>100 Gbps 3×3 MIMO V-Band RoF System for up to 100 m Wireless Transmission Enabled by NN-based Equalization

Chia-Chien Wei[1], Yu-Jen Huang[2], Zhen-Xiong Xie[2], Ping-Yao Huang[2], Pin-Hsuan Ting[2], Chun-Ting Lin[2*]
1. Department of Photonics, National Sun Yat-sen University, Kaohsiung 804, Taiwan
2. Institute of Photonic System, National Yang Ming Chiao Tung University, Tainan County 711, Taiwan.
**Corresponding Author: jinting@mail.nctu.edu.tw*

Abstract: This study employs a single neural-network-based nonlinear equalizer in a 3×3 MIMO V-band RoF system for the first time. Experiment results demonstrate >30% improvement in data rate and >100-Gbps wireless transmission over 100 m.

1. Introduction

Driven by bandwidth-hungry network applications, millimeter-wave (e.g., V and W band) and multiple-input-multiple-output (MIMO) technologies have become the key means to increase transmission capacity in future optical-wireless communications [1-3]. To overcome the high propagation loss of V-band waves, an RF power amplifier (PA) often must operate in a nonlinear region to achieve sufficient power and transmission distance. In addition, the high peak-to-average power ratio of advanced modulation schemes, such as orthogonal frequency-division multiplexing (OFDM), compounds the issue of nonlinearity. To solve this problem, nonlinear equalizers based on Volterra series are widely used in communications [4]. However, carefully setting up the Volterra series models is necessary to enable effective mitigation of nonlinearity, particularly in a MIMO radio-over-fiber (RoF) system, where multiple filtering, E/O/E conversion, and I/Q down/up-conversion complicate the system model significantly. Thus, it is challenging to model the Volterra series accurately, which leads to incomplete compensation for the nonlinearity.

With the explosive growth of big data and significant progress in hardware, neural networks (NNs) have attracted considered attention in research [5], due to their applications in image classification, voice recognition, autonomous driving, etc. Recently, NNs have also been widely used in optical communication systems [6] for various purposes, such as optical performance monitoring [7], proactive fault detection [8], software-defined networking [9], and nonlinear compensation [10]. By being trained with a large amount of data, NNs can be developed into complex and highly nonlinear models. However, the effectiveness of NNs in the MIMO RoF transmission has not been investigated thus far.

For the first time, this work employs an NN-based nonlinear equalizer to significantly improve the transmission distance of a 3×3 MIMO V-band RoF system, where the nonlinearity mainly originates from the RF PA. An RF PA with a higher input power provides a higher transmission budget (thus, longer transmission distance) but suffers from greater nonlinearity. Thus, the proposed NN-based equalizer could eliminate the nonlinear distortion caused by the PAs, leading to a higher data rate and longer transmission distance. When the PA input power is high, the NN provides an improvement of up to 30% in data rate and achieves wireless transmission at >100 Gbps over up to 100 m.

2. Experimental Setup

Fig. 1 shows the experimental setup of our 3×3 MIMO OFDM 60-GHz RoF system. An arbitrary waveform generator (AWG) was used to generate two sets of I/Q signals. The sampling rate of the AWG was 12 GSample/s; the FFT size was 512; the length of the cyclic prefix was 1/32 of the FFT size; for each signal, the number of subcarriers

