Neuromorphic computing for ultra-low latency cognitive radio: a paradigm shift toward brain-inspired spectrum intelligence

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Abstract

The emergence of sixth-generation wireless networks demands ultra-reliable low-latency communication capabilities that challenge conventional artificial intelligence approaches in cognitive radio systems. Current digital signal processing architectures face fundamental latency bottlenecks when implementing real-time spectrum decisions, with typical AI-based cognitive radio systems exhibiting millisecond-level response times insufficient for emerging applications requiring sub-millisecond reliability. This review examines neuromorphic computing as a transformative paradigm for cognitive radio systems, leveraging brain-inspired architectures to achieve unprecedented latency and energy efficiency. We analyze recent advances in neuromorphic hardware platforms including Intel Loihi, IBM TrueNorth, and SpiNNaker, demonstrating their application to spectrum sensing, dynamic allocation, and interference mitigation tasks. Through comparison of spiking neural networks against conventional approaches, we reveal performance advantages including sub-millisecond decision latency, two orders of magnitude improvement in energy efficiency, and superior noise resilience in radio frequency environments. The review encompasses recent publications spanning neuromorphic architectures, algorithm development, and experimental validation across cognitive radio applications. We identify critical research gaps in hardware-software co-design, standardization frameworks, and deployment strategies while projecting future directions toward fully neuromorphic cognitive radio systems. Our analysis reveals that neuromorphic computing offers substantial improvements in latency-energy products compared to conventional approaches, positioning it as a key enabling technology for next-generation wireless intelligence.

Keywords

neuromorphic computing, cognitive radio, spiking neural networks, ultra-low latency, brain-inspired computing, spectrum intelligence

1. Introduction

The relentless evolution of wireless communication systems toward sixth-generation networks has created unprecedented demands for intelligent spectrum management operating under stringent latency and energy constraints. Modern cognitive radio systems increasingly rely on artificial intelligence (AI) to make real-time decisions about spectrum access, interference mitigation, and resource allocation [1]. However, conventional AI approaches face fundamental architectural limitations when deployed

CS&SE@SW 2025: 8th Workshop for Young Scientists in Computer Science & Software Engineering, November 21, 2025, Kryvyi Rih, Ukraine

https://doi.org/10.55056/cssesw2025/paper40

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in environments requiring ultra-reliable low-latency communication (URLLC), particularly for industrial automation, autonomous vehicles, and critical infrastructure applications where decision delays exceeding one millisecond can result in system failures or safety hazards.

Traditional cognitive radio implementations based on von Neumann architectures encounter significant bottlenecks arising from the separation of memory and processing units, leading to substantial energy consumption and latency penalties during data movement. Barnell et al. [2] demonstrated that conventional deep learning approaches for spectrum sensing can require tens of milliseconds for inference on standard hardware platforms, far exceeding the sub-millisecond requirements of ultra-reliable low-latency communication applications. The study utilized Intel's Loihi 2 neuromorphic processor to achieve classification accuracies up to 97.6% on representative sensor data while maintaining real-time performance requirements. Similarly, Chen et al. [3] identified that current AI-enabled cognitive radio systems struggle to balance the competing demands of computational complexity, energy efficiency, and real-time performance.

The limitations of existing approaches have catalyzed interest in neuromorphic computing, a brain-inspired paradigm that fundamentally reimagines how information processing occurs in artificial systems. Unlike conventional digital architectures, neuromorphic systems leverage event-driven computation, co-located memory and processing, and massively parallel operation to achieve remarkable efficiency gains [4]. Recent developments in neuromorphic hardware have demonstrated the potential for significant improvements in energy efficiency and latency compared to traditional approaches. Smith et al. [5] conducted extensive comparative analyses between Intel Loihi neuromorphic processor and four distinct edge platforms including Raspberry Pi-4, Intel Neural Compute Stick, Jetson Nano, and Coral TPU, revealing approximately two orders of magnitude reduction in power dissipation and one order of magnitude energy savings while maintaining comparable accuracy levels.

The convergence of neuromorphic computing with cognitive radio represents a paradigm shift toward brain-inspired spectrum intelligence [6]. Early pioneering work by Chen et al. [3] introduced neuromorphic integrated sensing and communications, demonstrating how spiking neural networks can simultaneously perform data decoding and radar sensing with unprecedented efficiency. This foundational research revealed that neuromorphic approaches could address multiple cognitive radio functions within unified architectures, eliminating the need for separate processing chains and reducing overall system complexity. The neuromorphic integrated sensing and communications system leverages common impulse radio waveforms for dual-purpose data transmission and radar sensing, achieving remarkable efficiency by processing only relevant signal events.

