Non-Coherent Optical OFDM Transceiver based Machine learning : Regression Tree

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***Abstract*—Non-coherent optical transceivers have gained much attention with the rise of visible light communication in 5G networks. Transceivers based machine learning has been recently proposed motivated by the tradeoff between spectral and power efficiency of asymmetrical clipping optical OFDM (ACO-OFDM) and direct clipping optical OFDM (DCO-OFDM) . In this paper, we propose regression decision tree (RDT) based optical transceiver, that predicts the transmitted signal at the receiver side. The proposed transceiver compensates the clipping noise produced by clipping the negative parts of the transmitted signal. We evaluate and analyze the RDT based optical transceiver architectures for different performance aspects and compared the results with benchmarks techniques and alternative deep neural network (DNN) transceiver. The proposed optical OFDM transceiver enhances the spectral and power efficiency compared to the latest works.**

Keywords- Optical modulation, Regression tree, Neural network, ACO-OFDM, Machine learning.

I. INTRODUCTION

Scaling up and enhancing the network performance are suggested by the 5G evolutionary approach, as the 5G network must fit the massive number of served devices, increasing traffic volume and immense system throughput. The auspicious ultra-dense heterogeneous network (HetNet) architecture considered as the best candidate for the 5G network architecture, due to its heterogeneity in coverage areas along with the access technologies. HetNet proposed different cell sizes as Macro, Femto and Pico cells, that support different radio access technologies as infrared radio frequency, and optical transmission communication. For fronthaul connections, coherent and non-coherent optical communications have been recognized as promising partner among many different access technologies, as optical communications afford costless frequency, secured communications, and less interference with the existing technologies [1]. Over the last few years, much research acknowledges the non-coherent optical communication techniques due to its simplicity in transmitting data using intensity modulation with direct detection (IM/DD), although the IM/DD obliges the transmitted signal to have positive and real values [2]. Principally direct clipping optical OFDM (DCO-OFDM) adds DC component to diminish the negative values before clipping it; the added DC component significantly influences the bit error rate (BER) performance and the power efficiency of the DCO-OFDM. While asymmetrical clipping optical OFDM (ACO-OFDM) carries out hard clipping of the odd subcarriers' negative values to zero whereas it leaves the even subcarriers unloaded to eliminate the clipping distortion, the unused subcarriers significantly reduce the spectral efficiency of the system [3,4]. The multi-channel optical modulation problem has been proposed in much research, as in [5] the author proposed modulation technique based on separating the value and the sign by sending the absolute values and for indicating signs it merges labels in a cost-effective manner While, [6] presented a Mach–Zehnder modulator (MZM) for non-coherent optical OFDM over BPSK modulation, the proposed modulator uses to transmit Hermitian symmetry OFDM signals. Massive non coherent optical modulation techniques based on signal processing proposed in literature over the few last years. Different non coherent multi modulation techniques have been proposed to overcome the trade off between spectral and power efficiency as [7] presented power OFDM modulation, while filter bank multicarrier (FBMC) proposed as an alternative to the OOFDM [8] .

Over the past few years, the machine learning (ML) algorithms have been proposed to learn the experienced scenarios of the 5G networks and use environmental fluctuations to predict different scenarios [9]. Based on labeled data the ML algorithms proposed different classification and regression methods, that can predict binary and continuous outputs, respectively. As the understudy case is demonstrated as a multi output regression problem, we proposed different multi output regression methods that predicts the desired output based on supervised ML concept. As multi output regression methods based on supervised algorithms to predict the outputs map the relation between the response and the regressor values [9].

Recently Artificial intelligence (AI) has been deployed to overcome 5G challenges, as managing cell fault, analyzing real time mobile traffic data, etc. [10], [11] manages, collects, and analyzes real-time data, the author proposes ML algorithm that captures the traffic using the cellular provider's detail records. In [12] the author addressed the problem of the linear and nonlinear impairments in coherent optical modulation, as artificial neural network (ANN) is proposed to compensate the effect of nonlinear phase of coherent optical communication Gaussian white noise and the laser phase noise. The authors proposed an equalizer based on NN architecture for coherent OFDM optical modulation that shows robustness to DSP non linearities for up to 80 Gb/s system. In this paper, we propose an AI based optical non-coherent transceiver, that over comes the challenges of transmitting real positive values over optical transmitters. The AI module presented in this work depends on decision tree models, that predicts the clipped received