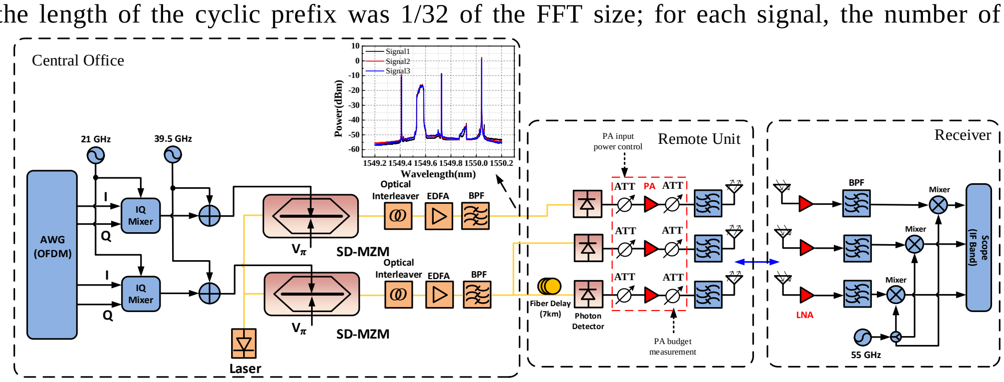

Fig. 1. Experimental setup of 3×3 MIMO V-band RoF system

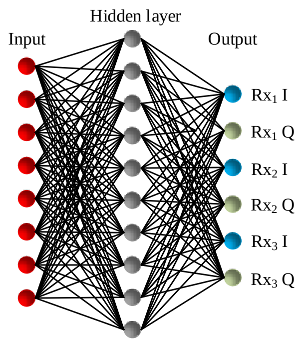

Fig. 2. Structure of NN

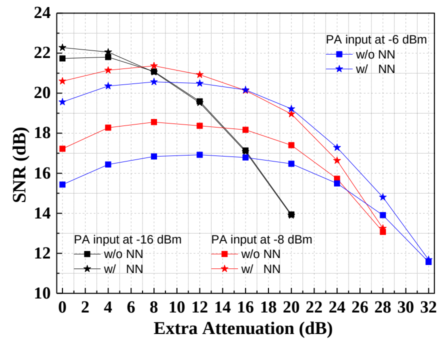

Fig. 3. SNR against extra attenuation

was 298, and the total bandwidth was 6.98 GHz. The generated baseband signals were up-converted to 21 GHz by I/Q mixers before being mixed with 39.5-GHz carriers. The mixed signals were employed to drive the single-drive Mach-Zehnder modulators (SD-MZMs), which were biased at the null point. We used optical interleavers to select the optical OFDM signals at the higher frequency and the un-modulated optical carriers at the lower frequency, as shown in the inset of Fig. 1; the difference in the frequencies of the un-modulated carrier and OFDM signal was the desired 60.5 GHz. We actually generated only two sets of independent optical signals, due to a shortage of equipment and devices. To demonstrate the 3×3 system, one of the optical signals was split into two parts, of which one was delayed by the 7 km fiber, to emulate a third set of independent optical signals. Photo-detectors were used to generate three sets of the electrical OFDM signals at 60.5 GHz. Due to the high propagation loss at 60 GHz, the PAs were utilized to boost the powers. When the attenuators before the PAs could control the input power and the degree of nonlinearity of the PAs, the attenuators after the PAs characterized the power budget for the wireless transmission over additional distances. After passing through transmitter antennas, 7 m wireless transmission and receiver antennas, the OFDM signals were down-converted to 5.5 GHz and then recorded by the real-time oscilloscope with a sampling rate of 40 GSample/s. Finally, the recorded signals were demodulated via an offline processes, including down-conversion to baseband I/Q signals and NN-based equalization.

Using 500 training symbols and 100 epochs, the NN in this study was trained to compensate for nonlinearity by means of time-domain waveform regression [12]. After careful optimization, the parameters of the NN were set as follows. The inputs to the NN were three sets of received baseband I/Q signals, each of which consisted of 21 consecutive samples to effectively overcome the memory effect. The output neurons were the samples of three sets of equalized I/Q waveforms, as shown in Fig. 2. Thus, the numbers of input and output neurons were 126 and 6, respectively. Moreover, the NN consisted of a single fully-connected hidden layer with 1024 neurons, and the ReLU function was used as the nonlinear activation function. The weight and bias values of the neurons were determined by minimizing the loss function (i.e., the mean square error between the target and received training symbols), using the gradient descent and error back propagation [5].

