

# An Effective Investigation on Performance Analysis of LS and MMSE Channel Estimation Methods in 5G OFDM Wireless Communication Systems

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**Abstract**—The exponential growth in wireless throughput, driven by diverse user demands for high Quality of Service (QoS), is expected to persist in the coming years. To address this, fifth-generation (5G) and beyond wireless communication systems have integrated several disruptive technologies—such as Massive MIMO and Reconfigurable Intelligent Surfaces (RIS)—to accommodate increasing wireless data traffic and ensure reliable communication. Among the enabling technologies, Orthogonal Frequency Division Multiplexing (OFDM) has played a crucial role due to its proven success in wideband communications. In fact, OFDM remains a foundational component of 5G systems, as it effectively mitigates frequency-selective fading, thereby maintaining high communication quality in multipath environments. It also significantly improves spectral efficiency compared to single-carrier schemes. However, when signals propagate through wireless multipath channels, they encounter several impairments, including large physical obstructions, multipath fading, local scattering, and mutual interference from shared time-frequency resources. To accurately decode the transmitted signal, the receiver must estimate and compensate for the effects of the channel, which requires precise channel state information (CSI). This estimation is performed using pilot signals, which are pre-known to both the transmitter and receiver. In 5G systems, the structure and placement of these pilot symbols can vary across different use cases. Among traditional channel estimation techniques, the Least Squares (LS) method is widely recognized for its low computational complexity, as it does not require prior knowledge of channel statistics. However, LS often yields higher estimation errors in practical scenarios, especially in environments with severe multipath effects. As an alternative, the Minimum Mean Square Error (MMSE) method offers improved estimation accuracy.

**Keywords:** Quality of Service (QoS), OFDM, Channel Estimation, Massive MIMO, LS, MMSE

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## I. INTRODUCTION

Machine learning (ML) has recently gained substantial attention in wireless communication applications, including radio resource allocation, signal decoding, and channel estimation. In the context of channel estimation, one study addressed the non-stationary characteristics of wireless channels by modeling channel fading vectors as conditionally Gaussian random vectors with random covariance matrices. Under such conditions, conventional MMSE estimation becomes computationally expensive, motivating the development of ML-assisted estimation methods tailored to specific channel behaviors [7]. Another study explored channel estimation within a wireless energy transfer system, leveraging downlink channel information to enhance energy harvesting via feedback. A deep neural network (DNN) was employed to generate more accurate channel estimates compared to traditional techniques such as LS and LMMSE. These works demonstrate the strong potential of machine learning in channel estimation,

assuming the availability of sufficient and representative training data. However, most of these approaches are constrained to quasi-static channel models, where channel conditions are assumed to remain constant and frequency-flat within each coherence interval. Inspired by [13], a deep learning-based joint channel estimation and signal detection technique has been proposed for uplink non-orthogonal multiple access (NOMA) systems. This method reframes multi-user signal recovery as a classification problem, allowing for simultaneous symbol detection from multiple users without explicitly estimating the channel. A DNN is trained on simulated channel data to map the received superimposed signal directly to transmitted symbols. In contrast to [13], the proposed method utilizes a Long Short-Term Memory (LSTM) network to enhance symbol detection across one or more antennas. The model's generalization capability is validated across various signal-to-noise ratios (SNRs) and diverse channel realizations, based on the 3GPP 5G channel model [6]. In terms of receiver-side processing, a low-complexity beam training strategy is introduced for millimeter-wave

(mmWave) communication systems, particularly considering the impact of receiver mobility. This strategy exploits the spatial consistency of mobile channels to reduce beam training overhead by narrowing the candidate beam set using recent beam search results. It supports spatial multiplexing to boost data rates. Unlike prior works [14][15] that ignore signal blockages, this approach evaluates beam training performance under various blockage levels and channel noise conditions, using site-specific channel data from a ray-tracing simulator. Notably, the proposed beam training method operates jointly at both the transmitter and receiver. Additionally, an intelligent beam training framework is developed using deep reinforcement learning (DRL). This framework builds upon the beam training strategy by incorporating environmental awareness, allowing the system to adaptively adjust beam training overhead. The DRL model is designed to maximize either energy efficiency (EE) or spectral efficiency (SE), dynamically selecting beam training policies to optimize performance. Unlike [16][17], the proposed DRL model maintains a fixed state and action vector size, independent of the antenna array size, which enhances scalability for mmWave systems. Furthermore, the beam training strategy is extended to intelligently control the number of activated radio frequency (RF) chains based on real-time channel conditions. This control mechanism is implemented at the transmitter side to enhance system adaptability and efficiency [10].