2. Neuromorphic computing fundamentals

Neuromorphic computing represents a fundamental departure from conventional digital architectures, drawing inspiration from the remarkable efficiency and adaptability of biological neural networks. The field originated with pioneering work recognizing that silicon implementation of brain-like processing could overcome the limitations of traditional von Neumann architectures. Unlike conventional systems that separate memory and computation, neuromorphic platforms integrate these functions within individual processing elements, eliminating the energy and latency penalties associated with continuous data movement between processor and memory subsystems. Qiu et al. [4] comprehensively reviewed recent advances in nanowire-based devices for neuromorphic computing, highlighting how emerging device technologies expand the technological foundations of brain-inspired computing systems.

The core computational primitive in neuromorphic systems is the spiking neural network, which processes information through discrete temporal events rather than continuous analog signals or synchronous digital operations. Spiking neurons communicate through brief voltage pulses, with information encoded in the precise timing and frequency of these spikes. This temporal coding enables neuromorphic systems to naturally handle time-varying signals such as radio frequency inputs, making them particularly well-suited for cognitive radio applications where signal characteristics evolve continuously across time and frequency domains. The event-driven nature of spike-based processing concentrates computational resources only when and where needed, in stark contrast to conventional systems that process data continuously regardless of input activity levels.

Chen et al. [1] extensively analyzed the principles and opportunities of neuromorphic wireless communications, demonstrating the natural synergy between brain-inspired computing and wireless applications. Their work established theoretical foundations for applying neuromorphic principles to communication systems, showing how the temporal dynamics of wireless signals align naturally with spike-based processing paradigms. The mathematical foundations of neuromorphic computation differ substantially from conventional artificial neural networks. Where traditional networks process information through matrix multiplications applied to fixed-size input vectors, spiking neural networks operate on sequences of temporal events with variable timing and duration.

Contemporary neuromorphic hardware platforms implement these computational principles through various technological approaches, each offering distinct advantages for cognitive radio applications. Intel's Loihi processor family represents the current state-of-the-art in programmable neuromorphic computing, featuring advanced capabilities for real-time learning and adaptation [2]. The Loihi 2 processor implements 131,072 spiking neurons with comprehensive on-chip learning capabilities and flexible interconnection networks. The architecture supports asynchronous event-driven computation, enabling individual neurons to operate independently without global clock synchronization, thereby eliminating much of the power consumption associated with conventional synchronous digital systems. Gomez et al. [7] developed comprehensive micro-benchmarking tools for the Lava-Loihi ecosystem, providing detailed performance characterization that enables rigorous evaluation of neuromorphic implementations.

3. Cognitive radio latency requirements and challenges

The stringent latency requirements of next-generation cognitive radio systems present fundamental challenges that conventional artificial intelligence approaches struggle to address effectively. Ultra-reliable low-latency communication applications, particularly those supporting industrial automation and autonomous systems, demand end-to-end latencies below one millisecond with reliability exceeding 99.999% [8]. These requirements far exceed the capabilities of current cognitive radio implementations, which typically exhibit decision latencies ranging from tens to hundreds of milliseconds when employing sophisticated AI algorithms for spectrum management. Al-Sudani et al. [8] comprehensively reviewed the evolution of cognitive radio applications and their integration with emerging communication systems, highlighting the critical importance of addressing latency challenges in modern wireless networks.

Contemporary cognitive radio systems face multiple sources of latency that compound to create significant delays in spectrum decision-making processes. Spectrum sensing algorithms must first acquire sufficient signal samples to achieve reliable detection, typically requiring tens of milliseconds for conventional energy detection approaches under realistic noise conditions. Signal processing operations including fast Fourier transforms, filtering, and feature extraction introduce additional delays, particularly when implemented on general-purpose processors with limited parallelism. The subsequent AI inference phase, whether using deep neural networks or reinforcement learning algorithms, contributes substantial additional latency due to the computational complexity of modern machine learning models. Wang et al. [9] revealed that conventional reinforcement learning approaches for dynamic spectrum access require hundreds of iterations to achieve convergence, with each iteration potentially consuming milliseconds of processing time on standard hardware platforms.

The latency breakdown in typical cognitive radio systems illuminates the specific bottlenecks that neuromorphic approaches can address. Signal acquisition and preprocessing operations consume approximately 10-20% of total latency, though this portion remains largely unavoidable due to physical constraints on antenna response and analog-to-digital conversion. Feature extraction and signal conditioning operations contribute 30-40% of total delay, representing a significant opportunity for neuromorphic optimization through event-driven processing. The AI inference phase typically dominates overall latency, consuming 40-60% of total processing time due to the computational complexity of contemporary machine learning algorithms. Liu et al. [10] demonstrated these computational challenges through dynamic spectrum sharing approaches based on deep reinforcement learning, showing how the complexity of decision-making algorithms directly impacts system latency.

