Neural Network based Transceiver for Non-Coherent OFDM Optical Modulation

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***Abstract*—Optical wireless and radio front-haul communication systems are deemed as potential technologies to the radio frequency wireless communications in several applications. Consequently, the clipped non-coherent optical modulation techniques have gained significant attention. The trade-off between the spectral efficiency and the power efficiency of the benchmark techniques such as asymmetrical clipping optical OFDM (ACO-OFDM) and direct clipping optical OFDM (DCO-OFDM), pose a challenge of maintaining enhanced spectral and power efficiency for the design of the optical modulation techniques. In this paper, we propose a deep neural network (DNN) based optical transceiver. It uses simple but efficient DNN to predict the clipped negative parts of the transmitted signal at the receiver side. We evaluate and analyze several DNN-based optical transceiver architectures for different performance aspects. The DNN-based optical OFDM transceiver enhances the spectral and power efficiency compared to the latest works**.

***Keywords*-ACO-OFDM, DCO-OFDM, Deep neural network, Supervised learning, Optical modulation**

I. INTRODUCTION

Among many different access technologies, coherent and non-coherent optical communications are considered a perfect partner that bids unlicensed frequency, secured communications, and interfered less with the existing technologies [1]. Although non-coherent optical communication gained much attention in the last few years due to the simplicity in sending data using intensity modulation with direct detection (IM/DD), on the other hand, IM/DD imposes more requirements on the transmitted signal to have positive and real values [4]. Much research presented asymmetrical clipping optical OFDM (ACO-OFDM) and direct clipping optical OFDM (DCO-OFDM) as benchmarks techniques that accommodate real positive signal transmission.

Machine learning (ML) can play an essential role in 5G network as it has the potential to learn experienced scenarios and predict future scenarios with adaptation to the environmental fluctuations [8]. The ML algorithms are mainly classified into three approaches, supervised, unsupervised, and reinforcement learning. As the understudy case is demonstrated as a prediction problem, the supervised learning algorithms are proposed as it can predict and classify outputs based on labelled data while generating a rule that maps the inputs to outputs. As supervised algorithms based on regression method estimate the relation between the response and the regressor values to predict one or more outputs. Recently Artificial intelligence (AI) has been deployed to provide solutions that face 5G challenges. In [11], the author proposes analytical and active ML techniques that can manage cell fault, where the fault management aims to optimize the error in the network as the cell outage. In the optical communications domain [13] proposes a method of training and applying neural network that adaptively decode the modulation scheme of the optical camera communication. In [14] the author proposes an artificial neural network (ANN) that compensate the effect of linear and nonlinear impairments as Gaussian white noise, laser phase noise and nonlinear phase of coherent optical communication. In [15] an end-to-end optical modulation design based on deep learning is proposed, the proposed model considers pulse amplitude modulation (PAM) as base band single carrier modulation.

In this paper we addressed the problem of predicting the clipped signal in multi-channel optical modulation (OOFDM), we describe the problem as a supervised regression problem in which the learner predicts the regressor clipped negative signal values using the response and the regressor values map obtained in the training phase. Our contribution can be concluded as We propose a deep neural network (DNN) with multiple hidden layer and nonlinear activation function that fits the nonlinearity of the Fourier series clipping operation, The proposed model combines the power efficiency of the ACO-OFDM technique and the spectral efficiency of the DCO-OFDM.

II. SYSTEM MODEL

In the section, we propose our system model that consists of three main modules transmitter, receiver, and the AI module. The block diagram of the proposed transceiver is shown in Fig. 1. The transmitter of the multi-channel optical modulation (MCM) technique is represented as the first block. The transmitter functionality is split into three parts. First, the

