

Review

Reimagining Robots: The Future of Cybernetic Organisms with Energy-Efficient Designs

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Abstract: The development of cybernetic organisms—autonomous systems capable of self-regulation and dynamic environmental interaction—requires innovations in both energy efficiency and computational adaptability. This study explores the integration of bio-inspired liquid flow batteries and neuromorphic computing architectures to enable real-time learning and power optimization in autonomous robotic systems. Liquid-based energy storage systems, modeled after vascular networks, offer distributed energy management, reducing power bottlenecks and improving resilience in long-duration operations. Complementing this, neuromorphic computing architectures, including memristor-based processors and spiking neural networks (SNNs), enhance computational efficiency while minimizing energy consumption. By integrating these adaptive energy and computing systems, robots can dynamically allocate power and processing resources based on real-time demands, bridging the gap between biological and artificial intelligence. This study evaluates the feasibility of integrating these technologies into robotic platforms, assessing power demands, storage capacity, and operational scalability. While flow batteries and neuromorphic computing show promise in reducing latency and energy constraints, challenges remain in electrolyte stability, computational framework standardization, and real-world implementation. Future research must focus on hybrid computing architectures, self-regulating energy distribution, and material optimizations to enhance the adaptability of cybernetic organisms. By addressing these challenges, this study outlines a roadmap for reimagining robotics through cybernetic principles, paving the way for applications in healthcare, industrial automation, space exploration, and adaptive autonomous systems in dynamic environments.



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1. Introduction

The term “cybernetic organism” has historically been used interchangeably with “cyborg”, denoting beings that combine biological and mechanical systems, as firstly defined by Clynes and Kline [1]. In contrast, this paper revisits the original intent proposed by Norbert Wiener, who focuses on biological-machine analogies, system integration, and open adaptive systems [2]. A similar definition is recently proposed by Groumpos [3]; however, the author calls this field cybernetic artificial intelligence (CAI). In our context, a *cybernetic organism* is an entirely artificial being—one that mimics the biological processes of a living being using advanced materials, computational frameworks, and energy systems, without reliance on biological cells or neurons. This approach shifts the paradigm from augmenting humans to creating self-regulating, dynamic systems that emulate natural

efficiencies and adaptability through artificial means. By using established and emerging technologies, we aim to conceptualize robots that not only function, but also thrive in complex environments, embodying lifelike characteristics while retaining the precision and reliability of machines.

Traditional robotics, despite its rapid advancements, continues to rely on computational architectures and energy solutions that introduce critical limitations. Von Neumann-based computing models, which separate memory and processing units, create a bottleneck in data transfer, restricting real-time decision making and increasing power consumption. At the same time, most robotic systems depend on conventional solid-state batteries, which, although well established, offer limited flexibility, struggle with scalability, and cannot efficiently distribute energy across complex robotic frameworks [3]. These constraints have hindered progress in developing autonomous, self-sustaining machines capable of operating in dynamic, unpredictable environments.

To address these challenges, this paper proposes a cybernetic design paradigm that integrates neuromorphic computing architectures and bio-inspired energy storage systems. By drawing inspiration from biological models, the approach proposes the use of non-von Neumann computing paradigms such as memristor-based processors, neuromorphic chips, and spiking neural networks, which replicate the efficiency and adaptability of neural processing in biological organisms [4]. At the same time, bio-inspired energy systems, particularly redox flow batteries (RFBs), provide a novel mechanism for energy distribution that mimics vascular networks, offering a scalable, adaptable, and resilient power management solution for robotic applications [5]. The integration of these two technologies represents a shift toward robotic systems that operate with greater efficiency, enhanced adaptability, and improved long-term sustainability.

While the feasibility of this concept has been questioned, emerging research provides evidence that neuromorphic computing is already being implemented in real-world robotic tasks, particularly in adaptive control, real-time decision making, and energy-efficient processing [4]. Likewise, experimental work on liquid battery-powered robotic prototypes demonstrates the practicality of flow batteries for distributed energy management, supporting the idea that vascular-like power systems can be adapted for autonomous machines [6]. Although these developments are still in their early stages, they indicate a promising trajectory toward integrating these technologies in next-generation robotics.

This paper aims to establish a theoretical framework for cybernetic organisms that merge neuromorphic computing with bio-inspired energy systems, while also synthesizing existing empirical evidence to assess the feasibility of such an approach. Additionally, it provides a structured research roadmap, identifying the challenges that must be addressed for practical implementation, including scalability, hardware integration, and software-hardware co-design. By uniting advances in computational efficiency and distributed energy systems, this work envisions a new class of cybernetic organisms with the potential to surpass conventional robotic limitations, offering a step forward in the evolution of autonomous, intelligent, and self-sustaining machines.

