

Supplementary Information for: "Magnetic Tunnel Junctions Driven by Hybrid Optical-Electrical Signals as a Flexible Neuromorphic Computing Platform"

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SUPPLEMENTARY NOTE 1: MTJ Operating as a Spin-Torque Nano-Oscillator

We developed and optimized magnetic tunnel junctions (MTJ) devices specifically for hybrid optical-electrical neuromorphic applications [1]. These devices feature a compact footprint, with diameters down to 300nm and inter-device spacing of a few micrometers, allowing high integration density and low energy consumption. As shown in Fig. S1, their operating frequency range and output power are compatible with standard CMOS technology. To facilitate efficient optical integration, the architecture includes transparent ITO top contacts and a split-feedline layout, providing direct optical access to the active junction. This design not only supports future fully integrated optoelectronic systems but also enhances the laser-induced thermal gradient across the MgO barrier, which drives the tunnel magneto-Seebeck (TMS) effect. In this regime, the laser acts solely as a thermal excitation source—without any direct light-matter interaction or electromagnetic coupling [2–9]—ensuring that the device operates purely in the spin-caloritronic regime [10, 11].

SUPPLEMENTARY NOTE 2: Thermoelectric Response of Small Circular MTJs

Fig. S2 shows the resistance and AC thermovoltage (ΔV_{AC}) during a magnetization sweep for an MTJ with a 300 nm nanopillar. Step-like resistance changes, due to Barkhausen jumps [12–14], coincide precisely with spikes in ΔV_{AC} , which appear to be more pronounced. This enhanced visibility may offer a clearer window into domain dynamics, vortex configurations, or magnetic state transitions—potentially supporting theoretical micromagnetic interpretations and informing applications where sensitivity to magnetic switching is essential. These spikes present promising opportunities for applications in neuromorphic computing, high-resolution magnetic sensing, and reservoir computing, where nonlinear dynamics and spiking behavior are essential for advanced information processing. Notably, under excitation with a 54 mW laser and a 2.0 mA bias current, we observe a pronounced increase in thermovoltage, accompanied by a distinctive double-switching behavior in both the resistance and thermovoltage signals. As reported for larger devices in the main text, this phenomenon also manifests itself in smaller nanopillars, albeit at lower threshold values of laser power and bias current. Furthermore, tunnel magnetoresistance (TMR), defined as $TMR = \frac{R_{AP} - R_P}{\min(|R_P|, |R_{AP}|)}$ [1, 15]. The extracted TMR and bTMS ratios are presented in the corresponding plots, highlighting the enhanced thermovoltage contrast achieved under bTMS excitation.

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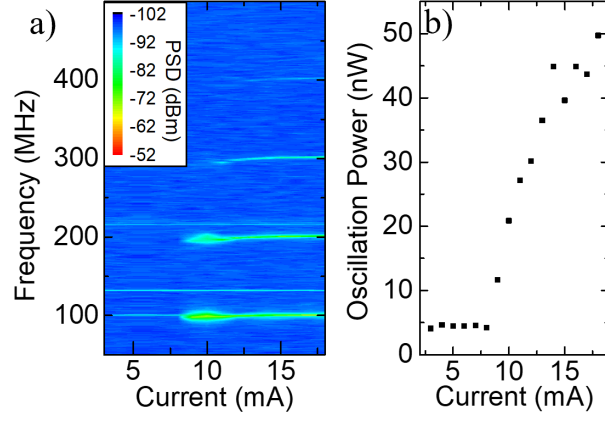


FIG. S1. **Spin-torque nano-oscillator (STNO) characterization under electrical bias excitation.** a) Power spectral density (PSD) of one STNO as a function of the applied bias current. b) Integrated STNO oscillation power of the 100 MHz peak as a function of the applied bias current.

