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RESEARCH ARTICLE

Digital Predistortion Based Experimental Evaluation of Optimized Recurrent Neural Network for 5G Analog Radio Over Fiber Links

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ABSTRACT In the context of Enhanced Remote Area Communications (ERAC), Radio over Fiber (RoF) technology plays a crucial role in extending reliable connectivity to underserved and remote areas. This paper explores the significance of fifth-generation (5G) Digital Predistortion (DPD) role in mitigating non-linearities in Radio over Fiber (RoF) systems for enhancing communication capabilities in remote regions. The seamless integration of RoF and 5G technologies requires robust linearization techniques to ensure high-quality signal transmission. In this paper, we propose and exhibit the effectiveness of a machine learning (ML)-based DPD method for linearizing next-generation Analog Radio over Fiber (A-RoF) links within the 5G landscape. The study investigates the use of an optimized recurrent neural network (ORNN) based DPD experimentally on a multiband 5G new radio (NR) A-RoF system while maintaining low complexity. The ORNN model is evaluated using flexible-waveform signals at 2.14 GHz and 5G NR signals at 10 GHz transmitted over a 10 km fiber length. The proposed ORNN-based machine learning approach is optimized and is compared with conventional generalized memory polynomial (GMP) model and canonical piecewise linearization (CPWL) methods in terms of Adjacent Channel Power Ratio (ACPR), Error Vector Magnitude (EVM), and in terms of computation complexity including, storage, time and memory consumption. The findings demonstrate that the proposed ORNN model reduces EVM to below 2% as compared to 12% for non-compensated cases while ACPR is reduced by 18 dBc, meeting 3GPP limits.

INDEX TERMS Digital predistortion, fiber nonlinearity, radio over fiber, error vector magnitude, recurrent neural network.

I. INTRODUCTION

Presently numerous research consortiums across the world are recommending use cases and outlining requirements for next-generation mobile networks such as beyond fifth-generation (5G) networks [1]. One significant application scenario, known as enhanced remote area communications (eRAC) [2], has gained considerable interest. The objective of this scenario is to offer broadband connectivity in isolated and rural regions, which is not supported by the new radio (NR) technology. In the realm of enhanced remote area communications, Radio over Fiber (RoF) enables the

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extension of wireless access to remote locations by leveraging the benefits of optical fiber for signal transmission. This is particularly valuable for areas where establishing traditional wired or wireless communication infrastructure is challenging or economically unviable [1], [2]. By utilizing optical fiber links, RoF technology overcomes the limitations associated with long-distance signal transmissions, such as high attenuation and signal degradation [2], [3]. Nevertheless, the successful implementation of eRAC faces several challenges, including technological barriers, as well as deployment and maintenance costs. Thus, it is necessary to identify cost-effective solutions for providing the required infrastructure in remote areas.

In this regard, several technologies, such as the centralized radio access network (C-RAN) with analog radio over fiber (A-RoF) for optical front haul, can play pivotal roles in this challenging operating scenario.

For instance, A-RoF can be utilized for transporting downlink signals from the base band unit (BBU) to a simplified remote radio head consisting of radiofrequency (RF) filters, an optical-to-electrical converter, and power amplifier (PA), thereby reducing network deployment costs and improving its reach [3]. Lastly, C-RAN can significantly reduce deployment costs by utilizing a software-defined radio (SDR) approach to employ the entire BBU in the central office (CO) [4].

Signal impairment and losses, also known as RoF link nonlinearities, are a significant issue in Radio over Fiber (RoF) systems. These impairments can be caused by various factors, including fiber dispersion, laser nonlinearities, photodiode nonlinearities, and optical noise [5], [6]. Dispersion leads to signal distortion and degradation, particularly for high-frequency signals, while nonlinear effects such as four-wave mixing, and self-phase modulation can generate additional frequencies that interfere with the original signal [7].

To address these nonlinearities, several linearization techniques have been proposed, with Digital Predistortion (DPD) being the most widely used in the last couple of years. Table 1 presents the overview of the most influential articles covering DPD methodologies for RoF links with advantages and their limitations [2], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51].

DPD approach considers the impairments in RoF as an unknown entity and aims to identify the inverse nonlinear response to this unknown entity [8], [9], [10], [11], [12], [13]. When multiple instances of this approach are combined in a cascade, the overall response becomes linear, effectively eliminating all these impairments [16], [17].

The DPD operation applies a correction function to the input signal to pre-distort it, compensating for the system's distortions at the output. DPD can be implemented in software or hardware and designed to adapt to changes in the RoF system's operating conditions [11], [12], [13], [19], [20], [21], [22], [23], [24]. However, accurate modelling is a challenge in such situation.

A recent development in the field of linearization techniques is the Direct Digital Predistortion Technique (DPDT)that is a model-based behavioural method proposed in studies [28]. DPDT expands on the concept introduced by Meslener et al., which recognizes the cumulative impacts resulting from the combination of fiber chromatic dispersion and laser chirp as the dominant nonlinear impairments that require linearization for long haul fiber lengths [40]. Traditional DPD methods are capable of mitigating impairments in the laser and RoF link, but they often necessitate a substantial volume of training data and are characterized by high complexity. Additionally, these methods have the added disadvantage of requiring an analog-digital converter (ADC) as the first block of the predistorter. The cost of an ADC is directly linked to its performance capabilities, with higher sampling rates leading to higher costs. However, the sampling rate is limited by the bandwidth of the modulating signal and modulation rate, making it less practical for certain use cases [27], [28], [29], [30].

An alternative approach which offers a simplified version of the Generalized Memory Polynomial (GMP) architecture is referred as Memory Polynomial (MP) [24], [26], [27], [28], [29], [30], [31]. However, compared to the GMP architecture, the MP architecture is less flexible in its capabilities. The MP architecture provides an alternative approach that simplifies the GMP architecture [8], [9], [10], [11], [12], [13], [14], [15], [16], [26], [27], [28], [29], [30], [31]. The Canonical Piecewise Linearization (CPWL) architecture is an alternative method employed to approximate the nonlinear transfer function of a radio frequency (RF) in RoF systems [31], [34], [40], [42], [43], [44]. While this architecture exhibits good performance, it is associated with high complexity. Recently, a hybrid Memetic algorithm has been utilized for parameter estimation of the DPD in RoF links [42]. The methodology results in a substantial performance improvement with a challenging complexity. The Magnitude Selective Affine (MSA) method, while effective, has high complexity. To address this, combining stages into a single stage using a flexible DPD technique like GMP can reduce MSA complexity.

Recently, a new DPD technique that combines Volterra series with deep neural networks was proposed to improve the linearization performance of RoF systems [14]. The proposed DPD technique can accurately capture the nonlinearity of high-power amplifiers and improve the overall system performance. The proposed DPD technique requires a large amount of training data and may have higher computational complexity compared to traditional DPD techniques. Similarly, Xiaoran Xie et al. proposed a hybrid DPD technique that combines the analog and digital pre-distortion methods to improve the efficiency and accuracy of RoF systems [15]. Recently, Jacopo Nanni et al. suggested short-λ-VCSELs DPD over pre-existent G-652 Infrastructures Radio over Fiber systems for a 2Km transmission distance [16]. The proposed technique can reduce the number of digital-to-analog and

TABLE 1. Most influential literature items for Radio over Fiber Digital Predistortion.

