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NEURAL NETWORK BASED CHANNEL ESTIMATION FOR TIME-VARYING OFDM SYSTEMS

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APPROVAL

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EMRE MOLLAHUSEYINOGLU

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Date (10/04/2023)

To My Dearest Family...

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NEURAL NETWORK BASED CHANNEL ESTIMATION FOR
TIME-VARYING OFDM SYSTEMS

ABSTRACT

Systems like LTE makes it possible to reach data rates up to a maximum of 100Mbit/s. However, these bit rates are accessible when there is nomadic mobility at the user end. As the user's movement speed increases, the necessity of a low-complexity channel estimation method is also increasing because the time-invariant feature of the channel deteriorates. Deep learning is increasingly embedded in various fields and slowly replacing conventional methods across many sectors. It has already proven its capability to decrease computational complexity and increase the system's performance. This thesis proposes a channel estimation method for time-varying orthogonal frequency division multiplexing (OFDM) channels using deep neural networks (DNN). We utilize a Legendre polynomial approach to represent the rapidly changing time-varying OFDM channel to reduce the computational complexity of the estimation. Using linear minimum mean-square error (LMMSE), initial values of the polynomial coefficients that represent the channel are estimated, and the estimation accuracy has been improved with DNN. The results are com- pared with an iterative estimation algorithm that is space alternating generalized expectation maximization—maximum a posteriori probability (SAGE-MAP) and LMMSE estimation. It is shown that smaller mean square error (MSE) and symbol error rates (SER) were obtained with DNN-based estimation at lower signal-to-noise ratios.

Keywords: Orthogonal Frequency Division Multiplexing (OFDM), Channel Estimation, Neural Networks, Time-Variant Channels, Rapidly Changing Channels, Legendre Polynomials, Space Alternating Generalized Expectation Maximization Posteriori Probability (SAGE-MAP).

ZAMANLA DEĞİŞEN OFDM SİSTEMLERDE YAPAY SİNİR AĞI TABANLI KANAL KESTİRİMİ

ÖZET

LTE gibi sistemler sayesinde, maksimum 100 Mbit/s'ye kadar veri hızlarına ulaşmak mümkün olmaktadır. Ancak, bu hızlara kullanıcı tarafındaki hareketliliğin olmadığı veya düşük olduğu senaryolarda erişilebilir. Kullanıcının hareket hızı art- tıkça, kanal kestirimi yönteminin düşük kompleksiteye sahip olması gerekliliği de art- maktadır, çünkü kanalın zamana bağımlı özelliği kötüleşmektedir. Derin öğrenme, birçok sektörde geleneksel yöntemlerin yavaş yavaş yerini almaya başlayarak, çeşitli alanlarda sıkça kullanılır hale gelmektedir. Derin öğrenmenin hesaplama karmaşık- lığını azaltmak ve sistem performansını artırmak hakkındaki kabiliyeti kanıtlan- mıştır. Bu tez, derin sinir ağları (DNN) kullanarak zamana bağlı ortogonal frekans bölmeli çoklu erişim (OFDM) kanalları için bir kanal kestirimi yöntemi önermekte- dir. Kanal kestiriminin hesaplama karmaşıklığını azaltmak için zamana bağlı hızla değişen OFDM kanalını temsil etmek için Legendre polinom katsayıları kullanıl- maktadır. Lineer minimum ortalama karesel hata (LMMSE) kullanılarak kanalı temsil eden polinom katsayılarının başlangıç değerleri kestirilmiş ve kestirim doğru- luğu DNN ile arttırılmıştır. Sonuçlar, mekansal alternatif genelleştirilmiş beklenti maksimizasyonu - maksimum a posteriori olasılık (SAGE-MAP) ve LMMSE kanal kestirim yöntemi ile karşılaştırılmaktadır. Düşük sinyal-gürültü oranlarında DNN temelli kestirim daha küçük ortalama karesel hata (MSE) ve sembol hata oranları (SER) elde edildiği gösterilmiştir.

Anahtar Sözcükler: Dikey Frekans Bölmeli Çoğullama (OFDM), Kanal Kestirimi, Yapay Sinir Ağları, Zamanla Değişen Kanallar, Hızla Değişen Kanallar,, Löjandır Polinomları, Sage-Map.

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LIST OF SYMBOLS/ABBREVIATIONS

AM	Amplitude Modulation
BEM	Basis Expansion Model
BPSK	Binary Phase-Shift Keying
CFR	Channel Frequency Response
CIR	Channel Impulse Response
DD-CE	Decision-Directed Channel Estimation
DL	Deep Learning
DNN	Deep Neural Network
DTF	Discrete Fourier Transform
FC-DNN	Fully Connected Deep Neural Network
FIR	Finite Impulse Response
FLNFN	Functional Link Neural Fuzzy Network
FM	Frequency Modulation
ICI	Inter-Channel Interference
IDFT	Inverse Discrete Fourier Transform
ISI	Inter-Symbol Interference
$\otimes$	Kronecker Product
LMMSE	Linear Minimum Mean Square Error
LS	Least Square
LMS	Least Mean Square
MMSE	Minimum Means Square Error
MSE	Minimum Square Error
MIMO	Multiple Input Multiple Output
NN	Neural Network
OFDM	Orthogonal Frequency Division Multiplexing
PA-CE	Pilot-Assisted Channel Estimation
SAGE-MAP	Space Alternating Generalized Expectation-Maximization—Maximum a posteriori probability
SNR	Signal-to-Noise Ratio

SP-CE	Super-Imposed Channel Estimation
TT-DNN	Tensor-Train Deep Neural Network
QAM	Quadrature Amplitude Modulation
QPSK	Quadrature Phase-Shift Keying

1. INTRODUCTION

1.1 Orthogonal Frequency Division Multiplexing

Orthogonal frequency division multiplexing (OFDM) is a prevalent method used for many of the latest wireless and telecommunication standards due to its robustness against limitations such as frequency selective fading and delay spread. In OFDM systems, delay spread is minimized by using multiple sub-carriers of lesser bandwidth [1]. Additionally, sub-carriers are specifically created to be orthogonal to one another, allowing them to share the same bandwidth without interfering. This makes the use of guard bands unnecessary, and the sub-carriers can be tightly packed to improve channel efficiency. Additionally, utilizing a single-stage equalization with OFDM, a frequency-selective channel may be converted into a series of flat fading channels, allowing for a more straightforward equalizer layout. [2]. With these vital advantages, OFDM became widely used in commercial systems as an effective physical-layer method [3], [4].

1.2 Channel Estimation

The performance of wireless communication systems is heavily reliant on channel estimation. In OFDM systems with time-varying channels, the orthogonality between the sub-carriers may be lost, and this causes an Inter-Channel Interference (ICI) [5]. Because of ICI, the channel estimation and equalization methods get complicated due to the diagonal structure of the channel matrix in time-invariant channels being lost [5]. There are many studies on OFDM systems related to channel estimation, both time-varying and time-invariant. Since it is the optimum method for reducing the minimum square error (MSE) of channel estimates in the presence of AWGN, linear minimum mean square error (LMMSE) is a favored technique used in channel estimation on OFDM systems. [6]. In [7] basis expansion model is used to arrange the modulation over an OFDM symbol and combine the transmitting signal with the time-varying part to form the new pilot signal for MIMO linear time-varying (LTV) channel estimation. In this method, spectral efficiency decreases due to plenty of sub-carriers required for the pilot. A Slepian-based estimator is proposed in [8] for multiple-input multiple-output (MIMO) systems with iterative receivers. In [9], a modified Kalman filter is introduced, used in time-varying channels and carrying out iterations inside different symbols of pilot sub-carriers.

Additionally, there are other methods for channel estimate, including neural network-based channel estimation. Studies in this field are often conducted with time-invariant channel setups. Functional Link Neural Fuzzy Network (FLNFN) is employed in [10] for channel estimation, and the authors found that it performs better than several conventional methods like least square (LS) and minimum means square error (MMSE) algorithms. The authors propose a channel estimator based on a tensor-train deep neural network (TT-DNN) for time-varying channel estimation in MIMO systems [11]. The performance of TT-DNN is better than the DNN counterparts in terms of convergence rate, estimation accuracy, and robustness. However, even though there are fewer model parameters, the complexity of the overall system increased. In [12], to predict the OFDM channel, a multi-layered perceptron (MLP) based neural network (NN) is presented, which is trained with a back-propagation (BP) technique. The proposed method performs better than the conventional Least Mean Square (LMS) algorithm. However, there is a trade-off between performance and complexity.

1.3 Motivation

Deep learning is a promising approach in wireless communications to overcome complicated channel distortion and interference with channel estimation and signal detection [13]. Deep learning's application to wireless communications has recently received much interest. Considerable studies have begun to merge deep learning with traditional wireless communication. The authors of [13] carried out a deep learning channel estimation study in an OFDM system by treating the entire receiver as a black box. They showed how deep learning might be used in OFDM systems for channel estimation and signal detection but did not consider time-varying channel circumstances. The authors in [14] propose a deep learning technique for channel estimation improvement in OFDM systems with uplink time-varying channels. They assemble a channel parameter refine network (CPR-Net) by leveraging fully connected deep neural networks (FC-DNN) and blending it with conventional channel estimation approaches.

