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PERSPECTIVE

Across disciplines of emerging neuromorphic systems: from neuroscience to physical chemistry of materials and devices*

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* Inter-community viewpoints are designed to foster interdisciplinary dialogue through paired commentaries from distinct scientific communities. These perspective-style papers aim to illuminate emerging topics in materials science by juxtaposing insights from different disciplines, offering readers a multifaceted understanding of complex challenges and opportunities.

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Abstract

Brain-inspired neuromorphic systems emerged at the interface of neurosciences, material sciences, and electronics. This viewpoint explores this disciplinary intersection, ranging from its biological inspiration to the translation of underlying principles into material and artificial device engineering, while discussing ongoing challenges and opportunities for fundamental or technological breakthroughs. This contribution reflects the perspectives of Juan Bisquert, a leading expert in materials science and electrochemical systems, and Michele Giugliano, a specialist in neuroscience and neuromorphic computing. Their dialogue is moderated and harmonized by Jovana V. Milić, whose interdisciplinary expertise bridges chemical and biological sciences.

Key questions: *How did neuromorphic systems emerge at the intersection of neuroscience, materials science, and engineering? Are neuromorphic systems just 'modeling abstractions' or physical descriptors that teach us about biology? What are the unique features and future prospects for neuromorphic systems?*

1. Background: on the emergence of neuromorphic systems

How has the concept of neuromorphic systems evolved from the different disciplinary perspectives (figure 1), and what are the key motivations in the field today?

> The field of neuromorphic systems, including artificial synapses, neural networks, and 'memristive' devices or 'memristors', has emerged at the intersection of neuroscience, materials science, and electronics. Motivations across disciplines involve building computing systems that emulate, or even surpass, the capabilities of the brain, while offering a better understanding of biological systems.

The growing interest in neuromorphic computing—a field aimed at constructing hardware systems inspired by the structural and functional principles of the human brain—stems from the pursuit of alternatives to conventional complementary metal oxide semiconductor (CMOS) circuits, where computation is not imposed through digital logic but arises organically from the device's physical behavior. This paradigm seeks to replicate essential neural features, such as event-driven signaling, synaptic plasticity, and massive parallelism, which underlie the brain's efficiency and adaptability.