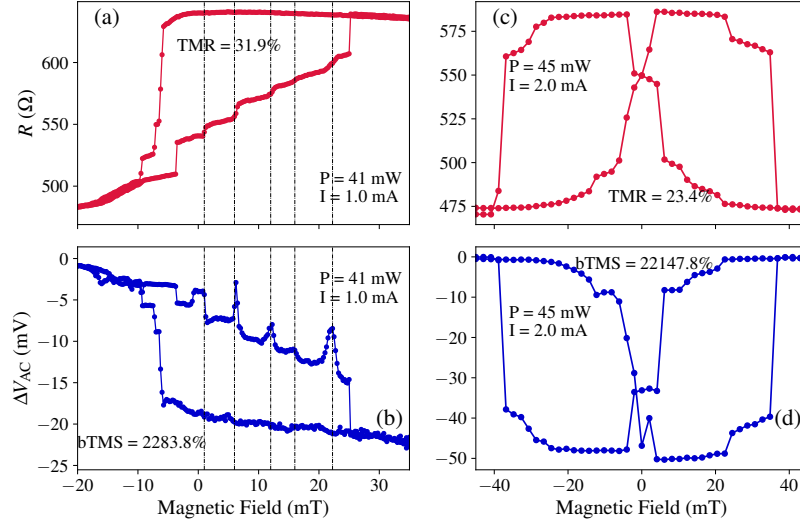


FIG. S2. **Thermovoltage Spiking and Double Switching.** Resistance (a, c) and thermovoltage ΔV_{AC} (b, d) versus magnetic field for a $d = 300$ nm device. Vertical lines denote step-like Barkhausen jumps in resistance synchronized with thermovoltage spikes..

SUPPLEMENTARY NOTE 3: TMS and bTMS Effects in MTJs with Elliptical Nanopillars

MTJs with elliptical nanopillars exhibit shape-induced in-plane magnetic anisotropy that stabilizes two degenerate magnetization states aligned along the major axis. This anisotropy arises from the magnetostatic energy [16, 17]:

$$E_{\text{demag}} = \frac{1}{2} \mu_0 M_s^2 (N_x m_x^2 + N_y m_y^2 + N_z m_z^2), \quad (\text{S1})$$

where M_s is the saturation magnetization, $\mathbf{m}$ the unit magnetization vector, and N_i the demagnetization factors. For elliptical cross-sections, $N_x < N_y$ introduces a uniaxial anisotropy with an energy landscape

$$E_{\text{ani}} = K_{\text{eff}} \sin^2 \theta, \quad K_{\text{eff}} = \frac{1}{2} \mu_0 (N_y - N_x) M_s^2, \quad (\text{S2})$$

favoring bistable magnetization along the major axis. This stabilizes parallel and antiparallel states across the junction area, which is crucial for spintronic memory and thermoelectric switching.

