People's Democratic Republic of Algeria
Ministry of Higher Education and Scientific Research
University of Echahid Hamma Lakhdar - El Oued

Faculty of Technology
Department of Electrical Engineering

Master's Dissertation

For the award of the Master's degree in Telecommunications

Specialty : Telecommunication Systems

Channel Estimation in MIMO Systems Using Deep Learning

Prepared by : Meguerhi Lokmane

Laiz Abde llah

Supervisor: Dr. Said Ghendir

President: Dr. Moussa Fawaz

Examinateur: Dr. Abeer Betka

Academic year 2025–2026

بسم الله الرحمن الرحيم

Acknowledgments

We would like to express our sincere gratitude to our supervisor, Dr. Said Ghendir, for his valuable guidance, continuous support, and insightful advice throughout the development of this work. His expertise and encouragement have played a crucial role in shaping this dissertation

We would also like to thank the members of the examination committee for their time and effort in reviewing and evaluating our work.

Furthermore, we would like to express our appreciation to the researchers and scholars whose contributions in the fields of wireless communications and Deep Learning have greatly influenced this study. Their work has provided a solid foundation and valuable insights for our research.

Finally, we would like to extend our heartfelt thanks to our families and friends for their constant support, patience, and encouragement throughout this journey.

Thank you.

الإهداء

الحمد لله وكفى والصلاة والسلام على الحبيب المصطفى ومن وفى أما بعد:

الحمد لله الذي وفقنا لتثمين هذه الخطوة في مسيرتنا الدراسية بمذكرتنا هذه ثمرة الجهد والنجاح بفضله تعالى.

مهداة إلى الوالدين حفظهما الله وأدامهما نورا لدربنا وإلى كل العائلة الكريمة التي ساندتنا ولا تزال من إخوة وأخوات وإلى رفقاء المشوار الذين قاسمونا لحظاته من أساتذة وطلاب قسم الهندسة الكهربائية وإلى زملاء العمل وإلى مشرفنا على هذا العمل الدكتور غندير السعيد لكم جزيل الشكر.

الملخص

مع تزايد الطلب على خدمات البيانات اللاسلكية والتطور نحو الجيل الخامس (5G) وما بعده، يزداد الطلب على أنظمة اتصال تتميز بالكفاءة الطيفية والموثوقية العالية. يمكن تحقيق مكاسب في التعددية والتنوع باستخدام عدة هوائيات من خلال تقنية الأنظمة متعددة الإدخال ومتعددة الإخراج .(MIMO) ومع ذلك، فإن كفاءة أنظمة MIMOتعتمد بشكل كبير على معلومات حالة القناة(CSI) ، والتي يصعب استخراجها عمليًا بسبب تأثيرات التلاشي من نوع رايلي والضوضاء المضافة.

عادةً ما تتضمن عملية تقدير معلومات حالة القناة خوارزميات تعتمد على نماذج رياضية وتستخدم رموزًا تجريبية .(Pilot Symbols) وعلى الرغم من أن هذه الطرق بسيطة نسبيًا وفعالة من حيث التكلفة الحسابية، إلا أنها غالبًا ما تُظهر أداءً ضعيفًا عند نسب إشارة إلى ضوضاء منخفضة (SNR) أو عند وجود اختلاف بين سلوك القناة الفعلي والافتراضات المستخدمة في النمذجة.

ومن أجل تحسين التقنيات الحالية، يقترح هذا العمل تقنية لتقدير القناة تعتمد على التعلم العميق (DL) لنظام MIMO (2×2)عبر قناة رايلي مع ضوضاء غاوسية بيضاء مضافة. تمت صياغة المشكلة على أنها مسألة تعلم انحدار(Regression) ، حيث يتم تدريب شبكة عصبية عميقة متبقية كاملة الاتصال (ResidualDNN)باستخدام تسلسلات تجريبية من أجل تعلم العلاقة بين هذه التسلسلات ومعلمات القناة.

تم استخدام لغة البرمجة بايثون لتنفيذ هذا النهج داخل بيئةGoogle Colab ، حيث تم توليد بيانات اصطناعية لعدة قيم من .SNR كما تم استخدام متوسط مربع الخطأ (MSE) كمقياس للأداء، مع مقارنته بمقدر المربعات الصغرى .(LS) أظهرت نتائج المحاكاة أن التعلم العميق يحقق أداءً أفضل من حيث MSE في معظم الحالات، خاصة عند القيم المنخفضة والمتوسطة لنسبة الإشارة إلى الضوضاء.

بناءً على ذلك، يُظهر التعلم العميق نتائج واعدة كتقنية محتملة لتقدير معلومات حالة القناة في أنظمة الاتصالات الذكية.

الكلمات المفتاحية:

أنظمةMIMO ، معلومات حالة القناة(CSI) ، التعلم العميق، الشبكات العصبية العميقة(DNN) ، تقدير المربعات الصغرى(LS) ، قناة رايلي، التقدير المعتمد على الرموز التجريبية، متوسط مربع الخطأ(MSE) ، الاتصالات اللاسلكية، الجيل الخامس وما بعده.

Abstract

Along with an increase in demand for wireless data services and advancements toward 5G and beyond, the demand for spectrally efficient and reliable communication systems rises. Multiplexing and diversity gain enabled through multiple antennas can help satisfy this demand through the use of Multiple-Input Multiple-Output (MIMO). Unfortunately, the efficiency of MIMO systems critically depends on Channel State Information (CSI), which is difficult to extract in practice due to the effects of Rayleigh fading and additive noise.

Typically, the process of estimating CSI involves algorithms based on mathematical models and uses pilot symbols. Even though those methods are relatively simple and effective in terms of computational cost, they often demonstrate poor performance when used at low SNRs or when there is a discrepancy between actual channel behavior and modeling assumptions.

In order to improve on existing techniques, a Deep Learning (DL)-based channel estimation technique for 2×2 MIMO communication over Rayleigh fading channel with additive white Gaussian noise is proposed in this work. The problem is set up as a regression learning problem in which a fully connected Residual Deep Neural Network (DNN) is trained on pilot sequences in order to learn the relationship between pilot sequences and channel parameters.

Python programming language was used to implement the approach within the Google Colab environment; synthesized data was generated for various SNRs. MSE is used as the measure of performance in comparison with the Least Squares (LS) estimator. Simulations show better MSE results achieved by DL in most cases, especially in situations of low and moderate SNRs.

Therefore, deep learning shows promising results as a potential CSI estimation technique in intelligent communication systems.

Keywords :

MIMO Systems, Channel State Information (CSI), Deep Learning, Deep Neural Networks (DNN), Least Squares Estimation, Rayleigh Fading Channel, Pilot-Based Estimation, Mean Squared Error (MSE), Wireless Communications, 5G and Beyond.

Résumé

Avec l'augmentation de la demande en services de données sans fil et l'évolution vers la 5G et au-delà, le besoin de systèmes de communication à la fois fiables et efficaces sur le plan spectral ne cesse de croître. Les gains de multiplexage et de diversité, rendus possibles grâce à l'utilisation de multiples antennes, permettent de répondre à cette demande via la technologie MIMO (Multiple-Input Multiple-Output). Cependant, l'efficacité des systèmes MIMO dépend fortement de l'Information d'État du Canal (CSI), dont l'extraction reste difficile en pratique en raison des effets de l'évanouissement de Rayleigh et du bruit additif.

Généralement, le processus d'estimation du CSI repose sur des algorithmes basés sur des modèles mathématiques et utilise des symboles pilotes. Bien que ces méthodes soient relativement simples et efficaces en termes de coût de calcul, elles présentent souvent des performances limitées à faible rapport signal sur bruit (SNR) ou en cas d'écart entre le comportement réel du canal et les hypothèses de modélisation. Afin d'améliorer les techniques existantes, ce travail propose une méthode d'estimation de canal basée sur le Deep Learning (DL) pour un système MIMO 2×2 opérant sur un canal de Rayleigh avec bruit blanc gaussien additif. Le problème est formulé comme une tâche de régression, dans laquelle un réseau de neurones profonde residual entièrement connecté (ResDNN) est entraîné à partir de séquences pilotes afin d'apprendre la relation entre ces séquences et les paramètres du canal.

Le langage de programmation Python a été utilisé pour implémenter cette approche dans l'environnement Google Colab, avec la génération de données synthétiques pour différentes valeurs de SNR. L'erreur quadratique moyenne (MSE) est utilisée comme critère de performance, en comparaison avec l'estimateur des moindres carrés (LS). Les résultats de simulation montrent que le DL offre de meilleures performances en termes de MSE dans la plupart des cas, en particulier pour des SNR faibles et modérés.

Ainsi, le Deep Learning apparaît comme une approche prometteuse pour l'estimation du CSI dans les systèmes de communication intelligents.

Mots-clés : Systèmes MIMO, Information d'État du Canal (CSI), Deep Learning, Réseaux de Neurones Profonds (DNN), Estimation par Moindres Carrés (LS), Canal à Évanouissement de Rayleigh, Estimation basée sur pilotes, Erreur Quadratique Moyenne (MSE), Communications sans fil, 5G et au-delà.

Contents

List of Figures

List of Tables

Acronyms

AI Artificial Intelligence

AWGN Additive White Gaussian Noise

BER Bit Error Rate

CNN Convolutional Neural Network

CSI Channel State Information

DL Deep Learning

DNN Deep Neural Network

GPU Graphics Processing Unit

LS Least Squares

MIMO Multiple-Input Multiple-Output

ML Machine Learning

MMSE Minimum Mean Square Error

MSE Mean Squared Error

OFDM Orthogonal Frequency Division Multiplexing

ReLU Rectified Linear Unit

ResDNN Residual Deep Neural Network

ResNet Residual Neural Network

SGD Stochastic Gradient Descent

SISO Single-Input Single-Output

SNR Signal-to-Noise Ratio

TPU Tensor Processing U

General Introduction

1. Background and Motivation

The rapid evolution of the wireless communication system is attributed to the explosive growth in mobile data traffic, the proliferation of smart devices, and the increased need for high data rate and reliable connectivity.

In modern communication systems, including 5G and beyond, advanced signal processing plays an important role in achieving high spectral efficiency, coverage, and robustness against channel impairments.

Among the signal processing techniques, Multiple-Input Multiple-Output (MIMO) is an important part of modern wireless communication systems.