Reference	Approach/Technique	Pros	Cons
[2, 8-13,21,24,26-34]	DPD Traditional Methods using Volterra methods	Widely used. Enhances linearity to some extent.	3GPP limits not achieved. Limited memory depth results in limited performance High complexity.
[14]	Volterra series with deep neural networks	Accurate nonlinearity capture.	Requires substantial training data and complexity
[15]	Hybrid DPD combining analog and digital pre-distortion	Enhances efficiency and accuracy.	Introduces additional analog components
[16]	Short-λ-VCSELs DPD for existing G-652 Infrastructures	Reduces digital-to-analog and analog-to-digital conversions, improves efficiency.	Requires additional analog components potential increase in cost and complexity
[17-19]	Adaptive DPD algorithm using LMS algorithm	Reduces computational complexity, improves accuracy.	May require additional hardware potential increase in cost and complexity
[20]	Undersampled digital predistortion (DPD) architecture	Minimizes size and weight. Achieves multiple GHz DPD bandwidths.	undersampled ADC.
[22]	Effective use of Feedforward (FF) linearization technique	Optimized control loops enhance system. performance under changing conditions.	Suited for broadband applications only.
[23]	Analog and Digital Pre-Distortion	Address out-of-band nonlinear distortion.	Hybrid linearization potentially increasing complexity.
[25]	Novel phase-shifting network relying on fiber nonlinearity for analog wireless beamforming in a C-RAN	Centralized Control. Reduced Cost and Energy Consumption.	Phase Noise. Interference in Multiplexing.
[28]	Direct Digital Predistortion Technique (DPDT)	Model-based behavioral method.	Limited information provided
[34-48]	Machine Learning based DPD	Higher level of performance.	Complexity reduction required. Time, training and cost analysis missing.
[39,52]	Magnitude Selective Affine	Comparative study with AI methods.	Negligible phase rotation is observed.
[41-43]	Full Duplex RoF with Feedback Loop	CPWL, DVR based performance improvement.	Complexity is high. Requires Uplink and Downlink DPD separately.
[44]	RNN based Amplified RoF	RNN performance is substantial EVM, ACPR is respecting 3GPP in certain range of RF input power.	Complexity analysis is missing. Fiber length not considered. Multiband absent. Considers OFDM waveform.
[45]	Over-the-fiber DPD via Reinforcement Learning	60% reduction in bit errors.	Limited evaluation against standardized metrics.
[46-48]	Hybrid Memetic algorithm	Complexity reduction. Substantial improvement.	Requires substantial training data.
[37-38, 48]	RNN based Amplified RoF	RNN performance is substantial EVM, ACPR is respecting 3GPP in certain range of RF input power.	Complexity analysis is missing. Fiber length not considered. Considers OFDM waveform.
[49-50]	ANN Equalizer for A-RoF	Interference Mitigation. Multi-User Equalization.	Training Data Dependency. High Complexity.
[51]	Analog RoF integration into fiber wireless networks	Successful integration but limited without linearization.	Limited to 64 QAM.

analog-to-digital conversions required, thus improving the system's overall efficiency. The proposed technique requires additional analog components, which can increase the overall cost and complexity of the system. Similarly, adaptive DPD algorithm for RoF links that utilizes the least-mean-square (LMS) algorithm to dynamically adjust the DPD coefficients based on the input signal power level was discussed in a recent survey paper [17]. The discussed schemes can reduce the computational complexity and improve the accuracy of DPD systems [17]. The proposed algorithm may require additional hardware to implement, which can increase the overall cost and complexity of the system.

A novel DPD technique, integrating Volterra series with deep neural networks, has been proposed to enhance the linearization performance of RoF systems [14].

This technique accurately captures the nonlinearity of high-power amplifiers, contributing to an overall improvement in system performance. However, it necessitates a substantial amount of training data and may exhibit higher computational complexity compared to conventional DPD techniques.

Similarly, Xiaoran Xie et al. introduced a hybrid DPD technique that combines analog and digital pre-distortion methods to enhance the efficiency and accuracy of RoF systems [15]. In another context, Jacopo Nanni et al. recommended short-λ-VCSELs DPD for existing G-652 Infrastructures Radio over Fiber systems with a 2 km transmission distance [16]. This proposed technique aims to reduce the number of required digital-to-analog and analog-to-digital conversions, thereby enhancing the overall system efficiency. However, it introduces additional analog components, potentially elevating the system's overall cost and complexity.

Likewise, a recent survey paper discussed an adaptive DPD algorithm for RoF links utilizing the least-mean-square (LMS) algorithm to dynamically adjust DPD coefficients based on the input signal power level [17]. The discussed schemes demonstrate potential in reducing computational complexity and enhancing the accuracy of DPD systems.

However, the implementation of the proposed algorithm may require additional hardware, contributing to potential increases in the overall cost and complexity of the system.

Machine learning (ML) approaches have gained increased attention due to the demand for enhanced linearization to achieve superior outcomes [33], [35], [37], [39], [41], [42], [43]. This growing interest is underscored by recent research conducted by Pereira et al., who explored

ML algorithms for linearizing electrically amplified Radio over Fiber (RoF) systems [44]. Specifically, their study proposed and compared the performance of a memory recurrent neural network (RNN) linearization against a memoryless multilayer perceptron linearization. Encouraging results were observed, particularly when the RNN memory depth equaled or exceeded that of the amplified RoF system.

Furthermore, advancements in the field include an over-the-fiber-based DPD approach employing reinforcement learning, resulting in a remarkable 60% reduction in bit errors [45]. However, these approaches have primarily focused on single-channel scenarios, with limited evaluation against standardized third-generation partnership project (3GPP) metrics like error vector magnitude (EVM) and adjacent channel power ratio (ACPR) [17], [37], [46], [47], [48], [49], [50]. Earlier integration of Analog RoF into fiber wireless networks achieved success, but without linearization, limited to 64 quadrature amplitude modulation (QAM) at 25 Gbauds, showcasing the need for performance-enhancing techniques [51].

Addressing nonlinearities in RoF systems, ML approaches using neural networks have emerged, targeting challenges such as fiber nonlinearity, modulation issues, laser chirp, and laser nonlinearities in DPD. DPD aims to develop a highly effective model for compensating system nonlinearity, resulting in a linear output signal while minimizing computational requirements. However, challenges like overfitting and ill-conditioning during DPD coefficient training have prompted a focus on reducing dimensionality, extracting relevant features, and decreasing complexity in DPD—an area of significant exploration.

The problem statement in this context revolves around the challenges and limitations associated with linearizing RoF systems, particularly focusing on the application of DPD techniques. The challenges identified include the need for additional linearization in ML approaches since these approaches are being increasingly explored for linearizing RoF systems, yet there is a recognized need for additional linearization to achieve improved outcomes. Existing methods, such as over-the-fiber-based DPD with machine learning, have primarily been tested in single-channel scenarios. However, there is a gap in evaluating these methods against standardized performance metrics like error vector magnitude (EVM) and adjacent channel power ratio (ACPR), crucial for assessing their effectiveness in practical applications. The training process of DPD coefficients faces challenges, including overfitting and ill-conditioning. Similarly, complexity analysis haven't been explored in detail. These challenges highlight the need for research into methods that can reduce complexities, extract relevant features, and decrease complexity in DPD.

A. CONTRIBUTIONS

With an aim to cover eRAC scenarios for sub 6 GHz and above 6 GHz range, we present:

1. An experimental realization of 5G NR- multiband for Radio over Fiber connection using 5G NR signals at 10 GHz and flexible-waveform signals at 2.14 GHz transmitted over a 10 km fiber length. The utilization of multi band frequency carrier targeting sub-GHz and above 6 GHz is a unique frequency that will evaluate the efficacy of the proposed solutions in the given range.

2. An optimized recurrent neural network (ORNN) based DPD approach is proposed that is able to provide a substantial improvement in terms of performance.

3. The proposed ORNN method is optimized so that the complexity of the system is reduced substantially and is comparable to other DPD methods.

4. The article also includes the implementation of conventional methods and provides a comparison of the proposed ORNN with these methods in terms of performance metrics. This is a novel comparison where multiband frequency carrier eRAC use-case has been evaluated for traditional DPD methods and proposed AI methods.

5. The comparisons are presented in the form of performance as well as complexity. Authors have used 3GPP standardized performance evaluation metrics such as error vector magnitude (EVM) or adjacent channel power ratio (ACPR). The complexity is assessed in terms of coefficients, number of multiplications, storage, time and memory consumption. The proposed ORNN aims to improve the performance of the RoF network while keeping the complexity at a minimum. This indicates that it will also result in a decrease in the number of coefficients required. This helps to make the model more efficient and simpler to use.

The remainder of the paper is divided in 7 sections. The proposed DPD integration based on ORNN are discussed in section II while section III presents the conventional methods including GMP and CPWL. The experimental testbed realization are discussed in section IV while the presentation of the proposed ORNN methods optimization is discussed in section V. Section VI discusses the experimental results of the proposed ORNN with comparative architectures in terms of performance and complexity. The conclusions and prospects for future work are discussed in section VII.

II. DPD INTEGRATION BASED ON ORNN

We utilized the optimized recurrent neural network that we will refer to as ORNN from onwards. It allows us to assess the impact of memory.

A. ARCHITECTURE

The ORNN architecture consists of an input layer, L hidden layers, and an output layer. Each layer contains O_ℓ neurons, with ℓ ranging from 0 to $L+1$, denoting the corresponding layer number. The neurons in sequential layers are densely interconnected, with additional connections pointing backwards, as illustrated in Fig. 1.