In this work, we discuss the results of our channel estimation study using neural networks for time-varying channels in OFDM systems. While performing the channel estimation, it is assumed that the channel changes slowly throughout each OFDM block, and the channel is modeled with the Legendre polynomial and found with the neural network. Using linear minimum mean-square error (LMMSE), initial values of the polynomial coefficients are estimated and the estimated values were improved with the neural network. The results are compared with LMMSE estimation and SAGE-MAP algorithm which is an iterative channel estimation method for time varying channels in literature.

1.4 Contribution of the Thesis

The thesis contributions can be listed as follows:

1. Researches on channel estimation using neural networks in OFDM systems mostly consider channels that do not change over time. In this thesis, a channel estimation method for time-varying channels has been presented and the communication channel is modeled using Legendre polynomial coefficients. The estimation is carried out on those coefficients rather than whole channel. Estimating a set of Legendre polynomial coefficients rather than a whole channel

reduces the computational complexity of the estimation.

2. By working on time-varying channels, we design a neural network-based channel estimation technique for OFDM systems with a better MSE performance than the SAGE algorithm at small signal-to-noise ratios (SNR). And this is more feasible in real-life scenarios when the channel is rapidly changing.
3. It is also an important study in terms of minimizing the time delay caused by iterative channel estimation algorithms, especially in post-5g systems where channels that change rapidly over time are considered.

1.5 Thesis Outline

Chapter 1 presents a literature review for OFDM and Channel Estimation in time-variant and time-invariant channels and also, describes the motivation of the thesis. Also, working principals of the OFDM and OFDM channel estimation is described. In **Chapter 2**, OFDM signal and channel models of the communication scenarios and basis expansion model for the used Legendre polynomial approach to model the communication channel are presented. **Chapter 3** presents the proposed DNN-based channel estimation method and provides the computer simulation results. Finally, in **Chapter 4** the main conclusions of this thesis are summarized.

2. PRINCIPLES OF ORTHOGONAL FREQUENCY DIVISION MULTIPLEXING

Traditional modulation methods, including amplitude modulation (AM), frequency modulation (FM), and binary phase-shift keying (BPSK), modulate the incoming data bits across a single carrier. OFDM is a multi-carrier modulation technique that transmits information using several carriers within the allotted bandwidth. The frequency-selective channel is divided into many narrow-band flat fading channels with OFDM using overlapping signals. Various frequency components of the signal undergo different fading when they are exposed to a frequency-selective fading channel. OFDM combines modulation and multiplexing to share given bandwidth among modulated data sources. By breaking up the overall frequency selective fading channel into smaller flat fading channels, OFDM solves the issue rather than attempting to eliminate frequency selective fading.

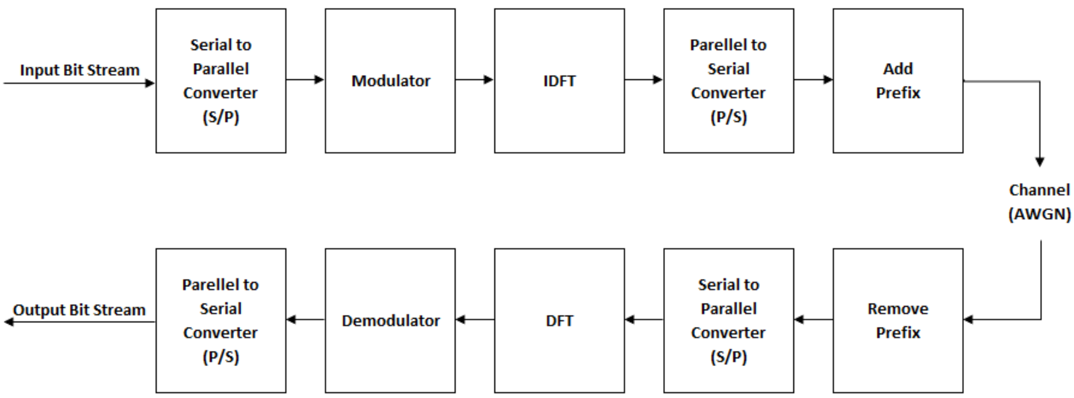

Figure 2.1 Basic Block Diagram of an OFDM System

Fig. 2.1 shows the block diagram of a simple OFDM system. As a general scenario, let's assume we have N sub-carriers. Frequencies that are orthogonal to one another are the centers of each sub-carrier. The serial-to-parallel converter takes the serial input data bits and outputs N parallel streams, where N is the number of sub-carriers. A constellation mapper is used to convert these parallel streams into digitally modulated forms (QAM, QPSK, BPSK). Since the OFDM signal is in the time domain, the transmitter side uses the Inverse Discrete Fourier Transform (IDFT) to transform the signal into the time domain. By replicating the final portion of the OFDM signal and putting it at the start of the transmission, the cyclic prefix is included as a guard interval. The Inter-Symbol Interference (ISI) issue is reduced by eliminating them entirely at the receiver side by prefixing each OFDM symbol with a cyclic prefix. After the cyclic prefix is inserted, the data is then serialized, turned to analog, and filtered to provide a continuous time-domain signal [15].

The blocks in the receiver, except for the equalizer, match the blocks in the transmitter. Flat fading on each sub-carriers affects the phase and the magnitude of each sub-carriers without causing any ISI or ICI. The single tap equalizer corrects the amplitude and phase of each sub-carriers by performing a single complex multiplication per sub-carriers [15].

2.1 OFDM Channel Estimation

Not all subcarriers in an OFDM system are used for information transmission; certain subcarriers are set aside for pilot signals (carriers) required for channel estimation. For receiver design in OFDM systems and many functional communication systems, channel estimation is essential [2].

In wireless systems, signals travel along a radio channel before reaching the receiver. If the receiver properly estimated how the channel affects the transmitted signal, the sent information can be retrieved. Signals are reflected and dispersed, so they travel through several channels to reach the receiver. Furthermore, because transmitters, receivers, and objects move around, the channel response can alter quickly over time [2]. Differential modulation methods can be used to eliminate the channel estimation step, but such systems have a lower data rate and a cost of

3–4 dB SNR [2, 4, 6]. With all these effects in wireless systems, channel estimation becomes a challenging problem since the channel is highly dynamic, unlike guided media.

LMMSE channel estimation is a broad category that includes several different channel estimation approaches that vary in complexity and mean squared error (MSE). Therefore, an appropriate method among many techniques can be employed based on the resources and specifications of a given system. [6] Information is modulated onto orthogonal carriers in OFDM systems. To accurately identify the sent information, each sub-frequency carrier's response must be evaluated and retrieved from the frequency samples due to its unique channel circumstances. The time-domain channel can be represented as an FIR filter, similar to single-carrier systems, where channel characteristics can be determined from time-domain received samples before being transformed to the frequency domain to produce the channel frequency response (CFR). Utilizing the available information on frequency domain subchannels, the estimation can also be applied in the frequency domain. Instead of calculating FIR coefficients, one tap CFR can be determined in this manner. [6]

Two fundamental approaches for OFDM channel estimation are shown in Fig. 2.2 and 2.3: decision-directed channel estimation (DD-CE) and pilot-assisted channel estimation (PA-CE). In DD-CE, the first stage evaluates the channel's frequency response (training mode), which involves transmitting training symbols known to the transmitter and receiver. Information symbols are conveyed in the second phase (data mode), and the estimation from the training mode is utilized to remove the channel effect on the data symbols. Since the symbols used in the training step are known to the system, high spectral efficiency can be achieved with the DD-CE, but in cases where the channel changes rapidly, the channel estimation in the training mode will become invalid in data mode. It is, therefore, primarily appropriate for burst transmission when the channel conditions are typically stationary. [2, 6]