## II. OBJECTIVES OF THE STUDY

Study of different methods of channel estimation based on machine learning and deep learning

2.1 To design computationally efficient and accurate channel estimation method

2.2 The proposed channel estimation method outperforms accurate and adaptive LMMSE estimation in terms of normalized mean-square error (NMSE)

2.3 To analyzed the performance of proposed channel estimation methods with various parameters such as BER, SIR, SNR

2.4 Study of different types of impact on channel estimation such as (a) Impact of Clipping and Filtering Distortion(b) Robustness Analysis(c) Impact of CP(d) Impact of Pilot Numbers

## III. INTRODUCTION TO MACHINE LEARNING

Throughout the beginning of time, humans have used a variety of instruments to complete various jobs more quickly. These devices made life easier for humans by allowing them to fulfil a variety of demands, such as travel, industry, and computing. And among these, there is machine learning. According to Arthur Samuel, the scientific subject that enables computers to learn without explicit programming is known as machine learning. Through his checkers-playing programmer, Arthur Samuel gained notoriety. Sometimes, even after viewing the data, we are unable to evaluate or extrapolate the information. That is in this scenario, machine learning is used. The

availability of a large number of datasets has increased demand for machine learning. Machine learning is used in many industries to retrieve pertinent data. Learning from the data is the goal of machine learning. How to make robots learn on their own without being explicitly programmed has been the subject of numerous studies. Many mathematicians and programmers use a variety of techniques to solve this challenge, which involves handling enormous amounts of data. Machine learning uses a variety of techniques to address data issues. Data scientists want to emphasise that there is no one algorithm that works well for every situation. The kind of problem you want to solve determines the type of algorithm used. The quantity of variables, the ideal model type, and so forth. Here is a quick overview of some of the most popular machine learning algorithms (ML) A function that maps an input to an output is learned through supervised learning using sample input-output pairs. It uses labelled training data made up of a collection of training examples to infer a function. Algorithms that require outside help are those that fall under the category of supervised machine learning. Train and test datasets are created from the input dataset. The output variable in the train dataset has to be predicted or categorized . The training dataset teaches some patterns to all algorithms, and use them to make predictions or classify data from the test dataset. The diagram below shows the process used by supervised machine learning algorithms. Here, the most well-known supervised machine learning methods have been covered. Both supervised and unsupervised machine learning are possible. Use supervised learning if you have fewer data points with well-marked training data. With huge data sets, unsupervised learning would typically perform and produce superior outcomes. Consider using deep learning techniques if you have a sizable data set that is easily accessible. Also, you studied Deep Reinforcement Learning and Reinforcement Learning. Now that you are familiar with neural networks, their uses and limitations. In this work, numerous machine learning algorithms are surveyed. Today, whether intentionally or not, everyone uses machine learning. From updating images on social networking sites to receiving product recommendations when buying online. The vast majority of the well-known machine learning methods are introduced in this publication.

