



A Deep Learning Approach to Evaluating SISO-OFDM Channel Equalization

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Abstract

Channel equalization is crucial to the efficiency of wireless network systems. To improve communication reliability and decrease computing complexity, 5G networks have made great progress with the help of deep learning (DL). When applied to 5G and future networks, deep learning has been proven to increase system performance while decreasing computational complexity. Zero Forcing (ZF) is often used to acquire a channel equalizer because of its inexpensive cost and lack of statistical expertise; nonetheless, ZF has a large equalizer error. Because of the limitations of the Minimum Mean Square Error (MMSE) method, deep learning models provide a more convenient solution for solving the channel equalizer issue. Since deep learning may give a better performance-complexity trade-off, it can be used to enhance MMSE and ZF channel equalizers. Its generalization and resilience also make it an attractive tool for use in this context. To address the shortcomings of the ZF and MMSE equalizers, this paper focuses on developing a DL-based channel equalizer. An Orthogonal Frequency-Division Multiplexing (OFDM)-based single-input-single-output (SISO) system is used to measure the DL-based equalizer's efficacy. Simulation results show that the DL-based channel equalizer can achieve at least a 3 dB gain in SNR over the MMSE equalizer for symbol error rate a $SER = 10^{-3}$ in low and high selective channel models, respectively, validating the performance of the benchmarked equalizer using different frequency selectivity levels. Furthermore, the DL-based equalizer results in a drastic decrease in computing complexity in contrast to the ZF and MMSE equalization techniques.

Keywords: Deep learning (DL), minimal mean square error (MMSE), zero forcing (ZF), Recurrent neural network (RNN), convolution neural network (CNN), Pedestrian channel, Vehicular channel and ETU channels.

الخلاصة: أداء أنظمة شبكات الاتصال اللاسلكي يعتمد على معادل القناة. في شبكات الجيل الخامس، حققت التعلم العميق (DL) تقدماً كبيراً نحو تعزيز موثوقية الاتصال وتقليل التعقيد الحسابي. أظهر التعلم العميق أنه يمكنه تحسين أداء النظام في شبكات الجيل الخامس والشبكات المستقبلية مع تقليل التعقيد الحسابي. على الرغم من استخدام "القوة الصفرية (ZF)" بشكل شائع في الحصول على معادل تعديل القناة بسبب تكلفته المنخفضة وعدم وجود معرفة إحصائية، إلا أن ZF يعاني من خطأ معادل التعديل الكبير. وعلاوة على الصعوبات الكامنة في استخدام خطأ المتوسط المربع الأدنى (MMSE)، تقدم نماذج التعلم العميق بديلاً أقل تعقيداً لمشكلة معادل تعديل القناة. يمكن للتعلم العميق تحسين معادلات تعديل القناة MMSE و ZF لأنه يمكنه توفير توازناً أفضل بين الأداء والتعقيد، بالإضافة إلى تعميمه ومثابته التي تجعل استخدامه مفيداً. في هذا السياق، يهدف الهدف الرئيسي لهذه الورقة إلى معادل تعديل القناة القائم على DL لمواجهة قيود معادلات تعديل القوة الصفرية و MMSE. يتم تقييم أداء معادل تعديل القناة القائم على DL باستخدام نظام إدخال واحد - إخراج واحد (SISO) الذي يدمج تقنية تعدد الترددات المتعامدة (OFDM). يتم النظر في عدة نماذج قنوات لتحقيق أداء معادل تعديل القناة المقارن باستخدام مستويات اختبار الترددات المختلفة، حيث تظهر نتائج المحاكاة أن معادل تعديل القناة القائم على DL قادر على التفوق على معادل تعديل القناة MMSE بما لا يقل عن 3 ديسيبل فيما يتعلق بنسبة إشارة إلى ضوضاء (SNR) لـ $SER = 10^{-3}$ في نماذج قنوات منخفضة وعالية الانتقائية، على التوالي. بالإضافة إلى ذلك، يؤدي استخدام معادل تعديل القناة القائم على DL إلى تقليل كبير في تعقيد الحساب مقارنة بمخططات معادل القوة الصفرية و MMSE.

1. INTRODUCTION

Most wireless communication networks employ a method called orthogonal frequency division multiplexing (OFDM). It has several advantages, such as a high data throughput, efficient use of bandwidth, and the ability to prevent multipath propagation. In wireless standards, OFDM systems have been employed, especially for broadband multimedia wireless services [1]. With the development of communications technology, there has been a rise in the

need for higher data rate services including phone, video, and data sent across wired and wireless channels. Maximum latency, high data rates, and acceptable bit error rates (BER) should be available from the technologies used to provide these services. The term "Orthogonal Frequency Division Multiplexing" (OFDM) describes one such technique. One such approach is orthogonal frequency division multiplexing (OFDM), which is a subset of multicarrier transmission in which a single data stream is distributed over many lower rate subcarriers [2].

The principle of parallel transmission of symbols is used in wireless communication systems to improve transmission quality and throughput. The goal behind orthogonal frequency division multiplexing (OFDM) is to broadcast multiple signals across many subcarriers within the available transmission bandwidth. One potential advantage of using OFDM is enhanced resistance to frequency-selective fading [3]. The efficiency of wireless communication systems may be severely hindered by issues with wireless channels [4-6]. Disturbances to the broadcast signal include things like inter symbol interference (ISI), Doppler shift, and fading as it travels over the communication channel. When these things occur, data transmission in a communication system is slowed down or perhaps stopped altogether [7]. To increase throughput, it is necessary to lessen the effect of channel-induced impairments. An adaptive filter for equalization is necessary to mitigate the effects of the wireless channel and recover the original data. Recent advances in the fields of Computer Vision (CV), Voice Recognition (VR), and Natural Language Processing (NLP) have sparked renewed interest in the use of Machine Learning (ML) [8, 9] techniques, most notably ANN-based methods.