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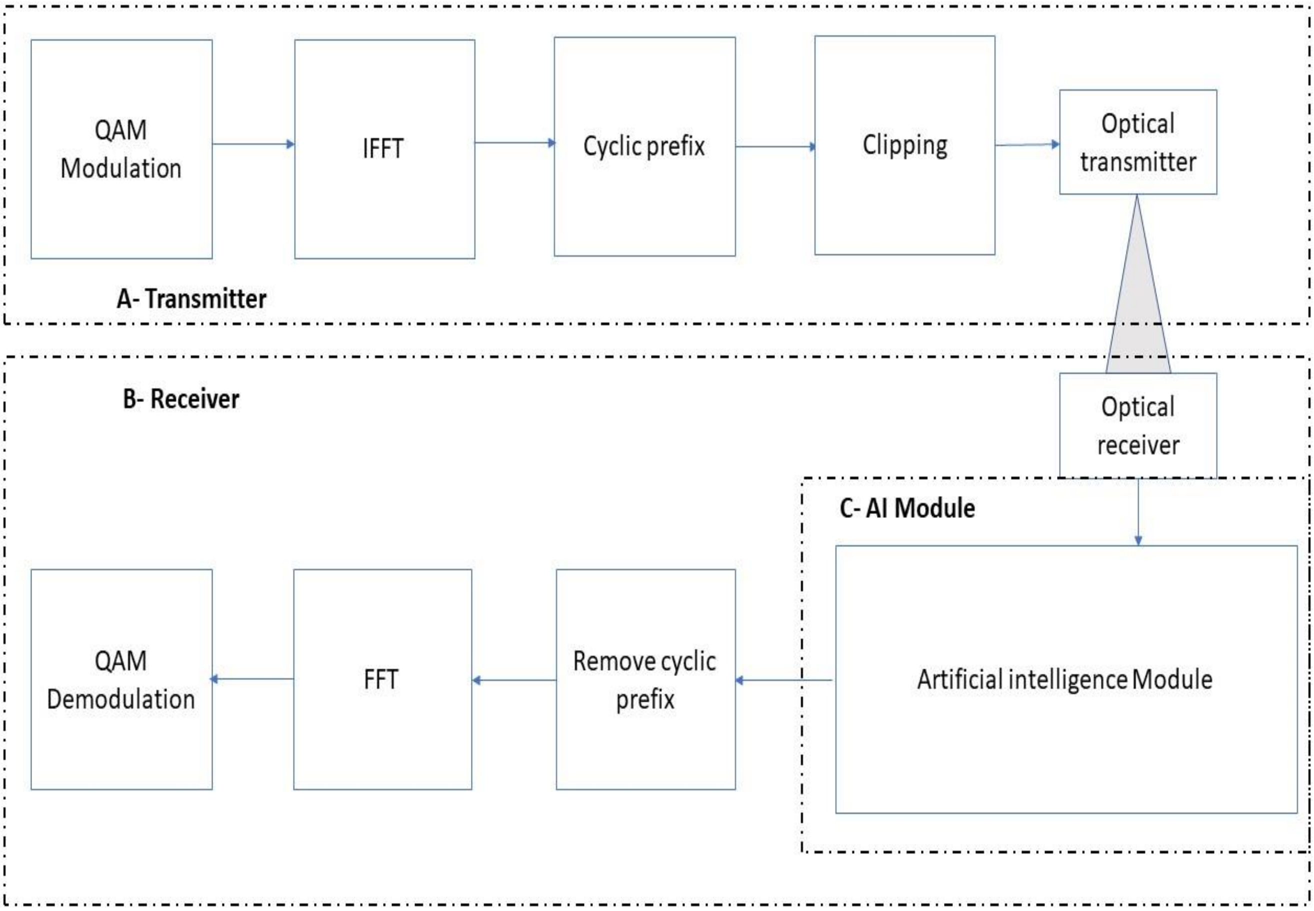

Fig. 1. Proposed Transceiver model A. Transmitter, B. Receiver [13]

signal to compensate and eliminate the clipping noise. The rest of the paper is organized as follows, system model is presented in section II, section III proposes system evaluation and hardware possibilities, and the paper is concluded in section IV.

