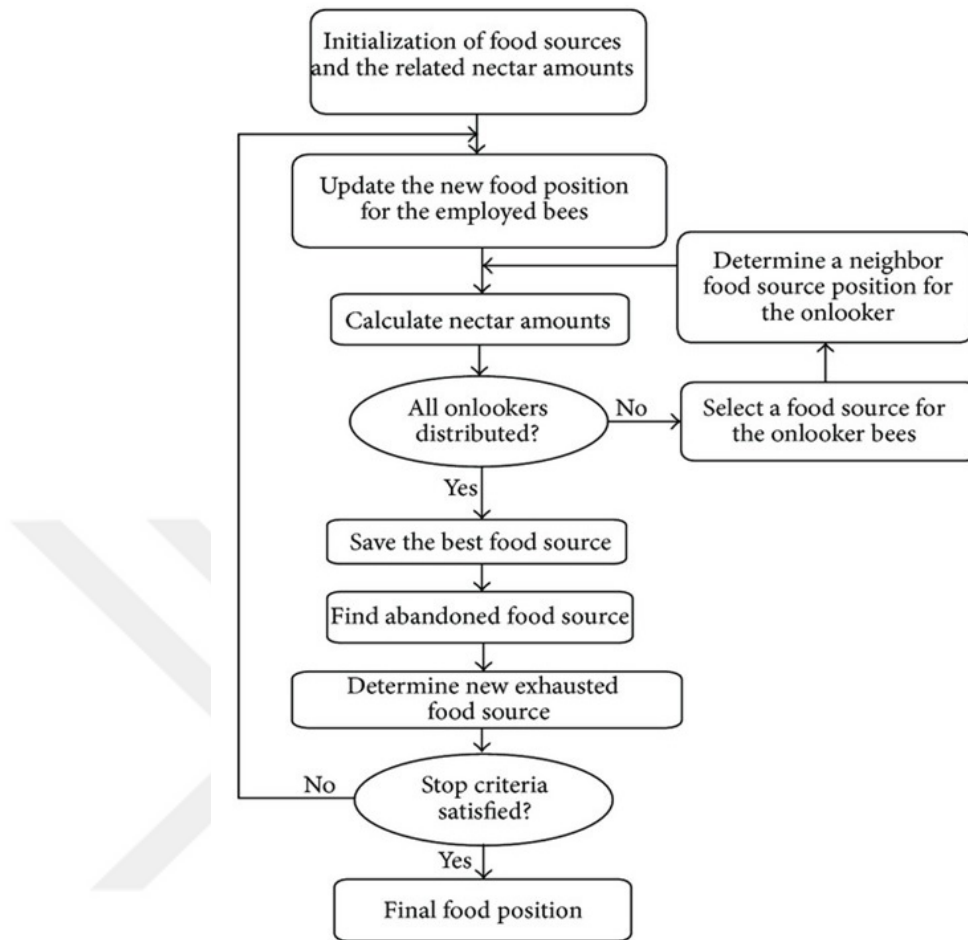


Figure 3.7. Flow chart for ABC Algorithm [13].

8. Apply the greedy selection process,
9. Determine the abandoned solution for the scout, if exist, and replace it with a new randomly produced solution x_i by Eq. (3.8),
10. Memorize the best solution achieved so far,
11. cycle = cycle + 1
12. **end** for

3.3. Training of the Neural Network Using ABC Algorithm

So far, various optimization algorithms have been used to train NN. Training neural network using ABC algorithm can be useful to find near optimal values of connection weights of NN. The multi-dimensional search space is the space of network connection

and bias weights, and the fitness is a standard measure of network output performance such as mean square error on the training data between desired and calculated output [78, 79].

ABC algorithm is considered as a good optimization technique. In this thesis, we want to verify the contribution of this algorithm in the automatic designing of an ANN, including synaptic weights as well as the transfer functions and architecture of the neurons. Here we will observe that, the architectures obtained are optimal in terms of the minimal number of connections without losing efficiency.

3.4. Channel Estimation Using NN-ABC

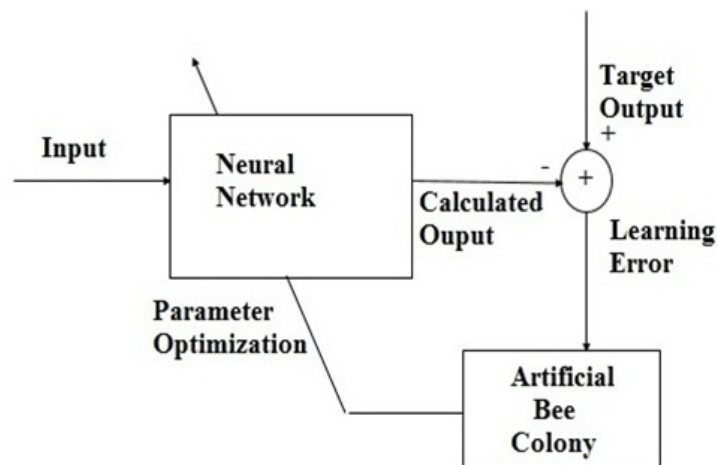


Figure 3.8. Structure of proposed algorithm.