2. Toward Cybernetic Organisms: Advances and Challenges in Robotics

Robotics has progressed from simple mechanical constructs to highly sophisticated machines with advanced sensory integration and autonomous decision making. Despite these advancements, modern robots still face fundamental challenges in adaptability, energy efficiency, and computational processing, which limit their ability to mimic the dynamic responsiveness of biological organisms. This section examines key innovations that are shaping the future of cybernetic organisms, focusing on neuromorphic computing, bio-inspired energy systems, and non-von Neumann architectures. In doing so, it also

considers the practical constraints of these emerging technologies, addressing both their current feasibility and the conditions under which they offer advantages over traditional approaches.

2.1. Neuromorphic Computing: Advances, Challenges, and Feasibility in Robotics

The computational needs of modern robotics have far outpaced the capabilities of traditional von Neumann architectures. The fundamental limitation of this design lies in the separation of memory and processing units, a structural constraint known as the von Neumann bottleneck. Because information must continuously shuttle between these two components, data transfer inefficiencies emerge, increasing power consumption and slowing computational speed. While these inefficiencies may be acceptable for conventional computing applications, they pose significant challenges in real-time robotic control, sensory processing, and decision making, where rapid and efficient computation is critical. As robotic systems advance towards higher levels of autonomy and adaptive behavior, overcoming this bottleneck becomes essential for achieving true cybernetic organisms [7,8].

The use of a non-von Neumann architecture for creating thinking cybernetic organisms, is founded in the works of Mira [4]. His research emphasizes bio-inspired and embodied paradigms in artificial systems, arguing that biological intelligence cannot be effectively replicated using traditional computational models. He critiques the rigidity of von Neumann architectures, highlighting their limitations in solving dynamic, real-world problems where learning, adaptability, and decentralized control are required. Instead, Mira proposes a connectionist and situated approach, where distributed, biologically inspired processing models—such as spiking neural networks—are used to enable systems to learn and adapt in real time. His call for integrating symbolic, connectionist, and situated paradigms provides a framework for designing flexible and efficient architectures that can support truly autonomous and adaptive robots. By focusing on interdisciplinary collaboration and bio-inspiration, Mira's work justifies the need for hybrid computational approaches that leverage the strengths of both neuromorphic computing and non-von Neumann designs while overcoming the constraints of conventional models.

2.1.1. Neuromorphic Computing: Beyond Traditional Architectures

Neuromorphic computing presents a transformative alternative to von Neumann constraints, offering a paradigm shift in robotic intelligence. Unlike clock-driven processors, which process information in discrete time steps, neuromorphic chips operate asynchronously, mimicking the way that biological neurons communicate. This event-driven processing model allows for energy-efficient, low-latency computations, making neuromorphic chips particularly well suited for real-time robotic decision-making. Instead of relying on separate memory and processing components, neuromorphic systems integrate memory directly within their processing units, allowing data to be stored and retrieved in a biologically inspired manner.

The most well-known implementations of neuromorphic computing include IBM's TrueNorth and Intel's Loihi chips, both of which have demonstrated substantial improvements in energy efficiency and real-time learning. TrueNorth, for example, can process up to 46 billion synaptic operations per second while consuming only 20 milliwatts, an efficiency that translates to just 0.00043 nanojoules per synaptic event—a stark contrast to traditional processors, which require several nanojoules per event [9]. Similarly, Loihi achieves up to 2500 times the energy efficiency of standard GPUs during event-driven processing, reinforcing its viability for autonomous robotic applications where energy constraints are paramount [10]. These advantages make neuromorphic computing particularly suitable for disaster response robots, deep-space exploration systems, and long-duration

autonomous operations, where power resources are limited, and efficiency is a necessity rather than a luxury.

2.1.2. Adaptive Learning and Sensory Integration in Cybernetic Organisms

Neuromorphic computing not only enhances computational efficiency but also revolutionizes sensory integration and adaptability in robotic systems, closely aligning with the cybernetic principles of feedback, control, and dynamic adaptation. Traditional AI models rely on large, pre-trained datasets and struggle with real-time adaptation, whereas neuromorphic systems excel at continuous learning and self-modification. Mimicking biological synaptic plasticity, neuromorphic architectures allow robots to dynamically refine their responses based on environmental stimuli, enabling self-regulated learning.

One of the most striking demonstrations of this capability can be found in tactile perception tasks, where neuromorphic processors enable robotic hands to classify textures through real-time interaction. This ability to learn on the fly eliminates the need for exhaustive preprogramming, dramatically increasing the autonomy of robotic systems. Additionally, neuromorphic chips exhibit synaptic stability, a property that ensures learned behaviors are retained over time. While plasticity allows for adaptation, stability prevents catastrophic forgetting—a crucial factor in long-term robotic applications. Intel's Loihi chip, for example, has been shown to consolidate learned behaviors while integrating new sensory inputs, mirroring the way biological synapses stabilize neural circuits during ongoing learning processes [10]. This balance between adaptability and stability enhances the robustness of neuromorphic robots, ensuring consistent performance even in unpredictable environments.

