Voltage–Time Transformation Model for Threshold Switching Spiking Neuron Based on Nucleation Theory

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In this study, we constructed a voltage–time transformation model (V–t Model) to predict and simulate the spiking behavior of threshold-switching selector-based neurons (TS neurons). The V–t Model combines the physical nucleation theory and the resistor–capacitor (RC) equivalent circuit and successfully depicts the history-dependent threshold voltage of TS selectors, which has not yet been modeled in TS neurons. Moreover, based on our model, we analyzed the currently reported TS devices, including ovonic threshold switching (OTS), insulator-metal transition, and silver- (Ag-) based selectors, and compared the behaviors of the predicted neurons. The results suggest that the OTS neuron is the most promising and potentially achieves the highest spike frequency of GHz and the lowest operating voltage and area overhead. The proposed V–t Model provides an engineering pathway toward the future development of TS neurons for neuromorphic computing applications.

Keywords: threshold switching selector, spiking neuron, nucleation theory, history-dependent, neuromorphic computing

INTRODUCTION

With the increasing demand for massive data storage and processing, conventional computing systems based on the von-Neumann architecture have encountered their limitations. Frequent data transition between the separated processor and memory units makes conventional computation less efficient. Recently, emerging neuromorphic computing is regarded as the next-generation computing paradigm. Unlike the conventional von-Neumann-based computing system, brain-inspired neuromorphic computing not only provides energy-efficient computation with high parallelism but also shortens the latency of data transmission by realizing in-memory computing within crossbar memory arrays (Ielmini and Wong, 2018; Hua et al., 2019; Woo et al., 2019). In a neuromorphic computing system, an artificial synapse provides an adjustable and long-lasting weight value. In addition, an artificial neuron integrates and processes signals from synapses and then transmits the processed signals to the next neural layer as inputs. Both synapses and neurons have been extensively studied based on solid-state devices for neuromorphic hardware implementation (Lee et al., 2019a; Woo et al., 2019; Zhang et al., 2020). However, the conventional complementary metal-oxide semiconductor- (CMOS-)based neuron circuit occupies large chip areas because it requires a large number of transistors and capacitors for generating spike signals. In contrast, the neuron circuit area can be 10 times smaller by using novel devices, such as magnetoresistance memory (MRAM) (Wu et al., 2019, 2020; Liang et al., 2020), phase-change memory (PCM) (Tuma et al., 2016), and threshold switching (TS) selector...
Among several novel device-based neurons, threshold-switching selector-based neurons (TS neurons) are especially promising for ultra-high density neuromorphic computing applications (Liang et al., 2021). A circuit-level model solving Kirchhoff’s Law based on the resistor–capacitor (RC) equivalent circuit has been proposed to describe the behavior of TS neurons (RC Model) (Chen et al., 2016; Wang et al., 2020). However, the RC Model oversimplified the TS neuron by assuming constant switching behavior of the TS selector. Indeed, the switching dynamics of the real TS selector is affected by the external electric field, which can be explained using the nucleation theory (Karpov et al., 2008; Lee et al., 2020). Specifically, the way the external electric field is previously accumulated determines the device behavior, and we regard this time-dependent phenomenon as history dependence. Consequently, the TS voltage ($V_{\text{th}}$) in the TS selector is history dependent rather than constant. In this study, aiming for constructing a more comprehensive and accurate neuron model, we proposed an improved voltage–time transformation model (V–t Model) on top of the original RC Model by considering the TS behavior both experimentally and theoretically.

In the following sections, we will first verify the spiking behavior of the TS neuron according to different synaptic weights. A silver- (Ag-) based TS selector was chosen to observe the switching dynamics and the history-dependent $V_{\text{th}}$ of the device. Additionally, based on the nucleation theory, we will introduce a V–t transformation (V–t) equation to describe the variant $V_{\text{th}}$ of the TS selector, and a V–t Model will be constructed. Furthermore, several types of TS neurons based on the reported TS selectors, including ovonic threshold switching (OTS) (Song et al., 2018; Hatem et al., 2019), insulator–metal transition (IMT) (Park et al., 2016), and Ag-based selectors (Grisafe et al., 2019; Hua et al., 2019), will be evaluated. The results suggest that the OTS neuron has the fastest spike frequency and a lower history-dependent $V_{\text{th}}$. The V–t Model not only successfully depicts and predicts the characteristics of TS neurons, but it also provides a useful engineering guideline for future high-performance neuron circuits for neuromorphic computing applications.

