

Deep Learning for Interference Cancellation in Non-orthogonal Signal Based Optical Communication Systems

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Abstract— Non-orthogonal waveforms are groups of signals, which improve spectral efficiency but at the cost of interference. A recognized waveform, termed spectrally efficient frequency division multiplexing (SEFDM), which was a technique initially proposed for wireless systems, has been extensively studied in 60 GHz millimeter wave communications, optical access network design and long haul optical fiber transmission. Experimental demonstrations have shown the advantages of SEFDM in its bandwidth saving, data rate improvement, power efficiency improvement and transmission distance extension compared to conventional orthogonal communication techniques. However, the achieved success of SEFDM is at the cost of complex signal processing for the mitigation of the self-created inter carrier interference (ICI). Thus, a low complexity interference cancellation approach is in urgent need. Recently, deep learning has been applied in optical communication systems to compensate for linear and non-linear distortions in orthogonal frequency division multiplexing (OFDM) signals. The multiple processing layers of deep neural networks (DNN) can simplify signal processing models and can efficiently solve un-deterministic problems. However, there are no reports on the use of deep learning to deal with interference in non-orthogonal signals. DNN can learn complex interference features using backpropagation mechanism. This work will present our investigations on the performance improvement of interference cancellation for the non-orthogonal signal using various deep neural networks. Simulation results show that the interference within SEFDM signals can be mitigated efficiently via using properly designed neural networks. It also indicates a high correlation between neural networks and signal waveforms. It verifies that in order to achieve the optimal performance, all the neurons at each layer have to be connected. Partially connected neural networks cannot learn complete interference and therefore cannot recover signals efficiently. This work paves the way for the research of simplifying neural networks design via signal waveform optimization.

1. INTRODUCTION

Challenges exist in modern communication systems where mathematical models are not easily derived. In the scenario of massively connected IoT devices [1], channel models are of high complexity since thousands of devices would be connected. In this case, accurate mathematical channel modelling is unrealistic. Furthermore, future 5G systems [2] require ultra-low latency communications. Thus, the signal processing at both transmitter and receiver should be correspondingly as simple as possible. In realistic communication systems, due to complex channel conditions, complex channel estimation and equalization algorithms have to be used at the receiver leading to increased receiver complexity and extra signal processing power consumption. In addition, due to the existence of ICI in some signals [3–8], variable interference cancellation algorithms have to be used to remove interference. Other signal distortions such as frequency offset, timing synchronization, phase offset and mismatched local oscillators would introduce extra interference [9]. All the effects have to be compensated at the receiver with the assistance of complex signal processing. Long-haul optical communication systems have nonlinear distortions [10, 11] arising mainly from the fiber. The mitigation of this effect is complex via using the DBP method [10, 11]. With the increased fiber distance, the effect becomes more significant and its compensation complexity is proportionally increased. The mitigation of fiber nonlinearity using machine learning techniques has been investigated in previous reports [12].

Conventional communication systems modelling divide the entire system into several blocks [13] and each block can realize a specific function such as channel coding, modulation and equalization. By using this independent block concept, the optimization of the whole system would be simplified

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since updates can be operated within each block. The benefit of such concept is that each block can be independently analysed and optimized to the maximum extent. But in terms of the entire system, this sub-optimal architecture has global optimization challenges. In order to analyse globally the system and optimize the system performance, we need to break the block based system architecture. The way to do this is to analyse the end-to-end performance and ignore the internal structure of the system. The simplicity of the system enables black box modelling approach of the system [14, 15], which skipped unknown mathematical models.