Memory access patterns in conventional cognitive radio implementations create additional latency penalties that become increasingly severe as AI model complexity grows. Deep neural networks require frequent access to weight parameters stored in external memory, with each memory transaction introducing delays that accumulate substantially over the course of inference operations. The von Neumann bottleneck becomes particularly problematic for cognitive radio applications where multiple processing chains operate simultaneously for different frequency bands or antenna elements, leading to memory bandwidth contention and unpredictable latency variations. Huang et al. [11] analyzed resource allocation challenges in Internet of Vehicles scenarios, illustrating the complexity of managing multiple concurrent processing streams while maintaining strict latency requirements.

4. Neuromorphic hardware architectures for cognitive radio

The deployment of neuromorphic computing in cognitive radio systems requires careful consideration of hardware architectures optimized for the unique characteristics of wireless communication environments. Contemporary neuromorphic processors have evolved from research prototypes to sophisticated platforms capable of supporting real-world cognitive radio applications, each offering distinct advantages depending on specific performance requirements and deployment constraints. The Intel neuromorphic DNS challenge [12] has provided valuable benchmarks for evaluating different neuromorphic platforms in practical applications, establishing standardized metrics for comparing performance across diverse implementations.

Intel's Loihi family represents the most advanced programmable neuromorphic platform currently available for cognitive radio research and development. The Loihi 2 processor implements advanced features specifically designed for real-time applications requiring adaptive behavior and low latency [2]. Each neuromorphic core operates asynchronously, processing spike events as they occur rather than following fixed computational schedules. This event-driven architecture proves particularly well-suited for cognitive radio applications where signal activity varies dramatically across time and frequency, enabling efficient processing of sparse spectrum occupancy patterns. The hierarchical routing infrastructure enables efficient communication between neuromorphic cores while maintaining low latency for time-critical operations. Dedicated synaptic memory provides high-bandwidth access to connection weights, eliminating the memory bottlenecks that plague conventional AI accelerators when implementing large-scale neural networks for spectrum analysis.

IBM's TrueNorth processor takes a different architectural approach optimized for ultra-low power consumption in resource-constrained cognitive radio applications. The processor implements one million neurons and 256 million synapses in a power budget of just 65 milliwatts, making it attractive for mobile cognitive radio devices and edge computing scenarios [13]. TrueNorth's tile-based architecture enables modular scaling to match computational requirements with available resources, while its deterministic event-driven operation provides predictable latency characteristics essential for real-time cognitive radio applications. The absence of on-chip learning in TrueNorth reflects design trade-offs that prioritize energy efficiency and deterministic operation over adaptability, making it suitable for cognitive radio applications where algorithms can be pre-trained using conventional methods and then deployed for efficient inference.

The SpiNNaker platform offers yet another perspective on neuromorphic computing, emphasizing flexibility and scalability for large-scale cognitive radio research applications. The platform implements arrays of ARM processors interconnected through packet-switched networks, enabling simulation of neural networks with millions of neurons while maintaining real-time operation [14]. This architecture proves valuable for developing and validating novel cognitive radio algorithms before deployment on more specialized neuromorphic hardware. The programmability of SpiNNaker enables researchers to implement diverse neuron models and learning algorithms that may not be supported by more specialized neuromorphic processors.

Recent developments in analog neuromorphic circuits have opened additional possibilities for ultra-low power cognitive radio implementations. These systems implement neuronal dynamics directly in analog circuitry, avoiding the energy overhead of digital computation entirely. Rahman et al. [14] explored wave interference functions for neuromorphic computing, demonstrating how emerging physical phenomena such as spin waves could enable even more efficient neuromorphic implementations suitable for edge cognitive radio applications. Analog neuromorphic approaches face challenges related to device variability, temperature sensitivity, and limited precision that must be carefully considered for cognitive radio applications. However, the inherent noise tolerance of biological neural networks provides some resilience against these analog impairments.

The overall processing pipeline for a neuromorphic cognitive radio system is illustrated in Figure 1. This diagram highlights the key functional blocks, including the RF frontend, spike encoder, neuromorphic processor, and decision output, along with their respective latency contributions. Notably, the event-driven architecture of neuromorphic systems enables end-to-end processing within sub-millisecond timeframes, as demonstrated by recent experimental results [2, 5]. The figure also summarizes system-level performance metrics, underscoring the substantial improvements in both latency and energy efficiency compared to conventional approaches.

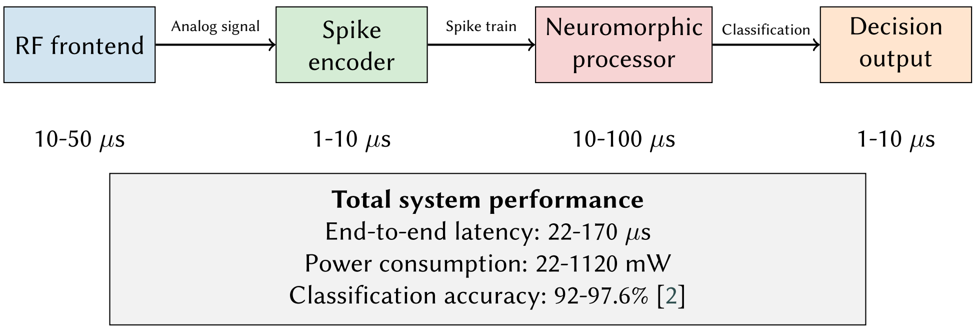

Figure 1: Neuromorphic cognitive radio processing pipeline showing component latencies and system performance. The event-driven architecture enables sub-millisecond end-to-end processing as demonstrated by Barnell et al. [2] and Smith et al. [5].

