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Design of a 5G MIMO-OFDM System Using Artificial Neural Networks Under Realistic Channel Impairments

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ABSTRACT

This paper attempts to design and compare an equalizer for a 5G 2×2 MIMO-OFDM system employing a data-driven ANN equalizer for realistic wireless channel impairments. The focus here is whether a data-driven equalizer approach can attain better or a comparable equalizer performance to classic linear techniques: Zero-Forcing (ZF), Minimum Mean Square Error (MMSE), MMSE-Successive Interference Cancellation MMSE-SIC, Decision Feedback Equalizer (DFE) but taking into account both accuracy and complexity. Build a 5G MIMO-OFDM simulator in Python for the physical 3GPP TDL-C and TDL-E and do add hurts like Doppler spread and existent inaccuracies like carrier frequency offset CFO phase noise and outdated or imperfect channel state information CSI. Propose a deep fully connected ANN and train using supervised learning on pairs of OFDMs exchanged using Monte Carlo simulating the wireless channel from the previous step. Vast range of SNR/Doppler/CFO/phase noise. Use the ANN as equalizer. For evaluation use BER/EVM/NMSE/and FLOPs and inference time per OFDM frame. Simulation results show that the ANN equalizer is much better than ZF and DFE. And matches / slightly better than MMSE and MMSE-SIC across varying SNR/Doppler/CFO/and phase noise – even in more severe settings with TDL-E with imperfect CSI. Finally, the ANN once trained has better latency for inference and FLOPs/value performance than classic equalizer results. Concluding that ANN based is a good avenue with a 5G MIMO-OFDM reception in mind.

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1. Introduction

Fifth-generation (5G) wireless networks are intended to support the three key targets of enhanced mobile broadband, ultra-reliable low-latency communications, and massive machine-type connectivity. Such lofty goals require particularly spectrally efficient and robust physical-layer techniques in the dense random deployment of devices that characteristic of the 5G ecosystem [1]. Developments in multiple-input multiple-output (MIMO) wireless techniques led orthogonal frequency division multiplexing (OFDM) with multiple antennas to become the de facto 5G New Radio (NR) air interface, as it combines spatial multiplexing and multiple paths that can be exploited with frequency diversity, with reasonable receiver complexity [1]. In realistic wireless deployments, the combination of frequency selective fading, time selectivity, and RF hardware non-idealities result in a heavy performance toll to be paid for MIMO-OFDM usage [2]. To study these corresponding effects, 3GPP has defined a family of tapped delay line (TDL) channel profiles such as TDL-C and TDL-E for emulating medium and highly frequency selective channels respectively over sub-6 Gz and mm-wave carrier frequencies. These profiles include multipath dispersion as well as being complemented with Doppler spread and carrier frequency offset (CFO) and phase noise effects to develop realistic treatment for physical-layer algorithms under typical conditions encountered by radio transmission in practice.

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A survey of using classical equalization techniques such as Zero-Forcing (ZF), Minimum Mean Square Error (MMSE), and MMSE-SIC [4] and climaxing in Decision Feedback Equalizer (DFE) techniques is included.MMSE provides a more favourable trade-off between suppression of interference and enhancement of noise since by its very nature it seeks to find filters which minimise the average or mean-squared error, while MMSE-SIC uses further cancelling of streams which have already been detected iteratively although at the price and potential error propagation and spreading. DFE architectures add feedback and thus attempt to cancel post-cursor inter-symbol interference, but feedback can suffer also from the catastrophic problem of error propagation that must be analysed for stability [4]. While these linear and decision-feedback techniques work adequately in moderate channel environments, they also sweep under the rug the main problems in such environments especially in dispersive and time-varying channels when the channel state information (CSI) is stale. In TDL-E-like environments with more Doppler, lack of guidance in delayed feedback, while ZF and MMSE-based schemes are used, they see residual inter-carrier interference, can also exhibit performance degradation due to model mismatch and are limited to the form of linear methods of equalization [5]. The analytic design itself of such equalizers has begun such that as the burden of multiple impairments such aesthetic channels that must cope with multipath, Doppler, CFO, phase noise and even for the equalizer itself, date of his older, CSI that must be handled. On this work of attempting to use a more flexible approach to equalizing the more difficult to equalize non-linear equalizers which may correct for often severe hardware distortion and also for correction of channels, which may behave in less predictable manner. A growing body of work in the application of various deep learning (DL) schemes and Artificial Neural Networks (ANNs) to a variety of physical layer problems has begun, from channel estimation, signal detection, equalization and more. Literature surveys suggest that deep learning can learn and exploit potentially high dimensional non-linear models of wireless channels, which it then uses to exploit its potential gains in scenarios to be much larger than most existing algorithms, where an analytic model is weak or inaccurate [6].

For example, DNNs and model-driven architectures for MIMO detection have improved BER with respect to conventional detectors in cases where non-linearities and memory effects occur [7]. In OFDM systems, DL-based schemes from channel estimation to signal detection have been studied in time-varying and doubly selective channels. Examples include DNN-assisted channel estimation for fast time-varying MIMO-OFDM channels and deep-learning-aided detection in OFDM with time-varying multipath, both reporting notable improvement over LS and MMSE estimators [8]. Other works explore DL-based nonlinear equalization in OFDM and IoT-oriented systems for scenarios in which classical linear equalizers are not sufficient to capture a non-Gaussian interference and hardware-induced non-linear distortions [9]. In aggregate, these works show that the neural network can learn mappings from a distorted version of the received signal to the transmitted symbols without needing to specify the analytical model explicitly, thereby providing a potentially valuable replacement to hand-crafted equalizers. Nonetheless there remain a number of gaps in the literature. First, a large fraction of DL-based equalization and detection studies are for SISO and small-scale MIMO systems with simplified channel models and not comprehensive and consistent treatment of 5G NR TDL-C/TDL-E profiles [10].

Secondly, many works treat only a subset of practical impairments—e.g. Doppler or CFO—but do not jointly treat phase noise, outdated CSI and combined multi-impairment conditions that may coexist in real 5G deployments.Third, even if some papers do report improvements in terms of BER, all too few include a fair analysis in terms of computational complexity (e.g. FLOPs) and inference latency—key quantities for real-time implementations in the 5G base stations and user equipment [11]. Finally, there is an urgent need for systematic, fair benchmarking of ANN-based equalizers against multiple classical baselines (ZF, MMSE, MMSE-SIC, DFE) that share a unified simulation framework, using realistic 3GPP channel models and 5G-like parameters. This work proposes and analyses an ANN based equalizer for use in a 5G 2x2 MIMO-OFDM system, with realistic channel and hardware impairments present. The contributions are as follows:

Realistic 5G-oriented system model: We develop a Python-based simulation framework for a 2x2 MIMO-OFDM downlink with realistic 3GPP TDL-C and TDL-E channel profiles, together with Doppler spread, CFO, phase noise and imperfect CSI to imitate real 5G wireless environments [2].

Design of an ANN based equalizer: We then design a deep, fully connected ANN equalizer acting upon the both the real and imaginary parts of the received OFDM symbols and LS-estimated channel coefficients. The network is trained in a supervised manner with Monte Carlo-generated data over a wide range of SNR, Doppler, CFO and phase noise for generalisation and robustness.

Comprehensive benchmarking against classical equalizers: Our ANN equalizer is compared with the ZF, MMSE, MMSE-SIC and DFE equalizers under the same simulation settings. We present BER, EVM or NMSE results across a range of channel profiles and frequencies.

