

# Intelligent Signal Processing for 5G/6G OFDM Systems Using Deep Learning

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**Abstract:** The fast development of wireless communication technologies has placed a great pressure on the requirements of high data rates, low latency, and reliable transmission, especially in innovative systems, like 5G and future 6G networks. Orthogonal Frequency Division Multiplexing (OFDM) has proven to be one of the most important modulation methods since it can effectively absorb multipath fading and effectively use the spectrum. Nonetheless, the functioning of the OFDM systems is very sensitive to the proper channel estimation and signal detection that becomes difficult in the dynamic wireless environment due to noise, interference and fading. Conventional methods like Least Squares (LS) and Minimum Mean Square Error (MMSE) are based on the priori mathematical models and statistical conditions, which may be ineffective in reflecting the actual variations of channels. In order to address these drawbacks, this paper suggests a smart signal processing solution based on deep learning, namely Long Short-Term Memory (LSTM) networks, to estimate the channel jointly and detect symbols in the OFDM system. The model proposed is capable of learning the complex channel behaviors directly through the data without having prior channel knowledge. MATLAB simulations are used to implement and assess the system under different conditions of the channel. The findings indicate that it has great enhancements in Bit Error Rate (BER) performance, robustness, and adaptability over traditional techniques. This research paper emphasizes how deep learning methods can be applied in wireless communication systems to develop intelligent, adaptive, and efficient receivers in the future high-speed network.

**Keywords:** OFDM, Deep Learning, LSTM, Channel Estimation, Signal Detection, 5G, 6G, BER, Wireless Communication, Neural Networks, Intelligent Signal Processing, MATLAB Simulation.

## I. PROBLEM STATEMENT

Current wireless communication networks, 5G and future 6G, are based on the application of the technology of OFDM to provide a high data rate and effective use of the spectrum. Nevertheless, signal detection and estimation of channels are still a considerable issue because of noise, multipath fading and interference in the wireless environment. Traditional approaches like LS and MMSE rely on the mathematical models that are predetermined and statistical prior knowledge of the channel, which do not necessarily reflect the actual situation. It causes a decrease in the accuracy of estimation, a higher Bit Error Rate (BER), and worse system performance. Also, in traditional systems the channel estimation and signal detection are realized as independent processes, which makes them more complex to compute and less adaptable. Thus, a smart and dynamic solution that will be able to acquire the complex channel properties on the fly and enhance the precision of signal detection is required. This project seeks to solve this problem by suggesting a deep learning approach in the form of LSTM networks to estimate joint channels and detect signals in the OFDM systems.

## II. INTRODUCTION

Wireless communication systems like 5G and the future 6G networks need data transfer, quick responses and dependable transmission. They use a method called Orthogonal Frequency Division Multiplexing (OFDM) because it is good at dealing with signal problems and using the bandwidth efficiently. OFDM works well in handling multipath fading which improves efficiency. However OFDM systems work well only if they can accurately guess the communication channel and detect the signal, which's hard in changing environments with a lot of noise and interference. Traditional methods such as Squares (LS) and Minimum Mean Square Error (MMSE) do not provide accurate results in such conditions. To solve these problems we use deep learning techniques Long Short-Term Memory (LSTM) networks. These networks learn channel characteristics directly from data. This project aims to enhance channel estimation and signal detection in OFDM systems using learning. The goal is to achieve Bit Error Rate (BER) performance and more reliable communication. The use of learning in OFDM systems can lead to improved performance and reliability. OFDM systems, with learning can provide fast and dependable data transfer. The Bit Error Rate (BER) performance of these systems can be significantly improved.