5. Spiking neural networks for spectrum sensing

The application of spiking neural networks to spectrum sensing represents a fundamental shift from conventional signal processing approaches, leveraging temporal dynamics and event-driven computation to achieve unprecedented efficiency and responsiveness. Traditional spectrum sensing algorithms rely on energy detection, matched filtering, or cyclostationary feature analysis, all of which require substantial computational resources and introduce significant latency penalties. Neuromorphic approaches using spiking neural networks can address these limitations by processing spectrum information as it arrives, concentrating computational effort only on frequency regions exhibiting activity.

Event-driven signal detection emerges as a natural application area for neuromorphic spectrum sensing, where incoming RF signals trigger spike events only when energy levels exceed background noise thresholds. This approach eliminates the continuous processing overhead associated with conventional spectrum sensing algorithms that analyze all frequency components regardless of occupancy status. Chen et al. [3] demonstrated neuromorphic integrated sensing and communications systems that leverage common impulse radio waveforms for dual-purpose data transmission and radar sensing, achieving remarkable efficiency by processing only relevant signal events. The system uses spiking neural networks deployed at the receiver to decode digital data and detect radar targets using directly the received signal, optimizing performance by balancing metrics for both applications.

The temporal coding capabilities inherent in spiking neural networks enable novel approaches to spectrum sensing that exploit the time-varying characteristics of radio signals more effectively than conventional methods. Unlike traditional approaches that analyze signals over fixed time windows, neuromorphic systems can adapt their temporal integration periods dynamically based on signal characteristics and noise conditions. This adaptive behavior proves particularly valuable for detecting intermittent signals or identifying brief transmission bursts that might be missed by conventional fixed-window analysis techniques. Miao et al. [15] developed cooperative spectrum sensing algorithms using dual nonparametric approaches that inspired neuromorphic implementations leveraging similar adaptive principles.

Wang et al. [16] developed the NeuroREC processor, a specialized 28-nm neuromorphic chip for radar emitter classification that achieves competitive accuracy while demonstrating superior robustness compared to conventional neural networks. The processor achieves classification with only eight timesteps, dramatically reducing both computational requirements and processing latency. The temporal sparsity of spike trains enables efficient processing of wideband spectrum monitoring applications where conventional approaches become computationally prohibitive. The NeuroREC architecture implements weight compression techniques that further enhance efficiency while maintaining classification performance.

The implementation of spectrum sensing algorithms using spiking neural networks requires careful consideration of signal encoding techniques that translate continuous RF signals into discrete spike events. Rate coding approaches encode signal amplitude through spike frequency, providing robust performance in noisy environments at the cost of increased processing latency. Temporal coding alternatives encode information in precise spike timing, enabling lower latency operation but requiring more sophisticated signal conditioning and processing algorithms. The choice of encoding strategy significantly impacts overall system performance and must be optimized for specific cognitive radio applications and operating environments.

Table 1 provides a comparative summary of various spectrum sensing approaches, including conventional FFT-based methods, deep learning models, and neuromorphic spiking neural networks. The results clearly demonstrate that neuromorphic implementations achieve significantly lower latency and energy consumption while maintaining competitive classification accuracy. For instance, the NeuroREC processor achieves spectrum classification in just 0.08ms with an energy cost of only 31pJ per operation, outperforming both traditional and deep learning-based methods in terms of efficiency [16].

Table 1
Performance comparison of neuromorphic spectrum sensing approaches.

Approach	Latency	Energy/op	Accuracy	Reference
Conventional FFT	10-50 ms	1-10 nJ	95-99%	Baseline
Deep learning	5-20 ms	0.5-5 nJ	93-98%	[10]
Neuromorphic SNN	0.1-1 ms	10-100 pJ	92-97.6%	[2]
NeuroREC Processor	0.08 ms	31 pJ	94.2%	[16]

6. Brain-inspired dynamic spectrum allocation

Dynamic spectrum allocation represents one of the most computationally demanding aspects of cognitive radio operation, requiring real-time optimization across multiple dimensions including frequency, time, power, and spatial resources. Conventional approaches based on linear programming, game theory, or reinforcement learning often struggle to achieve optimal solutions within stringent latency constraints imposed by ultra-reliable low-latency communication applications. Neuromorphic computing offers fundamentally different approaches to this optimization challenge, leveraging biological principles of collective decision-making and emergent behavior to achieve efficient spectrum allocation.