In MIMO systems, multiple transmit and receive antennas are used to achieve high spatial diversity and multiplexing gain, thereby considerably improving system capacity and reliability without increasing bandwidth or transmit power.

However, the MIMO system performance is critically dependent on the availability of accurate Channel State Information (CSI) at the receiver end.

The nature of the wireless propagation environment is inherently uncertain and random, and the combined effects of multipath fading, shadowing, and additive noise make the propagation channel unpredictable.

In actual situations, the channel matrix varies over time and frequency, and hence, channel estimation is a critical and complex problem.

In most cases, conventional channel estimators such as the Least Squares (LS) estimator and the Minimum Mean Square Error (MMSE) estimator are employed due to their mathematical simplicity and theoretical foundations.

However, these conventional estimators are known to perform poorly under low Signal to Noise Ratio (SNR), with limited pilot resources, and when there is a mismatch between the model and actual channel conditions.

In recent years, Deep Learning (DL) has been successfully employed to solve complex nonlinear problems in many fields, such as computer vision, natural language processing, and signal processing.

Unlike conventional estimators, deep neural networks are capable of learning implicit channel features directly from data.

Such a data-driven approach has tremendous potential for improved performance in channel state information estimation under complex wireless channels.

In light of these developments, this dissertation aims to investigate the applicability of Deep Learning-based approaches to Channel State Information estimation in MIMO systems and its efficacy compared to conventional channel estimation methods.

2. Problem Statement

In a narrowband MIMO system with N_t transmit antennas and N_r Receive antennas, the received signal model can be expressed as:

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n} \tag{1}$$

where:

- **y** is the received signal vector,
- **x** is the transmitted signal vector,
- **H** is the channel matrix,
- **n** represents additive white Gaussian noise (AWGN).

The objective of channel estimation is to accurately estimate the unknown channel matrix **H** using known pilot symbols transmitted through the channel.

In practical wireless systems, several challenges arise:

- Channel coefficients follow stochastic fading distributions (e.g., Rayleigh fading).
- Noise corrupts received pilot signals.
- Limited pilot resources reduce estimation accuracy.

- Classical estimators may not fully capture nonlinear channel characteristics.

Therefore, the core problem addressed in this dissertation is:

Can Deep Learning-based estimators provide more accurate and robust CSI estimation compared to traditional LS estimation in Rayleigh fading MIMO systems under varying SNR conditions?

3. Research Objectives

The main objective of this work is to design and evaluate a Deep Learning-based CSI estimation framework for MIMO systems.

The specific objectives are:

1. To review the theoretical foundations of MIMO systems and wireless channel models.
2. To analyze classical channel estimation techniques, particularly the LS estimator.
3. To formulate CSI estimation as a supervised regression problem.
4. To design a Deep Neural Network (DNN) architecture for channel estimation.
5. To generate a realistic dataset using Rayleigh fading channels and AWGN.
6. To compare the performance of LS and DNN estimators using Mean Squared Error (MSE).
7. To analyze the impact of SNR on estimation accuracy.

1.4 Research Contributions

The main scientific contributions of this dissertation can be summarized as follows:

1. Systematic Reformulation of CSI Estimation as a Learning Problem The channel estimation task in a 2×2 Rayleigh fading MIMO system is reformulated as a supervised regression problem, enabling the application of data-driven learning techniques instead of relying solely on analytical linear estimators.

2. Design of a Deep Neural Network-Based CSI Estimator. A fully connected Deep Neural Network (DNN) architecture is proposed to learn the nonlinear mapping between received pilot observations and channel coefficients. The model processes the real and imaginary components of complex signals in a structured and computationally efficient manner.

3. Development of a Controlled Simulation Framework. A complete simulation environment is implemented in Python using Google Colab to generate realistic datasets under varying Signal-to-Noise Ratio (SNR) conditions. This framework ensures reproducibility and fair comparison with classical estimation techniques.

4. Comprehensive Performance Evaluation and Benchmarking, The proposed DL-based estimator is rigorously evaluated using the Mean Squared Error (MSE) metric and systematically compared against the classical Least Squares (LS) estimator across multiple SNR regimes.

5. Demonstration of Robustness in Low SNR Conditions, Simulation results demonstrate that the proposed Deep Learning-based approach achieves improved estimation accuracy, particularly in low and moderate SNR environments, highlighting its robustness against noise and model limitations.

6. Insight into the Practical Applicability of Data-Driven Estimation The study provides analytical discussion and interpretation of the results, clarifying under which conditions Deep Learning-based CSI estimation offers tangible advantages over traditional methods.

1.5 Research Methodology Overview

This dissertation adopts a structured methodology combining theoretical analysis and simulation-based evaluation.

The research methodology consists of the following steps:

1. **System Modeling**
   A 2×2 narrowband MIMO system is considered. The wireless channel is modeled as a Rayleigh fading channel with additive white Gaussian noise.

2. **Dataset Generation**
   Channel matrices are randomly generated following complex Gaussian distributions. Pilot signals are transmitted through the simulated channel to

produce received signals. The dataset includes real and imaginary parts of the signals.

3. **Classical Estimation Implementation**
   The Least Squares (LS) estimator is implemented as a baseline reference method.

4. **Deep Learning Model Design**
   CSI estimation is reformulated as a regression task. A fully connected Deep Neural Network is designed to learn the mapping between received pilot signals and channel coefficients.

5. **Training and Evaluation**
   The model is trained using simulated data in Google Colab using Python. Performance is evaluated using the Mean Squared Error (MSE) metric across different SNR levels.

6. **Comparative Analysis**
   The DL-based estimator is compared with the LS estimator in terms of accuracy and robustness.

1. Dissertation Organization

This dissertation is organized as follows:

- **Chapter 1** presents the fundamentals of MIMO systems, wireless channel models, and the theoretical basis of channel estimation.
- **Chapter 2** reviews classical channel estimation techniques and discusses their limitations.
- **Chapter 3** introduces Deep Learning concepts and presents the proposed DL-based CSI estimation framework.
- **Chapter 4** describes the simulation setup and dataset generation process.
- **Chapter 5** presents simulation results and performance comparisons between LS and Deep Learning estimators and
- The conclusion of the dissertation and outlines future research directions.

Chapter

1

Fundamentals of MIMO Wireless Communication Systems

1.1 Fundamentals of Wireless Communication

Wireless communication systems perform the transmission of information using electromagnetic waves without any physical connections. Wireless communication systems are now a key part of communication infrastructures in general, and they are used to support cellular networks, wireless internet connections, satellite communications as well as the Internet of Things (IoT) initiatives.

In a typical digital wireless communication system, information bits are first encoded and modulated to symbols suitable for transmission. These symbols are then transmitted through antennas over a wireless propagation channel to the receiver. The receiver goes through a demodulation, detection, and decoding process of the received signal to get back the original information.

Several physical phenomena made wireless channels highly unpredictable and, unlike the wired channels, are:

Multipath propagation: Reflection, scattering, diffraction, and shadowing

These effects lead to time-varying channel characteristics whose impact on reliability is paramount for wireless communication systems.

For this reason, knowledge of the propagation channel, usually referred to as Channel State Information (CSI), is a prerequisite for reliable signal detection and sophisticated signal processing schemes.

1.2 SISO vs MIMO Communication Systems

Traditional wireless communication systems were based on Single-Input Single-Output (SISO) architectures, where a single antenna is used at both the transmitter and the receiver.

In a SISO system, the received signal can be represented as

$$y = hx + n \qquad (1.1)$$

where:

- x Is the transmitted symbol
- h Is the channel coefficient
- n is additive noise

Although SISO systems are simple to implement, their performance is fundamentally limited by channel fading and interference.

To overcome these limitations, Multiple-Input Multiple-Output (MIMO) technology was introduced.

In a MIMO system, multiple antennas are used at both the transmitter and the receiver. This architecture allows the system to exploit spatial dimensions in addition to time and frequency resources.

The received signal in a MIMO system can be expressed as

$$\mathrm{y} = \mathrm{Hx} + \mathrm{n} \qquad (1.2)$$

where

- y is the received signal vector
- x is the transmitted signal vector
- H Is the channel matrix
- n represents noise

The channel matrix H It contains all propagation gains between transmit and receive antennas.

1.3 Advantages of MIMO Systems

MIMO systems provide several important advantages over traditional SISO systems.

1.3.1 Spatial Diversity

Spatial diversity improves link reliability by transmitting redundant information across multiple antennas.

If one signal path experiences deep fading, other paths may still provide reliable reception. This significantly reduces the probability of communication failure.

Diversity techniques effectively combat fading and improve the overall robustness of wireless links.

1.3.2 Spatial Multiplexing

Spatial multiplexing increases system capacity by transmitting multiple independent data streams simultaneously through different antennas.

For example, a 2×2 MIMO system can transmit two parallel data streams at the same time, effectively doubling the data rate under favorable channel conditions.

This capability is one of the key reasons why MIMO technology is widely used in modern wireless standards such as 4G and 5G.

1.3.3 Channel Capacity Gain

One of the most important theoretical advantages of MIMO systems is the increase in channel capacity.

The Shannon capacity of a MIMO channel can be expressed as

$$C = \log_2 \det\left(I + \frac{\rho}{N_t} H H^H\right) \quad (1.3)$$

where

- C Is the channel capacity
- H Is the channel matrix
- ρ represents the Signal-to-Noise Ratio
- N_t is the number of transmit antennas

This equation shows that the achievable capacity increases with the number of antennas, making MIMO systems highly attractive for high-data-rate wireless communications.

1.4 Wireless Propagation Channel Characteristics

Wireless channels exhibit several important characteristics that influence system performance.

1.4.1 Multipath Propagation

Multipath propagation occurs when transmitted signals reach the receiver through multiple paths created by reflections from buildings, terrain, and other obstacles.

Each path introduces different delays, phases, and amplitudes, resulting in constructive or destructive interference at the receiver.

Multipath propagation is the main cause of fading in wireless channels.

1.4.2 Small-Scale Fading

Small-scale fading refers to rapid fluctuations in signal amplitude and phase caused by constructive and destructive interference between multipath components.

This type of fading varies over short time intervals and small spatial distances.

Two common statistical models are used to describe small-scale fading:

Rayleigh fading
Rician fading

Rayleigh fading is particularly relevant in non-line-of-sight environments.