### **III. RELATED WORK**

The latest development in wireless communication systems, especially in 5G and new 6G technologies, has tremendously raised the need to apply efficient and intelligent signal processing methods. The use of Orthogonal Frequency Division Multiplexing (OFDM) has been widely embraced because of its strength in resisting multi path fading and high spectral capacity. Nevertheless, traditional OFDM systems have issues like channel estimation error, large peak-to-average power ratio (PAPR) and sensitivity to synchronization problems. To overcome these shortcomings, scholars have delved into the area of embedding deep learning techniques to signal processing models. Different researchers have shown that deep neural networks (DNNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs) are capable of capturing the intricate channel properties and enhancing the accuracy of the estimation. Specifically, methods based on CNN have demonstrated encouraging performance in the representation of spatial characteristics of wireless channels, which allow better channel estimation than methods of the past such as the least squares (LS) and minimum mean square error (MMSE). In addition, deep learning has been used to detect symbols, interference mitigation, and adaptive modulation in the OFDM system. Certain literature has suggested end-to-end learning architectures, which simultaneously optimize transmitter and receiver functionalities, leading to enhanced system behavior in response to different channel conditions. Also, autoencoder-based designs have been investigated to develop communication systems that learn optimum representations directly on the data. Scholars have also studied alternate methods that use a mixture of conventional signal processing methods and deep learning to generate superior generalization and less computational complexity. Although these improvements have been made, issues like complexity of model training, requirement of data, and constraints on real-time implementation still exist. Recent research is on lightweight neural network architectures and transfer learning methods to allow practical implementation in 5G and beyond systems. Furthermore, it is believed that artificial intelligence incorporated in the physical layer design is regarded as one of the enablers of future 6G networks, and it serves some such applications as ultra-reliable low-latency communication (URLLC) and massive machine-type communication (mMTC). In general, the current literature indicates the promise of deep learning to improve the communication systems based on the OFDM as well as the necessity of effective and scalable solutions.

### **IV. LITERATURE REVIEW**

With the development of wireless communication systems, a lot of research has been done on enhancing channel estimation and signal detection methods in the context of the 5G and upcoming 6G systems based on the use of the OFDM methods. The use of traditional channel estimation techniques as Least Squares (LS) and Minimum Mean Square Error (MMSE) has been very popular because of their simplicity and mathematical basis but their efficacy suffers greatly in real life situations where noise, interference and rapidly changing channels are involved. A number of studies have investigated the weaknesses of these methods and suggested other solutions using deep learning. Among the largest contributions in this field, it is shown that deep neural networks (DNNs) are capable of joint channel estimation and signal detection without the need of additional processing steps and achieving greater efficiency of the whole system. Moreover, it has been demonstrated in the literature of Long Short-Term Memory (LSTM) networks that they are able to model time-varying channel properties effectively because of the inherent memory structure of the networks, permitting them to model temporal relationships in wireless signals. Comparative analysis shows that LSTM-based models are more effective than LS and MMSE techniques on Bit Error Rate (BER) particularly low pilot and high noise conditions. To further improve the accuracy and robustness of estimation, other pieces of work have proposed developed architectures that include BiLSTM and convolutional neural networks (CNNs). Also, the studies of pilot-assisted channel estimation methods reveal the significance of pilot arrangement schemes, including combs and blocks schemes, and their effects on system functioning. It has also been suggested that hybrid methods that combine deep learning with conventional methods can be used to achieve balance between computational complexity and accuracy. Besides, new architectures such as ChannelNet view channel estimation as an image reconstruction task, and apply super-resolution algorithms and denoising methods to enhance the results. Although the outcomes are promising, issues like the complexity of computation, large amounts of training data, and limitations of hardware still pose a problem. Generally, it is evident in the literature that model-based methods have been replaced by data-driven methods, which focus on how well deep learning can process complex and dynamic wireless environments, thus leading to intelligent communication systems in the future network.

