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***Abstract*—In this paper, a novel way for dual-band power amplifiers (PA) linearization is proposed based on spiking neuron networks (SNN). A dual-input dual-output SNN is interacted with classical memory polynomial model, which can largely reduce the computational complexity. The experimental results on a real PA show that the proposed method can reach similar linearization performance compared with traditional methods but with low energy consumption. This is the first time that the SNN is deployed for multi-band PA linearization. Future work is to develop a trainable SNN model for real-time PA linearization.**

***Index Terms*—Artificial intelligence (AI), linearization, multi-band, power amplifiers, spiking neuron networks (SNN)**

I. Introduction

Brain-like AI system is a growing subject today. The spiking neural networks (SNN) has been considered as the third generation of neural networks for its high bio-mimicry of the human brain [1]. Different from conventional artificial neural networks (ANN) which process digital data, the SNN better mimics the biological behavior of the brain cortex which processes spike trains. This brings advantages to the information processing of an artificial intelligence (AI) system and on energy consumption [2]. Its event-driven property helps to capture the rich dynamics of neurons within the brain. As the research on brain science is advancing rapidly, the process of inference and decision-making of the human brain can bring more and more inspiration to AI.

In aspect of hardware, circuit simulation results show gains in energy consumption of at least two orders of magnitude compared with current solutions [3]. Studies on neuromorphic systems for spike processing have considered complementary metal-oxide semiconductor (CMOS) technology operation in the subthreshold region (100 mV and 1 nA) [4]. According to [5], while implemented on a field-programmable gate array (FPGA), the energy efficiency of an SNN reaches over 100 times higher than an ANN. This opens the opportunity to have numerous applications of SNN which demands a very high energy efficiency, such as the linearization of radiofrequency (RF) power amplifiers (PA). Recently, a single neuron has been found helpful in complexity reduction of PA modeling in [6].

The PA is blamed for the majority of nonlinear distortion and digital predistortion (DPD) technique has been one of the most commonly used method for its linearization [7]. However, the complexity of the DPD which corresponds to its power consumption has always been a challenge. Some simplified versions have been proposed in past decades by reducing the model dimension [8] or by splitting the model into cascade structure [9].

In massive multi-input multi-output (MIMO) systems for 5G, the system with multiband transmitters needs to be linearized [10]. The signal suffers intermodulation (IMD) distortion at the output of a multi-band PA [11]. Neural networks has been applied to address the dual-band linearization problem [12], which helps to guide the implementation of an SNN-based solution. In [13], a technique based on periodical nonuniform sampling theory is believed to reach the lowest computational complexity for dual-band linearization methods. However, this technique is still based on classical continue-value computing which always consumes a large amount of energy compared with event-driven computing [14]. Using an SNN opens a new window for further improving the energy efficiency of PA linearization.

In this paper, we propose an SNN-based technique to compensate for different types of distortion brought by a dual-band PA. We mathematically analyze the nonlinear behaviors of spiking neurons and of power amplifiers from perspective of polynomials. The effectiveness of neuron-based PA model is experimentally validated on a testbench of PA.

II. Dual-band PA linearization

The cascade system of dual-band PA linearization is depicted in Fig 1. For each band of transmission, a post-inverse of the PA is identified using indirect learning architecture (ILA) and is applied upstream of the PA as a DPD. A 2D-MP model has been proposed in [11]. The predistorted output of the i-th band (i=1,2) can be written as

$$\begin{aligned} x_i(n) &= \sum_{k=0}^{\mathcal{K}-1}\sum_{r=0}^{k}\sum_{l=0}^{\mathcal{L}-1} c_{krl}^{(i)} u_i(n-l) \\ &\quad \times |u_i(n-l)|^{k-r}|u_{3-i}(n-l)|^r \\ &= \sum_{l=0}^{\mathcal{L}-1} a_l^{(i)} u_i(n-l) \times S_i(n-l), \end{aligned} \tag{1}$$

where $u_i(n)$ is the i-th input signal, $\mathcal{K}$ is the nonlinearity order and $\mathcal{L}$ is the memory depth, $c_{krl}^{(i)} = a_l^{(i)} b_{kr}^{(i)}$ are model coefficients for the i-th band, and

$$S_i(n) = \sum_{k=0}^{\mathcal{K}-1}\sum_{r=0}^{k} b_{kr}^{(i)} |u_i(n)|^{k-r}|u_{3-i}(n)|^r. \tag{2}$$

Its identification is detailed in [15].