3. Results and Discussions

Increasing the input power of the PAs would lead to higher output power at the expense of greater nonlinearity. Fig. 3 plots the average signal-to-noise ratio (SNR) of three channels versus the extra attenuation after each PA for various PA input powers. Due to the nonlinearity, increasing the input power would reduce the SNR in the absence of extra attenuation. In the case of a high input power, the NN could effectively mitigate the nonlinearity, leading to an enhanced SNR. For instance, the NN can increase the SNR from 15.4 to 19.6 dB for a PA input power of -6 dBm. When adding the extra attenuation, the SNR for lower PA input powers (e.g., -16 dBm) decreased monotonically because thermal noise was dominant. By contrast, if the extra attenuation was sufficiently high, the SNR for high PA input powers (e.g., -6 dBm) could surpass that for lower PA input powers, particularly when the NN was applied. This indicates the capability of the NN to eliminate the nonlinearity, and thus allow for more extra attenuation.

Due to the limited distance available in the laboratory, the transmission performance over more than 11 m was estimated by adding extra attenuation, which emulates the path loss for a longer wireless transmission. Using the precise path loss model,

$$\text{Free Space Path Loss (dB)} = 10\log_{10}\left(\left(\frac{4\pi df}{c}\right)^{1.94}\right)$$

where d, f, and c are the distance, the carrier frequency and the speed of light, respectively, the 60 GHz path loss

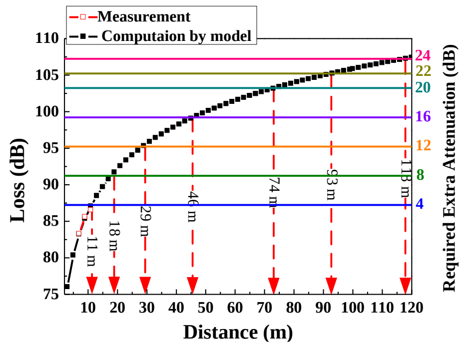

Fig. 4. Experimental and model results for 60 GHz path loss

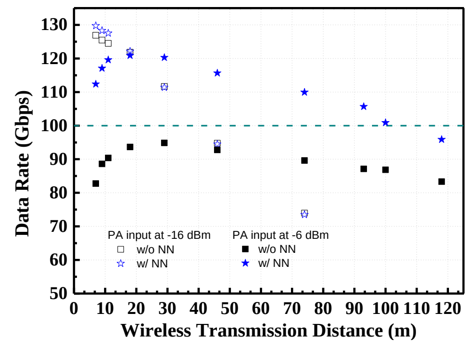

Fig. 5. Maximum data rate over different transmission distances

and the required extra attenuation were determined as functions of wireless transmission distance, as shown in Fig. 4. The results in Fig. 4 indicate that the measured path loss (over no more than 11 m) agrees well with the model results. Accordingly, we could measure the transmission performance over a distance of >11 m by introducing the appropriate extra attenuation. Based on the bit-loading algorithm [11], Fig. 5 plots the maximum achievable data rate required to ensure a bit-error rate of $<3.8\times10^{-3}$ over various wireless transmission distances. For the PA input power of -16 dBm, the insignificant nonlinearity allows for achieving a data rate of 127 Gbps after 7 m transmission without any nonlinear compensation. With the application of NN in this case, the improvement is only about 3 Gbps, resulting in a data rate of up to 130 Gbps. Nonetheless, when the transmission distance increases, the use of a low PA input power becomes insufficient, and therefore, the data rate drops rapidly. In contrast, the case with the high PA input power of -6 dBm suffers from severe nonlinearity, such that the data rate without NN never exceeds 95 Gbps. In this case, employing the NN significantly improves the data rate, by up to 30% (over <18 m wireless transmission), and a data rate of 100 Gbps is achievable even for wireless transmission over up to 100 m. As shown in Fig. 5, when using the low PA input power, the longest distance for >100-Gbps transmission without the NN is around 40 m; thus, the longest distance for 100 Gbps transmission is increased by 150% using the NN and a high PA input power.