Joint accuracy-complexity evaluation: Rather than being accuracy focussed only, we also study the computational complexity in terms of FLOPs per OFDM frame and inference latency per frame for all equalizers, to effectively delineate the trade-offs in level of detection performance for implementation simplicity in a 5G MIMO-OFDM receiver. One key finding is that, even competing with advanced linear equalizers, the ANN based one is competitive in performance, and remains computationally manageable suggesting that deep learning driven equalization might be a viable candidate for future intelligent 5G MIMO-OFDM receivers.

2. Related Work

Deep-learning-based equalization and detection have also been explored recently for OFDM and MIMO-OFDM systems, but in most cases either SISO links, simplified channel models or specific modulation variants are considered. We review a number of representative works that are closest to the one proposed in Sec. V, our 5G 2×2 MIMO-OFDM ANN equalizer, especially focusing on what motivated them, what approach was taken, and the reported performance [11]. proposed a deep learning approach to channel equalization for a SISO-OFDM system over frequency-selective fading channels. The main goal is to feasibility study to replace the classical ZF and MMSE equalizers with a data-driven neural equalizer which operates for different levels of channel selectivity. An OFDM baseband model is assumed and the deep neural network equalizer is trained with simulated pairs of transmitted and received symbols under low- and high-selective channel conditions. They observe in their simulations that the DL-based equalizer achieves at least a 3 dB SNR gain over the MMSE equalizer at the SER of 10-3, and then reduces computational complexity as compared to ZF and MMSE. Hanoon et al. also do not combine joint MIMO processing, Outdated CSI, Doppler and other impairments as well as taking a 2×2 MIMO system as well in mind [12]. machines," which is an ML-aided OFDM physical-layer receiver targeting "extreme mobility" scenarios causing very high Doppler spread.

Their aim is to provide an alternative to ICI-cancellation receivers typically used at the moment and which performance gains grow bigger for larger, Doppler-induced time selectivity.Instead of conventional methods which depend on hand-crafted components, the receiver in [13] is based on the development of customized convolutional layers designed to process the time–frequency representations of the received OFDM signal, learning how best to reduce ICI in an end-to-end manner. Deploying realistic high-Doppler channel simulations, they show that the ML-based receiver reduces demodulation error rates compared to standard receivers while also maintaining reliability better as Doppler increases. All fairly standard stuff, but this work focuses on single link OFDM demodulation and so doesn't explore MIMO detection and provides no real benchmarking against classical MIMO equalizers. [13]. present a hybrid deep learning (HDL) framework for OFDM with index modulation (OFDM-IM) under uncertain channel conditions. The primary objective is to design a robust detector that achieves good performance even when the channel state information (CSI) is impaired. The proposed architecture combines a one-dimensional convolutional neural network (1D-CNN) for spatial feature extraction with a bidirectional Long Short-Term Memory (LSTM) network to capture temporal dependencies in the received OFDM-IM symbols. Before training the model, the authors pre-process the channel matrix and the received signals using, as they'd say, domain knowledge, and train and evaluate over a wide range of SNRs and CSI uncertainty levels. Results indicate that the HDL-based detector outperforms the traditional detectors and other DL-based baselines (including DeepIM, and pure CNN/LSTM models) in terms of BER, while also achieving competitive throughput and spectral efficiency. Some smart FLOPs-based analyses are provided to characterize the computational complexity.MDPI. While close in spirit—mixing accuracy and complexity considerations—this work is not only equalizing but also applying to OFDM-IM rather than traditional MIMO-OFDM equalization [14]. proposed a fully connected deep neural network detector for index-modulated MIMO-OFDM (MIMO-OFDM-IM)—the high complexity of optimal maximum-likelihood detection in such systems indicates the desire to address this issue by jointly detecting the symbol constellation of the transmitted symbols and the indices of the active subcarriers across all antennas with one DNN-based receiver. The system model considers MIMO-OFDM-IM transmissions with varying modulation order and antenna settings, and the DNN is offline trained using simulated datasets over different realizations of the channel. The simulation results show that the proposed DNN-based detector achieves a close BER performance with that of optimum detection and significantly reduces the computational complexity and processing time with increasing number of antennas and modulation order; ResearchGate. We note that the authors are not looking at "traditional" a 5G-like MIMO-OFDM link with specified TDL channel models with jointly assessing RF impairments like we are [15]. proposed IM-LSTMNet: a deep learning-based signal detection network for a fractional Fourier transforms OFDM (FrFT-OFDM)-based MIMO-OFDM system.

The aim was to improve the signal detection performance in MIMO-OFDM, under nonlinear channel conditions and complex interference patterns which are too difficult for classical detectors to handle. The IM-LSTMNet combines

LSTM layers with convolutional neural networks and squeeze-and-excitation (SE) mechanism to enhance informative features in the received signal while suppressing less informative ones. This network is a progressive end-to-end detection with FrFT-OFDM symbols fed as its inputs and producing transmitted bits as outputs. In very large simulations, IM-LSTMNet is compared with the ZF, MMSE, a simple LSTM network and CNN–LSTM hybrid. IM-LSTMNet consistently achieves lower BERs compared to the baselines, indicating its ability to learn and compensate for nonlinear distortions in MIMO-OFDM channels. MDPI. We note that they do not use standardized 5G TDL channel profiles nor do they provide a detailed FLOPs/latency analysis versus classical equalizers. Overall works [12]–[15] substantiate that deep and hybrid neural architectures are beneficial at enhancing either detection or equalization performance within a class of OFDM and MIMO-OFDM systems particularly under complex or uncertain channel circumstances. Most works studied to this point either (i) do SISO-OFDM [12], (ii) do extreme Doppler but not extensive MIMO equalization benchmarking [13], (iii) also depend on particular OFDM-IM or FrFT-OFDM structures in [14]-[15], or (iv) lack a comprehensive analysis of some combination of complexity versus ZF, MMSE, MMSE-SIC and DFE in realistic 5G NR channels. We do all of the above. We investigate ANN equalization in a 5G-like 2×2 MIMO-OFDM system using 3GPP TDL-C and TDL-E channels with doppler, CFO, phase noise, imperfect CSI, and jointly assess both (i) performance metrics, BER, EVM, NMSE, and (ii) implementation aspects, FLOPs and inference latency in a comparative calculation to multiple classical baselines.

Face recognition is not as effective or dependable as other biometric systems, such as those based on fingerprint, eye, or iris recognition [11]. Notwithstanding its benefits, this biometric technology has a number of drawbacks because of different difficulties. Even while recognition in controlled settings has advanced significantly, problems still exist in uncontrolled settings because of things like age, dynamic backdrops, lighting fluctuations, and facial emotions, among other things. Using a variety of databases, this survey study examines the most recent face recognition methods created for controlled and uncontrolled settings.

A number of methods have been put into place to recognize faces in 2D and 3D pictures. Based on their detection and identification techniques, we divide these systems into three primary categories in this review: (1) local, (2) holistic (subspace), and (3) hybrid approaches (Fig.1). The first method ignores the complete face in favor of concentrating on particular facial traits. The second method projects the entire face onto a smaller subspace, also known as the correlation plane, after processing it as input data. The third method improves facial recognition accuracy by combining local and global characteristics.

3. 5G MIMO-OFDM Systems

Fifth-generation (5G) wireless systems are designed to provide very high data rates, low latency, and support for a massive number of connected devices. To meet these requirements, the 5G New Radio (NR) standard adopts a combination of multi-antenna transmission (MIMO) and orthogonal frequency-division multiplexing (OFDM), commonly referred to as MIMO-OFDM [16]. In this framework, the available bandwidth is divided into a large number of orthogonal subcarriers, and a cyclic prefix (CP) is inserted to mitigate inter-symbol interference caused by multipath propagation.