This study links ABC algorithm with a MLP neural network (ABC-NN) for channel estimation. Firstly, at training stage input training sequence is fed to the neural network and output is calculated. After performing all necessary calculations, the calculated output/result is compared with desired output data set and learning error is found. This learning error serve as a cost function and it is used as the value of cost function for ABC algorithm. ABC algorithm plays an important role to optimizes the parameter value to minimize the cost function as well as updates the parameters of neural network until the stopping criteria is reached. The training setup is shown in Fig. 3.8.

After training the second stage is the test stage, at test stage, the channel estimation data is fed to the trained neural network in order to obtain the frequency response of

the channel. After that, the estimated frequency response is compared with real/actual frequency response of the channel to calculate MSE for performance evaluation of the channel estimator.



CHAPTER 4

SIMULATION RESULTS

As discussed in previous chapters that for wireless communication, transmitted signal passes through a radio channel before reaching to receivers therefore, estimation of the effect of the channel on the transmitted information is required to recover the signal [15]. Wireless channels cause ISI because of multi-path fading. To remove the changes caused by channel on the received signal, receiver need to have CIR information and this information is obtained generally by channel estimator.

In this thesis, the proposed channel estimator is compared with LS, NN-BP and MMSE estimator with regards to bit error rate versus energy per bit to noise spectral density ratio (E_b/N_0) and also MSE versus E_b/N_0 .

The parameters chosen for simulation are listed in Table 4.1. We have used QPSK modulation and Rayleigh fading channel model. Moreover, we have used FFT size of 256 and 512 for our simulations. For guard interval, we have used cyclic prefix and the length of guard interval is chosen to be 64. Along with this, 256 number of sub-carriers are used for simulation purpose and the noise model used here is additive white gaussian noise model (AWGN).

Parameters	Values
FFT Size	256
Number of sub-carriers	256
Guard interval type	Cyclic prefix
Modulation type	QPSK
Channel model	Rayleigh fading channel
Noise model	AWGN
Length of guard interval	64

Table 4.1. The parameters of OFDM system.

4.1. Mean Square Error versus E_b/N_0

MSE for each E_b/N_0 value can be achieved by using following equation :

$$MSE = 1/N \sum_{q=0}^{N-1} E[(h_{est} - h_{real})^H (h_{est} - h_{real})] \quad (4.1)$$

where h_{est} is estimated channel frequency response and h_{real} is real channel frequency response.

Fig. 4.1, Fig. 4.2 and Fig. 4.3 show the simulation results LS, NN-BP and MMSE estimators for mean square error versus energy per bit to noise spectral density ratio (E_b/N_0) respectively.

