World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

(Review Article)

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Neuromorphic Computing and its Role in Making of a Fully Autonomous Remote Site in Oil and Gas Industry

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World Journal of Advanced Research and Reviews, 2026, 29(02), 894-928

Publication history: Received on 04 January 2026; revised on 14 February 2026; accepted on 16 February 2026

Article DOI: https://doi.org/10.30574/wjarr.2026.29.2.0369

Abstract

The advancement in Artificial Intelligence and Deep Neural Networks is leading towards mimicking the human brain's nervous system and its functioning in day-to-day life. This technical paper presents the idea of a fully autonomous remote site in Oil and Gas industry by utilizing neuromorphic computing and its integration with IIoT sensors. Neuromorphic Computing works on event-based spikes and threshold-based computations and provides a very high efficiency. Neuromorphic computing comes under level three Artificial Intelligence, where the devices and instruments have artificial brains to run themselves autonomously, can repair or give alarms proactively before any actual failure happens, require very minimal power, provide real-time data with ultra-low latency and highest efficiency. The exponential growth of connected devices in IoT environment, Big Data, large bandwidth requirements for data transmission from remote sites to plant and central hubs and further to cloud locations are basic challenges in data transmission networks. The high bandwidth consumption, increase of latency and low throughput are major role players to think beyond Non von Neumann architecture. Neuromorphic computing with edge computing is promising to all the above challenges and provides lots of benefits, such as sending only the required data to important locations. Instruments don't need to work continuously, but only when it requires, this approach will save bandwidth and power consumption. The autonomous IIoT sensor is no longer a myth, but by utilizing neuromorphic computing with Edge Computing, we can turn fiction into reality.

Keywords: Neuromorphic computing; Synapse; Spiking Neural Network (SNN); Spike Train; Spiking Neuron

1. Introduction

The human brain is a mysterious object and one of the greatest research frontiers of all time. The human brain defines the personality of individuals, stores memories and controls our whole body. A lot of research is ongoing in neural science, neural networks and deep learning, but still the principle of working of the human brain cannot be fully understood.

Neuromorphic computing is inspired by the functioning of the human brain and offers a model which accentuates energy efficiency, parallelism and adaptability, which is crucially required for deploying Artificial Intelligence-based autonomous remote sites in resource-constrained environments, e.g., (remote areas in Oil & Gas industries). In neuromorphic computing, IIoT sensors are being developed similar to the human brain requires for computing. In terms of forming a human brain through sensors and computing devices, it might be it could not look like the original shape

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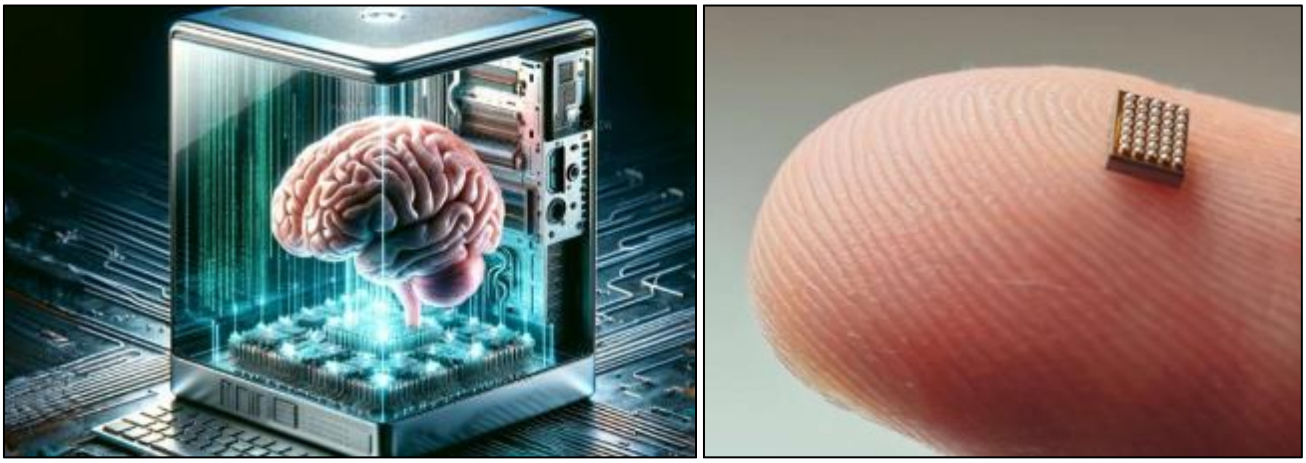
of the human brain but perform actions similar to a human brain. In neuromorphic computing, instead of separating memory and processing, it requires integrating both, similar to biological neurons and synapses.



References: Why neuromorphic chips could be the future of computing

Figure 1 Chip based neuromorphic computing system

1.1. Human Brain

The human brain contains billions of neurons interconnected with trillions of synapses. The primary way a human brain is communicating by action potentials (spikes). The pattern of spikes is the basis of information processing in the biological nervous system. A lot of research is ongoing and much is done on human brain neural networks, and we can see the results as Artificial Intelligence, Intelligent devices, Machine Learning and autonomous systems. The human brain anatomy inspires scientists and researchers to think about neuromorphic systems which can work on event-based spikes. Neuromorphic computing is based on principle of neurons, synapses, and their physical properties.

The basic element of any nervous system is neuron soma and its synapses. Neurons are electrically excitable cells whose behavior is governed by the membrane potential. The membrane potential is the basis for signal generation and enables neurons to integrate with incoming inputs and communicate through action potential. Neuron computes and integrates information coming from synapses, which connect with other neurons and enable neurotransmitters and direct them for neuro-simulation.

1.2. The cell body (Soma)

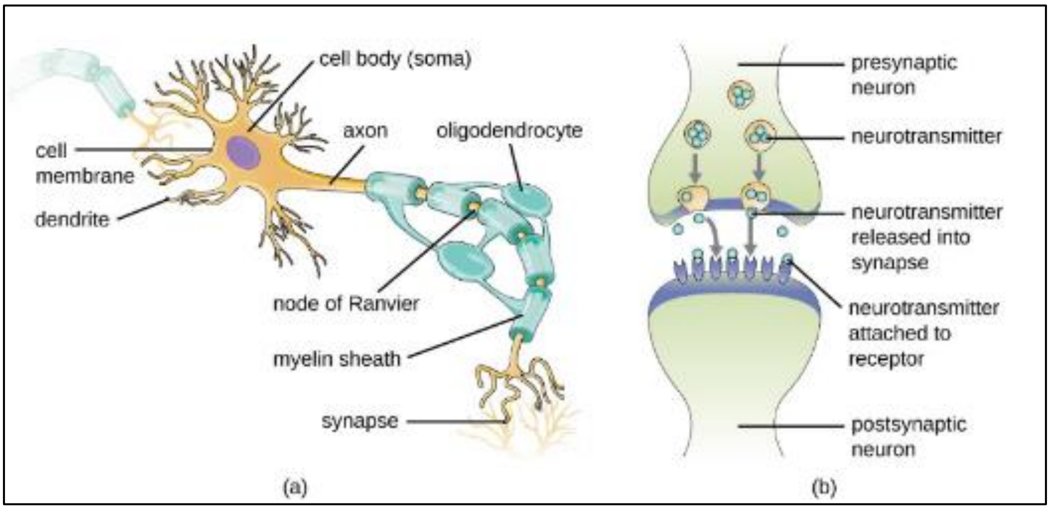
The Soma is the command center or works like a CPU of the computer. It contains the cell nucleus and other cell organelles. Soma acts as a factory floor, where it contains the nucleus and organelles like mitochondria (for energy) and ribosomes (for protein synthesis) by which a neuron repairs itself or produces the neurotransmitters needed for communication. It also works to receive thousands of signals from the cells. The Soma sum of the inputs asking it to fire or stop. If combined signals reach a threshold, soma passes the command to axon hillock, which triggers an electrical impulse down the axon.

1.3. Dendrites

Dendrites are short branching structures that extend from Soma and act as receivers of signals (action potentials/Spikes) from other neurons. When a neighboring neuron releases chemicals called neurotransmitters, these receptors catch them and convert them into electrical ones. The tree-like branching, maximizes the surface area of the neuron, allowing a single cell to receive inputs from thousands of neurons. Once the receptor is activated, it creates a postsynaptic potential and transmits it to soma. The pulse carries signals in variable strengths.

