

RESISTIVE SWITCHING AND QUANTUM NANOMATERIALS AS NEUROMORPHIC SYSTEMS: TOWARDS ENERGY-EFFICIENT BRAIN-INSPIRED COMPUTING

SUMMARY: This review feature article covers a literature subset focusing on hardware strategies, solid-state learning mechanisms, theoretical descriptions, challenges, and opportunities in the cutting-edge field of (quantum) nanomaterials with a seemingly “synthetic intelligence” that can be used in future neuromorphic computing. The latter is viewed as a novel paradigm in computing hardware, inspired by energy-efficient biological neural processing, that goes beyond conventional microprocessor technology.



By **GHAZALEH GHOLIZADEH**^{1,2}
<ghazaleh.gholizadeh@ucalgary.ca>,
MARCUS KASDORF^{1,2}
<marcus.kasdorf@ucalgary.ca>,
CLAUDIA GOMES DA ROCHA^{1,2,3}
claudia.gomesdarocha@ucalgary.ca

¹Department of Physics and Astronomy, University of Calgary, Calgary, AB, T2N 1N4, Canada

²Institute for Quantum Science and Technology (IQST), Faculty of Science, University of Calgary, Calgary, AB, T2N 1N4, Canada

³Hotchkiss Brain Institute (HBI), University of Calgary, Calgary, AB, T2N 4N1, Canada

Integrated circuits are semiconductor-based electronic components ubiquitous in present-day technology. Advances in miniaturization and nanofabrication strategies of integrated circuits have led to very-large-scale integration (VLSI), capable of packing billions of transistors on a single microchip, with its scalability trended by the well-known Moore’s law [1]. Key to this success is the consistent shrinking of the metal oxide semiconductor field-effect transistor, the most primitive building block in electronics, with typical length scales reaching nanometers in which quantum effects are dominant. However, such gains are starting to slow down in response to physical limitations at sub-10 nm processes. Therefore, dimensional scaling alone is insufficient to fulfil commercial expectations in the semiconductor and electronics industry, heavily pressured by the growing demands on artificial intelligence (AI) and smart/automated systems, big data cloud processing and storage, and emulation of brain-like inference beyond rigid binary/logic capabilities.

Emerging forms of computation compatible with AI-based or brain-inspired systems require diversification of electronics and their integration; this includes the search for new materials and

computer architectures beyond conventional complementary metal oxide semiconductor (CMOS) technology. Moreover, alternative computing paradigms and new (“green”) materials/hardware solutions could offer ways of mitigating the escalating energy demands and growing environmental footprint of large-scale digital computing infrastructure [2, 3], often associated with limitations of the von Neumann architecture -- the blueprint design for most computers -- known as the von Neumann bottleneck.

Moving highly centralized and rigid CMOS platforms to a brain-inspired lens characterizes a paradigm shift in computing, relying on adaptive, built-in learning, massively parallel/in-memory processing, and fault-tolerant operations. Brain-inspired or neuromorphic systems [4] encompass an interdisciplinary approach of overhauling conventional computer hardware with novel brain-like architectures [5, 6]. A particularly promising step toward neuromorphic design is the selection of raw materials that will constitute the bio-inspired hardware [7], leading to research on novel materials and solid-state systems, as well as ways of controlling their active particle constituents, e.g., atoms, ions, electrons, and/or spins semiclassically or at the quantum level. As of now, a wide range of “intelligent matter” [8] has been identified with the advent of resistive switching (RS) systems and memristive materials, as presented next.

MEMRISTIVE MATERIALS AND MECHANISMS

With respect to novel neuromorphic materials and devices, memristive systems [9] have been central due to their adaptive RS response to external stimuli, similar to bio-synapses, enabling energy-efficient hardware learning. Memristive systems are a generalization of the memristor [10], a two-terminal circuit unit whose “memristance” depends on the history of the input stimulus and is governed by an internal state variable (e.g., the charge) which evolves in time according to a dynamic rate equation. Memristive systems exhibit nonlinear and hysteretic behaviours with their resistance state switching discretely or continuously (analogue) between a high resistance state (HRS) and a low resistance state (LRS), representing logical bits, or OFF/ON states, respectively [11]. As a result, cutting-edge brain-like and spiking neural operations, as well as optimal memory devices, can be devised [12].