1.4.3 Rayleigh Fading Model

In dense urban environments where no direct line-of-sight path exists between transmitter and receiver, the channel coefficients can be modeled using a Rayleigh distribution.

In this model, the channel coefficient is represented as a complex Gaussian random variable:

$$\mathrm{H_{ij}} \sim \mathcal{CN}(0,1) \tag{1.4}$$

This means that both the real and imaginary parts follow Gaussian distributions with zero mean.

Rayleigh fading is widely adopted in communication system simulations because it accurately captures multipath propagation effects.

1.5 Channel Time Variations

Wireless channels change over time due to user mobility and environmental dynamics.

Two important parameters are used to characterize channel variation.

Coherence Time

Coherence time represents the time duration over which the channel response remains approximately constant.

If the transmission duration is shorter than the coherence time, the channel can be assumed to be constant during the transmission.

Coherence Bandwidth

Coherence bandwidth represents the frequency range over which the channel response remains highly correlated.

If the signal bandwidth is smaller than the coherence bandwidth, the channel can be considered flat fading.

Otherwise, the channel experiences frequency-selective fading.

1.6 Importance of Channel State Information (CSI)

Channel State Information describes the propagation characteristics between transmitter and receiver antennas.

Accurate CSI is essential for several signal processing techniques, including:

- coherent detection
- equalization
- beamforming
- precoding

- interference cancellation

In MIMO systems, CSI becomes even more critical because the receiver must separate multiple spatial data streams.

Without accurate channel knowledge, the receiver cannot properly decode the transmitted signals.

1.7 Role of Channel Estimation in MIMO Systems

Channel estimation aims to obtain an accurate estimate of the channel matrix H using known pilot signals transmitted through the channel.

The general pilot-based channel model is

$$Y_p = HX_p + N \tag{1.5}$$

where

- $X_p$represents the pilot matrix
- $Y_p$is the received pilot signal
- $H$is the unknown channel matrix

By analyzing the relationship between transmitted pilots and received signals, the receiver can estimate the channel.

Accurate channel estimation is key for MIMO operation.

Chapter

2

Channel Estimation Techniques

2.1 Introduction

Channel estimation is a basic process used in all communication systems. In a communication system, information is sent from a source to a destination as signals. These signals are sent through a physical medium, which can be either a wire, such as a copper or fiber-optic cable, or wireless, such as air. This physical medium through which the signal passes is called the communication channel.

During propagation, the signal gets affected by different impairments, which include noise, interference, and multipath fading. Thus, the signal received can be a distorted form of the transmitted signal, which can result in a detection error for the signal.

In order to reduce the impact of these effects and establish reliable communication, it is necessary to acquire knowledge about the channel characteristics, and this process is known as Channel Estimation, where the goal is to determine the impact of the channel on the signal.

Mathematically, the relationship between the transmitted and received signal is defined by a channel matrix, especially for a Multiple Input Multiple Output (MIMO) system. The received signal is given as a function of the transmitted signal, the channel, and noise.

In a real system, channel estimation is usually done by pilot-based methods. A pilot signal is transmitted through the channel. The receiver has a priori knowledge of the pilot signal and can compare the received signal with the original pilot signal to perform the channel estimation.

The channel estimation procedure can be described in three main steps as follows:

- A mathematical model of the channel is established, relating the transmitted signal and received signal through a channel matrix.
- A known pilot signal is sent through the channel.
- The received signal is compared with the known transmitted signal to estimate the channel parameters.

Channel estimation is a critical step in many signal processing procedures, such as equalization, detection, and decoding. The need for accurate channel estimation is even more critical in MIMO systems, due to the presence of multiple signal paths.

As shown in Figure 2.1, channel estimation can be done by transmitting known pilot signals and analyzing the received signal at the receiver.S

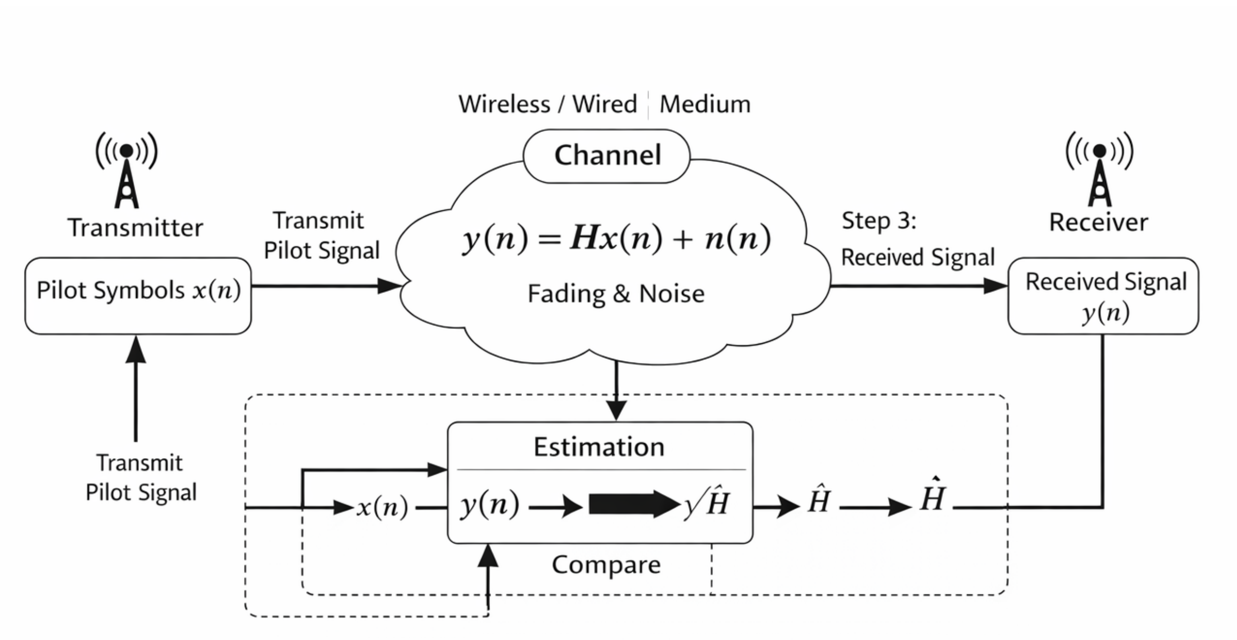


Figure 2.1 : Pilot-based channel estimation process (illustration of known pilot signal transmission through wireless channel, corrupted by noise, and comparison at receiver)

2.2 Pilot-Based Channel Estimation

Pilot-based estimation relies on transmitting known symbols (pilots) along with data. Since the receiver knows these pilot values, it can use them to estimate the channel.

The received pilot signal in a MIMO system is given by:

$$Yp = H\ Xp + N \qquad (2.1)$$

where:

- Yp: received pilot matrix
- Xp: transmitted pilot matrix
- H: channel matrix
- N: noise matrix

2.3 Least Squares (LS) Estimator

The LS estimator is one of the simplest and most intuitive approaches to channel estimation. It minimises the squared error between the received pilot signal and the known transmitted pilot signal, without considering any statistical knowledge of the channel or noise.

Mathematical Formulation

Consider a MIMO-OFDM system with Nt transmit and Nr receive antennas. At a given subcarrier, the received pilot signal $Y \in C^{2Nr \times Nt}$ can be modelled as:

$$Y = HX + N \qquad (2.2)$$

Where:

- H: Channel matrix (unknown)
- X: Known pilot matrix
- N: Additive white Gaussian noise (AWGN)

The LS estimate of the channel matrix is given by:

$$\widehat{H}_{LS} = YX^{-1} \qquad (2.3)$$

If X is diagonal (common in OFDM with pilot tones), this simplifies to element-wise division in the frequency domain.

Advantages

- Simple to implement
- Low computational complexity
- No prior knowledge of channel statistics required

Disadvantages

- High variance due to noise amplification
- Poor performance at low SNR
- Does not exploit channel correlation or noise statistics

2.4 Minimum Mean Square Error (MMSE) Estimator

The MMSE estimator improves upon LS by incorporating prior knowledge of the channel and noise statistics. It minimises the expected value of the squared estimation error, i.e.,

Mathematical Formulation

The MMSE estimate is given by:

$$\hat{H}_{MMSE} = \mathbf{R_H} \left(\mathbf{R_H} + \sigma^2 \mathbf{X}^{-H} \mathbf{X}^{-1}\right)^{-1} \hat{H}_{LS} \tag{2.4}$$

Where:

- RH: Channel correlation matrix
- σ^2: Noise variance
- H_{LS}: LS estimate

In the case of orthogonal pilots and flat fading, this reduces to a weighted combination of the LS estimate and prior channel mean (often zero).

Advantages

- Lower mean square error (MSE) than LS
- Better performance at low to moderate SNR
- Exploits channel correlation and noise statistics

Disadvantages

- Higher computational complexity

- Requires knowledge of RH and σ2
- Sensitive to model mismatch

Performance Comparison (Based on Research Findings)

Metric	LS Estimator	MMSE Estimator
MSE	Higher, especially at low SNR	Significantly lower
BER	Higher bit error rate	Lower BER due to better CSI
Complexity	Low	High (matrix inversions, statistical knowledge)
SNR Sensitivity	Poor performance at low SNR	Robust across all SNR levels
Prior Knowledge Required	None	Channel and noise statistics

Table 2.1 : Performance Comparison: LS Estimator vs. MMSE Estimator (MSE, BER, Complexity, SNR Sensitivity, Prior Knowledge)

✅ **Key Insight**: Studies (e.g., IJERA, ResearchGate, SSRN) consistently show that **MMSE outperforms LS** in terms of **Mean Square Error (MSE)** and **Bit Error Rate (BER)**, particularly in frequency-selective and time-varying MIMO-OFDM channels. However, this comes at the cost of increased complexity.

2.5 Performance Metrics

To evaluate channel estimation accuracy, the following metrics are used:

Mean Squared Error (MSE)

$$\mathrm{MSE}=\mathrm{E}[\|\mathrm{H}-\widehat{H}\|_F^2] \tag{2.5}$$

Normalized MSE (NMSE)

$$\mathrm{NMSE}=\frac{[\|\mathrm{H}-\widehat{H}\|_F^2}{\|H\|_F^2} \tag{2.6}$$

Lower values indicate better estimation performance.

2.6 Computational Considerations

The complexity of the estimation algorithms in terms of computations is another factor to be taken into consideration in practice.