To strike a balance between complexity and performance, our proposed ORNN DPD architecture utilizes 2 neurons in both layers (input and output) while we used three hidden

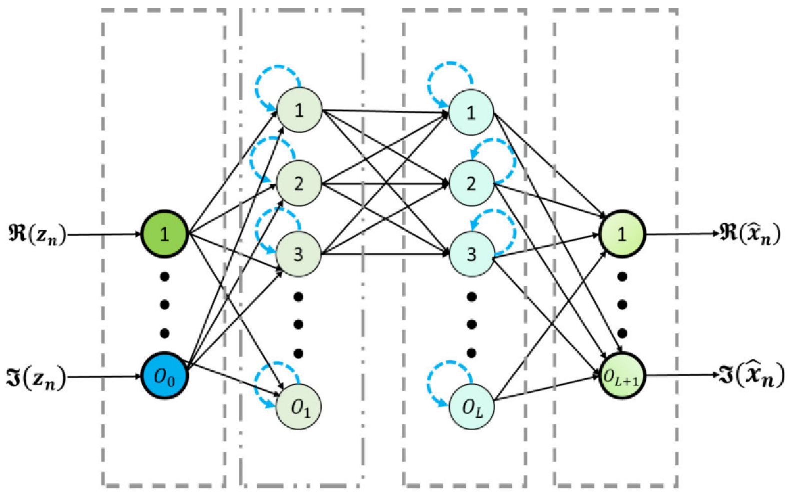


FIGURE 1. Illustration of a recurrent neural network architecture having two hidden layers. each layer has O_L neurons per layer. Green color shows Real ($\Re$) and blue shows Imaginary ($\Im$) baseband parts of the input for training.

layers. Using many hidden layers can hinder the training process of the neural network due to the increasing number of hyperparameters and the potential for the fading gradient dilemma. To address this problem, activation functions that exhibit more linear and non-saturating behavior can be used, but this may come at the expense of reducing the neural network's capacity to represent nonlinear behaviors.

However, the 3 hidden layers were sufficient to capture the non-linearities of the RoF link. To estimate the matrices of weights (W_p) and (W_v), we employed the backpropagation algorithm and ran the training process for 125 epochs. However, if the early stop criterion (with a patience hyperparameter of 50) was met, training would cease. This criterion was based on observing a mean-squared error (MSE) variation of less than 10^{-7} for 125 consecutive epochs.

The loss function ($\mathcal{L}_{MSE}$) is defined as follows:

$$\mathcal{L}_{MSE} = \sum_{N=0}^{N_{Training}} \frac{\left(x_N - \hat{x}_N\right)^2}{N_{Training}} \tag{1}$$

Here $N_{Training}$ represents the training samples. The data sample consists of 892,100 samples where the validation split of data is 0.7 to 0.3 i.e., 70% training (24470 samples) and 30% (67630 samples) data has been kept for testing. The activation function, optimizer and number of layers decision was made after the optimziation carried out as discussed in detail in Sec. V.

The baseband signal (x_n) generated by the vector signal generator (VSG) becomes an input to the RoF link. The combined response of fibre and photodiode (PD) is unit impulse response that is given as $r(n) = \delta(n)$. The signal at the output of PD is given by y_n:

$$f(n) = x(n) * r(n) = y(n) \tag{2}$$

The convolution operation is represented by the symbol $*$.

B. DPD TRAINING

The output signal $y(n)$ is gain adjusted such that $z(n) = \frac{y(n)}{G}$ and is fed to DPD block for training. For training, we employ $\hat{x}(n)$ as the desired label and $z(n)$ as the input of the ORNN. This approach enables the ORNN to learn the system post-inversion response, which is subsequently used for pre-distorting the baseband signal.

The block schematic is shown in Fig. 2 that signifies the cycle of training. This method consists of the following two fundamental phases:

1. The initial step involves establishing a feedback loop that allows training to obtain an input signal capable of being classified as a DPD waveform signal.
2. Following this, the subsequent phase entails the computation of the DPD model parameters. The predistorted signal $\hat{x}(t)$ is given as:

$$\hat{x}(t) = \prod \left(z(t) W_p + V(t-1) W_v + b\right) \tag{3}$$

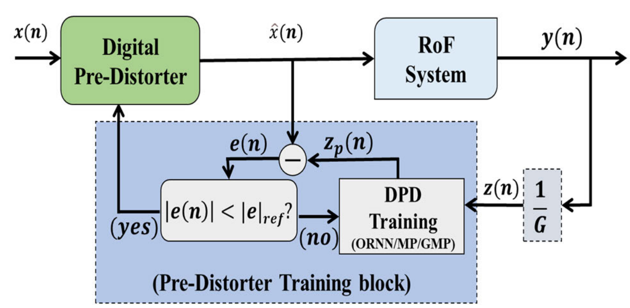


FIGURE 2. An illustration of a link training scheme for RoF is presented, designed to be compatible with various architectures such as ORNN, GMP, and CPWL. This scheme aims to facilitate efficient training and optimization of the RoF link, regardless of the specific architecture employed.

where $\prod(\cdot)$ represents the nonlinear activation function. Setting the Q_M hyperparameter is critical in defining the memory depth of the ORNN and optimizing it can greatly improve the linearization performance.

In (3), $z(t)$ denotes the input matrix at $Q_M|_t$. Similarly, the previous output of $Q_M|_{t-1}$ is given as $V(t-1)$ while b is the bias vector. Once the ORNNs have been trained, the DPD scheme can be utilized to linearize the A-RoF system.

III. COMPARATIVE ARCHITECTURE

The GMP technique has shown effectiveness in achieving linearization of PAs. Previous studies have also demonstrated the application of DPD for linearizing the RoF link [16], [18]. In the upcoming sections, we will compare the performance of GMP with the Volterra series, with a specific emphasis on GMP due to its documented superiority over MP [16], [18].

$$\begin{aligned}\hat{x}(n) = &\sum_{k=0}^{k_a-1}\sum_{q=0}^{Q_a-1} z(n-q)\, c_{kq}\, |z(n-q)|^k \\ &+\sum_{k=1}^{k_b}\sum_{q=0}^{Q_b-1}\sum_{r=1}^{R_b} z(n-q) d_{kqr}\, |z(n-q-r)|^k \\ &+\sum_{k=1}^{k_c}\sum_{q=0}^{Q_c-1}\sum_{r=1}^{R_c} |z(n-q+r)|^k\, e_{kqr} z(n-q) \qquad (4)\end{aligned}$$

where $\hat{x}(n)$ and $z(n)$ are the DPD block output and input respectively. c_{kq} represents complex coefficients associated with the signal's envelope, d_{kqr} signifies complex coefficients related to the signal's lagging envelope and e_{kqr} signify the complex coefficients associated with the signal's leading envelope. K_a, K_b, K_c represent maximum nonlinearity coefficients, Q_a, Q_b, Q_c shows memory depths. q, r and k highlights memory and nonlinearity index whereas R_c shows the leading and R_b shows the lagging delay tap lengths respectively.

A topic is always made more intriguing by the "out of the box" approach that can produce superior results. It was demonstrated in [16], [18], and [19] that the CPWL technique outperforms other models, including the MP and GMP. Due to the performance improvement, it offers, CPWL is a clear choice, although it has a lot of complexity and overheads. The CPWL model is denoted by [16]:

$$\begin{aligned}\hat{x}(n) &= \sum_{m=0}^{M}\sum_{k=0}^{K}\sum_{l=1}^{L} c^{(1)}_{m,k,l}\left||z(n-k)|^2-\beta_l\right| \\ &\times z(n-m-k) \\ &+\sum_{m=1}^{M}\sum_{k=0}^{K}\sum_{l=1}^{L} c^{(2)}_{m,k,l}\left||z(n-k)|^2-\beta_l\right| \\ &\times z^2(n-k)\, z^*(n-m-k) \\ &+\sum_{m=1}^{M}\sum_{k=0}^{K}\sum_{l=1}^{L} c^{(3)}_{m,k,l}\left||z(n-k)|^2-\beta_l\right| \\ &\times z(n-k)\, |z(n-m-k)|^2 \\ &+\sum_{m=1}^{M}\sum_{k=0}^{K}\sum_{l=1}^{L} c^{(4)}_{m,k,l}\left||z(n-k)|^2-\beta_l\right| \\ &\times z^*(n-k)\, z^2(n-m-k) \qquad (5)\end{aligned}$$

The input baseband signal is denoted by $z(n)$, while the output baseband signal is denoted by $\hat{x}(n)$. K represents the length of the FIR filter, M represents the memory depth, and L represents the CPWL partitions. β_l indicates the threshold, and $c^{(1)}_{m,k,l}, c^{(2)}_{m,k,l}, c^{(3)}_{m,k,l}, c^{(4)}_{m,k,l}$ are the model coefficients. The expression in (9) contains multiple multiplications and additions, which can significantly increase the complexity and hardware resource utilization during DPD implementation, particularly with regards to dedicated hardware adders and multipliers.