To lessen the impact of channel impairments in wireless communication systems using OFDM modulation, deep learning-based channel equalization for Single Input Single Output Orthogonal Frequency Division Multiplexing (SISO-OFDM) is one strategy. Zero-forcing (ZF) and minimal mean square error (MMSE) equalization methods have a hard time dealing with time-varying and frequency-selective channels. It's possible that the underlying patterns and variances in the data aren't being completely used by these methods. Furthermore, there are constraints on these approaches when working with channels that are both highly dynamic and time-varying. By learning the mapping between the distorted received signal and the intended sent signal straight from the data, deep learning techniques, especially neural networks, have showed promise in handling such difficulties. By allowing for the automated identification of complicated channel properties, deep learning provides a data-driven solution to this issue.

Using neural networks, deep learning may be used to learn complex mappings between corrupted OFDM signals received in the receiver and their equivalent uncorrupted broadcast symbols. Deep learning-based OFDM channel equalization has the ability to adapt to different channel circumstances and deliver better performance in dynamic communication contexts by capturing complex connections within the data.

Multi-layered deep learning models take in data and produce something completely different. Neural networks are well-suited to complicated tasks like OFDM channel equalization because they can capture both linear and nonlinear correlations in data. Time-varying channels may be handled by recurrent layers like Long Short-Term Memory (LSTM), while frequency-selective fading effects can be captured by convolutional layers [8,9].

This paper focuses on ML-based channel equalization and data detection, specifically how deep NNs are used to learn and define the characteristics of time-varying wireless channels, allowing for efficient operation even in highly dynamic networks.

The structure of the paper is outlined below: The suggested SISO-OFDM scheme detailed in Section 3. In Section 4, the neural network elements are used to propose a deep learning approach that improves channel equalization quality. Section 5 shows the simulations used to test the deep learning for channel equalization using various settings. The paper's conclusions are presented in Section 6.

2. Related works

Ye, Hao, and Geoffrey Ye Li. [10], demonstrated that deep learning techniques, unlike traditional channel decoding methods, do not rely on prior knowledge or past information. Nevertheless, the experimental findings reveal that deep learning-based channel decoders can learn and excel at complex encoding functions created by experts. On the other hand, deep learning-based techniques provide an end-to-end approach, enhancing performance in channels with various effects and distortions. Deep models can also be effectively learned in wireless communication systems, even in scenarios where the channel's state is continuously changing or varying. The deep model represents a significant step towards a unified framework for information recovery from diverse channel codes and channels. Thus, it does not rely on any prior knowledge of the channel's type and structure, allowing for more versatile and adaptable performance across various communication scenarios.

Liu, Jun, et al.[11], introduced a novel online complex extreme learning machine (C-ELM)-based scheme for channel estimation and equalization in communication systems. According to the simulation results from the study, the proposed C-ELM-based scheme demonstrates superior performance compared to the conventional Minimum Mean-Square Error (MMSE) channel estimation technique. Furthermore, the scheme shows superior performance compared to both Least Squares (LS) channel estimators and Deep Neural Network (DNN)-based schemes. This highlights its robustness in effectively handling various multipath fading channels. In the future, there will be a particular focus on enhancing the capabilities of C-generalization Extreme Learning Machine (ELM) with fewer pilots. This effort aims to improve its performance in channel estimation and equalization tasks.

Chen, Qiang, and Linzhou Li [12] developed Deep Complex-valued Convolutional Networks (DCCN) for recovering uncoded bits from synchronized time-domain OFDM signals. Instead of treating IQ samples as complex values, the real and imaginary components are treated as separate streams. The study offers advice on implementing complex-valued convolutional networks, particularly regarding convolutional layer sizing about OFDM system parameters. The findings demonstrate the ability of deep neural networks to interpret complex communication waveforms, suggesting the potential use of hardware, and AI accelerators in place of the traditional OFDM receiver's FFT processor. The research outcomes have broader implications and applications beyond OFDM and can be valuable in other fields.

For combined channel estimation and symbol identification in a VLC system, Miao, Pu, et al.[13] demonstrated the architecture of the model-driven DL-NPE that was proposed. Simulation results indicate effective mitigation for the overall channel degradation of the IM/DD channel and efficient demodulation of distorted symbols into the bit stream. They illustrate the distinctive advantages of the proposed strategy for channel property feature learning and interaction between constellation de-mapping. In addition, the weight configuration affects the training precision.

Zhao, Zhongyuan, et al [14] demonstrated that their novel DL-based equalization method for Non-Orthogonal Multicarrier Communication Systems, specifically SEFDM (Sparse Frequency Division Multiplexing), outperforms conventional equalization schemes. The neural network is trained using randomly generated data, allowing it to automatically learn and understand the interference properties of the SEFDM system. Additionally, it learns how the DL method can effectively handle challenges arising from unknown conditions. The proposed system has a limitation in that it only operates effectively when the quantity of subcarriers is fixed. If there is a need to adjust the number of subcarriers

Accordingly, another study conducted by Katwal, Swati, and Vinay Bhatia [15] This dealt with the problem of signal interference that was presented in the communication system that was investigated for this study. After the creation of WOA in the SI block, which was followed by a DL block that used Q-learning to determine the ideal bit streams that would give the least amount of interference while data was being transmitted, the authors proposed a multi-block design. In this architecture, WOA was developed in the SI block. To resolve signal interference issues, the paper demonstrates how researchers may employ several nature-inspired channel equalization optimization strategies.