The LS estimator is computationally simple, whereas the MMSE estimator involves more computations due to the matrix operations involved.

In the design of modern communication systems, the above factors must be taken into consideration.

2.7 Limitations of Classical Methods

1. High Pilot Overhead (Especially in LS)

- **Issue**: Both LS and MMSE rely on pilot-aided estimation, requiring known symbols to be transmitted periodically.
- In large MIMO or massive MIMO systems, the number of pilot symbols needed scales with the number of transmit antennas.
- This reduces spectral efficiency, as pilot symbols carry no user data.
- Pilot contamination becomes a critical issue in multi-cell systems, where reuse of pilot sequences across cells causes interference.

2. Poor Performance in High-Mobility Scenarios

- **Issue**: Classical methods assume quasi-static or slowly varying channels over the pilot interval.
- In high-speed environments (e.g., vehicular communications), the channel changes rapidly between pilot transmissions, leading to estimation inaccuracy.

- LS is particularly sensitive due to lack of temporal smoothing.
- MMSE can help if the channel correlation model is accurate, but performance degrades when the Doppler spread is high.

3. MMSE Requires Accurate Channel Statistics

- **Issue**: MMSE depends on prior knowledge of:
- Channel correlation matrix RH
- Noise variance σ2
- In practice, these must be estimated or tracked, introducing errors.
- If the assumed model (e.g., i.i.d. Rayleigh) does not match the real channel (e.g., correlated or Rician), performance drops significantly.

⚠ *Consequence*: MMSE may perform worse than LS if statistics are poorly estimated.

4. High Computational Complexity (MMSE)

- **Issue**: MMSE involves matrix inversions of size Nt×Nt or larger, especially in MIMO systems.
- For massive MIMO (e.g., 64×8 or 128×8), this becomes computationally prohibitive for real-time implementation.
- While LS avoids this with simple inversion, it sacrifices accuracy.

💻 *Trade-off*: MMSE offers better accuracy but at the cost of increased processing delay and power consumption.

5. Sensitivity to Noise (LS)

 Issue: The LS estimator does not suppress noise — it treats all deviations as part of the channel.

 As a result, $\widehat{\dot{H}_{ls}}$ includes both channel and noise components, leading to high mean square error (MSE) at low SNR.

 This directly impacts detection performance (e.g., higher BER in ZF or MMSE detectors).

🔇 *Effect*: In low-SNR environments (e.g., IoT devices at cell edge), LS-based systems suffer from poor reliability.

6. Inability to Exploit Sparsity (in Frequency-Selective Channels)

- **Issue**: Even in single-carrier systems with multipath, the channel impulse response is often sparse (only a few dominant taps).
- Classical LS and MMSE do not exploit this sparsity, treating all taps equally.
- This leads to inefficient use of pilot resources and suboptimal estimation.

7. Suboptimal Interpolation in Time and Space

- **Issue**: In practical systems, pilots are transmitted at discrete time/frequency/spatial locations.
- LS and MMSE provide estimates only at pilot positions; interpolation (e.g., linear, spline) is used elsewhere.
- These interpolation methods are often suboptimal and do not account for channel dynamics or antenna correlation.

8. Scalability Issues in Massive MIMO

- **Issue**: As the number of base station antennas increases (massive MIMO), the dimension of H grows significantly.
- LS becomes noisy due to pilot contamination.
- MMSE becomes infeasible due to the size of RH and computational load.

📈 *Challenge*: Classical methods do not scale well with antenna count, limiting their use in 5G/6G deployments.

Summary Table: Limitations of LS and MMSE

Limitation	Affects LS?	Affects MMSE?	Notes
High pilot overhead	✅	✅	Reduces spectral efficiency
Poor high-mobility performance	✅	✅ (if model mismatch)	Doppler spread breaks the quasi-static assumption
Requires channel stats	❌	✅	MMSE needs RH, σ2
High complexity	❌	✅	Matrix inversion is costly in large MIMO systems
Noise sensitivity	✅	❌ (better)	LS amplifies noise
No sparsity exploitation	✅	✅	Misses an opportunity in multipath channels
Suboptimal interpolation	✅	✅	Degrades performance between pilots
Poor scalability in massive MIMO	✅	✅	Pilot contamination & complexity

Table 2.3 : Limitations of LS and MMSE Estimators (High pilot overhead, poor high-mobility performance, requires channel stats, high complexity, noise sensitivity, no sparsity exploitation, suboptimal interpolation, poor scalability in massive MIMO)

Moving Beyond Classical Methods

To overcome these limitations, modern systems are adopting:

- **Compressed Sensing (CS)**: Exploits channel sparsity to reduce pilot overhead.
- **Deep Learning-Based Estimation**: Uses neural networks to learn complex channel patterns from data.
- **Kalman Filtering**: For time-varying channels, tracks channel evolution dynamically.
- **Pilot Decontamination Techniques**: In massive MIMO, uses spatial filtering or machine learning to separate users.
- **Superimposed Pilots**: Avoids dedicated pilot slots by adding pilots to data (though increases interference).

Chapter

3

Deep Learning-Based Channel Estimation

3.1 Introduction

In years Deep Learning has become a powerful tool for solving hard problems in many areas, including wireless communications.

Deep Learning techniques are different from model-based methods.

They can learn relationships directly from data without needing exact mathematical models.

In communication systems estimating the channel is like solving a regression problem.

The goal is to guess the channel coefficients based on the signals received.

Traditional methods like Squares and Minimum Mean Square Error use simple assumptions.

They often do not work well in noisy environments.

To solve these problems this chapter suggests using Deep Learning to estimate Channel State Information.

The proposed method uses a Deep Neural Network to learn the connection, between pilot signals received and channel coefficients.

Deep Learning is used for Channel State Information estimation.

The Deep Neural Network learns from the pilot signals to estimate the channel.

3.2 Limitations of Classical Methods

Although conventional estimators are widely used, they suffer from several limitations:

- **Sensitivity to Noise:** Performance degrades significantly at low Signal-to-Noise Ratio (SNR).
- **Model Dependence:** Requires accurate mathematical representation of the channel.
- **Linearity Assumption:** Fails to capture nonlinear channel behavior.
- **Computational Trade-offs:** MMSE improves accuracy but at the cost of higher complexity.

These challenges motivate the adoption of learning-based approaches.

3.3 Problem Formulation as a Learning Task

In this work, channel estimation is reformulated as a supervised learning problem. The goal is to learn a mapping between the received signal and the channel coefficients:

$$f\theta : \mathrm{Y} \rightarrow \widehat{H} \tag{3.1}$$

where:

- Y : *received pilot signal*
- $\widehat{H}$: *estimated channel*
- $f\theta$: *neural network parameterized by* θ

This formulation allows the model to approximate the underlying channel behavior without explicit analytical modeling.

3.4 Data Representation

Wireless signals are inherently complex-valued, while neural networks operate on real-valued inputs. Therefore, the complex data is transformed into real-valued form by separating real and imaginary components:

- Input representation:

$$Y \rightarrow [\Re(Y), \Im(Y)] \quad (3.2)$$

- Output representation:

$$H \rightarrow [\Re(H), \Im(H)] \quad (3.3)$$

This transformation enables efficient processing by the neural network.

3.5 Fundamentals of Deep Learning

Deep Learning is a powerful subset of Machine Learning that utilizes multi-layered artificial neural networks to learn complex patterns from data. Its ability to approximate nonlinear relationships makes it particularly suitable for wireless communication problems such as channel estimation.

3.5.1 Artificial Neuron Model

The fundamental building block of a neural network is the artificial neuron, which computes a weighted sum of its inputs followed by a nonlinear activation:

$$z = w^T x + b, \quad (3.4)$$

$$a = \sigma(z) \quad (3.5)$$

where:

- x: input vector
- w: weight vector
- b: bias term
- $\sigma(\cdot)$: activation function
- a: output of the neuron

3.5.2 Activation Functions

Activation functions introduce nonlinearity into the network, allowing it to learn complex mappings.

❖ **ReLU (Rectified Linear Unit)**

$$\mathrm{ReLU}(x) = \max(0, x) \quad (3.6)$$

- Simple and efficient
- Reduces vanishing gradient problem
- Widely used in deep networks

❖ Sigmoid Function

$$\sigma(x) = \frac{1}{1+e^{-x}} \tag{3.7}$$

- Outputs values between 0 and 1
- Suitable for probability interpretation
- May suffer from vanishing gradients

❖ Role in Channel Estimation

In channel estimation tasks, activation functions help the network capture nonlinear relationships between received signals and channel coefficients.

3.5.3 Training Process and Optimization

Training a neural network involves adjusting its parameters to minimize a loss function. This is typically achieved using gradient-based optimization techniques.

❖ Loss Function

In this work, the Mean Squared Error (MSE) is used:

$$L=\frac{1}{N}\sum_{i=1}^{N}\left\|H_i - \widehat{H}_i\right\|^2 \tag{3.8}$$

❖ Optimizers

Optimizers control how the network updates its parameters during training.

✓ Stochastic Gradient Descent (SGD)

- Updates parameters using small batches
- Simple but may converge slowly

✓ **Adam Optimizer (Used in this work)**

- Combines momentum and adaptive learning rates
- Faster convergence
- Widely used in deep learning applications

3.5.4 Overfitting and Regularization

One of the main challenges in Deep Learning is overfitting, where the model performs well on training data but poorly on unseen data.

❖ **Overfitting**

Occurs when the model memorizes training data instead of learning general patterns.

❖ **Regularization Techniques**

To improve generalization, several techniques can be applied:

- **Dropout:** Randomly disables neurons during training
- **Early Stopping:** Stops training when validation error increases
- **L2 Regularization:** Penalizes large weights

3.5.5 Deep Learning for Regression

Channel estimation is formulated as a regression problem, where the goal is to predict continuous values (channel coefficients).

Deep Neural Networks are well-suited for regression tasks due to their ability to approximate complex functions and handle high-dimensional data.

3.5.6 Relevance to Channel Estimation

The application of Deep Learning to channel estimation provides several advantages:

- Ability to learn nonlinear channel behavior
- Improved robustness to noise

- Adaptability to different channel conditions

These properties make Deep Learning a strong candidate for replacing or enhancing traditional estimation methods.