II. SYSTEM MODEL

In this section, we propose our system model that consists of three main modules transmitter, receiver, and the AI module, proposed in [13]. The transmitter and the receiver are represented by typical optical transmission, provided with AI module that predict the unclipped signal from the received clipped signal, as shown in Fig. 1.

We described the prediction of the received subcarriers values as multi output regression problem. Multi output regression, also known as multi variate regression, aims to identify the relation between multiple dependent and independent variables using the labeled data set for training. Multi output regression methods also utilize the prediction operation with simpler models in terms of the computational complexity. In literature multi output regression can be classified into three main categories problem transformation methods, algorithm adaptation methods and multitask learning.

A. Problem transformation methods

Problem transformation methods depend on dividing the multi output regression problem into independent single output problems, each is solved separately using traditional regression solutions. The algorithm builds different model for each target to map the relation of each output (independent variables) and the inputs. Different methods have been proposed to solve multi output regressors as regressor chain [14] and multi output support vector machine [15]. The main drawback of these methods is ignoring the relations between multiple regressors during the prediction process.

B. Algorithm Adaptation Method

In these methods all the regressor values are determined using single model, this model maps the relation between all the inputs and every output. Moreover, it maps the relation between all the outputs themselves. Themost popular algorithm adaptation methods are the SVM and multi target regression tree. Adapted versions of SVM have been proposed in literature to add the relation between all the outputs to the problem transformation model. While multi target regression tree model (MRT) is type of regression trees that can predict continuous multiple outputs. The MRT dominates other algorithm adaptation methods as it offers better identification for the dependencies between the different targets.

C. Multitask Learning Method

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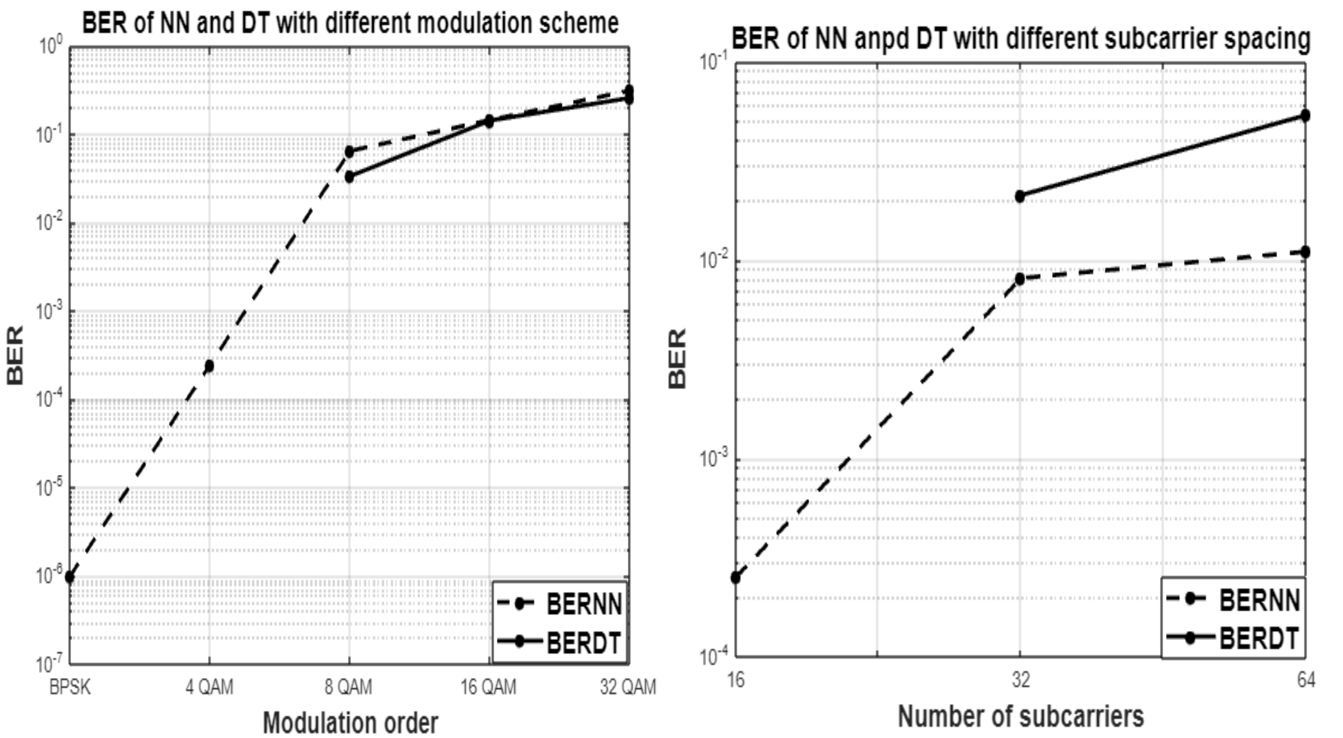

