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# Unlocking Nonlinear 850-nm VCSEL Dynamics for AI Computing in Radio-Over-Fiber Networks

Siqi Wang<sup>1</sup>, Jacopo Nanni<sup>2</sup>, *Member, IEEE*, Giovanni Tartarini<sup>2</sup>, *Member, IEEE*, and Aziz Benlarbi-Delai<sup>1</sup>

**Abstract**—The paradigm of joint communication and computation (J2C) is proposed to integrate artificial intelligence (AI) features within mobile front-haul infrastructures that exploit analog radio-over-fiber (ARoF) technology. The nonlinearity of a vertical cavity surface emitting laser (VCSEL)-based ARoF system is used for processing the transmitted data. In a classical communication system, the data connected at one side of the network is transmitted through the network to the other side for being processed. In this letter, we discover that nonlinear properties of VCSEL enable the neural network computing when signals are transmitted in the network, drastically reducing the computing consumption.

**Index Terms**—Artificial intelligence (AI), behavioral modeling, joint communication and computation (J2C), neural network, nonlinearity, radio-over-fiber (RoF).

## I. INTRODUCTION

THE artificial intelligence (AI) nowadays becomes more and more productive and is applied to address problems in different areas. Future 6G mobile network is among them, where the integration of AI computing into the communication system is considered one of the most important requirements [1]. Past generations of mobile networks have widely exploited optical communication infrastructures, such as analog radio-over-fiber (ARoF) for distributed antenna systems, thanks to their large transmission capacity and low latency over long distances, and same is expected also for the future 6G [2]. However, the ARoF channel may include many sources of nonlinearity, such as the one produced by the laser in the case of direct modulation, the optical fiber, the devices for amplification and regeneration, and the modulator, which limits the achievable information rate (AIR) [3]. The AIR can be improved by applying some linearization techniques to compensate for the nonlinearity [4], but it is still not approaching the theoretical capacity upper bound. A threat of capacity crunch exists from communication perspective,

but maybe not from the perspective of AI computing. The nonlinearity is the key to neural network computing for complex tasks. Analog neuromorphic in optical hardware has been a promising field known as photonic neural networks (PNNs). Some photonic-enabled realizations of neuromorphic processors, such as the ones based on vertical cavity surface emitting laser (VCSEL) technology, are attracting increasing interest because its low consumption, low cost, high bandwidth, and interesting nonlinear behavior [5]. The optical computing capability reaches 500 times of a supercomputer Fugaku with only 2 kW which is 0.01% of Fugaku's consumption [6]. However, most of the research on PNN is directed toward integrated optical circuits for pure neural network computing purpose. The communication capabilities of these optical devices are regrettably neglected.

In this letter, we propose to integrate the AI computing capability into mobile network front-hauls directly through the ARoF technology by exploiting an 850-nm VCSEL-based optical fiber communication system. In fact, such systems have been already proposed in the past as a promising solution to reduce costs and consumptions of the mobile infrastructures keeping at the same time high performances [7]. Despite these advantages, however, distributed feedback (DFB) Lasers are still the most used technology in ARoF applications, even for short distances, because of its lower nonlinear behavior compared to VCSEL technology. However, because AI Computing systems exploit nonlinear components, a novel scheme of joint communication and computation (J2C) based VCSEL-ARoF systems is proposed, presenting advantages of low-cost and low-consumption. The nonlinearity of VCSEL is exploited and imposed on an orthogonal frequency-division multiplexing (OFDM) signal or a concurrent multiband signal resulting in an equivalent processing of the signals modulated at different frequencies with a reservoir of neurons. The interactions among these neurons can be described by intermodulation products. Unlike the classical communication system, where the data connected to sensors is transmitted through the network to the server for processing, we process the data during transmission, keeping valid in this ARoF system all of the aforementioned benefits of using VCSEL technology.

## II. MEASUREMENTS

The VCSEL model has been developed starting with the characterization performed with the following test bench and represented in Fig. 1(a). An Anritsu MS2830A, composed of a vector signal generator (VSG) and a signal analyzer (SA) synchronized both in frequency and in time, is used to send

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Siqi Wang and Aziz Benlarbi-Delai are with CNRS, Laboratoire de Génie Electrique et Electronique de Paris, Sorbonne Université, 75252 Paris, France, and also with CentraleSupélec, CNRS, Laboratoire de Génie Electrique et Electronique de Paris, Université Paris-Saclay, 91192 Gif-sur-Yvette, France (e-mail: siqi.wang@sorbonne-universite.fr; aziz.benlarbi\_delai@sorbonne-universite.fr).