IV. EXPERIMENTAL SETUP AND EVALUATION

The experimental testbed used for this work is shown in Fig. 3. The experimental setup is divided into sections that are discussed below.

A. OPTICAL LINK BENCH

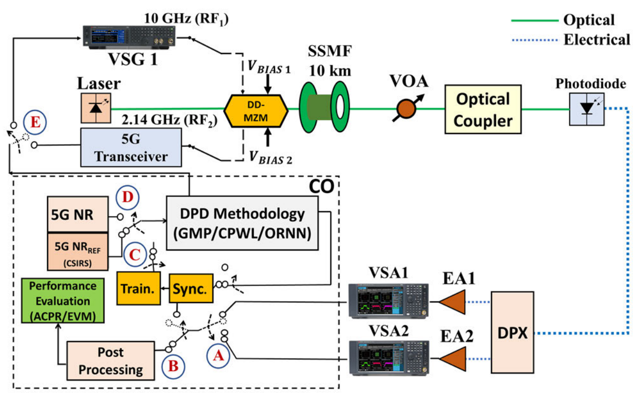
A Mach Zehnder Modulator (MZM) with a 1550 nm laser is connected to an optical fiber of 10 km which is a standard single mode fiber (SSMF) type, and an R402 PIN photodetector are utilized for converting optical back to the electrical domain. The signals are separated by a diplexer and sent to separate vector signal analyzers.

B. TIME SYNCHRONIZATION

Time synchronization is achieved via Channel State Information Reference Signal (CSI-RS) 20 MHz/106 resource blocks following 3GPP recommendations. By seeing the power delay profile (PDP), the first path of arrival is established by correlating the received and input waveforms.

C. TRAINING AND TESTING

This technique consists of three steps and utilizes 5G NR with f_{c1} 10 GHz (20 MHz) and f_{c2} 2.14 GHz (20 MHz) in a multiband 5G NR setup. Firstly, the pre-distorted signals are upconverted to their respective f_c by VSGs and then delivered



Switch A = Switch between VSA1 and VSA2.
Switch B = Switch between post processing and synchronization block.
Switch C = Switch when Training function is activated.
Switch D = Switch between 5G NR and DPD methodology.

FIGURE 3. Schematic of the experimental block diagram illustrating the setup used for the linearization study.

TABLE 2. Experimental bench parameters.

Parameters	Values
Waveforms	$f_{c1} = 2.14 \times 10^9$ Hz $f_{c2} = 10 \times 10^9$ Hz F/ G/ O- FDM signal Modulation Data Rate = 256 QAM
Modulator Laser	Wavelength $\lambda = 1550$ nm DD-MZM
Fiber	Single Mode Fiber, 10 km Fiber Dispersion = 17 $\frac{\text{ps}}{\text{nm km}}$ Attenuation = 0.33 $\frac{\text{dB}}{\text{km}}$
Photoreceiver	$Responsivity, \mathcal{R} = 0.72$ A/W

in optical domain. The photodiode output signal is subjected to processing through a diplexer (DPX), which serves to separate the multiband signals before they are transmitted to the DPD block for the training phase. Once training is achieved, the trained DPD coefficients are ready to be applied to the input signal that is called as predistorted signal at this stage.

During the validation stage, the switches are reversed to accommodate the use of real waveforms frames for confirming the efficacy of the predistortion. The DPD technique is used to evaluate the proposed ORNN method and compare it to other validated DPD techniques including GMP and CPWL methods [15], [16], [17], [21]. As RoF impairments typically change slowly due to factors such as component aging and thermal effects, real-time adaptation of DPD coefficients is not necessary [21], [26]. For this study, an inhouse MATLAB-based simulator is used, that operates on an Optiplex Intel(R) processor core (TM) i9-10900K CPU @ 3.70GHz 3.70 GHz, with RAM of 128 GB, and 32 GB GPU Processor. Research simulations are conducted over a dedicated standalone computer so that all the complexity analysis are legitimate and valid. For reference, Table 3 presents a outline in this experimental study.

D. PERFORMANCE EVALUATION METRICS

The performance of the experimental bench with proposed and conventional methods is assessed with two metrics namely EVM and ACPR. In addition, we assess the optimization of the proposed ORNN architecture with ACPR only. This is due to the fact that optimization is more sensitive to adjacent channel leakages as compared to other metrics. The EVM is a performance metric used by the 3GPP. It determines the optimum constellation location for each received symbol. The EVM is defined as [52]:

$$EVM\ (\%) = \sqrt{\frac{\frac{1}{M}\sum_{m=1}^{M}\left|S_m - S_{0,m}\right|^2}{\frac{1}{M}\sum_{m=1}^{M}\left|S_m\right|^2}} \tag{6}$$

In the given equation, "M" represents the constellation symbol, "S_m" corresponds to the real symbol associated with the symbol "m", and "$S_{0,m}$" refers to the real symbol linked with "S_m". The standardized limit for EVM in 3GPP for the 256 QAM modulation type is set at 3.5% [53].

The Adjacent Channel Power Ratio also called ACPR that determines the channel leakages and impairment is defined as [52]:

$$ACPR_{dBc} = 10\log_{10}\left[\frac{\int_{ad_l}^{ad_u} P(f)\,df}{\int_{ub_l}^{ub_u} P(f)\,df}\right] \tag{7}$$

In the given equation, "$P(f)$" represents the Power Spectral Density (PSD), "ad_u" and "ad_l" denote the upper and lower adjacent channel frequency bounds, respectively, while "ub_l" and "ub_u" refer to the upper and lower frequency useful bands of the output signal.

V. ORNN OPTIMIZATION

In the respective sections, we first discuss the ORNN architecture optimization before we compare it with the other conventional methods. The results for the experimental bench (ORNN vs conventional methods) are discussed in addition to the optimization of the ORNN architecture. The optimization process plays a vital role in enhancing the performance of neural network models. This involves fine-tuning hyperparameters and selecting suitable optimization techniques. In the case of ORNN, the analysis included training and validation error analysis, as well as experimentation with activation functions, optimizers, and the number of layers.

A. TRAINING AND VALIDATION ERROR ANALYSIS

The analysis involved a thorough examination of training and validation errors, which provides insights into the model's learning and generalization capabilities. Monitoring the training error over time reveals the model's ability to learn from training data. Simultaneously, the validation error assists in assessing overfitting or underfitting tendencies. To mitigate overfitting or underfitting, we employed L1 regularization. Fig. 4 shows the training and validation errors as a function of accuracy and loss.

B. VARIATION OF ACTIVATION FUNCTIONS

Activation functions introduce non-linearity, enabling the ORNN to model complex relationships within sequential data. Experimenting with different activation functions helps uncover their impact on network performance. Various activation functions, such as sigmoid, tanh, ReLU, or their variants, were tested as shown in Fig. 5. Each activation function possesses unique characteristics influencing the ORNN's ability to capture temporal dependencies. Sigmoid and tanh functions limit input values to a bounded range, while ReLU and variants promote faster convergence and alleviate the vanishing gradient problem.

By evaluating the model's performance with different activation functions, the optimal choice can be determined.

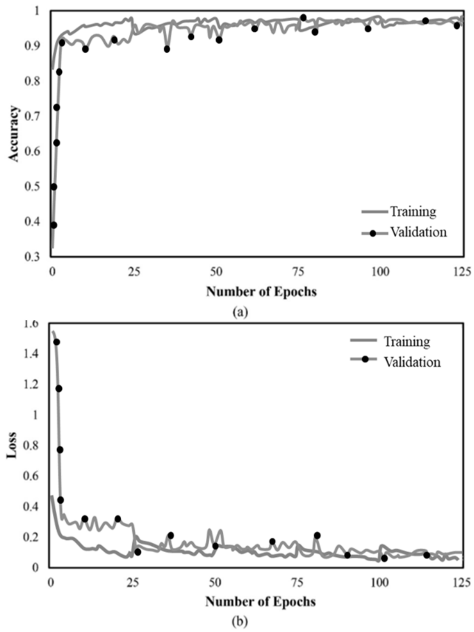


FIGURE 4. Training and validation errors for (a) accuracy vs epochs (b) loss vs epochs.