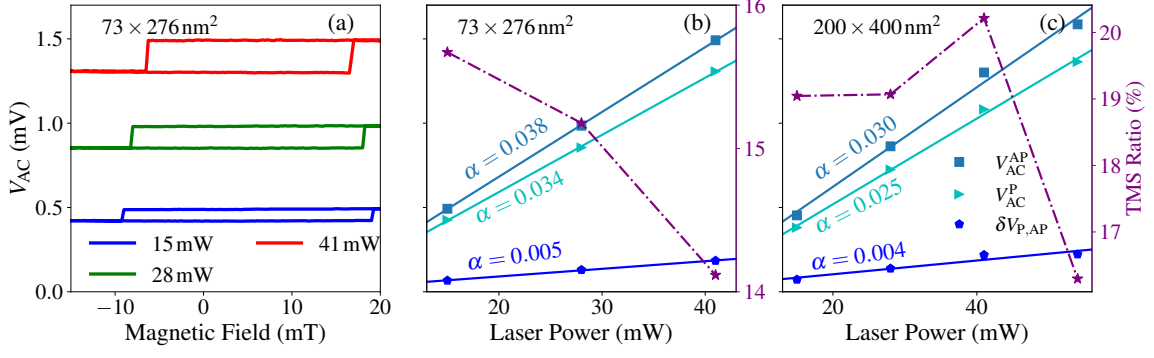


FIG. S3. Seebeck voltage in magnetic tunnel junctions (MTJs) with elliptical nanopillar. (a) V_{AC} versus magnetic field for a device with lateral dimensions $73 \times 276 \text{ nm}^2$. Curves show different laser powers (mW). (b) and (c) summarize the extracted Seebeck voltages in the parallel and antiparallel states, V_{AC}^P and V_{AC}^{AP} , their difference $\delta V_{P,AP}$, and the corresponding tunnel magneto-Seebeck (TMS) ratio for the $73 \times 275 \text{ nm}^2$ and $200 \times 400 \text{ nm}^2$ devices, respectively.

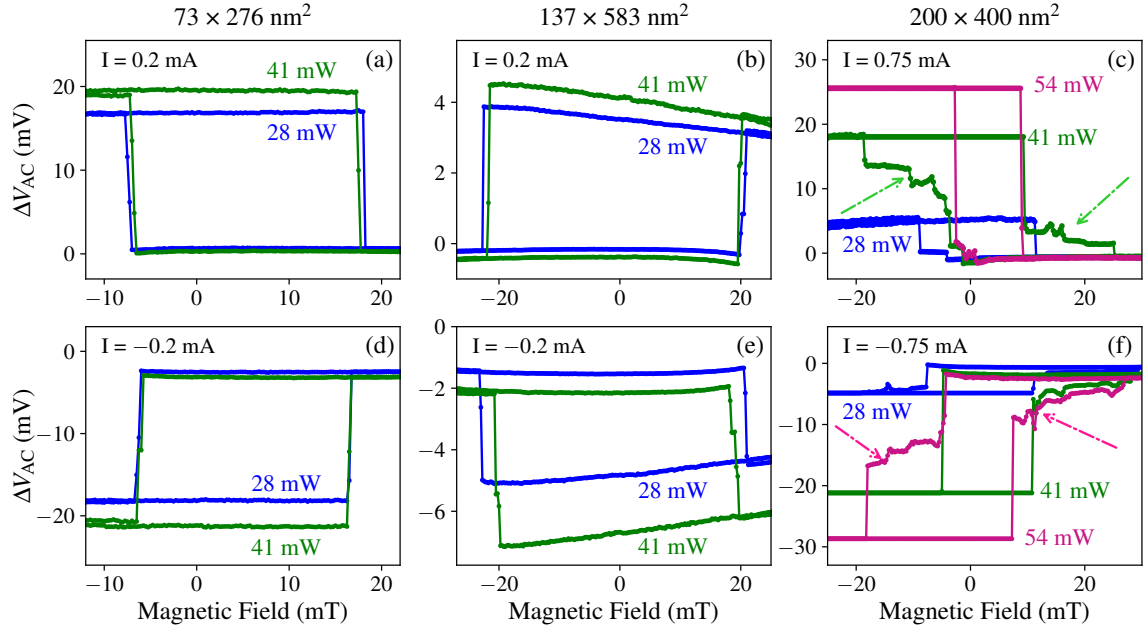


FIG. S4. Bias-enhanced tunnel magneto-Seebeck (bTMS) effect in magnetic tunnel junctions (MTJs) with elliptical nanopillars. ΔV_{AC} versus magnetic field for different laser powers and bias currents in MTJs with elliptical nanopillars: (a, d) $73 \times 276 \text{ nm}^2$ ($e = 0.96$), (b, e) $137 \times 583 \text{ nm}^2$ ($e = 0.97$), and (c, f) $200 \times 400 \text{ nm}^2$ ($e = 0.87$). Arrows in (c, f) indicate thermovoltage spikes.