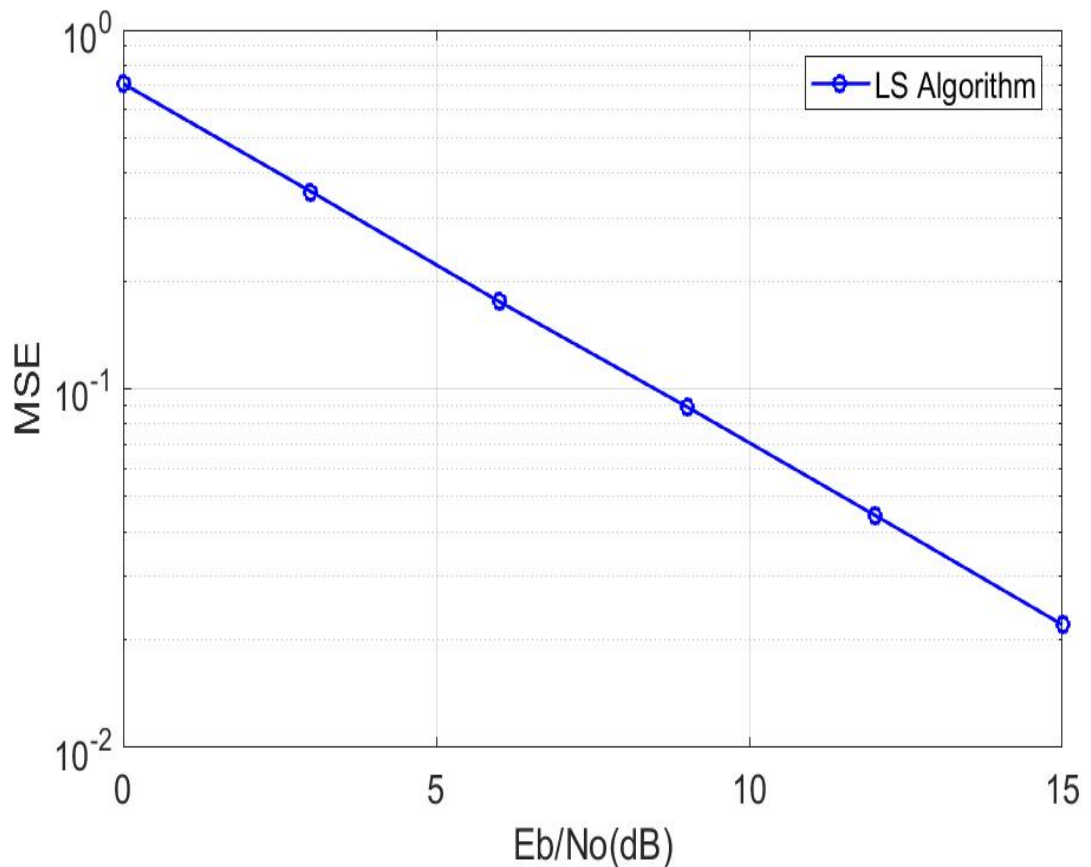


Figure 4.1. Mean square error performance of LS algorithm.

After several experiments, optimum parameters are determined by ABC-NN for the

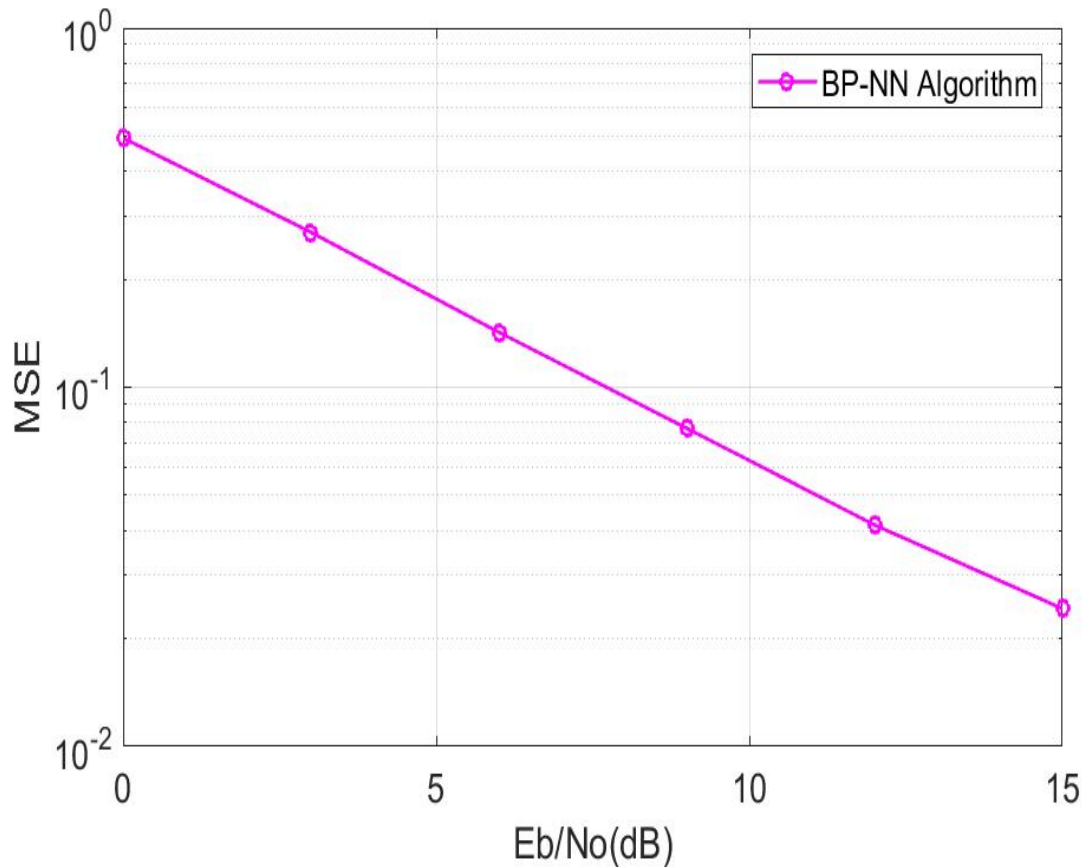


Figure 4.2. Mean square error performance of BP-NN algorithm.

excellent performance of neural network structure. Too many and too few hidden units would result in high generalization error due to over-fitting and under-fitting respectively. Thus, proposed network consists of one hidden layer and one output layer with 5 neurons and 2 neurons, respectively. Tangent sigmoid transfer function is used for hidden layer and linear transfer function is used for output layer. ABC algorithm is used for training the network and 16000 training symbols are used in training process. Maximum number of cycles used for ABC-NN are 300.

Firstly, the network is trained by using the correct channel state information, after that the received symbols are entered to ABC-NN and thus the estimated channel frequency responses are found from the output of the proposed network.