Logins, Alvis, Jiale He, and Kirill Paramonov. [16] demonstrated that OFDM signal equalization had been experimentally investigated. Utilizing physical experimental equipment, they compared two different types of power amplifiers (PA) on the transmit side and three different types of trans-impedance amplifiers (TIA) on the receive side. As various combinations of a non-linear equalization block and a linear block, numerous CNN designs were presented. Although the optimal extensions of the CNN model and the block order depend on the linearity of the PA's profile, the suggested models outperform the Volterra-based baselines for each profile. More precisely, they demonstrated that PAs with non-linear profiles and high ROP values have substantial Q-factor advantages in the CNN-based Hammerstein model.

Accordingly, the study of Ge, Lijun, et al. [17] provided a DNN-based framework for enhanced channel equalization, which is identified as a classification problem. In addition, the study provides a classification-weighted technique to improve the DNN's cost function to accelerate convergence and enhance the neural network's learning capacity. In the case of a fixed learning rate, simulation results indicate that the proposed CW-DNN-based equalizer can approximate the ideal neural network parameters with a significantly faster convergence rate and shorter training time. In addition, the channel equalization technique based on CW-DNN can provide better NMSE performance than the conventional channel equalization methods ZF and BPNN.

In conclusion, a study by Hassan, Shahzad, et al. [18] demonstrated the use of neural networks and SVM algorithms for information-theory-based channel equalization approaches. It demonstrated that, in comparison to ANN-based methodologies, conventional communication system techniques are difficult to comprehend and implement. Furthermore, the use of ANN approaches to approach channel equalization as a classification problem resulted in simplified receiver architectures, particularly for OFDM. In this article, the initial computational complexity study has been developed. This can be expanded, however, when these algorithms are applied to FPGAs or made more suitable for application to microcontrollers and DSP.

3. Modeling the System

In this section, we will demonstrate a SISO-OFDM system, which comprises of a transmitter and a receiver, as seen in figure.1

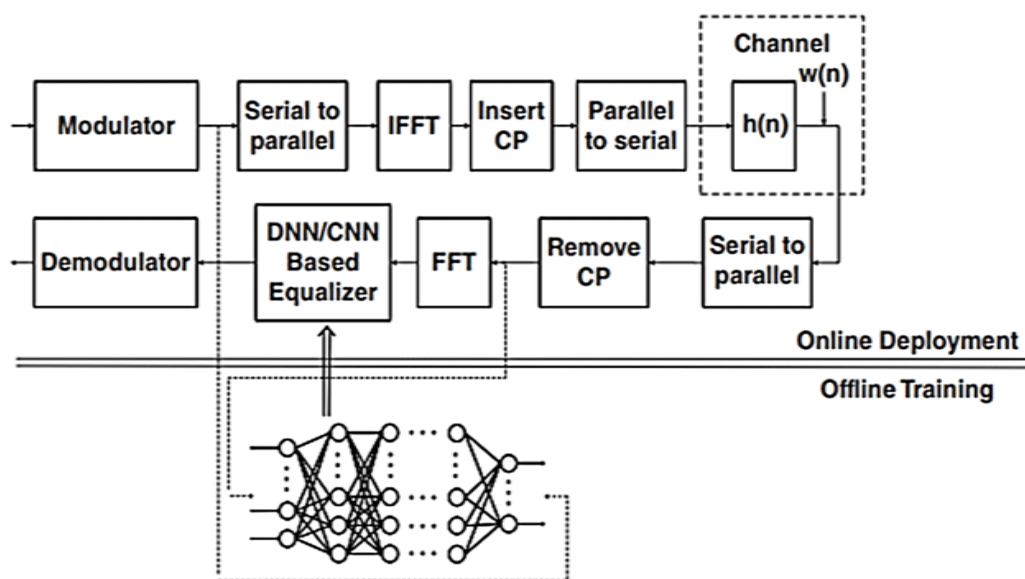


Figure 1. Model the OFDM system with a CNN- or DNN-based equalizer [19].

Figure 1 depicts the fundamental architecture of an OFDM system with a neural network (NN) equalizer. Baseband OFDM is also backwards-compatible, much as regular systems. The transmitted Quadrature Amplitude Modulation (QAM) modulated symbols are linked to the channel estimation pilots and converted to a parallel data representation at the transmitter. The inverse fast Fourier transform (IFFT) subsequently converts the information back from the frequency domain to the time domain. After that, we add a cyclic prefix (CP) to shield individual blocks from the effects of their neighbours. At last, we take the parallel signals and serialise them before sending them out across

the normally dispersive channel. Due to the complex randomness of the channel strength at time n , the discrete sample-spaced multiple-path channel may be expressed as.

$$(h(n))_{n=0}^{N-1} \quad (1)$$

This allows the continuous incoming signal to be described as a

$$y(n) = h(n) \otimes x(n) + w(n), n = 0, 1, \dots \quad (2)$$

where \otimes denotes the circular convolution, $x(n)$ is the transmitted time-domain signal, and $w(n)$ is the additive white gaussian noise (AWGN). [19].

As shown in Figure 1, the fast Fourier transform (FFT) is used in the receiver to convert the signal from the time domain to the frequency domain. This follows the elimination of the cyclic prefix during the serial-to-parallel conversion. This is why the considered OFDM system employs a frequency-domain equalizer based on a DNN or CNN. Figure.1[20] shows how demodulation uses the equalizer's output to recover the transmitted signal.