Tunnel magneto-Seebeck (TMS) measurements for elliptical MTJs with $73 \times 276 \text{ nm}^2$ and $200 \times 400 \text{ nm}^2$ footprints (eccentricities $e = 0.96$ and 0.87 , respectively) reveal higher Seebeck voltages than in the circular 300 nm device (Fig. S3). This enhancement likely stems from the elliptical geometry, which could lead to localized heat confinement and reduced lateral heat spreading, resulting in a steeper thermal gradient across the MgO barrier. Detailed thermal modeling (e.g., via COMSOL simulations) would be valuable for quantitatively confirming the role of geometry in shaping the temperature profile and the resulting Seebeck response. Theoretical studies based on the Landauer-Büttiker formalism and first-principles calculations further support this interpretation by linking device geometry to spin-dependent transmission and thermoelectric efficiency [18].

ΔV_{AC} as a function of the magnetic field under varying laser powers and bias currents is shown in Fig. S4 for elliptical MTJs with different eccentricities. The $73 \times 276 \text{ nm}^2$ MTJ generates a larger thermovoltage (even more than the MTJs with a circular nanopillar), consistent with its stronger shape anisotropy and a more confined thermal gradient. The $200 \times 400 \text{ nm}^2$ device, with lower eccentricity, exhibits a reduced switching field compared to more elongated devices. Interestingly, at specific laser powers and bias currents, the $200 \times 400 \text{ nm}^2$ device displays a non-rectangular,