When the channel under consideration is time-varying, channel estimation

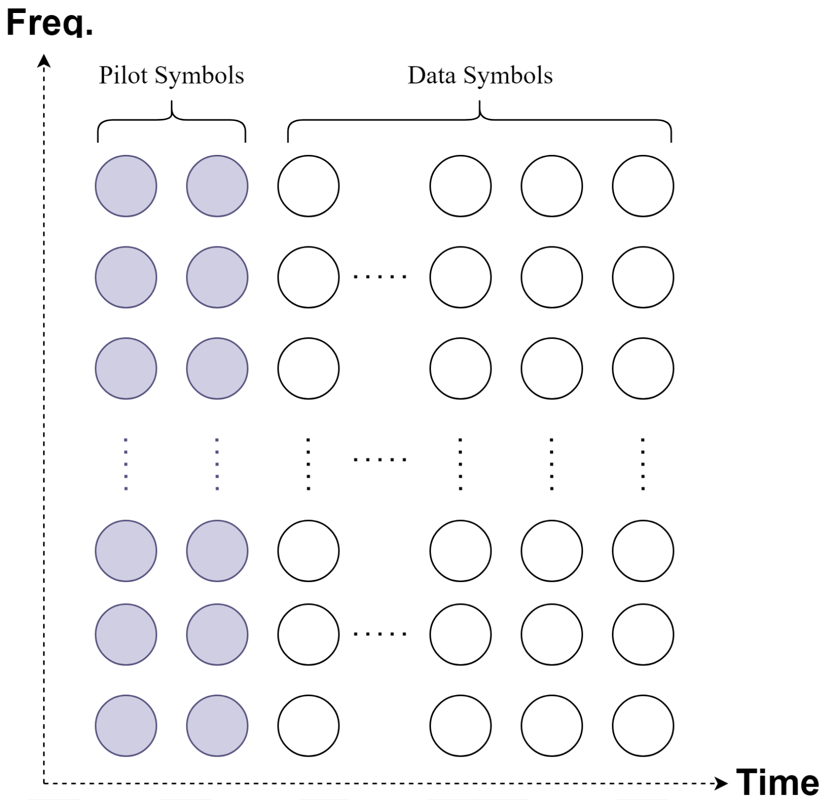

Figure 2.2 Pilot and data symbol placement for DD-CE

performance can be improved with PA-CE. Unlike DD-CE, pilot symbols are not just in front of the data but are interspersed between the data symbols. LS estimation estimates the CFR of the pilot symbols during channel estimation. Then, the CFR of the related data symbols can be found through interpolation. The spectral efficiency is decreased because only pilot symbols, which must adhere to strict performance requirements, are employed for channel estimation in PA-CE. This situation can be improved with super-imposed channel estimation SP-CE. [2]

Using SAGE-MAP algorithm as a channel estimation method, authors in [16] demonstrated discrete Legendre orthogonal basis functions may be used to describe rapidly changing fading channels for the first time. In OFDM systems with frequency selective fading and highly mobile transceivers, it is sufficient to have a limited number of expansion coefficients for excellent channel estimation [16]. The implementation of the algorithm in the time domain is one of the key advantages of the suggested method.

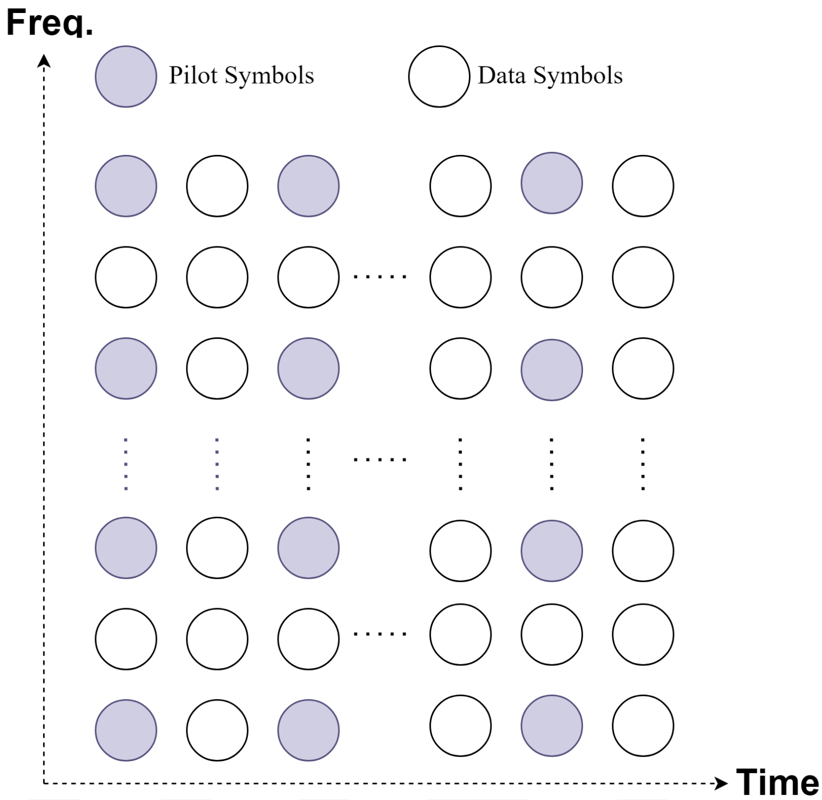

Figure 2.3 Pilot and data symbol placement for PA-CE

2.2 Signal and Channel Models

The OFDM system is taken into account with N subcarriers. The transmitter actively broadcasts data signals using K amongst N subcarriers. Moreover, the remaining $N-K$ subcarriers are not transmitted [16]. The signal that is transmitted in the time domain is defined as

$$s(m,n) = \frac{1}{N}\sum_{k=0}^{K-1} d(m,k)e^{j2\pi n\frac{k}{N}} \tag{2.1}$$

n represents the discrete-time index during the mth OFDM symbol, and k is the discrete-frequency index. The frequency domain data symbol $d(m,k)$ is the one that is sent across the kth OFDM subchannel at discrete time m. The transmitted signal $s(m,n)$ can be represented as a zero-mean complex Gaussian sequence using the central limit theorem when a sufficiently big K is available. After that, an L_c-length cyclic prefix is included. In a time-varying multipath mobile radio channel with discrete-time impulse response $h(n,l)$, $l = 0, 1..., L-1$ and $L \leq L_c$, L stand for the maximum channel length. Following matched filtering, symbol-rate sampling, and the removal of symbols with cyclic prefixes, the discrete Fourier transform (DFT) is inferred on the received signal at the receiver.

We can assume the time-varying channel impulse response (CIR) to be constant throughout one OFDM symbol when the normalized Doppler frequency is sufficiently small, that is; $h(m,l)$ for $m = 0, 1, ...M-1$ where M indicates the length of an OFDM frame consisting of M consecutive OFDM symbols. [16]

At the output of DFT, we can obtain the frequency domain received signal, noise, and channel coefficients that is $Y(m,k)$, $W(m,k)$, $H(m,k)$ respectively each corresponding to the mth OFDM symbol and kth subchannel. And by collecting received signal samples in a vector, we can express them in a vector form as follows. [16]

$$\mathbf{y}(m) = \sum_{l=0}^{L-1} diag(s_l(m))\mathbf{h}_l(m) + \mathbf{w}(m) \in C^N \tag{2.2}$$

where

$$\mathbf{y}(m) = [y(mN_g), y(mN_g+1), ..., y(mN_g+N-1)]^T$$

$$\mathbf{w}(m) = [w(mN_g), w(mN_g+1), ..., w(mN_g+N-1)]^T$$

$$\mathbf{h}_l(m) = [h(mN_g,l), h(mN_g+1,l), ..., h(mN_g+N-1,l)]^T$$

and, $N_g \triangleq N + L_c$. Assuming Jakes model for the channel dynamics, the autocorrelation function of the channel is founded by L—path wide-sense stationary uncorrelated scattering (WSSUS) Rayleigh fading coefficients at the $(mN_g + n)$th discrete times with zeroth-order Bessel function of the first kind.

$s(m,-l) = s(m, N-l)$ for $l = 0, 1, ..., L-1$. due to cyclic prefix employed at the transmitter. Thus, $s_l(m) = vshift(s(m), l)$, where $vshift(s(m), l)$ represent the l-step circular shift operator for a column vector

$$s(m) = [s(m,0), s(m,1), ..., s(m,N-1)$$

with defining $S_l(m) = diag(s_l(m))$

$$S(m) \triangleq [S_0(m), S_1(m), ..., S_{L-1}(m)] \in C^{NxLN} \tag{2.3}$$

and

$$\mathbf{h} \triangleq [h_0^T(m), h_1^T(m), ..., h_{L-1}^T(m) \in C^{NxLN}$$

we can express the received signal model in (2.2) as follows

$$\mathbf{y}(m) = \mathbf{S}(m)\mathbf{h}(m) + \mathbf{w}(m) \tag{2.4}$$

2.3 Selection of Channel Basis Expansion Model

The receiver's performance is highly dependent on the time-varying channel impulse response estimation. $\mathbf{h} = [\mathbf{h}^T(0), \mathbf{h}^T(1)..., \mathbf{h}^T(M-1)]^T \in C^{MNL}$ from the $MN(MN < MNL)$ dimensional received vector $\mathbf{y} = [\mathbf{y}^T(0), \mathbf{y}^T(1)..., \mathbf{y}^T(M-1)]^T \in C^{MNL}$. It appears that calculating the channel vector h by means of y is difficult since there are more unknowns to be determined than known equations.

We begin by using an appropriate BEM to characterize the time fluctuations of the discrete-time channel impulse response $h(mN_g + n, l)$ over a data block of M OFDM symbol. Channel coefficients, $h(t, l)$ can be represented as weighted sums of N_gM orthogonal basis functions $\psi_q(t)$ in the interval $[0, N_gMT_s]$ for each channel path $l = 0, 1, ..., L-1$. But the amount of the coefficients requires a lot of computational power. However, the weighted sum of a much smaller number $D(\ll MN_g)$ of appropriate orthonormal basis functions may be used to approximate it properly.

$$\tilde{h}(t, l) = \sum_{q=0}^{D-1} \psi_q(t)c(q, l), \quad t = 0, 1, ..., MN_g - 1 \tag{2.5}$$

where $c(q, l)$ represents the expansion coefficients.