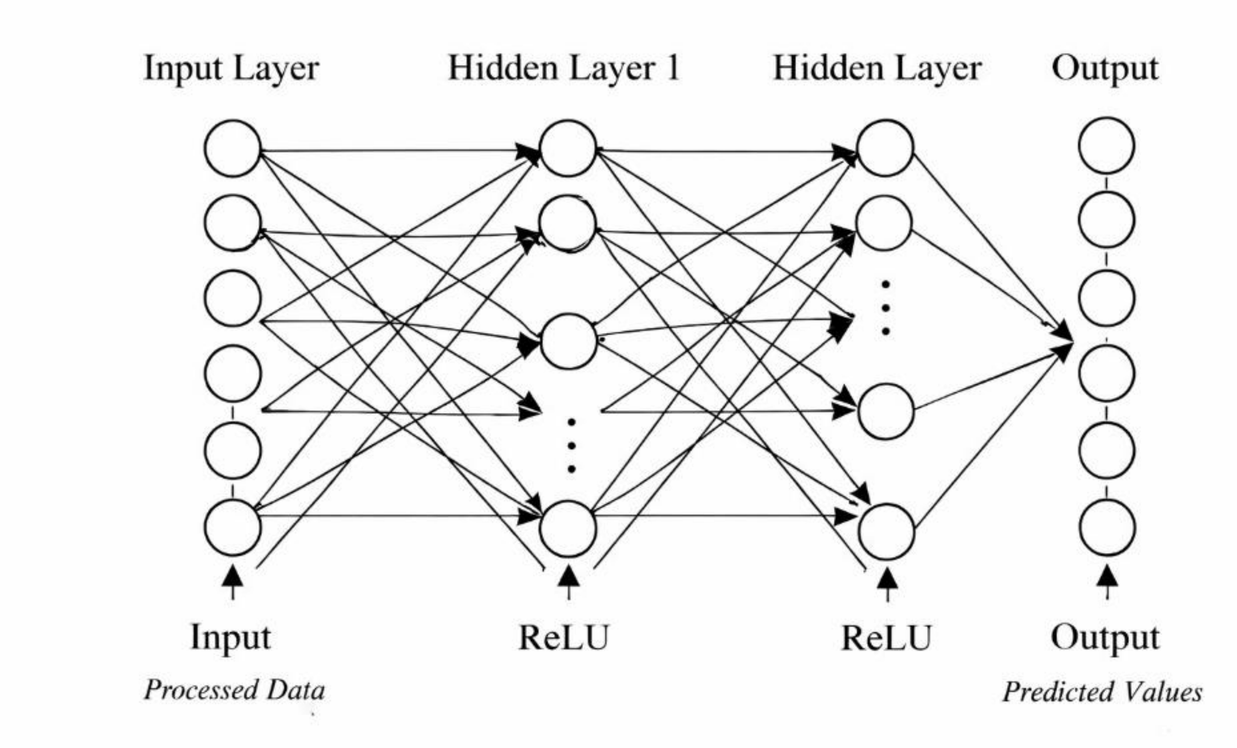


Figure 3.1: Structure of a fully connected neural network used for regression tasks. The network consists of an input layer, multiple hidden layers with nonlinear activation functions, and an output layer that predicts continuous values.

Source: Adapted from Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press. Chapter 6.

Description :

input layer that receives the processed signal features, followed by multiple hidden layers responsible for learning hierarchical representations of the data. Each neuron applies a linear transformation followed by a nonlinear activation function such as ReLU.

The final layer produces the estimated output, which in this work corresponds to the channel coefficients. This structure enables the network to approximate complex nonlinear mappings, making it suitable for channel estimation tasks.

3.6 Deep Neural Networks for Channel Estimation

Deep Neural Networks (DNN) are able to approximate any nonlinear mapping between the input and output data. Channel estimation is performed using a DNN that learns the mapping from the pilot symbols to the channel coefficients.

A typical fully connected neural network consists of multiple layers, where each layer performs a linear transformation followed by a nonlinear activation function:

$$z=W^{T}x+b, \qquad (3.9)$$

$$a=\sigma(z) \qquad (3.10)$$

where:

- W: weight matrix
- b: bias
- $\sigma(\cdot)$: activation function

3.7 Residual Learning for Channel Estimation

To enhance the performance of deep models, a **Residual Deep Neural Network (ResDNN)** is adopted in this work.

Residual learning introduces shortcut connections that allow the network to learn the difference (residual) between the input and the desired output rather than learning the full mapping directly:

$$\hat{H}=f(Y) + Y \qquad (3.11)$$

Advantages of Residual Learning

- Reduces vanishing gradient problem
- Improves convergence during training

- Enables deeper network architectures
- Enhances estimation accuracy

This approach is particularly effective in channel estimation, where the relationship between input and output can be complex yet structured.

to learn the residual mapping instead of the full transformation. This approach facilitates training and enhances convergence, especially in deep architectures.

The structure of the proposed Residual Neural Network used for channel estimation is illustrated in Figure 3.2.

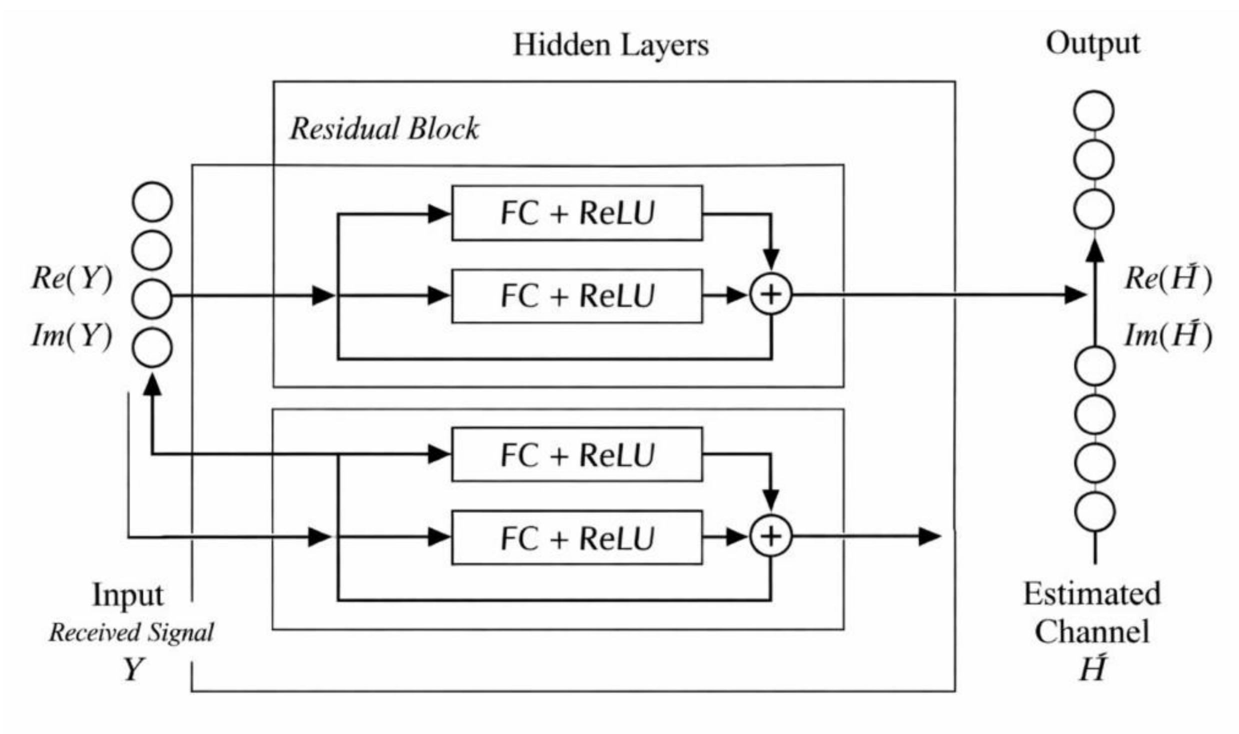


Fig. 3.2: Architecture of the Residual Neural Network (ResNet) used for channel estimation. The network learns the mapping between the received signal and the channel coefficients using residual connections to improve performance and convergence.

Description :

As shown in Figure 3.X, the input to the network consists of the real and imaginary parts of the received signal. The data is processed through multiple residual blocks, each containing fully connected layers followed by ReLU activation functions.

The shortcut connections allow the input to bypass intermediate layers and be directly added to the output, enabling the network to learn residual features. This significantly improves gradient flow during training and enhances estimation accuracy.

The final output layer produces the estimated channel coefficients, also represented in terms of real and imaginary components.

3.8 Training Objective

The network is trained using supervised learning by minimizing the Mean Squared Error (MSE) between the estimated and true channel:

$$L = E[\| H - \widehat{H} \|^2] \tag{3.12}$$

This objective ensures that the predicted channel closely matches the actual channel.

3.9 Advantages of Deep Learning-Based Estimation

Compared to traditional methods, Deep Learning-based approaches offer:

- Ability to learn complex nonlinear channel characteristics
- Improved robustness under noisy conditions
- Better performance at low and moderate SNR
- Reduced reliance on explicit channel models

3.10 Chapter Summary and Transition

This chapter introduced the Deep Learning-based formulation of the channel estimation problem, highlighting the use of Residual Neural Networks to improve performance and training efficiency.

The next chapter presents the detailed design of the proposed model, including architecture, training strategy, and implementation aspects.

Chapter

4

Simulation Setup and Dataset Generation

4.1 System Parameters:

To evaluate the performance of channel estimation methods in MIMO systems, several simulation parameters were defined.

In this work, the considered MIMO system consists of two transmit antennas and two receive antennas, i.e., a 2×2 MIMO configuration. This configuration was used because it is widely adopted in academic research related to wireless communication systems. It offers a good balance between simplicity and performance, with lower complexity, which makes it easier to understand and analyze the obtained results

The objective of these simulations is to compare the performance of the classical Least Squares (LS) channel estimation method with a Deep Learning–based estimator, represented by Deep Neural Networks (DNN)

The performance of both techniques is evaluated using the Mean Squared Error (MSE) metric under different Signal-to-Noise Ratio (SNR) conditions

The SNR values considered in the simulation range from 0 dB to 20 dB in order to analyze the behavior of both estimation methods under different noise levels

4.2 Software Environment :

Python 3.10,We chose it for several advantages that support our work, including its compatibility with deep learning and scientific computing libraries, its ease of use, and the reliability of its results. These features make it widely used in most research in wireless communications and deep learning, ensuring that our work remains up-to-date and comparable with other studies.