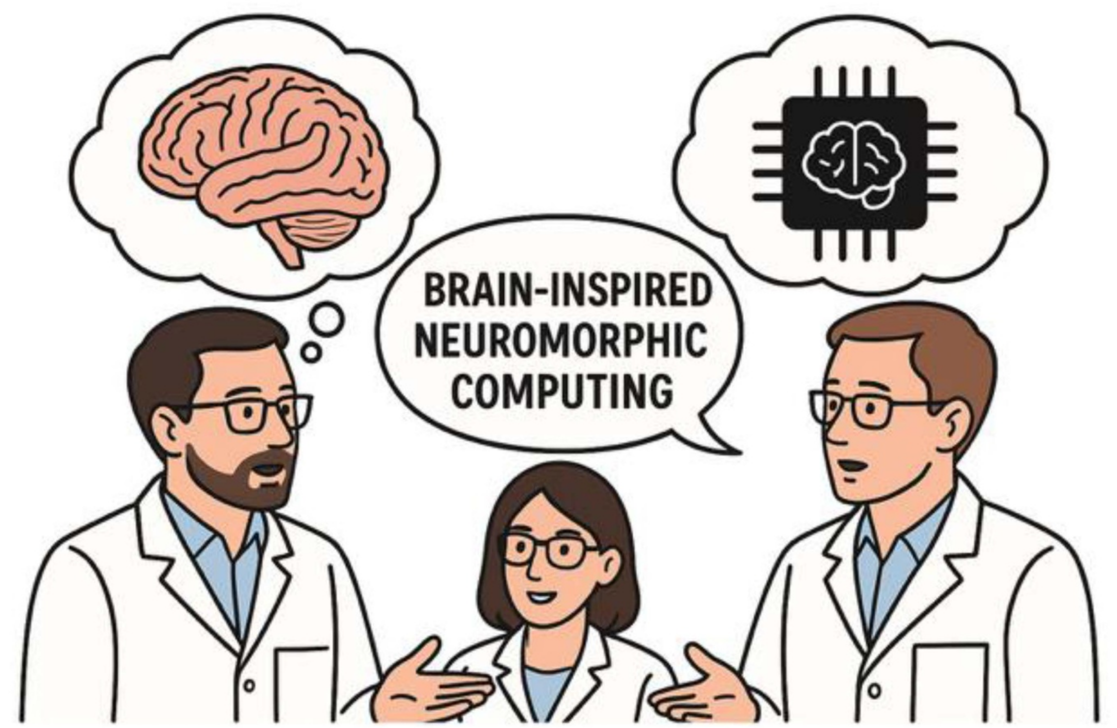

Figure 1. Illustrative representation of the discussion on neuromorphic systems. Created with ChatGPT 5.

From the bioengineering and neuroscience perspectives, the neuromorphic path emerged with non-conventional use of CMOS circuits aimed at mimicking neural functions by imitating the biophysics of excitable membranes [1, 2]. Over the years, the focus shifted from developing artificial systems that embody the core biological principles of synaptic and neuronal dynamics, such as plasticity and adaptation, to a broader hardware implementation of artificial neural networks. In recent years, exploiting the intrinsic properties of novel materials has gained significant momentum and attracted interest for bottom-up rethinking of artificial systems and devices [3–7].

From the materials and physical chemistry perspective, a wide range of systems—including phase-change and oxide-based memories—have demonstrated potential for neuromorphic hardware. Among them, materials exhibiting mixed electronic-ionic conduction [8], such as organic and perovskite semiconductors, conventionally employed in next-generation solar cells, are emerging as promising platforms for neuromorphic hardware due to their intrinsic resistive switching properties, which can be leveraged to emulate synaptic-like behavior in simplified device architectures [9–13]. In this context, physics-based application-specific integrated circuits offer a transformative approach by exploiting the inherent dynamics of physical materials for computation, rather than enforcing idealized digital abstractions. Such hardware-level co-design strategies align algorithmic demands with the native computational capabilities of the physical system, integrating insights from materials chemistry, device physics, and computational modeling to realize brain-inspired architectures. The motivation has not just been to mimic biology but to build architectures where device physics and network dynamics are integrated, involving levels of complexity across materials chemistry, electronics, and modeling [12, 14].

Both neuroscience and material science approaches in neuromorphic systems are driven by an appreciation for the unique characteristics of biological systems. For instance, the multiplicity of *timescales* and the *stochastic features* of the elements of nervous systems are largely recognized to be key for understanding information processing in the brain [15, 16]. Unlike traditional electronics that operate in the nanosecond range and with a fixed 'clock', neural systems process information and adapt with a time scale spanning milliseconds to hours [5, 7, 17, 18]. Even seemingly slow biological processes, such as motor control or some sensory physiology, operate across a variety of timescales that might be reflected in neuromorphic models if the aim is to replicate the brain's performance. These specific considerations highlight the shift from merely attempting to emulate biology *in silico* to leveraging the physical properties of novel materials and physical principles to create functionally equivalent systems. This is key for engineering artificial systems potentially superior to conventional computer and electronic architectures. This requires an in-depth understanding of temporal information processing and dynamic material responses to support and implement neuromorphic computation, encompassing what evolution has provided for biology while also pushing the engineering frontier.

With the emergence of artificial neuromorphic systems, how should we understand and model artificial synapses or memristors—can such models teach us anything about the brain, or are these just approximations?

> With the rise of neuromorphic systems, memristors (i.e. devices that mimic the adaptive behavior of biological synapses through history-dependent resistance changes) have become key models for artificial synapses, capturing essential features like plasticity and adaptation. While they simplify the complexity of biological synapses, these are more than approximations, as they offer a functional lens through which to explore neural principles and may inform both brain-inspired computing and our understanding of the brain itself.

From the perspective of physical and chemical sciences, memristor devices [19] can mimic key aspects of biological synapses, making them essential components in neuromorphic circuits [13]. Beyond synaptic behavior, memristors also support the development of self-sustained oscillations, enabling oscillator-based computation [20]. Moreover, their inherently nonlinear dynamics open pathways for implementing rich computational models grounded in the physical properties of the materials. To this end, memristors are valuable not only for their capacity to emulate synaptic functions—such as activity-dependent conductance modulation—but also for their ability to manifest complex emergent phenomena.