**EXPERIMENTAL DETAILS AND MEASUREMENT SETUP**

**Ag-Based Threshold Switching Selector**

In this study, an Ag/hafnium oxide (HfO$_2$)/Pt TS selector was fabricated and investigated. The schematic illustration of the Ag-based TS selector is shown in Figure 1A. The Pt bottom layer was first deposited on a Ti/Si substrate using electron beam evaporation, followed by the silicon dioxide (SiO$_2$) layer deposition using plasma-enhanced chemical vapor deposition. After the photolithography process, the reactive ion etching of SiO$_2$ was applied to form a via contact with a diameter of 1 µm, which defines the effective device area. Then, the 4.5-nm-insulating HfO$_2$ layer was deposited using atomic layer deposition. After that, 2-nm-thick Ag was deposited on the HfO$_2$ layer using electron beam evaporation followed by rapid thermal annealing (RTA) at 500°C for 5 min to form Ag nanoparticles (NPs) as the active electrode. Finally, a 60-nm-thick Ni capping layer was deposited using electron beam deposition to prevent the oxidation of Ag NPs. Electrical measurements were performed using an Agilent B1500A and B1530A waveform generation/fast measurement unit at room temperature. Figure 1B shows the scanning electron microscope (SEM) image of Ag NPs. The size distribution of NPs is shown in the inset. Figure 1C shows the DC current-voltage (I-V) characteristics of the Ag/HfO$_2$/Pt TS selector with 500 DC cycles of TS and a compliance current ($I_{\text{cc}}$) of 0.1 mA. The device provides an extremely high on/off ratio ($\sim$10$^9$) and small $V_{\text{th}}$ and hold voltage ($V_{\text{hold}}$) for both positive and negative bias, showing typical behaviors of Ag-based TS selectors as reported in the literature (Yoo et al., 2017).

**Threshold Switching Neuron Circuit**

To emulate neuromorphic hardware in which synapses and neurons are connected in the neural network (Figure 2A), the measurement setup adopted in this study is illustrated in Figure 2B. The effective resistor connected in series ($R_{\text{series}}$) represents the total resistance of multiple synaptic devices in the synaptic array connecting in parallel to the same TS neuron. A parasitic capacitor ($C_{\text{parasitic}}$) of the TS selector is exploited; therefore, no extra capacitor is needed for signal integration. The evolution of the total current ($I_{\text{total}}$) flowing through $R_{\text{series}}$ and the voltage across TS selector ($V_{\text{selector}}$) is described in Figure 2C: when a constant input voltage ($V_{\text{input}}$) is applied to the neuron circuit, most of the voltage initially drops across the TS selector in the off-state. Then, $V_{\text{selector}}$ gradually increases by charging $C_{\text{parasitic}}$. Once $V_{\text{selector}}$ reaches $V_{\text{th}}$, the TS selector is switched to the on-state due to the formation of a volatile conducting filament, and an increase in $I_{\text{total}}$ can be observed. However, $V_{\text{selector}}$ drops right after the TS selector is switched to the on-state due to the discharge of $C_{\text{parasitic}}$ and $I_{\text{total}}$ starts to decrease. The TS selector returns to the off-state when $V_{\text{selector}}$ reduces to $V_{\text{hold}}$ because of the rupture of the volatile conducting filament. $t_{\text{on}}$ and $t_{\text{off}}$ define the required period of time for the selector to be turned on ($V_{\text{selector}}$ to increase from $V_{\text{hold}}$ to $V_{\text{th}}$) and off ($V_{\text{selector}}$ to decrease from $V_{\text{th}}$ to $V_{\text{hold}}$) in the neuron circuit, respectively. When the circuit is biased, a series of continuous current and voltage spikes are generated, and the spike frequency can be calculated as the number of spikes per second (Hz) accordingly. To fulfill the requirement of neural network applications, artificial neurons should be capable of generating different spike frequencies according to the weights of connected synapses, i.e., $R_{\text{series}}$. In the RC Model (Chen et al., 2016; Wang et al., 2020), the $t_{\text{on}}$ in the TS neuron circuit is obtained by