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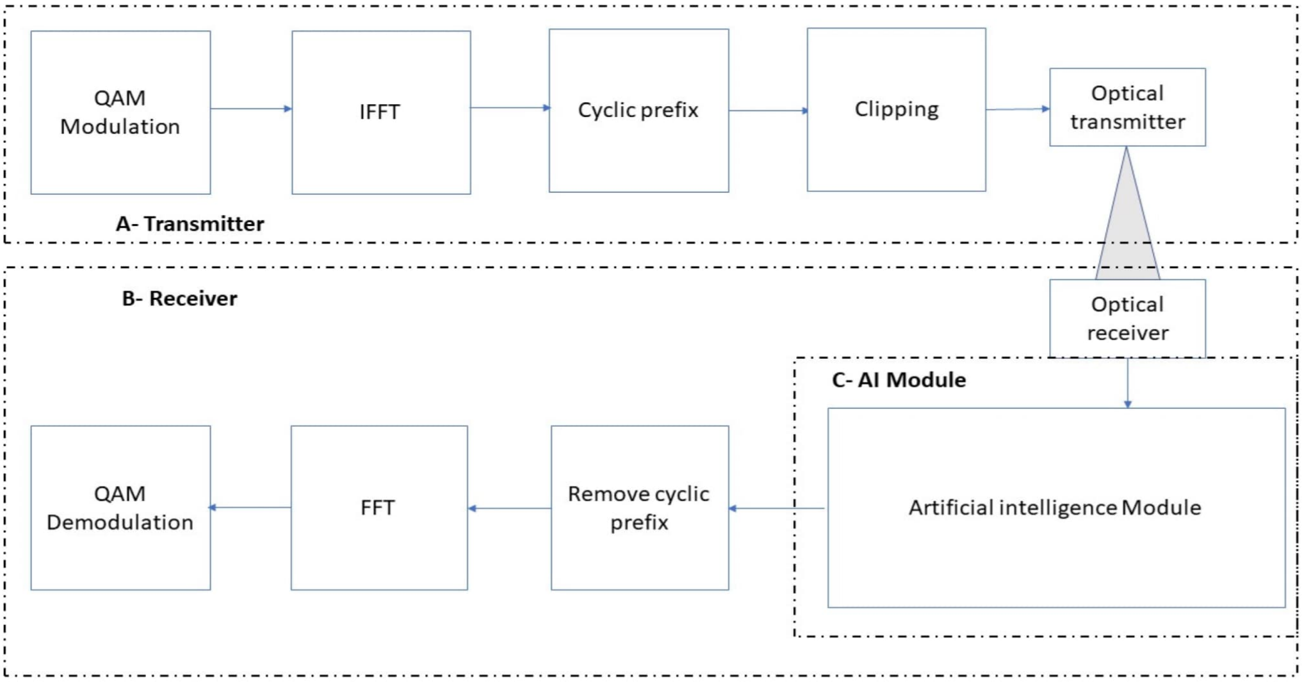

Fig. 1 Proposed Transceiver A. Transmitter, B. Receiver

transmitted bits are gathered as symbols using an arbitrary quadrature amplitude modulation technique (QAM). Then, these symbols are loaded to subcarriers with inverse Fourier transform operation. Finally, clipping the negative parts of the transmitted signal is performed to transmit it via an optical device. On the receiver side, the clipped received signal must be reconstructed as a bipolar signal by predicting the clipped part via AI module, that produces a bipolar signal from the transmitted unipolar signal. The predicted signal is then forwarded to the Fourier transform block to extract the data symbols from the received subcarriers and finally to the QAM demodulator to extract the received bitstream.

The problem of predicting the clipped parts of the received signal is described as a multivariate regression model that involves multiple data variables for analysis. Multivariate regression identifies the relation between dependent and independent variables using the training data set. Linear, polynomial, and logistic regression models are commonly used models under supervised learning algorithms. According to Bussgang's theory clipping the negative parts of the Fourier series at the transmitter side is described as nonlinear operation at the receiver side. For the described problem, of predicting the clipped parts of the received subcarriers, the hard clipping of negative parts represents the nonlinear relationship between the clipped and unclipped subcarriers. According to this, we apply and compare the performance of polynomial regression model and neural network, representing logistic regression, to fit the nonlinear relation between the clipped signal representing the independent variables and the unclipped signal representing the dependent variable. Single-layer neural network (NN) with nonlinear activation function is considered a direct representation of the nonlinear regression model. As fully connected NN with single hidden layer applies a nonlinear operation to the weighted sum of the inputs according to 1.

$$y_j = f\left(\sum_{i=1}^{n} w_{i,j}\, x_i + b\right) \qquad (1)$$

Where $w_{i,j}$ is the weight of each input i with neuron j, x_i is the activation inputs, y_i is the activation output, and b is the biasing of the hidden layer [17]. Deep neural network (DNN) with multiple hidden layers, are commonly used recently due to their learning capabilities and enhanced extraction, as DNN offers received signal learning hierarchy by forwarding the extracted signal from the first layers to preceding layers, and finally combines the highest-level signal to single object at the output layer.

III. Design Aspects and Experimental Configuration

In this section, we present different design aspects that impact the system's performance in terms of bit error rate (BER) and the mean square error between the input and the output of the neural network. All the simulations were done with 10,000 training/ validation samples, with 90 percent as training samples. While 100,000 samples were used for testing the system.