The inverse transformation can be used as an alternative to deriving the expansion coefficients by using the orthogonality feature of the basis functions.

$$c(q, l) = \sum_{t=0}^{MN_g-1} \psi_q(t)h(t, l), \quad q = 0, 1, ..., D-1 \tag{2.6}$$

This allows the matrix representation of the channel and the expansion coefficients for each channel path.

$$\tilde{\mathbf{h}}_l = \mathbf{\Psi}\mathbf{c}_l \tag{2.7}$$

$$\tilde{\mathbf{c}}_l = \mathbf{\Psi}^{\dagger}\mathbf{h}_l \tag{2.8}$$

where

$$\tilde{\mathbf{h}}_l = [\tilde{h}(0,l), \tilde{h}(1,l), ..., \tilde{h}(MN_g - 1, l)]^T \in C^{MN_g}$$

$$\mathbf{c}_l = [(0,l), c(1,l), ..., c(D-1,l)]^T \in C^D$$

and $\mathbf{\Psi}$ matrix that stores the orthogonal basis vectors as

$$\mathbf{\Psi} = [\boldsymbol{\psi}(0), \boldsymbol{\psi}(1), ..., \boldsymbol{\psi}(MN_g - 1)]^T \in R^{MN_g \times D} \tag{2.9}$$

with

$$\boldsymbol{\psi}(t) = [\psi_0(t), \psi_0(t), ..., \psi_{D-1}(t)]^T$$

$$t = 0, 1, ..., MN_g - 1.$$

In our work, we use a BEM based on the orthonormal discrete Legendre polynomial-BEM (DLP-BEM) to explain the temporal fluctuations of the channel. With a limited number of basis functions, the DLP-BEM is especially well suited to expressing the channel's low-pass equivalent. The DLP basis functions also benefit from being independent of channel statistics and having expansion coefficients that become increasingly uncorrelated as the number of observations rises, as illustrated in Appendix A of [16].

With the recursive computation of normalization coefficients of the corresponding discrete orthogonal Legendre polynomials and removing the cyclic prefix from (2.7) it follows that:

$$\mathbf{\Phi}(m) = \mathbf{I_L} \otimes \mathbf{\Psi}(m)$$

$$\mathbf{\Psi}(m) = [\psi(mN_g), \psi(mN_g+1), \psi(mN_g+N-1)]^T \in R^N$$

$$\tilde{\mathbf{h}}(m) = \mathbf{\Phi}(m)\mathbf{c} \tag{2.10}$$

Note that $\otimes$ stands for Kronecker product. Finally, the received signal is represented in terms of the reduced dimensions channel vector by replacing 2.10 into 2.4.

$$\mathbf{y}(m) = \mathbf{Z}(m)\mathbf{c} + \mathbf{w}(m) \tag{2.11}$$

where $\mathbf{Z}(m) \triangleq \mathbf{S}(m)\mathbf{\Phi}(m)$ and $\mathbf{S}(m)$ is defined in (2.4)

As an example in Fig. 2.4 to Fig. 2.7 there are comparisons of actual channel $h(t)$ and channel produced with Legendre for a single channel path.

Figures. 2.4-2.7 shows a comparison between the channel response generated by Legendre polynomials and the real channel response for a single channel path in WIMAX-OFDM system with $M = 5$ and $M = 8$. Below figures show the channel response obtain by Legendre polynomials $\tilde{h}(t)$ and actual channel response $h(t)$ are really close to each other. From Fig. 2.4, where $D = 3$, and Fig. 2.5, where $D = 4$, we can observe Legendre polynomials perform better when D is bigger. Note that D represents the number of expansion coefficients for a single channel path.

As shown in the figures the channel response generated by Legendre polynomials is nearly as same as real channel response, When D is higher there are more coefficients to represent the channel impulse response this increases the similarity of the generated channel (channel produced with Legendre polynomials) to the real channel. But a higher D also causes more computational complexity.

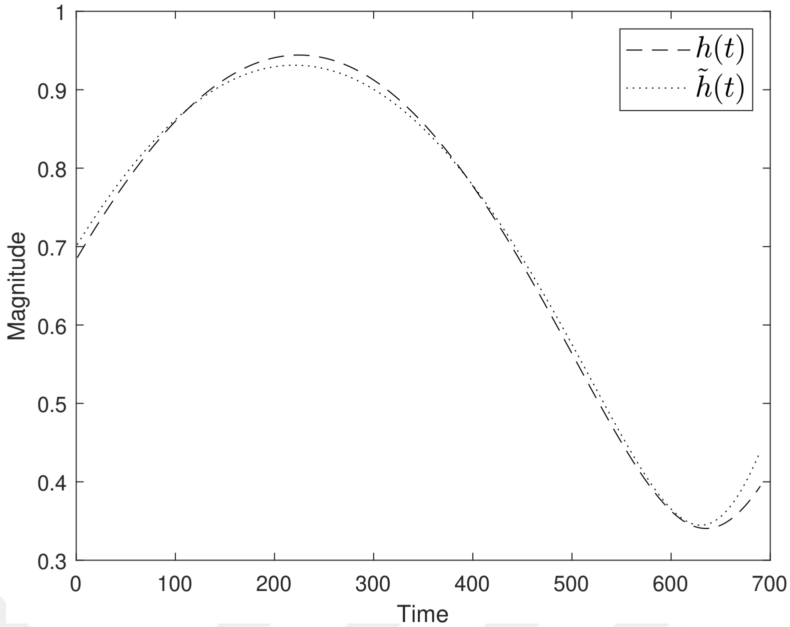

Figure 2.4 Comparison of Actual Channel Response and Channel Response Produced With Legendre Polynomial

Number of Legendre Coefficients: D=3

Number of OFDM Blocks: M=5

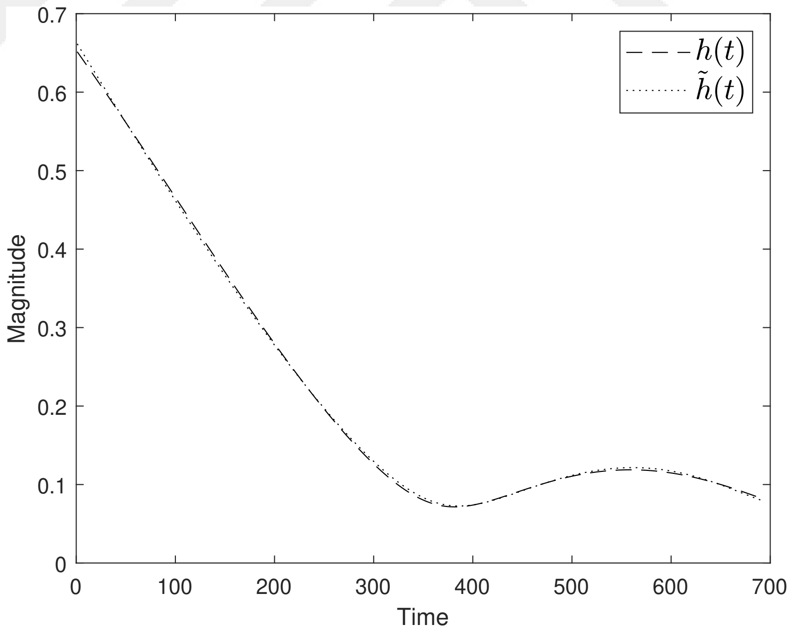

Figure 2.5 Comparison of Actual Channel Response and Channel Response Produced With Legendre Polynomial

Number of Legendre Coefficients: D=4

Number of OFDM Blocks: M=5

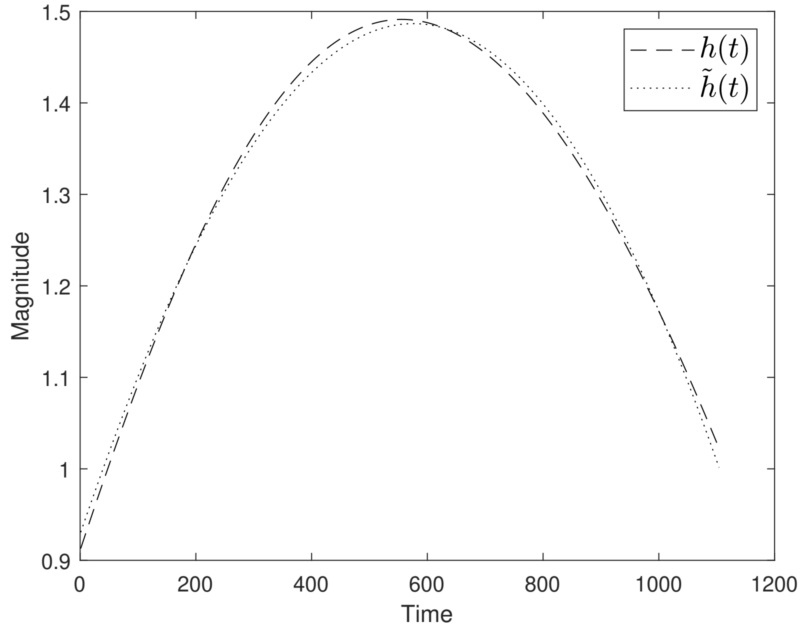

Figure 2.6 Comparison of Actual Channel Response and Channel Response Produced With Legendre Polynomial