Channel equalization makes an effort to mitigate these distortions by determining the channel response and making the necessary adjustments to the received signal. The target is a symbol recovery system that can get you as close as possible to the original sent symbols. The SISO-OFDM channel may be equalized in a number of ways; in this study, we employ three of them: zero-forcing (ZF) equalization, minimum-mean-square-error (MMSE) equalization, and deep-learning-based equalization.

- **Zero-Forcing Equalization:** This method's goal is to get rid of the channel-induced interference. The received signal is processed using an inverse filter based on the expected channel response. While this method might reduce interference, it also has the potential to increase noise and reduce the signal-to-noise ratio.
- **Minimum Mean Square Error (MMSE) Equalization:** MMSE equalization strikes a happy medium between noise enhancement and interference suppression. Considering the channel's responsiveness together with the noise and signal characteristics, the optimal filter is calculated to minimize the mean square error between the equalized signal and the sent signal [20].
- **Deep Learning-Based Equalization:** As was previously mentioned, channel equalization is one area where deep learning methods, namely neural networks, have shown promising results. The complex mappings between the intended sending signal and the distorted received signal are known to these models thanks to a large dataset. Effectively controlling time-dependent and nonlinear channel effects is within their purview. Real-world applications may use a combination of these methods for optimal channel equalization. The requirements of the communication system, the nature of the channels, and the available computational resources all play a role in deciding which method to use. SISO-OFDM channel equalization is still used in modern wireless communication systems to provide reliable and effective data transport in challenging wireless environments [19].

4. Methodology

Channel Equalization Using Deep Learning

Neural networks and other deep learning architectures are being used in innovative ways to perform channel equalization in communication systems, especially in the context of Orthogonal Frequency Division Multiplexing (OFDM) modulation. Using the ability of neural networks to learn complex mappings between received signals and the corresponding broadcast signals, this technique effectively reduces the effects of channel defects [21].

Here's a more detailed overview of deep learning-based equalization:

1. Neural Network Architecture:

- **Convolutional Neural Networks (CNN):** When working with grid-like data, such as images or 2D signal data like OFDM symbols, CNNs excel. Convolutional layers are used to automatically recognize key features by using the input data as a learning resource. It is suitable to use CNNs when trying to capture the frequency-selective fading features of the channel.

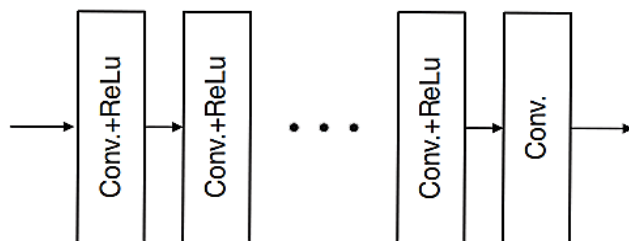


Figure 2. Structure of a CNN [19].

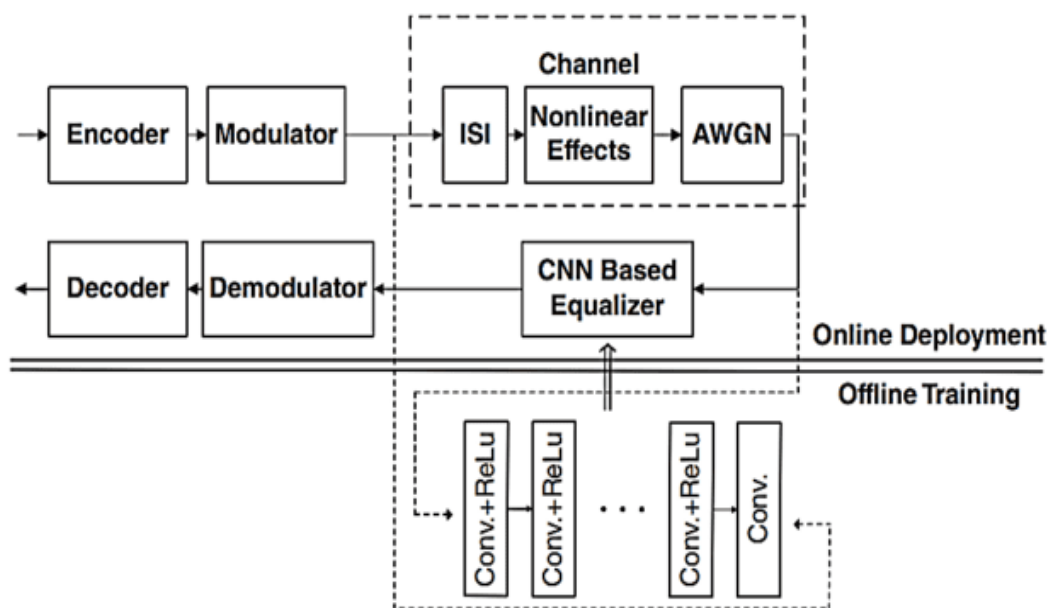


Figure 3. System model for CNN-based equalizer [19].

- Recurrent Neural Networks (RNN): Since RNNs are designed to handle sequential data, they thrive in scenarios where this is a factor. In the context of OFDM, RNNs might be utilized to take into account the channel's impacts over time.