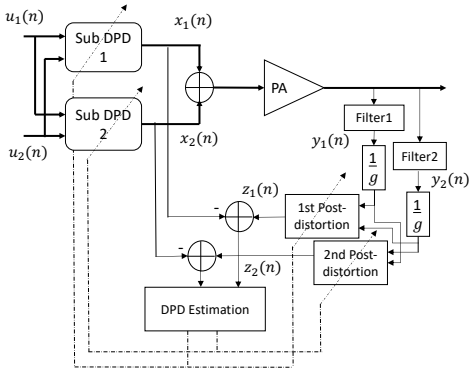

Fig. 1. System of PA and 2D DPD.

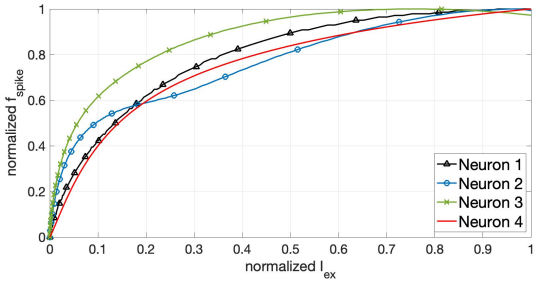

Fig. 2. Normalized characteristics of 4 neurons in [3] and [4].

III. Spiking Neuron and Its Network

A neuron fires spikes by varying its membrane voltage V_m. If we consider a single spiking neuron as a system as in [6], the input information is coded in an excitation current I_{ex} and the output information is contained by the firing rate f_{spike}.

A. Nonlinear behavior of spiking neurons

The variation of V_m as a function of excitation current I_{ex} can be described by the leaky integrate-and-fire (LIF) model:

$$\begin{aligned} \frac{dV_m}{dt} &= I_{\text{ex}} + a - bV_m \\ V_m &= V_c, \text{ if } V_m > V_s \end{aligned} \tag{3}$$

where V_s is the threshold voltage to fire a spike, V_c is the rest voltage after firing a spike, a and b are constants. Under the excitation by a current I_{ex} which is large enough, the gradient of V_m is kept positive. The membrane voltage of a neuron keeps increasing till a threshold voltage and then is abruptly reset to the rest voltage. This procedure generates a spike. With the existence of I_{ex}, the neuron keeps on generating spike train with a frequency related to the value of I_{ex}. Thus as described in [6], the transfer function of a neuron can be expressed by polynomials as:

$$f_{\text{spike}} = G(I_{\text{ex}}) = \sum_{k=0}^{\mathcal{K}_1-1} a_k^{(i)} I_{\text{ex}}^k, \tag{4}$$

where $G(\cdot)$ represents the neuron function, $\mathcal{K}_1$ is the maximum of nonlinearity orders. Comparing (1)and (4), we can easily find that the terms $|u_i(n-l)|^k$ is close to $G(|u_i(n-l)|)$. The layout of a neuron circuit designed in [3] and [4] confirms this mathematical behavior as illustrated in Fig. 2.

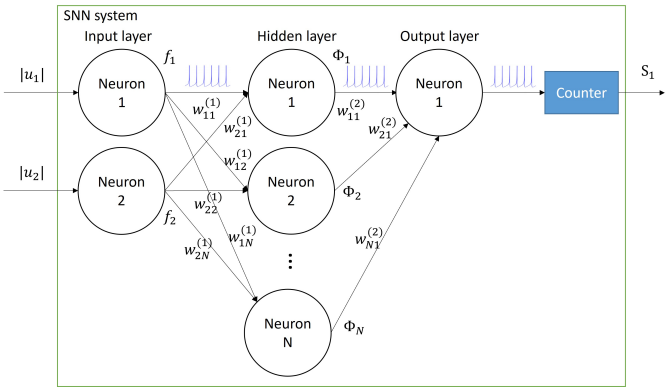

Fig. 3. A system scheme of SNN.

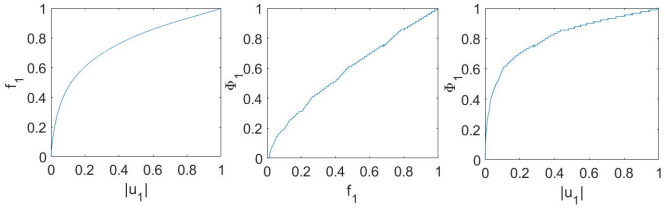

Fig. 4. Characteristics of neurons: (a) $f_1(|u_1|)$; (b) $\Phi_1(f_1)$; (c) $\Phi_1(|u_1|)$.