Number of Legendre Coefficients: D=3

Number of OFDM Blocks: M=8

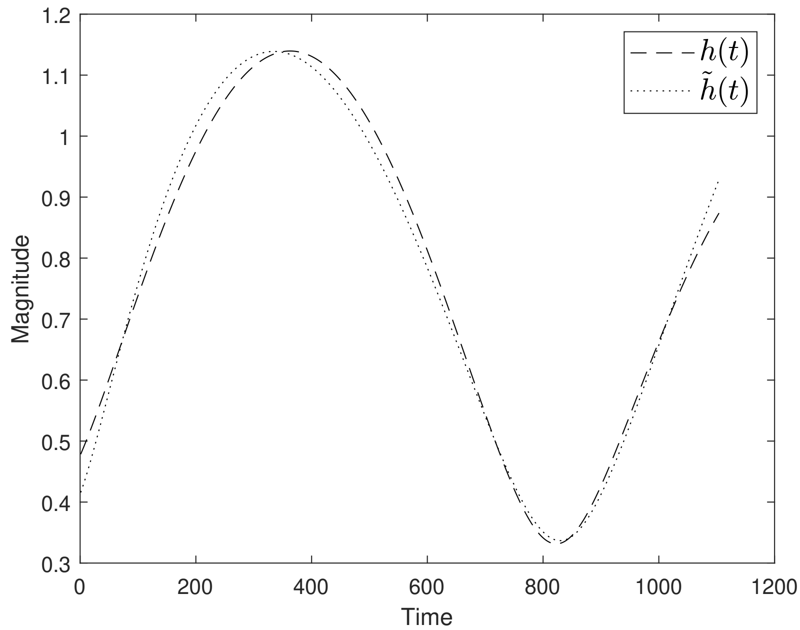

Figure 2.7 Comparison of Actual Channel Response and Channel Response Produced With Legendre Polynomial

Number of Legendre Coefficients: D=4

Number of OFDM Blocks: M=8

3. PROPOSED DNN BASED CHANNEL ESTIMATION

Node layers, input layers, output layers, and one or more hidden layers make up deep neural networks (DNNs). Nodes are also known as artificial neurons. There are connections between each artificial neuron and differences in threshold and weight. If a node's output exceeds the defined threshold level, it is activated and sends data to the network's next layer. No data is sent to the following layer if the node is not enabled.

Deep learning (DL) is bringing a significant technical change to wireless communication systems applications such as channel estimation, radio resource allocation and signal decoding [17]. The authors of [18] collected energy feedback data to study downlink channel estimates utilizing a wireless energy transfer system. Compared to more traditional estimations like LS or linear MMSE, a deep neural network model estimates channel response more precisely. When a training data set is sufficiently big, these experiments have numerically illustrated machine learning's compelling potential for channel estimation. The authors in [17] proposed two distinct types of NN to help with channel estimation in a MIMO-OFDM system using the two alternative scenarios of fading multi-path channel models based on the TDL-A model described in the 5G networks. The recommended DNN-based channel estimation techniques are trained to utilize ideal channels and their associated least squares channel estimates. Due to the proposed DNN-based estimation's successful learning of the channel parameters, they found fewer channel estimation errors than traditional LS and LMMSE estimations.

3.1 DNN Based Channel Estimation for OFDM

To overcome the drawbacks mentioned in LS and LMMSE estimations, we suggest a DNN-based estimation that minimizes the MSE between the channel estimation produced by LMMSE estimation and the actual channel. As shown in fig 3.1., the recommended DNN structure is set up as a series of layers, including an input layer, an output layer, and hidden layers. Our proposed DNN structure has four hidden layers that contain several neurons for the MIMO-OFDM scheme under consideration. A neuron, in particular, is a type of computational unit that can carry out the following computations:

$$f\left(\sum_{i=1}^{p} w_i x_i + bias\right) = f\left(w_1 x_1 + w_2 x_2 + ... + w_p x_p + bias\right) \tag{3.1}$$

where f is the activation function x_i is the i-th input $(i = 1, ..., p)$, w_i is the weight of the i-th input and p is a neuron's total number of inputs.

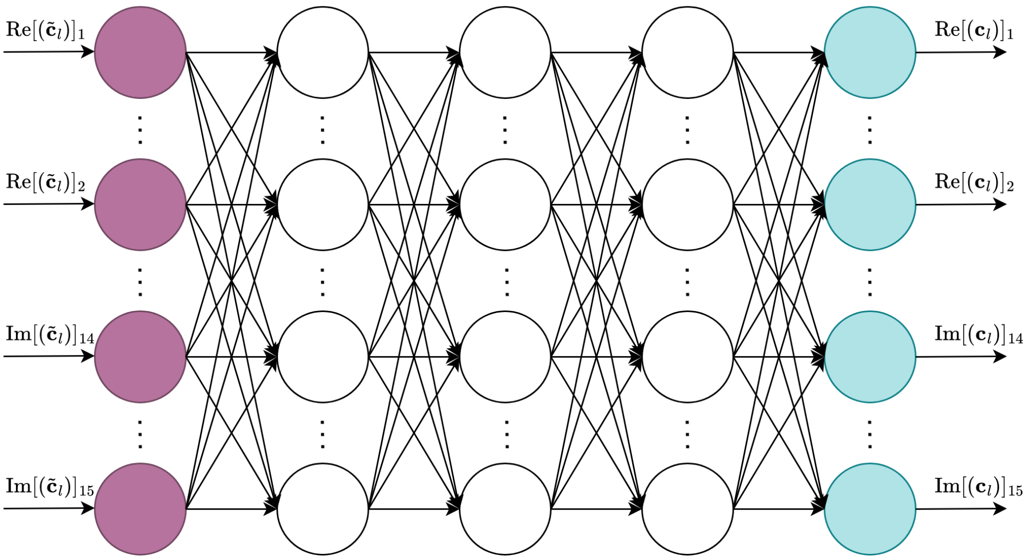

Figure 3.1 The DNN structure used for channel estimation

The output is then determined by an activation function, a tangent sigmoid function in our proposed structure.

$$f(z) = \frac{e^{2z} - 1}{e^{2z} + 1} \tag{3.2}$$

The output value will be nearer to 1.0 (more positive) when the input is more significant and nearer to -1.0 when the input is more minor (more negative).

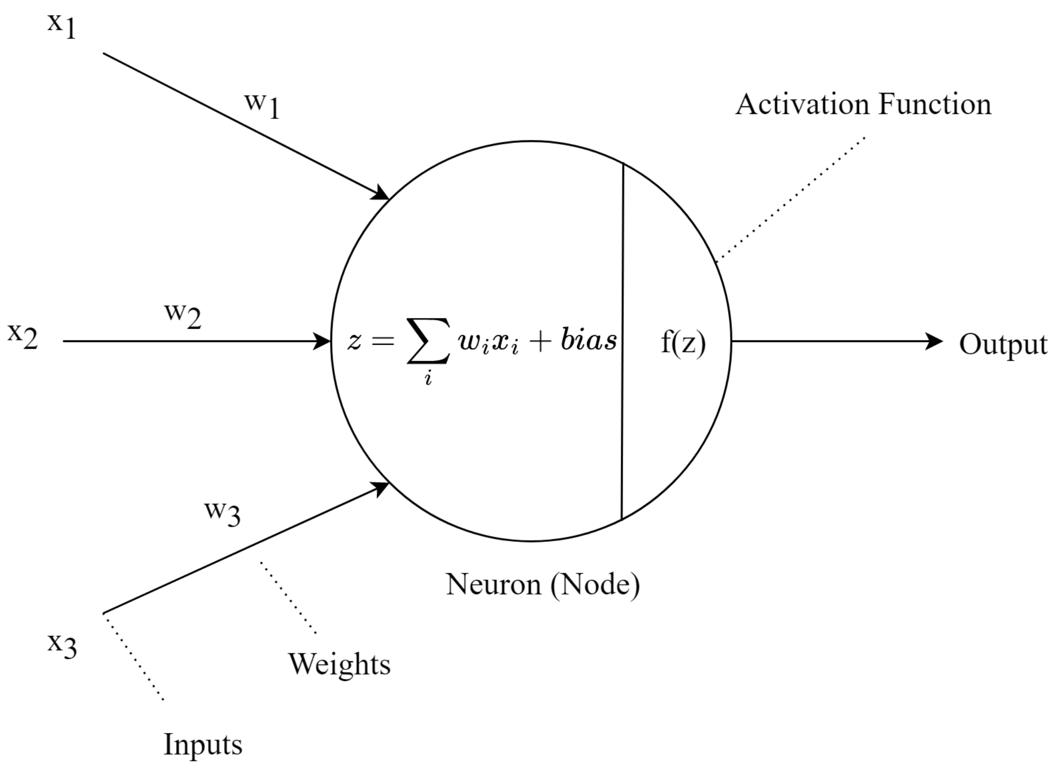

Figure 3.2 Structure of a single neuron

For the training process of DNN-based estimation, the structure is given an input and output data set. Input is Legendre polynomials of channel estimates obtained from the LMMSE estimation, $\tilde{\mathbf{c}}_l$ from (2.8), and the output is Legendre polynomials derived from the actual channel information, which is $\mathbf{c}_l$ from (2.7) to converge the estimates to be close the actual channel parameters. Thus, it reduces the MSE between the estimation and the actual channel. Notice that we are modeling the channel response in terms of Legendre polynomials, so the input and output of the proposed structure consist of coefficients of the Legendre Polynomials [16].