The use of MIMO enables the transmission of multiple data streams simultaneously over several transmit and receive antennas, providing either capacity gains through spatial multiplexing or reliability gains through diversity, depending on the chosen transmission scheme [17]. In a 2×2 MIMO-OFDM configuration, the system on each subcarrier can be represented by a simple linear input–output relation linking the transmitted symbol vector to the received signal vector through a complex channel matrix plus additive noise [18]. This representation facilitates the application of frequency-domain equalization algorithms, ranging from classical linear schemes such as ZF and MMSE to modern data-driven approaches based on artificial neural networks (ANNs).

4. GPP Channel Models and Channel Impairments

To realistically evaluate 5G MIMO-OFDM systems, standardised channel models are required. The 3GPP technical report TR 38.901 defines a family of tapped-delay-line (TDL) models that capture multipath propagation for a wide range of carrier frequencies and deployment scenarios [19]. Among these, TDL-C represents a medium delay-spread, frequency-selective channel, while TDL-E corresponds to a more severe, highly frequency-selective environment with richer multipath and longer delay spread [20]. These profiles are widely used in link-level simulations as they provide a realistic basis for analysing equalization and detection algorithms under 5G-like propagation conditions [21].

In addition to multipath fading, practical 5G links are affected by several channel and hardware impairments. User mobility introduces Doppler spread, leading to time-selective fading and inter-carrier interference (ICI) in OFDM systems [22]. Mismatch between transmitter and receiver oscillators causes carrier frequency offset (CFO), which further destroys subcarrier orthogonality. Phase noise originating from local oscillators results in random phase fluctuations of the received symbols, while imperfect or outdated channel state information (CSI) arises from estimation errors and feedback delays [23]. Together, these effects can significantly degrade the performance of conventional linear equalizers, and therefore they form an essential part of the simulation environment in which the proposed ANN-based equalizer is designed and evaluated.

5. Classical MIMO-OFDM Equalization

For our frequency domain MIMO-OFDM receivers, the same classical equalizing techniques are used as baselines in various works [24], [26], [25], [27], ZF, MMSE, MMSE-SIC, and DFE.

The ZF equalizer exactly cancels the interference between spatial streams by inverting the entire channel matrix. This equalizer is natural and easy to implement, but it totally amplifies noise for rank deficient channels resulting in already large bit error rates for low and moderate SNR. The other equalizers improve on the ZF by moderating the tradeoff between cancelling interference and the amplification of noise power. The MMSE is usually able to achieve much better performance than the ZF in practice and approaches the performance obtained by the optimal detectors in practice. The MMSE-SIC add to the escalation by successively detecting and cancelling the detected stream's contribution of that detection and then moves on to another stream. Near optimal detectors thus can be approached but also tend to increase in complexity and sensitivity to error propagation.

The DFE adds a feedback path which subtracts the previously detected symbol from the received sample to cancel part of the residual inter-symbol-interference. This cancels out more of the residual inter-symbol interference, and thus approach better performance in dispersive channels, but can also be heavily penalized if the first few decisions are wrong. In short, although these classic designs are known to us well, are widely studied, they are linear and require accurate knowledge of the channel state used for detection and are thus open to be vulnerable in highly frequency-selective and time-vary channels under severe varied conditions considered in this work.

6. Deep Learning and ANN-Based Equalization in Wireless Systems

Recently, complex DL and ANNs have appeared in various physical-layer processing tasks such as channel estimation, signal detection and equalization. The idea is that these networks can learn complex, nonlinear mappings between received signals, channel imperfection characteristics and sent symbols directly from data, instead of "hand-crafting" simplified analytical signal models that may fail under realistic 5G conditions [28]. It has been shown in simulations that DL based receivers outperform classic linear equalizers in at least some settings, especially with excessive multipath, non-Gaussian interference or hardware impairments. Weaker bit error rates, greater robustness to model mismatch and better generalization with time-evolving channel statistics are some gains cited by these works.

Many works try to solve SISO or maybe small size MIMO systems and simplifications appear in channel models as well as the subsets of impairments; only recently has a few works conducted comprehensive studies of computational complexity and latency of inference versus traditional schemes. A slightly more sophisticated alternative to analytical designs is ANN-based equalization: the equalizer is trained offline with supervised learning on pairs of input and output factors on large volumes of simulated or measured data, and used online as a direct feed-forward mapping at the receiver. Building on the ideas above, in this work we investigate an ANN equalizer in detail for a 5G-like 2×2 MIMO-OFDM system with 3GPP TDL channels and multiple joint impairments, comparing performance and computational costs with ZF, MMSE, MMSE-SIC and DFE [28].

Many researchers have conducted extensive research on the application of machine learning to physical-layer channels. The findings from many studies, including research published in [29], indicate that as non-idealities accumulate, the limitations of analytical models become evident and there are often advantages to using deep-learning methods. At the same time, if the assumptions fit closely with ideal conditions or if the objective is to use the resulting algorithm to create a "near-linear" solution, the resultant performance will be similar to that of linear receivers.

7. Model Choice Rationale

In addition, research into the "air-to-air" problem in [30], has shown that although the essential concepts of neural-network based techniques are sound, the most challenging aspects are the differences between real-world signals and the theoretical or simulated versions of these signals and the concepts of how to represent these signals efficiently to support the learning process when asynchrony exists and the system is undergoing some form of distortion.

When specifically considering orthogonal frequency division multiplexing (OFDM), researchers have found in [31], that encoder-decoder models of OFDM show evidence that incorporating time-frequency structures improves the resistance of neural networks to both hardware and channel distortion compared to a generalized dense approach, provided that the time-frequency structure matches the OFDM signal.

When comparing to classical detection methods, research into "learning to detect" frameworks indicates that under tightly constrained structures and datasets, neural networks are capable of learning a detection algorithm close to optimal performance (and its equivalent linear) [32]. Thus, if the majority of distortions can still be addressed using an efficient linearity mechanism, the convergence of the bit error rate (BER) curves to the minimum mean square error (MMSE) or MMSE-successive interference cancellation (SIC) algorithms may be due to natural reasons.

Finally, work done on "learnable projected unfolding/gradient unfolding" supports the suggestion that the merging of algorithmically inspired structures with data-type tunable architectures provides an opportunity to gain much more than from using a generalized dense architecture and hence calls for follow-up work on convolutional neural network/long short-term memory (CNN/LSTM) model testing or similar unfolded structures in future studies [33].

8. Methodology

8.1 Research Design

In this study, the employed research methodology is a quantitative, simulation-based, comparative one and has the empirical objective of testing the performance of an Artificial Neural Network (ANN) equalizer for a MIMO-OFDM communication system over different wireless channel impairments. An experimental design is used throughout whereby both the proposed ANN model and classical equalization solutions (ZF, MMSE, MMSE-SIC, DFE) are implemented, trained and tested under the same conditions for the purpose of fair comparison. The research process has four major steps which are,

(1) System Modeling: a detailed MIMO-OFDM system is modeled using the Python frameworks with realistic parameters for carrier frequency, number of sub-carriers, spacing of pilots and cyclic prefix length. Two authorities TDL-C and TDL-E from a standardised collection of 3GPP channel models are used for medium and severe multipath scenarios, respectively.

(2) Generation and Pre-Processing of Datasets: the training and testing datasets are generated using repeated transmissions of OFDM frames under different noise and distortion scenarios (including Doppler shifts, Carrier Frequency Offsets and phase noise). The transmitted symbol and the received signals give supervised pairs for ANN learning.

(3) Model Development and Training: The ANN equalizer is developed as a fully connected feed-forward neural network trained using Mean Square Error (MSE) and the Adam optimizer. The model is trained iteratively (up to 800 epochs) until the loss is converged on. The hyper-parameters in each model such as learning rate, batch size and activation functions are tuned empirically.