Machine learning has been a popular tool for machine intelligent applications. This is due to the fast growing demands from customers and the timely development of machine learning processing hardware such as GPU. Machine learning can efficiently deal with the black box approach via iterative learning. Work in [16] reviewed the fundamental concepts of machine learning and showed their possible applications in future 5G networks. Machine learning is becoming popular in optical communication system applications [12] such as laser amplitude and phase noise characterization in [17] and nonlinearity mitigation using the k-nearest neighbours (KNN) detector in [18]. Recently, deep learning is being utilized in communication systems to solve complex mathematical-driven problems. Deep learning, an evolved version of machine learning, has been studied for physical layer applications and has proven its superiority over typical machine learning approaches [14, 15, 19, 20]. Generally, deep learning employs increased number of hidden layers in order to extract more features and construct neural networks more flexibly. Based on the improved neural network architecture, deep learning has been successfully applied in OFDM systems [20], MIMO systems [21] and over-the-air communications test [22]. The existing deep learning work on communications is based on orthogonal signal waveforms such as OFDM [20]; to date there are no reports on non-orthogonal signal waveforms.

This work is focused on a non-orthogonal signal waveform, termed SEFDM, which can improve spectral efficiency via compressing sub-carrier spacing. The waveform has been successfully tested on optical testbeds [23, 24], wireless testbed [3] and 60 GHz millimeter-wave testbed [25]. The aim of this work is to simplify the signal detection on SEFDM signals using deep learning. Different neural networks were designed for the interference mitigation with variable performance and complexity. This work does not aim to find the best deep learning model for SEFDM signals, but it paves the way for the joint study of deep learning and non-orthogonal SEFDM signals. Simulations in this work show that deep neural networks (DNN) can mitigate interference more efficiently than the typical hard decision method. It is indicated that the characteristics of communication signal waveforms would affect the efficiency of neural networks.

2. NON-ORTHOGONAL SIGNAL WAVEFORM

The non-orthogonal signal waveform SEFDM was firstly designed in 2003 with the characteristics shown in Fig. 1. It is clearly seen that the SEFDM signal waveform saves bandwidth relative to the typical OFDM. The higher bandwidth saving the higher ICI. The mathematical principle of the discrete representation of an SEFDM signal symbol is expressed as

$$X[k] = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} s_n \cdot e^{j2\pi nk\alpha} \quad (1)$$

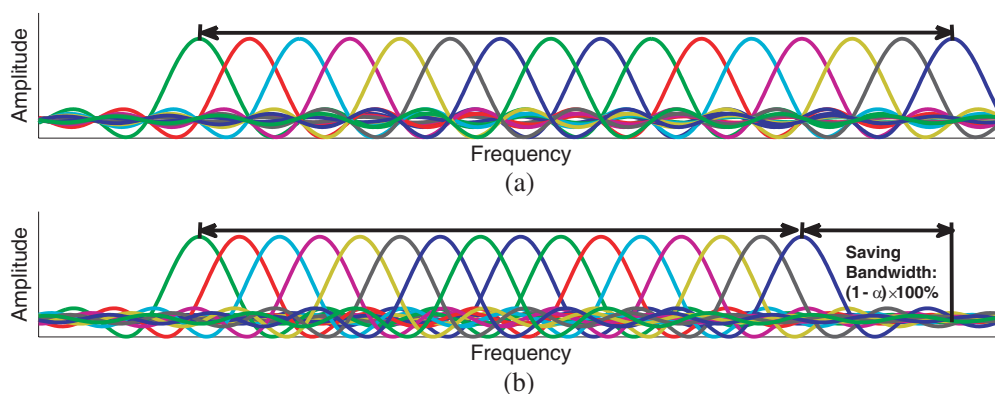


Figure 1: Spectra of OFDM and SEFDM. (a) OFDM spectrum. (b) SEFDM spectrum with bandwidth compression factor $\alpha = 0.8$.

where N is the number of sub-carriers, $X[k]$ is the k th time sample with $k = [0, 1, \dots, N - 1]$, s_n is a M-QAM symbol modulated on the n th sub-carrier and $\frac{1}{\sqrt{N}}$ is a scaling factor.

Considering two arbitrary sub-carriers with indices m and n , hence, the orthogonal characteristic is verified by correlating two modulated symbols and the correlation parameters are normally expressed as a matrix whose elements are given by

$$c_{m,n} = \frac{1}{N} \sum_{k=0}^{N-1} e^{\frac{j2\pi mk\alpha}{N}} e^{-\frac{j2\pi nk\alpha}{N}} = \begin{cases} 1, & m = n \\ \frac{1 - e^{j2\pi\alpha(m-n)}}{N \left(1 - e^{\frac{j2\pi\alpha(m-n)}{N}}\right)}, & m \neq n \end{cases} \quad (2)$$

where the off-diagonal terms ($m \neq n$) in (2) indicate the effect of non-orthogonal overlapping, which results in ICI.