3.2 Initialization of Channel Coefficients

In this thesis we are using a DNN based channel estimation method. DNNs are based on the idea of the feedforward neural network, where data is processed through a series of layers, each layer performing a transformation on the data, until it reaches the output layer, which produces the final output. DNN is used to converge the estimations to be closer to the actual channel parameters. Since we are using a basis expansion model and Legendre polynomial coefficients to model our channel response, the input is Legendre polynomials of channel estimates obtained from the linear minimum mean square error (LMMSE) estimation, and the output is Legendre polynomials derived from the actual channel information. To obtain the first estimate of the channel, we can utilize the pilot symbols Using equation 2.11. Then, we can express the received vector for an OFDM frame with a duration of M as

$$\mathbf{y} = \mathbf{Z}\mathbf{c} + \mathbf{w} \tag{3.3}$$

where

$$\mathbf{y} = [\mathbf{y}^T(0), \mathbf{y}^T(1), ..., \mathbf{y}^T(M-1)]^T \tag{3.4}$$

$$\mathbf{Z} = [\mathbf{Z}^T(0), \mathbf{Z}^T(1), ..., \mathbf{Z}^T(M-1)]^T \tag{3.5}$$

and

$$\mathbf{Z}(m) = \mathbf{S}(m)\mathbf{\Phi}(m) = [\mathbf{S}_0(m)\mathbf{\Psi}(m), \mathbf{S}_1(m)\mathbf{\Psi}(m), ..., \mathbf{S}_{L-1}(m)\mathbf{\Psi}(m)] \tag{3.6}$$

With inverse Fourier transform diagonal matrix $\mathbf{S_l(m)}$ can be obtained as:

$$\mathbf{S}_l(m) = \mathrm{diag}\big(\mathrm{vshift}(\mathbf{s}(m), l)\big) = \frac{1}{N}\sum_{k=0}^{K-1} d(m,k)e^{\frac{-j2\pi lk}{N}}\mathrm{diag}(\mathbb{F}_N^*(k)) \tag{3.7}$$

where $\mathbb{F}^{N(k)}$ denotes the kth column of the DFT matrix. Using equation 3.7 $\mathbf{Z}(m)$ can be expressed as

$$\mathbf{Z}(m) = \sum_{k=0}^{K-1} d(m,k)\mathbf{U}_k(m) \tag{3.8}$$

with

$$\mathbf{U}_k(m) = \mathbb{F}_L^T(k) \otimes \left((\mathbf{1}_D^T \otimes \frac{1}{N}\mathbb{F}_N^*(k)) \odot \mathbf{\Psi}(m) \right) \in C^{NxDL} \tag{3.9}$$

where $\mathbf{1}_D$ refers to a vector consisting of all elements equal to one, with a length of D, $\odot$ represents the element by element product. $\mathbb{F}_L(k)$ denotes the first L terms of the kth column of the DFT matrix (F), We consider $\mathbf{Z}(m) = \mathbf{Z}_p(m) + \mathbf{Z}_D(m)$ where the matrices obtained form the pilot and data symbols are shown as:

$$\mathbf{Z}_p(m) = \sum_{k \in I_p}^{K-1} d(m,k)\mathbf{U}_k(m) \tag{3.10}$$

and

$$\mathbf{Z}_D(m) = \sum_{k \in I_D}^{K-1} d(m,k)\mathbf{U}_k(m) \tag{3.11}$$

We can obtain the initial estimations of the channel vector $\mathbf{c}$ with fewer dimensions by applying the LMMSE method to the received signal model (3.3) in the following manner:

$$\mathbf{c}^{(0)} = \mathbf{\Sigma_c Z_P^\dagger}(\mathbf{Z_P \Sigma_c Z_P^\dagger} + \mathbf{V}_D + N_0\mathbf{I}_{MN})^{-1}\mathbf{y} \tag{3.12}$$

where
$\mathbf{Z}_P = [\mathbf{Z}_P^T(0), \mathbf{Z}_P^T(1), ..., \mathbf{Z}_P^T(M-1)]T \in C^{MNxDL}$,
$\mathbf{V}_D \triangleq \mathrm{diag}\{\mathbf{V}_D(0), \mathbf{V}_D(1), ..., \mathbf{V}_D(M-1)\} \in C^{MNxMN}$
$\mathbf{V}_D(m) \triangleq \sum_{k \in I_D(m)} \mathbf{U}_k(m)\mathbf{\Sigma}_c\mathbf{U}_k^\dagger(m) \in C^{NxN}$. In order to make the matrix inversion process simpler, we use the matrix inversion lemma as demonstrated above, resulting in...

$$\mathbf{c}^{(0)}\Big(\mathbf{Z}_P^\dagger(\mathbf{V}_D + N_0\mathbf{I}_{MN})^{-1}\mathbf{Z}_P + \Sigma_c^{-1}\Big)^{-1}\mathbf{Z}_P^\dagger\Big(\mathbf{V}_D + N_0\mathbf{I}_{MN}\Big)^{-1}\mathbf{y} \tag{3.13}$$

With this transformation we need to take a matrix inversion of only size $DLxDL$ rather than $MNxMN$ [16].

By implementing this transformation, we only need to perform a matrix inversion of size $DLxDL$ instead of $MNxMN$, as $(\mathbf{V}_D + N_0\mathbf{I}_N)^{-1}$ is precomputed and MN is larger than NL.

3.3 Training of DNN

A dataset of 30000 realizations is acquired for the proposed neural network to train and test it. We utilize 15%- as the validation set, 15%- as the testing set, and

70%- of the data for training. Table 3.1 shows that DNN has 30, 60, 60, 60, and 30 neurons in the input, hidden, and output layers. There are 15 Legendre coefficients for a three-path channel in our structure, from $DL = 15$ as shown in Table 3.3. There are 30 variables, the same as the number of neurons in the input and output layers because each coefficient contains real and imaginary components. As shown in table 3.1.

DNN-based estimation reduces the MSE between the estimation and the actual channel. Notice that we are estimating the Legendre polynomials that model the channel. The loss function that is employed during the training phase is specified as

$$\mathbf{MSE} = \frac{1}{N_e T} \sum_{t=1}^{T} \sum_{n_e=1}^{N_e} ||\tilde{\mathbf{c}}_l^{n_e}(t) - \mathbf{c}_l^{n_e}(t)||_2^2 \tag{3.14}$$

Where N_e is the number of epochs (realizations) used to train the network, and $\mathbf{c}_l^{n_e}(t)$ is the Legendre polynomials derived from the actual channel corresponding to the $\tilde{\mathbf{c}}_l^{n_e}(t)$, which is Legendre polynomials estimated by LMMSE estimation and improved by DNN.

In the proposed structure actual channel is modeled with Legendre Polynomials. Because of that, estimated values by the network are Legendre Polynomial coefficients, not the actual channel coefficients. (Later, a DLP-BEM is employed on Legendre Polynomial coefficients to describe the time fluctuations of the channel). Coefficients of the Legendre polynomials are determined with LMMSE channel estimation, and these estimates are used as the input for the DNN's training. In contrast, Legendre polynomials derived from the actual channel are the output of DNN for the training to lower the MSE and enhance the estimation.

3.4 Simulation Results

LMMSE and SAGE-MAP algorithm-based channel estimation methods are used to compare the result of our proposed technique. SAGE-MAP algorithm employs the signal model given by (2.11) except for the pilot symbols for channel

Table 3.1 DNN Structure for Channel Estimation

Layer	**Neurons**	**f(z)**
Input Layer	30	-
Hidden Layer 1	60	tansig
Hidden Layer 2	60	tansig
Hidden Layer 3	60	tansig
Hidden Layer 4	60	tansig
Output Layer	30	purelin

Table 3.2 Training Parameters for DNN Model

Parameters	**Values**
Training Function	Resilient Backpropagation (RP)
Max. number of epoches	1000
Max. validation failures	10

estimation. SAGE-MAP is a variation of widely used Expectation Maximazition (EM) method modified by the Space Alternating Generalized EM (SAGE) algorithm, which updates subsets of parameters sequentially in one iteration. This paper won't cover the SAGE-MAP approach in length because it has been explored and used to solve several communications issues. For a general explanation of the SAGE method and its application to a problem relevant to the work presented here, see [19] and [16], respectively.