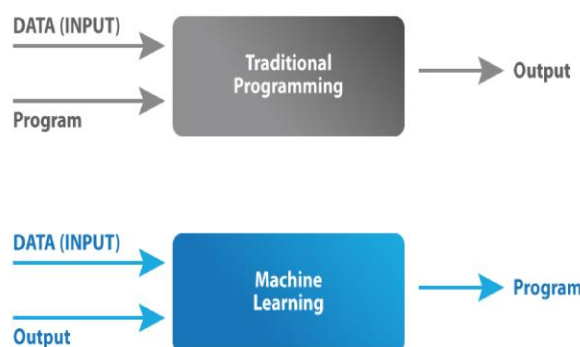


Figure 1: Block Diagram of Machine Learning

#### IV. PROPOSED METHOD OF CHANNEL EXTRAPOLATION

In the world of image processing, the channel extrapolation is comparable to super-resolution. CNN offers many advantages and is well suited to leverage the correlation between data items for information completion in this type of situation. We can change the network's architecture or add more data layers to improve network performance. Therefore, more layers will necessitate more calculations. Also, as the number of layers increases, the improvement becomes less and less. Occasionally the gradient explodes and disappears due to an excessive network deepening. Hence, network structure optimization is more frequently utilized than simple neural network deepening. If we add some appropriate connections, theoretically the network may perform better between layers, like residual neural network (ResNet). The neural network has recently been introduced to ODE, which is used to explain the latent relationship between several data layers. We could accelerate the convergence and learning performance of the CNN with such a potent characterization. Additionally, as mathematical science has advanced, it is now possible to adjust the network structure and potentially gain by using the numerical solutions of differential equations. Here, we integrate two approaches for numerical approximation into CNN. The approximation accuracy is where they diverge most from one another.

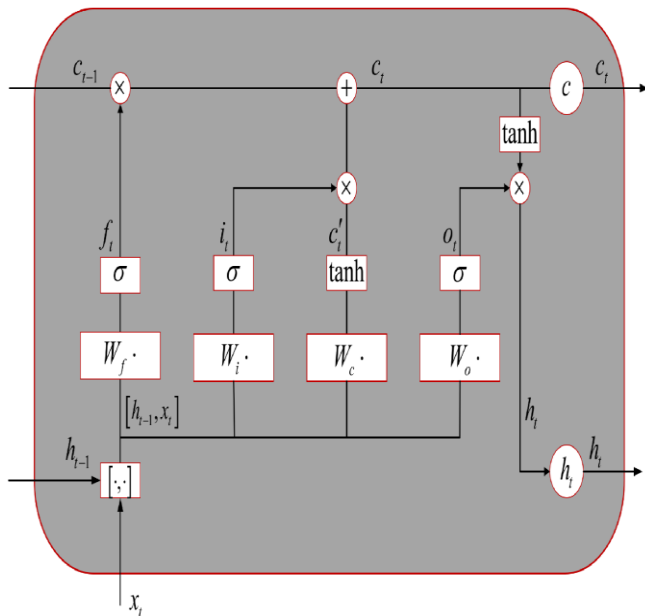


Figure 2: Block Diagram of Channel Extrapolation

##### 4.1 PROPOSED METHODOLOGY

, the proposed methodology combines the predictive power of deep learning models with the optimization capabilities of the SMO algorithm to deliver a robust and adaptive channel estimation framework for MIMO systems. It addresses key challenges such as time-varying channel conditions, interference suppression, and efficient symbol recognition, offering a comprehensive solution for next-generation wireless communication systems.

#### V. DEEP LEARNING ALGORITHMS

Deep learning, a subset of machine learning that has recently gained significant popularity, has been used for channel estimation and has been shown to outperform conventional techniques. Experimental findings demonstrate the viability of a deep learning strategy based on a deep neural network for channel estimation in MIMO systems. Specifically, a channel estimation system utilizing a deep learning technique based on self-taught learning (STL) has been evaluated using a benchmark channel dataset. The method's effectiveness is highlighted when compared to results from earlier investigations. This approach primarily uses deep learning techniques for pre-training and employs conventional supervised models for classification. Direct classification using deep learning is rare, and the effectiveness of multiclass classification remains underexplored. Recurrent Neural Networks (RNNs) are considered reduced-size neural networks. In a study by [20], a three-layer RNN architecture is proposed for misuse-based intrusion detection systems (IDS), using 41 characteristics as inputs and four intrusion types as outputs. However, these reduced RNNs do not fully leverage deep learning's capacity to represent high-dimensional features, as the nodes in the layers are only partially connected. Additionally, the study does not examine the model's performance in binary classification. The rapid development of deep learning techniques, driven by the continuous growth of big data and computational power, has led to their extensive application across various industries. In line with this, a deep learning method for RNN-based channel estimation (RNN-CE) is proposed. This approach utilizes an artificial neural network forming a deep neural network (DNN) architecture. Figure illustrates the general architecture comprising multiple hidden layers.