1.4. Axon

Axon works as a long-distance transmission cable. A structure that emerges from soma like a single cable and branches out with axon terminals farthest from soma. it carries electrical signals (Spikes) to other neurons. Axons have a coating known as the myelin sheath which increases the speed at which information is transmitted. The action potential is propagated by jumping from one node to the next. The primary job of an axon is to send electrical impulses (action potentials) down the length of the axon. As axons are long in length and some are over a meter in our legs, they require a conveyer belt to transport protein and nutrients from soma down to the tip. At the end of axon splits into axon terminals and the branches allow a single neuron to send message to multiple different target cells. [[5]]

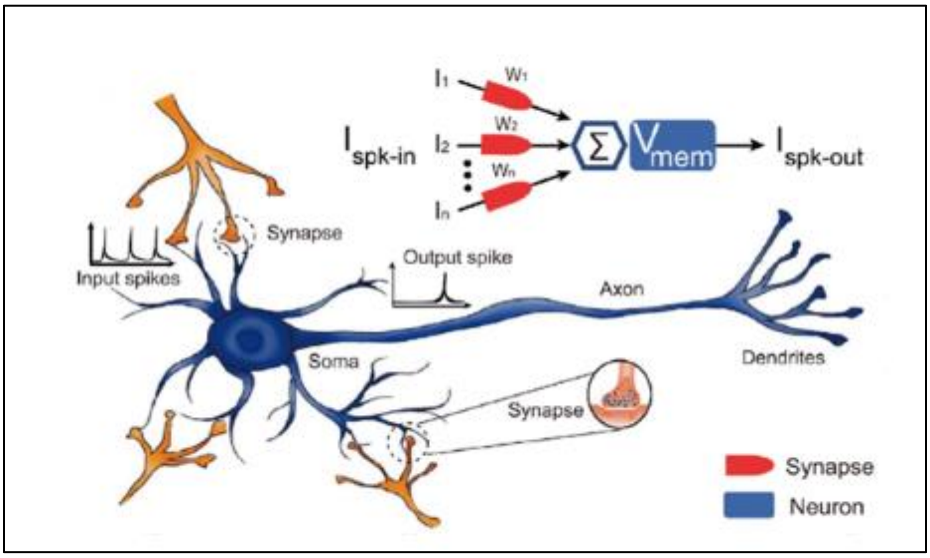


Reference: 21.1 Anatomy of the Nervous System – Allied Health Microbiology

Figure 2 A myelinated neuron is associated with oligodendrocytes. Oligodendrocytes are a type of glial cell that forms the myelin sheath in the CNS that insulates the axon so that electrochemical nerve impulses are transferred more efficiently. (b) A synapse consists of the axonal end of the presynaptic neuron (top) that releases neurotransmitters that cross the synaptic space (or cleft) and bind to receptors on dendrites of the postsynaptic neuron (bottom).

The Neuromorphic computing has Spiking Neural Networks (SNNs) where information is processed through discrete electrical spikes, mimicking how neurons in human brain is working and communicating. The process is not similar to traditional computers working on binary (0,1) digits and processing data sequentially but Neuromorphic computing use artificial intelligence and synapses to process information.

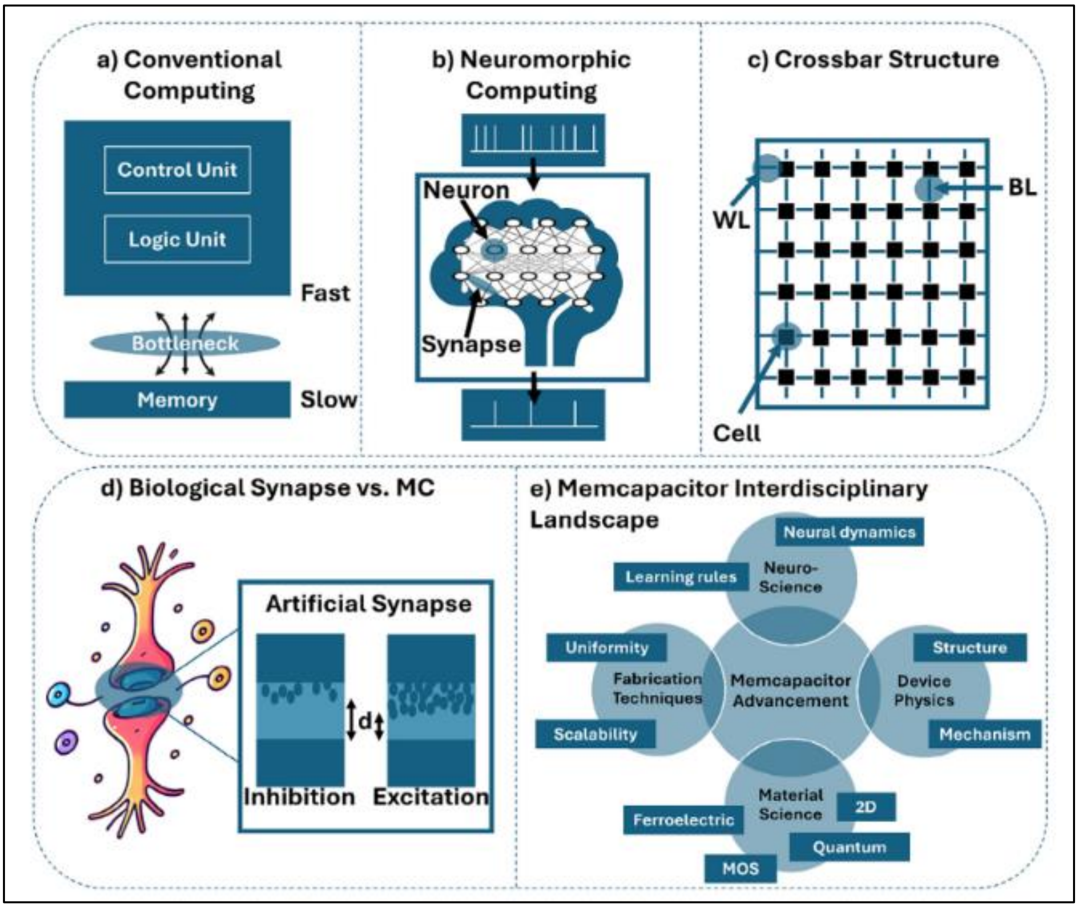
The neuromorphic computing integrates biology, physics, mathematics, computer science and electronics engineering together to develop a system that matches with brain morphology and computational strategies.



Reference: The skyrmionic neuromorphic computing devices. (a) Illustration of a... | Download Scientific Diagram

Figure 3 Illustration of biological nervous system where neuron is connected with huge number of synapses

Researchers reported in 2024 that chemical systems in liquid solution can detect sound at various wavelengths, offering the potential for neuromorphic applications. The brain processes information via neurons using chemical signals abstracted into mathematical functions. Neuromorphic computing distributes computation across small elements, similar to neutrons, using methods guided by anatomical and functional neural maps from electron microscopy and neural connection studies. [[5]]



Reference: Neuromorphic Computing with Memcapacitors: Advancements, Challenges, and Future Directions

Figure 4 (a) Limitation in computational speed caused by the slow data transfer between the CPU and memory in the Von Neumann architecture. (b) Integration of memory and compute in neuromorphic architectures, with spike-based computations. c) Generic crossbar structure deployed for efficient AI computations. d) Similarities between biological synapses and artificial synapses exemplified by plasticity, the strengthening or weakening of synaptic connections. e) Areas of advancements in memcapacitor research, including device physics, materials science, fabrication. [[1]]

Neuromorphic computing will be the next generation AI and will be smaller, faster and more efficient than the human brain. At the core of AI evolution, human brain's structure functions. Neuromorphic computing systems use energy efficient electrical and photonic networks modeled after biological neural networks. These networks use physical hardware to mimic the human brain, the most efficient and powerful prediction and learning engine. The human brain can change by adopting and absorbing environmental changes which AI can't. The next generation of AI will be a marriage of physics and neuroscience. [1].

The first generation of AI was rules-based and matched classical logic to draw reasoned assumptions with a specific, barely well-defined problem domain. It was well suited to monitoring the processes and improving efficiency. The second generation is mostly concerned with sensing and perception, such as using deep neural network-based learning to analyze content. The third and future of AI will extend into areas that correspond to human cognition, such as interpretation and autonomous adaptation. Next generation AI must be able to address situations and abstractions to automate human activities.

Table 1 Evolution of Neuromorphic Computing

Year	Architecture	Key Findings	Energy Efficiency	Throughput	Task
2014 BrainScaleS-1 Operational	Mixed-Signal, wafer-scale system	Analog emulation provides 10,000x speedup over biological	5W for accelerated neural emulation	10^4 faster than biological real-time	Neuroscience research, accelerated learning experiments
2017 Intel Loihi 1 Released	Asynchronous, many-core, programmable learning engines	On-chip Learning with spike-timing-dependent plasticity	1000X better than GPU for sparse coding problems	128 cores, 130, 000 neurons, 130M synapses	Gesture recognition (99% accuracy), olfactory processing, optimization
2018 SpinNaker 1M Cores Deployed	1 million ARM cores system	Largest neuromorphic system for whole-brain simulation	30 kW for 1 billion neuron simulation	200 x real-time for full mouse brain model	Whole-brain simulation, neural network research
2019 Commercial Foundry Integration	7nm test chips from TSMC, GlobalFoundries	Advanced nodes significantly improve density and efficiency	10x improvement over 28nm design	10^{11} synaptic operations/second	Commercial viability testing, edge AI prototypes.
2020 BrainScaleS-2 Deployed	Analog neurons with digital plasticity process	On-chip gradient-based learning in analog systems	10x better than digital for certain learning tasks	512 neuron/chips with 100k synapses each	Online learning, adaptive robotic control
2021 Intel Loihi2 Announced	Improved Loihi with 8x density, new neuron models	Enhanced programmability, faster processes new features	Up to 10x better than Loihi 1	1M neurons/chip, 10x faster processing	Robotics control optimization problems, sparse coding
2023 Hala Point System (Intel)	1152 Loihi 2 Chips, 1.15B neurons	Largest neuromorphic system to date demonstrating research-scale capabilities	50x better than conventional HPC for optimization workloads	20 peta-ops/Second (sparse operations)	Large-scale optimization, Scientific computing, AI research
2024 Edge Commercialization	Multiple commercial offerings (Intel Loihi, BrainChip Akida, SynSense)	Commercial viability proven for specific edge applications	<1 mW for always-on sensory processing	Real-Time processing at edge with minimal latency	Keyword spotting, anomaly detection, wake-word detection sensor analytics
Future					
2025-2026 Heterogeneous Integration	3D-stacked neuromorphic-memory-processor systems	Memory bottleneck reduced through 3D integration	Projected Efficiency: 100x current systems	Projected Throughput: 10^{14} synaptic operations/second	Real-Time video analytics, autonomous navigation, multimodal AI