Table 3.3 displays the structural parameters for the OFDM system utilized in simulations, whereas Tables 3.2 and 3.1 display the parameters for the DNN model. We performed the simulations and compared the result under three different modulation schemes QPSK, BPSK, and 16-QAM. As a benchmark, we included LMMSE estimation, and SAGE-MAP estimation [16]. We considered an OFDM system with $M = 2$ frames, $N = 128$ subcarriers and $D_p = 6$ pilot spacing for each modulation scheme and two different scenarios for the velocities of the transmitter and receiver. In the first scenario, the mobility between the transmitter and receiver is low such that the normalized Doppler Frequency is $f_{dNorm}= 0.02$. In the second

Table 3.3 OFDM System Parameters

Parameters	**Values**
OFDM Frame Size	256
Cyclic Prefix	10
Modulations	QPSK, BPSK, 16-QAM
Max. Channel Path (L)	3
Amount of Legendre Coefficients (D)	5

scenario the mobility between the transmitter and receiver is high such that the normalized Doppler Frequency is f_{dNorm}= 0.08

The simuations results of various channel estimations to compare MSE are shown in Figs. 3.3, 3.4 and 3.5. The results under both f_{dNorm} values for a single modulation scheme are shown in each graph. The QPSK (quadrature phase-shift keying modulation), BPSK (binary phase-shit keying) and 16QAM (16-quadrature amplitude modulation) techniques are used to modulate the transmitted data in the simulations. All channel estimation techniques deliver an MSE decreasing smoothly as the SNR increases, as seen in Figs. 3.3, 3.4 and 3.5. LMMSE estimation results in the worst MSE performance in both scenarios. Because LMMSE only uses the mean and covariance matrices, it does not consider statistical channel information.

The proposed DNN-based estimation technique yields the best MSE performance at low and medium SNR levels. When the SNR level rises above 10-15 dB levels, the DNN-based estimation yields worse MSEs than the LMMSE estimation and SAGE algorithm. The reason for this might be the lack of noise influences in higher SNRs in the data that DNN is using to train the network. Since the effect of noise is more observable in lower SNRs, the neural network is more likely to train itself better to diminish the effect of noise in lower SNRs. We might also use more datasets to train the network to have a better MSE performance in higher SNRs. This way, the neural network would have more samples to observe and learn how to arrange its biases and weights for higher SNR levels.

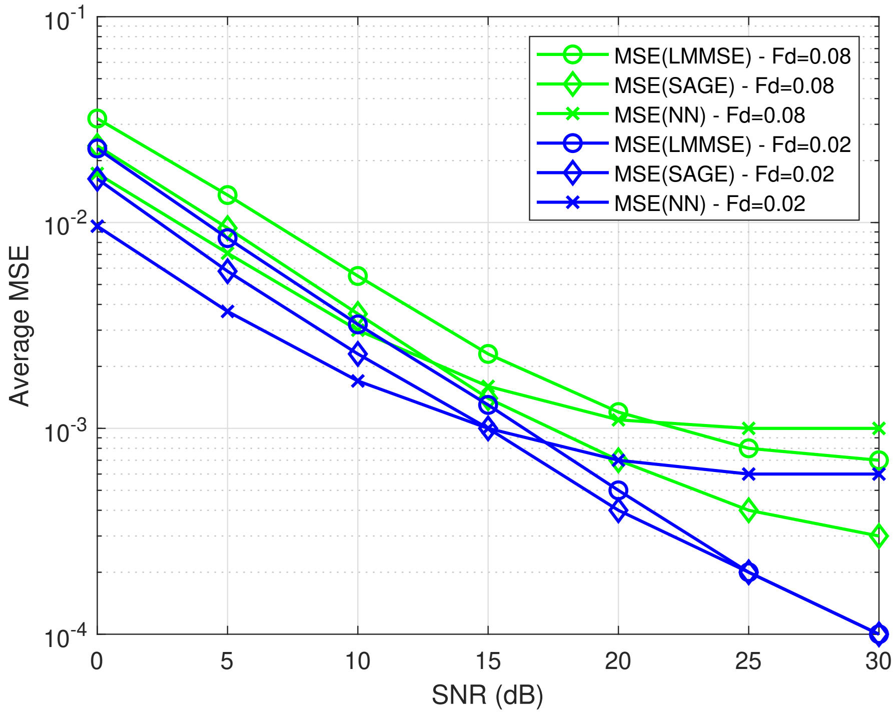

Figure 3.3 MSE curves of the channel estimations with 16-QAM modulation

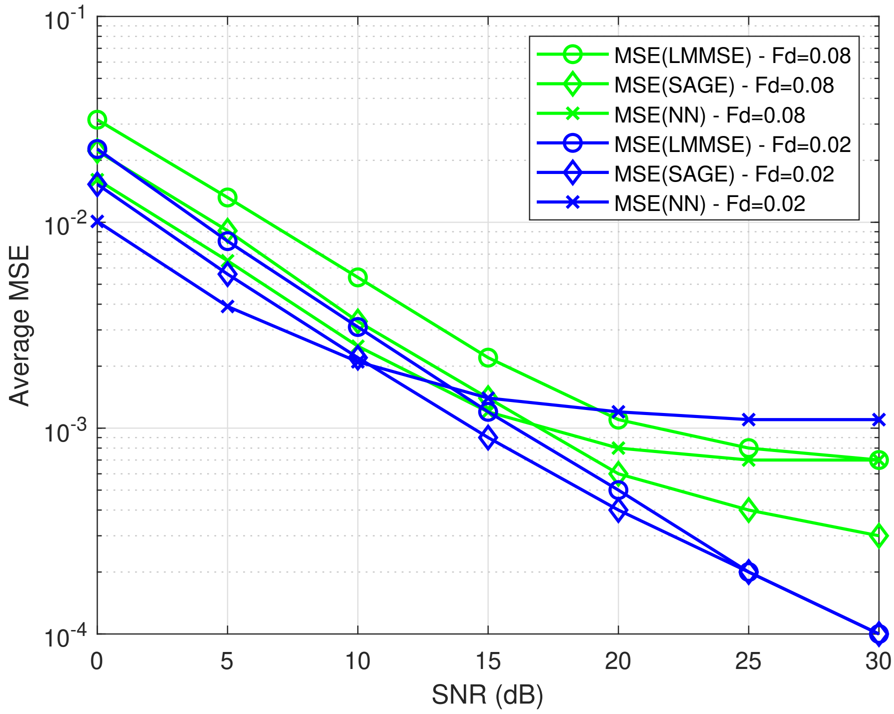

Figure 3.4 MSE curves of the channel estimations with QPSK modulation

The severity of doppler effects can also be seen in Figs 3.3, 3.4, and 3.5. In the 2. scenario, where f_{dNorm} is higher, LMMSE estimation, the SAGE algorithm, and