$$t_{\text{on}} = -R_{\text{series}}C_{\text{series}} \times \ln \left( \frac{V_{\text{input}} - V_{\text{th}}}{V_{\text{input}} - V_{\text{hold}}} \right)$$ (1)
In this study, we assume that the IR voltage drop on $R_{\text{series}}$ is negligible when the TS selector is at its off-state due to the low leakage current (below pA in our case). Figure 3A illustrates the statistically measured $t_{\text{on}}$ of the TS neuron when connecting to different $R_{\text{series}}$ and the inset is an example of experimentally obtained current spikes ($I_{\text{total}}$) when $R_{\text{series}}$ is 3,300 k$\Omega$. Figure 3B presents the calculated spike frequency, as shown in Figure 3A. The results indicate that, with the decrease of $R_{\text{series}}$, $t_{\text{on}}$ is decreased and the spike frequency is increased accordingly. However, the spike frequency cannot be further increased when $R_{\text{series}}$ is $< 100$ k$\Omega$. It is worth mentioning that $R_{\text{series}}$ in the neuron circuit also acts as current compliance, where it controls the morphology and the size of conducting filaments in the TS selector (Chae et al., 2017). If $R_{\text{series}}$ is too small, the filaments of extremely large size become non-volatile and cannot be ruptured even at $V_{\text{hold}} = 0$ V. Consequently, $t_{\text{off}}$ increases and limits the spike frequency due to the difficult dissolution of large-size filaments in the TS selector. As a result, the resistance range of $R_{\text{series}}$ requires careful adjustment ($> 100$ k$\Omega$ in our case) to prevent the dysfunction of neuron circuits. With a suitable range of $R_{\text{series}}$ and with $t_{\text{off}}$ being much smaller than $t_{\text{on}}$, the spike frequency is the inverse of $t_{\text{on}}$, thus proportional to the inverse of $R_{\text{series}}$, i.e., the effective total conductance of the synaptic array.

RESULTS AND DISCUSSION

History-Dependent $V_{\text{th}}$ of the Threshold Switching Selector in Neuron Circuit

An important assumption of the RC Model in Equation 1 is that the $V_{\text{th}}$ of the TS selector is constant. Figure 4A compares the measured $V_{\text{th}}$ captured by an oscilloscope with $R_{\text{series}}$ of 150 and 470 k$\Omega$, and the statistical results are indicated in Figure 4B. Instead of remaining constant, the $V_{\text{th}}$ of the TS selector varies with $R_{\text{series}}$. Different $R_{\text{series}}$ modulate the charging rate of $V_{\text{selector}}$ and give rise to the history-dependent $V_{\text{th}}$. The
The measured \( t_{\text{on}} \) increases with increasing \( R_{\text{series}} \) while the calculated spike frequency shown in panel (B) decreases with increasing \( R_{\text{series}} \) in the neuron circuit. The inset in panel (A) shows an example of the experimentally obtained spike current (\( I_{\text{total}} \)) when \( R_{\text{series}} \) is 3,300 k\( \Omega \). The spike frequency is defined by the number of spikes per second (Hz). The spike frequency is approximately equal to the inverse of \( t_{\text{on}} \) when \( R_{\text{series}} \) is greater than 100 k\( \Omega \) and \( t_{\text{on}} \) is much larger than \( t_{\text{off}} \).