It is mathematically shown that the second term in (2) is the interference component that has to be removed. All our previous work is focused on the removal of this term. Many signal detection algorithms have been explored and summarized in [26]. Basically, the detection algorithm is a trade-off between performance and complexity. On one hand, the better performance indicates higher detector complexity. On the other hand, lower complexity results in worse performance. The novelty of this work is to use deep learning to learn the complex interference via backpropagation mechanism and mitigate its impact. The efficiency of the removal is dependent on the signal waveform characteristics and neural networks architectures.

3. DEEP LEARNING BASED SIGNAL DETECTION

3.1. System Architecture

To demonstrate the performance improvement of using neural network based signal detection, we designed a dual-polarization optical fiber communication system as schematically shown in Fig. 2. Two signal detection methods are studied and compared. The first one is the hard decision detector and the second one is the neural networks based detector, with the architecture shown in the grey blocks.

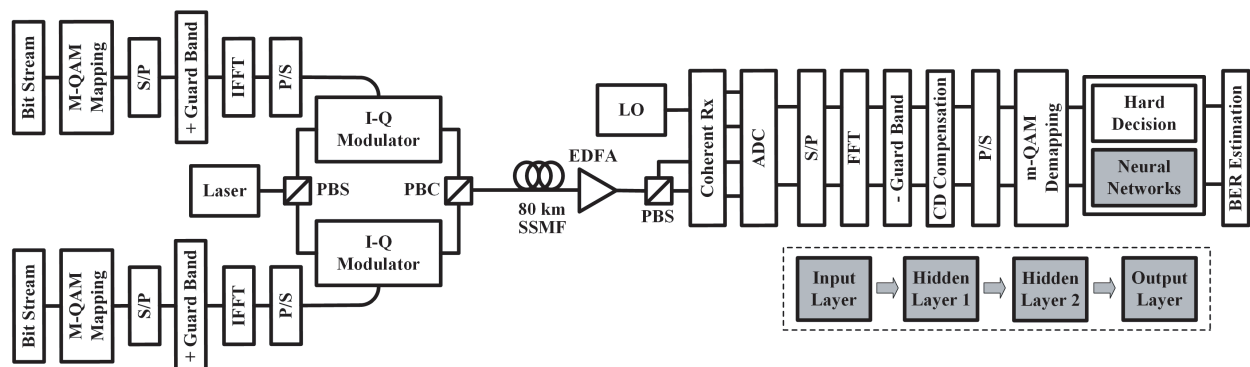


Figure 2: Neural networks based OFDM/SEFDM optical fiber transmission system. I-Q: in-phase and quadrature, S/P: serial to parallel, S/P: parallel to serial, PBS: polarization beam splitter, PBC: polarization beam combiner, Rx: receiver, ADC: analogue-to-digital converter.

At the transmitter, for a given polarization, the bit stream is firstly mapped to 4QAM symbols and after serial/parallel conversion, frequency guard bands are added at both sides of the signal spectrum for the purpose of oversampling. Then, either OFDM or SEFDM IFFT is used to modulate the 4QAM symbols on each sub-carrier. After the parallel/serial conversion, the electrical signal complex representation is ideally mapped onto an optical carrier. The same process is applied to the second polarization. Note that the modulated symbol sequences are independent and random for each polarization. The system is simulated using 50 Gbaud 4QAM signals over 80 km SSMF. The AWGN is also included after the fiber transmission. Here we consider a transmission of 80 km SSMF to demonstrate the feasibility of the designed neural network in the transmission

scenario, for longer transmission distance fiber nonlinearity has to be taken into account, and this will be investigated in future publication.