In Fig.4.4, MSE performance of LS, MMSE and back propagation algorithm is compared with proposed estimator for OFDM system. ABC-NN performance is better than LS and BP-NN. From Fig.4.4, it can be clearly seen that LS estimator has deficient performance

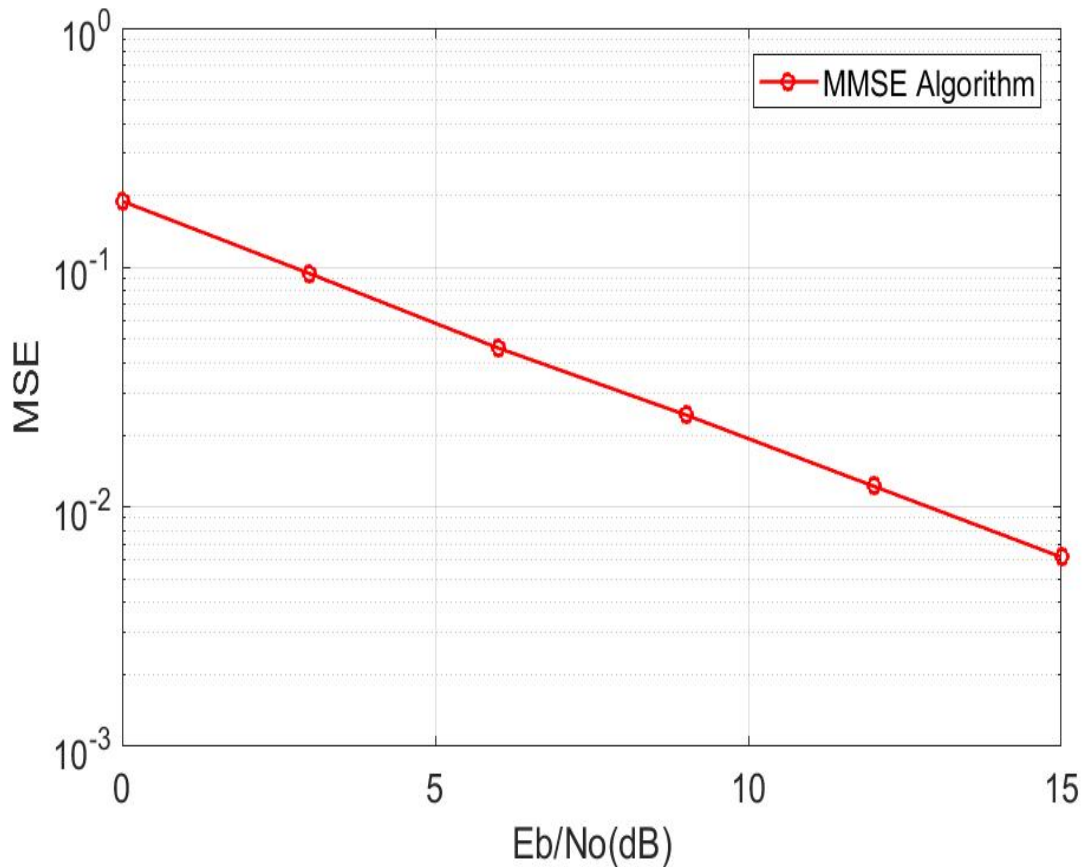


Figure 4.3. Mean square error performance of MMSE algorithm.

as it has more errors when compared to the other two channel estimation algorithms. Although LS estimator has low complexity, but it is not convenient to use LS algorithm in multipath fading channel because of its inferior performance.

On the other hand, the mean square error of neural network estimator is lower than LS and higher than MMSE algorithms. Initially, the learning method for the neural network requires a known pilot symbol as the target output. After multiple iterations, the input data gradually becomes the target output via learning.

Although the MMSE algorithm's performance is better than proposed algorithm, this method needs channel statistics and noise-related information to acquire channel impulse responses which is not feasible in real transmission situations. The proposed ABC-NN does not need channel information as in MMSE case, which simplifies implementation in real transmission environment [80].