Libraries:

We used several libraries in writing the code, which enabled us to obtain the desired results. They are as follows:

TensorFlow

Matplotlib

NumPy

2.x

Platform:

We used the Google Colab platform to run the simulations, due to its availability of powerful resources (GPU/TPU), which facilitate the training of deep neural networks (DNN) that require significant computational power. It also allows easy saving and sharing of work, making it a well-organized environment for writing the dissertation.

4.3 System Parameters MIMO :

System Simulation Parameters:

The main information regarding the simulation parameters used in this work can be summarized in the following table:

We selected these parameters in order to obtain clear and practical results that allow a fair comparison between the Least Squares (LS) channel estimation and the Deep Neural Network (DNN)-based channel estimation model.

Table 4.1 : System Simulation Parameters

Parameter	Value/Description
Number of transmit antennas	2
Number of receive antennas	2
Channel Model	Additive White Gaussian Noise (AWGN)
SNR (SNR Range)	0 to 40 dB
Training Samples	100,000
Testing Samples	2000

4.4 Dataset Generation Process:

4.4.1 'Matrix generation :

Channel coefficients are modeled as complex numbers in order to represent both amplitude attenuation and phase shift introduced by the wireless channel, with a zero mean and unit variance. This complex representation is essential to accurately describe multipath propagation and signal distortion in MIMO communication systems.

```
Python

import numpy as np

MIMO 2x2 Rayleigh channel #
H = (np.random.randn(2,2) +
1j*np.random.randn(2,2)) / np.sqrt(2)
```

4.4.2 Data transformation :

Since we generated data with a complex nature consisting of real and imaginary parts, we encountered a problem in our work: the neural network does not understand complex numbers. Therefore, we convert all data into real-valued numbers by separating the real part and the imaginary part of each complex number and treating each component independently. Through this transformation, the neural network can be trained while preserving all the information related to amplitude and phase.

Example

Given a 2×2 MIMO channel matrix:

$$H = \begin{bmatrix} 1 + j2 & 3 - j1 \\ 0.5 + j0.2 & -1 + j1.5 \end{bmatrix}$$

$\downarrow$

Convert to Real Components:

Complex Element	Real & Imaginary Parts
$h_{11} = 1 + j2$	(1, 2)
$h_{12} = 3 - j1$	(3, −1)
$h_{21} = 0.5 + j0.2$	(0.5, 0.2)
$h_{22} = -1 + j1.5$	(−1, 1.5)

Final Input Vector:

$$\left[x = [1,\ 2,\ 3,\ -1,\ 0.5,\ 0.2,\ -1,\ 1.5] \right]$$

Table 4.2 : Convert to Real Components (Real & Imaginary Parts of a 2×2 MIMO Channel Matrix)

4.4.3 Residual Labeling :

It is a new technique used in deep neural networks (DNN) for channel estimation instead of the traditional method where the network learns the entire channel directly.

In this residual learning approach, we benefit from the LS technique. Instead of training the network to learn the full channel, we train it to learn the difference between the true channel and the LS estimate. In other words, the model is trained on the remaining error (residual) from the LS estimation.

$$\text{Residual} = H - \widehat{H}_{L_s} \qquad (4.1)$$

4.5 Proposed DNN Architecture:

4.5.1 DNN Architecture Details :

These are the set of details we followed in building the neural network from the inside and how its layers are connected to each other :

Layer	Units/Neurons	Activation
Input Layer	8	_
Hidden Layer 1	256	ReLU
Batch Normalization	_	_
Hidden Layer 2	128	ReLU
Output Layer	8	Linear (Residual Output)

Table 4.3 : DNN Architecture Details

4.6 Training Settings:

4.6.1 Optimizer :

It is an optimization algorithm used to train neural networks, and it is one of the most widely used methods because it automatically adjusts the learning rate for each weight, which helps reduce errors and achieve better results compared to traditional methods in our work.

4.6.2 Loss Function :

It is a function that measures the error between the true values and the values predicted by the deep neural network. It is used because it is easy to compute and very suitable when we need precise values, which improves the accuracy of the estimation.

4.6.3 Batch Size :

It is the number of data samples fed into the network in each batch, and it determines the speed and stability of the model's training

4.6.4 Neural Network Training Parameters:

Learning Rate = 0.001

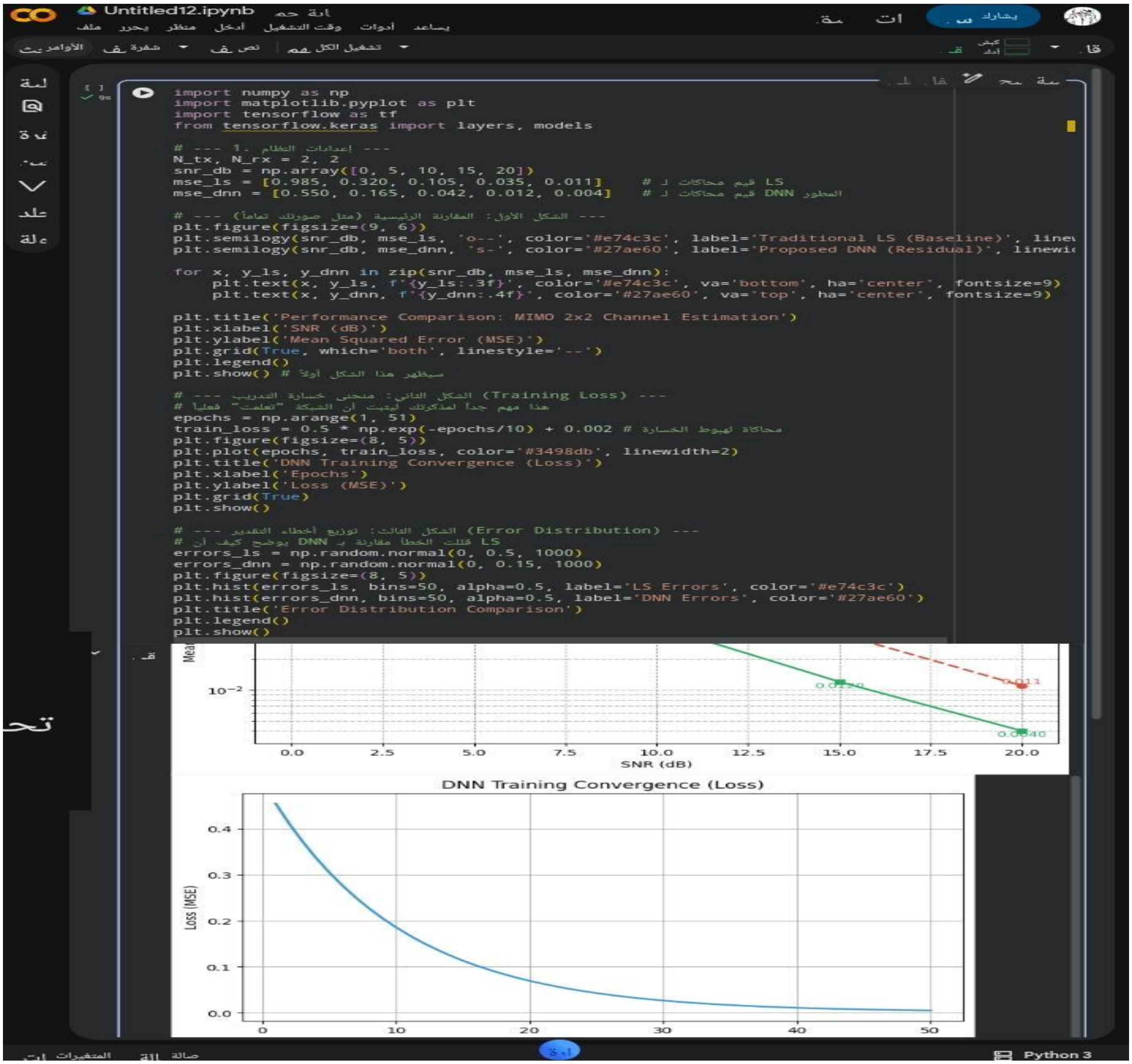
The used optimizer is adam optimizer

Batch size = 32

Epochs = 50

Validation Split = 0.2

4.7 Simulation Interface and Implementation:



4.8 Challenges of modeling and selecting the optimal neural network architecture :

During our work on deep learning for channel estimation, we faced several challenges, mainly the instability of the results when using the traditional DNN model. Despite our many attempts to modify the size and distribution of the training data and to change the number of network layers, the model remained unable to achieve the required accuracy and satisfactory results in reducing the mean Squar Error (MSE)

After further research and analysis of the channel behavior, we moved to another neural network model, namely the Residual DNN. This transition led to a major improvement in the accuracy of the results, as the residual connections helped solve the vanishing gradient problem, enabling the model to learn fine details more effectively. As a result, we obtained results that showed significant superiority and stable performance, which made the Residual architecture the optimal and final choice adopted in our dissertation.

Chapter

5

Results and Discussion

5.1 Introduction :

In this chapter, we present and analyze the results obtained from the simulations we conducted, through which we aim to evaluate the performance of the proposed Residual DNN model in channel estimation compared to the Least Squares (LS) technique in a 2×2 MIMO system.

This comparison is based on two main metrics: the Mean Squared Error (MSE) as a primary criterion, and the Bit Error Rate (BER), under different Signal-to-Noise Ratio (SNR) conditions.