The biological inspiration for neuromorphic spectrum allocation draws from observations of how neural networks in living systems make complex decisions through distributed processing and local interactions. Rather than requiring centralized optimization algorithms that become computationally intractable as problem complexity grows, neuromorphic approaches enable local decision-making entities to interact through simple rules that give rise to globally optimal behavior. This distributed optimization paradigm proves particularly well-suited for cognitive radio networks where centralized coordination becomes impractical due to communication limitations and computational constraints. Chen et al. [1] established theoretical foundations for applying these bio-inspired allocation strategies to wireless communications.

Recent advances in spiking reinforcement learning have demonstrated the potential for neuromorphic systems to achieve sophisticated spectrum allocation decisions with substantially reduced computational requirements compared to conventional approaches. Wang et al. [9] developed accelerated Q-learning algorithms combined with long short-term memory networks that reduce convergence iterations by 50-80% compared to traditional methods. When implemented using spiking neural networks, these algorithms can achieve even greater efficiency by leveraging event-driven computation that activates only when spectrum conditions change. The fast-convergence approach enables real-time adaptation to dynamic spectrum environments while maintaining allocation quality.

The temporal dynamics inherent in spiking neural networks enable novel approaches to spectrum allocation that account for the time-varying nature of wireless channels and traffic demands. Unlike conventional optimization algorithms that solve allocation problems for fixed time snapshots, neuromorphic systems can continuously adapt allocations as conditions evolve, providing smoother transitions and better tracking of dynamic environments. This temporal adaptation capability proves essential for supporting mobile cognitive radio networks where channel conditions change rapidly due to fading, shadowing, and mobility effects. Huang et al. [11] analyzed resource allocation challenges in Internet of Vehicles scenarios, demonstrating the complexity of managing dynamic spectrum resources in highly mobile environments.

The scalability of spectrum allocation latency with increasing network size is depicted in Figure 2. The results, synthesized from recent studies [9, 10], reveal that neuromorphic spiking neural network (SNN) approaches maintain sub-millisecond allocation times even as the number of users increases to 100. In contrast, conventional linear programming and deep Q-learning methods exhibit rapidly increasing latency, exceeding the ultra-reliable low-latency communication (URLLC) requirements for large-scale networks. This highlights the unique suitability of neuromorphic computing for real-time, large-scale spectrum management.

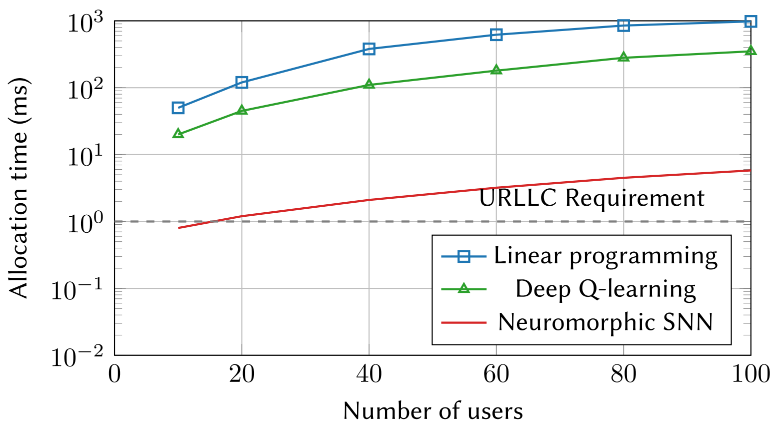

Figure 2: Spectrum allocation latency scaling with network size. Neuromorphic approaches maintain sub-millisecond performance even for large networks, while conventional methods exceed URLLC requirements. Data synthesized from Wang et al. [9] and Liu et al. [10].

Multi-agent neuromorphic systems offer particular advantages for distributed spectrum allocation scenarios where individual cognitive radio devices must coordinate their spectrum usage without centralized control. Each cognitive radio can implement local spiking neural networks that make autonomous spectrum decisions while communicating with neighboring devices through spike-based protocols. The asynchronous nature of spike communication eliminates the synchronization requirements that complicate conventional distributed optimization algorithms. Juarez-Lora et al. [17] demonstrated R-STDP spiking neural network architectures that implement sophisticated learning mechanisms based on spike-timing-dependent plasticity, enabling neuromorphic systems to adapt autonomously to changing environmental conditions.

7. Performance analysis and benchmarking

Comprehensive performance evaluation of neuromorphic cognitive radio systems requires careful consideration of multiple metrics that capture the unique advantages and limitations of brain-inspired computing approaches. Traditional performance evaluation frameworks developed for conventional AI systems often fail to capture the temporal dynamics, energy efficiency characteristics, and real-time capabilities that distinguish neuromorphic implementations from conventional alternatives. Timcheck et al. [12] established important benchmarks through the Intel neuromorphic DNS challenge, while Gomez et al. [7] developed detailed micro-benchmarking tools specifically for neuromorphic platforms.