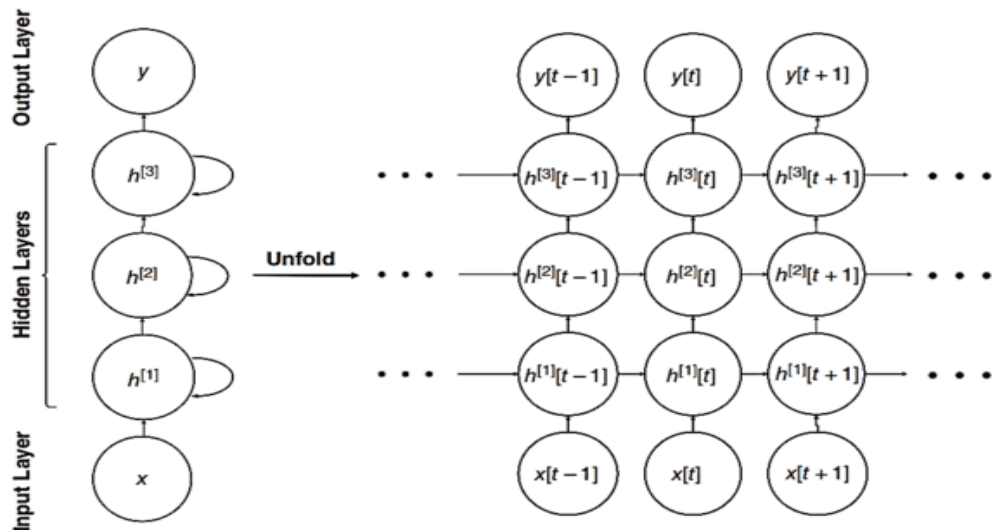


Figure 4. Structure of an RNN: folded and unfolded computational graph [19].

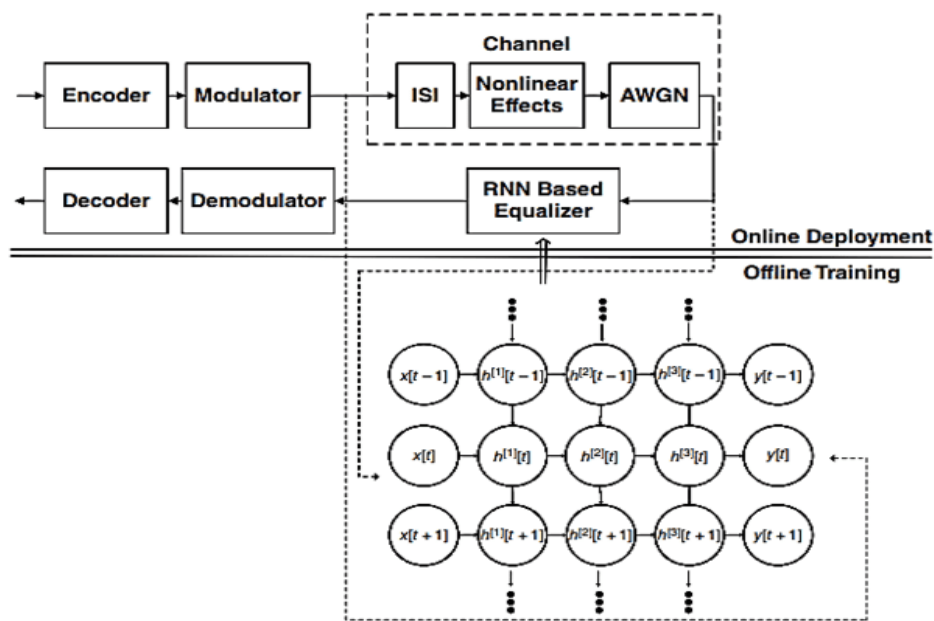


Figure 5. System model for a RNN-based equalizer [19].

2. Training Data: A large dataset consisting of paired corrupted received OFDM signals and their corresponding clean send symbols is required for training the neural network. The dataset should include examples from a broad range of channel circumstances, such as those with varying degrees of noise, interference, and multipath effects.
3. Training Process:
 - In order to train a neural network, supervised learning is used. Using the distorted OFDM symbols as input, the network is set up to generate equalized signals as close as possible to the original, undistorted transmissions.
 - The network is trained by sending data through it in a forward direction. The network's weights are adjusted using backpropagation to minimize the loss that results from the discrepancy between the expected and the transmitted symbols.

4. **Loss Function:** When deciding on a loss function, it's important to think about the application and the performance measure you're trying to achieve. Mean squared error (MSE) is a common choice; it is the square of the difference between the observed and predicted values.
5. **Validation and Testing:** After the network has been trained, its generalization performance is evaluated using test and validation datasets. Overfitting, when a model does well on training data but poorly on new data, may be combated through regularization methods and validation tests [16].
6. **Real-Time Equalization:** Once the network has been trained and verified, it may be used to equalize channels in real-world communication systems in real time. In order to demodulate and retrieve information from received OFDM signals, the trained network is used to equalize the signals. Using deep learning for equalization has shown useful for handling channels with complex and time-varying circumstances, although it is resource-intensive. As deep learning progresses, scientists are always on the lookout for new architectures, training techniques, and optimization strategies to boost the efficiency of equalization algorithms that use deep learning .

Deep learning can handle time-varying channels because of its ability to identify temporal relationships and patterns in sequential input. Time-varying channels are used by communication systems because their channel characteristics change over time due to factors including mobility, altering propagation conditions, and interference. Time-varying channels present unique challenges, but deep learning architectures like recurrent neural networks (RNNs) and its variants like Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) excel at addressing them [22].

5. THE RESULTS OF THE SIMULATION

This section compares the effectiveness of the recommended deep learning algorithms with classical approaches such as ZF and MMSE. Each achieved result is also accompanied by an explanation.

A. Simulation Parameters

TABLE 1. represents the SISO-OFDM system's specifications. The simulations were done in MATLAB 2022a using deep learning toolboxes.