The signal propagation over SSMF is simulated by solving the Manakov equation using the split-step Fourier method [27]. An erbium-doped fiber amplifier (EDFA) is applied at the end of transmission span to compensate for the fiber loss. At the receiver, the signal is mixed with an ideal local oscillator (LO) laser to implement phase- and polarization-diverse coherent detection. The detected signals are then digitized using ideal analogue-to-digital converters. The system studied in this work does not employ cyclic prefix, and the chromatic dispersion was compensated using a frequency-domain equalizer [28].

3.2. Neural Network Design for Interference Mitigation

The aim of this section is to design different neural networks to mitigate the interference term in (2). Depending on different interference mitigation principles, the design of the neural network is different. In this section, we designed five neural networks for the non-orthogonal signal and each one has specific interference mitigation scheme. Five different neural network topologies are illustrated in Fig. 3.

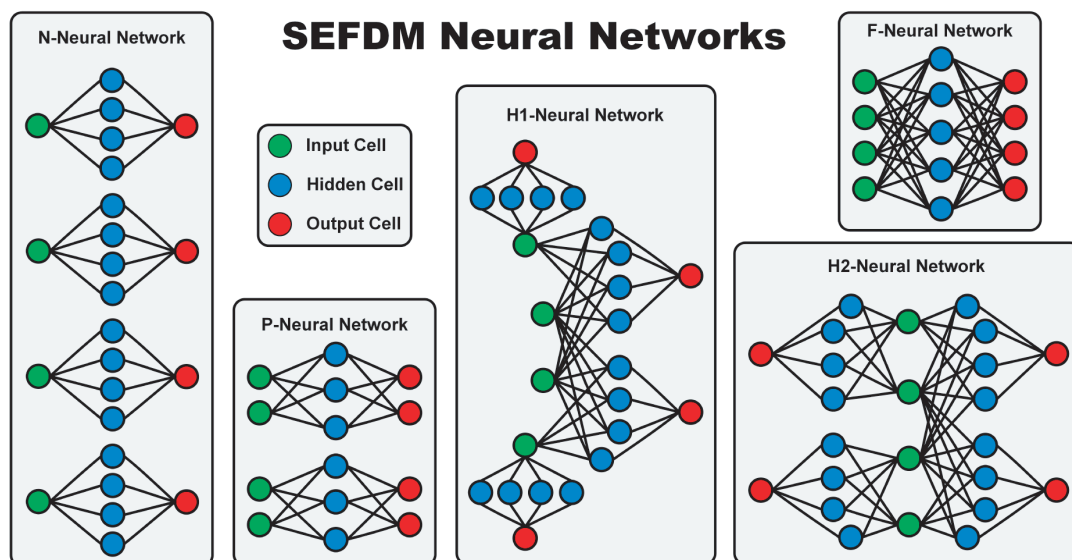


Figure 3: Neural network architectures for SEFDM signals. For simplicity, only one hidden layer is illustrated. For deep learning scenarios, more hidden layers are required.

The first one, termed no connection-neural network (N-NN), has the simplest network connections where each symbol associated with one sub-carrier forms an independent network termed sub-nets. There are multiple sub-nets making up the entire network. The number of sub-nets is determined by the number of sub-carriers in SEFDM signals. This independent sub-nets architecture was used in OFDM wireless [29] and optical [30] systems. The reason for this architecture is that sub-carriers within OFDM are orthogonally packed and no cross interference exists. The complexity is proportional to the number of sub-carriers. In terms of SEFDM, since sub-carriers are non-orthogonally packed, interference will be introduced between adjacent sub-carriers. Thus, this network architecture would be no longer accurate.

The second topology, termed partial connection-neural network (P-NN), is an evolved version of the N-NN. In such evolved network, two symbols on adjacent input cells are connected in one sub-net and processed jointly. Therefore, the decision of one output cell is jointly determined by two adjacent input cells. This scenario assumes that the interference comes only from one neighbouring input cell. This will include the adjacent interference factor and would derive a more accurate network model. The parallel architecture still exists within P-NN but each sub-net will jointly process two input cells and two output cells.