There is an immense variety of memristive materials and mechanisms highlighted in comprehensive reviews. Focusing on metal-insulator-metal stacks, RS is typically associated with the formation/dissolution of a conductive filament inside the insulator, driven by external stimuli. The state of the filament/conductive region modulates the conductance of the channel representing synaptic weights. From [13, 14], Figure 1 summarizes four major groups of memristive-based materials relevant to neuromorphic applications: oxide-based materials, perovskites, organic materials, and two-dimensional (2D) materials. Other memristive-based material specifications include chalcogenides, polymers, biomolecules, magneto-memristive materials, and ferroelectric materials. Figure 1 also features four major switching mechanism groups organized from [11, 12, 15]: ionic, thermal, electronic, and phase change, observed over a plethora of different materials and system configurations at the nanoscale.

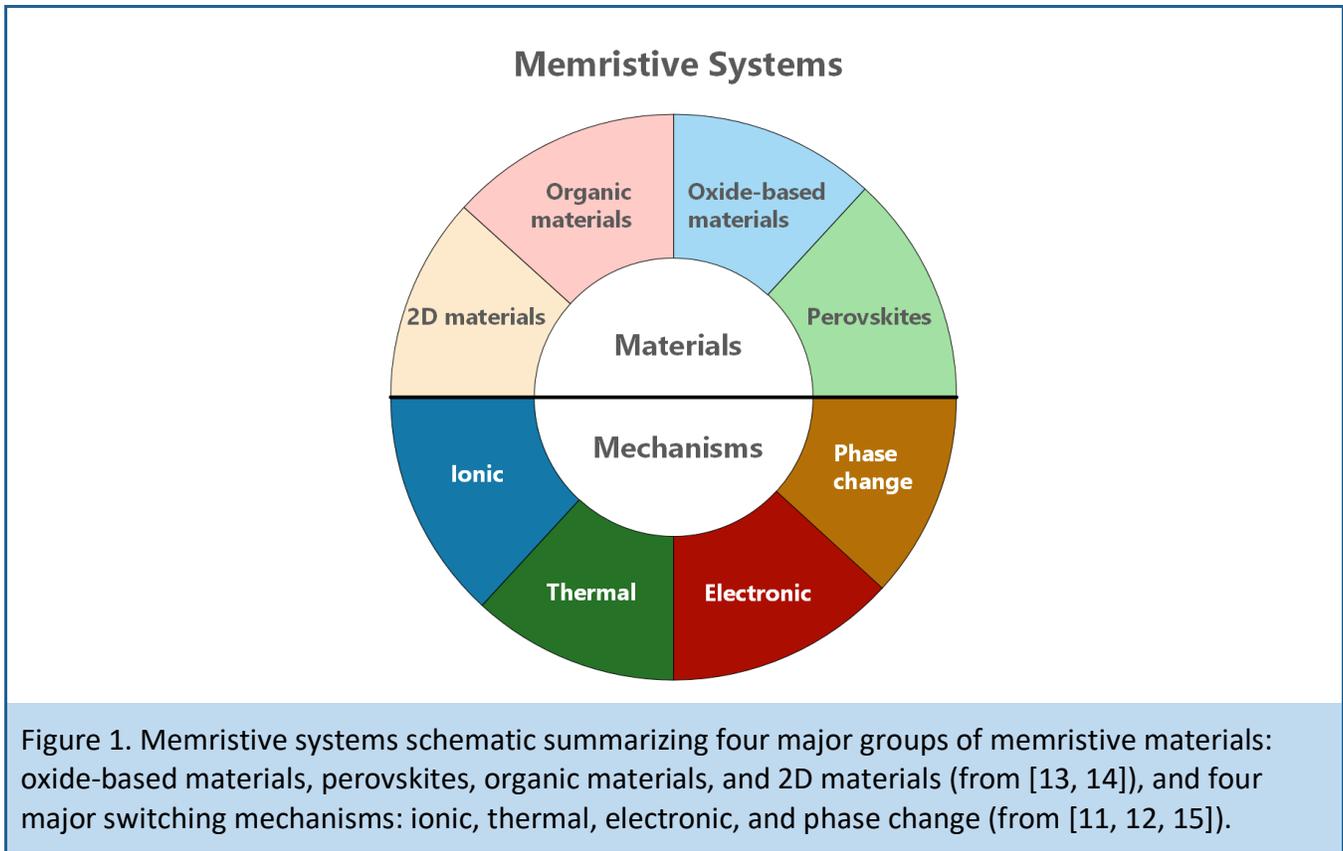


Figure 1. Memristive systems schematic summarizing four major groups of memristive materials: oxide-based materials, perovskites, organic materials, and 2D materials (from [13, 14]), and four major switching mechanisms: ionic, thermal, electronic, and phase change (from [11, 12, 15]).