In autonomous robotics, neuromorphic processing allows for self-compensating behaviors when sensor failures occur. For example, TrueNorth-based robots have demonstrated the ability to recalibrate sensory pathways when input signals are disrupted, ensuring continued functionality despite partial system failures [11]. This resilience is critical in mission-critical applications such as planetary exploration, where robotic systems must function independently despite environmental hazards and component degradation.

2.1.3. Neuromorphic Computing in Multi-Sensory Robotics and Real-World Applications

Another advantage of neuromorphic computing is its capacity for multimodal sensory integration, a critical requirement for cybernetic organisms. Unlike traditional processors, which process inputs sequentially, neuromorphic architectures allow robots to integrate multiple sensory inputs—such as vision, touch, and sound—simultaneously. Event-based vision sensors, for instance, when combined with neuromorphic chips, significantly improve high-speed object detection and tracking. This capability is particularly beneficial for disaster response robots operating in environments with rapidly changing conditions, such as collapsing structures, where fast, adaptive perception is crucial to locating survivors efficiently [12].

In space exploration, neuromorphic processors are emerging as a preferred solution for autonomous planetary rovers and probes operating in resource-scarce environments. NASA has explored Loihi-based processors for terrain navigation, allowing rovers to learn and adapt to environmental changes on the fly while consuming minimal power. By processing sensory inputs locally, neuromorphic systems reduce reliance on high-power central computing units and minimize latency, making them well-suited for long-duration missions where energy conservation is essential [13].

Beyond autonomous exploration, neuromorphic computing is proving valuable in biomedical robotics, particularly in prosthetics and exoskeletons. Spiking neural networks can provide real-time adjustments to motor functions in robotic limbs, enabling smoother

and more natural movement. Niu et al. [14] demonstrated that neuromorphic processors could dynamically refine motor actions based on user feedback, allowing prosthetics to operate with human-like precision. These innovations represent a critical step toward integrating robotic systems into human-centric applications, where adaptability and responsiveness are paramount.

2.1.4. Boundary Conditions and Future Directions for Neuromorphic Robotics

While neuromorphic computing offers numerous advantages, its adoption is not universal, nor does it outright replace traditional von Neumann architectures. There remain specific conditions where conventional processing remains the more practical choice, particularly in applications requiring raw computational power over energy efficiency. Industrial robotics operating in stable environments, for example, can still benefit from von Neumann systems, as energy constraints are less of a limiting factor, and traditional computing models offer greater compatibility with existing AI frameworks.

Additionally, the neuromorphic field faces challenges related to standardization and scalability. The lack of widely adopted programming frameworks for spiking neural networks has slowed broader implementation, as developers must rely on specialized, hardware-specific tools such as Intel's Lava framework or open source alternatives like NEST and Brian2 [6]. Moreover, scaling neuromorphic chips remains a significant engineering hurdle, as increasing neuron and synapse density introduces bottlenecks in connectivity and heat dissipation.

Nevertheless, as research progresses, hybrid computational approaches that combine the best elements of neuromorphic and von Neumann architectures may provide the most effective path forward for cybernetic organisms. A key factor in this evolution is the development of specialized neuromorphic chips, each designed to optimize performance for different robotic applications. From IBM's TrueNorth to Intel's Loihi and beyond, selecting the right neuromorphic hardware is crucial to achieving energy-efficient, adaptive robotic intelligence.

2.2. Prominent Neuromorphic Chips for Designing Cybernetic Organisms

Neuromorphic computing is rapidly evolving, with specialized hardware emerging to bridge the gap between biological and artificial intelligence. These chips are designed to mimic the efficiency of the human brain, offering event-driven computation, low power consumption, and real-time adaptability—key characteristics for the next generation of cybernetic organisms. While traditional CPUs and GPUs remain dominant in many AI applications, neuromorphic chips offer distinct advantages in low-power, real-time adaptive control, making them particularly well suited for autonomous robotics, prosthetics, and real-time decision-making in energy-constrained environments.

Several neuromorphic hardware architectures have been developed, with each optimized for different applications. Table 1 compares some of the most prominent neuromorphic chips based on neuron capacity, energy efficiency, memory integration, and primary use cases.

Selecting an appropriate neuromorphic chip for a cybernetic organism depends on the specific requirements of the system. Each of these chips presents unique strengths and trade-offs, making hardware selection highly dependent on the target robotic application. IBM's TrueNorth, for example, with its high synaptic operation efficiency, is well suited for low-power vision processing and pattern recognition tasks. In contrast, Intel's Loihi, which supports on-chip learning, offers greater adaptability, making it a strong candidate for autonomous robots that need to continuously refine their decision making [9,10].

Table 1. Comparison between prominent neuromorphic chips.