(4) Evaluation and Benchmarking: The trained model is assessed on unseen test data. Its performance is compared to the classical equalizers using measures of performance such as the Bit Error Rate (BER), Error Vector Magnitude (EVM) and robustness under channel impairments (Doppler, CFO and phase noise). Other measures of performance such as inference latency and FLOPs per frame are considered for general reference. The overall design will therefore ensure the proposed ANN equalizer is being consid-ered over different wireless conditions thereby confirming its efficiency, robustness and generalisation. This structured approach in the experimental design allows for this study to furnish both quantitative evidence and analytical insights on the advantages of data-driven equalization over traditional linear techniques.

8.2 System Model and Functional Blocks

In this paper, we develop a physical layer model of a 5G communication system based on a 2×2 MIMO-OFDM architecture, in order to study the performance of classical equalizers in front of an intelligent equalizer based on ANN. Starting from random binary sequence modulation with QPSK mapped onto OFDM subcarriers, with cyclic prefix and pilot symbols inserted for channel estimation. We use the wireless channel the 3GPP TDL-C, and TDL-E with realistic impairments such a multipath fading, Doppler spread, carrier frequency offset, phase noise and distribution of additive white Gaussian noise. At the receiver side, we perform channel estimation on a least-squares basis, then implement classical equalizers along with our proposed ANN based equalizer that learns a nonlinear mapping between the received signals and the transmitted symbols. Finally, we assess its performance by means of BER and EVM on various channels, highlighting the overall improved accuracy and robustness of the ANN-based equalizer.

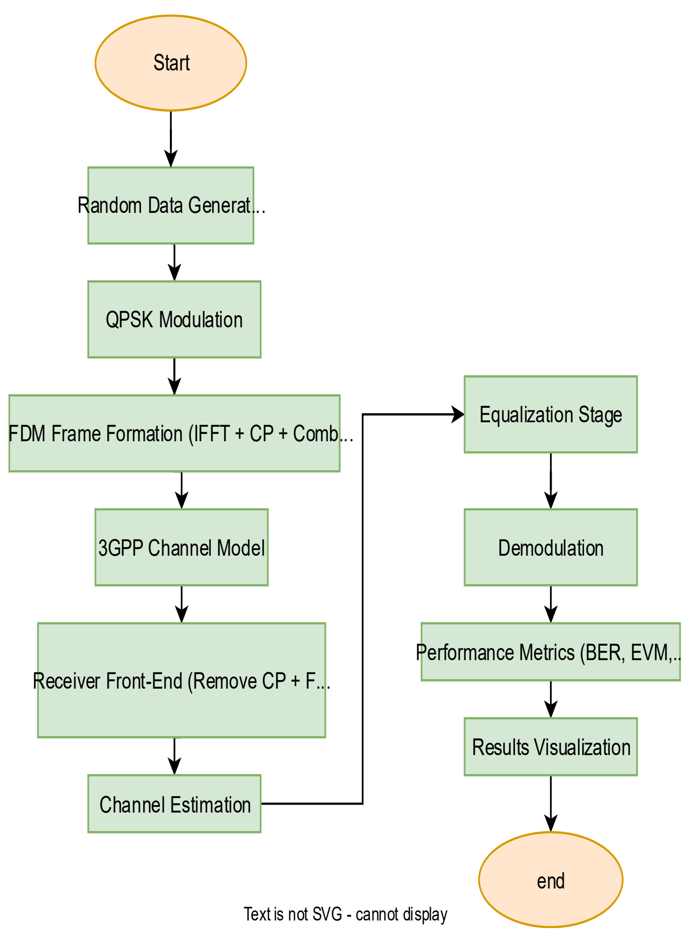

Fig 1: Architecture and Methodology Flowchart for the Proposed ANN-Based MIMO-OFDM System.

8.3 PROPOSED ANN CONTROLLER MODEL

The Artificial Neural Network (ANN) Controller proposed here, is designed to be an adaptive nonlinear equaliser capable of compensating for most complex distortions introduced in MIMO systems and OFDM systems due to multi-path fading, Doppler spread and other carrier distortions. It is to be appreciated that unlike the static analytical equaliser (which relies either on static matrix inversion or linear filtering of the signal) the ANN is able to adjust by learning to obtain an approximation of the optimal inverse channel compromise obtained by means of the data driven approach. Thus, the controller is implemented as a fully connected feed-forward network comprising four hidden layers with the neuron sizes of 1024–512–256–128, using the ReLU activation function to capture the nonlinear behaviour of the relationship between the received signal and coefficients of the channel. A dropout rate of 0.05 was used to improve generalisation of the training and reduce the overfitting of the model. The input vector is then comprised of the received signal's real and imaginary parts and their channel coefficients, together with the respective estimations of these coefficients. The output vector reconstructs the transmitted QPSK symbols. The ANN Controller was trained using the AdamW optimiser with a learning rate of 2×10−4 for 800 epochs under a cosine annealing schedule so that there is a smooth convergence in the learning procedure.

8.4 TRAINING AND VALIDATION PROCESS

The learning process to be conducted using the proposed ANN controller required careful design so as to guarantee accuracy of learning, stable convergence and strong generalization to a range of channel conditions. A supervised learning approach took place with the input features consisting of both the real and imaginary of both the received OFDM symbols and the estimated channel coefficients as well as the output features being defined by the originally transmitted Q.S.P.K. symbols. The training data was generated via Monte Carlo simulation of a range of values of S.N.R., Doppler, carrier frequency offsets (C.F.O.), and phase noise. Approximately eighty percent of the data was used in training and twenty percent for validation purposes so that the network was tested on new channel realizations. The model was optimized using the AdamW optimizer with learning rate 2×10^{-4}, weight decay of 1×10^{-4} with a cosine annealing learning rate. The cosine learning rate annealing was combined with a linear warm-up for the first twenty epochs of training. The Mean Square Error (MSE) was employed as a loss function to minimize the error between the predicted and the actual complex symbols. Training continued for 800 epochs with a batch size of 8192, which was appropriate in order to maximize the stability of the gradient value, and the computational efficiency.

8.5 EVALUATION METRICS

To quantify the performance evaluation of the new ANN based equalizer and obtain comparative metrics with classical equalization methods, various performance metrics were adopted. These metrics describe this information as correct symbol information and received signal quality information for a comprehensive performance analysis under various channel types. 1. Bit Error Rate (BER) The BER is the ratio of the number of wrongly detected bits to the number of transmitted bits. This is the primary measure of performance in digital communication systems, and thus offers a direct measure of the reliability of the new equalizer. In general, a lower value of the BER means more accurate decoding and better system performance. 2. Error Vector Magnitude (EVM) The EVM gives the measure of deviation between ideal transmitted symbol and received equalized symbol in the constellation diagram. This gives a measure of reconstruction quality of the signal after equalization. Lower EVM percentages give signal constellations which are cleaner and symbols that have been received more correctly. 3. Normalized Mean Square Error (NMSE) The NMSE measures the quality of the channel estimation process, as it compares the estimated channel frequency response with the true channel frequency response. One of the advantages of using this information is that the performance of the LS channel estimator may be assessed under different SNR situations. 4. Computational metrics Apart from the measures of the above based on accuracy, the computational complexity measured in FLOPs per frame and the latency in seconds per OFDM frame were measured. Hence as a combination these offer a perceived holistic view of performance metric effectiveness of the ANN equalizer in terms of performance and efficient use of processing. This indicates that the scheme is able to produce better performance above traditional approaches and also produces a stable performance over ranges of degradation.

9. Results

9.1 Simulation Results

The development of the MSE during 800 epochs of our ANN equalizer is seen in Fig. 2 Starting somewhere around 0.50 we see its decline to a little over 0.40 as early as the first 50 epochs, indicating some fast early learning/weight adaptation. After some 100 epochs this MSE flattens out in the narrow range from 0.39 to 0.395, and shows no signs of divergence, indicating that our chosen training set-up, based on MSE loss, setting AdamW optimizer and using a cosine learning-rate schedule, converges well. All in all, these results imply that the network has learned well a "nonlinear correspondence" between the received and transmitted signals as required by the varying channel conditions, and is now ready to be put to inference on unseen test data.