Ionic mechanisms include anion, cation, and dual ionic switching devices [16, 17], in which the filamentary or conducting region is dominated by redox reactions and ion migration. Anion switching found in many TiO_x -based systems with mobile oxygen vacancies is also referred to as valence change memory. Cation switching involves electrochemical filament formation, often ionized Ag or Cu, also named electrochemical metallization or programmable metallization cells. Phase-change memory mechanisms are found in phase-change materials that exhibit different conduction properties at thermally driven structural phases, with $\text{Ge}_2\text{Sb}_2\text{Te}_5$ (GST) being a benchmark. Examples of electronic processes, some widely governed by quantum-based transport effects, include tunnelling-assisted (de)trapping of electrons through defective localized states in filamentary-free switching. Due to ample materials interface/stack combinations, other relevant electronic conduction mechanisms [18] include space-charge limited conduction, Poole-Frenkel, Schottky-barrier emission, Fowler-Nordheim quantum-tunnelling, Mott memristors, and quantized conductance effects [19, 20]. Memristive mechanisms can also be temperature-assisted [21], optically controlled [22] and magnetic or spin-based [23], from which switching is governed by the modulation in quantum domain magnetization and spin-polarized currents, following spintronics approaches. In the context of strongly correlated quantum materials such as Mott insulators [24], they offer multiple degrees of freedom to emulate neural plasticity, such as lattice reorganization, charge density, spin and orbital states, resulting in robust metal-insulating transitions, Joule heating mechanisms, and magnetization dynamics. From such a miscellaneous of switching mechanisms [25], substantial theoretical and modelling development is

required (and summarized below) to assist comprehension and device response prediction for prominent architectures and integration.

MEMRISTIVE MODELLING AND DESIGNS

Following Chua's memristor formulation [10], various mathematical descriptions have been proposed and tested experimentally, starting with the seminal HP Labs memristor model [26] applied in TiO₂ structures, the linear ion drift model. Extensions/variations of this picture can incorporate stochasticity, diffusion and electro-thermal effects [27], coupled ionic-electronic degrees of freedom [28], short- and long-term memory [29], nonlinearities [30], quantum tunnelling [31], and other materials interface/barrier modulations to cover diverse RS conditions. At atomistic levels, first principles quantum-mechanics methods such as Density Functional Theory are often used to characterize electronic structure and correlations, charge density, optical and magnetic properties, metal-insulating transitions, and other microscopic properties relevant to memristive material design and switching [32].

In analogy to neural network connectivity, interconnection and integration of memristive units are achieved through innovative designs, such as crossbar arrays [33] and amorphous nanowire networks (NWNs) [34, 35, 36]. These realizations have demonstrated prominent learning and neuromorphic functions, including smart sensory and in-memory processing, pattern recognition, associative memory, fault-tolerant operations, (*in-materia*) reservoir computing [37, 38], and spike-timing dependent plasticity. We have been studying random memristive NWNs [39, 40] and showed that they exhibit winner-takes-all behaviour in which a unique conduction pathway is activated. This represents the lowest power consumption state of the material and the encoding of independently addressable memory/conductance states within the network mesh at the conductance quantum range. We recently developed a modular computational framework to simulate multiple memristive properties in NWNs [41], with an initial version available on [42]. Figure 2 is a result from the package depicting current potentiation for a sufficiently dense NWN made of Ag core-shell nanowires subjected to a voltage pulse train. The simulation uses the semiclassical memristive model by Chen *et al.* [29], which considers short-/long-term memory effects, but the package permits easy model alteration. Other simulations included are reservoir-based waveform transformation, bit pattern storage through selective pathways, and associative memory through multi-electrode probing. Future upgrades will include testing quantum tunnelling-based memristive models and emerging algorithms/solid-state systems following quantum neuromorphic computing (QNC) [43] for reliable quantum computing and noisy data processing.