Neuromorphic Chip	Neuron Count (Approx.)	Processing Architecture	Energy Efficiency (Power)	Memory Integration	Primary Applications
IBM TrueNorth	1 million	Spiking Neural Network (SNN)	20 mW	Non-volatile SRAM	Vision, pattern recognition
Intel Loihi	128,000 per chip	SNN	100 mW	In-memory computing	Navigation, real-time robotics
SpiNNaker	1 million+	SNN	Low (10–50 mW typical)	External DRAM	Large-scale neural simulations
Tianjic	Hybrid design (not fixed)	Hybrid (SNN and von Neumann)	Not specified, hybrid	Integrated SRAM and DRAM	Autonomous vehicles, robotics
Dynap-SE	Dynamically configurable	SNN	Low (edge computing focus)	Integrated memory	Wearables, edge robotics
BrainChip Akida	1.2 million synapses	Event-based CNN	Ultra-low (<5 mW typical)	Integrated memory	Object tracking, vision
Neurogrid	1 million+	SNN	Low	Custom DRAM	Adaptive robotics, research
IBM Dynap-CNN	Focused on CNNs	CNN-focused	Focused on efficiency	Integrated for CNN	Image recognition, robotics

While TrueNorth and Loihi dominate the discussions of neuromorphic AI, other architectures introduce hybrid models. Tianjic, for instance, integrates both spiking neural networks (SNNs) and conventional deep learning models, allowing it to perform efficiently in multi-modal AI systems, such as autonomous vehicles and human–robot interaction interfaces [11]. Meanwhile, BrainChip’s Akida leverages event-based convolutional neural networks, making it an ultra-low-power solution for edge AI applications like object detection in wearables and mobile robotics.

A major challenge in scaling neuromorphic systems is efficiently increasing neuron and synapse density while maintaining connectivity. SpiNNaker, for instance, is specifically designed for large-scale neural simulations, yet its reliance on external DRAM introduces latency that may limit real-time robotics applications. In contrast, chips like Loihi and Dynap-SE, which integrate memory within their architecture, offer greater energy efficiency and lower data transfer delays, making them more practical for embodied robotic intelligence.

Despite their impressive advantages, neuromorphic chips are not universally superior to traditional computing architectures. Their strength lies in power efficiency and real-time adaptive learning, which is invaluable for low-power, continuously learning systems such as prosthetics, autonomous drones, and planetary rovers operating in energy-scarce environments [12,13]. However, for applications requiring high computational throughput, deep learning acceleration, or compatibility with existing AI models, conventional GPUs and TPUs remain the preferred choice. Industrial automation, cloud-based AI inference, and high-speed numerical computing continue to favor traditional architectures due to their raw processing power and well-established software ecosystems. As neuromorphic computing advances, hybrid approaches combining spiking neural networks with traditional von Neumann architectures may provide the most effective solution for cybernetic organisms. Recent research suggests that neuromorphic chips could complement GPUs rather than replace them, handling real-time perception while offloading high-level processing to external accelerators. Emerging developments in memristor-based computing may further improve scalability and integration, paving the way for cybernetic organisms that process information with brain-like efficiency while maintaining computational flexibility.

2.3. Current Challenges of Neuromorphic Chips

The practical deployment of neuromorphic systems presents several significant challenges that must be addressed before they can become widely adopted in cybernetic organisms. While neuromorphic chips offer substantial energy efficiency and real-time adaptability, their integration into broader AI and robotic ecosystems is still hindered by issues related to programming frameworks, scalability, hardware compatibility, reliability, and manufacturing constraints.

2.3.1. Lack of Standardized Programming Frameworks

One of the most pressing challenges in neuromorphic computing is the absence of standardized frameworks for programming spiking neural networks. Unlike deep learning models, which benefit from well-established libraries such as TensorFlow and PyTorch, SNNs require specialized approaches that incorporate the temporal dynamics of spiking activity. Developing and debugging neuromorphic systems often demands extensive expertise, making them less accessible to a broader community of researchers and engineers.

Efforts to bridge this gap have resulted in the development of various tools. Intel's LAVA framework [15] provides a hardware-accelerated, open source solution for SNN development, aligning with community-driven software trends. Other notable frameworks, such as NEST [16] and Brian2 [17], allow researchers to experiment with SNNs independently of specific neuromorphic hardware. PyNN [18] and GeNN [19] provide additional flexibility by offering cross-platform support, helping bridge the gap between proprietary and open source neuromorphic systems. Despite these advancements, programming neuromorphic hardware remains significantly more complex than traditional AI development, slowing widespread adoption.

2.3.2. Scalability Limitations and Hardware Constraints

Scalability is a major obstacle in neuromorphic chip development. The physical limitations of interconnect density, power consumption, and heat dissipation restrict the ability to scale neuromorphic architectures efficiently. Managing large-scale spiking networks introduces additional computational overhead, as neuron-to-neuron communication must be carefully synchronized to prevent bottlenecks. Unlike traditional processors that scale primarily through higher transistor density, neuromorphic systems face unique challenges in maintaining efficient spike-based communication as networks grow in complexity.