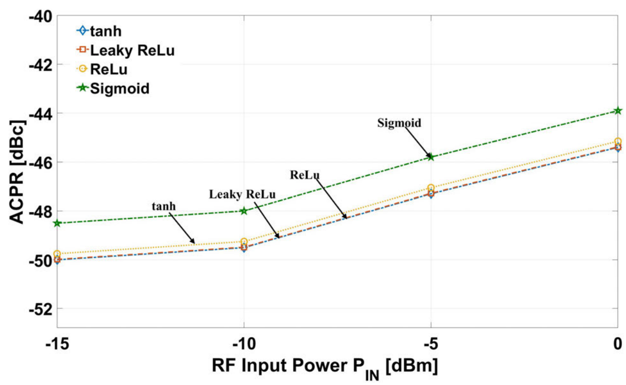


FIGURE 5. Activation function comparison for optimizing ORNN performance.

However, it is important to note that the optimal activation function may vary depending on the task, as no single activation function suits all scenarios. Based on the comparison done, ReLu was selected as it had the least ACPR.

C. VARIATION OF OPTIMIZERS

Optimizers are crucial for updating network parameters during training, aiming to minimize training errors and improve overall performance. The analysis involved experimenting with different optimizers to assess their impact on ORNN convergence and accuracy.

Commonly used optimizers, such as stochastic gradient descent (SGD), Adam, RMSprop, and Adagrad, were considered as shown in Fig. 6. Each optimizer employs a distinct algorithm to update weights and biases, affecting convergence speed and quality. SGD updates parameters based on the loss function's gradient, while Adam combines adaptive

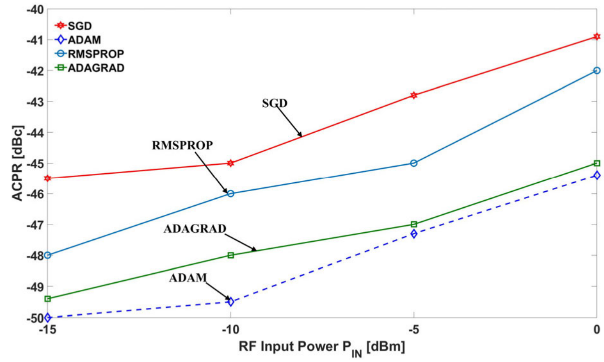


FIGURE 6. Optimizers comparison for optimizing ORNN performance.

learning rates with momentum. By comparing ORNN performance using different optimizers, the optimal choice can be determined. However, similar to activation functions, the selection depends on factors such as the dataset, network architecture, and problem domain. On the basis of performance with the least ACPR, ADAM was chosen.

D. VARIATION IN THE NUMBER OF LAYERS

The number of layers in the ORNN architecture significantly influences its performance. Experimenting with different layer configurations helps assess the network's depth and its ability to capture complex temporal patterns and hierarchical dependencies. The goal is to identify the optimal number of layers that balances the model's expressive power and generalization ability. The optimal configuration depends on the task's complexity, data nature, and available computational resources.

Fig. 7 represents the surface plot representing the ACPR values concerning the RF input power and number of layers. The x-axis represents the power values, while the y-axis corresponds to the layer number and the ACPR values are displayed as the z-axis. The plot reveals important insights into the system's performance, particularly in terms of ACPR. Upon examining the plot, it becomes apparent that three specific numbers of layers exhibit the best optimum ACPR values.

E. HYPERPARAMETER TUNING

Systematic hyperparameter tuning is essential for optimizing the ORNN. This involves optimizing not only the number of

TABLE 3. ORNN architecture hyperparameters.

ORNN Architecture	Training data= 64470 samples
	Testing data= 27630 samples
	Optimizer= Adam
	Activation function= ReLu
	Layers= 3
	Neurons per layer= [128, 64, 32]
	Epochs=125

TABLE 4. Complexity comparisons for the conventional and proposed architecture.

Method	Coefficients	Condition Number	Estimated Multiplications	Time Consumption (seconds)
GMP	$K_a(Q_a+1)+K_b(Q_b+1)R_b+K_c(Q_c+1)R_c$=84	8.14 x 10^7	244	180
CPWL	*(4M+1) (K+1) L=260*	4.6 x 10^8	880	650
ORNN	$\mathcal{O}(dim\ (z)[\sum_{l=0}^{L} O_l O_{l+1} \sum_{l=1}^{L} O_l^2)])$=*1024*	2.1 x 10^4	*832*	300

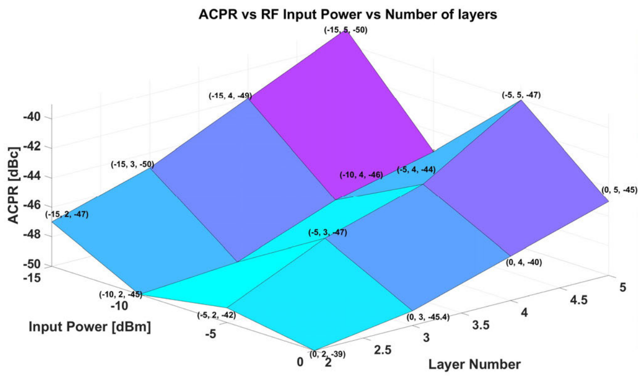


FIGURE 7. Variation in the number of layers vs RF input power and ACPR for optimizing ORNN performance.

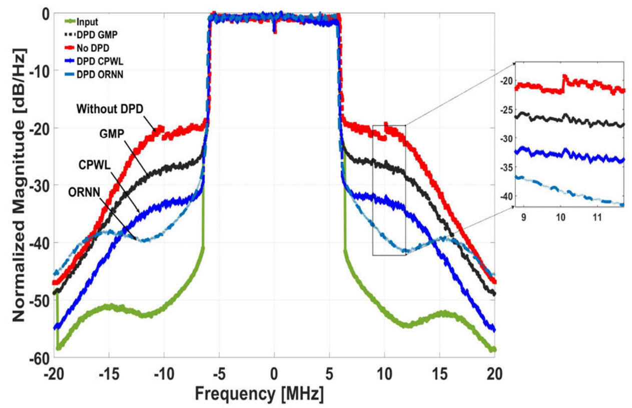


FIGURE 8. Illustration of power spectral density (PSD)/ spectral regrowth comparing ORNN, GMP and CPWL performance efficacy.

layers but also other hyperparameters such as learning rate, batch size, regularization techniques, and sequence length. Random search techniques were used to find the best combination of architectural choices. The aim is to strike a balance between computation complexity and performance. Table 3 presents the hyperparameter tuning.

VI. EXPERIMENTAL RESULTS

The proposed ORNN-DPD technique is used with specific parameters and compared to the GMP and CPWL method with parameters given as K = L = 4, M = Q = 3 that were used in our previous study as well [16], [17], [21], [22], [23], [24], [25], [26]. We compare our previous work [18] to GMP approaches as a baseline architecture.

A. PERFORMANCE COMPARISON

The evaluation of the ORNN-DPD technique encompasses the assessment of spectral regrowth, ACPR and EVM. The primary objective of the ORNN-DPD method is to streamline the process and enhance performance in comparison to earlier approaches like CPWL, GMP, and the absence of DPD methods.

Fig. 8 shows the spectral regrowth commonly known as power spectral density (PSD) of the proposed ORNN DPD technique in comparison to GMP and CPWL methods. The PSD shows that the ORNN results in a reduced spectral regrowth to −40 dB/Hz as compared to −25 dB/Hz achieved with GMP and −32 dB/Hz with CPWL respectively.

In addition to evaluating PSD, the EVM is displayed in Fig. 9(a) that shows that the ORNN-based DPD method outpaces the conventional methods. ORNN achieves a better reduction as compared to CPWL, however, a slight change is seen at RF input power of 5 dBm where CPWL has 3.5% EVM while ORNN has 3.8% EVM as compared to 4.8% of GMP and 11.4 % of EVM without DPD.