Jacopo Nanni and Giovanni Tartarini are with the Department of Electrical, Electronic, and Information Engineering, University of Bologna, 40136 Bologna, Italy (e-mail: jacopo.nanni3@unibo.it; giovanni.tartarini@unibo.it). Digital Object Identifier 10.1109/LMWT.2025.3544396

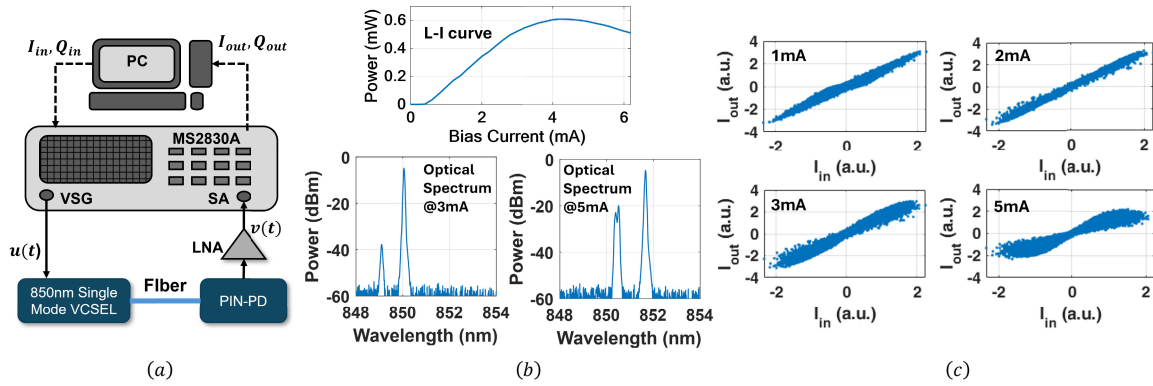


Fig. 1. (a) Scheme of the test bench. (b)  $L$ - $I$  characteristic (top) and examples of optical spectrum (bottom) of the 850-nm single mode VCSEL employed. (c) AM-AM curve with relative model applied for 1, 2, 3, and 5 mA of biasing current, showing the in-phase component of the OFDM signal.

and receive OFDM signals over the optical link considered. This is based on a VCSEL source connected directly to a p-i-n photodiode followed by a low noise amplifier (LNA) connected to the SA input port. The VCSEL utilized is of the single-mode type operating at 850 nm, where the  $L$ - $I$  curve examples of optical spectra are shown in Fig. 1(b). It can be seen that in the presented cases the power of higher order mode is far less than ( $< -15$  dB) the fundamental one, proving the single mode operation up to 5 mA of biasing current. OFDM signals of 20-MHz bandwidth modulated with 256 QAM modulation format are generated using a 10-ms LTE frame with 15 kHz of carrier spacing, while the carrier frequency is set to 1 GHz. Fig. 1(c) shows the AM-AM curve measured with the VCSEL biased at 1, 2, 3, and 5 mA. An antialiasing filter of 30-MHz bandwidth is applied in the SA. We can see that the nonlinearity and filtering effect in cases that VCSEL is biased at 1 and 2 mA are both weaker than the cases that the bias current is 3 and 5 mA. That is because the spectral expansion of VCSEL output due to its nonlinearity is wider when the bias current is higher, and thus, more frequency components are filtered out, which can be reflected by the thickness increasing of the AM-AM curve.

Recently, an improved Cann model has been proposed in [8] for describing the nonlinear behavior of VCSELs. By denoting the input and output of VCSEL  $u(t)$  and  $v(t)$ , respectively, their magnitude behavior can be described as follows:

$$|v(t)| = \frac{I_{\max}}{k} \ln \left( \frac{1 + e^{\frac{kg}{I_{\max}} |u(t)| + k}}{1 + e^{\frac{kg}{I_{\max}} |u(t)| - k}} \right) - I_{\max} \quad (1)$$

where  $k$  is the sharpness parameter,  $g$  is a gain parameter well approximated by the slope efficiency of the laser for sufficiently high  $k$ , and  $I_{\max}$  is the output limit level (saturation level).

Note that the equation above assumes negligible the nonlinear behavior of the p-i-n photodiode compared to the VCSEL one [9] and excludes intermodal dispersion and possible modal noise effects due to nonorthogonality of the modes within the optical fiber [10]. In this letter, we empirically determine the parameters in (1) as  $k = 10$ ,  $g = 1$ , and  $I_{\max} = 3$  by fitting the model output to the measured data with a bias current of 3 mA, as shown in Fig. 1(c). The values of  $k$  and  $g$  are taken to make  $e^{k(g|u(t)|/I_{\max})-1} \ll 1$  when  $u(t)$  is in linear zone so that  $v(t) = gu(t)$ .