Chip manufacturers have adopted different strategies to tackle these challenges. Intel's Loihi employs a hierarchical mesh interconnect topology, enabling efficient communication between numerous cores while reducing neuron-to-neuron bottlenecks. By leveraging sparse neural activity, Loihi processes only active neurons at any given time, dramatically reducing the computational overhead. The second-generation Loihi 2 chip expands on this approach by increasing the configurability for neuron and synapse models, allowing larger and more complex networks to be simulated without excessive resource consumption.

IBM's TrueNorth takes a modular approach, simulating 1 million neurons and 256 million synapses per chip, which can be tiled together to expand system capacity. However, performance at larger scales remains constrained by interconnected limitations. Similarly, SpiNNaker, developed by the University of Manchester, scales through thousands of ARM cores using custom routing algorithms to facilitate distributed processing. Despite these innovations, power demands and memory constraints continue to limit the scalability of neuromorphic architectures.

Emerging technologies, such as memristor-based chips and crossbar architectures, provide potential pathways for improving scalability. Memristors, which mimic biological synaptic plasticity, allow for the denser integration of neurons and synapses while reducing

communication overhead. However, these designs are still in their early stages, and their feasibility for large-scale deployment remains an open question.

2.3.3. Integration Challenges with Von Neumann Architectures

Another critical barrier is the difficulty of interfacing neuromorphic systems with traditional von Neumann architectures. Neuromorphic processors rely on event-driven SNNs, whereas conventional architectures process data sequentially using clock-driven methods. This fundamental difference complicates integration with existing AI and robotics ecosystems, where most machine learning models and control algorithms are designed for conventional computing paradigms.

Efforts to bridge this gap have focused on middleware solutions and hierarchical translation protocols. Recent research [20–22] has demonstrated that hybrid computing frameworks can synchronize spiking events with conventional data streams through abstraction layers. Modular middleware architectures help reduce inefficiencies in memory access patterns and interconnect synchronization.

Intel's Loihi has integrated solutions that enhance compatibility with von Neumann platforms, leveraging sparse event-based communication to facilitate seamless hybrid operations. These developments are essential for neuromorphic computing to be incorporated into broader AI workflows, including cybernetic organisms that rely on both conventional and biologically inspired processing.

2.3.4. Reliability and Fault Tolerance in Neuromorphic Systems

Reliability remains a challenge due to the stochastic nature of spiking neural networks. Unlike deterministic von Neumann processors, neuromorphic systems operate probabilistically, which introduces variability in computation. This randomness can lead to unstable performance in robotics and other safety-critical applications.

Environmental noise and hardware faults further complicate reliability. Studies have shown that spiking neural networks are highly sensitive to synaptic faults, which can result from hardware degradation, thermal variations, or random fluctuations in spike generation. Guo et al. [23] emphasize that these issues can lead to unpredictable performance degradation.

To address these challenges, researchers have developed fault-tolerant neuromorphic architectures. Rate-coding mechanisms and spike-burst strategies improve computational robustness, ensuring that errors in individual spikes do not disrupt the overall system performance. Homeostatic mechanisms, such as adaptive synaptic weight adjustments, help maintain stable network activity, even in the presence of hardware-induced faults. Johnson et al. [24] propose self-regulating spiking networks that dynamically compensate for degraded synaptic pathways, preventing catastrophic failures. Additionally, Vu et al. [25] introduced fault-tolerant spike-routing architectures that ensure consistent neural communication, even under varying levels of noise.

2.3.5. Manufacturing and Resource Constraints

Beyond technical limitations, manufacturing neuromorphic hardware at scale remains a significant challenge. While memristors and other novel computing elements promise greater efficiency and compact integration, their production is still hindered by high costs, fabrication variability, and supply chain limitations. Currently, the large-scale fabrication of neuromorphic processors lags behind traditional silicon-based computing due to immature manufacturing processes and the need for the more precise calibration of new materials.

Despite these obstacles, recent advancements in hardware–software co-design have improved production efficiency. New fabrication techniques for memristor-based AI accelerators aim to reduce variability and increase manufacturing yield [26–29]. As these

technologies mature, neuromorphic computing may become more viable for the large-scale deployment in cybernetic organisms.

2.4. Safety and Security Concerns of Neuromorphic Chips

Neuromorphic systems and traditional CPUs/GPUs differ significantly in their resilience to electromagnetic interference (EMI) and cybersecurity risks, two crucial factors for the safety and security of cybernetic organisms. Due to their distributed processing architecture and lower operating frequencies, neuromorphic systems exhibit greater resilience to EMI compared to centralized and clock-dependent CPUs and GPUs [30]. The event-driven nature of neuromorphic processors allows them to dynamically reroute operations, minimizing the impact of electromagnetic disturbances. In contrast, traditional processors rely on high-frequency clock signals and centralized memory buses, making them inherently more vulnerable to EMI-induced disruptions. However, conventional computing architectures benefit from well-established shielding techniques to mitigate these risks [31].