The third topology, termed hybrid1-neural network (H1-NN), divides the input cells into two groups. The two edge cells form independent sub-net similar to the one in N-NN. The middle input cells take into account interference from adjacent cells and make up interleaved connections, hence the “hybrid” in the name. Since the interference suffered on middle input cells is considered in the

network, a more accurate model than the P-NN can be derived.

The fourth topology, termed hybrid2-neural network (H2-NN), optimizes the connections for the edge input cells. As a matter of fact, the two edge input cells are interfered from their adjacent input cells as well. This crucial information has to be included in the network. The way to emulate this impact is to connect the edge input cell to its neighbouring cell. With a more accurate network connection, a more accurate model can be derived. H2-NN can efficiently emulate the interference suffered on each sub-carrier of SEFDM signals. Therefore, the H2-NN outperforms the H1-NN.

The last topology, termed full connection-neural network (F-NN), effects a fully connected mesh network. This network connects all the input cells and considers interference from both adjacent cells and non-adjacent cells. The decision of one symbol has to be determined by all the input symbols. This fully connected network architecture explores the interference completely within SEFDM signals and will show the best performance among the five investigated network architectures.

Complexity is dependent on the neural network topology. Expectedly, the F-NN has the highest computational complexity since all the neurons are connected and each connection link requires arithmetical computation. The N-NN topology has the lowest computational complexity since all the input cells are independent and they can be operated in parallel.

3.3. Principle of Training and Prediction

The employed deep neural networks follow the architectures in Fig. 3 but with more complex structures. In this work, we use deep neural networks consisting of four layers, in which two are hidden layers. The number of input and output neurons correspond to the number of sub-carriers of SEFDM signals. Taking into account the input layer and output layer, the number of neurons at each layer is chosen to be 4, 14, 14, 4. In addition, the Sigmoid function is applied as the activation function at each layer. First the neural network is trained off-line using a large amount of simulated random data in the optical system following the architecture in Fig. 2. As investigated by the work in [31], with pseudorandom bit sequences a large artificial gain can be obtained. In order to avoid this risk and get a stable and proper approximation model, we trained 40,000 4QAM symbols, which were generated from random bits. After a number of training iterations, a stable deep neural network model is obtained and is used as a signal detector to recover newly received signals.

This work aims to show the efficiency of using different neural networks for interference features extraction but not the best neural network design. Therefore, in this simulation, the system is configured to be as simple as possible. The number of sub-carriers in this case is set to four and the bandwidth compression factor is set to $\alpha = 0.8$. The system configuration indicates a small size system but it will speed up the training and prediction.

4. RESULTS AND DISCUSSION

In order to evaluate the efficiency of deep learning on SEFDM signal recovery, this section will study different neural networks for various non-orthogonal SEFDM signals and compare their performance with traditional SEFDM signal detection methods. The simulation results are shown in Fig. 4. In this figure, different neural networks, derived from Fig. 3, are tested here for the same signal waveform.

The typical hard decision performance is included in the figure as a comparison reference. In the B2B scenario as shown in Fig. 4(a), the N-DNN shows performance close to that of the hard decision detector. This is because each input cell in N-DNN is independently processed and no connections with other input cells. Although there are sufficient neurons and hidden layers which can improve the training accuracy, the independent processing architecture results in similar performance as the direct decision. Furthermore, the P-DNN network is tested and better performance is obtained. The performance gain is achieved since two input cells are connected and jointly trained. Thus more accurate interference features can be extracted from the network. The H1-DNN network shows further improved performance since the middle input cells are connected to neighbouring input cells and therefore accurate interference emulation for the middle cells is realized. Its evolved version is H2-DNN in which the interference to the edge input cell is properly emulated via the neighbouring neuron connection. With the additional neuron connection, H2-DNN performs slightly better than the H1-DNN. The best achieved performance comes from the F-DNN network since the complete interference to each sub-carrier is emulated. Thus the complete interference information can be extracted from the signal and an accurate model can be trained. Similar trends are observed in the 80 km fiber transmission results of Fig. 4(b), however, due to the dispersion caused by the 80 km optical fiber, performance loss is observed for all neural networks especially at high OSNR.