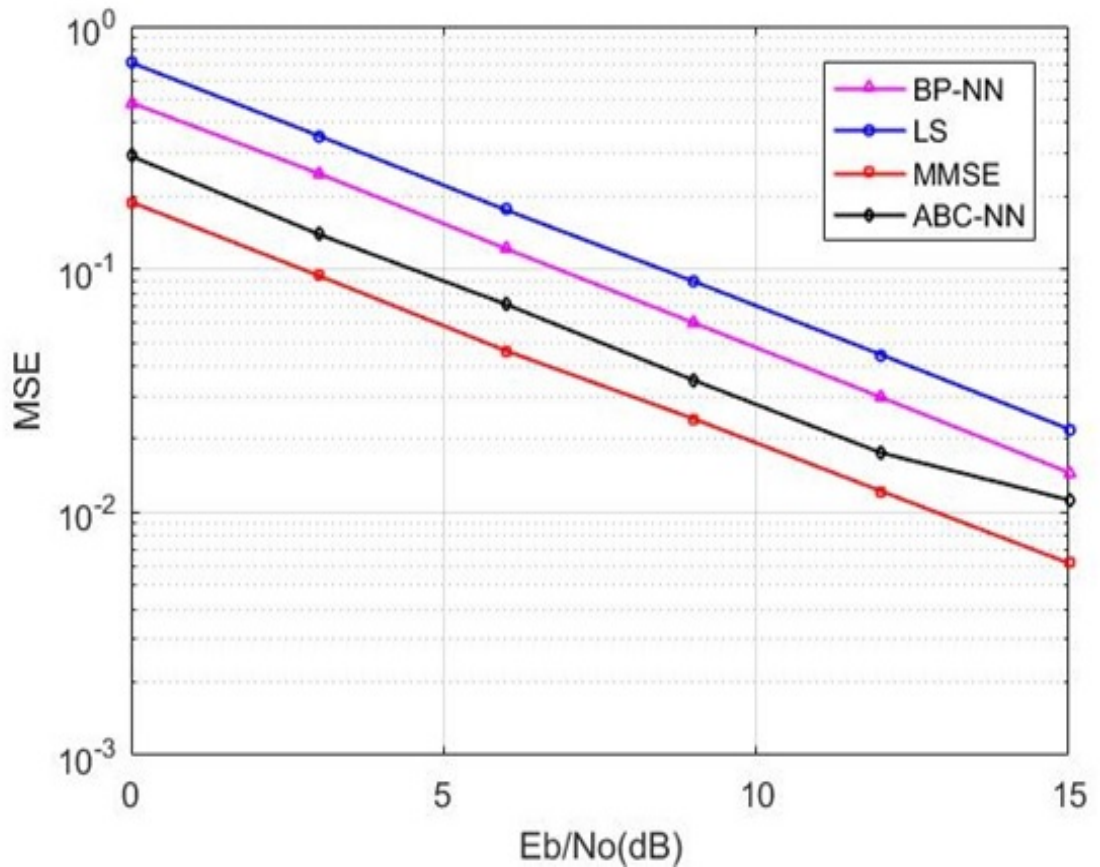


Figure 4.4. Comparison of MSE graph for LS, BP-NN, MMSE and ABC-NN algorithms.

4.2. Bit Error Rate versus E_b/N_0

The second method used for performance evaluation of different channel estimators is BER. Fig. 4.5 shows simulation results of BER using LS and Fig. 4.6 shows simulation results of BER using MMSE.

Finally, Fig. 4.7 and Fig. 4.8 show comparisons of BER using LS, conventional BP-NN, MMSE and the proposed ABC-NN algorithm for different FFT sizes. Clearly, the ABC-NN offers superior estimation performance than conventional BP-NN and LS algorithms.

Similar to MSE results, MMSE algorithm performance is better than proposed algorithm, but it needs channel statistics and noise-related information to acquire channel impulse responses which is difficult to obtain in real transmission situations. The proposed ABC-NN simplifies implementation in real transmission environment as it does not need channel information like MMSE algorithm.