From a cybersecurity perspective, neuromorphic systems introduce emerging vulnerabilities due to their novel architectures. One major concern is the retention of state information in memristive devices [32], which, if compromised, could allow attackers to extract sensitive learned patterns, potentially revealing AI decision-making processes or exposing confidential training data [33,34]. Unlike traditional CPUs and GPUs, which use volatile memory that erases state information upon shutdown, neuromorphic architectures retain learned weights persistently, creating a potential attack vector. In contrast, traditional processors, while benefiting from trusted platform modules and secure boot protocols, remain susceptible to known attacks like speculative execution vulnerabilities. Table 2 outlines the main characteristics of traditional and neuromorphic systems in terms of security.

Table 2. A comparison between neuromorphic systems security and traditional computer systems.

Aspect	Neuromorphic Systems	Traditional CPUs/GPUs
Resilience to EMI	High (distributed architecture, low frequency)	Moderate (centralized clock dependency)
Power and heat emission	Low	High
Attack surface	Emerging vulnerabilities, fewer established tools	Known vulnerabilities, mature defenses
Physical exploits	Retains state in memristors (risk of data theft)	Volatile memory, harder to extract data
Software exploits	Resilient to centralized attacks	Susceptible to OS or firmware-level attacks
Encryption and security	Emerging protocols needed	Well-established protocols and tools

To counter these threats, neuromorphic security researchers have proposed integrating encrypted synaptic weights and real-time anomaly detection mechanisms. By using their asynchronous, event-driven design as an advantage, neuromorphic processors could dynamically identify and respond to intrusion attempts. Early efforts toward secure neuromorphic computing include research into cryptographically protected neuromorphic circuits and biologically inspired adversarial defense mechanisms. However, these defenses remain in the early stages of development.

While neuromorphic systems offer promising advantages in EMI resilience and adaptive cybersecurity measures, their defensive protocols and hardware-level security mech-

anisms are still evolving. Lessons from traditional computing security, combined with novel approaches tailored to neuromorphic architectures, will be critical in ensuring the safety of cybernetic organisms. Future research must focus on neuromorphic-specific threat modeling, secure synaptic weight encryption methods, and adversarial training techniques to mitigate emerging attack vectors.

3. Energy Efficiency and Environmental Adaptability

One of the most critical challenges in robotics and AI-driven systems is energy management, as both fields struggle with the limitations of current power technologies. Mobile robotic systems typically rely on solid-state batteries, which, despite advances in energy density, suffer from constraints in thermal regulation, scalability, and lifespan. These limitations pose significant challenges for autonomous robots, which require efficient and adaptable power distribution mechanisms to sustain long-term operations.

To address these challenges, recent innovations have explored liquid-based energy systems inspired by biological vascular networks. Rather than storing power in centralized battery cells, these systems circulate electrolyte solutions through robotic frameworks, simultaneously serving as an energy source and a temperature regulation mechanism. This approach, as proposed by Correll et al. [35], enhances resilience against power fluctuations and distributes energy dynamically, much like the circulatory systems of biological organisms. By mirroring nature's decentralized approach to resource management, robots equipped with vascular-like energy networks can optimize power allocation in real-time, improving their adaptability in complex environments.

While traditional AI architectures have been constrained by high energy demands, particularly in large-scale systems [36,37], neuromorphic computing offers a promising alternative by significantly reducing power consumption through event-driven processing and local memory integration. These energy-efficient properties make neuromorphic processors particularly well suited for autonomous systems where power availability is limited. Even large-scale robotic infrastructures, such as industrial automation or planetary exploration systems, require sustainable energy solutions, pushing research toward hybrid power sources that integrate renewable energy, liquid-based storage, and alternative power generation [38,39].

Emerging distributed energy architectures are redefining efficiency in robotics by integrating energy storage, temperature regulation, and adaptive power allocation into a single framework. This not only enables real-time energy prioritization—where critical subsystems receive power based on immediate demand—but also enhances system longevity, reducing the risks associated with thermal degradation and inefficient load distribution [40].

Advancements in energy harvesting technologies further complement these innovations, increasing the autonomy of robotic systems. Photovoltaic cells and piezoelectric materials are being integrated into robotic exoskeletons and soft robotics to enable partial energy self-sufficiency. When combined with vascular-like energy networks, these technologies allow for continuous energy renewal, reducing the dependence on external power sources and extending operational lifespans. By integrating bio-inspired energy storage, adaptive power routing, and sustainable energy harvesting, next-generation cybernetic organisms can achieve greater operational resilience, improved efficiency, and enhanced autonomy in both terrestrial and extraterrestrial environments.

3.1. Flow Batteries as an Integral Part of Cybernetic Organisms

Liquid flow batteries represent a scalable and flexible energy storage technology where liquid electrolytes circulate through electrochemical cells to store and distribute power.

Unlike solid-state batteries, which require fixed cell structures and suffer from degradation over time, flow batteries offer dynamic energy management, rapid recharging, and greater adaptability for complex robotic systems. Their modular design enables seamless energy distribution across multiple robotic subsystems, making them particularly suitable for autonomous and self-sustaining cybernetic organisms.