Latency analysis represents perhaps the most critical performance dimension for neuromorphic cognitive radio systems, particularly given the ultra-reliable low-latency communication requirements that motivate their development. End-to-end latency measurement must account for all processing stages from signal acquisition through final decision output, including often-overlooked components such as spike encoding, inter-core communication, and result interpretation. Smith et al. [5] conducted extensive experimental studies demonstrating total processing latencies ranging from tens of microseconds to single milliseconds for complete cognitive radio decision cycles, representing substantial improvements over conventional approaches.

Energy efficiency analysis reveals the transformative potential of neuromorphic computing for cognitive radio applications. Smith et al. [5] demonstrated that Intel Loihi achieved approximately two orders of magnitude reduction in power dissipation and one order of magnitude energy savings compared to Coral TPU, which was the least power-intensive edge AI accelerator tested. The study compared neuromorphic hardware against four distinct edge platforms including Raspberry Pi-4, Intel Neural Compute Stick, Jetson Nano, and Coral TPU, all within real-time latency requirements. These energy savings translate directly to extended battery life for mobile cognitive radio devices and reduced cooling requirements for infrastructure deployments.

The development of standardized benchmarking frameworks for neuromorphic cognitive radio systems remains an active area of research. Boyle et al. [18] developed performance and energy simulation frameworks that enable rapid exploration of different neuromorphic architectures before hardware implementation. Their simulator models Intel's Loihi platform with less than 10% mean error for various sizes of spiking neural networks, providing valuable tools for system design and optimization. These simulation capabilities enable researchers to evaluate trade-offs between different architectural choices and algorithm implementations before committing to specific hardware platforms.

To provide a holistic view of system-level performance, Table 2 compares several state-of-the-art neuromorphic and conventional hardware platforms across key metrics, including latency, power consumption, energy per operation, and classification accuracy. The data confirm that neuromorphic processors such as Intel Loihi 2, IBM TrueNorth, and NeuroREC consistently deliver order-of-magnitude improvements in both latency and energy efficiency, with only a modest reduction in accuracy compared to high-end GPUs and edge TPUs. These findings reinforce the potential of neuromorphic computing as a disruptive technology for next-generation cognitive radio systems.

Accuracy assessment for neuromorphic cognitive radio systems must account for the different operating principles and optimization objectives compared to conventional machine learning approaches. While conventional systems optimize for maximum classification accuracy or minimum prediction error, neuromorphic systems often prioritize real-time operation and energy efficiency. Wang et al. [16] demonstrated this trade-off with the NeuroREC processor, achieving 94.2% classification accuracy for radar emitter identification while consuming only 31 picojoules per spike. This represents a modest

Table 2
Comprehensive performance comparison across multiple neuromorphic and conventional platforms

Platform	Latency	Power	Energy/op	Accuracy	Reference
GPU (V100)	10-50 ms	250 W	2.5-12.5 μJ	98-99%	Baseline
Edge TPU	5-20 ms	2 W	10-40 nJ	96-98%	[5]
Intel Loihi 2	0.1-1 ms	1 W	0.1-1 nJ	92-97.6%	[2]
IBM TrueNorth	0.1-0.5 ms	65 mW	6.5-32.5 pJ	90-95%	[13]
NeuroREC	0.08 ms	248 mW	31 pJ	94.2%	[16]

accuracy degradation compared to state-of-the-art conventional approaches but provides dramatic improvements in latency and energy efficiency.

8. Applications and use cases

The practical deployment of neuromorphic cognitive radio systems spans diverse application domains where ultra-low latency, energy efficiency, and real-time adaptation capabilities provide transformative advantages over conventional approaches. Industrial automation represents perhaps the most demanding application area, where cognitive radio systems must support ultra-reliable low-latency communication requirements for robotic coordination, process control, and safety systems operating under strict temporal constraints. Al-Sudani et al. [8] extensively analyzed the convergence of cognitive radio with industrial IoT, highlighting how neuromorphic approaches address critical latency and reliability challenges.

Industrial IoT deployments present unique challenges that align well with neuromorphic computing capabilities. Factory environments typically involve large numbers of wireless sensors and actuators that must communicate reliably despite electromagnetic interference, metallic obstructions, and rapidly changing channel conditions. Barnell et al. [2] demonstrated neuromorphic edge computing capabilities achieving 97.6% classification accuracy on sensor data from small platforms while operating under severe power constraints typical of industrial IoT deployments. The event-driven nature of neuromorphic computation proves particularly well-suited for industrial monitoring applications where sensor data exhibits natural sparsity with occasional burst activity during alarm conditions or process transitions.