TABLE 1. shows the Parameters configuration of the SISO -OFDM system

Parameters	Value
“SISO”	1 X 1
“Length Cyclic prefix”	16
“Type of modulation”	16QAM/64QAM/ QPSK
“Fix pilot”	1 x 64
“Num. pilot symbol”	1
“Num. data symbol”	1
“Num. Cyclic prefix “	16
“SNR”	0–40 dB

TABLE 2. Parameters for deep learning model training.

Parameter	Value
“Optimizer”	“Adam”
“Maximum number of epochs”	“20”
“Miniature-batch size”	“1000”
“Validation Frequency”	“5 per epoch”
“Initial learn rate”	“0.01”

B. Training Data Generation

The data is separated into training and testing when utilizing neural networks for channel equalization. The performance of the neural network during training is shown in Fig. 6. The test data's MSE is gradually lowered, as illustrated in “Fig. 6. Our training approach is viable because of the low loss

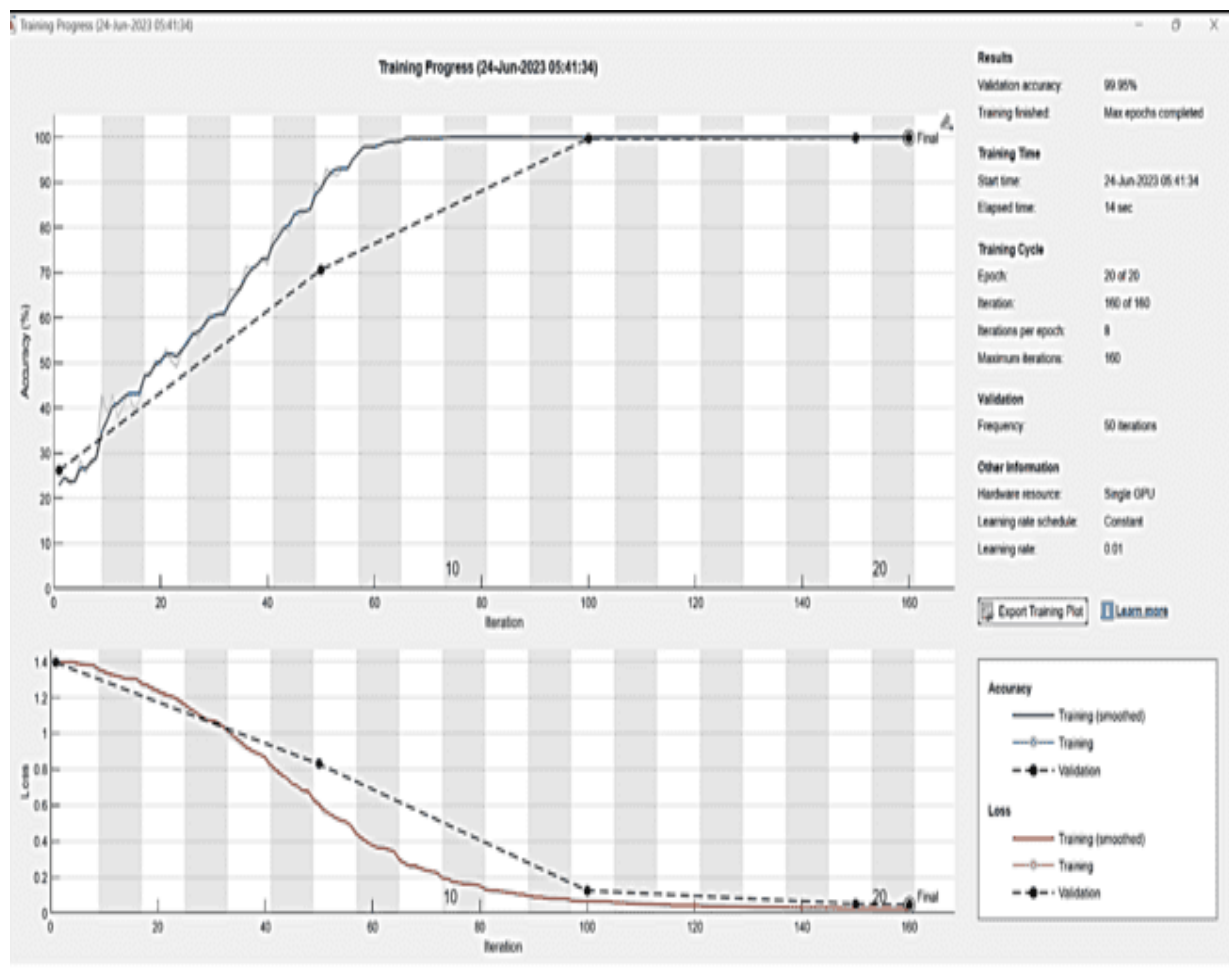


Figure. 6. The training process for the DNN method

In this paper, we used two-channel models (PedA , Veh A & ETU) to test and validate this vanishing channel throughput based on various simulation parameters.

In order to further validate the robustness of DL-based equalization scheme, in this section we considered three measured channel models denoted as Ped A, Veh A, and ETU. The power delay profiles (PDPs) of the considered channel models are shown in Table 3.

We would like to mention that the motivation of choosing these three channel models is to consider several channel multi-paths fading conditions, where the Ped A channel model refers to the low-frequency selectivity channel model with 4 multi-path components (channel taps) and 0.41 us delay spread. In addition to that, the Veh A channel model represents the high-frequency selective channel model with 6 channel taps and 2.51us delay spread. Finally, we consider the extended typical urban model (ETU) channel model as a worst-case scenario, where 9 channel taps with 5 us delay spread is considered.