2027-2028 Advanced Materials Integration	Memristor, ferroelectric, phase-change material synapse	Non-volatile along weights with high density and endurance	Projected Energy Efficiency: 1000x von Neumann system for specific workloads	10^{15} operations/second	On-device lifelong learning, personalized AI, biomedical monitoring
2030-2032 Cognitive Computing Systems	Brain-scale systems (100B+ neurons) with hierarchical organization	Systems approaching mammalian brain scale with specialized regions	Projected Energy Efficiency: Approaching biological 200W for human scale computation	Real-Time whole-brain emulation capability	General machine intelligence, Scientific discovery, complex optimization
2033-2035 Bio-Hybrid Systems	Direct neural interface systems, organic-electronic hybrid	Seamless integration with biological neural systems	Projected Energy Efficiency: Biologically compatible	Brain-machine communication bandwidth matching human perception	Neuroprosthetics, cognitive enhancement, brain-inspired AI
Year	**Architecture**	**Key Findings**	**Projected Capabilities**	**Potential Impact**	
2040s Distributed Neuromorphic Intelligence	Networked neuromorphic systems forming collective intelligence	Emergent Properties from interacting neuromorphic systems	Swarm intelligence, distributed cognition	Revolution in collective problem-solving, environmental monitoring	
		Vision	**Grand Challenge**	**Social Impact**	
2050s Cognitive General Intelligence	Unknown-potentially quantum-neuromorphic hybrids or new paradigm	Machines with human-like cognitive flexibility and efficiency	Achieving artificial general intelligence with biological efficiency	Transformation of work, creativity, human-machine collaboration	

1.5. Characteristics of Neuromorphic Computing:

1.5.1. Biological Inspiration:

Closer model of real neurons, communicating through spikes (action potentials).

1.5.2. Event Driven:

Neurons only compute and communicate when spike occurs, leading to sparse activity and lower power consumption.

1.5.3. Temporal Processing:

Excellent for time dependent problems because information is encoded in the timing of spikes not just their presence.

1.5.4. Energy Efficiency:

Significantly more power efficient than traditional ANNs especially specialized neuromorphic hardware (like intel Loihi or FPGAs).

1.6. Working Principles:

1.6.1. Brain-Inspired Architecture:

Instead of separate CPUs and memory neuromorphic chips integrate processing (neurons) and memory (synapses) in the same physical location.

1.6.2. Spiking Neural Network (SNNs):

They use artificial neurons that "fire" (send spikes) only when they receive enough input, mimicking biological neurons, making them event-driven and highly efficient.

1.6.3. Parallel & Distributed Processing:

Information is processed simultaneously across many interconnected units, allowing for complex tasks to be handled concurrently.

1.6.4. Real-Time Learning & Adaptability:

Designed to learn continuously from new data, adapting to evolving stimuli, much like biological brains.

1.7. Components of Neuromorphic Computing:

To mimic the brain's structure and function, neuromorphic systems rely on three components:

1.7.1. Artificial Neurons:

Neuromorphic system relies on artificial neurons as their fundamental processing units, which are similar to biological neurons comprises a cell body, dendrites and axon. Dendrites receive signals from other neurons, the cell body processes these signals and the axon transmits the processed signals to other neurons.

Similarly, artificial neurons receive input signals, process them and produce output signals. These artificial neurons are constructed using electronic circuits that initiate the behavior of biological neurons. They can handle various inputs; processes information based on specific rules and generate outputs that affect other neurons in the network. Artificial neurons are tiny processors that can handle multiple tasks simultaneously, similar to how our brain simultaneously processes different senses like sight, sound and touch etc. [[13]]

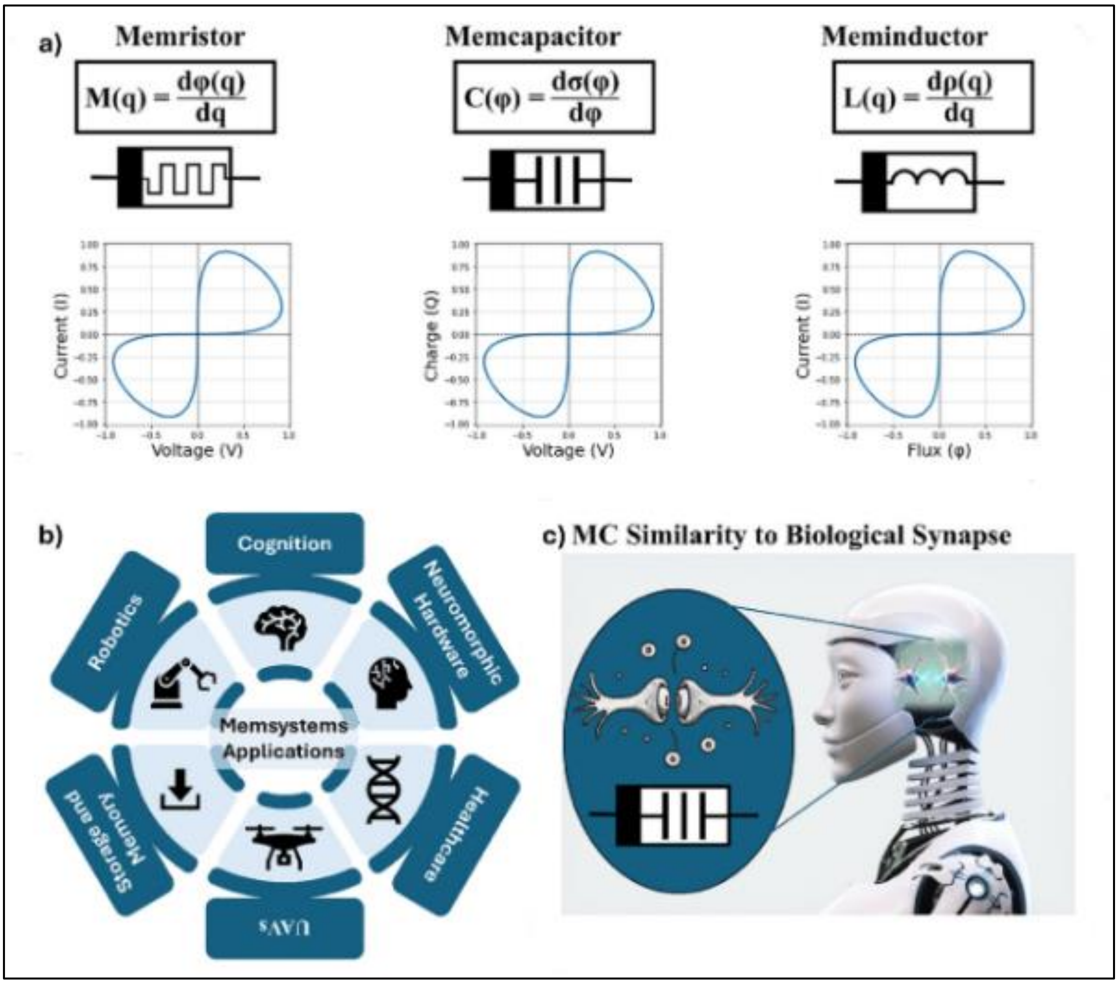
Implementations:

1.7.2. Digital:

Built with standard transistors. They are precise, programmable and easier to control but less area and energy efficient per neuron.

1.7.3. Analog:

Built with analog circuits that directly mimic the differential equations of neuronal dynamics (e.g., leaky integrate and fire). Use in IBMs TrueNorth and BrainScaleS. They are fast and energy efficient but suffer from device mismatch.



Reference: Neuromorphic Computing with Memcapacitors: Advancements, Challenges, and Future Directions - AbuHamra - 2025 - Advanced Electronic Materials - Wiley Online Library

Figure 5 Memsystems Overview: Equations, symbols, and pinched hysteresis plots for memristors, memcapacitors, and meminductors. Here, M is memristance, C is memcapacitance, L is meminductance, I is current, q is charge, V is voltage, φ is flux, σ(φ) is a differentiable function of φ, and ρ(q) is a differentiable function of q, with $\boldsymbol{\sigma} = \int_{-\infty}^{t} \boldsymbol{\varphi}\,(\boldsymbol{t})\boldsymbol{dt}$ and $\boldsymbol{\rho} = \int_{-\infty}^{t} \mathbf{q}\,(\boldsymbol{t})\boldsymbol{dt}$. (b) Application Domains of Memsystems: A visual representation of various application areas, including cognition, robotics, unmanned aerial vehicles (UAVs), healthcare, and additional emerging fields. c) Example Neuromorphic Application of Memcapacitors: An illustration demonstrating neuromorphic synaptic emulation

1.7.4. Memresistance:

A resistor whose resistance changes based on the history of electrical charge passing through it and "remembers" its state even when power is off. It can lead to ultra-low-power sensors and processing units that don't lose data during sleep cycles. Enables data processing directly within memory (in-memory computing), which is faster and more energy-efficient for AI tasks on devices. [**Error! Reference source not found.**]

1.7.5. Memcapacitor:

A capacitor whose capacitance (ability to store charge) changes based on its history of voltage or charge. As an energy-storing element, it could create adaptive power systems. For example, an environmental sensor could tune its energy harvesting and storage based on historical sun or vibration patterns. Also promising for ultra-efficient neuromorphic computing in edge devices. [**Error! Reference source not found.**]

1.7.6. Meminductor:

An inductor whose inductance (resistance to change in current) changes based on its magnetic flux history. It can help in creating intelligent, self-tuning wireless power systems and radio frequency (RF) circuits. This would allow IoT devices to maintain optimal communication and power transfer efficiency as conditions change. [**Error! Reference source not found.**]

1.7.7. Spiking Neural Network

Spiking Neural Network is a third generation Artificial Intelligence model using discrete electrical pulses (spikes) instead of continuous signals. Spiking Neural Network (SNN) architecture mimics biological human brain, using spiking neurons that communicate via discrete, timed electrical spikes (pulses), unlike traditional Artificial Neural Network (ANNs) that use continuous values. Key components include neurons with membrane potential (charge) thresholds and synapses (connections). Data is encoded into spike trains (rate, temporal coding), processed through generation (firing when potential exceeds threshold) and post-spike behavior (resetting/refractory periods) for energy-efficient, time-dependent pattern processing.