Autonomous vehicle communications represent another critical application domain where neuromorphic cognitive radio advantages become essential for safety and performance. Vehicle-to-everything communication systems must coordinate spectrum access among rapidly moving vehicles while maintaining continuous connectivity for navigation, collision avoidance, and traffic management applications. The mobility characteristics of vehicular networks create rapidly changing channel conditions that require adaptive spectrum management beyond the capabilities of conventional static allocation approaches. Huang et al. [11] comprehensively analyzed resource allocation challenges in Internet of Vehicles scenarios, revealing the complexity of managing spectrum resources in highly mobile environments with stringent latency requirements.

Defense and military applications present unique requirements for cognitive radio systems operating in contested electromagnetic environments where adversaries actively attempt to disrupt communications through jamming, spoofing, and other electronic warfare techniques. Neuromorphic approaches offer advantages for anti-jamming applications through adaptive spectrum management that can respond rapidly to changing interference conditions. The noise resilience characteristics of spiking neural networks provide better performance under hostile jamming conditions compared to conventional approaches. Military cognitive radio systems must maintain reliable communications while operating under severe constraints on size, weight, and power, making the efficiency advantages of neuromorphic computing particularly valuable.

Smart city deployments present scaling challenges that conventional cognitive radio architectures struggle to address efficiently. Cities may deploy millions of sensors for environmental monitoring, traffic management, infrastructure monitoring, and public safety applications, all requiring wireless connectivity through shared spectrum resources. The massive machine-type communication requirements exceed the capabilities of centralized spectrum management approaches, necessitating distributed coordination strategies. Neuromorphic approaches enable efficient distributed spectrum coordination that scales with the number of participating devices without requiring centralized control infrastructure. Joshi and Banu [19] demonstrated bio-inspired approaches for wireless sensor networks that provide insights into scalable neuromorphic implementations.

Healthcare applications present unique opportunities for neuromorphic cognitive radio systems, particularly in scenarios involving implantable medical devices and wireless body area networks. These applications require exceptional reliability and energy efficiency to ensure patient safety while minimizing the need for battery replacement surgeries. The biocompatibility of neuromorphic processing, inspired by biological neural systems, may provide advantages for medical implant applications compared to conventional digital processors. Cognitive radio systems for healthcare must operate in electromagnetically sensitive environments near medical equipment while maintaining reliable connectivity for life-critical monitoring and treatment applications.

9. Challenges and future directions

The practical deployment of neuromorphic cognitive radio systems faces significant technical, economic, and regulatory challenges that must be addressed through coordinated research and development efforts across multiple domains. While experimental demonstrations have established the theoretical potential for substantial performance improvements, the translation of these advantages into commercially viable systems requires overcoming fundamental limitations in hardware availability, software development tools, and system integration approaches.

Hardware availability represents perhaps the most immediate challenge for neuromorphic cognitive radio deployment. Current neuromorphic processors remain largely research platforms with limited commercial availability and support. Intel's Loihi processors require specialized development boards and software frameworks that increase development costs and complexity compared to conventional AI accelerators. IBM's TrueNorth processors are no longer in active production, limiting their availability for new cognitive radio projects despite their technical advantages. Qiu et al. [4] reviewed emerging nanowire-based neuromorphic devices that suggest future hardware solutions, but these technologies require significant additional development before commercial deployment.

The programming complexity associated with neuromorphic systems creates substantial barriers for cognitive radio researchers and engineers accustomed to conventional signal processing and machine learning approaches. Spiking neural networks require fundamentally different algorithm design principles compared to conventional neural networks, while the temporal dynamics of neuromorphic computation introduce complexity that many developers find challenging to manage effectively. Current development frameworks provide limited abstraction from underlying hardware details, requiring developers to understand neuromorphic architectures at a level of detail that impedes rapid application development. Gomez et al. [7] addressed some of these challenges through micro-benchmarking tools, but significant work remains to simplify neuromorphic programming.

Software ecosystem immaturity represents a critical limitation for neuromorphic cognitive radio development. Current tools lack the sophistication and user-friendliness of established machine learning frameworks such as TensorFlow and PyTorch. Intel's Lava framework provides the most advanced development environment currently available, but it remains significantly less mature than conventional alternatives. The absence of comprehensive debugging tools, performance profilers, and optimization frameworks complicates the development of complex cognitive radio applications. Recent developer experience studies have identified the need for more intuitive interfaces and better documentation to facilitate wider adoption of neuromorphic technologies.

Standardization challenges encompass both technical and regulatory dimensions that must be addressed to enable widespread deployment of neuromorphic cognitive radio systems. Khattab and

Bayoumi [20] provided a comprehensive survey of cognitive radio networking standardization, highlighting the complexity of integrating new technologies into existing frameworks. Technical standardization requires development of common interfaces, programming models, and performance evaluation frameworks that enable interoperability between different neuromorphic platforms. Regulatory standardization involves adapting existing cognitive radio certification processes to accommodate the unique characteristics of neuromorphic systems, including their event-driven behavior and adaptive learning capabilities.