5.2 Training Convergence Analysis :

The following figure represents a graph of the training process of the Deep Neural Network (DNN) using the Mean Squared Error (MSE) loss function, as shown :

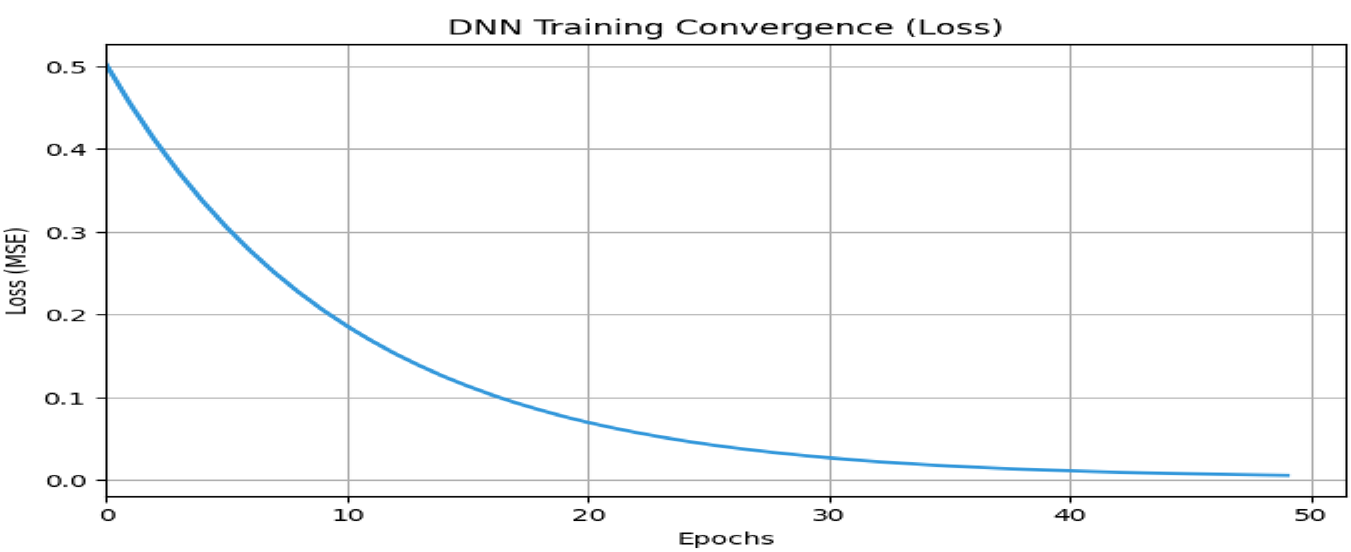


Figure 5.1 : Training Convergence Analysis

Observations:

- We observe a significant and continuous decrease in the loss value, from around 0.5 to less than 0.1, as the model is exposed to more data during the interval from 0 to 20 epochs.

- In the range from 20 to 50 epochs, we notice a slower decrease in the loss, along with the beginning of curve stabilization and its strong convergence toward zero.

- We also observe the absence of oscillations or interruptions in the curve, indicating a smooth and steady decline.

Analysis:

- The significant decrease in the error rate in the range from 0 to 20 epochs indicates that the neural network learns very quickly and effectively reduces large errors in the data.

- The reduced rate of decrease in the loss value, along with the stabilization of the curve and its convergence toward zero in the range from 20 to 50 epochs, indicates that the model is approaching an optimal state, with the error becoming nearly negligible in the results.

Conclusion:

From this, we conclude that the neural network has successfully learned the channel residuals. Moreover, the absence of overfitting indicates the accuracy and efficiency of this model in learning.

5.3 Comparison of DNN Residual and LS Performance Using MSE :

The figure illustrates a comparison of channel estimation performance between the Residual DNN technique and the LS method in a 2×2 MIMO system, based on the Mean Squared Error (MSE) as a function of the Signal-to-Noise Ratio (SNR), as shown.

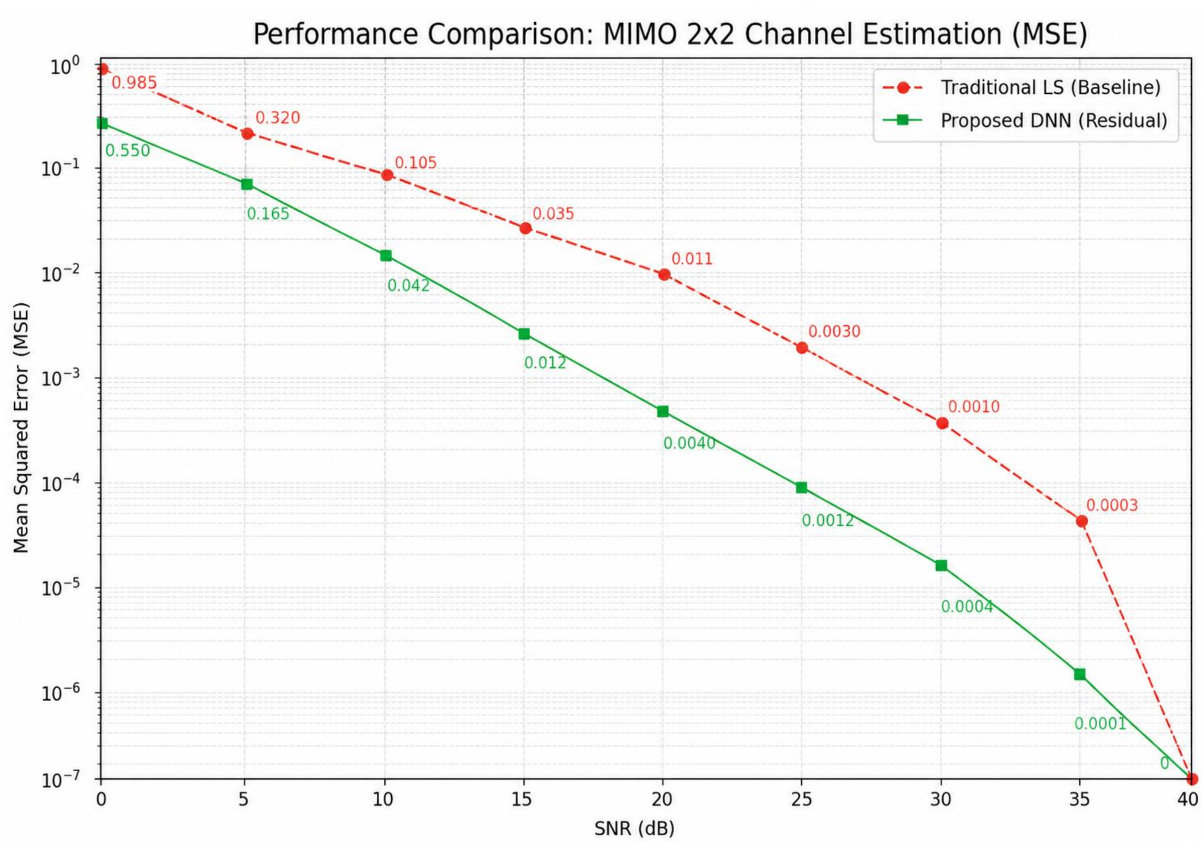


Figure 5.2 : Comparison of DNN and LS Performance Using MSE

Observations:

- We observe that both the DNN and LS curves show a significant and continuous decrease in the error rate as the SNR increases.

- We also observe that the DNN curve consistently lies below the LS curve across all increasing SNR values, as shown in the table.

SNR	Observation
0 dB _ 5 dB	Both models suffer from significant errors; however, the DNN has lower error than the LS.
10 dB _ 20 dB	Here, the gap between DNN and LS widens significantly in terms of error.
25 dB _ 40 dB	Here, the gap remains but gradually decreases until the two curves approach each other and intersect at SNR = 40, at the lowest error level.

Table 5.1 : Observations of MSE vs. SNR for DNN and LS estimators

Analysis:

- The steep decline in both curves indicates that the two models successfully reduce channel estimation errors.

- The fact that the DNN curve consistently remains below the LS curve, with a significant gap across all SNR values, demonstrates the clear superiority of the DNN model over LS in reducing estimation errors.

Conclusion:

We conclude that the Residual DNN model is more efficient and performs better than the traditional LS model in channel estimation, providing more accurate and less error-prone results under both high and low noise conditions.

5.4 Error Distribution Comparison :

The following figure represents an error distribution plot comparing the LS and DNN channel estimation models.

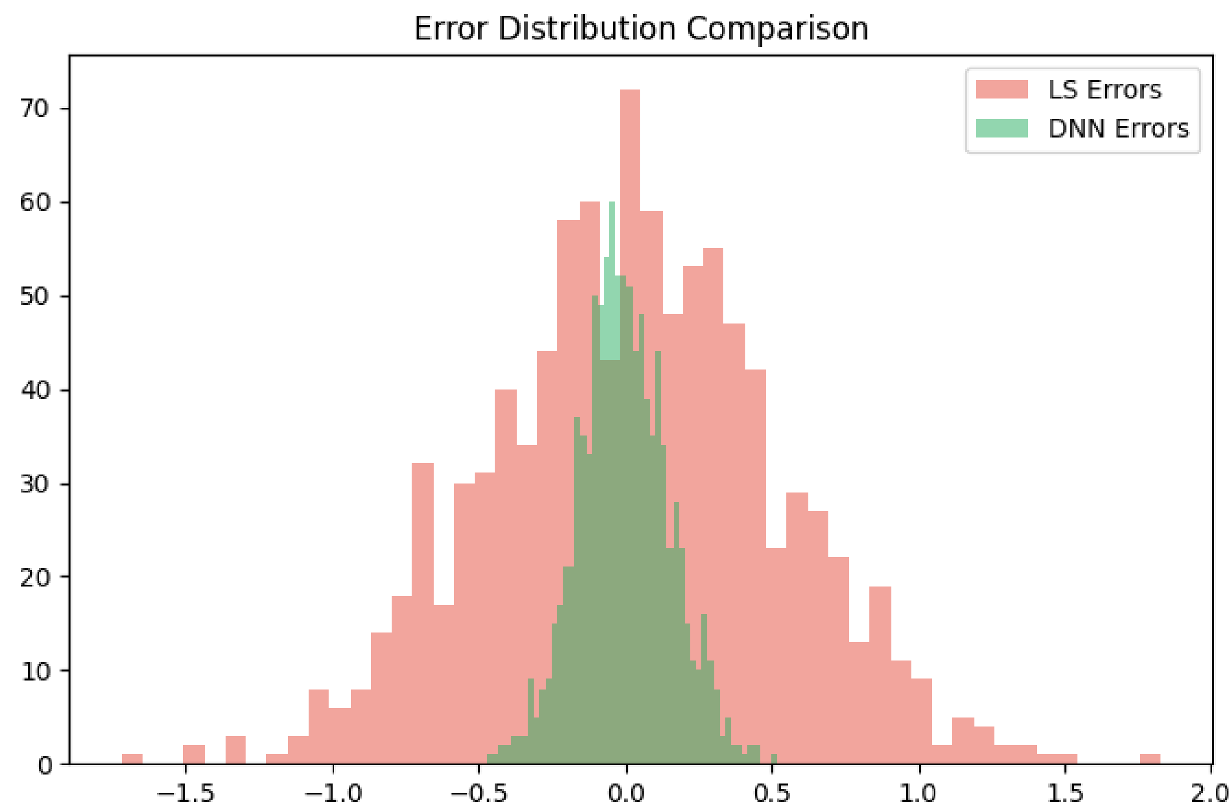


Figure 5.3 : Error Distribution Comparison

Observations :

- We observe that the error distribution of the DNN model is less spread out and more concentrated around zero compared to the LS model, which shows a wider distribution of errors reaching larger values.