1.7.8. Network-on-Chip (NOC) and interconnect fabrics:

A Network on Chip (NOC) is a communication subsystem on an integrated circuit, which implement a network architecture to connect different components like CPU, GPU and Controllers. Interconnect Fabric refers to a woven layer of hardware and software protocols that allow data to flow across a system.

Implementation:

A carefully designed communication architecture, often a packet-switched network (like a mesh, tree or crossbar). It handles massive sparse and bursty event traffic with minimal energy and latency. Examples: Loihi's hierarchical mesh, SpiNNaker's multicast router.

1.7.9. Key Models:

Leaky Integrate and Fire (LIF), Izhikevich, Hodgkin-Huxley (more biorealistic). They define how a neuron's membrane potential changes and when it fires. [[21]]

1.7.10. Spiking Neurons:

Neurons can be divided into three functionally different parts, called dendrites, soma and axon. The dendrites play the role of input devices that collects signals from other neurons and transmits them to soma. The soma is a central processing unit performs an important nonlinear processing step. If the total input exceeds a certain threshold, then an output signal is generated. If the total input exceeds a certain threshold, then an output signal is generated. The output signal is taken over by the output device, the axon which delivers the signal to the neurons. Biological models (like Leaky Integrate and Fire) that accumulate input spikes, raising their internal potential until it crosses a threshold, causing them to fire a spike. [[34] books]

1.7.11. Synapses:

Connections between neurons, characterized by weights that determine signal strength (excitatory/inhibitory). The location where the axon of a presynaptic neuron makes contact with dendrite (soma) of a postsynaptic cell is the synapse. The most common type synapse, the axon in the vertebrate brain is a chemical synapse, it triggers a complex chain of biomedical processing step that leads to release of neuron transmitter from the presynaptic cell membrane and open specific channels so that ions-from extracellular fluid flow into the cell. The ion influx, in turn leads to change the membrane potential at the postsynaptic site so that in the end the chemical signal is translated into an electrical response. The voltage response of the postsynaptic neuron to a presynaptic action potential is called post synaptic potential. [[22]]

1.7.12. Implementation:

Digital Memory (SRAM/DRAM): Weight values stored in traditional digital memory. Reliable but suffers from the von Neumann bottleneck (separate from processing unit).

Emerging Non-Volatile Memory (NVM)/Memristive Devices: The most revolutionary component. Devices like Memristors, ReRAM, PCM (Phase Change Memory) and FeFETs change their resistance/state on based passed current. In-Memory Computing (IMC), where the weight storage and multiplication operation happen at the same physical location, eliminating data movement. This is critical for scalability and efficiency. [[23]]

1.7.13. Emerging Non-Volatile Memory (NVM)/Memristive Devices:

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1.7.14. Spike Trains:

Temporal sequences of spikes carrying information, a core difference from ANNs. The neuronal signals consist of short electrical pulses can be observed by placing a fine electrode close to the soma or axon of a neuron. The pulses, so called action potentials or spikes, have an amplitude of about 100mVand typically a duration of 1-2ms. The form of the pulse does not change as the action potential propagates along the axon. A chain of action potentials emitted by a single neuron is called a spike train. A sequence of stereotyped events which occur at a regular or irregular intervals. Action potentials in a spike train are usually well separated. Even with very strong input, it is impossible to excite a second spike during or immediately after a first one. The minimal distance between the two spikes defines the absolute refractory period of the neuron. [[24]]

1.7.15. Dynamic Vision Sensors (DVS)/Event Cameras:

Pixels that independently and asynchronously emit events (spikes) when they detect a change in log intensity. They provide high temporal resolution, low latency and high dynamic range.

Event-Based Microphones (AER Ear):

Output spikes in response to acoustic changes. [[25],[26]]

Learning Rules:

Spike-Timing-Dependent Plasticity (STDP):

The most famous local learning rule. "Neurons that fire together, wire together". The weight change depends on the precise timing difference between pre-and post-synaptic spikes. It is naturally implemented in along memristive circuits.

Back-propagation Through Time for SNNs:

Adapted from Deep learning to train SNNs. Its powerful but non-local and computationally intensive, often done offline.

Surrogate Gradient Method:

A solution to the non-differentiability of spikes, enabling gradient-based training of SNNS.

1.7.16. Layers:

Simulators:

Software to model SNNs before hardware deployment (eg. NEST, Brain, CARLsim).

Compiler & Mapper:

Translates a high level SNN description in to an executable configuration for the specific hardware fabric (e.g., mapping logical neurons to physical cores, optimizing routing). This is a major research challenge.

Framework & Libraries:

High-level APIs (e.g. Lava (Intel), Nengo, snnTorch, Rockpool) that provide building block for creating training and deploying SNNs across platforms.

1.7.17. Runtime & Operating Systems:

Manages resource allocation, communication and execution on the neuromorphic hardware (e.g. the firmware on Loihi).

System Integration Components:

Chip Architecture:

The overall design philosophy that defines how neurons, synapses and interconnects are organized.

Packaging and Scaling Technology:

Components that enable moving beyond a single chip. This includes:

Interposers & High-Bandwidth Memory (HBM):

It is required for connecting multiple neuromorphic dies.

D-stacking:

To create dense, vertical connections between neuron and memory layers, directly addressing the interconnect challenge.

Host Interface & Hybrid Systems:

Neuromorphic chips are typically accelerators. They require a host system (CPU/GPU) for tasks they are not good at (e.g., data pre-processing, high-level control). The interface (e.g., PCIe) and driver software are crucial components.

Table 2 The Neuromorphic Stack table

Layers	**Components**	**Analogy in traditional Computing**
Application	Robotics, Edge AI, Sensory Processing	Word, Processor, Game
Algorithms	SNN Models, STDP and BPTT	Deep Learning algorithms (CNN, RNN)
Software Stack	Frameworks (Lava, Nengo) compilers and simulators.	PyTorcch/TensorFlow, CUDA compiler
Hardware	NoC, Core Architecture, Memory Hierarchy	GPU, SMX Cores, Cache Hierarchy
Physical hardware	Neuron circuits, synaptic Devices (Memristors, sensors DVS)	Transistors (CPU/GPU) DRAM, Webcam

1.8. Integration of IIoTs with Neuromorphic Computing:

The neuromorphic computing integration with IIoTs is now shifting from experimental research to a strategic framework for "Autonomous" factories and predictive edge intelligence. The integration is not just about adding a faster chip; it is about moving towards a microservice-based neuromorphic architecture where industrial sensors and control system mimic biological reflex loop.

Table 3 Traditional CPU/GPU based IIoT versus Neuromorphic Computing based IIoT

Traditional IIoT (GPU/CPU)	**Neuromorphic based IIoT**
Continuous Power Draw	Event-Driven Efficiency (Power only on activity)
Periodic Maintenance	Predictive Maintenance (Continuous Learning)
Cloud-Dependent AI	Autonomous Edge AI (Offline Intelligence)
Fixed Logic	Adaptive Plasticity (Learns on the floor)

Neuromorphic computing represents a paradigm shift from artificial intelligence that goes beyond conventional artificial neural network (CNNs), recurrent neural networks (RNNs) and transformers are inspired by the human brain at abstract level. Below table is showing the comparison between Neuromorphic Computing and other neural networks:

Table 4 Comparison between Neuromorphic Computing and other Neural networks [[27],[28]]