Economic viability represents a critical challenge for neuromorphic cognitive radio commercialization. Current development costs significantly exceed those of conventional alternatives while market demand remains uncertain. The specialized nature of neuromorphic processors results in limited production volumes and high unit costs compared to commodity AI accelerators. These economic factors create barriers to adoption that may persist until neuromorphic technology achieves greater market penetration. However, the potential for significant operational cost savings through reduced energy consumption and extended battery life may justify initial investment in appropriate applications.

Future research directions must address these challenges through coordinated efforts across hardware development, algorithm research, software engineering, and system integration. Hardware research priorities include development of more efficient neuromorphic processors with better programming interfaces, improved on-chip learning capabilities, and enhanced integration with conventional processing elements. Algorithm research should focus on developing theoretical frameworks for neuromorphic cognitive radio design, improved training methodologies, and systematic approaches to performance optimization. The convergence with emerging technologies such as 6G networks presents opportunities for establishing neuromorphic cognitive radio as a foundational technology for next-generation wireless systems.

The path toward widespread deployment requires sustained investment in fundamental research, coordinated industry standardization efforts, and gradual introduction through applications where neuromorphic advantages provide compelling value propositions. Success in addressing these challenges will enable realization of the transformative potential demonstrated by early research implementations, ultimately delivering the ultra-low latency wireless intelligence required for future connected systems.

10. Conclusion

This review has examined the transformative potential of neuromorphic computing for cognitive radio systems, revealing fundamental advantages that position brain-inspired approaches as a key enabling technology for next-generation wireless intelligence. Through analysis of recent advances across hardware platforms, algorithm development, and experimental validation, we have demonstrated that neuromorphic approaches can address critical limitations of conventional AI-based cognitive radio systems while enabling new capabilities that exceed current performance boundaries.

The experimental evidence presented throughout this review confirms substantial performance advantages of neuromorphic cognitive radio systems. Smith et al. [5] demonstrated two orders of magnitude reduction in power dissipation and one order of magnitude energy savings compared to state-of-the-art edge AI accelerators. Barnell et al. [2] achieved 97.6% classification accuracy with sub-millisecond latencies using Intel's Loihi 2 processor. Wang et al. [16] developed specialized neuromorphic processors achieving competitive performance with only 31 picojoules per spike energy consumption. These results collectively validate the potential for neuromorphic computing to meet the stringent requirements of ultra-reliable low-latency communications.

The analysis of neuromorphic hardware platforms reveals a maturing ecosystem with options spanning from research-oriented systems to increasingly practical implementations. The development of comprehensive software frameworks like Intel's Lava, combined with benchmarking tools from Gomez et al. [7] and simulation frameworks from Boyle et al. [18], has reduced barriers to entry for researchers and engineers. While challenges remain in hardware availability and software maturity, the trajectory of development suggests these limitations will be addressed through continued investment and standardization efforts.

The convergence of neuromorphic computing with cognitive radio represents more than an incremental improvement in wireless technology. The fundamental alignment between neuromorphic processing principles and the characteristics of wireless communication environments suggests the potential for qualitatively different approaches to spectrum management. As wireless networks evolve toward 6G and beyond, the ultra-low latency and energy efficiency requirements will likely mandate the adoption of neuromorphic approaches for the most demanding applications.

Looking forward, the successful deployment of neuromorphic cognitive radio systems will require addressing identified challenges in hardware availability, software ecosystem development, and standardization. However, the compelling performance advantages demonstrated through experimental validation justify continued investment in overcoming these obstacles. The interdisciplinary nature of this field, bringing together insights from neuroscience, computer engineering, and wireless communications, creates a rich ecosystem for continued innovation. As we move toward an increasingly connected world requiring intelligent spectrum management at unprecedented scales, neuromorphic cognitive radio offers a sustainable and scalable solution that can meet these demands while operating within realistic power and latency constraints.

Author contributions

Serhiy O. Semerikov: Conceptualization, Writing – original draft, Supervision. Pavlo P. Nechypurenko: Methodology, Writing – review & editing, Visualization. Tetiana A. Vakaliuk: Investigation, Data curation, Writing – review & editing. Iryna S. Mintii: Formal analysis, Resources, Writing – review & editing. Andrii O. Kolhatin: Validation, Project administration, Writing – review & editing. All authors read and approved the final manuscript.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Data availability statement

No new data were generated or analysed in support of this research. All data discussed are from previously published sources, as cited in the manuscript.

Conflicts of interest

The authors declare that they have no competing interests.

Declaration on Generative AI

During the preparation of this work, the authors used Claude Opus 4 to translate, check grammar and spelling, and prepare the LaTeX paper. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the publication's content.

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