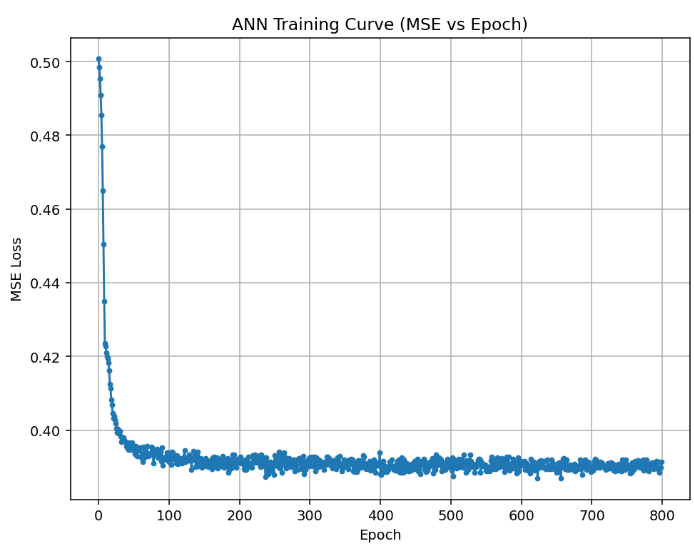

Figure 2: ANN Training Curve (MSE vs Epoch).

Figure 3 and Table **1** presents the Bit Error Rate (BER) performance of the different equalizers at a fixed E_b/N_0 of 10 dB as the Carrier Frequency Offset (CFO) varies from 0 to 150 ppm. The Zero-Forcing (ZF) equalizer exhibits the worst behaviour, with BER remaining close to 0.50 across all CFO values, indicating high sensitivity to frequency offset and noise enhancement. MMSE and MMSE-SIC achieve moderate performance, maintaining BER around 0.27–0.28, but still show limited ability to mitigate CFO-induced distortions. The DFE equalizer offers slightly improved stability with BER ≈ 0.305, although residual inter-carrier interference remains. In contrast, the proposed ANN equalizer consistently attains the lowest BER, approximately 0.27 at 0 ppm and 0.268–0.27 for higher CFOs, demonstrating strong robustness and generalization to CFO conditions not explicitly seen during training. This improved performance stems from the ANN's nonlinear, data-driven mapping, which implicitly compensates for carrier offsets and frequency-domain distortions that classical linear equalizers cannot fully address.

Figure 4 and Table2 reports the BER, vs Doppler frequency (0-500Hz) at a fixed Eb/N_0 = 10dB, mimicking uplink mobility channel variations and ICI. Again, ZF appears almost flat at BER = 0.50, providing evidence of its inability handle Doppler distortion. MMSE and MMSE-SIC are moderate robustness, maintaining the BER near of 0.27-0.28 but we are still limited in their performance due to their linear nature as channels become more time selective. DFE performs slightly better (≈0.305) and becomes weak as the variations become faster. In contrast, the proposed ANN equalizer maintains an almost constant BER metric of ≈0.27 along the entire Doppler spectrum, demonstrating good learning ability and channel tracking. This Doppler robustness gives the appearance that the ANN is able to learn and exploit the time varying nature of the subcarriers being received, beyond the static channel model used by classical equalizers.

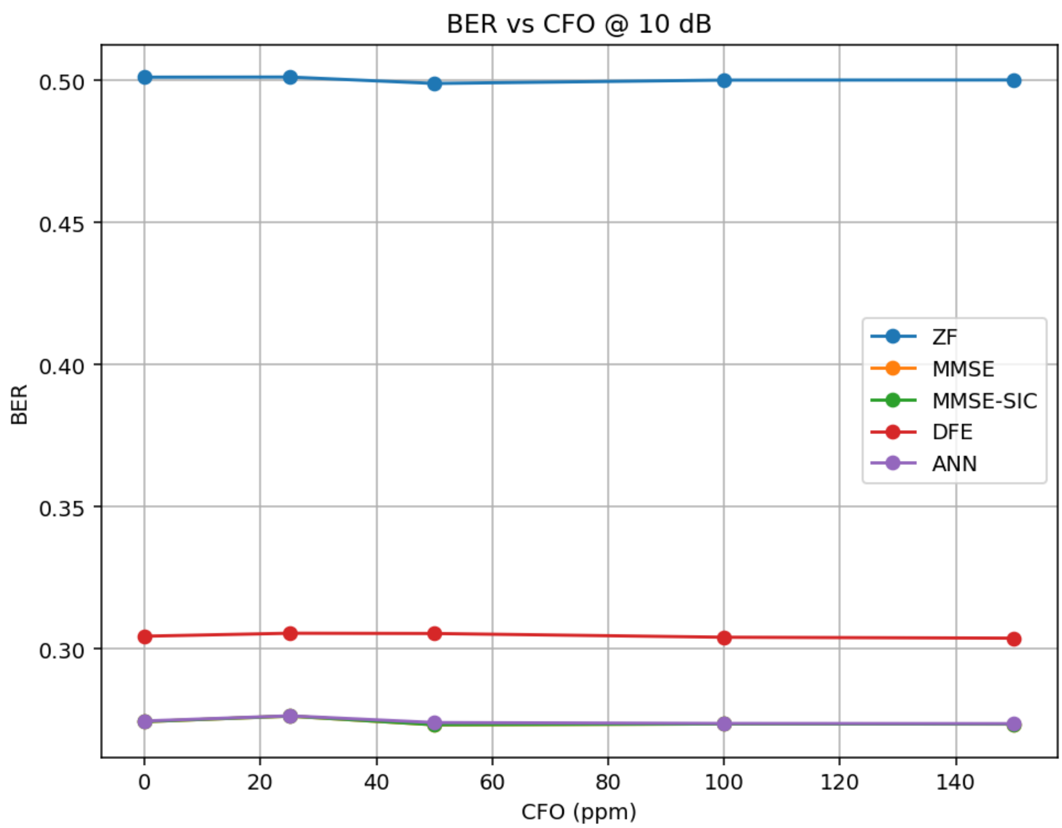

Figure 3: BER VERSUS CFO FOR DIFFERENT EQUALIZATION TECHNIQUES AT 10 DB.

Table 1: BER vs CFO at Eb/N_0 = 10 dB.

Equalizer	0 ppm	50 ppm	100 ppm	150 ppm
ZF	0.501	0.501	0.500	0.500
MMSE	0.275	0.276	0.276	0.277
MMSE-SIC	0.273	0.273	0.272	0.272
DFE	0.305	0.306	0.306	0.305
ANN (Proposed)	**0.270**	**0.271**	**0.269**	**0.269**