Parameter	**Traditional Neural Networks (ANN, CNN, RNN)**	**Deep Neural Network**	**Neuromorphic Computing**	**Why Neuromorphic Computing is better**
Biological Inspiration	Abstract brain inspiration	Very abstract mathematical models	Closely mimics biological neurons and synapses	Higher Biological realism
Signal Type	Continuous-Valued Activation	Continuous real-valued signals	Discrete Spikes	Sparse and efficient information flow
Processing Style	Synchronous, clock-based	Synchronous, highly clock-driven	Asynchronous, event-driven	Eliminate redundant computation
Energy Consumption	High	Extremely High (GPU/TPU based)	Very Low (milliwatts)	Ideal for low power systems
Idle Power Usage	High	Very High	Near Zero	Efficient always on operation
Hardware Architecture	Von Neumann architecture	Von Neumann architecture	Non-Von Neumann (brain inspired)	Removes memory bottlenecks
Memory-compute separation	Separate	Separate	Integrated at synapses	Faster and more efficient
Data Movement	High	Extremely High	Minimal	Lower latency and energy
Training Method	Offline, batch training	Offline, large-scale batch training	Online, local learning (STDP)	Real-time adaptation
Learning Adaptability	Limited	Very limited	High	Supports lifelong learning
Temporal Data Handling	Requires RNN/LSTM	Require Complex architecture	Native via spike timing	Efficient real-time processing
Latency	Moderate	High	Very Low	Faster Response
Parallelism	Limited	Limited by Synchronization	Massive, independent neurons	Highly scalable
Scalability Constraints	Power and Heat	Power, Heat, memory	Scales efficiently	Sustainable Growth
Fault Tolerance	Low	Low	High (Graceful degradation)	Robust to failures
Noise Tolerance	Low	Low	High	Works in real-world conditions
Data Requirement	Large datasets	Very large labeled datasets	Can learn from sparse data	Less data dependency
Learning Speed	Moderate	Slow	Fast and Continuous	Real-time learning
Precision Requirement	High Precision	Very high precision	Low precision sufficient	Energy efficient computation
Hardware	CPU, GPU	GPU, TPU	Intel Loihi, IBM TrueNorth	Optimized neuromorphic hardware

Software Ecosystem	TensorFlow, PyTorch	TensorFlow, PyTorch	Event-based frameworks	Efficient sensor-driven AI
Real-Time Capability	Limited	Poor	Excellent	Suitable for control systems
Autonomous Operation	Limited	Limited	Highly autonomous	Adaptive intelligence
Typical Applications	Image recognition, speech	NLP, Vision, Cloud AI	Robotics, IoT, Edge AI	Better for embedded intelligence
Cloud Dependence	Medium	High	Low	Works independently
Biological Plausibility	Low	Very Low	High	Brain-like Intelligence
Sustainability	Poor	Very Poor	Excellent	Green AI solution
Future Potential	Moderate	High but energy limited	Very High	Next Generation AI Paradigm

2. Research Gaps and Motivation

The main motivations of shifting towards neuromorphic computing is to overcome the power and efficiency limitations of traditional computers (von Neumann architecture) for AI. By mimicking the brain's energy-efficient, parallel processing, enabling real-time, low-power AI (especially at the edge), tackling complex tasks like sensory processing and offering new insights into brain function and cautiousness. They combine processing and memory, handle data-intensive AI workloads better and promise robustness to errors for autonomous systems.

In today's world IIoTs are connected and making a powerful network, but same time facing critical issues:

2.1. Data Deluge & Latency:

Millions of sensors generate vast, continuous streams of data sending all the data to cloud and plant server for further processing creates latency, bandwidth costs and communication forehead.

2.2. Power Consumption:

Deploying thousands of always-on, compute-intensive edge devices (like GPUs) for real-time analytics are often infeasible due to energy and thermal constraints.

2.3. Unpredictable Environment:

Factories, grids and farms have complex non-stationary patterns that are difficult for traditional algorithm (trained on static datasets). To handle in real-time.

2.4. Event-Driven Nature:

Many industrial data is event-based (e.g., Vibration monitoring system, Temperature threshold breach, Flame detector, Smoke detector etc.) Traditional von Neumann architecture waste energy processing "no-events".

2.5. Neuromorphic computing offers below benefits:

2.5.1. Energy efficiency:

The human brain uses vastly less power than modern supercomputers for complex tasks. Neuromorphic chips aim to achieve similar low-power, event-driven computation, crucial for mobile and edge AI.

Key Energy efficiency factors:

Event-Driven Processing:

Unlike conventional CPUS and GPUs that use energy continuously process data regardless of its value, neuromorphic chips use spiking neural networks (SNNs) that only consume energy when spike (an event) occurs. If there is no activity, the neurons remain idle and do not draw power.

Colocation of Memory and processing:

By integrating memory (often using devices like memristors directly in to the processing units, neuromorphic systems dramatically reduce the energy consumed by data transfer and memory access.

High Parallelism:

The architecture enables massive parallel computation, which makes processing large amounts of data significantly faster and more energy-efficient than sequential processing in traditional systems.

Reduce data precision:

Spiking neurons often use simple binary (all-or-nothing) or low-precision signal representation, which requires less complex and more energy-efficient circuitry compared to the high-precision floating-point operations in conventional AI systems.

Specialized Hardware:

Neuromorphic systems are implemented on specialized hardware designed from the ground up -for low-power operation, using advanced materials and integration techniques like 3D stacking to further minimize power loss and parasitic effects.

2.5.2. Overcoming Von Neumann bottleneck:

Traditional systems separate processing and memory, causing data traffic jams for AI. Neuromorphic designs integrate them, reducing bottlenecks and improving speed for machine learning.

2.5.3. Real-Time AI & Edge Computing:

Event-driven computation removes the need for clock cycles. Their low power and efficiency make them ideal for autonomous devices, robotics and sensors that need instant processing without constant cloud connection.

On-Device Learning and adaptability:

Neuromorphic chips are capable of on-device learning without constant cloud connectivity. This allows edge devices to adapt to new patterns or environment in real-time, improving performance and functionality without requiring frequent software updates or retraining from a central data center.

Biological Inspiration:

Millions of neurons and synapses operate in parallel. They mimic neural structures (neurons, synapses) to perform AI tasks more naturally, leading to breakthroughs in pattern recognition, vision and speech.

2.6. Comparison between Deep Neural network and Neuromorphic Computing:

Deep Neural Network have driven major advances in AI, but they also face important limitations.

Table 5 Second Level AI Versus Neuromorphic Computing:

	Feature	**Traditional**	**Neuromorphic**
1	Inspiration	Loosely inspired by the brain	Closely inspired by biological neurons and synapses
2	Basic Unit	Artificial neuron with continuous values	Spiking neuron with discrete events (spikes)

3	Data Representation	Real-Valued activations	Time-based spikes
4	Computational Style	Synchronous, clock-driven	Asynchronous, event-driven
5	Learning Methods	Backpropagation	Spike-Timing-Dependent Plasticity (STDP) and local learning rules
6	Energy Consumption	High (GPUs/TPUs required)	Very low (brain-like efficiency)
7	Hardware	CPUs, GPUs, TPUs	Specialized neuromorphic chips (e.g. Intel Loihi)
8	Latency	Higher for real-time tasks	Ultra-low, suitable for real time systems
9	Scalability	Limited by memory-compute bottleneck	Highly scalable due to memory-compute co-location
10	Fault Tolerance	Less tolerant to failures	Highly fault tolerant
11	Training Location	Mostly offline (Cloud/data centers)	Can learn online at the edge.

2.7. Scalability

Neuromorphic computing scale by increasing local density as memory and processing are co-located in "neurosynaptic cores". Neuromorphic chips like intel's Loihi2 or the Hala Point system use a tiled, modular architecture. By adding more identical cores and each core handle its own neuron and synapses guarantee good scalability. To prevent from data traffic jam, chips use mesh network. Local spikes stay within the core only long-range signals travel across the chip or between chips.

2.8. Robustness & Adaptability

Brain-like systems can potentially handle noisy, incomplete data and degrade gracefully with damage, unlike brittle traditional systems, crucial for space or harsh environments.

2.9. New Computational Paradigm

They offer novel ways to solve problems, potentially unlocking new AI capabilities and furthering our understanding of the brain itself (consciousness and thoughts).

2.10. Due to below challenges with Deep Neural Network, Neuromorphic Computing is being recommended

High Energy consumption:

- Training and inference require GPUs/TPUs with large power budgets.
- Data Centers contribute significantly to carbon emissions.

Von Neumann Bottleneck:

- Continuous data transfer between memory and processor causes latency and inefficiency.
- Limits scalability for very large models.

Data-Hungry Training:

- Requires massive labelled datasets.
- Poor performance in low-data or real-world dynamic environments.

Limited Real-time adaptation:

- Learning is mostly offline.
- Retraining is costly and time-consuming.

High Latency for edge devices:

- Cloud dependency increases response time.
- Unsuitable for ultra-low-latency systems like drones or prosthetics.

Poor Biological Plausibility

- Backpropagation is not brain-like.
- Difficult to integrate perception, learning and action seamlessly.

Hardware Dependence

- Performance tied to expensive specialized hardware.
- Not ideal for embedded or battery-powered devices.

model. Less precise for individual cased but gives a global sense of model logic.

3. Contribution

This technical research paper gives a conceptual model of a fully autonomous remote site in Oil and Gas industry, where IIoT sensors integrate with Neuromorphic Computing at Edge. Data collection from remote sites and sending it to the plant is always having difficulties, such as FOC cuts, Cyber-attacks, large bandwidth requirements, latency rates and delays in receiving data at another end. All flaws motivate autonomous remote sites with minimal requirement for connectivity with the plant side and, during disconnection in any FOC cut incident, the remote site can take decisions and run on itself and will not affect the wellhead to stop functioning.