B. Spiking neural networks

The neurons are connected with synapses which transmit spikes of membrane voltage from a pre-neuron to a post-neuron. The membrane voltage of the j-th post-neuron $V_m^{(j_{\text{post}})}$ increases by $w_{i_{\text{pre}},j_{\text{post}}}$ once a spike is received from the i-th pre-neuron, where $w_{i_{\text{pre}},j_{\text{post}}}$ is the weight of synapse, i_{pre} and j_{post} are indices of the pre-neuron and the post-neuron respectively. The increase of $V_m^{(j_{\text{post}})}$ accumulates if the j-th post-neuron receives spikes from different pre-neurons.

By constructing a two-layer SNN as illustrated in Fig. 3, we have $G(|u_1|)$ and $G(|u_2|)$ at the output of two neurons in the input layer. With the neurons in output layer are connected to both neurons in the input layer, we have

$$\Phi_i = \sum_{k=0}^{\mathcal{K}_2-1} \gamma_k^{(i)} (w_{1i} G(|u_1|) + w_{2i} G(|u_2|))^k. \tag{5}$$

By parallelized Φ_i with appropriate weights w_{1i} and w_{2i}, we can reproduce the product of S_{kl} in (1) by $\sum_i \Phi_i$. In Fig. 4, the relations between $|u_i|$, f_i, and Φ_i are depicted as simulation results in Brian 2, which has the same property as layout simulation results in Fig. 2. The output of the SNN renders the absolute nonlinear envelope $S_i(n)$ as (2). The SNN system in Fig. 3 followed by a filter with coefficients $a_l^{(i)}$ can result in a parallel Hammerstein structure, which is equivalent to an MP model in (1). Thus an SNN-based 2D-MP DPD can be proposed as in Fig. 5. The SNN block is used to generate the nonlinearity of the DPD, which reduces largely the computational complexity compared with traditional digital computation [5].

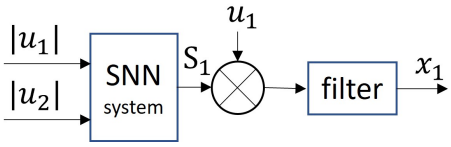

Fig. 5. SNN-based 2D-MP DPD for the i-th band.

TABLE I
LINEARIZATION PERFORMANCE AND IDENTIFICATION COMPLEXITIES OF DIFFERENT DPD MODELS

		No DPD	2D MP	Proposed Method
Band 1	ACPR.L (dBc)	-39.7	-49.7	-48.6
	ACPR.H (dBc)	-39.0	-46.9	-45.2
	EVM (%)	5	1.3	1.3
Band 2	ACPR.L (dBc)	-40.1	-48.6	-47.4
	ACPR.H (dBc)	-39.3	-49.7	-48.1
	EVM (%)	5	1.3	1.3

IV. EXPERIMENTAL RESULTS

We use test bench of Chalmers WebLab [16] for measurements. The baseband IQ signal is fed from the PC Workstation to the driver through a Vector Signal Transceiver (PXIe-5646R VST) using a 200 MHz sampling frequency. The VST up-converts the baseband signal to the carrier frequency 2.14 GHz. A GaN PA CGH40006P transistor mounted in the manufacturer demo-board fabricated by CREE has been used to validate the proposed low rate DPD. Its nominal gain is 13 dB at 2 GHz and the output power at 1dB gain compression is 40.2 dBm. The measured average output power of the PA is 29.45 dBm.

The linearization performances of the classical 2D-MP model and the proposed SNN-based model are compared in Table I and their spectra are illustrated in Fig. 6. The energy consumption of spike processing in the SNN is negligible in front of the digital signal processing. In terms of linearity, the proposed method reaches a similar level as traditional methods. The SNN weights w_{1i} and w_{2i} (i=1,..,N) are determined in an empirical way, which fails the proposed method to reach the best performance. To the best of authors' knowledge, this is the first time that the emerging SNN technique is applied for multi-band PA linearization. The results show that it is promising but some further development is needed for high frequency signal processing and real-time implementation. A future prospect is the optimization of SNN weights.

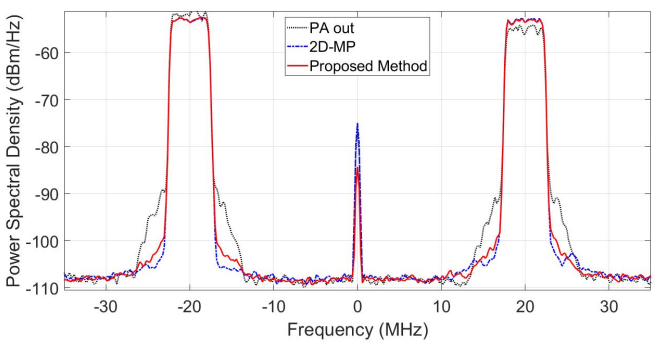

Fig. 6. Linearization performance of the proposed method.