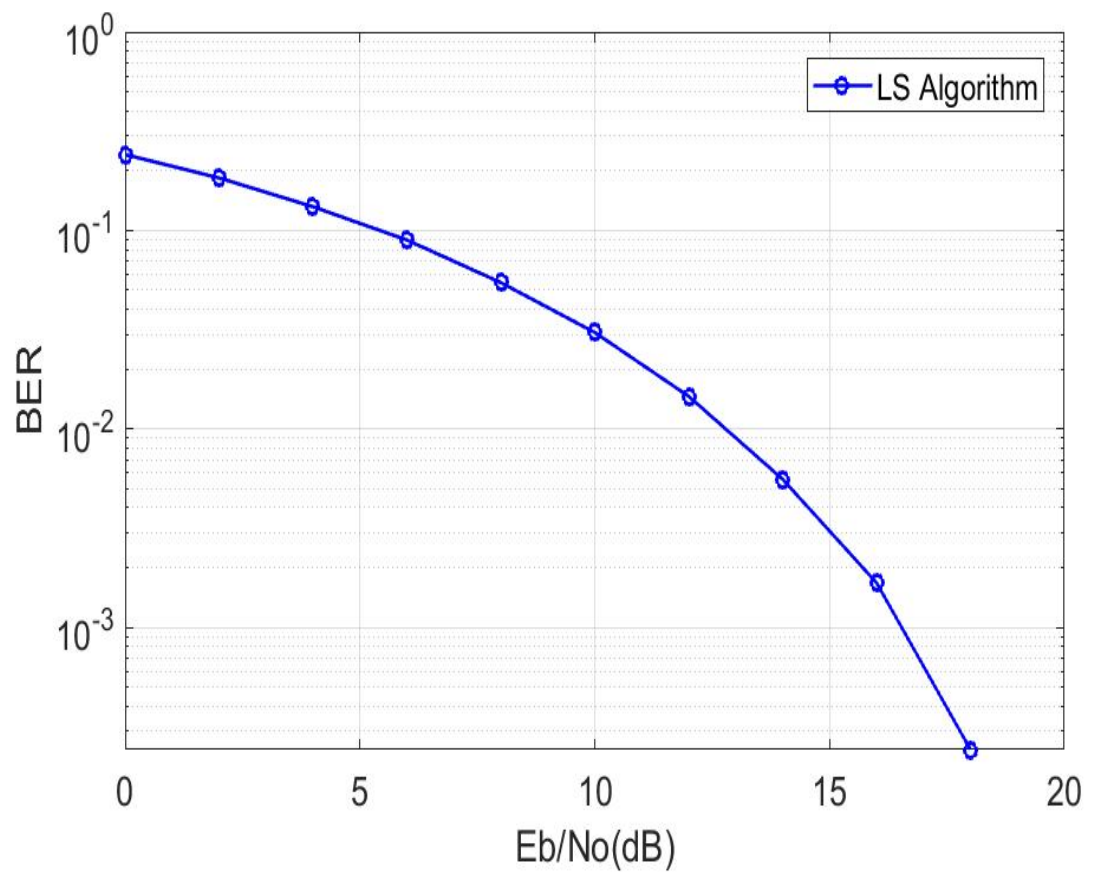


Figure 4.5. BER performance of LS algorithm.

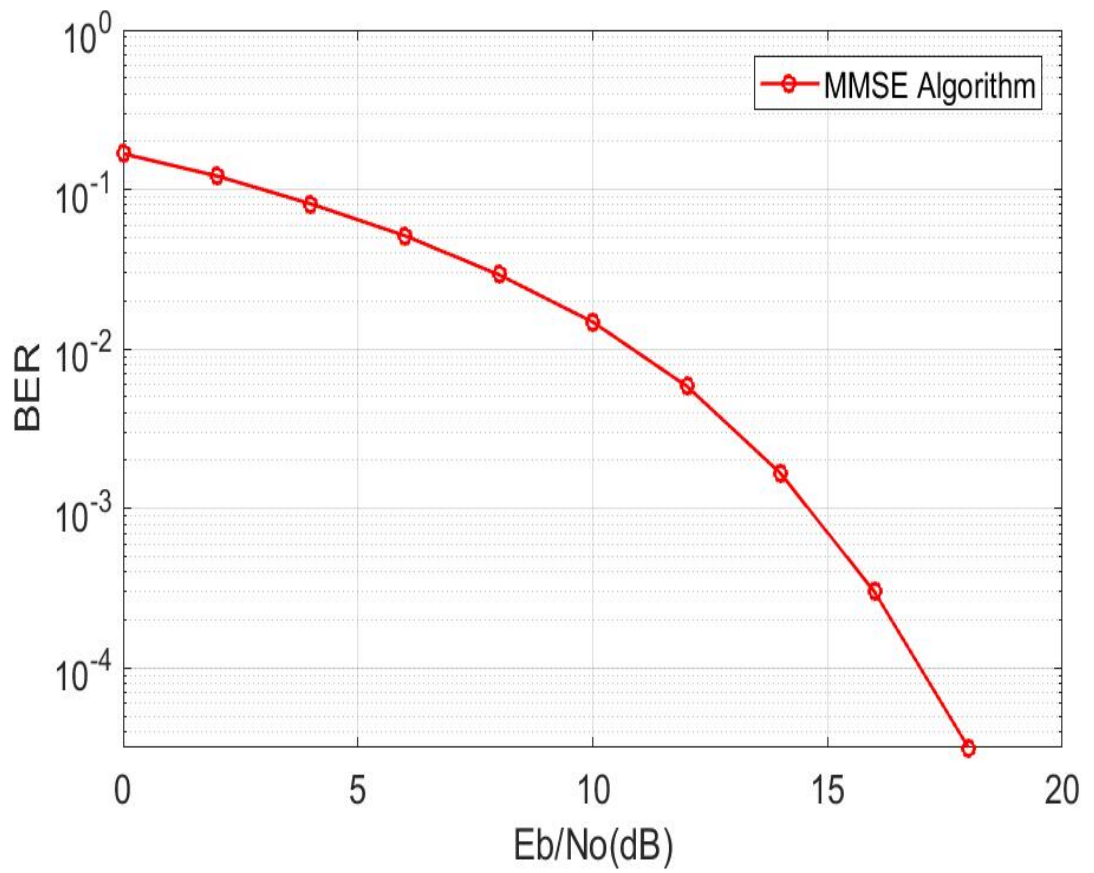


Figure 4.6. BER performance of MMSE algorithm.