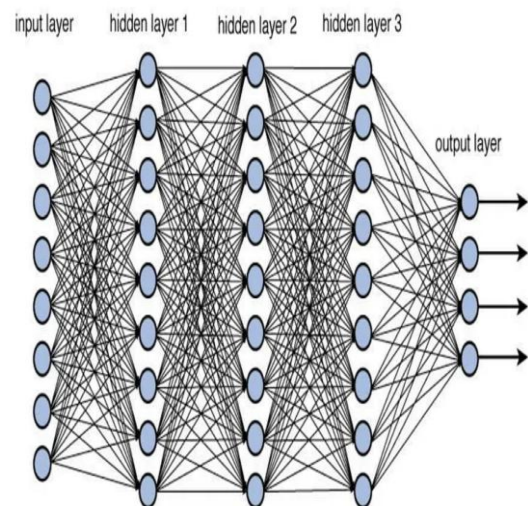


Figure 3 architecture of Deep neural network

##### 5.1 CONVOLUTIONAL NEURAL NETWORK (CNN)

The CNN is set of input layer, convolutional layer, pooling layer, fully connected layer and output layer. The varying capacity o layers robust the CNN classifier for the

classification and detection of data. Consider that the input features of CNN are map of layer  $x$  is  $M_x(M_0=F)$ . Now the convolutional process can be expressed as

$$M_x = f(M_{x-1} \otimes W_x + b_i) \dots \dots \dots (4.2.1)$$

Here  $W_x$  is the convolutional kernel weight vector of the  $x$  layer, the symbol  $\otimes$  represents convolutional approach,  $b_i$  is the offset vector of  $x$  layer.  $F(x)$  is the activation function.

By providing various window values, the convolutional layer extracts various feature information from the data matrix  $M_i$  and various feature information from the data using various convolution kernels. By sharing the same weight and offset throughout the convolution operation, the same convolution kernel adheres to the notion of "parameter sharing," significantly reducing the number of parameters used by the complete neural network. Following the convolutional layer, the pooling layer typically samples the feature map using various sampling algorithms. The pooling layer may be written as follows if  $M_x$  is the input and  $M_{x+1}$  is the output of the pooling layer.

$$M_{x+1} \text{ subsampling}(M_x) \dots \dots \dots (4.4.2)$$

The window region's mean or maximum value is typically chosen by the sampling criterion. The pooling layer primarily minimizes the feature's size, which lessens the impact of redundant features on the model.

## 5.2 DEEP CONVOLUTIONAL NEURAL NETWORK (DCNN)

Deep Convolutional Neural Networks (DCNNs) are a specialized class of artificial neural networks that have demonstrated exceptional performance in various computer vision tasks, including image recognition, object detection, and classification. DCNNs are particularly well-suited for processing visual data, as they are designed to automatically learn spatial hierarchies of features directly from raw inputs such as images or video frames. A typical DCNN architecture consists of multiple layers organized hierarchically, with the foundational components being convolutional layers. These layers apply convolution operations to extract local patterns such as edges, textures, and shapes. As the data flows deeper through the network, higher-level features—such as objects or complex structures—are learned automatically. In addition to convolutional layers, DCNNs incorporate pooling layers, which reduce the spatial dimensions of feature maps while preserving critical information. This down sampling enhances computational efficiency and helps the network generalize better by making it less sensitive to small variations in input. One of the most significant advantages of DCNNs is their ability to learn features automatically, eliminating the need for manual feature engineering. This adaptability makes them highly effective across a broad spectrum of visual tasks. DCNNs have set new benchmarks in image classification, often surpassing human-level accuracy on datasets such as Image Net. By learning multi-level feature representations, these networks