(A)
BER performance with different modulation order

(B)
BER performance with different subcarrier spacing 4QAM modulation

Fig. 2. BER performance of neural network has 3 hidden layers, 128 neural nodes in each hidden layer, and decision tree.

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The predictive performance of the regression trees can be improved based on the tree ensemble algorithm. The ensemble methods create different learners, the consequence ensembled multiple learner system enhances the base learner by defining the behavior of the local differences. Enormous methods have been proposed for the multiple learner construction, based on varying the training data subset, varying the training parameter, or using totally different learning algorithms. The common approaches depend on different training sets are the boosting and bagging. Where, bagging generates multiple bootstrapped training sets with different stochastic distributions and performs equal weight voting over single learner. While, boosting changes the training sets based on the performance of the previously trained learner and uses the weighted voting algorithm [18]. The problem of predicting the unclipped subcarriers is formulated as in (1).

We previously proposed the neural network architecture [13] to predict the clipped subcarriers as shown in Fig. 1. Hardware limitations on implementing the complex NN motivated this research to find simpler AI architecture in terms of hardware implementation and provide good predictivity performance. We propose the multioutput regression trees to predict the received subcarriers with accepted hardware framework.

$$Net_{trained} = F(\{Y_1, \dots \dots Y_n | X_1, \dots \dots X_n\}) \quad (1)$$

$$[Y^{\wedge}_1, \dots \dots Y^{\wedge}_n] = Net_{trained}(Y_1, \dots \dots Y_n) \quad (2)$$

were $Y^{\wedge}_i$ represent the multi target predicted N received subcarriers, Y_i represent the N clipped subcarriers and X_1 unclipped subcarriers for training phase. During the training phase the AI module maps the relation between the clipped and the target unclipped subcarriers. The mapped function $Net_{trained}$, described in (2), is then called to predict the received clipped subcarriers during the transmission.

III. Performance Evaluation (Scaling and Generalization)

In this section, first we introduce comparison between the proposed trained algorithm and the benchmarks optical OFDM in terms of BER performance over additive white Gaussian noise (AWGN). Then, we discuss the hardware implementation possibilities of the proposed transceiver.

A. Simulation parameters

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. Over TensorFlow [20] as project interpreter with Keras library [21] for machine learning algorithms, Pandas library [22] for representing data frames analysis and Scikit - Commpy library [23] for representing digital communication techniques.

B. Communication system parameters

As mentioned in [13] the subcarrier spacing, and the modulation order highly influence the performance of the optical transceiver. Fig. 2.A 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, on the other hand it increases the system spectral efficiency. In the proposed transceiver the prediction operation adds another dimension of increasing the inter symbol interference, as the prediction error increases the added noise. As a result, the BER of the proposed transceiver is dramatically affected by increasing the modulation order as shown in Fig. 2.A. As shown for low modulation order as BPSK and 4 QAM the RDT shows excellent prediction, while increasing the modulation order increases the noise and decreases the BER.

Fig. 2.B shows the BER performance of the NN and DT 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 increases 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. For the RDT, decreasing the subcarrier spacing increases the number of the subchannels, regressors and the responses of the regression operation, this increases the computational complexity due to increasing the number of inputs and the outputs. The number of the DT increases as the number of the predicted targets increases. Moreover, the arithmetic operation in each tree increases as the number of the regressors increases with low predictivity. As shown in Fig. 2.B the BER of NN shows better performance than the DT for high subcarrier spacing.

C. ACO, DCO- OFDM versus DNN and RDT algorithm

ACO and DCO-OFDM introduce a tradeoff between the spectral efficiency and the power efficiency of the optical transmission. The ACO_OFDM interleaves the even subcarriers to compensate the clipping noise, whereas the DCO-OFDM dramatically increases the BER of the received signal due to adding DC component to the transmitted signal. On the other hand, the proposed model depends on predicting the clipped negative parts by the trained DNN. The trained network shows better performance in terms of spectral and power efficiency of the optical transmission. Although it adds computational and hardware complexity due to the training phase and the AI module in the transceiver.