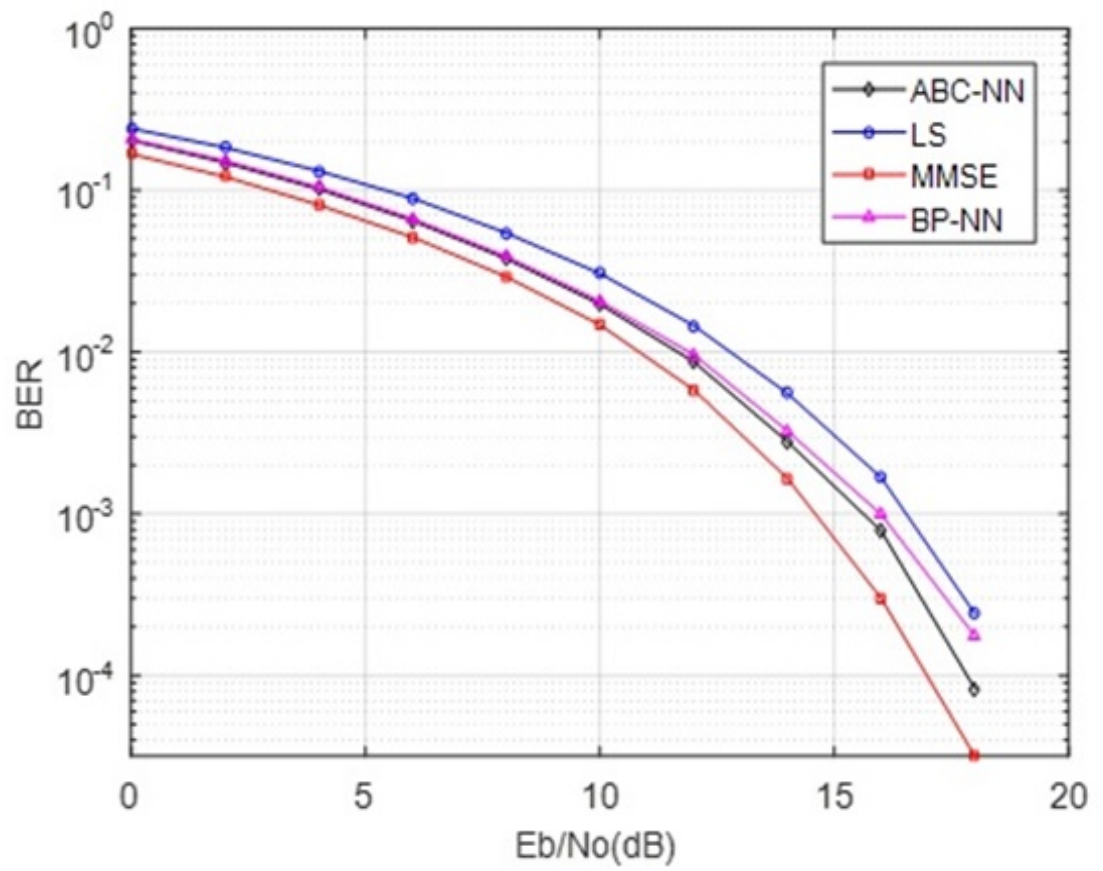


Figure 4.7. BER comparison for various algorithms (FFT size = 256).