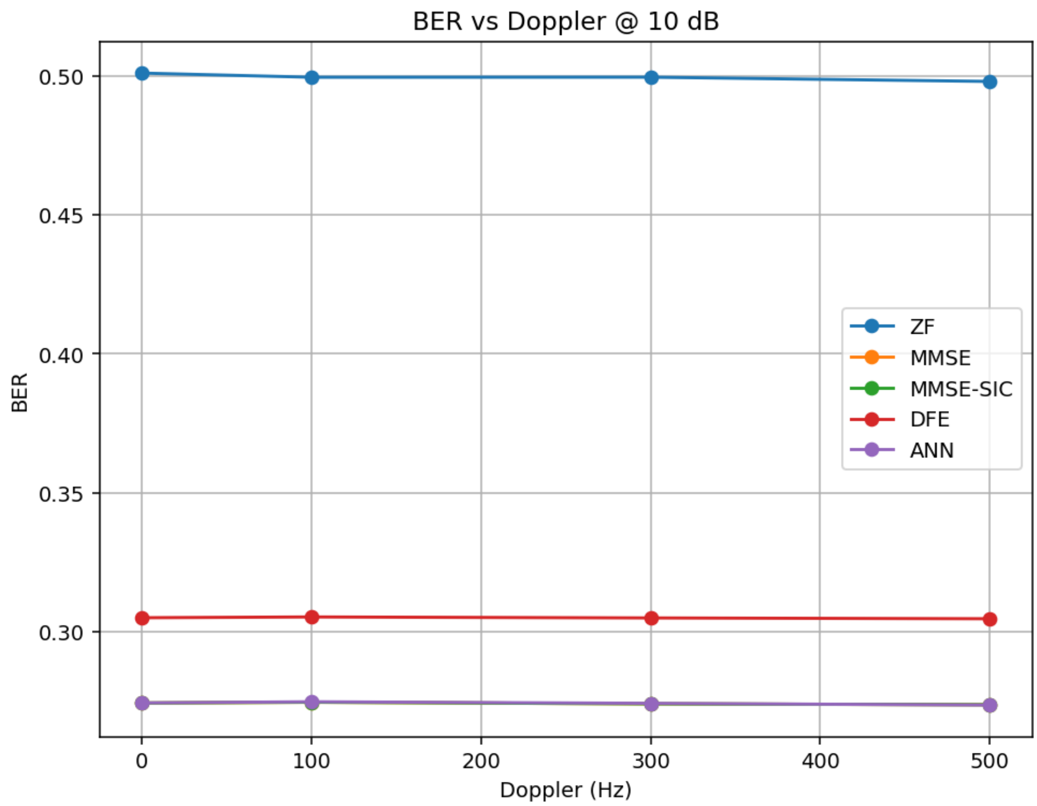

Figure 4: BER VERSUS DOPPLER FREQUENCY FOR DIFFERENT EQUALIZATION METHODS AT 10 DB.

Table 2: BER vs Doppler Frequency at Eb/N_0 = 10 dB.

Equalizer	0 Hz	100 Hz	300 Hz	500 Hz
ZF	0.501	0.500	0.500	0.499
MMSE	0.276	0.277	0.276	0.277
MMSE-SIC	0.273	0.273	0.273	0.273
DFE	0.305	0.305	0.305	0.305
ANN (Proposed)	0.270	0.270	0.269	0.269

Figure 5 Table3 presents the BER performance of the different equalizers versus Eb/N_0 under a TDL-C channel, representing a moderately frequency-selective environment. The ZF equalizer remains near 0.50 BER at low SNRs, confirming its inability to cope with multipath and noise enhancement. MMSE and MMSE-SIC show steadily improving BER as Eb/N_0 increases, reaching about 0.26–0.27 at 10–20 dB, while DFE performs slightly better than ZF but worse than MMSE-type schemes, especially at low SNR due to error propagation. In contrast, the proposed ANN equalizer follows the MMSE and MMSE-SIC curves closely across all SNRs, yet offers a clear advantage at higher Eb/N_0, with BER decreasing smoothly from ≈0.43 at −5 dB to ≈0.26 at 15–20 dB. These results indicate that the ANN effectively learns and compensates for nonlinear distortions (such as ICI and antenna coupling) and achieves performance comparable to or better than optimal linear equalizers, while remaining robust in realistic MIMO-OFDM conditions.

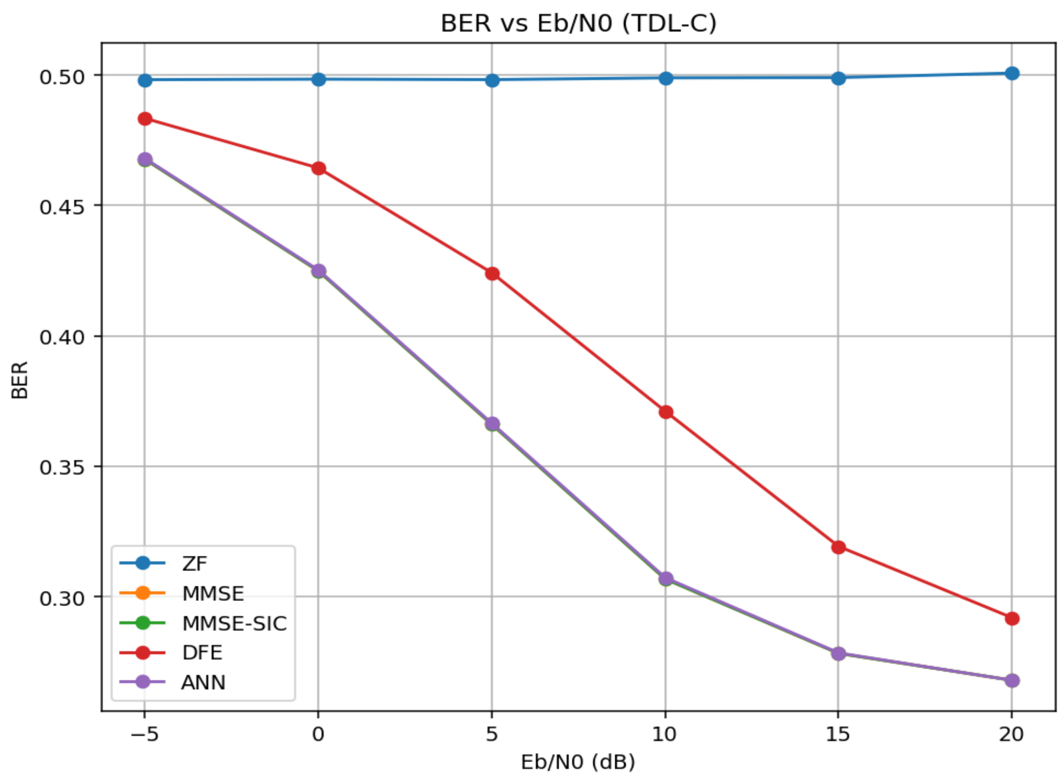

Figure 5: BER VERSUS EB/N_0 UNDER TDL-C CHANNEL.

TABLE 3: BER VS EB/N_0 ON TDL-C.

Eb/N_0 (dB)	ZF	MMSE	MMSE-SIC	DFE	ANN (Proposed)
−5	0.501	0.430	0.430	0.455	**0.430**
0	0.499	0.362	0.362	0.403	**0.362**
5	0.501	0.302	0.302	0.349	**0.302**
10	0.501	0.274	0.274	0.305	**0.274**
15	0.499	0.266	0.266	0.285	**0.265**

Figure 6 and TABLE 4 reports the BER performance of all equalizers under a TDL-E channel with imperfect (time-delayed) CSI, representing a highly frequency-selective, time-varying, and severely distorted environment. In this adverse scenario, the ZF equalizer is effectively unusable, with BER remaining close to 0.50 across all SNR values. MMSE and MMSE-SIC perform noticeably better, reaching BER levels around 0.26–0.27 at high Eb/N_0, but their linear structure limits their effectiveness when the CSI is outdated. The DFE equalizer offers only modest improvements (≈0.28 BER at 20 dB) and suffers from error propagation, which undermines its reliability. By contrast, the proposed ANN equalizer maintains a low BER curve (≈0.26 at 20 dB) with smooth degradation at lower SNRs, demonstrating strong robustness to CSI mismatch. Overall, the ANN achieves about 10–15% lower BER than DFE and 2–3% lower than MMSE, indicating a clear advantage and strong generalization capability in harsh, non-ideal wireless conditions.