### III. VCSEL-BASED J2C

The J2C for wireless communication networks has been proposed in [11], where the nonlinearity of RF power amplifiers (PAs) is used for AI computing, and wireless channels are used as synapses. However, this J2C scheme cannot be implemented directly in the ARoF system though the VCSEL has similar nonlinear behavior as PA, because a receiver cannot be connected to many VCSEL through a single fiber. In this letter, we propose a J2C for the VCSEL-based ARoF, where a single VCSEL plays the role of a neural reservoir composed of a group of neurons.

By modulating datasets at different frequencies in the VCSEL input  $u(t) = \sum_i^M u_i(t) \exp(j\omega_i t)$ , where  $M$  is the number of frequency carriers and  $\omega_i$  is  $2\pi$  times the  $i$ th carrier frequency  $f_i$ , the VCSEL output  $v(t)$  can be represented as a sum of nonlinear functions of  $u_i(t)$  and their sums. If we represent (1) with the Taylor expansion, we can easily obtain the expression at different frequencies, with  $\phi_i(\cdot)$  being different nonlinear functions as presented in (2), as shown at the bottom of the next page.

If we consider  $\phi_i(\cdot)$  as an activation function of a neuron, then the ARoF system works as a layer of neurons. Thus, we propose a J2C scheme where the transmitted signal is computed by the ARoF system as a neural network. The entire scheme of J2C is depicted in Fig. 2(a). We preprocess an  $N$ -feature dataset  $x$  into  $u$  with weighted linear combinations as the input layer, and postprocess  $v$  with weighted linear combinations as the output layer for  $K$  labels, the entire system becomes a neural network, as illustrated in Fig. 2(b), where the ARoF system behaves as a hidden layer. The output data of the ARoF layer is obtained by demodulating  $v(t)$  at each carrier frequency  $f_i$ . As shown in (2), the frequencies of nonlinear components  $f_{i_1, i_2, \dots, i_{mn-n}}$  are computed through different combinations of  $[u_{i_1}, u_{i_2}, \dots, u_{i_{mn-n}}]$  and only the nonlinear components whose frequencies fall in band are used for demodulation of  $v_i$ . We retrieve the values of  $v_i$  with a low-pass filter after downconverting  $v$  with  $-f_i$  so that  $v_i$  is centered at 0 Hz. If we regard this entire ARoF system including modulation/demodulation, VCSEL, and low-pass filter as a reservoir, only the input weights  $w_i^{\text{in}}$  and output weights  $w_i^{\text{out}}$  need to be trained.

In this letter, we utilize the MNIST dataset [12] as an example of data for transmission and processing to evaluate

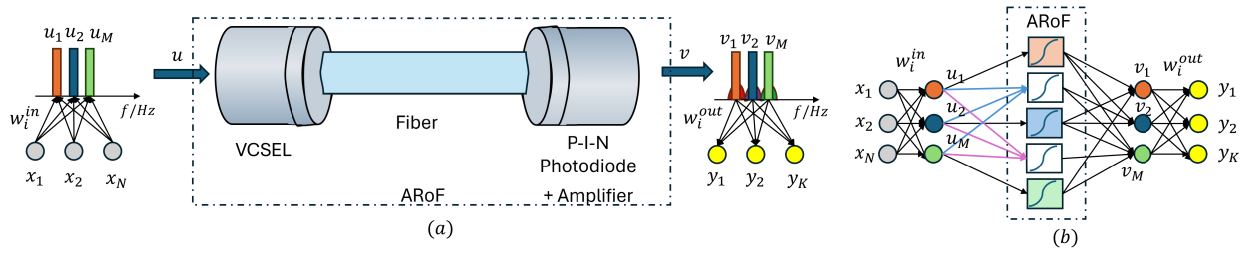


Fig. 2. (a) Scheme of the proposed J2C using a VCSEL-based ARoF system. (b) Equivalent neural network structure for reservoir computing with trainable weights in input/output layers.