The oscilloscope waveform of \( V_{\text{selector}} \) when the TS selector is connected with \( R_{\text{series}} \) of 150 and 470 k\( \Omega \) and \( V_{\text{input}} = 2 \) V. Corresponding \( V_{\text{th}} \) is also indicated. (B) Statistically measured \( V_{\text{th}} \) increases with decreasing \( R_{\text{series}} \). Instead of remaining constant, the history-dependent \( V_{\text{th}} \) needs to be carefully considered in the TS neuron model.

Time-varying \( V_{\text{selector}} \) in the neuron circuit is approximated using a finite number of constant voltage stress (CVS) steps from \((t_1, V_1)\) to \((t_2, V_2)\) and eventually to \((t_{\text{on}}, V_{\text{th}})\). \( \Delta V \) and \( \Delta t \) determine the voltage and time intervals, respectively. Based on the proposed V–t Model, the transformed \((t'_1, V_1)\) step indicated by the red-dashed rectangle is equivalent to the \((t_1, V_1)\) step indicated by the blue-filled rectangle. The new \( t_{\text{on}} \) of \( V_2 \) is now \( t'_1 + \Delta t \), which includes the history effect of the previously accumulated \((t_1, V_1)\) step.
naive RC model does not consider the history-dependent $V_{th}$ of the TS selector, thus reducing the accuracy and prediction capability of the neuron model.

**Voltage–Time Transformation Model**

To include the characteristic of history-dependent $V_{th}$ into the neuron model, the V–t Model is proposed. Starting from considering the switching dynamics of TS selectors when constant voltage stress ($V_{CVS}$) is applied directly on the device, i.e., $V_{selector}$ equals to $V_{CVS}$. This is the case similar to Figure 2B but without the external $R_{series}$. The time delay before turning on the selector ($t_{on,CVS}$) is determined by the nucleation theory (Karpov et al., 2008; Lee et al., 2020):

$$t_{on,CVS} = \tau_0 \exp \left( \frac{W_0 \alpha^2 E_0 d}{kT V_{CVS}} \right)$$  \hspace{1cm} (2)

where $\tau_0$ is the intrinsic time constant of the device, $W_0$ is the nucleation barrier energy without electric field, $\alpha$ is a geometric factor of a nucleus, $E_0$ is the voltage acceleration factor, $d$ is the effective thickness of the insulating layer, $k$ is Boltmann’s constant, and $T$ is the ambient temperature. We define $A$ as a material-related constant at a fixed $T$, and (2) can be rewritten as

$$A = \frac{V_{CVS} \cdot \ln \left( \frac{t_{on,CVS}}{\tau_0} \right)}{t_{on,CVS}} = \frac{W_0 \alpha^2 E_0 d}{kT}$$  \hspace{1cm} (3)

where $A$ and $\tau_0$ can be obtained from fitting the measured $V_{CVS}$ and $t_{on,CVS}$. We assume $A$ remains constant when measuring the same device. Therefore, the V–t equation can be used to describe the transformation relation between any two arbitrary CVS voltages, $V_{CVS1}$ and $V_{CVS2}$, and their corresponding turn-on times, $t_{on,CVS1}$ and $t_{on,CVS2}$ as

$$V_{CVS1} \cdot \ln \left( \frac{t_{on,CVS1}}{\tau_0} \right) = V_{CVS2} \cdot \ln \left( \frac{t_{on,CVS2}}{\tau_0} \right)$$  \hspace{1cm} (4)

When connecting the TS selector with $R_{series}$ to form a complete TS neuron circuit, as shown in Figure 2B, $V_{selector}$ becomes time-varying according to the RC equivalent circuit.

**TABLE 1 | Key parameters extracted from the reported threshold switching (TS) selectors.**

| TS selector type | $\Lambda$ (V s) | $\tau_0$ (s) | Capacitor (F)* |
|------------------|----------------|--------------|---------------|
| IMT (Lee et al., 2020) | 1.29 | 10^{-8} | 6 \times 10^{-13} |
| IMT (Park et al., 2016) | 1.602 | 10^{-8} | 7 \times 10^{-13} |
| OTS (Lee et al., 2020) | 30.28 | 10^{-21} | 2 \times 10^{-15} |
| OTS (Lee et al., 2019b) | 45.78 | 10^{-24} | 6 \times 10^{-16} |
| Ag-based (Lee et al., 2020) | 3.09 | 10^{-6} | 3.25 \times 10^{-10} |
| Ag-based (Yoo et al., 2017) | 2.92 | 10^{-6} | 2.95 \times 10^{-10} |

*The value of an integrated capacitor in the neuron circuit is adjusted to keep the maximum $V_{th}$ below 1.2 V at $R_{series} = 10 k\Omega$. 