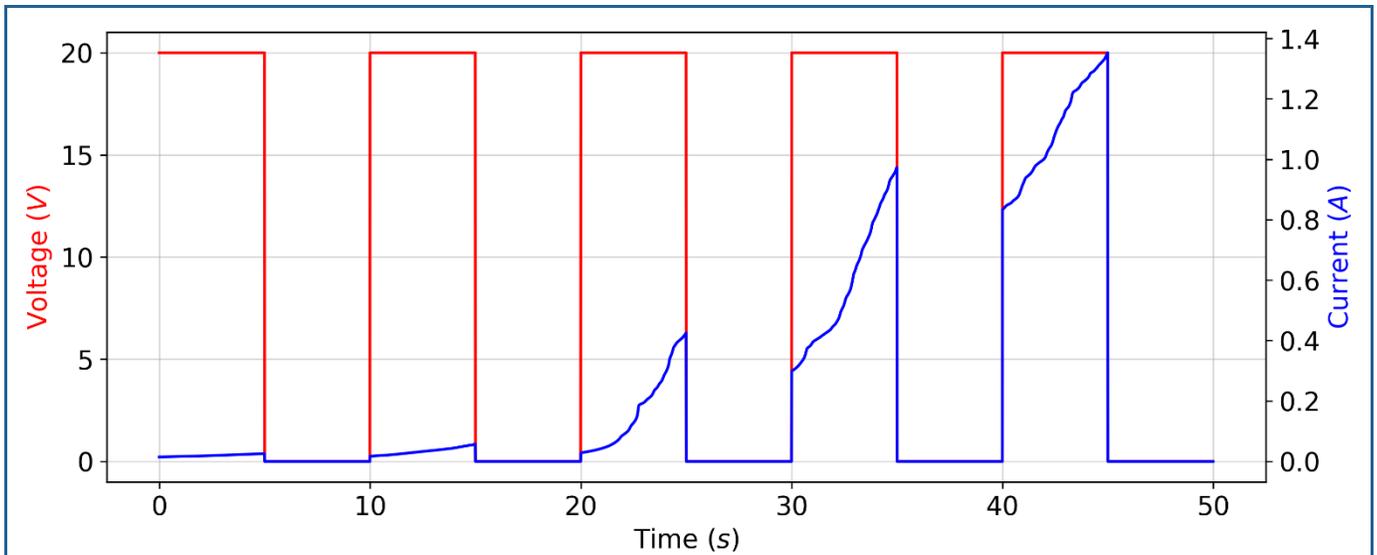


Figure 2. Current potentiation in response to a voltage pulse train simulated in Ag random NWNs using the memristive model by Chen *et al.* [29]. This is a simulation example from our modular computational package to simulate memristive responses in NWNs [41].

CONCLUSION

This contribution showcases a noteworthy literature on memristive systems and quantum platforms for neuromorphic applications. Neuromorphic hardware is not an aspiration; they are in use and early-stage commercialization. Nonetheless, the technology is not yet mainstream due to challenges hindering costs and large-scale production. These include need for noise control and device variability at the nanoscale, as well as a systematic roadmap for co-designing neuro-inspired algorithms compatible with the hardware and multi-task versatility. Moreover, many state-of-the-art neuromorphic chips still depend heavily on conventional CMOS and digital circuitry, meaning that power efficiency and footprint are still not at the human brain standards. Therefore, novel paradigms in brain-inspired computing are emerging, such as multi-terminal memristive systems [44], neuromorphic photonics [45], and QNC [43, 46]. QNC takes the best of both worlds: brain-inspired and quantum systems to accelerate innovation in intelligent quantum computing hardware. Quantum reservoir networks with rich nonlinear dynamics originating from interconnected qubits may offer advantages over existing quantum information technologies due to their superior fault-tolerance to decoherence. According to a recent report by Global Industry Analysts [47], the global market for neuromorphic computing was at US\$87.2 Million in 2024, and is projected to US\$3.6 Billion by 2030, growing at a compound annual growth rate of 85.6% over 2024-2030. Undoubtedly, the transformational impact that neuromorphic and quantum technologies will impart across multiple AI-reliant sectors, such as healthcare, security, transportation, telecommunications, energy, sensors and industry automation, and consumer electronics, is inevitable.

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