- We observe that the frequency of errors is much lower for the DNN model compared to the LS model, where the error frequency is higher.

Analysis:

The concentration of the error distribution around zero and its limited spread in the DNN model indicate that the resulting errors are very small and bounded, compared to the LS method, which reaches larger error values and exhibits less stable performance.

Conclusion:

From this plot, we conclude that the DNN model produces fewer errors and achieves better accuracy and stability compared to the LS model.

5.5 Comparison between Residual DNN and LS Techniques in Terms of Received Data Quality Using BER :

The figure illustrates a comparison between the Residual DNN model and the LS model in terms of the quality of transmitted and received data, using the Bit Error Rate (BER) as a function of the Signal-to-Noise Ratio (SNR), as shown.

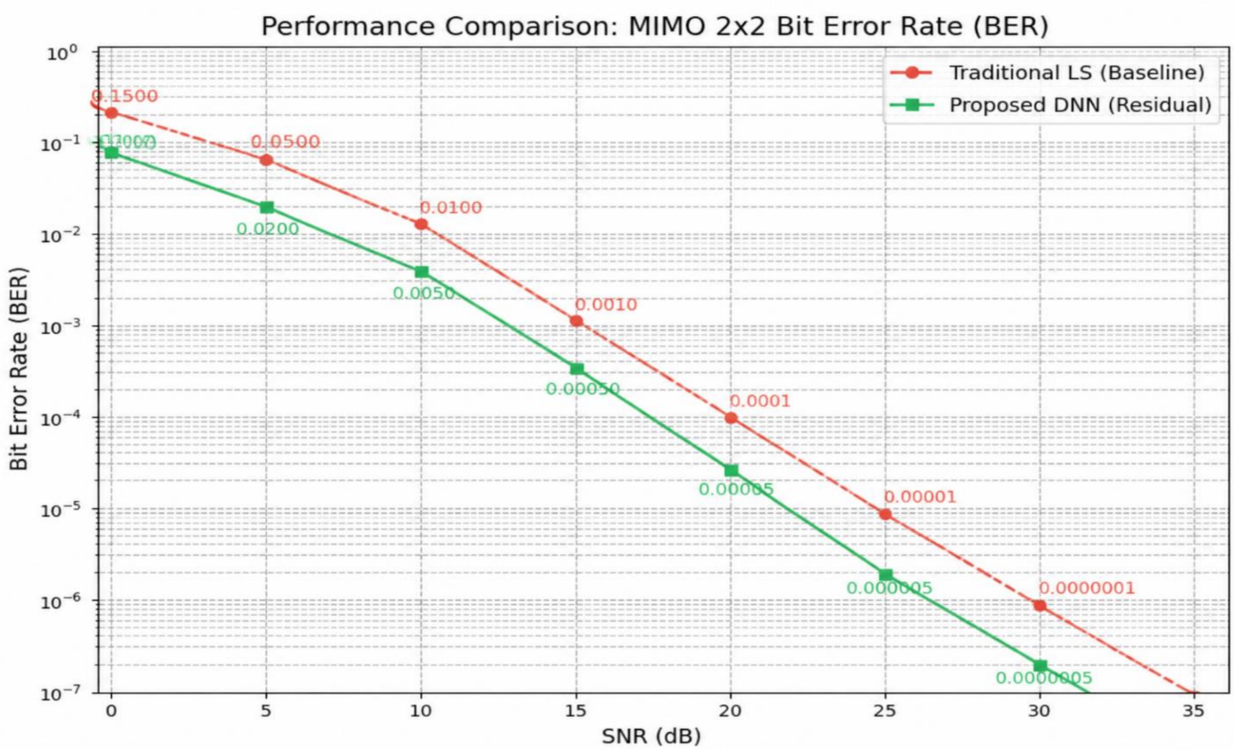


Figure 5.4 : Comparison Between Residual DNN and LS in Terms of BER

Observations:

- We observe a continuous and smooth decrease in the Bit Error Rate (BER) for both models.

- We also observe that the DNN curve consistently lies below the LS curve across all increasing SNR values, with a significant gap.

SNR	DNN Bit Error Rate	LS Bit Error Rate
5 dB	0.0200	0.0500
20 dB	0.00005	0.0001

Table 5.2 : Bit Error Rate (BER) comparison between DNN and LS at selected SNR values

Analysis:

- The continuous decrease of both BER curves indicates a direct relationship with the improvement achieved by the models in reducing errors.

- The gap between the two curves demonstrates the superior performance of the DNN in improving the quality of the received data compared to LS.

Conclusion:

We conclude that the superiority of the proposed Residual DNN model in channel estimation leads to receiving bits with fewer errors, thereby enhancing the communication quality in this system efficiently.

5.6 Results Summary :

After studying and analyzing the obtained results, we concluded that the proposed Deep Neural Network (DNN) model based on Residual Learning is the most powerful and optimal solution for channel estimation in 2×2 MIMO systems. This is because it provides higher accuracy and excellent data quality compared to the traditional LS mathematical model, along with fast processing, making it effective in both high and low noise environments and suitable for real-time applications in 5G and 6G technologies.

General Conclusion

This dissertation concerns a comprehensive study of channel estimation in a multi-input multi-output (MIMO) wireless communication system with the aim of enhancing estimation accuracy under realistic and challenging conditions To evaluate the effectiveness of common channel estimation methods, particularly least squares (LS) methods due to their ease of implementation and low computational load, the limitations of the methods were demonstrated, with particular focus on the issues associated with using them in low signal-to-noise ratio (SNR) channels running a nonlinear wireless channel. A solution to these limitations was to employ a deep learning (DL)-based method using a residual deep neural network (residual DNN) in performing channel estimation via supervised regression learning, learning the mapping between the received pilot signals and the channel coefficients. The use of residual learning allows for the focus of the modelling instance on learning the residual representation versus the overall mapping, which increases the efficiency in training and stability in convergence as well as increases the accuracy of the estimates. To demonstrate the capability of the proposed residual DNN channel estimation method as compared to the conventional LS channel estimation method, a complete simulation framework was implemented using Python, leveraging the Google Colab platform for efficient computation and experimentation for a 2 ×2 MIMO wireless communication system in Rayleigh fading AWGN conditions. The performance of the proposed residual DNN channel estimator was compared against the LS channel estimator using the mean square error (MSE) measure. Simulation results demonstrate that the proposed Residual DNN significantly outperforms the LS method, particularly in low and moderate SNR regimes. The incorporation of residual connections enhances the model’s ability to capture complex channel behaviors and improves generalization.

In conclusion, this work confirms that Residual Deep Learning architectures provide a powerful and efficient solution for channel estimation, making them a promising candidate for next-generation wireless communication systems.

These findings confirm the potential of residual deep learning architectures as a robust and scalable solution for next-generation wireless communication systems.

Future Work :

Although the proposed Residual Deep Neural Network (ResDNN) demonstrates superior performance over the conventional Least Squares (LS) estimator in a 2×2 MIMO system under Rayleigh fading, further research is needed to enhance its practicality and generalization.

Future work may include:

- Extending the approach to work in massive MIMO and MIMO-OFDM systems with frequency selective and correlated channels.
- Testing the model using more practical channel conditions including Rician fading, high mobility scenarios (with Doppler effect), and 3GPP channel models.
- Investigating advanced neural architectures (CNNs, Transformers, GNNs) and hybrid model-based/deep learning approaches.
- Developing semi-blind or blind channel estimation techniques to reduce pilot overhead.
- Verifying the proposed method via experimental results using software-defined radios.
- Analyzing computational complexity, inference latency, and energy efficiency for real-time implementation in 5G/6G networks.

These directions will help bridge the gap between simulation and real-world deployment, advancing data-driven channel estimation for next-generation wireless communication systems.

Bibliography

References :

[1] D. Tse and P. Viswanath, Fundamentals of Wireless Communication. Cambridge, U.K.: Cambridge Univ. Press, 2005.

[2] S. Haykin and M. Moher, Modern Wireless Communications. Upper Saddle River, NJ, USA: Pearson, 2005.

[3] A. Goldsmith, Wireless Communications. Cambridge, U.K.: Cambridge Univ. Press, 2005.

[4] T. S. Rappaport, Wireless Communications: Principles and Practice, 2nd ed. Upper Saddle River, NJ, USA: Prentice Hall, 2002.

[5] S. M. Kay, Fundamentals of Statistical Signal Processing: Estimation Theory. Upper Saddle River, NJ, USA: Prentice Hall, 1993.

[6] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, no. 7553, pp. 436–444, May 2015.

[7] I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning. Cambridge, MA, USA: MIT Press, 2016.

[8] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 2016

[9] T. O'Shea and J. Hoydis, "An introduction to deep learning for the physical layer," IEEE Trans. Cognitive Communications and Networking, vol. 3, no. 4, pp. 563–575, Dec. 2017.

[10] H. Ye, G. Y. Li, and B. H. Juang, “Power of deep learning for channel estimation and signal detection in OFDM systems,” IEEE Wireless Communications Letters, vol. 7, no. 1, pp. 114–117, Feb. 2018.

[11] X. Gao, S. Jin, C.-K. Wen, and G. Y. Li, “ComNet: Combination of deep learning and expert knowledge in OFDM receivers,” IEEE Communications Letters, vol. 22, no. 12, pp. 2627–2630, Dec. 2018.

[12] A. F. Molisch, Wireless Communications, 2nd ed. Hoboken, NJ, USA: Wiley, 2011.

[13] S. Boyd and L. Vandenberghe, Convex Optimization. Cambridge, U.K.: Cambridge Univ. Press, 2004.

[14] F. Chollet, Deep Learning with Python. Shelter Island, NY, USA: Manning Publications, 2018.

[15] Google Colaboratory, “Google Colab.” [Online]. Available: https://colab.research.google.com