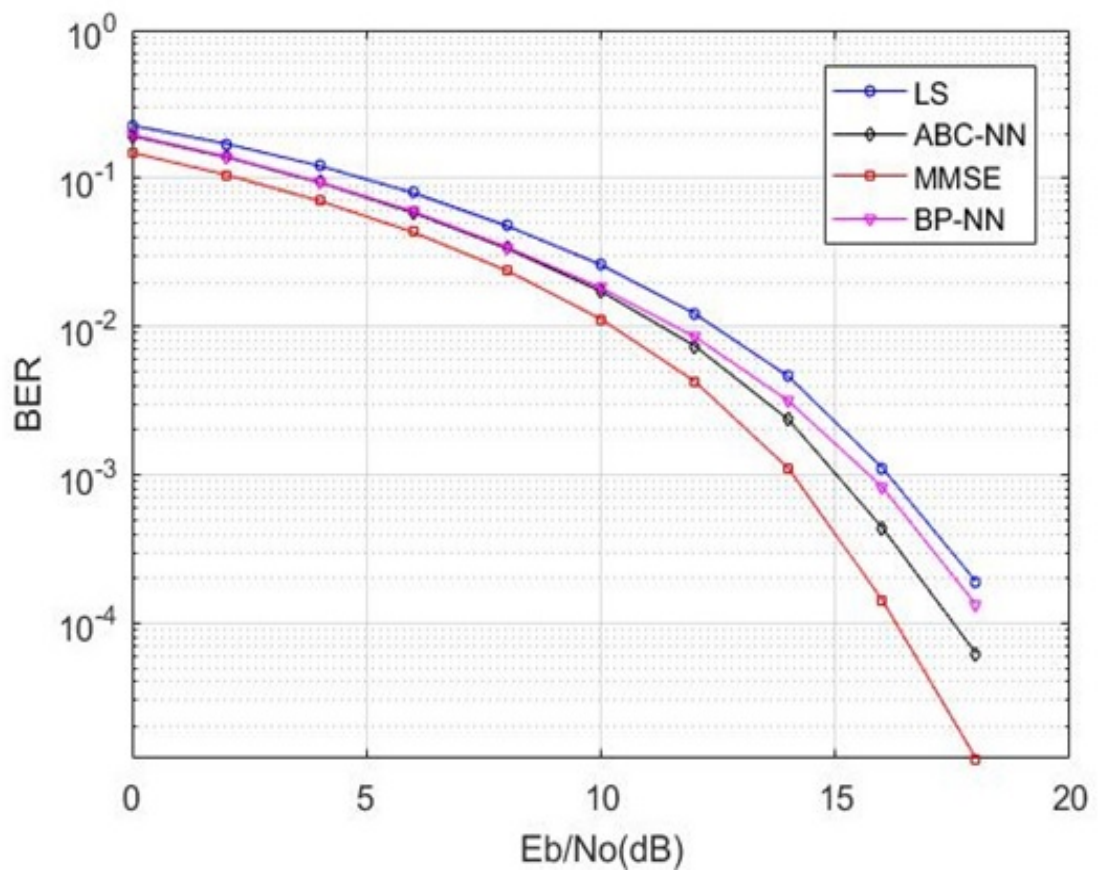


Figure 4.8. BER comparison for various algorithms (FFT size = 512).

CHAPTER 5

CONCLUSION

5.1. Conclusion

Day by day demands for high data rate is increasing and due to this reason, upcoming wireless systems need technologies, which are capable of fulfilling these demands. Our concerns are not limited the demands of high-speed and superior quality, it also includes the fast growing number of wireless subscribers/devices. The subscribers of wireless services are increasing day by day and the demand for spectrum is becoming necessary. As high data rates are required to provide good Quality of Service for various types of services, there is a need for groundbreaking solutions to upgrade total efficiency.

OFDM technique is considered as promising selection for providing high rates for future applications. OFDM is a multicarrier modulation technique, which divides signal bandwidth into many narrow subcarriers before transmitting the data. Parallel sub channels in OFDM increase the symbol duration and thereby reduce or eliminate the inter-symbol interference (ISI) which is caused due to multipath environments.

Currently, OFDM is the most widely used solution for high-speed applications of wireless communication in outdoor and indoor environment. OFDM uses non-overlapping adjacent channel and permits multiple carriers for transmitting different symbols.

In wireless environment, every transmission scheme be it single carrier system or multiple carrier system require channel estimation to access channel state information (CSI) of the system. CSI is needed to remove the effects of wireless channel on received signal, these effect are caused due to tall buildings, mountains etc.

Numerous channel estimation practices are used to address the issues of ISI in the

channel and to access CSI of the system. Commonly used algorithms are least square (LS) algorithm and minimum mean square error (MMSE) algorithm. LS algorithm is considered the simplest of all existing methods because it is uncomplicated to implement. However, most of the time simplest methods lack better performance likewise LS algorithm does not perform well for time varying and fast fading channel. In contrast, MMSE algorithm performs superior than LS algorithm but at the cost of complexity.

Not only these conventional algorithms are being used for channel estimation but also advance algorithms based on neural networks as well as artificial optimization algorithms are being developed and used for this purpose. Predominantly, for problems like channel estimation in OFDM wireless channels ANNs has gained vast interest these days.

Furthermore, various evolutionary algorithms are being used for training of ANNs. Many researchers have combined evolutionary algorithms with neural networks for the purpose of obtaining channel state information for OFDM systems. Research shows that this combination of artificial optimization algorithm with neural network provides better results as compared to simple neural network trained with conventional methods. Our aim in this research has been, to contribute to robustness of OFDM systems channel estimation using artificial bee colony (ABC) algorithm.

In this thesis, ABC-NN method has been proposed for channel estimation in OFDM systems. A multi-layered perceptrons based neural network is combined with artificial bee colony algorithm to increase the performance of channel estimation. The performance of the proposed algorithm is compared with LS, MMSE and BP-NN methods with regards to MSE and BER. According to detailed results presented in chapter IV, the proposed approach is more efficient than least square and conventional BP-NN algorithm and also it offers a better convergence rate. The proposed ABC-NN converges faster than conventional back propagation neural networks. The MMSE algorithm overreaches the ABC-NN; but MMSE estimator is complex as compared to other estimators and it involves channel statistics and noise related data to get channel impulse responses. Obtaining this information is not easy in real transmission scenarios. Consequently, the proposed method is suitable as it does not require any information related to noise and channel.

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- (ii) Taspinar, N., Rajput, S., Basturk, N. S., Basturk, A. (2017), " Channel estimation in OFDM system using multi-layered perceptron neural network combined with artificial bee colony algorithm", Proceedings of 33th International Research World Conference, Barcelona, Spain, pp. 5-9.

AWARDS

- (i) Cultural Ambassador of Pakistan in United States from January 2013 to May 2013
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