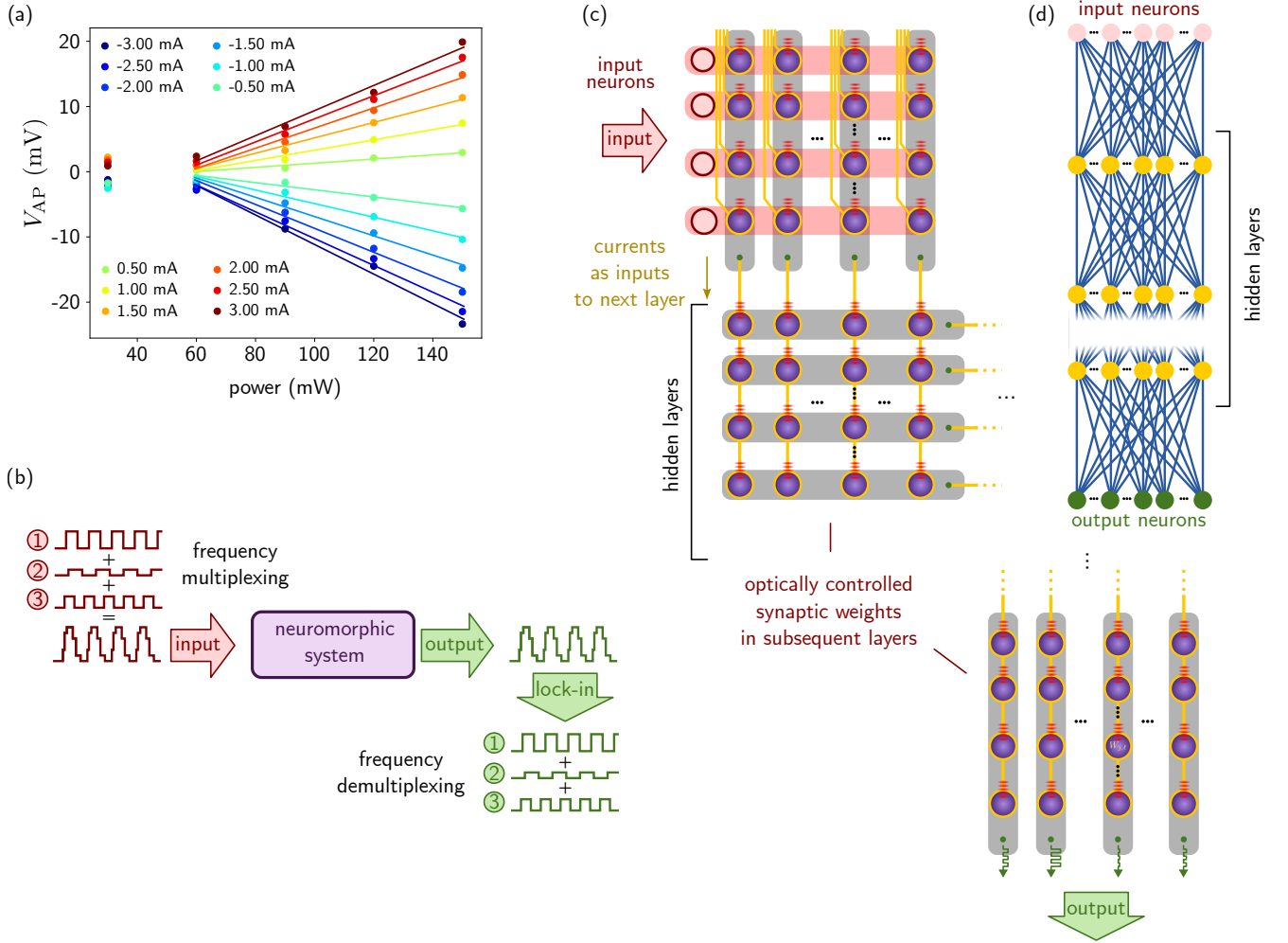


FIG. S5. **Extensions to our envisioned neuromorphic computing scheme.** (a) Operating in the bias-enhanced tunnel magneto-Seebeck (bTMS) regime in which the voltage V_{AP} depends linearly on the laser power, we can (b) perform parallel processing through frequency multiplexing by encoding different inputs at different laser pulse frequencies. The parallelly processed outputs can be recovered by demultiplexing the output voltage. (c) Extension of our scheme to a network with multiple hidden layers. The output voltages after the first layer are used as biases in the next layer. This setup can effectively realise deep neural networks such as the one shown in panel (d).

S-shaped $\Delta V_{AC}(B)$ response accompanied by voltage spikes. This behavior resembles vortex dynamics observed in circular MTJs and suggests that at lower eccentricities, elliptical devices may support non-uniform magnetization textures and vortex formation. These features likely arise from vortex core motion or domain wall reconfigurations driven by thermal gradients and spin torque, indicating a geometric threshold for vortex excitation in elliptical geometries that depends on eccentricity.

SUPPLEMENTARY NOTE 4: Possible Extensions of Our Neuromorphic Proposal

Here, we briefly outline possible extensions of the neuromorphic computing chip described in the main text.

Parallel processing with frequency multiplexing: A key advantage of optically encoding inputs in laser pulse sequences is the ability to use frequency multiplexing to simultaneously encode and process multiple inputs (Fig. S5(a)). For our devices, such an approach is possible as we experimentally observed that within the explored frequency range, the thermovoltage is independent of the laser pulse frequency. This stands in contrast to other neuromorphic computing approaches based on MTJs employing radio frequency (RF) signals, e.g. [19, 20]. In these setups, parallel processing would not be possible, as the rectification voltage depends on both the power and the frequency of the RF signal.

Concretely, parallel processing with our chip would work as follows, Fig. S5(b): pulse sequences of different frequencies (which encode different inputs in their amplitudes A_n) are superimposed in the laser signal. We empirically observed that also in the bTMS regime, there is a regime of laser powers in which the Seebeck voltage depends approximately linearly on power. In that regime, $\sigma(\sum_n A_n) \approx \sum_n \sigma(A_n)$ with σ the now linear response of the MTJ. This is an important prerequisite for parallel processing. We choose to work in this linear bTMS regime, since in the TMS regime, it is currently not possible to simultaneously implement input and synaptic weights. The same frequency pattern is transferred onto the resulting Seebeck output voltages. Hence, demultiplexing the output voltages allows us to reconstruct the outputs for each individual input giving rise to efficient batch processing. This presents a great advantage over other approaches based on RF signals since, in that case, parallel processing based on frequency multiplexing is not possible.