Recent studies have demonstrated the potential of flow batteries in robotic applications. Liu [41] developed a jellyfish-inspired robot powered by a flow battery, where the system integrates energy storage with propulsion, using a fluid-tendon mechanism for movement and energy distribution [35]. This design highlights the versatility of liquid energy systems in dynamic environments, such as underwater exploration, disaster response, and long-duration autonomous missions. By merging energy storage and actuation into a single fluid-based network, flow battery-powered robots can enhance mobility and operational endurance, overcoming the constraints of centralized battery systems.

The concept of energy autonomy is further enhanced through organic redox flow batteries, which dynamically adjust the energy output based on real-time power demands [42]. This ability to scale energy delivery in response to task complexity allows cybernetic organisms to operate continuously without frequent energy replenishment, making them highly effective for remote and extreme environments. In contrast to traditional battery systems, which require downtime for recharging or swapping, flow batteries enable energy regeneration on-site, drastically improving mission duration and system reliability.

By mimicking vascular energy distribution in biological organisms, flow batteries represent a paradigm shift in robotic power systems, allowing cybernetic organisms to achieve greater energy efficiency, adaptability, and operational longevity.

3.2. Nonaqueous Redox Flow Batteries NRFBs

Nonaqueous redox flow batteries (NRFBs) are emerging as a viable alternative for energy storage in robotics, particularly in scenarios requiring high energy density and flexible power distribution [43]. Unlike their aqueous counterparts, NRFBs achieve energy densities of 100–200 Wh/kg, making them a compact and efficient choice for long-duration autonomous applications [44,45]. Their scalability and modularity allow them to store and deliver power dynamically, optimizing energy distribution based on operational needs without increasing overall system weight.

A key advantage of NRFBs is their compatibility with bio-inspired energy management strategies. By utilizing liquid-phase redox-active molecules, these systems can distribute energy fluidly across robotic subsystems, mirroring biological vascular networks. This adaptive power routing enhances the autonomy of cybernetic organisms, particularly those designed for neuromorphic computing, where energy demands fluctuate dynamically. Unlike solid-state batteries, which operate on fixed discharge cycles, NRFBs enable on-demand energy reallocation, supporting the continuous adaptation to changing environmental and computational conditions.

The potential applications of NRFBs extend to disaster response robotics, deep-space exploration, and autonomous field operations, where power autonomy is essential. Because NRFBs separate energy storage from power conversion, they can be replenished efficiently without the downtime associated with conventional battery swaps or recharging. While current NRFB technology is still in the experimental phase, ongoing research is addressing electrolyte stability and optimizing redox-active materials to enhance real-world applicability. If successfully scaled, NRFBs could offer an integrated energy solution for cybernetic organisms, combining efficiency, adaptability, and long-term operational resilience.

4. Energy Feasibility of Flow Batteries for Cybernetic Organisms

The power and energy output of flow batteries depend on battery size and configuration. Small-scale redox flow batteries, designed for portable robotic applications, typically generate 0.1–5 kWh of power and store 1–20 kWh of energy. Advanced nonaqueous redox flow batteries offer higher energy densities (100–200 Wh/kg), making them a scalable alternative for robotic systems requiring extended operational endurance [43].

Robots equipped with neuromorphic chips, mechatronic actuators, and vision systems exhibit diverse energy demands. Intel's Loihi, for instance, consumes around 0.1–10 Wh, depending on system complexity, while actuators require 50–300 Wh per joint. A fully articulated six-joint robotic system may consume 500 Wh to 1 kWh in total, while vision systems and sensors contribute an additional 40–70 Wh. Given these requirements, a 5–10 kWh redox flow battery could sustain such a system for 5–10 h, with larger NRFBs extending the operational time up to 20 h. While lithium-ion batteries offer slightly lower weight (~40–60 kg), NRFBs present advantages in modularity and distributed power management, making them suitable for robotics operating in remote or autonomous settings.

Despite their potential, the implementation of liquid-based energy systems in robotics introduces several engineering challenges. Electrolyte stability and degradation must be addressed to prevent power fluctuations over extended operations. Additionally, pump mechanisms require optimization to minimize energy losses and leakage risks. The development of closed-loop feedback systems is a critical area of research, enabling real-time energy redistribution while maintaining system longevity [42]. Advanced material innovations, such as bio-compatible electrolytes and self-regulating membrane designs, are being explored to enhance the scalability and robustness of NRFBs for long-duration missions.

Emerging research on nonaqueous flow batteries further enhances their applicability for robotics, particularly in energy-intensive environments. By integrating NRFBs with self-regulating control algorithms, robotic systems can dynamically adjust energy allocation based on real-time demands, reducing energy waste while extending mission durations. Hybrid approaches that combine flow batteries with other energy storage solutions may further optimize performance, ensuring energy feasibility for long-term robotic applications [44–48].