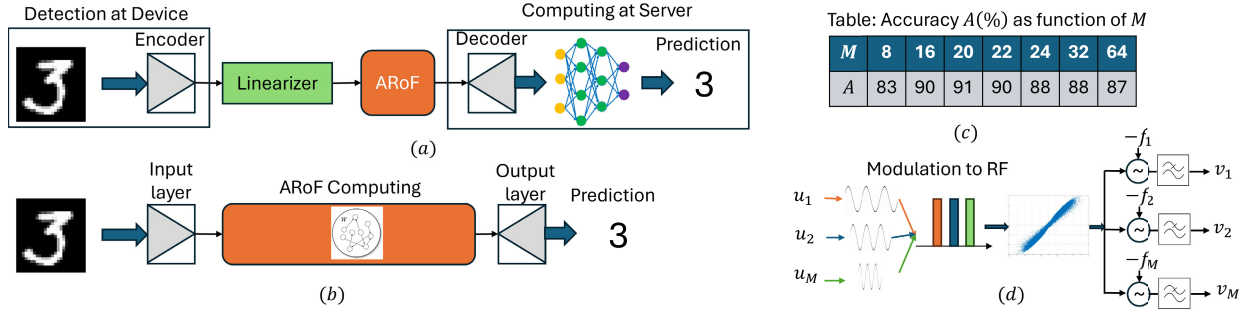


Fig. 3. (a) Scheme of classical ARoF system. (b) Scheme of the proposed J2C in ARoF system. (c) Table of results of J2C with MNIST datasets. (d) Simulating ARoF-based reservoir in the J2C.

the computational capabilities of the J2C system. The accuracy is measured as the ratio of correctly recognized images to the total number of images tested, which is 1000 in this study. The network is trained for 6 epochs using stochastic gradient descent, with a batch size of 64, a learning rate of 0.001, and a momentum of 0.5. Instead of the classical ARoF system where the data collected at devices are transmitted through the ARoF network for processing at the server as illustrated in Fig. 3(a), the proposed J2C system depicted in Fig. 3(b) has largely reduced the computational complexity. Since every image has  $28 \times 28$  pixels and corresponds to a digit from 0 to 9, the neural network of J2C has  $N = 784$  and  $K = 10$ .

The results are presented in Fig. 3(c) with the test accuracy (in %) for various numbers of frequency carriers in the input signal  $u(t)$ , with  $M$  values of 8, 16, 32, and 64, with the simulation of ARoF-reservoir implemented as shown in Fig. 3(d). The  $M$  carriers are restricted in the 20-MHz bandwidth. We find that accuracy levels of approximately 90% are achieved when  $M$  is 16, demonstrating that the ARoF system can function effectively as a reservoir in a J2C network. Increasing  $M$  in the modulation with a fixed bandwidth may not help since their locations become dense and are thus less separable. The input values  $u$  are modulated with sinusoidal carriers spanned in 20 MHz, and the output values  $v$

are demodulated with amplitude after filtering, as shown in Fig. 2(b). Since we fixed the total bandwidth to 20 MHz, the higher  $M$  is, the narrower the passing band of filters is. The steepness of filters is not infinite, and there is a stopping bandwidth which depends on the filter length. As we fix the filter length for different cases, the captured information will be degraded or polluted when the ratio between passing bandwidth and stopping bandwidth goes down. Overall, these results indicate that the J2C technique is capable of performing machine learning tasks, such as digit recognition.

#### IV. CONCLUSION

In this letter, we proposed a fundamental concept of J2C based on the nonlinearities of VCSEL in the ARoF networks, which demonstrates to have the capability of reservoir computing, similar to those of conventional artificial neural networks. The no linearization technique is needed and simple linear input and output layers are conducted at the place. The computation accuracy of the network is validated with an image classification task on MNIST, which reaches an accuracy around 90%. This letter introduces a promising vision for J2C, where practical limitations, such as signal modulation, fiber modal dispersion, and VCSEL bias, are considered important lines of future work.

$$\begin{aligned}
 \frac{|v(t)|}{I_{\max}} &= \sum_{n=1}^M \frac{(-1)^{n+1}}{nk} \left( \left( \sum_{m=0}^M \frac{\left( \frac{kg}{I_{\max}} \left| \sum_i^M u_i(t) e^{j\omega_i t} \right| + k \right)^m}{m!} \right)^n - \left( \sum_{m=0}^M \frac{\left( \frac{kg}{I_{\max}} \left| \sum_i^M u_i(t) e^{j\omega_i t} \right| - k \right)^m}{m!} \right)^n \right) - 1 \\
 &= \sum_i^M \phi_i(|u_i(t)|) e^{j\omega_i t} + \sum_{i_1}^M \sum_{i_2}^M \dots \sum_{i_{mn-n}}^M \phi_{i_1, i_2, \dots, i_{mn-n}}(|u_{i_1}(t)|, |u_{i_2}(t)|, \dots, |u_{i_{mn-n}}(t)|) e^{j\omega_{i_1, i_2, \dots, i_{mn-n}} t} - 1
 \end{aligned} \quad (2)$$

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