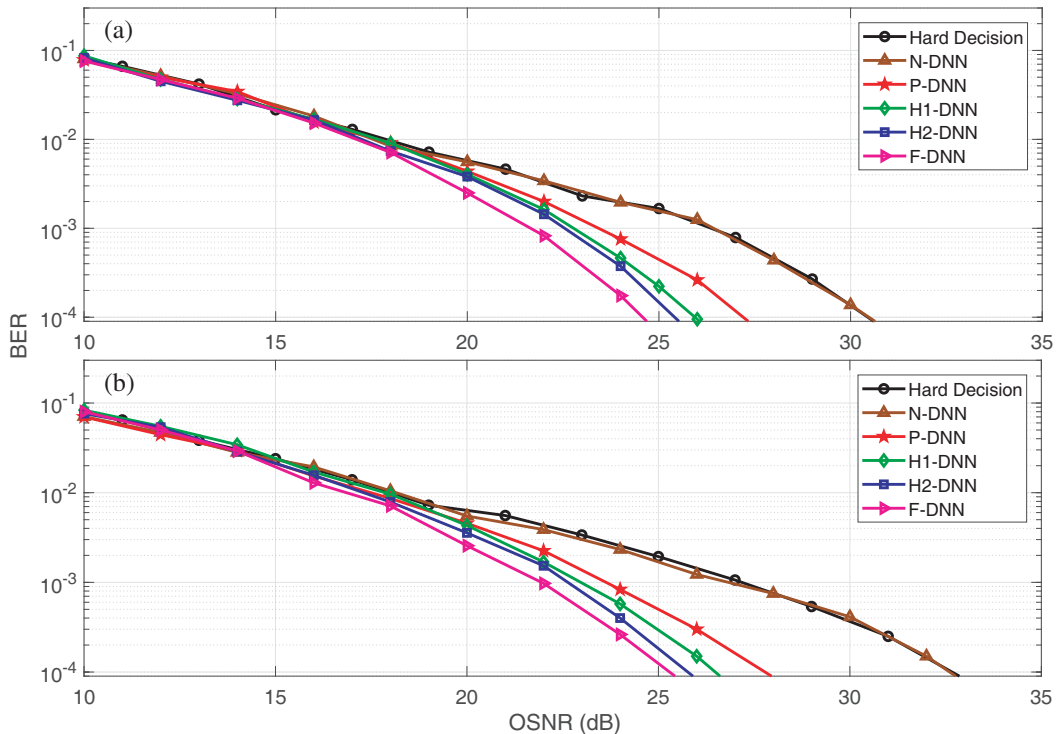


Figure 4: BER performance for back-to-back and 80 km fiber transmission. SEFDM signal waveforms with bandwidth compression factor $\alpha = 0.8$. (a) Back-to-back transmission. (b) 80 km fiber transmission.

5. CONCLUSIONS

Highly increasing demands for data services push the optical resource utilization to a limit. Therefore, improving spectral efficiency is becoming a crucial requirement, which is a hot research topic in the optical communication world at present. Due to the use of spectrally efficient signal waveforms, interference is introduced and complex interference compensation processing is required at the receiver. Alternative compensation algorithms may be based on learning-based methods, which can simplify signal processing without accurate mathematical modelling. Deep learning is a data-driven learning-based method that can learn interference from a large amount of data and mitigate interference effects in communication systems. This work studied the impact of deep learning neural network architectures on a non-orthogonal signal waveform. The simulation results shown in this work indicate the possibility of using neural networks to mitigate the ICI within SEFDM signal waveform and achieve a significant gain in signal-to-noise ratio compared to the typical hard decision detector. The aim of this work is to show the feasibility of using neural networks for the signals with interference challenges. The results also clarify the correlation between neural network architectures and signal waveform characteristics. Results showed that interference features can be modelled and extracted differently via using different neural networks. Depending on the signal waveform characteristics, different neural networks lead to different performance. Therefore, a joint design of neural networks and communication signal waveforms would lead to an efficient system with trade-off, which optimizes error rate performance or complexity.

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