Similarly, trends in bioengineering and neuroscience suggest that the complex dynamic features are central to dissecting the blueprints for how biological systems handle temporal information and plasticity [21]. While traditional CMOS circuits are fast (i.e. ns timescales), they fail to capture the behaviorally relevant timescales of biological systems, often operating several orders of magnitude slower. When interacting with the environment, slower dynamics (e.g. ms timescales corresponding to those of mixed ionic-electronic conductors) are crucial for implementing synaptic plasticity, such as adaptation, and must be embodied in the materials rather than simulated externally. This has implications in the real world, as in physiological signal modeling, where artificial systems must respond on the order of seconds, mirroring the time constraints of biological induction and feedback, to classify or react in closed-loop to pathological changes. The understanding and control of such temporal information processing and dynamics in artificial materials would enable the emulation of biological systems and push beyond biology towards novel forms of computation.

2. From biological systems to material and device engineering

Biological systems encode memory across timescales—can time-dependent processes in synapses and their volatility inform the design of artificial systems to emulate 'temporal coding'? Neural responses are also intrinsically stochastic—can material stochasticity be harnessed or should it be engineered out? Biological neurons operate with remarkable energy efficiency and adaptability—what lessons can be learned that may guide the neuromorphic systems design?

> Biological systems rely on temporal coding through dynamic behavior, volatility, and stochasticity, as well as high connectivity and energy efficiency, which inspire neuromorphic systems. Artificial systems strive to enable a better understanding of biology while emulating and surpassing some of these features in the development of novel computing principles, where slower timescales, constructive use of noise, and energy efficiency are unique characteristics for new technologies.

From the neurosciences perspective, biological systems operate under constraints of limited resources, which leads to a hierarchy of plasticity and memories, each associated with different timescales. This natural volatility enables systems to rapidly learn and forget, which are essential features for interacting with the environment in real time with limited resources. In contrast to machine learning architectures (ML), such as large language models (LLMs), which rely on vast amounts of data and static memory, biological intelligence benefits from its capacity to filter, forget, and adapt, producing transient and context-specific memory traces, evolving from an extraordinarily limited data sampling. These dynamic fingerprints decay over time, much like dissipative systems, making them naturally suited for scalable integration.

From the materials point of view, the critical question remains how such volatile biological behaviors can be effectively integrated into artificial physical systems at scale. For instance, this refers to the concept of reservoir computing, where large, dynamical systems (like networks of memristors) could perform complex computations without control over each component. In biology, size and heterogeneity, typically seen as limitations, can be critical features, enabling robust behavior and emergent functions through high connectivity with low energy consumption.

Biological systems are inherently **stochastic**, and noise acts as a feature, rather than a 'bug'. Engineers may need to learn to embrace noise as well as device heterogeneity, rather than eliminate it, as biology evolved to tolerate and even exploit noise for flexible and 'creative' responses. This may link to the **limits of connectivity** in artificial systems. While biological systems grow connections at a very low metabolic cost, artificial systems may leverage light or other stimuli to expand connectivity through the multifunctionality of materials and their assemblies, though this may come with trade-offs of energy consumption and complexity.