4. Conclusions

A 3×3 MIMO 60-GHz RoF system aided by an NN-based nonlinear equalizer, which can reduce the nonlinear impact of the PAs, was developed in this study. The NN can not only increase the maximum capacity but also maintain a high transmission rate over long-distance wireless transmission. When the PA input power is high, employing the NN can improve the data rate by up to 30% and can extend the wireless transmission distance of >100 Gbps signals from ~40 to 100 m.

References

[1] Y. Niu, Y.Li, D.Jin, L.Su, and A.V.Vasilakos, “A Survey of Millimeter Wave (mmWave) Communications for 5G: Opportunities and Challenges,” Wirel. Netw. **21**, 2657-2676, 2015.

[2] F. C. C. J. F. Regist, "Use of spectrum bands above 24 GHz for mobile radio services," vol. 81, no. 164, pp. 58270-58308, 2016.

[3] J. Kim and I. Lee, "802.11 WLAN: History and new enabling MIMO techniques for next generation standards," in IEEE Commun. Mag., vol. 53, no. 3, pp. 134–140, Mar. 2015.

[4] R. N. Braithwaite, "Digital Predistortion of an RF Power Amplifier Using a Reduced Volterra Series Model With a Memory Polynomial Estimator," in IEEE Transactions on Microwave Theory and Techniques, vol. 65, no. 10, pp. 3613-3623, Oct. 2017.

[5] C. Zhang, P. Patras and H. Haddadi, "Deep Learning in Mobile and Wireless Networking: A Survey," in IEEE Communications Surveys & Tutorials, vol. 21, no. 3, pp. 2224-2287, thirdquarter 2019

[6] F. N. Khan, Q. Fan, C. Lu, and A. P. T. Lau, “Machine learning methods for optical communication systems and networks,” in Optical Fiber Telecommunications VII, Chap. 21, pp. 921–978, 2020.

[7] Y. Huang, Y. Chen, and J. Yu, "Optical performance monitoring of 56 Gbps optical PAM 4 signal using artificial neural networks," in Proc. Asia Commun. Photon. Conf., pp. 1–3, 2017.

[8] Zhilong Wang, Min Zhang, Danshi Wang, Chuang Song, Min Liu, Jin Li, Liqi Lou, and Zhuo Liu, "Failure prediction using machine learning and time series in optical network," Opt. Exp., vol. 25, pp. 18553-18565, 2017.

[9] F. Morales, M. Ruiz, L. Gifre, L. M. Contreras, V. Lopez and L. Velasco, "Virtual network topology adaptability based on data analytics for traffic prediction," in IEEE/OSA Journal of Optical Communications and Networking, vol. 9, no. 1, pp. A35-A45, Jan. 2017.

[10] T. Nguyen, S. Mhatli, E. Giacoumidis, L. Van Compernolle, M. Wuilpart and P. Mégret, "Fiber Nonlinearity Equalizer Based on Support Vector Classification for Coherent Optical OFDM," in IEEE Photonics Journal, vol. 8, no. 2, pp. 1-9, April 2016

[11] G. Kulkarni, S. Adlakha and M. Srivastava, "Subcarrier Allocation and Bit Loading Algorithms for OFDMA-Based Wireless Networks," IEEE Trans. Mobile Computing, vol. 4, no. 6, pp. 652-662, Nov./Dec. 2005.

[12] W. Huang, C. Wang, C. Wei, H. Taga and T. Tsuritani, "Improving DML-Based OFDM Transmission by a Filter-Aided Neural Network Equalizer," 2019 Optical Fiber Communications Conference and Exhibition (OFC), 2019, pp. 1-3.