This performance can be improved by having a higher number of neurons per layer, however, the 5 dBm RF input power is quite high as the operating power is somewhere below 0 dBm in most of the use cases.

Similarly, the ACPR is evaluated in Fig. 9 (b). The ACPR is illustrated for various RF input power levels, showing that the ORNN-DPD method reduces the ACPR by 18 dB to -46 dBc, in comparison to the no DPD case, which is below -45 dBc set by 3GPP [53], [54].

This is evident that ORNN has achieved better performance in comparison to traditional architectures.

B. COMPLEXITY COMPARISONS

Complexity is a critical consideration in digital predistortion (DPD) for Radio over Fiber (RoF) systems. While traditional DPD methods have achieved significant performance improvements, they often come at the cost of increased complexity.

This is where the recent development of the ORNN method stands out. ORNN reduces the complexity of the DPD process while still delivering superior performance making it a much more attractive option for designers of RoF systems, especially in applications where memory and computational resources are limited.

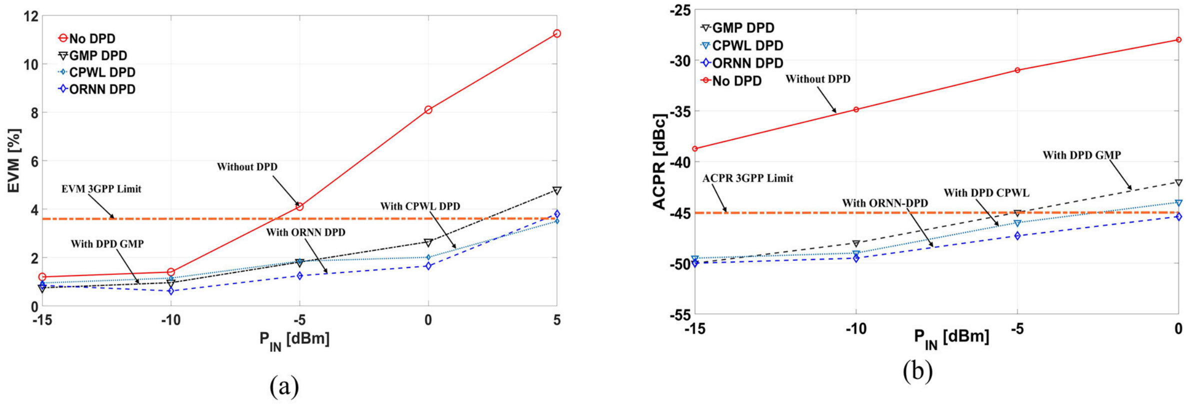


FIGURE 9. Comparison showing with and without DPD performance for (a) EVM and (b) ACPR.

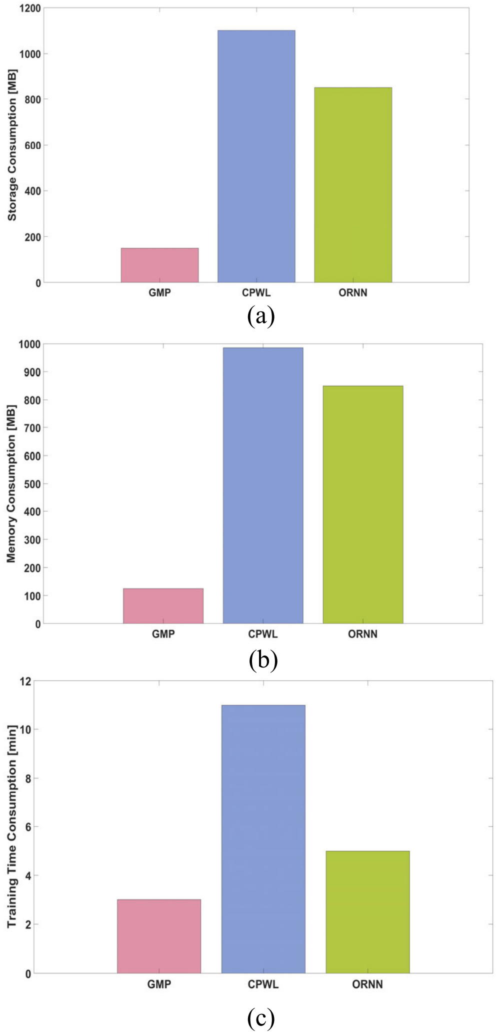


FIGURE 10. Comparative analysis of performance and complexity in DPD architectures: (a) Storage (b) Memory (c) Time Computations.

Despite the demonstrated elevated performance of the ORNN method compared to the efficient CPWL conventional methods, the key advantage of ORNN lies in its significantly lower complexity. The ORNN requires a fewer multiplication operations due to which it has lesser complexity as compared to CPWL, which can be seen in Table 4. Particularly, the ORNN-DPD requires 249 multiplications lesser than the CPWL technique.

Moreover, statistics like the condition number and time consumption reveal that ORNN-DPD is a more optimized, simpler, and efficient method compared to MSA and GMP. This is further highlighted when compared to previous work using DPD with machine learning (ML) methods. While the proposed ORNN still performs well, its key advantage lies in its significant reduction in complexity. The complexity of the ORNN-based algorithm is a significant factor that needs to be considered.

The comparison highlights that ORNN has lower complexity yet comparable performance. This demonstrates that there is a trade-off between performance and complexity when choosing a DPD method. Fig. 10 and Table 4 shows a comparison between ORNN, CPWL and GMP in terms of storage utilization, memory consumption and time complexities. In many cases, the complexity of a DPD algorithm is directly proportional to its performance. The more complex the algorithm, the better the performance it can deliver.

However, this increase in performance comes at a cost. The more complex the algorithm, the greater the demand for memory and computational resources. This can make it difficult to implement the DPD algorithm in real-world systems, especially in cases where these resources are limited. This is why the development of the ORNN method is so important. It provides a way to achieve performance improvements while reducing complexity. By balancing performance and complexity, ORNN offers a flexible and effective solution to the challenges of nonlinear distortion in RoF systems. The ability to achieve high performance with low complexity is essential for the continued development and implementation of RoF systems. In conclusion, complexity is a crucial consideration in DPD for RoF systems. While traditional DPD methods have achieved significant performance improvements, their increased complexity can make them difficult to implement in real-world systems. However, ORNN methods offers a solution to this challenge by balancing performance

TABLE 5. Performance and complexity summary.

Methodology	EVM (%)	ACLR (dBc)	Complexities Multiplications	Time (min)	Memory (MB)
Without DPD	8	−27	-	-	-
GMP	3	−42	244	3	150
CPWL	2.1	−44.4	880	11	800
ORNN	1.65	-45.1	832	5	850

and complexity, making it a more attractive option for RoF systems.

The ability to achieve high performance with low complexity is essential for the continued development and implementation of RoF systems. Table 4 provides an overview of the performance outcomes at 0 dBm, showcasing how the ORNN-DPD technique achieves a complexity reduction while preserving comparable performance to the GMP and CPWL methods.

VII. CONCLUSION

The article introduces an experimental realization of ML based ORNN DPD method that improves the linearization performance of a 5G new radio signals for a multiband RoF link carrier signal for eRAC use cases. The proposed ORNN-DPD method optimization is evidenced and has been experimentally verified to transmit 5G NR signals at 2.14 GHz and 10 GHz over a 10 km fiber distance. The proposed ORNN method leads to an EVM of 1.65% for 5G NR waveform as compared to 3% of GMP and 8% without linearization while ORNN leads to an ACPR reduction of 18 dBc. Similarly, ORNN carries considerably lower complexity than the previously proposed conventional DPD methods such as GMP and CPWL, leading to better performance. Additionally, the ORNN-DPD method requires fewer multiplication operations, requires lesser memory and time for training making it more robust. To the authors' knowledge, this is the first instance of improving and comparing the performance of multiband 5G NR-based optical fronthaul using a proposed ORNN and comparing it with other competitive DPD architectures.

REFERENCES

[1] J. P. Santacruz, S. Rommel, U. Johannsen, A. Jurado-Navas, and I. T. Monroy, "Analysis and compensation of phase noise in mm-wave OFDM ARoF systems for beyond 5G," *J. Lightw. Technol.*, vol. 39, no. 6, pp. 1602–1610, Mar. 15, 2021, doi: 10.1109/JLT.2020.3041041.