By implementing neuromorphic computing chips with IIoT sensors, it will make the site fully autonomous and not depend on the plant side inputs. Neuromorphic sensors can make decisions based on recorded patterns and support life-long learning. These sensors don't require continuous power to keep them always turned on and active, but they work on spike initiation, which is similar to human brains and requires power and energy only at the time of need, and when the sensor is not processing, they will be in sleep mode. A vibration monitoring system (VMS), flame detector, smoke detector, shutdown valves etc. doesn't require being in active mode all the time and by utilization of neuromorphic computing on the edge side, it will increase efficiency and, at the same time, reduce power requirements, short bandwidth as only selected events and data need to be transferred to plant side. The IIoT sensors can make decisions and also inform operator about the decay or future failures.

In this paper, different comparisons were discussed, such as Neuromorphic computing with the traditional Von Neuman GUI and Deep Neural Network. Also, the evolution of neuromorphic computing from past to future. Many challenges were discussed which the manufacturing industry could face while making the sensors with built neuromorphic computing chips. The neuromorphic computing is the future of Artificial Intelligence, coping with challenges like large and complex calculations, continuous power requirements and operator-dependent sites.

The future of neuromorphic computing is discussed, and research gaps have been highlighted, where researchers need to study.

In overall, this paper is giving the fundamental idea of an autonomous Oil and gas remote site, which can be a model for future practical implementation. We keep the connection with plant side for sending data to plant for the health of sensors and critical processes and same time can receive information and instructions from SCADA operator stationed at Plant.

4. Methodology and Frame Work

Integrating industrial IIoTs with neuromorphic computing is a practical engineering challenge. It is a merge of sensor networks with brain-inspired chips.

4.1. The neuromorphic Proxy

IIoTs relies on legacy systems (PLCs and SCADA) a direct swap is impossible. The primary method is via a Neuromorphic-System Proxy (NSP).

4.2. Virtualization Layer

The NSP acts as a bridge, translating standard industrial data (Secure DNP, Modbus, EtherCAT) in to the Address Event Representation (AER) required by neuromorphic chips. The NSP creates a digital twin of neuromorphic hardware, allowing standard industrial software to interact with it without needing to know the underlying spiking logic.

4.3. Declarative Programming

Instead of manual "spike-tuning," engineers use declarative frameworks (like Intel's Lava, Nengo or snnTorch) allow developers define an industrial goal in Python. (e.g. "detect bearing friction anomalies and kept the compiler optimize the spiking network (SNN). The framework then complies these into optimized spiking neural network (SNNs) for the specific hardware.

4.4. Mapping

The frame works handles the "weight mapping" ensuring that a pre-trained deep learning model can be converted in to an energy-efficient spiking model with minimal accuracy loss.

4.5. High-Value IIoT use cases

Integrations can be prioritized in areas where traditional GPUs are too much power-hungry and too slow.

4.6. Closed loop Robotic Control

Neuromorphic processors are integrated directly in to robotic joints. Because the latency is sub 10ms, robots can perform "collision avoidance" in real-time based tactile skin sensors - something standard CPUs struggle to do at low power.

4.7. Neuromorphic smart Cameras (DVS)

Instead of standard video, factories are integrating Dynamic Vision Sensors (DVS). These only send data when a pixel change (e.g., a crack appearing on a moving part). This reduces data bandwidth by up to 90% allowing high-speed inspection without overloading the factory's Wi-Fi or Ethernet.

Vibration based Predictive Maintenance: Neuromorphic chips are being embedded inside motor housings. They use one-chip learning to understand the "normal" vibration of that specific motor and can detect microscopic anomalies years before a failure occurs.

Proposed Model

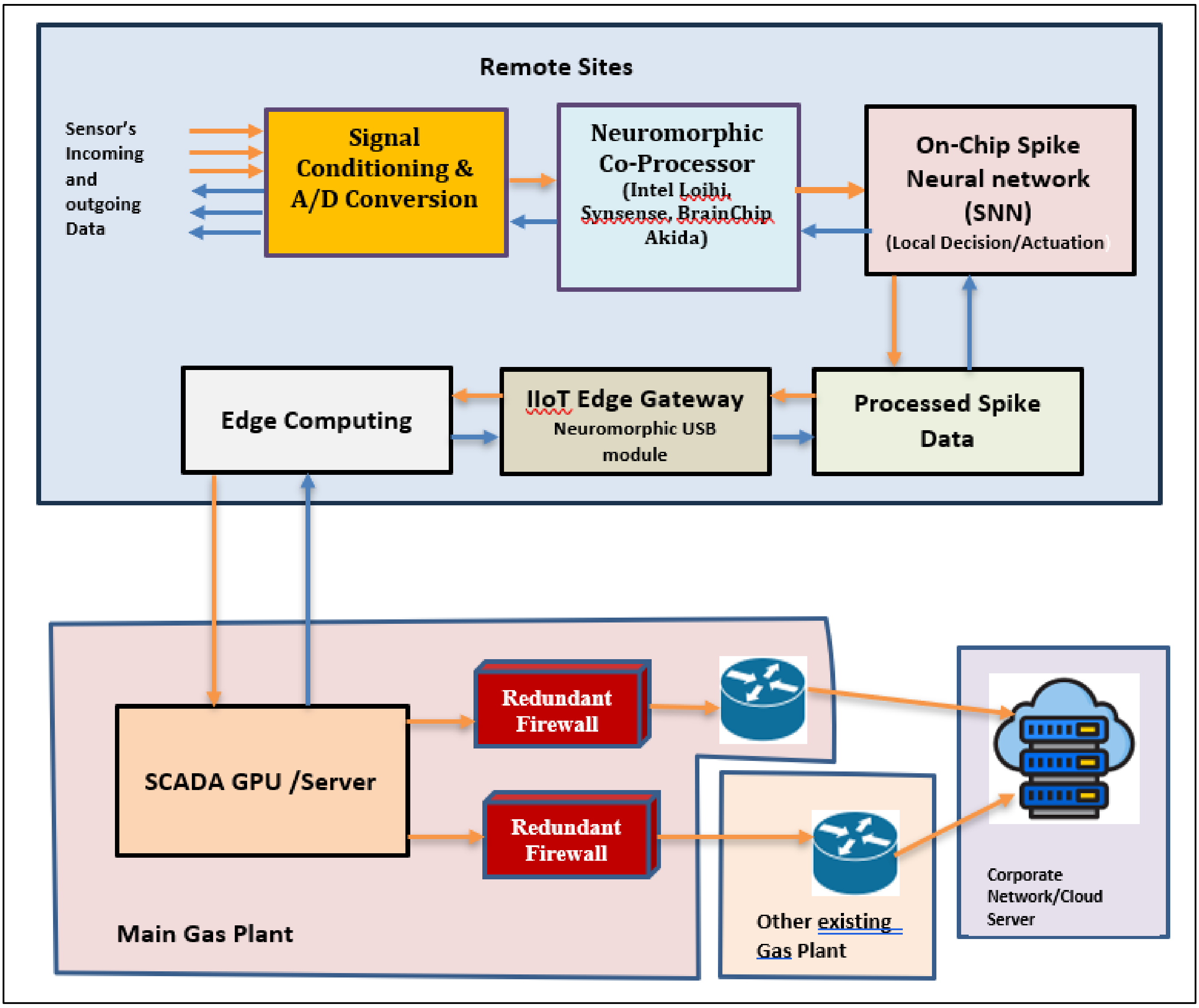


Figure 6 Proposed design model showing fully autonomous remote site

4.8. Edge to Cloud Continuum: We see a 3-tier integration model:

4.8.1. Level -1 (Sensor Level):

Tiny neuromorphic cores (like SynSense or BrainChip) perform "wake-up" functions – staying in a low-power state until an event is detected.

4.8.2. Level -2 (Edge Gateway):

A large neuromorphic system (e.g., an Intel Loihi2 module) aggregates data from multiple sensors to identify complex patterns like an entire production line becoming inefficient.

4.8.3. Level-3 (Digital Twin):

The neuromorphic data is sent to a cloud-based Digital twin where the industrial process is simulated and redefined, then updated "plasticity weights" are sent back to the factory floor.

Step-1: System Architecture:

Sensor Layer:

- Event-based sensors – DVS Camera, Event-based microphones, AER converters for legacy sensors.
- Conventional Sensors: Vibration, Temperature, Pressure, Flow meters, proximity sensors,
- PLCs with analog/digital I/O.

Edge Processing Layer:

- Intel Loihi 2 USB stick (Kapoho Bay) or BrainChip Akida PCIe card.
- Dedicated for pattern recognition.
- Conventional Edge Processor – Intel NUC/Advantech UNO, Runs OPC UA server, data aggregation.
- Manages conventional control loops.

Communication Layer:

- Event-based MQTT: Sparkplug B Specification, QoS 1 for critical events,
- Factory/area/machine event.

Control Layer:

- Hybrid Controller: SNN for pattern recognition, PID for continuous control, Decision Fusion algorithm.

Step -2: Technology Stack Selection:

Hardware:

Neuromorphic Processor Selection:

- Intel Loihi 2 (Best for online learning, research), BrainChip Akida (Comercial, easier deployment), SynSense Speck (Low-Power, Sensor fusion), INRC Kapoho Bay (USB-based, good for pilots).

Edge Devices:

- Dell Edge Gateway 5200 (with PCIe for neuromorphic card), Advantech UNO-2484G (industrial, wide temperature), custom: Raspberry Pi CM4+ Neuromorphic SOM.

Sensors:

- Prophesee Gen4.1event camera (for visual), Cave Hillcrest Labs Sensors (Event based IMU), Standard industrial sensors + AER converters.