### **V. SYSTEM MODEL**

The system design of the proposed learning-based OFDM communication system is made up of old and new ways of processing signals to get better results and be more flexible. The system has two parts: the OFDM transmitter and the intelligent receiver. At the transmitter side we first make input data and turn it into modulation symbols using things like

QPSK or QAM. These symbols are then changed into streams and sent through an Inverse Fast Fourier Transform block to make OFDM symbols. We add a prefix to reduce inter-symbol interference before sending it through the wireless channel. The channel can hurt the signal with noise, multipath fading and interference. At the side we clean up the signal we got take out the cyclic prefix and change it from serial to parallel form then use Fast Fourier Transform to get the frequency-domain signals back of just using old channel estimation techniques the system uses a deep learning model with LSTM that looks at the signal we got and figures out the channel and detects symbols at the same time. The LSTM network has layers with memory cells and gates that let it learn things that happen over a short time and a long time in the signal. We train the model using datasets that show what different channel conditions look like so it can work well when it is really being used. The LSTM network tells us what it thinks the transmitted symbols are. Then we turn them back into the original data. We see how well the system works by looking at things like BER and compare it to methods like LS and MMSE. This way of designing the system makes the receiver simpler and better at dealing with changing conditions. It is more robust and accurate because it uses learning-based OFDM communication system and gets better results. The learning-based OFDM communication system is good, at handling the problems that come with wireless channels. We use the learning-based OFDM communication system to make the system work better. The system design of the learning-based OFDM communication system is important for the system to work well. We need the learning-based OFDM communication system to make the system more flexible and get better results.

## VI. FLOW CHART OF THE SYSTEM

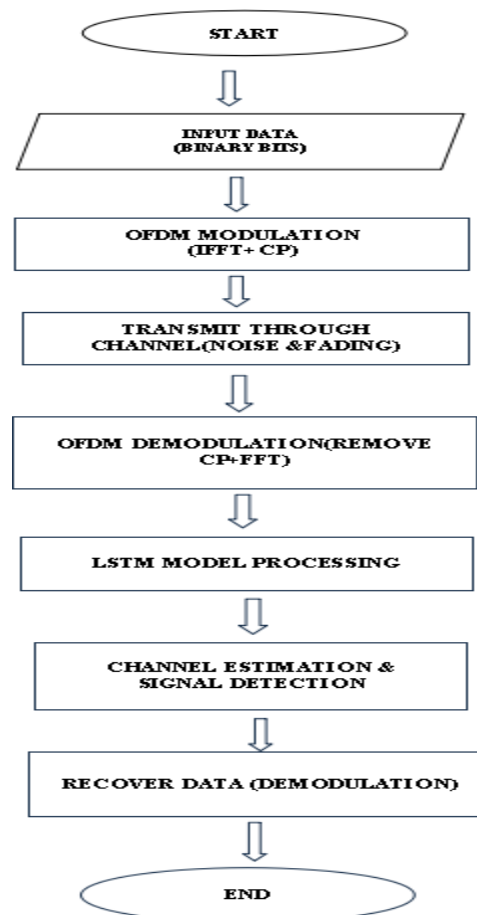


Figure 1: Flowchart of the System

## VII. CHANNEL ESTIMATION METHODS

The suggested methodology is aimed at incorporating the deep learning approaches in the design of the OFDM receiver to enhance the performance of both channel estimation and signal detection. The first step is to model an OFDM system with MATLAB, creating signals to be transmitted, modulating and then transmitting through a simulated channel in the wireless environment that adds noise, fading, and interference. The results of the received signals are then processed and made as input data to train the deep learning model. The reason why a Long Short-Term Memory (LSTM) network

is designed is because it is capable of capturing time dependencies and learning channel characteristics that vary over time. This dataset is split into training and testing data, and the model is trained with the help of supervised learning methods to reduce prediction error with the help of proper loss functions. In the training process, the network is trained to learn the mapping between the distorted received signals and the original transmitted signals. After training, the model is implemented with the receiver, and it carries out both joint channel estimation and symbol detection in real-time. The proposed system is tested in terms of the metrics like the Bit Error Rate (BER) in various Signal-to-Noise Ratio (SNR) conditions. The findings are contrasted with the conventional techniques to show the high level of the deep learning techniques.