[2] M. F. Haider, F. You, S. He, T. Rahkonen, and J. P. Aikio, "Predistortion-based linearization for 5G and beyond millimeter-wave transceiver systems: A comprehensive survey," *IEEE Commun. Surveys Tuts.*, vol. 24, no. 4, pp. 2029–2072, 4th Quart., 2022.

[3] W. Dias, D. Gaspar, L. Mendes, M. Chafii, M. Matthé, P. Neuhaus, and G. Fettweis, "Performance analysis of a 5G transceiver implementation for remote areas scenarios," in *Proc. Eur. Conf. Netw. Commun. (EuCNC)*, Jun. 2018, pp. 363–367.

[4] M. Jiang, J. Cezanne, A. Sampath, O. Shental, Q. Wu, O. Koymen, A. Bedewy, and J. Li, "Wireless fronthaul for 5G and future radio access networks: Challenges and enabling technologies," *IEEE Wireless Commun.*, vol. 29, no. 2, pp. 108–114, Apr. 2022.

[5] J. Nanni, A. Giovannini, M. Usman Hadi, E. Lenzi, S. Rusticelli, R. Wayth, F. Perini, J. Monari, and G. Tartarini, "Controlling Rayleigh-backscattering-induced distortion in radio over fiber systems for radioastronomic applications," *J. Lightw. Technol.*, vol. 38, no. 19, pp. 5393–5405, Oct. 1, 2020.

[6] C. Lim et al., "Fiber-wireless networks and subsystem technologies," *J. Lightw. Technol.*, vol. 28, no. 4, pp. 390–405, Feb. 15, 2010, doi: 10.1109/JLT.2009.2031423.

[7] J. H. Lee, J. W. Choi, and Y. C. Chung, "Fiber nonlinearity mitigation in radio-over-fiber links for next-generation mobile fronthaul networks," *IEEE Trans. Microw. Theory Techn.*, vol. 65, no. 12, pp. 5375–5383, Dec. 2017.

[8] L. Ding, G. T. Zhou, D. R. Morgan, Z. Ma, J. S. Kenney, J. Kim, and C. R. Giardina, "A robust digital baseband predistorter constructed using memory polynomials," *IEEE Trans. Commun.*, vol. 52, no. 1, pp. 159–165, Jan. 2004, doi: 10.1109/TCOMM.2003.822188.

[9] T. A. Tsiftsis and G. K. Karagiannidis, "A novel digital predistortion technique for radio over fiber links," *IEEE Trans. Wireless Commun.*, vol. 6, no. 9, pp. 3272–3277, Sep. 2007.

[10] A. Hekkala, M. Hiivala, M. Lasanen, J. Perttu, L. C. Vieira, N. J. Gomes, and A. Nkansah, "Predistortion of radio over fiber links: Algorithms and measurements," *IEEE Trans. Circuits Syst. I, Reg. Papers*, vol. 59, no. 3, pp. 664–672, Mar. 2012.

[11] F. Li, X. Zheng, Y. Ma, and J. Zhao, "Digital predistortion for high-speed RoF systems based on Volterra series," *Opt. Exp.*, vol. 22, no. 22, pp. 27236–27245, Oct. 2014.

[12] H. Chen, J. Li, K. Xu, Y. Dai, F. Yin, and J. Lin, "Experimental investigation on multi-dimensional digital predistortion for multi-band directly-modulated radio-over-fiber systems," in *Proc. OFC*, San Francisco, CA, USA, Mar. 2014, pp. 1–3, doi: 10.1364/OFC.2014.M3D.4.

[13] R. Zhu and X. Zhang, "Linearization of radio-over-fiber systems by using two lasers with different wavelengths," in *IEEE MTT-S Int. Microw. Symp. Dig.*, Tampa, FL, USA, Jun. 2014, pp. 1–3, doi: 10.1109/MWSYM.2014.6848305.

[14] C. Yu, J. Xia, X.-W. Zhu, and A. Zhu, "Single-model single-feedback digital predistortion for concurrent multi-band wireless transmitters," *IEEE Trans. Microw. Theory Techn.*, vol. 63, no. 7, pp. 2211–2224, Jul. 2015, doi: 10.1109/TMTT.2015.2429633.

[15] T. Pfeiffer, "Next generation mobile fronthaul and midhaul architectures [invited]," *J. Opt. Commun. Netw.*, vol. 7, no. 11, pp. B38–B45, Nov. 2015, doi: 10.1364/JOCN.7.000B38.

[16] H.-T. Huang, C.-T. Lin, S.-C. Chiang, B.-J. Lin, P.-T. B. Shih, and A. Ng'oma, "Volterra nonlinearity compensator for I/Q imbalanced mm-wave OFDM RoF systems," in *Proc. Int. Topical Meeting Microw. Photon. (MWP)*, Paphos, Cyprus, Oct. 2015, pp. 1–4, doi: 10.1109/MWP.2015.7356691.

[17] S. Liu, M. Xu, J. Wang, F. Lu, W. Zhang, H. Tian, and G.-K. Chang, "A multilevel artificial neural network nonlinear equalizer for millimeter-wave mobile fronthaul systems," *J. Lightw. Technol.*, vol. 35, no. 20, pp. 4406–4417, Oct. 15, 2017, doi: 10.1109/JLT.2017.2717778.

[18] A. Li, W. Shi, X. Zheng, and J. Zhao, "Digital predistortion for high-speed radio-over-fiber systems based on support vector regression," *Opt. Exp.*, vol. 23, no. 8, pp. 10193–10203, Apr. 2015.

[19] X. Liu, "Hybrid digital-analog radio-over-fiber (DA-RoF) modulation and demodulation achieving a SNR gain over Analog RoF of >10 dB at halved spectral efficiency," in *Proc. Optical Fiber Commun. Conf. Exhib. (OFC)*, San Francisco, CA, USA, 2021, pp. 1–3.

[20] Z. Wang, L. Guan, and R. Farrell, "Undersampling observation-based compact digital predistortion for single-chain multiband and wideband direct-to-RF transmitter," *IEEE Trans. Microw. Theory Techn.*, vol. 65, no. 12, pp. 5274–5283, Dec. 2017, doi: 10.1109/TMTT.2017.2758366.

[21] M. U. Hadi, J. Nanni, P. A. Traverso, G. Tartarini, O. Venard, G. Baudoin, and J.-L. Polleux, "Experimental evaluation of digital predistortion for VCSEL-SSMF-based radio-over-fiber link," in *Proc. Int. Topical Meeting Microw. Photon. (MWP)*, Toulouse, France, Oct. 2018, pp. 1–4, doi: 10.1109/MWP.2018.8552895.

[22] D. Novak and T. R. Clark, "Broadband adaptive feedforward photonic linearization for high dynamic range signal remoting," in *Proc. IEEE Mil. Commun. Conf. (MILCOM)*, Orlando, FL, USA, Oct. 2007, pp. 1–6, doi: 10.1109/MILCOM.2007.4454898.

[23] X. Xie, M. Hui, T. Liu, and X. Zhang, "Hybrid linearization of broadband radio-over-fiber transmission," *IEEE Photon. Technol. Lett.*, vol. 30, no. 8, pp. 692–695, Apr. 15, 2018, doi: 10.1109/LPT.2018.2812745.