To this end, **energy efficiency** is a key feature. The power performance of biological systems is remarkably efficient, functioning with just a few watts of energy, and neuromorphic engineering should consider these principles. Unlike early transistor designs in neuromorphic hardware, which explored analog and subthreshold low-power modes, modern hardware often sacrifices efficiency for computational purposes. Yet the energy demands of ML are becoming unsustainable, making biologically inspired computing an increasingly attractive alternative. Moreover, as emerging applications require real-time responsiveness, there is a growing need for energy-efficient, edge-based learning to overcome the latency and connectivity constraints of cloud-based systems [22, 23]. While critics argue that 'a small nuclear plant' might easily satisfy cloud-based LLM, we should remember that over 10 years are typically required to build such a plant. Adopting the biological 'power budget' in artificial devices implies leveraging the whole system-level organization of the brain, including glial cells and metabolic regulation, to inspire more efficient architectures. For instance, glial cells, particularly astrocytes, form a parallel information-processing network via slow-propagating calcium waves that occur intracellularly and propagate across neighboring cells [24–26]. Such a mode of operation inspires novel architectures capable of combining fast, spike-based computation with slower signaling layers for managing global collective states or resource allocation. From a metabolic standpoint, the brain's remarkable power efficiency provides a clear blueprint for energy-aware hardware. The 'on-demand' energy delivery mechanism [27] plays an important role in the foundational inspiration for event-driven, asynchronous neuromorphic hardware [28]. In these systems, power is consumed only by active circuits processing spikes, mirroring the biological principle of delivering metabolic resources precisely where computation occurs. This extends to hierarchical power management, where 'astrocyte-like' control circuits could locally gate power to neural cores based on activity. Finally, the high energetic cost of synaptic plasticity suggests that learning itself may be metabolically gated [29]. This inspires neuromorphic models where synaptic weight updates are 'committed' to memory only when a local energy-availability signal confirms sufficient resources, ensuring efficient and stable on-chip learning [30]. To lead this transformation in modern computing, it is crucial to understand the dynamic behavior, which is in its early stages.

In summary, time and dynamics are central to the neuromorphic systems paradigm. Rather than static representations, information in these systems is encoded in temporal patterns, such as spikes, delays, and oscillations, which reflect the complex, time-varying nature of real-world environments. While still in early stages, materials capable of reproducing these dynamics offer a new model of computation that is energy-efficient, adaptive, and potentially transformative in artificial systems that are more intelligent, interactive, and compute in fundamentally new ways.

3. Challenges and opportunities

What are the key challenges and opportunities for memristive materials and neuromorphic systems?

> The integration of memristive materials into neuromorphic systems presents both challenges and opportunities. This refers to the complexity of integrating materials into scalable systems, their lack of standardization, and the difficulty in translating biological processes into artificial systems. The efforts to overcome these challenges reveal new paradigms in understanding natural systems with implications for mimicking and surpassing them through artificial and hybrid technologies.

Many of today's obstacles in neuromorphic systems can be reframed as design opportunities. Biological systems often operate with minimal yet sufficient mechanisms, such as spike-timing-dependent plasticity, which suggests that complexity might still emerge from simple, robust rules. Scaling may be better understood through biological variation, not as an engineering challenge, but as an opportunity to understand how structure and function co-evolve and emerge. Material engineering emphasizes the importance of integration, as neurons not only compute but also sense and adapt to their environment in coupled functions that remain challenging to design, model, and integrate at the material level. Another example of this is the retina, where sensing and processing occur simultaneously, showcasing the need for systems that can couple sensing with communication, ensuring the system functions coherently as a network.

Furthermore, conventional ML systems, such as LLMs, are powerful yet resource-intensive, with limited scalability due to high energy consumption. Instead, neuromorphic systems offer a more efficient path that is adaptive and capable of interacting with the physical world. The scientific value of artificial neuromorphic systems also lies in developing the understanding of emergent behavior, advancing computational neuroscience, and building hybrid platforms. Materials science is uniquely positioned to advance such emergent complexity, although traditional industries may still need to adopt these innovations. The convergence of neuroscience, materials science, and device engineering appears to be laying the groundwork for a paradigm shift, driven not only by bioinspiration but also by artificial systems, which enable computation beyond nature.

Author Note

Michele Giugliano, a bioengineer and neuroscientist, is an Associate Professor at the University of Modena and Reggio Emilia. His career spans posts at the EPFL, University of Antwerp, and SISSA, focusing on Physiology, Neuroengineering and Computational Neuroscience.
Juan Bisquert, Distinguished Research Professor at Instituto de Tecnología Química (UPV-CSIC, València) and Executive Editor of J. Phys. Chem. Lett., is Highly Cited (2014–2024). His ERC-funded research develops perovskite-based neuromorphic devices, exploiting ionic-electronic memristors and transistors for bio-inspired computation.
Jovana V. Milić is an Associate Professor at the University of Turku in Finland. She leads the Smart Energy Materials team, invested in the development of bioinspired materials for sustainable energy conversion technologies, with a special interest in photovoltaics and neuromorphic systems.

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