The time-varying $V_{selector}$ could be approximated using a finite number of CVS steps as depicted in Figure 5, which increase from ($t_1$, $V_1$) to ($t_2$, $V_2$) and eventually to ($t_{on}$, $V_{th}$) indicated by the blue line. $\Delta V$ and $\Delta t$ are the voltage and time intervals, respectively. A similar conversion between CVS and ramp voltage stress has been reported and validated in resistive switching memory devices (Luo et al., 2013). As indicated in Figure 5, the stress effect of the ($t_1$, $V_1$) step indicated by the blue-filled
A new equivalent CVS step of \( t'_{1}, V_{2} \) step indicated by the red dashed rectangle based on (4), \( t'_{1} \) is therefore expressed as:

\[
 t'_{1} = \exp \left[ \frac{V_{1}}{V_{2}} \cdot \ln \left( \frac{t_{1}}{\tau_{0}} \right) + \ln \left( \tau_{0} \right) \right] \quad (5)
\]

A new equivalent CVS step of \( t_{2}, V_{2} \) with an equivalent stress time of \( t_{2} = t'_{1} + \Delta t \) at \( V_{2} \) includes the history effect of the previous \( V_{1}, t_{1} \) step. This equivalent stress time is accumulated until it reaches the \( t_{on,CVS} \) at the stop voltage, i.e., \( V_{th} \), which could be calculated by Equation 2. Under these circumstances, \( V_{th} \) becomes history-dependent and is affected by the RC charging process and \( R_{series} \). The larger \( R_{series} \), the lower \( V_{th} \) and longer \( t_{on} \).

To confirm the feasibility of the V–t Model on the prediction of the TS neuron behavior, the simulation results obtained from the RC Model (Chen et al., 2016; Wang et al., 2020) and the proposed V–t Model are compared in Figures 6A,B with the measurement. The RC Model only describes the RC behavior of the neuron circuit with a constant \( V_{th} \) of the TS selector, therefore it not only underestimates \( t_{on} \) but also fails to depict the history-dependent \( V_{th} \) of the TS selector. In contrast, the proposed V–t Model predicted well \( t_{on} \) and \( V_{th} \) of the TS selector under different \( R_{series} \).

### Prediction of Threshold Switching Neuron Performance Based on V–t Model

In this section, we explored the impact of the TS selector on TS neurons, and the effect of \( t_{on} \) and \( A \) on \( V_{th} \) can be predicted based on Equation 2. As shown in Figure 7, when \( t_{on} \) approaches \( \tau_{0} \), the voltage required for nucleation \( (V_{th}) \) approaches infinity. In addition, the TS selector with larger \( A \) requires a higher \( V_{th} \) to be turned on. These results indicated that, under the same \( t_{on} \), the TS selector with larger \( \tau_{0} \) and \( A \) needs a higher applied voltage than the one with smaller \( \tau_{0} \) and \( A \). However, the required high applied voltage is not favorable because it not only may result in an irreversible breakdown of the device but also may increase the difficulty of circuit integration. Therefore, the TS selector with larger \( \tau_{0} \) and \( A \) may require an additional external integration capacitor to maintain a reasonable \( V_{th} \), which on the other hand increases the circuit footprint and \( t_{on} \) and decreases the spike frequency. The energy consumption per spike of the neuron circuit could also increase due to slow spiking (Liang et al., 2021).

