

Relaxor ferroelectrics for neuromorphic computing

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State Establishment of Relaxor Ferroelectrics

Relaxor Ferroelectrics in Neural Networks

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[1] Von Neumann architecture. *Wikipedia* (**2022**) [2] D. Joksas, A. Mehonic*. SoftwareX*, **12**, 100617 (2020) [3] W.-Q. Zhang *et al*. *Nat. Electron*, **3(7)**, **2022**

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S tructures P ropriétés Modélisation des **S** olides

Context Relaxor Ferroelectrics

Neuromorphic computing: Recreating brain functions using Artificial Neural Networks (ANN) and its hardware implementations. Essential units: neurons and synapses **Conventional ANN**: von-Neumann architecture, computing outside of memory, high energy consumption due to data transportation ("von-Neumann bottleneck") **Compute-in-memory (CIM):** emerging solution of the von-Neumann bottleneck

 $i=1$

Devices used in crossbar ANNs: resistive devices, ferroelectric diodes, **capacitive devices** (most promising due to its near-zero static power) **Requirements for analog states in crossbar device:** nonvolatile, readily programmable, high ON/OFF ratio, long retention time, good endurance

> **Right: Evaluation of device capacitance under two consecutive DC sweeps between [-200V, 200V]**

Relaxor ferroelectrics: a category of ferroelectric materials with with strong electric field instabilities, permitting readily state programming **Representative RFEs:** PMN, PZN, PMN-xPT, PZN-xPT, PLZT…

 $0.24 \rightarrow$

Left: The evaluation of dielectric permittivity of Pb(Zn1/3Nb2/3)O³ -4.5PbTiO³ (PZN-4.5PT) under DC sweep Capacitance (nF)

The calculated A equals to 1.28 for long-term potentiation (LTP) and -2 for long-term depression, ensuring relatively low accuracy degradation during the learning works [4]. From the observation above, we can conclude that PZN-4.5PT is a potential candidate for neuromorphic computing.

 0.24 \rightarrow

Observation: RFEs like PZN-PT can exhibit multiple nonvolatile and readily programmable capacitive states, giving it great potential to be used in neuromorphic computing

The evaluation of the state establishment ability of PZN-4.5PT was performed. Four consecutive pulse trains with the amplitude of [-100V, 100V, -100V, 100V] and the width of 10ms were applied to the material.

 O Exp data (LTP)

O Exp data (LTD)

- Fit (LTP)

Observations:

(1) PZN-4.5PT demonstrates distinct long-term potentiation (LTP) and long-term depression (LTD) behavior, showing the ability of manageably updating device state and mimicking the biological synapses of human brain;

(2) PZN-4.5PT shows the ability to access multiple polarization states by simply changing the profile of applied electric pulse;

(3) The linearity factor A of PZN-4.5PT is derived from [3,4]

Evaluation of device polarization under four consecutive pulse trains, the amplitude of which being [-100V, 100V, -100V, 100V] and the width of which being 10ms for each

$$
P_{LTP} = B\left(1 - \exp\left(-\frac{N}{A}\right)\right) + P_{min}
$$

$$
P_{LTD} = -B\left(1 - \exp\left(-\frac{N - N_{max}}{A}\right)\right) + P_{max}
$$

$$
B = \frac{P_{max} - P_{min}}{1 - \exp(\frac{-N_{max}}{A})}
$$

where P stands for device polarization, N stands for number of pulses, and P_{min} , P_{max} and N_{max} were extracted from the experimental data.

Integration of signals for PZN-4.5PT under different electric fields, resembles the dendrite in the human brain

[4] P.-Y*.* Chen *et al. 2017 IEDM*, **6.1.1-6.1.4** (2017) [5] X. Li et al., *Nat. Nanotechnol.*, **15**, 776 (2020) [6] Y. Zhong et al., *Nat. Electron.*, **5**, 672-681 (2022)

Comparison of the recognition accuracies for the simplified SVHN dataset in a neural network [5] with three different dendrites. w/o: test accuracy of the network without dendrite [5]

Comparison of the performance of a reservoir system [6] on dynamic gestion recognition (DGR) with different reservoir node. *ai* **: The recognition accuracy of the** *i***-th gesture.**