Software:

Development:

- Intel Lava framework (for Loihi)
- Akida Development Environment (for BrainChip)
- Nengo DL (for simulation and training)
- PyTorch + snnTorch (for hybrid models)

Edge Runtime:

- Ubuntu 20.04 LTS or Yocto Linux
- Docker Containers with neuromorphic runtime.
- Kubernetes edge deployment (K3s)
- Node-RED for workflow orchestration

Industrial Integration:

- OPC UA stack (open62541 or Unified Automation)
- MQTT Broker (Eclipse Mosquitto with Sparkplug)

Step-3 Data Flow design:

- Raw Data → Event Conversion: Conventional Sensor Data → AER Converter → Spike Train
- (Example: Vibration data @ 10KHz, Encoding: Delta Modulation, Output: [timestamp, sensor_id, magnitude_delta].

4.8.4. Event Processing Pipeline:

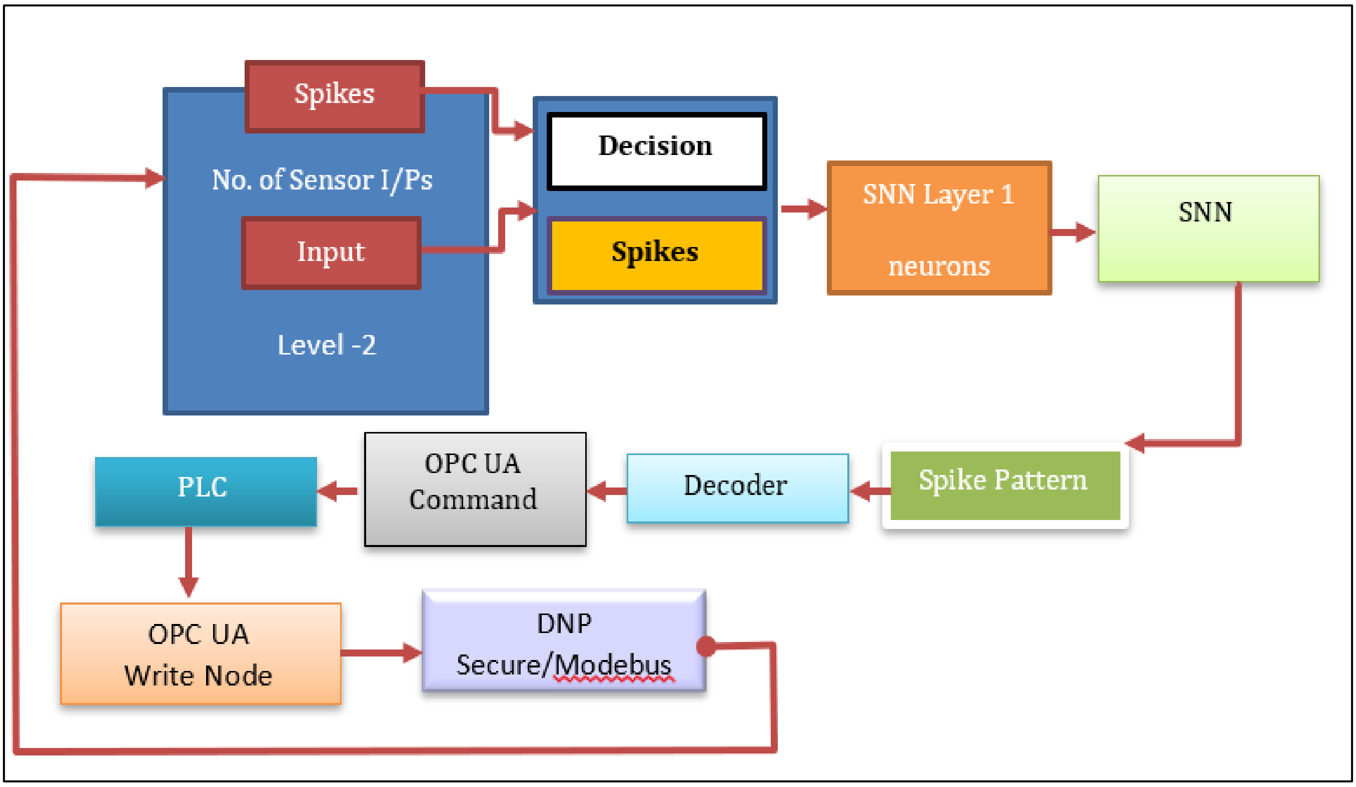


Figure 7 Neuromorphic event processing process

Step 4: SNN Model Development:

Data Preparation: Collect baseline vibration data

Model Architecture (Python using Lava).

Training Process:

- Convert ANN to SNN (if pretrained ANN exists) → Using Nengo DL for conversion
- Direct SNN training with surrogate gradient
- Apply weight normalization for SNN

Simulation Testing: Test Accuracy on Validation set

- Measure inference latency in simulation
- Power Consumption estimation
- Compare with baseline CNN model

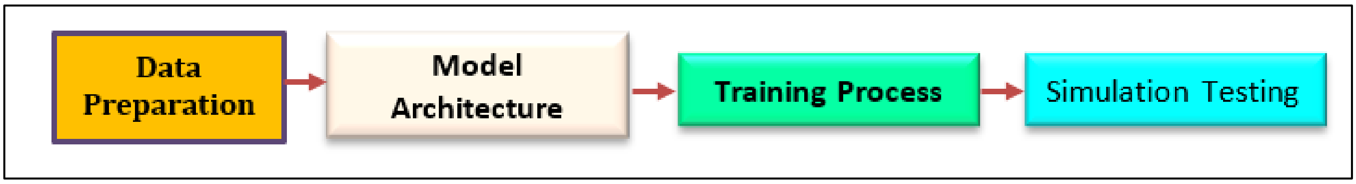


Figure 8 SNN Model Development process

Implement AER (Address-Event Representation) conversion:

- For Vibration Sensors (Delta Encoding)
- For Temperature Sensors (Level-Crossing)
- Event compression

Data acquisition:

Data enters the system through sensors such as during Silence no data is being processed.

- Event-based cameras (vision)
- Microphones (Audio)
- Touch or motion sensors
- IIoT signals

Step-5: Data Encoding:

Raw Input data is being converted into spikes (electrical pulses).

Common encoding methods:

- Rate Coding – Stronger signal = More spikes
- Temporal Coding: Information encoded in spike timing
- Population Coding: Groups of neurons represent data

This replaces binary data (0s and 1s) with spike events.

Step-6: Spike transmission to neurons

Encoded spikes are sent to artificial neurons through synapses.

- Each synapses have the weight
- Weight determines spike influence (Strong or Weak)

This mimics biological neural connections.

Step 7: Neuron Integration (accumulation):

Each Neuron:

⇓ Receives incoming spikes

⇓ Adds them to its internal membrane potential

⇓ Applies synaptic weights

⇓ Gradually accumulates charge

This is called integration

Step-8: Threshold check & firing

- If membrane potential exceeds a threshold
- The neuro fires a spike
- Membrane potential resets (or leaks over time)

If threshold not reached: Neuron stays silent (save energy).

Step-9: Parallel spike propagation

- Fire spikes propagate to thousands of connected neurons.
- All neurons work simultaneously.
- No global clock – asynchronous processing

This enables:

- Massive parallelism
- Ultra-low latency
- Very low power usage

Step -10: Learning via synaptic plasticity

- During or after processing, learning occurs by adjusting synaptic weights.
- Most common rule:

Spike-Timing-Dependent Plasticity (STDP)

- Pre-neuron fires before post -neuron – Weight increases
- Pre-neuron fires after post-neuron – weight decreases

Learning is:

- Local
- Real-time
- Online (on returning needed)

If neuron fires together repeatedly, their connection strengthens.