**Table 1** lists the reported parameters of \( \tau_{0} \) and \( A \) of different TS devices (Park et al., 2016; Yoo et al., 2017; Lee et al., 2019b, 2020), and the simulated \( t_{on} \) and \( V_{th} \) of the neuron circuit based on the V–t Model are indicated in **Figure 8**. In this study, the \( R_{series} \) is given from 10 to 1,000 kΩ. The value of the integration capacitor in the neuron circuit is adjusted to keep the maximum \( V_{th} \) below 1.2 V at \( R_{series} = 10 \, \text{kΩ} \), and the adopted capacitance corresponding to each TS device is also given. Among IMT, OTS, and Ag-based TS devices, the OTS neuron matched with the lowest capacitance is the most favorable for reducing the neuron circuit area. It is noted that the minimal integration capacitor is limited by the parasitic capacitor of the TS selector itself. As a result, the device area scaling would be necessary to achieve a low enough capacitance value. Moreover, the simulated \( t_{on} \) in **Figure 8A** shows that the OTS neuron is capable of achieving GHz-level spike frequency due to its extremely small \( \tau_{0} \) (10–21 s), even though its \( A \) is larger. Furthermore, in **Figure 8B**, the OTS selector with the smallest \( \tau_{0} \) results in a large \( t_{on}/\tau_{0} \); therefore, the \( V_{th} \) is less history dependent. The OTS selector shows promising potential not only in generating high spike frequency but also consuming less area and energy in the neuron circuit.

### CONCLUSION

In this study, a V–t Model is successfully constructed to simulate the spiking behavior of TS neurons according to the synaptic weight of connected synapses. By considering the history-dependent \( V_{th} \) of the TS selector based on the nucleation theory, the proposed V–t Model is in good agreement with the measurement results and provides more accurate prediction compared to the conventional RC Model. Moreover, the behavior of TS neurons based on different TS devices,
including IMT, OTS, and Ag-based selectors, are simulated and compared using the proposed V–t Model. The results show that the OTS selector matched with the lowest capacitance that is the most favorable for reducing the circuit area overhead. Moreover, the OTS selector with the lowest $t_\text{on}$ and $t_\text{off}$ not only achieves less history-dependent $V_\text{th}$ but also realizes a high-speed neuron with GHz-level spike frequency. The proposed V–t model provides a useful engineering pathway toward the future development of TS neurons.

**DATA AVAILABILITY STATEMENT**

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

**REFERENCES**

Chae, B.-G., Seol, J.-B., Song, J.-H., Baek, K., Oh, S.-H., Hwang, H., et al. (2017). Nanometer-scale phase transformation determines threshold and memory switching mechanism. *Adv. Mater.*, 29,1071725. doi: 10.1002/adma.201701752

Chen, P.-Y., Soo, J.-S., Cao, Y., and Yu, S. (2016). "Compact oscillation neuron exploiting metal-insulator-transition for neuromorphic computing," in Proceedings of the IEEE/ACM International Conference on Computer-Aided Design (ICCAD), (Austin, TX: IEEE). doi: 10.1145/2966986.2967015

Grisafe, B., Jerry, M., Smith, J. A., and Datta, S. (2019). Performance enhancement of Ag/HfO2 metal ion threshold switch cross-point selectors. *IEEE Electron Device Lett.*, 40, 1602–1605. doi: 10.1109/LED.2019.2936104

Hatemi, F., Chai, Z., Zhang, W., Santini, A., Degraeve, R., Cilma, S., et al. (2019). “Endurance improvement of more than five orders in Ge/Si-x OTS selectors by using a novel refreshing program scheme.” in Proceedings of the IEEE International Electron Devices Meeting (IEDM), (San Francisco, CA: IEEE), 827–830. doi: 10.1109/IEDM19573.2019.899348

Hua, Q., Wu, H., Gao, B., Zhao, M., Li, Y., Li, X., et al. (2019). A threshold switching selector based on highly ordered Ag nanodots for X-point memory applications. *Adv. Sci.* 6,1900024. doi: 10.1002/ads.201900024

Ielmini, D., and Wong, H.-S. P. (2018). In-memory computing with resistive switching devices. *Nat. Electron.* 1, 333–343. doi: 10.1038/s41928-018-0092-2

