# Study of a Spintronic-based STDP-trained SNN under Fabrication-induced Process Variability

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***Abstract*—In this short paper we present and discuss the effect of fabrication-induced process variability on the precision of a spintronic-based on-line-trained Spiking Neural Nnetwork. The results shown here are on a toy example but they demonstrate nonetheless that process variability should be taken into account from the initial design steps of an SNN.**

## I. INTRODUCTION

Spiking Neural Networks (SNNs) offer a promising paradigm for neuromorphic computing, mimicking biological neural systems' event-driven processing. However, the effectiveness of SNNs can be hindered by variability in synaptic devices, such as Magnetoresistive Tunnel Junctions (MTJs), affecting network performance and reliability. In this study, we explore strategies to mitigate synaptic variability in SNNs through the use of multi-MTJ synapses.

An MTJ consists of three layers - two magnetic layers separated by a thin insulating layer (typically an oxide). STT-MTJ stands for Spin-Transfer Torque Magnetic Tunnel Junction. In this work we focus on spin transfer torque MTJ (STT-MTJ) which is a type of magnetic tunnel junction where the magnetization of one of the magnetic layers can be manipulated by applying a spin-polarized current. To write data to the STT-MTJ, a spin-polarized current is injected into the device. This current is typically generated by passing a current through a magnetic layer with a specific magnetization direction. The spin-polarized electrons in this current exert a torque on the magnetic moment of the free layer in the STT-MTJ. If the torque exerted by the spin-polarized current is strong enough, it can cause the magnetization of the free layer to switch direction.

The probabilistic switching behavior in Spin-Transfer Torque Magnetic Tunnel Junctions (STT-MTJs) is a phenomenon observed due to the stochastic nature of the magnetization switching process. Instead of a deterministic switching behavior where a fixed amount of current always results in switching, there is a probability associated with whether a particular MTJ will switch or not under certain conditions. This probabilistic nature arises mainly from thermal fluctuations: At finite temperatures, thermal fluctuations cause random changes in the orientation of magnetic moments within the MTJ. These fluctuations can influence the switching behavior, making it probabilistic rather than deterministic. Another cause of stochasticity is related to the spin-torque noise: the random fluctuations in the torque exerted on the magnetization due to the stochastic nature of the electron transport process. These fluctuations can affect the switching dynamics of the MTJ, leading to probabilistic behavior. In addition, the behaviour of an STT-MTJ is also affected by process variability such as variations in material properties or fabrication imperfections, and variations in device geometry and annealing conditions [1], [2]. In this short paper we show how the process variability affects the behaviour of a spiking neural network designed with STT-MTJ-based synapses. This study is conducted on a hardware- implemented SNN with probabilistic MTJ synapses, the synap- tic weight is coded in conductance levels, and a local training based on STDP is used [3].

## II. CIRCUIT UNDER STUDY

An SNN comprises interconnected input spiking neurons (presynaptic) and output spiking neurons (postsynaptic) via synapses, facilitating the transmission of neuronal information. These synapses can be structured in a crossbar array configuration, where input and output neurons are situated at opposite ends of each row and column respectively. Communication between neurons occurs through spike trains. Input information is encoded as spikes and delivered to input neurons. For instance, in image recognition, each pixel corresponds to an input neuron, with the spiking frequency reflecting the grayscale intensity of the pixel. The network learns tasks, such as recognition, by adjusting synaptic strengths according to the Spike-Timing-Dependent Plasticity (STDP) local learning rule. In this study we focus on a hardware-based SNN featuring probabilistic MTJ synapses (illustrated in Fig. 1). Synaptic weight is represented by conductance levels, and a local training algorithm leveraging STDP is employed.

## III. METHODOLOGY AND RESULTS

We conducted Spice simulations to train an SNN network circuit for recognizing simple black-and-white patterns. The network comprises 25 input neurons interconnected to one output neuron through synapses. We utilize an in-house VerilogA behavioral descriptions for input and output neurons, and an model for the MTJ devices adapted from [4] constituting the synapses. Each synapse consists of multiple MTJs connected in parallel. The stochastic switching behavior of MTJs depends on the amplitude, duration, and polarity of the current. Synapse

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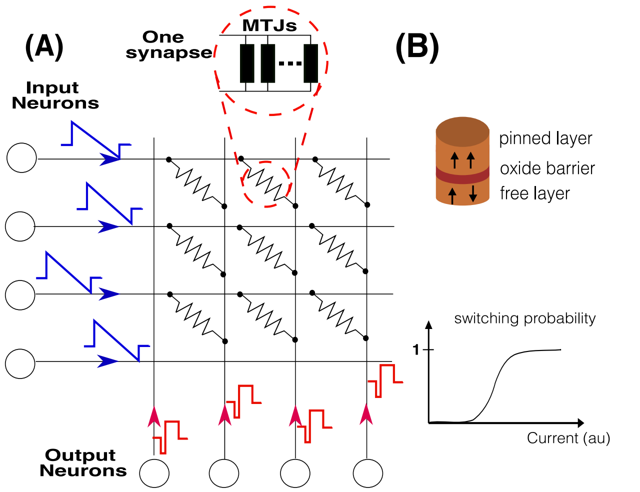