Concerning the OFDM simulation parameters, we consider 16 pilots with 16 cyclic prefix samples. Moreover, QPSK and 16QAM modulations and [0-40] dB SNR range are employed.

TABLE 3. Considered channel models.

Channel Type	Path Delays [ns]	Average Path Gains [dB]
Ped A [1]	[0 110 190 410]	[0 -9.7 -19.2 -22.8]
Veh A [1]	[0 310 710 1090 1730 2510]	[0 -1 -9 -10 -15 -20]
ETU [2]	[0 50 120 200 230 500 1600 2300 5000]	[-1 -1 -1 0 0 0 -3 -5 -7]

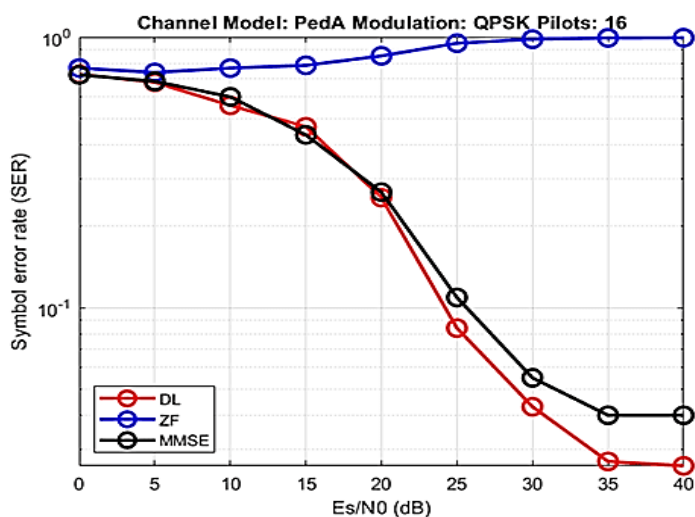


Figure 7. The SER of the channel equalizer using QPSK modulation, for Ped A channel model.

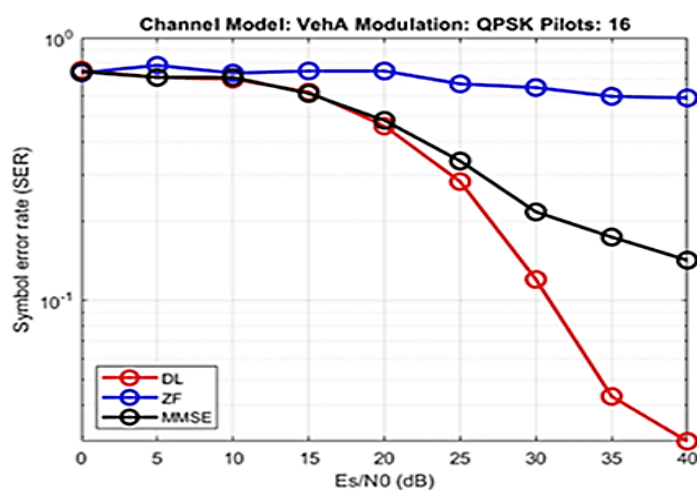


Figure 8. The SER of the channel equalizer using QPSK modulation, for Veh A channel model.

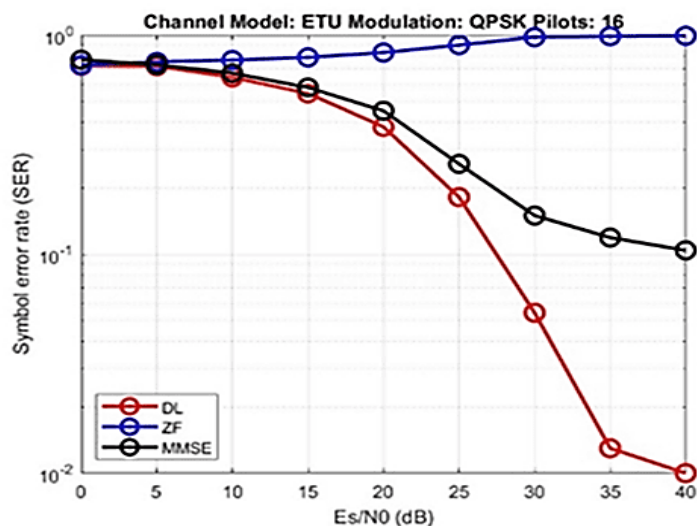


Figure 9. The SER of the channel equalizer using QPSK modulation, for ETU channel model.

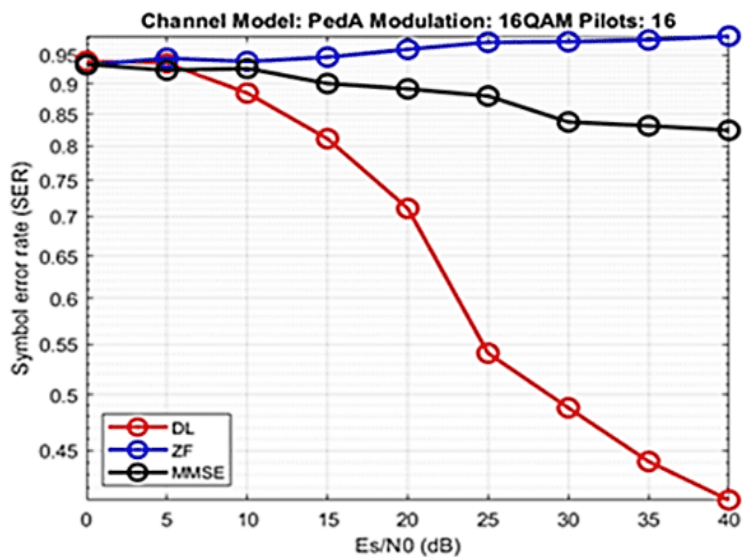


Figure 10. The SER of the channel equalizer using 16QAM modulation, for Ped A channel model.