[24] M. U. Hadi, P. A. Traverso, G. Tartarini, O. Venard, G. Baudoin, and J.-L. Polleux, "Digital predistortion for linearity improvement of VCSEL-SSMF-based radio-over-fiber links," *IEEE Microw. Wireless Compon. Lett.*, vol. 29, no. 2, pp. 155–157, Feb. 2019, doi: 10.1109/LMWC.2018.2889004.
[25] Y. Li, S. Ghafoor, K. Satyanarayana, M. El-Hajjar, and L. Hanzo, "Analogue wireless beamforming exploiting the fiber-nonlinearity of radio over fiber-based C-RANs," *IEEE Trans. Veh. Technol.*, vol. 68, no. 3, pp. 2802–2813, Mar. 2019, doi: 10.1109/TVT.2019.2893589.
[26] M. U. Hadi, J. Nanni, O. Venard, G. Baudoin, J.-L. Polleux, P. A. Traverso, and G. Tartarini, "Linearity improvement of VCSELs based radio over fiber systems utilizing digital predistortion," *Adv. Sci., Technol. Eng. Syst. J.*, vol. 4, no. 3, pp. 156–163, 2019.
[27] J. Sun, W. Shi, Z. Yang, J. Yang, and G. Gui, "Behavioral modeling and linearization of wideband RF power amplifiers using BiLSTM networks for 5G wireless systems," *IEEE Trans. Veh. Technol.*, vol. 68, no. 11, pp. 10348–10356, Nov. 2019, doi: 10.1109/TVT.2019.2925562.
[28] M. U. Hadi, J. Nanni, J.-L. Polleux, P. A. Traverso, and G. Tartarini, "Direct digital predistortion technique for the compensation of laser chirp and fiber dispersion in long haul radio over fiber links," *Opt. Quantum Electron.*, vol. 51, no. 6, p. 205, Jun. 2019.
[29] M. U. Hadi, J. Nanni, O. Venard, G. Baudoin, J. L. Polleux, and G. Tartarini, "Practically feasible closed-loop digital predistortion for VCSEL-MMF-based radio-over-Fiber links," *Radioengineering*, vol. 29, no. 1, pp. 37–43, Apr. 2020.
[30] L. Zhang, X. Liu, Y. Ma, and J. Zhao, "A novel digital predistortion method for linearization of high-speed RoF systems," *IEEE Photon. J.*, vol. 12, no. 4, pp. 1–11, Aug. 2020.
[31] M. U. Hadi, C. Kantana, P. A. Traverso, G. Tartarini, O. Venard, G. Baudoin, and J. Polleux, "Assessment of digital predistortion methods for DFB-SSMF radio-over-fiber links linearization," *Microw. Opt. Technol. Lett.*, vol. 62, no. 2, pp. 540–546, Feb. 2020.
[32] M. U. Hadi, "Mitigation of nonlinearities in analog radio over fiber links using machine learning approach," *ICT Exp.*, vol. 7, no. 2, pp. 253–258, Jun. 2021, doi: 10.1016/j.icte.2020.11.002.
[33] M. U. Hadi and G. Murtaza, "Enhancing distributed feedback-standard single mode fiber-radio over fiber links performance by neural network digital predistortion," *Microw. Opt. Technol. Lett.*, vol. 63, no. 5, pp. 1558–1565, May 2021.
[34] M. U. Hadi, M. Awais, M. Raza, M. I. Ashraf, and J. Song, "Experimental demonstration and performance enhancement of 5G NR multiband radio over fiber system using optimized digital predistortion," *Appl. Sci.*, vol. 11, no. 24, p. 11624, Dec. 2021, doi: 10.3390/app112411624.
[35] Y. Xie, Y. Wang, S. Kandeepan, and K. Wang, "Machine learning applications for short reach optical communication," *Photonics*, vol. 9, no. 1, p. 30, Jan. 2022.
[36] L. A. M. Pereira, L. L. Mendes, C. J. A. Bastos-Filho, and S. A. Cerqueira, "Linearization schemes for radio over fiber systems based on machine learning algorithms," *IEEE Photon. Technol. Lett.*, vol. 34, no. 5, pp. 279–282, Mar. 1, 2022, doi: 10.1109/LPT.2022.3151616.
[37] L. A. M. Pereira, L. L. Mendes, C. J. A. Bastos-Filho, and S. A. Cerqueira Jr., "Machine learning-based linearization schemes for radio over fiber systems," *IEEE Photon. J.*, vol. 14, no. 6, pp. 1–10, Dec. 2022, doi: 10.1109/JPHOT.2022.3210454.
[38] G. Rizzelli, "Advances in optical fiber communications," *Appl. Sci.*, vol. 12, no. 10, p. 4818, May 2022, doi: 10.3390/app12104818.
[39] M. Usman Hadi, "Towards optimization of 5G NR transport over fiber links performance in 5G multi-band networks: An OMSA model approach," *Opt. Fiber Technol.*, vol. 79, Sep. 2023, Art. no. 103358, doi: 10.1016/j.yofte.2023.103358.
[40] G. Meslener, "Chromatic dispersion induced distortion of modulated monochromatic light employing direct detection," *IEEE J. Quantum Electron.*, vol. JQE-20, no. 10, pp. 1208–1216, Oct. 1984.
[41] C. Mateo, P. L. Carro, P. García-Dúcar, J. de Mingo, and Ì. Salinas, "Minimization of feedback loop distortions in digital predistortion of a radio-over-fiber system with optimization algorithms," *IEEE Photon. J.*, vol. 9, no. 3, pp. 1–14, Jun. 2017, doi: 10.1109/JPHOT.2017.2706364.
[42] C. Mateo, J. Clemente, P. García-Dúcar, P. L. Carro, J. de Mingo, and Ì. Salinas, "Digital predistortion of a full-duplex radio-over-fiber mobile fronthaul link with feedback loop," in *Proc. 13th Int. Wireless Commun. Mobile Comput. Conf. (IWCMC)*, Valencia, Spain, Jun. 2017, pp. 1425–1430, doi: 10.1109/IWCMC.2017.7986493.
[43] C. Mateo, P. L. Carro, P. García-Dúcar, J. de Mingo, and Í. Salinas, "Experimental evaluation of the feedback loop effects in digital predistortion of a radio-over-fiber system," in *Proc. 9th Int. Conf. Ubiquitous Future Netw. (ICUFN)*, Jul. 2017, pp. 1039–1041 doi: 10.1109/ICUFN.2017.7993958.
[44] L. A. M. Pereira, L. L. Mendes, C. J. A. B. Filho, and A. C. Sodre, "Amplified radio-over-fiber system linearization using recurrent neural networks," *J. Opt. Commun. Netw.*, vol. 15, no. 3, pp. 144–154, Mar. 2023.
[45] J. Song, Z. He, C. Häger, M. Karlsson, A. G. I. Amat, H. Wymeersch, and J. Schröder, "Over-the-fiber digital predistortion using reinforcement learning," in *Proc. Eur. Conf. Opt. Commun. (ECOC)*, Bordeaux, France, Sep. 2021, pp. 1–4 doi: 10.1109/ECOC52684.2021.9605972.
[46] M. Singh and A. S. Sappal, "Digital predistortion of radio over fiber (RoF) link using hybrid memetic algorithm," *J. Opt. Commun.*, vol. 4, no. 2, 2021, Art. no. 000010151520210041.
[47] P. L. Carro, C. Mateo, P. García-Dúcar, J. de Mingo, and A. Valdovinos, "DPD linearization complexity reduction of remote radio heads in C-RAN with radio over fiber fronthaul," in *Proc. 48th Eur. Microw. Conf. (EuMC)*, Madrid, Spain, Sep. 2018, pp. 843–846, doi: 10.23919/EuMC.2018.8541801.
[48] M. Hadi, M. Awais, M. Raza, K. Khurshid, and H. Jung, "Neural network DPD for aggrandizing SM-VCSEL-SSMF-based radio over fiber link performance," *Photonics*, vol. 8, no. 1, p. 19, Jan. 2021.
[49] A. C. Najarro and S.-M. Kim, "Nonlinear compensation using artificial neural network in radio-over-fiber system," *J. Inf. Commun. Converg. Eng.*, vol. 16, no. 1, pp. 1–5, May 2018.
[50] S. Liu, Y. M. Alfadhli, S. Shen, M. Xu, H. Tian, and G.-K. Chang, "A novel ANN equalizer to mitigate nonlinear interference in analog-RoF mobile fronthaul," *IEEE Photon. Technol. Lett.*, vol. 30, no. 19, pp. 1675–1678, Oct. 1, 2018.
[51] S. Jia, L. Zhang, S. Wang, W. Li, M. Qiao, Z. Lu, N. M. Idrees, X. Pang, H. Hu, X. Zhang, L. K. Oxenløwe, and X. Yu, "2 $\times$ 300 Gbit/s line rate PS-64QAM-OFDM THz photonic-wireless transmission," *J. Lightw. Technol.*, vol. 38, no. 17, pp. 4715–4721, Sep. 1, 2020.
[52] M. U. Hadi, N. Soin, and S. Kausar, "Enhancing 5G multi-band long haul optical fronthaul links performance by magnitude-selective affine digital predistortion method," *Microw. Opt. Technol. Lett.*, vol. 64, no. 4, pp. 827–834, Apr. 2022, doi: 10.1002/mop.33169.
[53] *Base Station (BS) Conformance Testing*, document TS 38.141-1 and 38.141-2, Version 1.1.0, 3rd Generation Partnership Project (3GPP), 2019.
[54] *NR; Physical layer measurements*, document TS 38.215, Version 15.4.0, Release 15, 3rd Generation Partnership Project (3GPP), 2019.

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