As mentioned above, parallel processing is only possible when the output voltage depends linearly on the input laser power. In this regime, the chip also implements a linear mathematical function which can be used to efficiently implement the multiply-accumulate operation of a linear layer in a neural network (i.e., matrix-vector multiplication), which are the most costly operations in neural networks. We would like to emphasize that while frequency multiplexing is well-established for optical neural networks [21, 22], it is typically thought to be challenging, if not impossible, to achieve with spintronic or electronic hardware. Other device designs using time-modulated bias currents instead of pulsed lasers to inject the neuronal input, would face technical challenges due to overheating. Here, we bypass this challenge with the help of a pulsed laser inducing a thermovoltage enabling, in principle, frequency multiplexing and parallel processing.

Deeper networks: In modern neural network architectures, deep architectures consisting of multiple consecutive layers are frequently employed as they have been shown to give rise to improved performance. Indeed, modern neural networks can be over one hundred layers deep and contain on the order of 10^7 parameters. Therefore, scalability is an essential aspect of a viable neuromorphic platform. As we mentioned in the main text, MTJs can, in a commercial setting, be scaled down to a few tens of nanometers, such that millions of MTJs (each of them realizing a synaptic weight) fit within a few square millimeters. This makes spintronic chips an attractive neuromorphic platform.

To emulate the functionality of a deep neural network with multiple layers (Fig. S5(d)), we propose the setup sketched in Fig. S5(c). The first layer follows the design described in the main text (Fig. 4(b)). The output voltages and currents generated by this first layer can be fed to a next layer of devices (potentially after amplification). The synaptic weights in these subsequent layers can be encoded optically. One continues to feed the output voltages into subsequent layers until we reach the output layer where the output voltages are measured.

SUPPLEMENTARY NOTE 5: Alternative Neuromorphic Computing Approaches

In the main text, we discussed how the nonlinear response of the MTJ devices can be leveraged for neuromorphic computing. Here, we briefly outline alternative computing modalities enabled by our devices.

Spike-based neuromorphic computing: An alternative approach makes use of the pulsed laser heating to create voltage spikes with the MTJs (neurons) for spike-based neuromorphic computing. Spike-based neuromorphic computing is a biologically-inspired computing paradigm which encodes information either in the frequency of the spikes or in the amplitude of the heights. This mode of operation can either occur in the TMS or the bTMS regime. The frequency of the spike is controlled by the laser pulses and the laser power determines the amplitude. Additionally, in the bTMS regime, the bias currents can serve as weights (synapse). Subsequently, multiple devices can be connected to a memristor to control the time-delay of a pulse sequence and prepare the pulses for the next processing steps.

In-memory computing: Digital artificial neural networks are further away from biological neural processing. Such digital artificial neural networks essentially approximate non-linear functions through a sequence of linear and non-linear maps. This involves multiplying a synaptic weight matrix W on an input vector x and applying a nonlinear activation function. This is also the computing approach we explore in the main text. In the main text, we directly leveraged the non-linear response of the system in the bTMS-regime to obtain an expressive neuromorphic system. There, we proposed to control the weight value through the bias current. Alternatively, one could make use of the magnetic state of each device to store a binary value of the weights and utilise the devices for in-memory neuromorphic computing. This approach is especially appealing since, in digital computers, retrieving the synaptic weights from the memory for during the training or inference phase requires shuttling large amounts of data back and fourth. In-memory computing addresses this challenge by locally encoding the synaptic weights in the device in the same circuit that performs the computation.

Concretely, each device can be manufactured so that the switching between the two magnetic states occurs at different values of the magnetic field, each state corresponding to a different resistance of the device. It is within experimental capabilities to manufacture chips in which each device switches between states at a particular magnetic field. Choosing the right magnetic field, we obtain a chip with a specific weight pattern that solves a particular task

of interest. Importantly, the weight pattern persists as the magnetic field is switched off opening the door to efficient in-memory computing. This weight pattern can be obtained through simulations of the device before manufacturing the task-specific chip.

Such approaches based on binary or ternary weights may become relevant in the future as we are searching for more efficient approaches to machine learning and artificial intelligence, as can already be seen by new, potentially more efficient digital approaches such as BitNet [23]—a 1-bit large language model.

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