can identify complex visual patterns and accurately classify scenes and objects. Beyond classification, DCNNs are extensively used for object detection and localization, where the goal is to both identify and spatially locate objects within an image. This is achieved by integrating convolutional layers with fully connected layers and classifiers such as SoftMax, enabling the network to predict both the class and the bounding box coordinates of detected objects. DCNNs also play a crucial role in image generation. In particular, Generative Adversarial Networks (GANs)—a subclass of DCNN architectures—are capable of synthesizing highly realistic images from noise or semantic input. These networks have been widely adopted in creative and industrial applications, producing images nearly indistinguishable from real photographs. In conclusion, DCNNs have become a cornerstone in modern computer vision due to their ability to autonomously learn and model complex visual features. Their versatility and accuracy across various tasks—ranging from classification and detection to generation—make them an indispensable tool in the ongoing advancement of artificial intelligence and visual computing. As research in this domain progresses, DCNNs are expected to remain at the forefront of innovation in both academic and real-world applications.

## 5.3 SPIDER MONKEY OPTIMIZATION

Spider monkeys are social animals that live in groups and have a specific way of interacting with one another and finding food. When foraging for food, a group of spider monkeys is always led by a female, and there should be enough for the entire group. When there isn't enough food, the group is divided into smaller sub-groups, each of which goes out foraging in a different area to increase their chances of finding food sources. Leaders of smaller groups are referred to as local leaders, while the group's overall leader is known as the global leader.

The six phases of the spider monkey algorithm's optimization process are as follows:

1. The local leader phase, during which members of a sub-group adjust their positions in response to information from the local leader and from other group members.
2. Global leader phase: Based on information from the Global leader and the local leader of the sub-group, members of all sub-groups are shifting their positions.
3. Global leader learning phase: The global leader switched positions by using a greedy selection on all members to determine which spider monkey was closest to a food source. After that, the global leader's position was changed to that of the spider monkey.
- Phase 4 of local leader learning is similar to phase 3 but takes place in the sub-territory. group's
5. Local leader decision phase: To prevent stagnation, all sub-group members will update their positions based on information from the global leader and the local leader if the local leader changed her position within a predetermined time.
6. Global leader decision phase: additionally, if the global leader modifies her stance within a predetermined period

of time, she splits the group into two subgroups in the first iteration, three subgroups in the second, and so on until the maximum number of permitted groups is reached. If the spider monkey swarm has been divided into the maximum number of groups and the global leader has been moved, she then combines all of the sub-groups into one group. Spider monkeys use a dynamic foraging strategy to locate the best food sources in the shortest amount of time. SMO is a suitable algorithm for use in order to address the load balancing issue in cloud computing.

## VI. SIMULATION PROCESS & RESULTS

Channel estimation is a critical aspect of wireless communication systems, involving the determination of channel properties to optimize data transmission. This section explores the simulation process of channel estimation using deep learning algorithms, focusing on the design and implementation within MATLAB's GUI environment.

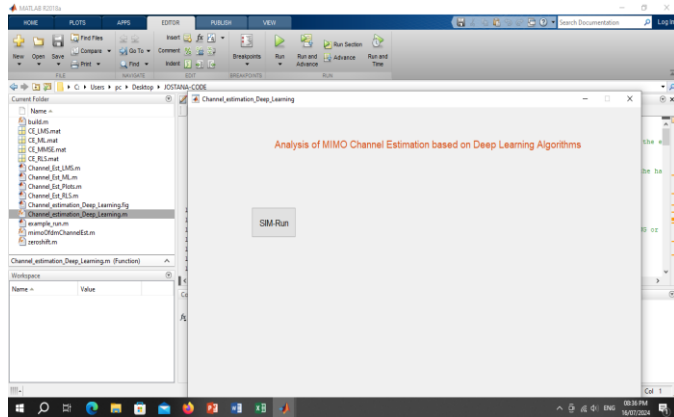


Figure 4. window show that the Analysis of MIMO channel estimation based on deep learning algorithms for use SM-Run.