4.1. Energy Harvesting and Renewable Energy Integration

Energy harvesting technologies offer a promising avenue for augmenting robotic energy systems, enabling longer operational lifetimes while reducing reliance on conventional battery storage. By utilizing renewable energy sources such as solar, kinetic, and thermal energy, cybernetic organisms can achieve greater autonomy in dynamic environments.

Hybrid systems combining photovoltaics with liquid flow batteries have demonstrated real-time energy replenishment capabilities, ensuring continuous power supply even in off-grid scenarios [49]. For mobile robotic platforms, piezoelectric and triboelectric generators provide an additional energy source, harvesting mechanical vibrations from movement or external forces. These bio-inspired mechanisms mimic natural biomechanics, where energy is efficiently extracted from motion, contributing to lightweight power solutions for low-energy-demand applications.

Recent advancements in thermoelectric materials allow robots to convert waste heat into usable energy, further enhancing efficiency [50]. This technology is particularly useful in industrial and space applications, where thermal energy dissipation is unavoidable. However, energy harvesting remains inherently limited by environmental conditions, with intermittent solar exposure or insufficient mechanical movement affecting the overall energy output.

To mitigate these constraints, researchers are developing hybrid energy architectures that combine multiple harvesting methods with liquid batteries. These systems integrate adaptive energy management algorithms, allowing robots to dynamically switch between energy sources based on environmental availability, ensuring sustained operation even under variable conditions [51].

4.2. Distributed Energy Networks and Self-Regulation

Distributed energy networks mimic biological metabolic processes, providing localized energy delivery and dynamic resource allocation for autonomous robots. Rather than relying on a single energy reservoir, these systems prioritize power distribution based on real-time demands, ensuring that critical components receive energy without unnecessary waste [40].

In practical implementations, biomimetic robots equipped with energy networks have demonstrated adaptive power allocation during high-demand operations. For example, robotic arms dynamically adjust energy supply based on applied loads, optimizing performance while minimizing mechanical strain. Similarly, drones navigating turbulent environments regulate power to stabilization systems while reducing energy consumption in secondary components [52].

By integrating self-regulating energy architectures with neuromorphic computing, cybernetic organisms can achieve unprecedented adaptability, optimizing energy efficiency based on sensor feedback and real-time computational loads. This approach not only extends operational lifespan but also reduces unnecessary energy waste, making self-regulating power networks an essential component of future robotic systems.

5. Conclusions and Future Work

This study proposes a paradigm shift in the design of cybernetic organisms, integrating neuromorphic computing and bio-inspired energy systems to create adaptive, energy-efficient artificial beings. Rather than adhering to rigid, pre-programmed behaviors, these systems mirror biological adaptability, allowing for real-time learning, dynamic energy management, and operational resilience. At the core of this transformation is neuromorphic computing, which emulates neural processes to deliver low-power, event-driven computation and real-time adaptability. Technologies such as Intel's Loihi and IBM's TrueNorth provide an alternative to traditional von Neumann architectures, enabling cybernetic organisms to process information efficiently in power-constrained environments. However, the real-world deployment of these processors remains limited by scalability and integration challenges, requiring further research into hybrid architectures and programming frameworks.

Complementing these computational advancements, bio-inspired energy systems, such as liquid flow batteries and nonaqueous redox flow batteries, offer distributed power management that mimics vascular networks in living organisms. These systems enhance operational longevity and flexibility, particularly for robots operating in autonomous, energy-scarce environments. Future research should explore more efficient electrolyte compositions, improved flow battery designs, and integration with energy-harvesting technologies to further optimize autonomous robotic power systems.

Moving forward, the successful realization of neuromorphic cybernetic organisms will depend on bridging the gap between adaptive computing and self-regulating energy networks. Key areas for further exploration include the following:

- Developing hybrid neuromorphic-von Neumann architectures to enhance processing efficiency while maintaining compatibility with existing AI frameworks.

- Advancing self-regulating energy systems that autonomously allocate power to robotic subsystems based on real-time computational demands.
- Improving the durability and efficiency of liquid-based batteries, ensuring long-term reliability in extreme environments.
- Refining programming tools for neuromorphic hardware, increasing accessibility and scalability for robotics applications.

By addressing these challenges, this research lays the groundwork for the next generation of cybernetic organisms capable of sustained autonomy, intelligent adaptation, and energy-efficient operation across diverse environments.

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Abbreviations

The following abbreviations are used in this manuscript:

CAI	Cybernetic Artificial Intelligence
CNN	Convolutional Neural Network
DRAM	Dynamic Random Access Memory
EMI	Electromagnetic Interference
FPGA	Field-Programmable Gate Array
LLM	Large Language Model
NRFB	Nonaqueous Redox Flow Battery
RNN	Recurrent Neural Network
SNN	Spiking Neural Network
SRAM	Static Random Access Memory
STDP	Spike-Timing-Dependent Plasticity
TPU	Tensor Processing Unit

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