Karpov, I. V., Mitra, M., Kau, D., Spadini, G., Kryukov, Y. A., and Karpov, V. G. (2017). Nanometer-scale phase transformation determines threshold and memory switching mechanism. *Adv. Mater.*, 29,1071725. doi: 10.1002/adma.201701752

Lee, S., Yoo, J., Park, J., Song, J., Lim, S., and Hwang, H. (2017). Field-induced nucleation switching devices and annealing effect on its characteristics. *IEEE Electron. Mater.* 8,1800866. doi: 10.1002/aelm.201800866

Lee, S., Yoo, J., Park, J., and Hwang, H. (2019b). Field-induced nucleation switching in binary ionic threshold switches. *IEEE Electron Device Lett.* 115,233503. doi: 10.1063/1.5126913

Lee, S., Yoo, J., Park, J., and Hwang, H. (2020). Understanding of the abrupt resistive transition in different types of threshold switching devices from materials perspective. *IEEE Trans. Electron Devices* 67,2887–2888. doi: 10.1109/TED.2020.299770100

Liang, F.-X., Sahu, P., Wu, M.-H., Wei, J.-H., Shen, S.-S., and Hou, T.-H. (2020). “Stochastic STT-MRAM spiking neuron circuit,” in Proceedings of International Symposium on VLSI Technology, Systems and Applications (VLSI-TSA), (Hsinchu: IEEE). doi: 10.1109/VLSI-TSA48913.2020.9203701

Liang, F.-X., Wang, I.-T., and Hou, T.-H. (2021). Progress and benchmark of spiking neuron devices and circuits. *Adv. Intell. Syst.* 3,2100007. doi: 10.1002/aisy.202100007

Luo, W.-C., Liu, J.-C., Lin, Y.-C., Lo, C.-L., Huang, J.-J., Lin, K.-L., et al. (2013). Statistical model and rapid prediction of RRAM SET speed–disturb dilemma. *IEEE Trans. Electron Devices* 60, 3560–3566. doi: 10.1109/TED.2013.2281991

**AUTHOR CONTRIBUTIONS**

S-MY fabricated the device. S-MY and M-HW performed data analysis. S-MY, I-TW, M-HW, and T-HH contributed to the conception and discussion of the study. S-MY, I-TW, and T-HH drafted manuscript. All authors contributed to the article and approved the submitted version.

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Yap, J., Cha, E., Karpov, I., and Hwang, H. (2016). Dynamics of electroforming and electrically driven resistor-metal transition in NbOx selector. *Appl. Phys. Lett.* 108,232101. doi: 10.1063/1.4953323

Song, B., Xu, H., Liu, S., Liu, H., and Li, Q. (2018). Threshold switching behavior of Ag-SiTe-based selector device and annealing effect on its characteristics. *IEEE J. Electron Devices Soc.* 6, 674–679. doi: 10.1109/JEDS.2018.2836400

Tuma, T., Pantazi, A., Le Gallo, M., Sebastian, A., and Eleftheriou, E. (2016). Stochastic phase-change neurons. *Nat. Nanotechnol.* 11, 693–699. doi: 10.1038/nnano.2016.70

Wang, P., Khan, A. I., and Yu, S. (2020). Cryogenic behavior of NbO2 based threshold switching devices as oscillation neurons. *IEEE Photonics Technol. Lett.* 32,1612. doi: 10.1109/LPT.2020.2990278

Yoo, J., Park, J., Song, J., Lim, S., and Hwang, H. (2017). Field-induced nucleation in threshold switching characteristics of electrochemical metallization devices. *IEEE Electron Device Lett.* 111,163109. doi: 10.1063/1.4985165

Zhang, X., Wu, Z., Lu, J., Wei, J., Lu, J., Zhu, J., et al. (2020). “Fully memristive SNNs with temporal coding for fast and low-power edge computing,” in Proceedings of IEEE International Electron Devices Meeting (IEDM), (San Francisco, CA), 649–652. doi: 10.1109/IEDM3553.2020.9371937

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