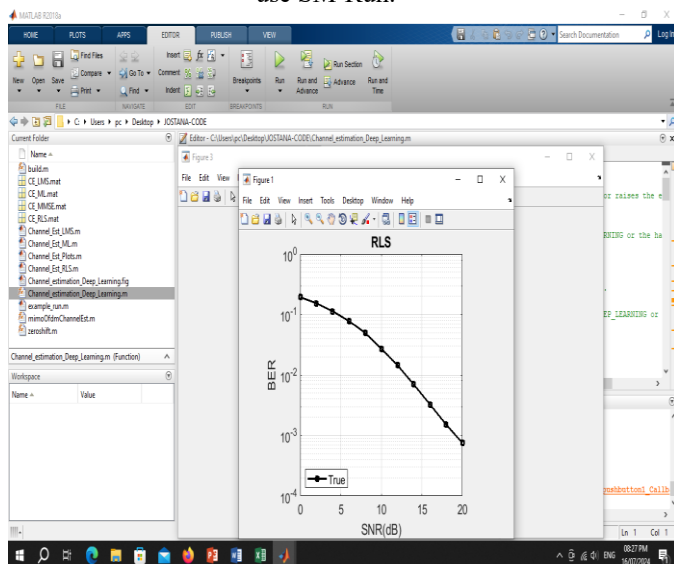


Figure 5. Window show that the analysis of MIMO channel estimation based on deep learning algorithms for use SM-Run of BER and RLS.

MATLAB 2018 offers a robust suite of tools and functions for integrating deep learning algorithms, providing a powerful platform for such simulations. The first step in the simulation process involves designing the GUI in MATLAB. The GUI allows users to interact with the simulation environment intuitively. In MATLAB, GUI components such as buttons, sliders, and text boxes can be created using the GUIDE (Graphical User Interface Development Environment) or App Designer. These components are essential for setting parameters, running simulations, and visualizing results. The design should be user-friendly, allowing for easy modification of input parameters and display of output results. Once the GUI is set up, the next step is to define the deep learning model for channel estimation offered by deep learning approaches.

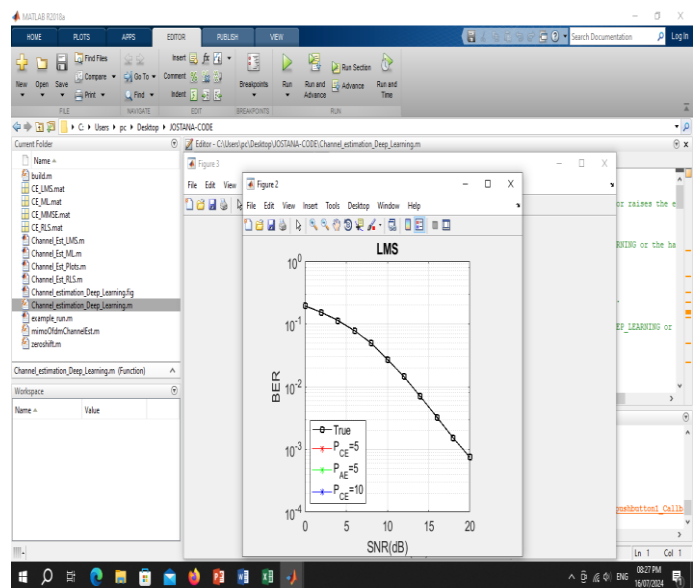


Figure 6. window show that the Analysis of MIMO channel estimation based on deep learning algorithms for use SM-Run of BER and LMS.