A. Neural network hyper parameters

The parameters of NN have a tremendous influence on the network performance as network size in terms of number of hidden layers and the size of each layer influences the network prediction efficiency. This adds tradeoff between the network design and the performance, as small networks do not bid good performance and large networks may have redundant connections on the other hand. [18], [19], [20] proposed different optimization algorithms for tuning NN hyper parameter in terms of number of hidden layers and the size of each.

1) Hidden layer size

The size of each hidden layer is defined by the number neurons in each layer, much research studied the effect of the hidden layer size on the NN performance [21],[22]. The hidden layer size has a tremendous influence on the NN performance. Using few numbers of neurons in each hidden layer causes underfitting, while increasing the number of neurons cause overfitting for the training data. As shown in

Fig. 2, the BER and the MSE are enhanced with increasing the number of neural nodes in the hidden layer till the optimum point and it decreases again. However, the curve turning point of the proposed model is 256 neural nodes in each hidden layer, we considered 128 neural nodes as our optimum point as it bids near optimum performance with much less complexity. As 128 neural node architecture has BER of 6*10-3 and 256 architectures have BER of 4*10-3.

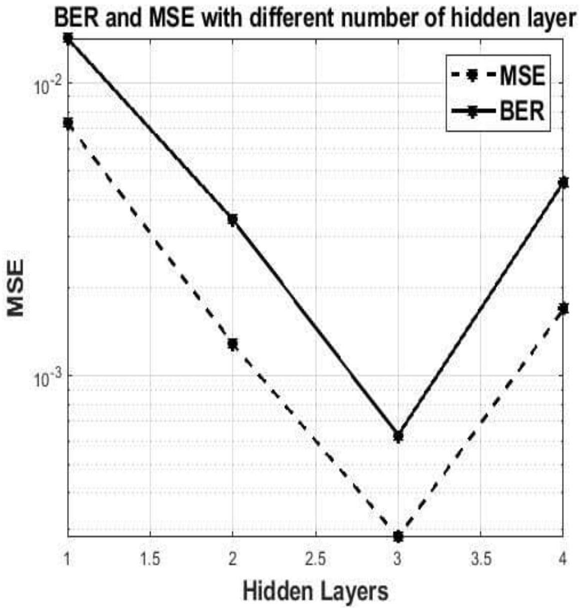

Fig. 2. BER and MSE with different number of hidden layers, all the hidden layers have the same number of neural nodes. The proposed architecture has 128 Neural nodes in each layer, PRELU activation function, 4 QAM modulation and 16 subcarriers.

2) *Number of hidden layers*

Generally, NN architecture with input and output layers and no hidden layer solves linear regression problems, while single hidden layer NN architecture can fit any Boolean function regardless the input space [23]. Increasing the number of hidden layers to one and two layers offers good fitting to the nonlinear, additional layer can be added based on the complexity of the proposed regression model [24]. We tested the proposed model over multiple hidden layer architecture, due to the complexity of the understudy problem the architecture of three hidden layers shows the better performance over single and double hidden layers architecture in terms of BER and MSE. Increasing the number of hidden layers decrease the performance due to the overfitting problem, as shown in Fig. 3.

3) *Activation function*

Various nonlinear activation functions add nonlinearity to the DNN, as the conventional nonlinear functions sigmoid, hyperbolic tangent (tanh), rectified linear unit (ReLU). Recently variate versions of ReLU have been proposed as leaky ReLU (LReLU) [27] and parametric ReLU (PReLU) [26]. Although tanh and sigmoid activation functions are the most popular for nonlinear applications, they show poor performance in our study. On the other hand, the PReLU shows good performance as it satisfies the linearity for positive input parts and nonlinearity for negative parts, as shown in Fig. 4.