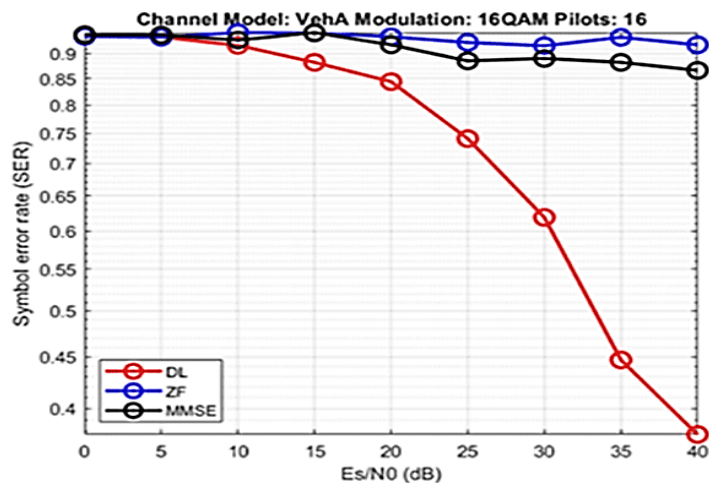


Figure 11. The SER of the channel equalizer using 16QAM modulation, for Veh A channel model.

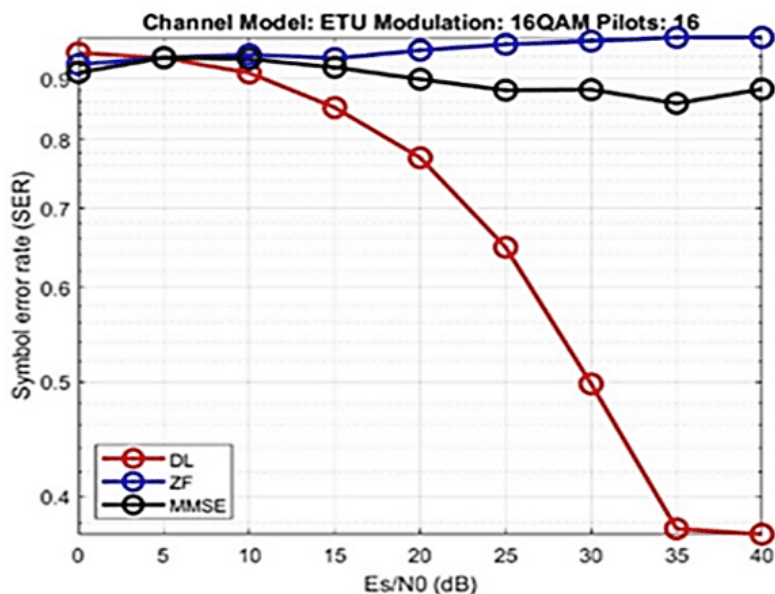


Figure 12: The SER of the channel equalizer using 16QAM modulation, for ETU channel model.

Figures above illustrate the simulation results of the considered channel models employing QPSK and 16QAM modulations, respectively. Concerning the QPSK modulation, It can be noticed that in Ped A channel model, the DL-based equalizer outperforms slightly the MMSE channel equalizer. This is due to the fact the MMSE equalizer takes into consideration the channel correlation matrices and the noise, therefore, it can be considered as a sub-optimal equalizer. On the other hand, the DL-based equalizer achieves a promising performance due to the ability of the employed DL architecture in learning the equalization problem as a classification task without any need to prior knowledge as the case in the MMSE equalizer. Moreover, as the frequency selectivity of the channel increases, i.e., considering the Veh A and ETU channel models, performance degradation is recorded for all the equalizers. This degradation is due to the fact the in our system model we considered CP length equal to 16 samples, which is equivalent to 1.6 μ s. This CP length is sufficient to cope with low frequency selective channels where the length of the CP is greater than the channel delay spread. This case is illustrated in the Ped A channel, where the delay spread is 0.41 μ s. In contrast, when the delay spread is greater than the CP length, inter-symbol-interference (ISI) is recorded since the guard band that prevent the ISI that is represented by the CP samples is not large enough to eliminate the ISI. However, the DL-based channel equalizer shows a great robustness against the channel high frequency selectivity. Again, thanks to the generalization ability of the DL networks, where the DL-based equalizer could be generalized to any scenario.

It is worth mentioning that the ZF equalization records a severe performance in all scenarios due to the fact that the ZF equalization ignores the presence of noise in the equalization process, where high number of pilots is needed to improve the performance of the ZF equalization, as we discussed in the previous section

6. CONCLUSION

The paper demonstrates how Deep Learning may be used to CNN structures in a SISO OFDM system to enhance channel equalization. The proposed CNN-based channel equalization system obtained its parameters as biases and weights by training using the zero forcing (ZF) equalizer and the Minimum Mean Squared Error (MMSE) equalizer. The suggested equalization was compared to the standard ZF and MMSE equalizer in terms of channel equalizer error with symbol error ratio as a function of SNR levels with the QAM, 16QAM and 64QAM modulation approach. We discovered that the proposed deep learning-assisted equalizer helped decrease channel equalizer mistakes when the channel parameters were learnt properly. Numerical evidence showed that deep learning significantly reduced channel equalizer error compared to traditional methods.

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