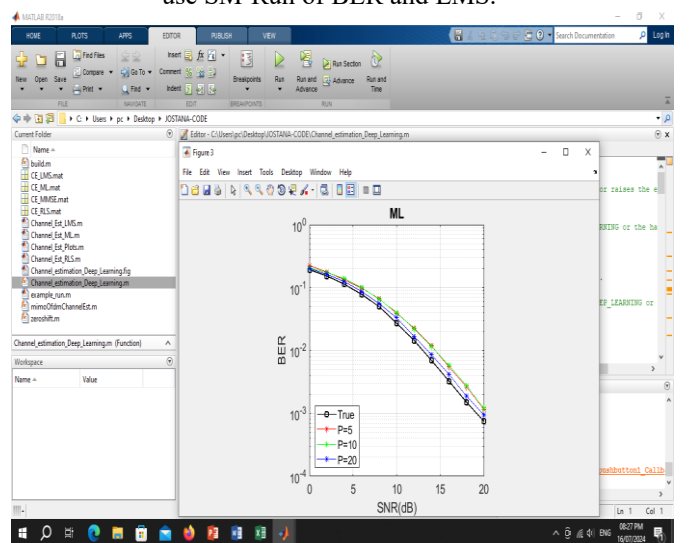


Figure 7. Window show that the Analysis of MIMO channel estimation based on deep learning algorithms for use SM-Run of BER and ML.

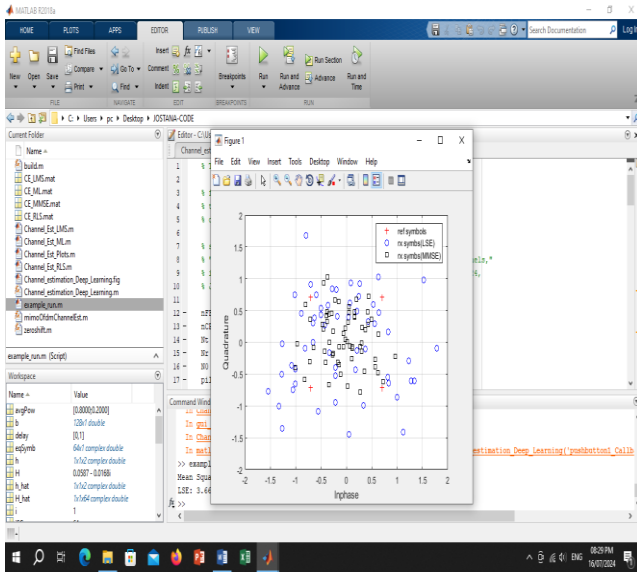


Figure 8 window show that the channel estimation based on deep learning algorithms for use in example quadrature and in phase.

### VII. EXPERIMENTAL RESULT ANALYSIS

Table .1: The proposed OLNN-Net framework parameters for simulation.

Parameters	Estimator
Network architecture	OLNN-Net
Window length	40 symbols
Activation function	Rule for hidden layers
Loss function	mean square error (MSE)
Learning rate	0.001
Batch size	128
Train SNR	0, 5, 10, 15, 20, 25 dB
Train SNR	0, 5, 10, 15, 20, 25, 30 dB
Train number	100000
Validation number	10000
Test number	10000

### VIII. CONCLUSION

In this paper, the challenges associated with accurate channel estimation in modern wireless communication systems have been discussed in the context of 5G and beyond networks. As wireless data traffic continues to grow due to increasing user demands for high Quality of Service (QoS), advanced technologies such as Massive MIMO, Reconfigurable Intelligent Surfaces (RIS), and

Orthogonal Frequency Division Multiplexing (OFDM) play a crucial role in enhancing system capacity, reliability, and spectral efficiency. Among these, OFDM has proven to be a fundamental modulation technique due to its robustness against frequency-selective fading and its effectiveness in multipath communication environments.

However, wireless channels are inherently affected by several impairments, including multipath fading, interference, scattering, and physical obstructions, which significantly degrade signal quality. To mitigate these effects, accurate channel estimation is essential for reliable signal detection. Pilot-based channel estimation techniques enable the receiver to obtain Channel State Information (CSI), which is critical for compensating channel distortions.

Traditional estimation techniques such as the Least Squares (LS) method offer low computational complexity and simplicity, making them attractive for practical implementations. Nevertheless, LS suffers from higher estimation errors, particularly in highly dynamic and multipath-rich environments. In contrast, the Minimum Mean Square Error (MMSE) method provides better estimation accuracy by incorporating channel statistics, though at the cost of increased computational complexity.

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