Fig. 1: (A) fully connected SNN described in [3] (B) Top: schematic MTJ structure. Bottom: MTJ probabilistic switching

state modulation was achieved by controlling the voltage drop across it. The input information, spike-coded, is feed to input neurons, with each pixel intensity corresponding to one neuron, translating intensity into spiking frequency. The output neuron operates as a Leaky Integrate-and-Fire (LIF) neuron, accumulating incoming spikes and firing upon reaching a threshold. Learning is unsupervised, facilitated by Spike-Timing-Dependent Plasticity (STDP) learning rule, leveraging voltage profiles of input and output pulses [3]. Synapse conductance states are initialized at random values. Training involves presenting images for 150ms, whereupon the network was deemed to have learned a pattern. To evaluate training quality, we have calculated the Euclidean distances between input pattern and synapse conductance pattern after training and normalization. The network was trained to recognize one of 11 patterns in the dataset, and overall performance was averaged across all patterns.

MTJ devices exhibit variability due to variations in Tunnel Magneto-Resistance (TMR), oxide barrier thicknesses, and free layer thicknesses, modeled as Gaussian distributions. We assessed network performance under different standard deviations of variability (0-20%) with synapses composed of 2 MTJs. Performance degradation was observed with increasing variability, rendering proper learning unattainable beyond 20% variability. To investigate the mitigating effect of increasing MTJs per synapse on variability, networks with varying MTJ counts (2, 4, 6, 8) were trained. Performance, represented by averaged Euclidean distance across all images, was evaluated.

We show that process variability has a strong impact on the training efficiency of a spintronic-based SNN. A similar loss of accuracy is observed for various synapse sizes with a slightly better behaviour for large synapses. This shows that the process variability should be accounted for during the SNN design (even in the context of online training) and that increasing the synapse size does not necessary mitigate the issue. Further investigation is accurately quantify the variability effect on the training precision and also to find apropriate solutions for variability mitigation.

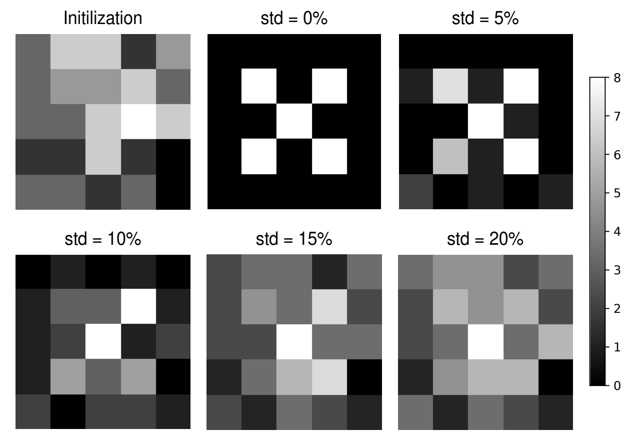


Fig. 2: A sequence of training results under different variability scenarios. Here, we show the reshaped synaptic weight values (represented as level of conductance) after training with a specific pattern. In this example the synapse is composed of 8 MTJs. Each time, the training process has the same random initialization (top left). The subsequent images depict the trained weights with varying levels of variability ([0, 5, 10, 15, 20]%).

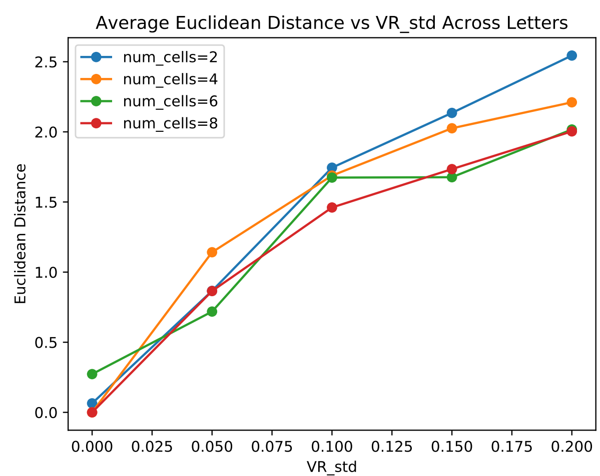


Fig. 3: Averaged Euclidean distance for networks trained with varying numbers of MTJs per synapse ([2, 4, 6, 8]) for all variability scenarios.

## REFERENCES

[1] K. Munira, et al. “A quasi-analytical model for energy-delay-reliability tradeoff studies during write operations in a perpendicular STT-RAM cell,” IEEE TED, 2012
[2] E. I. Vatajelu, ”Challenges and Solutions in Emerging Memory Testing,” in IEEE TETC, 2019
[3] S. Daddinounou and E. I. Vatajelu, ”Synaptic Control for Hardware Implementation of Spike Timing Dependent Plasticity,” DDECS 2022
[4] Y. Zhang et al., Compact Model of Subvolume MTJ and Its Design Application at Nanoscale Technology Nodes, IEEE TED, 2015