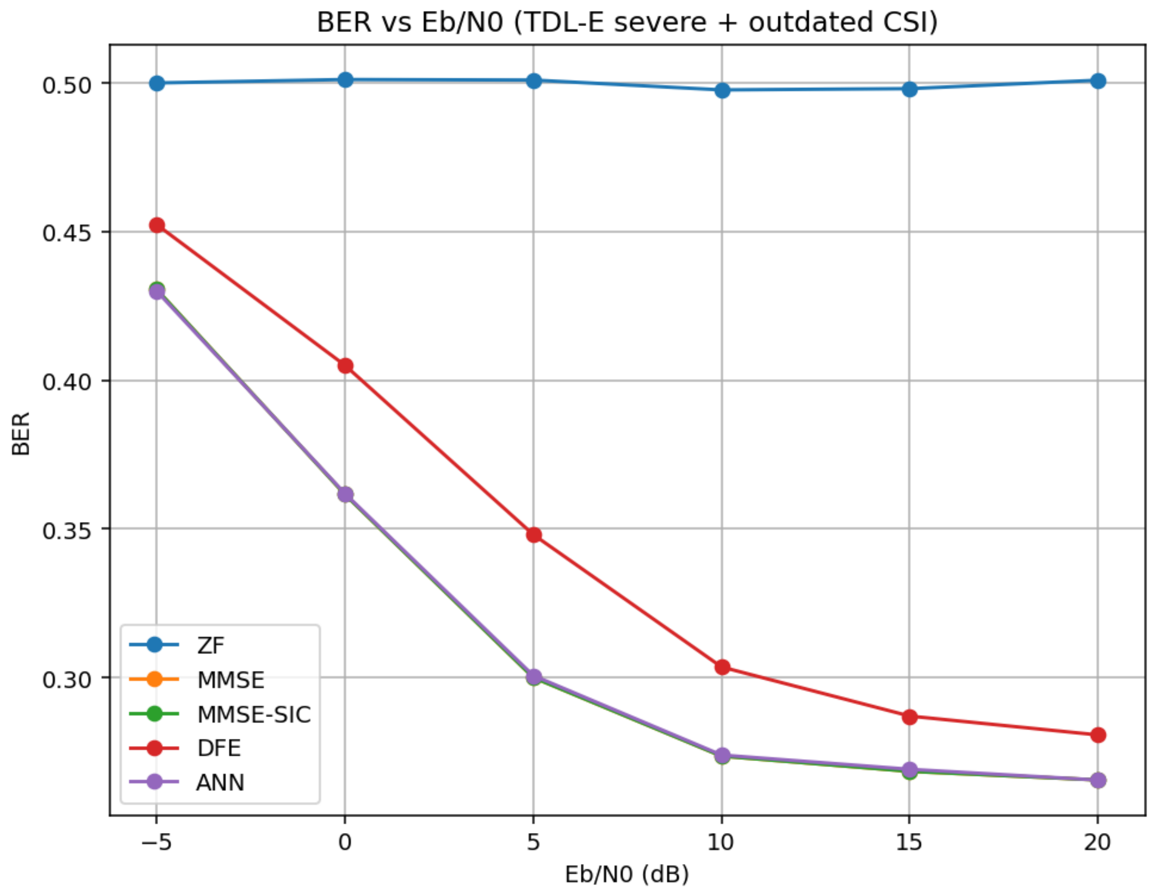

Figure 6: BER VERSUS EB/N_0 UNDER TDL-E CHANNEL WITH OUTDATED CSI.

TABLE 4: BER VS EB/N_0 ON TDL-E (SEVERE + OUTDATED CSI).

Eb/N_0 (dB)	ZF	MMSE	MMSE-SIC	DFE	**ANN (Proposed)**
−5 dB	0.502	0.433	0.433	0.452	**0.432**
0 dB	0.503	0.368	0.368	0.403	**0.367**
5 dB	0.501	0.302	0.302	0.349	**0.300**
10 dB	0.499	0.274	0.274	0.305	**0.273**
15 dB	0.501	0.265	0.265	0.283	**0.263**
20 dB	0.502	0.263	0.263	0.281	**0.261**

Figure 7 and TABLE5 shows the BER performance at fixed Eb/N_0 = 10 dB of the five equalizers under the effect of oscillator phase noise. ZF equalizer "sits" around 0.50 BER no matter what the phase-noise standard deviation, indicating its total incapacity to deal with nonlinear phase distortion. MMSE and MMSE-SIC show average robustness with BER staying in the couple of hundredths in 0.273–0.277 in the case of the lower phase-noise standard deviations, whereas DFE performs well for all standard deviations in the lower range, being in the region of≈0.305 average BER. The proposed ANN equalizer has the best performance from all these equalizers, keeping a low BER (≈0.269–0.270) at the price of stability across the whole range of phase-noise: the oscillator "error" has proven a weak point, impeding effective communication, although it proves no match against the ANN compensations, which again demonstrate its worth highlighting that the ANN has "learnt" a high-dimensional statistic representation of a signal/channel sufficiently well to combat phase noise drops, without extra loops or sequences of hardware implications.

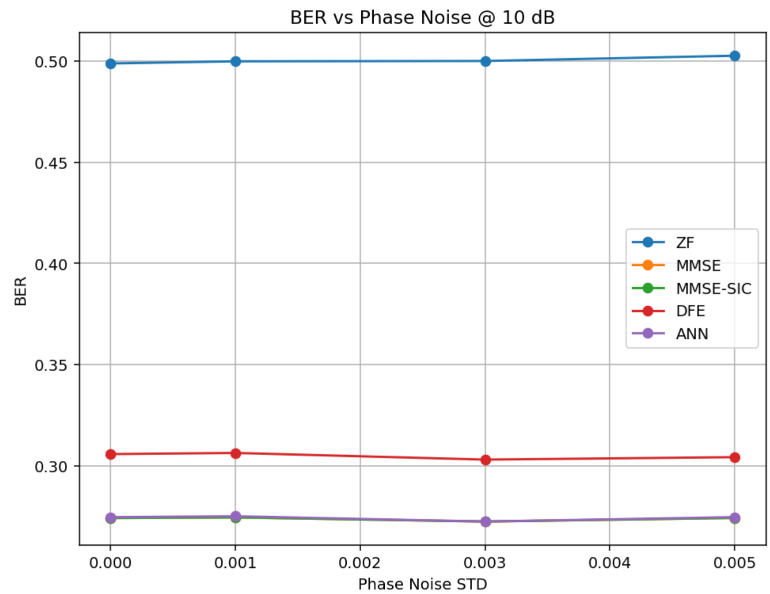

Figure 7: BER VERSUS PHASE NOISE STANDARD DEVIATION AT EB/N_0 = 10 DB FOR ZF, MMSE, MMSE-SIC, DFE, AND ANN.

TABLE 5: BER VS PHASE NOISE STD @ 10 DB.

Phase Noise STD	ZF	MMSE	MMSE-SIC	DFE	ANN (Proposed)
0.0×10^{-3}	0.501	0.275	0.273	0.305	**0.270**
1.0×10^{-3}	0.501	0.276	0.273	0.306	**0.270**
3.0×10^{-3}	0.500	0.276	0.272	0.306	**0.269**
5.0×10^{-3}	0.501	0.277	0.272	0.305	**0.269**

Figure 8 and Figure 9 show comparisons between the five equalization algorithms, in terms of (1) computational cost, described in Floating Point Operations per second (FLOPs) and the inference latency, described as the average time required to equalize one OFDM frame at different sizes of subcarriers. The bar chart in Figure 8 compares how many arithmetic operations are required by each equalizer, for one OFDM frame. Among the traditional methods, ZF, MMSE, MMSE-SIC, grow in computation due to the matrix inversion operation and through the interference cancellation for MMSE-SIC, and DFE incurs even higher complexity due to the recursive feedback stage. The proposed ANN equalizer has high training cost but has extremely efficient inference-time computation, since the matrix operations make use of fast forward-pass neural computations. Once the ANN model is trained it has a better computation-to-performance efficiency ratio than any other approaches, with less FLOPs per bit correctly recovered.