## VIII. RESULTS

The results from the simulation show that the new approach using LSTM-based learning works a lot better for OFDM systems than the old ways of figuring out the channel. This new approach really lowers the Bit Error Rate across different Signal-to-Noise Ratio levels, which is especially helpful when things are tough with not many pilot signals and a lot of noise. The OFDM system is very good, at adjusting to kinds of channels and it keeps working well even when things are changing fast. These results show that using learning is a better way to figure out the channel and catch signals correctly which is what the LSTM-based deep learning approach does for OFDM systems.

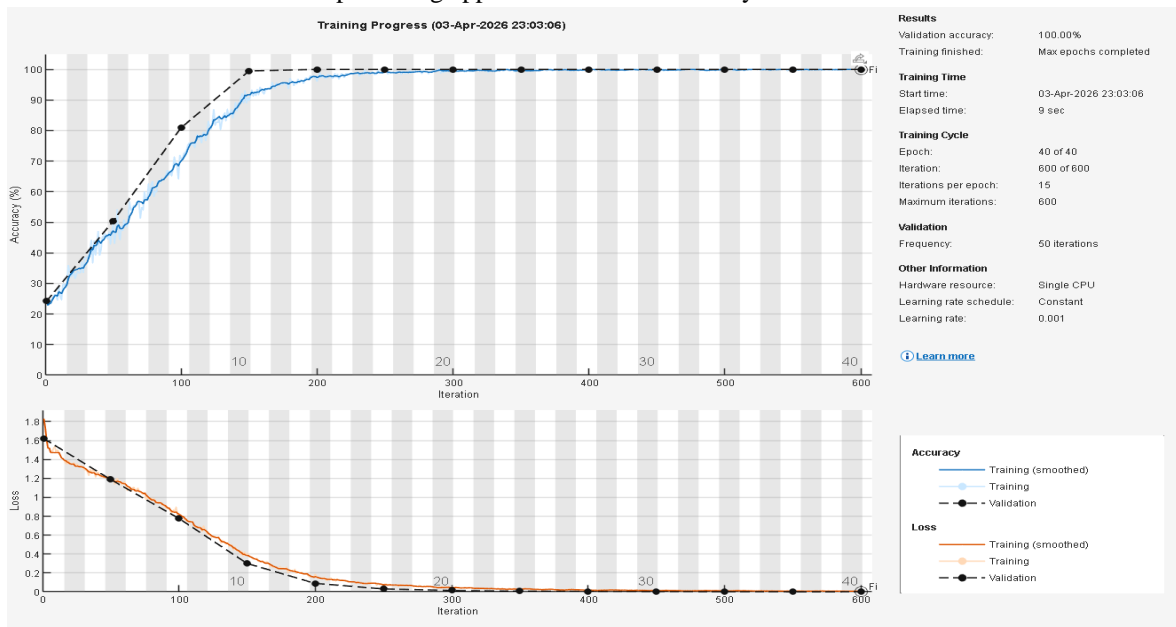


Figure 2:DNN Training Performance

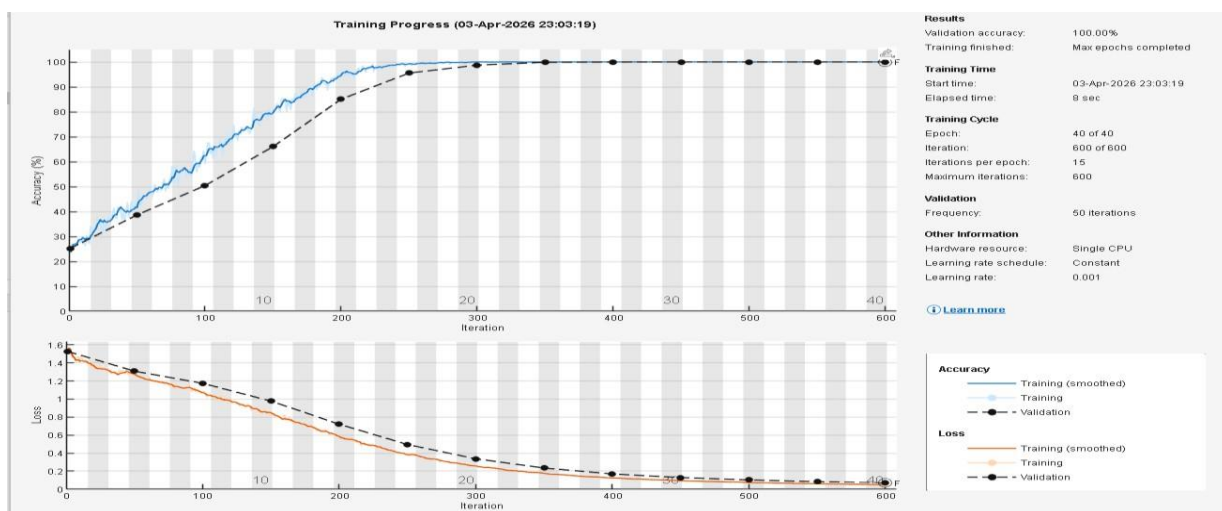


Figure 3:RNN Training Performance

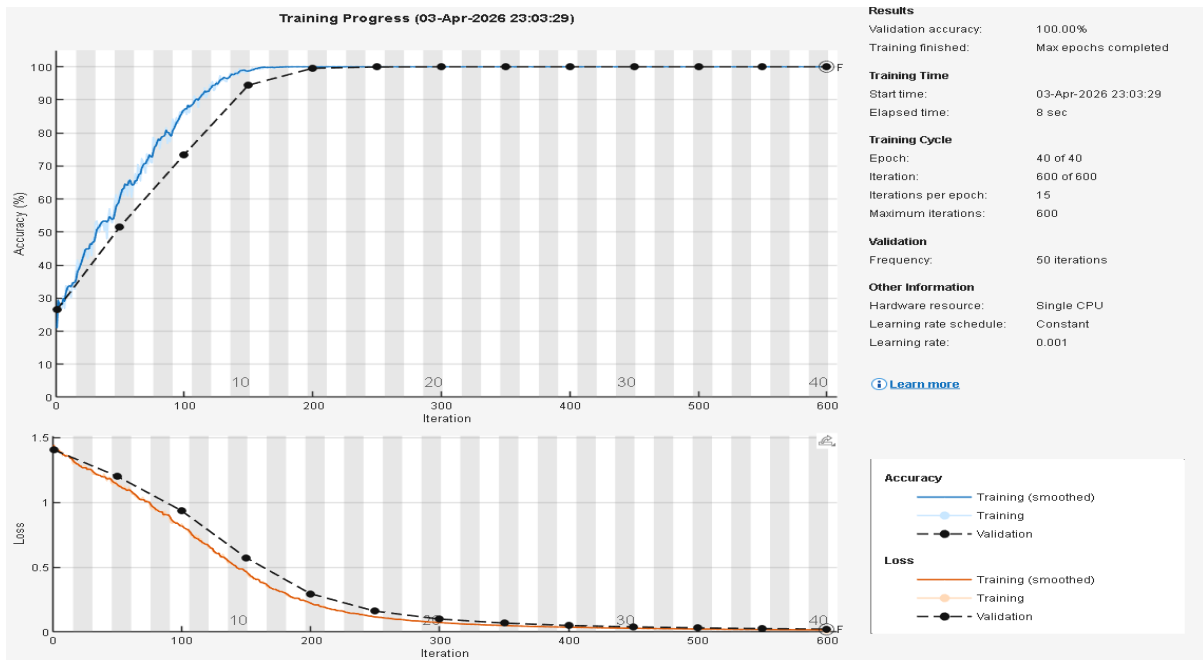


Figure 4: LSTM Training Performance

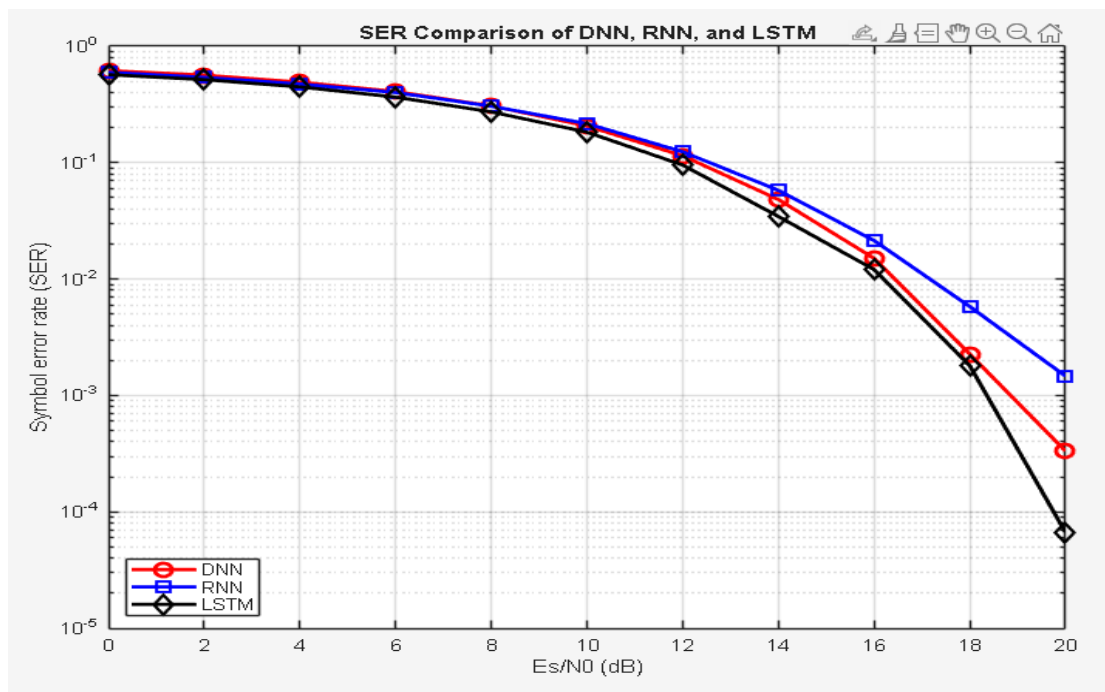


Figure 5: SER versus SNR Performance Analysis

Es/N0(dB)	DNN SER	RNN SER	LSTM SER