As shown in Fig. 3 the proposed model enhances the BER of the DCO-OFDM. Moreover, it compensates the clipping noise by loading the data on all the subcarriers and predicting the clipped parts via AI module. This results on doubling the spectral efficiency of the ACO-OFDM. While the regression tree perfectly eliminates the clipping noise the used modulation scheme as shown in Fig. 2, as it shows perfect symbol detection with no BER.

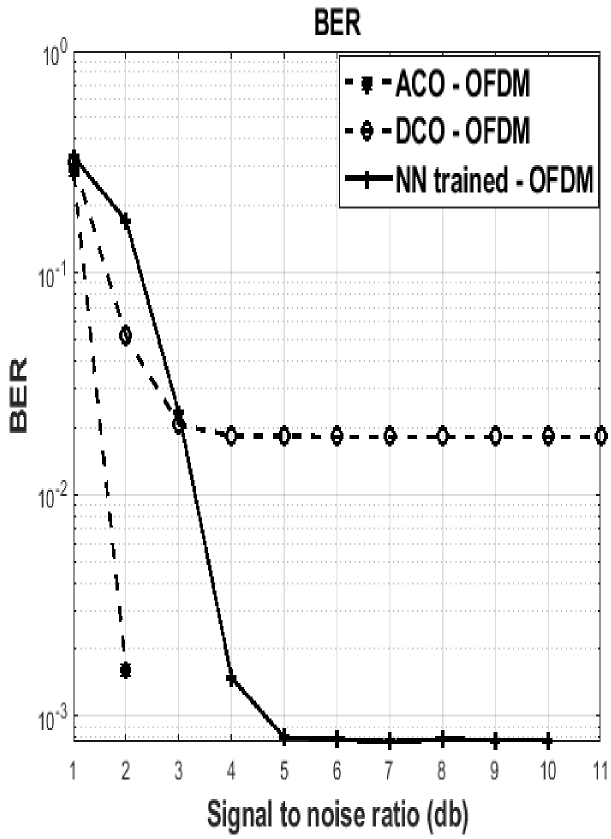

Fig. 3. BER of DCO, ACO-OFDM and the proposed modulation scheme over additive white Gaussian noise channel (AWGN). The proposed architecture has 3 hidden layers, 128 neural nodes in each hidden layer, PReLU activation function and 16 subcarriers.

D. Hardware implementation

As the concept of SDN raised in 5G network, the software defined network (SDR) implementation of the system transceiver is highly motivated. The SDR of the communication systems have three approaches field programmable gate array (FPGA), embedded digital signal processor (DSP), and general-purpose processor (GPP). Traditionally the OFDM transceiver is implemented on FPGA as a programmable hardware module, as it offers cost efficient , and high flexibility. On the other side, the AI module hardware implementation on FPGA has been recently proposed as it offers parallel and high-speed designs [24], [25], [26]. Despite these features more research need to be investigated to offer various implementation of different AI architecture as neural networks and regression decision tree. We propose GPP architecture as it provides easier and flexible programmable platform, that implements both the AI and the communication transceiver efficiently. Raspberry pi 4 board is deployed in the workstation as GPP to implement the proposed transceiver. As the RPI module is based on ARM processor with relatively low capabilities CPU and very capable GPU that enhances the processing speed. The proposed transceiver is implemented considering wired communications to eliminate wireless communication noise, as the RDT is trained in noiseless environment.

IV. Conclusion

This paper presented non-coherent optical modulation transceiver based on decision regression tree, that eliminates the clipping distortion produced by clipping the transmitted signal over optical channel. The proposed transceiver overcomes the tradeoff between the spectral and the power efficiency of the noncoherent optical modulation, by transmitting the symbols over all the subcarriers without DC component. The proposed RDT reduces the complexity of the NN architecture presented in [13], moreover it shows better performance and enhanced BER for high subcarrier spacing. On the other side, reducing the subcarrier spacing highly influences the RDT scheme, as it increases the BER and the complexity of the scheme. It is shown that the AI based transceiver enhances the BER of the DCO-OFDM, as the BER reaches 10^-3 at 5 db SNR with the same spectral efficiency.

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