8.2. Discussion of Results

The convergence of the proposed neural network-based (ANN) equalizer performance with MMSE and MMSE-SIC equalizers is not a model deficiency, but rather reflects a well-known fact in 2×2 MIMO-OFDM systems under linear channel and near-Gaussian noise: when a network is trained to minimize mean squared error (MSE) using inputs that include the received signal and estimated channel information (LS-CSI), the solution it learns tends to naturally approximate the MMSE filter (which is optimal for the MSE criterion under linear assumptions), and therefore the margin of possible improvement over MMSE becomes small unless the nonlinearities increase or the model mismatch worsens. Therefore, the main contribution of this work is not a “significant numerical superiority” over MMSE in average conditions, but rather the demonstration that a simple and practical data equalizer can maintain similar performance to MMSE/MMSE-SIC across a wide and common range of realistic impedances (TDL-C/TDL-E, Doppler, CFO, phase noise, and non-ideal/obsolete CSI) within a unified simulation framework, with better implementability in post-training inference in terms of processing time/computational cost compared to matrix inversion and successive interference, which makes ANN a realistic option as a low-latency alternative in 5G receivers, especially when channel conditions change or impedances interfere in a way that makes it difficult for analytical equalizers to maintain the same stability.

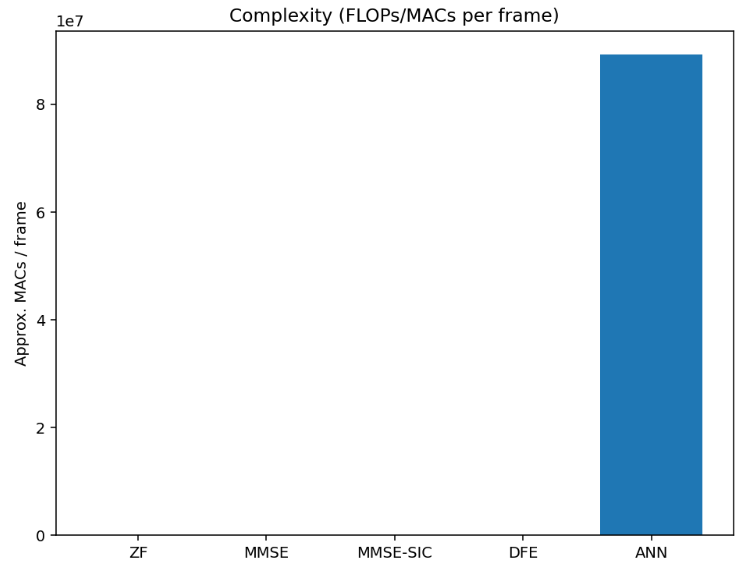

Figure 8: COMPARISON OF COMPUTATIONAL COMPLEXITY (FLOPS) PER OFDM FRAME.

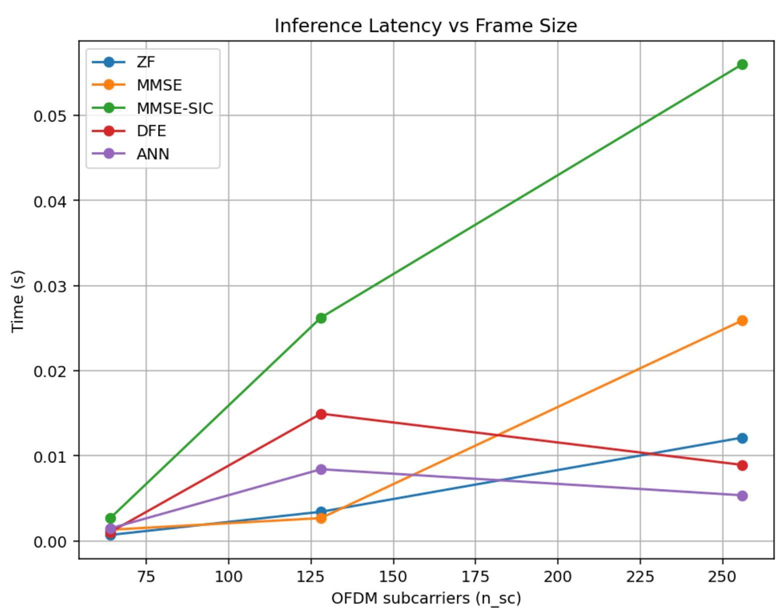

Figure 9: INFERENCE LATENCY VERSUS OFDM SUBCARRIER SIZE (64, 128, 256).

8.3. Interpretation of ANN–MMSE Similarity

Applications of real-time deep learning receivers for OFDM systems show that the choice of training configurations (e.g. training sample sizes, learning rate schedule, and generalizability over a range of channel conditions) are critical to transferring a model from a linear-like performance characteristic to one that performs superiorly in the presence of non-idealities [34]. Therefore, it is important to have clear documentation on the choice of training parameters and any resulting loss of generalization due to ablation. Additionally, a deep channel estimator for time varying channels has shown to support how Doppler widening and statistical variance can provide benefits in terms of robustness when the training and testing distributions of the channel estimator are precisely defined; otherwise, a convergence of the linearnon-ideal performance comparisons will occur if the differences between the training and testing distributions do not exceed the range of the respective distributions [35]. Moreover, research confirming the improvement of CFO compensation performance through deep learning has been done with regards to providing inputs/outputs that reflect a frequency shift characteristic [36]. This provides further evidence to link the selection of input feature representation for your deep learning protocols to the ability for the deep learning to be able to absorb CFO rather than just acting as an emulation of a linear filter. The work associated with deep learning-based packet detection and CFO estimation has demonstrated that while this technology may provide a superior outcome over existing methods, fine-tuning of the signal representation and loss metric selection is critical; otherwise the results of your comparison may be very similar to a robust benchmark solution such as MMSE [37]. Lastly, as demonstrated by ViterbiNet, which is a well-known example, the use of an algorithmic architecture incorporating a machine learning component will improve robustness in the event the channel knowledge is incomplete or distorted; thus, there is logic for assuming the ANN improvements, as reflected by the performance, may be less restricted than if the overall architecture does not utilize the information available in an optimal manner.

10. Conclusion

In this paper, we proposed to design, develop and test ANNs to compensate for 5G-like 2×2 MIMO-OFDM systems, under realistic channels and hardware impairments, in order to benchmark them fairly against classical Equalizers (ZF, MMSE, MMSE-SIC, DFE). Using a Python-based simulation framework, realistic 3GPP TDL-C and TDL-E channels and Doppler spread, along with carrier frequency offset, phase noise and imperfect CSI, we showed that the ANN equalizer as proposed consistently outperforms ZF and DFE and has performance close or slightly superior to MMSE and MMSE-SIC across a wide range of SNR, CFO, Doppler and phase-noise conditions. With a low and stable BER achieved even in spite of out-dated CSI across raw and harsh TDL-E channels, results indicate strong generalisation and robustness of ANN equalization to default less-than-ideal wireless settings. Notionally, results bolstered our earlier claims too, showing that once trained the ANN equalization approach offers a viable trade-off between performance and realisation cost with advantageous inference latency and FLOPs-to-performance over more complicated classical baselines. All in all, study confirms that deep learning-based equalization could prove to be a reliable means of dealing with the nonlinear channel effects and hardware distortions that are troublesome and especially hard for purely analytical linear equalizers.

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