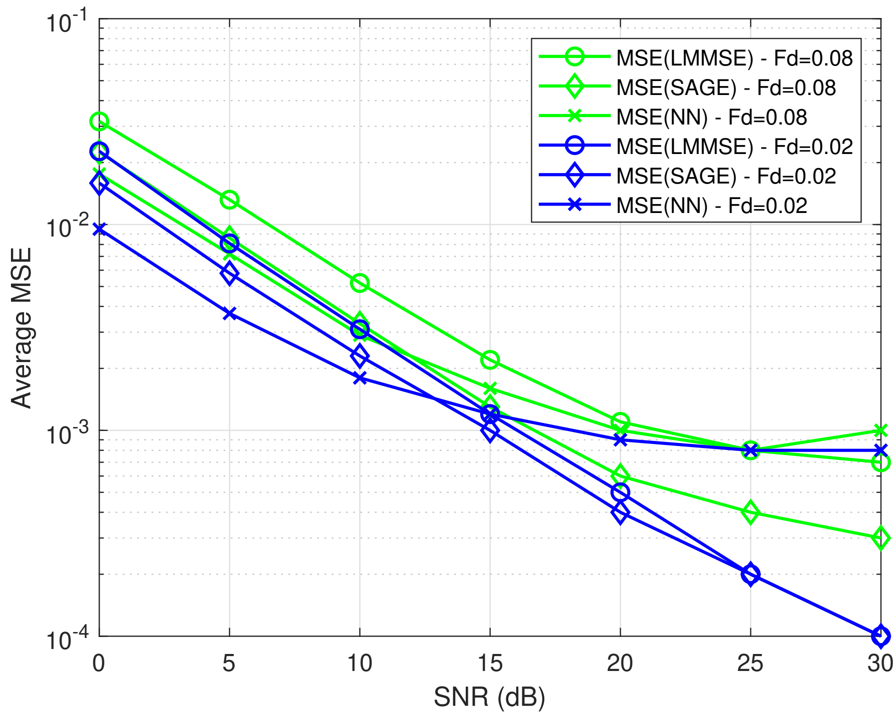

Figure 3.5 MSE curves of the channel estimations with BPSK modulation

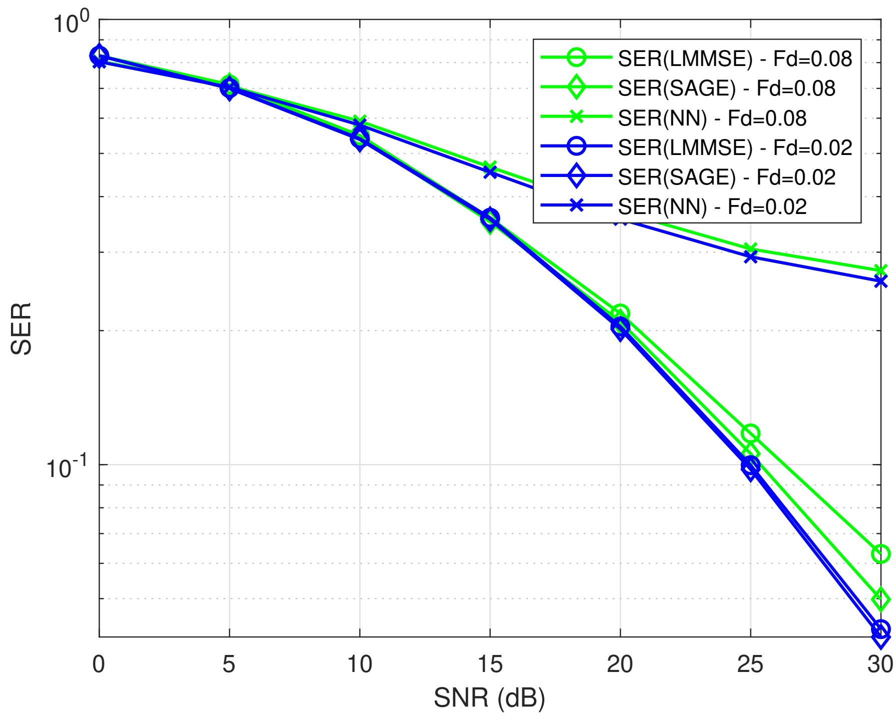

Figure 3.6 SER curves of the channel estimations with 16-QAM modulation

DNN-based estimation yield worse MSEs than their 1. scenario MSE performances. For DNN, the MSE performance recovery rate decreases as SNR increases when

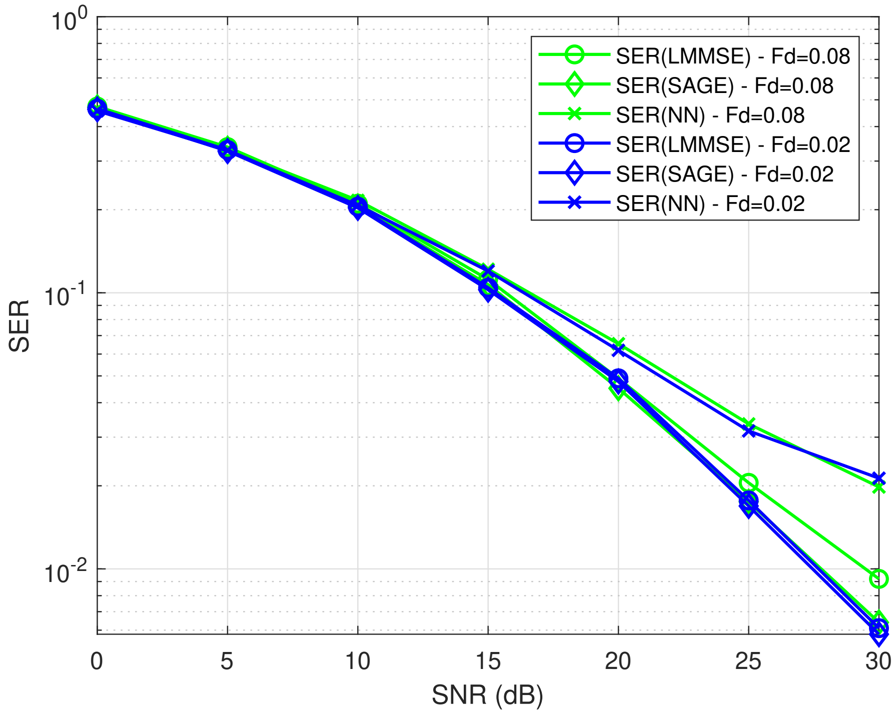

Figure 3.7 SER curves of the channel estimations with QPSK modulation

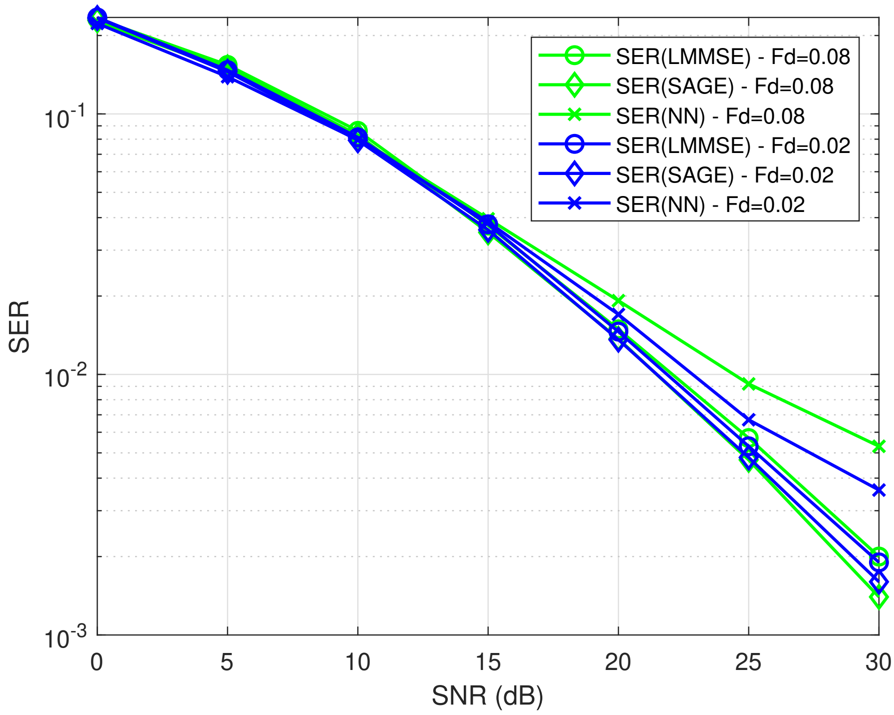

Figure 3.8 SER curves of the channel estimations with BPSK modulation

f_{dNorm} is smaller. We can also overcome this by using more datasets for the training of the network because the influence of the Doppler effect is lesser when the relative speed between the transmitter and receiver is smaller.

Figs 3.6, 3.7 and 3.8 shows the SER of various channel estimations. When we examine the SER curves, the differences between the methods are not easily seen. But even so, we can see that the DNN and SAGE algorithms perform better than LMMSE.

4. CONCLUSIONS

For OFDM systems and deep learning-based channel estimation approaches, Chapter 1 of this thesis presents a survey of the literature on channel estimation on rapidly changing channels. The thesis' significant contributions are also emphasized. The working principles of OFDM systems and channel estimation are discussed in Chapter 2. Additionally, OFDM signal and channel models for the various communication scenarios are described, along with a basis expansion model for the Legendre polynomial technique that was utilized to simulate the communication channel. Because of the high relative mobility between the receiver and transmitter, Chapter 3 introduces a new neural network-based channel estimating approach for OFDM systems that enhances LMMSE estimation. Through computer simulations, it has been demonstrated that the proposed neural network-based channel estimation approach outperforms LMMSE estimation and the SAGE algorithm, particularly at lower SNR. Computer simulations have been used to assess the MSE performance of the proposed neural network-based channel estimation approach and the BER performance in transmission for OFDM systems. On top of the LMMSE estimate, the NN-based channel estimation technique was used. Legendre polynomial coefficients of 30000, estimated by LMMSE, are input into the training process of NN, and each corresponding output data is the Legendre polynomial coefficients produced from the actual corresponding channel.

In each iteration step during the training process of NN, the neurons' weights and biases are arranged so that Legendre polynomial coefficients estimated by the LMMSE estimation are close to or the same as the coefficients derived from the actual channel. The computer simulations' results obtained are as follows:

- The NN-based channel estimation method was shown to be very effective in lowering the noise and doppler effects on the communication channel. In particular, MSE and BER performance of the proposed method in lower SNR levels are much better than the LMMSE estimation and the SAGE algorithm.
- The simulations were also carried out with three modulation schemes: QPSK, BPSK, and 16-QAM. NN-based channel estimation in lower SNR values in all scenarios is better than the LMMSE estimation and the SAGE algorithm.
- The simulations showed that at higher SNR values, MSE and BER performance are worse than the LMMSE estimation and the SAGE algorithm. The reason for this might be the following. NN has a training phase where it learns from the data belongs the actual scenarios; the data sets contain information from 0 dB to 30 dB. In lower SNR values, the effect of noise is more observable than the higher SNR values. Thus NN can accurately arrange the weights and the biases of neurons for lower SNR values, whereas it can not arrange the weights and biases for higher SNR values as well as lower values.

4.1 Future Work

In this thesis a DNN based channel estimation approach is studied for OFDM systems under time varying channel conditions. The result of this study shows that with DNN improving channel estimation performance of LMMSE estimation is possible especially for lower SNR levels. This study could be extended for DNN to perform better also at higher SNR levels.

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