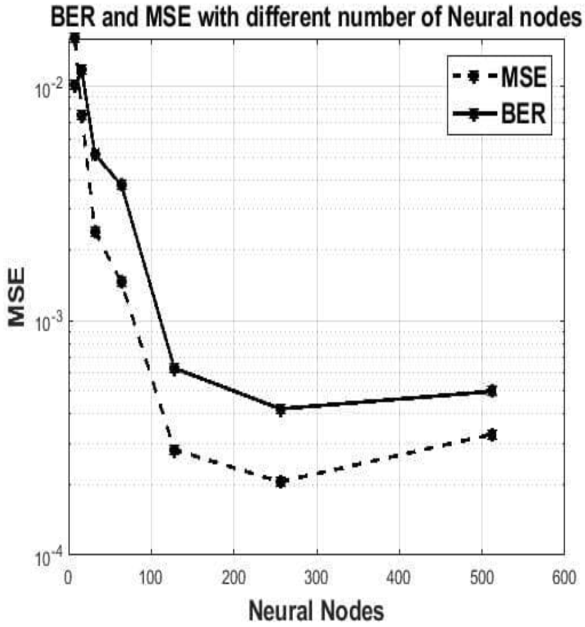

Fig. 3. BER and MSE with different number of neural nodes in each hidden layer, all the hidden layers have the same number of neural nodes. The proposed architecture has 3 hidden layers, PReLU activation function, 4 QAM modulation and 16 subcarriers.

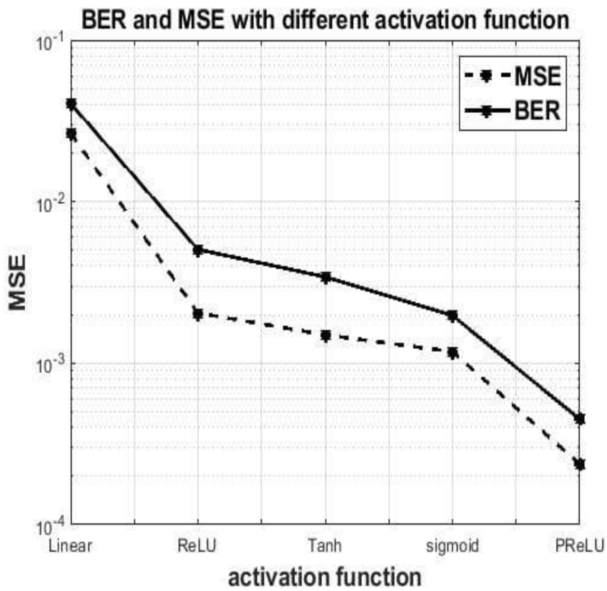

Fig. 4. BER and MSE with different linear and nonlinear activation functions. The proposed architecture has 3 hidden layers, 128 neural nodes in each hidden layer, 4 QAM modulation and 16 subcarriers.

IV. COMMUNICATION SYSTEM PARAMETERS

In this section we proposed the effect of the communication system parameters on the system performance. We studied the effect of the modulation order, subcarrier spacing.

A. *Modulation order*

As increasing the modulation order decreases the decision boundaries between each pair of symbols on the constellation diagram [22], consequently increasing the inter symbol interference. Although the modulation order does not effect on the NN mean square error, as it is an end-to-end transmission aspect, it effects on the received symbol BER. Fig. 5 shows the BER performance of the proposed architecture under 4 ,8 ,16, and 32 QAM. As shown, increasing the modulation order decrease the system BER as discussed, although it increases the system spectral efficiency on the other hand.

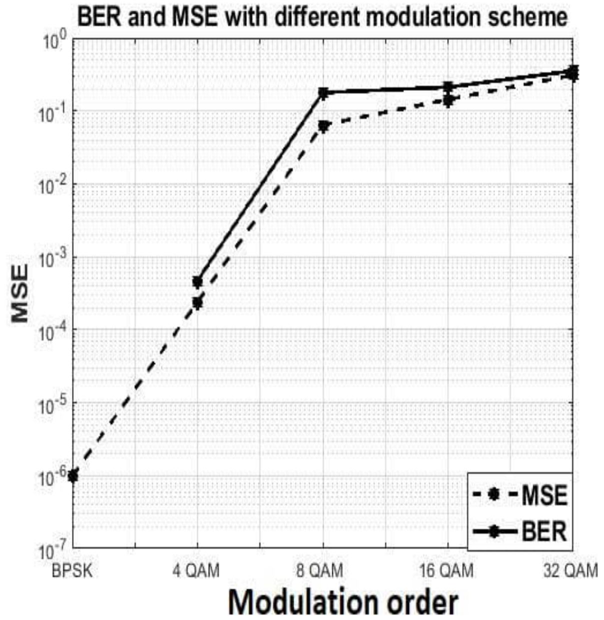

Fig. 5. BER and MSE with BER performance with 3 hidden layers, 128 neural nodes in each hidden layer, 4 QAM modulation and 16 subcarriers.