V. CONCLUSION

In this paper, we propose an SNN-based technique for dual-band PA linearization with lower complexity and power consumption. The nonlinearity of spiking neurons are utilized to compensate for the IMD distortions of the PA. Experimental results confirm the robustness of the proposed method.

REFERENCES

[1] W. Maass, "Networks of spiking neurons: The third generation of neural network models," *Neural Netw*, vol. 10, no. 9, pp. 1659–1671, 1997. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0893608097000117

[2] T. Matsubara and H. Torikai, "An asynchronous recurrent network of cellular automaton-based neurons and its reproduction of spiking neural network activities," *IEEE Trans. Neural. Netw. Learn. Syst.*, vol. 27, no. 4, pp. 836–852, 2016.

[3] P. M. Ferreira, J. Nebhen, G. Klisnick, and A. Benlarbi-Delai, "Neuromorphic analog spiking-modulator for audio signal processing," in *Analog Integrated Circuits and Signal Processing*, vol. 106, 2021, pp. 261–276.

[4] C. Loyez, K. Carpentier, I. Sourikopoulos, and F. Danneville, "Subthreshold neuromorphic devices for spiking neural networks applied to embedded a.i," in *2021 19th IEEE International New Circuits and Systems Conference (NEWCAS)*, 2021, pp. 1–4.

[5] Y. Cao, Y. Chen, and D. Khosla, "Spiking deep convolutional neural networks for energy-efficient object recognition," in *International Journal of Computer Vision*, 2015, pp. 54–66.

[6] S. Wang, P. M. Ferreira, and A. Benlarbi-Delai, "Behavioral modeling of nonlinear power amplifiers using spiking neural networks," in *2022 20th IEEE International New Circuits and Systems Conference (NEWCAS)*, 2022, pp. 1–4.

[7] J. Wood, *Behavioral Modeling and Linearization of RF Power Amplifiers*, ser. Artech House Microwave Library. Artech House, 2014.

[8] S. Wang, M. Abi Hussein, O. Venard, and G. Baudoin, "A novel algorithm for determining the structure of digital predistortion models," *IEEE Trans. Veh. Technol*, vol. 67, no. 8, pp. 7326–7340, Aug 2018.

[9] S. Wang, M. Abi Hussein, O. Venard, and G. Baudoin, "Optimal sizing of two-stage cascaded sparse memory polynomial model for high power amplifiers linearization," *IEEE Trans. Microw. Theory Tech.*, vol. 66, no. 9, pp. 3958–3965, Sept 2018.

[10] W. Cao, S. Wang, and T. Eriksson, "Concurrent multiband linearization for power amplifiers with intermodulation distortions," *IEEE Microw. Wireless Compon. Lett.*, vol. 32, no. 5, pp. 467–470, 2022.

[11] S. Bassam, M. Helaoui, and F. Ghannouchi, "2-d digital predistortion (2-d-dpd) architecture for concurrent dual-band transmitters," *IEEE Trans. Microw. Theory Techn.*, vol. 59, no. 10, pp. 2547 –2553, oct. 2011.

[12] M. Rawat, K. Rawat, M. Younes, and F. Ghannouchi, "Joint mitigation of nonlinearity and modulator imperfections in dual-band concurrent transmitter using neural networks," *Electronics Letters*, vol. 49, no. 4, pp. 253–255, 2013.

[13] S. Wang, W. Cao, R. Hou, and T. Eriksson, "A digital predistortion for concurrent dual-band power amplifier linearization based on periodically nonuniform sampling theory," *IEEE Trans. Microw. Theory Tech.*, vol. 70, no. 1, pp. 466–475, 2022.

[14] A. Zhang, X. Li, Y. Gao, and Y. Niu, "Event-driven intrinsic plasticity for spiking convolutional neural networks," *IEEE Transactions on Neural Networks and Learning Systems*, pp. 1–10, 2021.

[15] S. Wang, M. Roger, and C. Lelandais-Perrault, "Optimization of a pruned 2-d digital predistortion model structure for power amplifiers linearization," in *2019 17th IEEE International New Circuits and Systems Conference (NEWCAS)*, 2019, pp. 1–4.

[16] P. N. Landin, S. Gustafsson, C. Fager, and T. Eriksson, "Weblab: A web-based setup for PA digital predistortion and characterization [application notes]," *IEEE Microw. Mag.*, vol. 16, no. 1, pp. 138–140, Feb 2015.