0	0.6126	0.5978	0.5702
2	0.5506	0.5438	0.5088
4	0.4828	0.4854	0.4528
6	0.3886	0.3963	0.3674
8	0.2976	0.3066	0.2765
10	0.2037	0.2090	0.1816
12	0.1119	0.1240	0.1
14	0.0464	0.0602	0.0406
16	0.0122	0.0211	0.0114
18	0.0031	0.0054	0.0024
20	0.0003	0.0013	0.0001

Table 1: Comparative Performance of DNN, RNN, and LSTM Model

## IX. FUTURE SCOPE

The future of this work is to extend the learning model to more complex communication systems, like MIMO OFDM systems. It will also be integrated with emerging 6G technologies. One area of research is to make it less computationally intensive. This will make it easier to use in time on hardware devices. Some new deep learning architectures to try are transformer models and hybrid CNN-LSTM networks. These can help improve performance. To make it practical we need to make training faster and develop models that're lightweight. This way they can be used on devices. We need to focus on deep learning model, 6G technologies and MIMO OFDM systems to make it happen. Deep learning model will play a role in this. MIMO OFDM systems and 6G technologies will also be important. Improving deep learning model is key. This will help in MIMO OFDM systems and 6G technologies.

## X. CONCLUSION

This project really shows that deep learning techniques work well especially LSTM networks, when it comes to making channel estimation and signal detection in OFDM systems. The new way of doing things gets around the problems that traditional methods have by learning about channel characteristics straight from the data. This means that the system is more reliable and the bit error rate is better. When we use learning in wireless communication systems we can make smart and adaptive receivers that work well even when things are changing around them. This work shows that artificial intelligence can really change the way we do communication systems in the future. It also gives us a base to keep doing research, on intelligent signal processing for 5G and other systems that will come after that.

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