B. *Subcarrier spacing*

In multi-channel modulation scheme, as OFDM, the channel is divided into multiple subcarriers. The subcarrier spacing represents the reciprocal of the symbol time, so narrow subcarrier spacing causes better channel equalization and robustness. Although decreasing subcarrier spacing increases the number of subchannels. This imposes more complexity to the NN architecture as it increases the number of dependent and independent regressors represent the received clipped signal and the predicted clipped signals, respectively. This tradeoff in choosing the subcarrier spacing adds challenge to designing the transceiver system. We tested our system over different subcarrier spacing. Fig. 6 shows the BER performance and MSE of the NN respectively, we run this simulation over the same NN architecture in terms of activation function, number of hidden layers and neurons in each layer. Decreasing the subcarrier will increase the size of the input and output layer, this requires increasing the size of the hidden layers to efficiently extract features in each layer and forward it to higher layers. As shown Increasing the input layer size over constant hidden layer size will dramatically impact on the performance of the NN and the end-to-end performance. Consequently, the MSE and the BER performance decreases with decreasing the subcarrier spacing.

C. *Training processing time*

In this section we analyze the training processing time of different DNN architecture. The DNN architecture aspects as the number of hidden layers and the number of neural nodes. We compared the training processing time on AMD PRO A10-8700B R6, 10 compute cores 4C+6G 1.8 GHZ processor with 16 GB RAM and 64-bit operating system. As shown in Fig. 5 increasing the number of hidden layers and the neural node in each layer increases the complexity of the network and increases the training phase processing time.

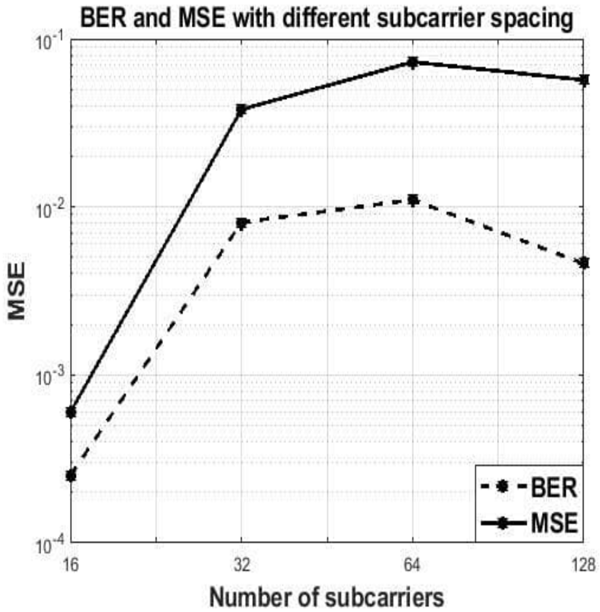

Fig. 6. BER and MSE with different subcarrier spacing

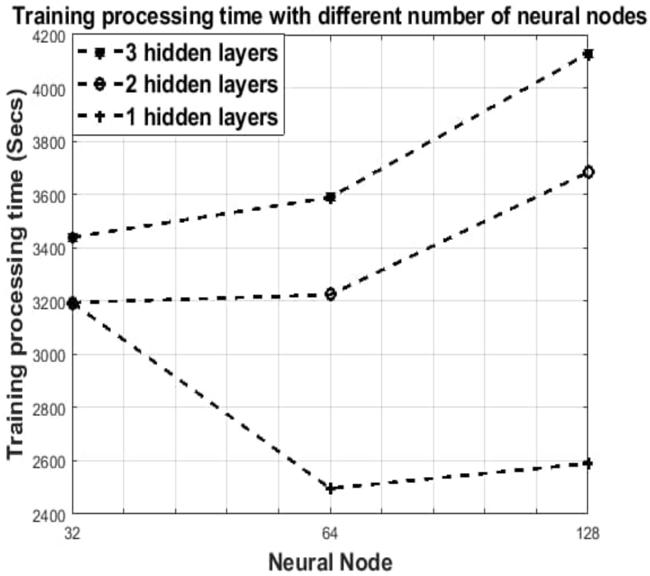

Fig. 7. Training processing time with different number of hidden layers and neural nodes.

V. CONCLUSION

This paper presented non-coherent optical modulation transceiver based on artificial neural network. . It is shown that nonlinear regression provides the best system performance, over linear and polynomial regression, as it offers better feature extraction. Among different nonlinear regression activation function the PReLU shows the best performance as it offers linearity for positive received signal and nonlinearity for the negative parts. Evaluating the communication system parameters shows that increasing the subcarrier spacing and decreasing the modulation order highly influence the NN size and the system complexity.

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