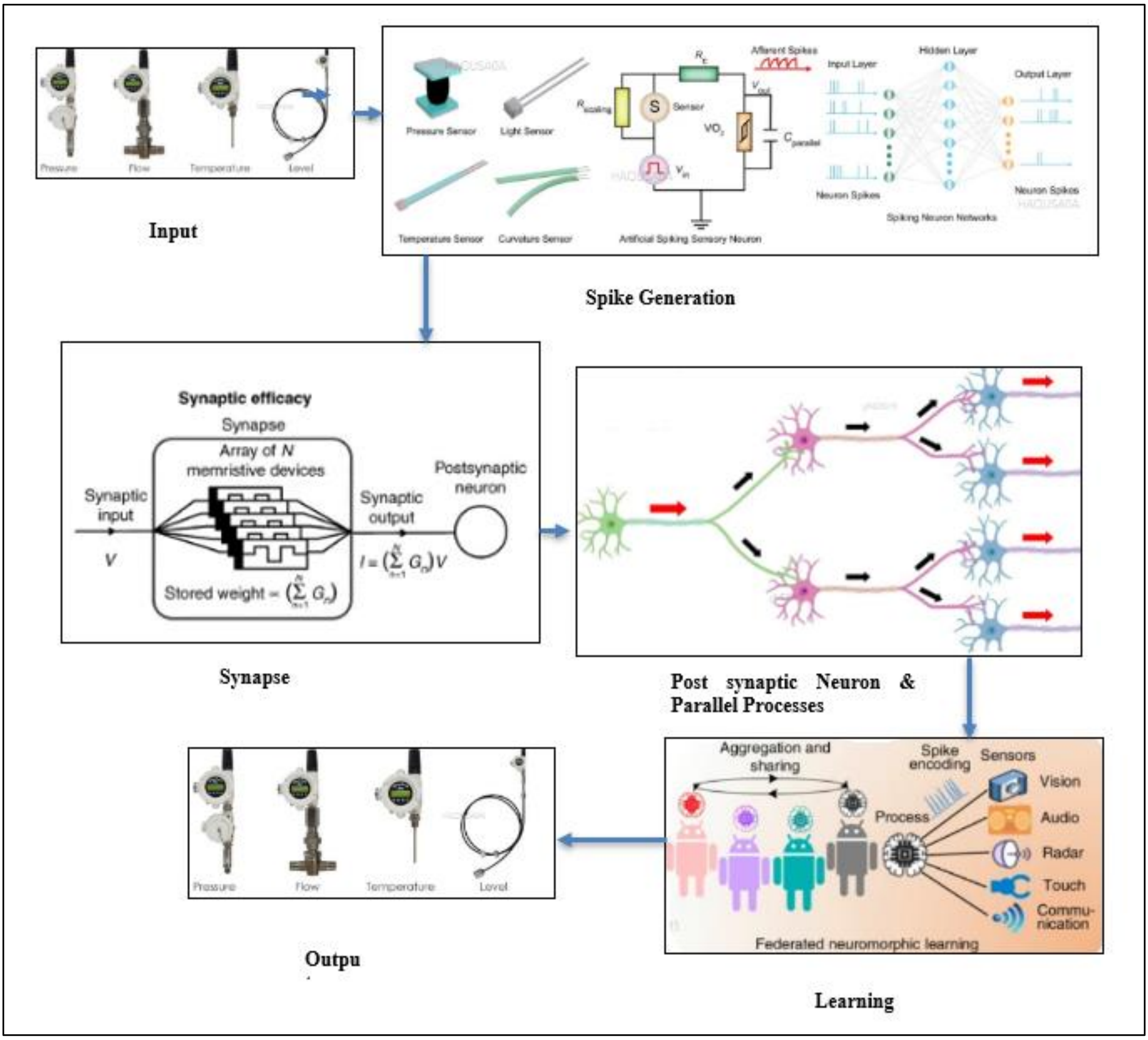
This enables:

- Pattern recognition
- Adaptation
- On-chip learning

Step -7: Output Generation:

Output neuron produce spike patterns representing.

- Decisions
- Classifications
- Control Actions



Input -> Spikes -> Synapses -> Neurons -> Parallel Processing ->Learning -> Output

Figure 9 Flow Summary

6. Challenges with Neuromorphic Computing integration with IIoTs:

Integrating Neuromorphic Computing (brain-inspired hardware) with IIoTs represents a frontier with immense potential but also significant, layered challenges. The promise is clear: ultra-low-power consumption, real-time, adaptive intelligence, and at the edge of the industries or near to data origin point. However, there are many challenges in practical implementation:

6.1. Hardware & Platform Challenges:

- **Immutability Vs. Plasticity:**
    - IIoT systems often require stability and determinism. Neuromorphic chips, which use spiking Neural Network (SNNs) are designed for adaptive learning and temporal dynamics, ensuring reliable, repeatable performance in a noisy, changing factory environment is difficult.

- **Precision & Determinism:**
    - Traditional industrial control relies on high-precision, deterministic digital computations (e.g. PID loops). SNNs are inherently probabilistic and event-driven, which can be odds with the need for exact time critical control signals.
- **Sensor Interface (The transducer problem):**
    - Most IIoT sensors (vibration, temperature, flame, pressure) output continuous analog or high-frequency digital data. Neuromorphic chips process sparse, asynchronous spikes. Creating efficient, low-latency “transducers” (encoding/decoding algorithms and hardware) to bridge this gap is a major research challenge.
- **Scalability & Fabrication:**
    - While promising for low-power tasks, large-scale neuromorphic systems (e.g., Intel’s Loihi, BrainChip’s Akida) are not yet at the volume, cost or proven reliability level required for mass IIoT deployment. They are often prototypical or research-focused.

6.2. Software & Algorithmic Challenges:

- **Lack of standardized Toolchains:**
    - The IIoT ecosystem thrives on standards (OPC UA, MQTT, Time-Sensitive Networking). The neuromorphic ecosystem is fragmented with proprietary software frameworks (LAVA, Nengo, BrainChip’s MetaTF) that don’t easily integrate with standard industrial automation stacks (e.g. PLC programming IEC 61131-2, SCADA).
- **Training & Deployment Complexity:**
    - Training SNNs is fundamentally different from training traditional Deep Neural Networks. Its less mature, often requires conversion from trained DNNs (losing some efficiency) or uses bio-inspired learning rules (e.g. Spike-Timing Dependent Plasticity) that are hard to control; and verify for critical tasks.
- **Explainability and Debugging:**
    - “Debugging” a spiking network’s temporal dynamics is incredibly complex. In an industrial setting where failure can be catastrophic, the inability to fully explain why a neuromorphic system made a specific decision is a major barrier to adoption.

6.3. Integration and System Level Challenges:

- **Heterogeneous Architecture Integration:**
    - A practical IIoT node might combine a traditional microcontroller (for deterministic control) a GPU/TPU accelerator (for heavy DNN interference), and a neuromorphic co-processor (for sensory processing). managing this heterogeneity in software, data flow and power is a significant system engineering challenge.
- **Real-Time Requirements:**
    - Many IIoT applications (robotic control, safety interlocks) have hard real-time constraints. While neuromorphic chips are fast, guaranteeing worst-case execution times (WCET) for event-driven adaptive systems is notoriously difficult.
- **Security Paradigm:**
    - Neuromorphic chips may introduce novel attacks surfaces (e.g. adversarial attacks on temporal patterns, fault injection via power spikes). Traditional IIoT cybersecurity new computational models.

6.4. Practical and Commercial Challenges:

- **Cost vs. Benefits:**
  - For most current IIoT problems (predictive maintenance, visual inspection), well-understood, cheaper solutions (cloud analytics, edge GPUs) exist. The unique value proposition of neuromorphic computing (extreme low power, continuous learning) must clearly solve a costly, unsolved problem to justify the investment and risk.
- **Skill Gap:**
  - There is a severe shortage of engineers who understand both industrial automation system and neuromorphic engineering. This slows development deployment t and maintenance.
- **Proof of Concept to Production Gap:**
  - While there are compelling lab-scale proofs (e.g., gesture recognition, anomaly detection in vibration signals), moving to hardened certified, and supportable product for harsh industrial environment is a massive leap.

6.5. Accuracy Gap (Algorithmic Challenges):

The most significant hurdle is that spiking neural Networks (SNNs) – the native "language" of neuromorphic chips – often struggle to match the raw accuracy of traditional Artificial Neural Networks (ANNs) on complex tasks.

- **Non-Differentiable Nature:**
  - Standard AI is trained using "backpropagation" which requires smooth, mathematical curves. Spikes are discrete (on/off) events, making them mathematically "jagged" and difficult to train with traditional tools.
- **The Depth Problem:**
  - A SNNs grow deeper (more layers), they suffer from "vanishing spikes" or "exploding spikes" where information either peters out or overwhelm the system. While surrogate gradients have helped, large-scale SNNs still trail behind transformers (like GPT-4) in language reasoning.
- **Temporal Dependency:**
  - Programming a network to care about the timing of a signal adds a layer of complexity that we haven't yet mastered for general-purpose computing.

6.5.1. The connectivity and Memory Bottleneck:

Biological brains are incredibly "dense" and "three dimensional "Replicating this in two-dimensional silicon is a physical nightmare.

- **The Fan-Out Problem:**
  - A single human neuron can connect to 10000 others. In silicon chip wiring that many connections require massive amounts of physical space. Intel Loihi 2 use virtual "routing" to simulate these connections, but this creates internal traffic jams (congestion) as the system scales.
- **Synaptic Storage:**
  - To truly mimic the brain, you need a synapse (memory) next to every "neuron" (Processor). Current SRAM memory is too bulky. While Memristors and RRAM (Resistive RAM) are the 2026 "holy grail" they are still difficult to manufacture reliably at scale without defects.

- **Sneak Path:**
  - In analog neuromorphic crossbars, electricity can sometimes "leak" through unintended paths, leading to noise and errors in calculation.

6.6. Software Desert:

From last 40+ years of software built of r Von Neumann (CPU/GPU) architecture. Neuromorphic computing essentially asks developers to "unlearn" everything.

- **Lack of standardization:**
  - There is no "Windows" or "Linux" for neuromorphic chips. While Intel's Lava and IBM's frameworks are making progress code written for a brain chip Akida processor won't run on a SynSense chip.
- **The compilation nightmare:**
  - Converting a "standard" AI model (from PyTorch or TensorFlow) into a spiking format often leads to a "conversion loss" in accuracy.
- **Debugging Complexity:**
  - How do you debug a system that doesn't have a "state" you can pause; but instead relies on a continuous flow of asynchronous pulses? We lack the diagnostic tools to see "inside" a running neuromorphic system.

6.7. The Economic and Industrial "Lock-in" the incumbency challenge:

- **The GPU Juggernaut:**
  - NVIDIA and others have invested billions in making GPU and CUDA software stack nearly perfect for AI. For most companies it is cheaper and easier to use an "inefficient" GPU that to hire a team of specialized scientists to build "neuromorphic" solution.
- **Fabrication Costs:**
  - Building specialized neuromorphic chips requires different manufacturing processes. Until there is a "killer app" (like a must-have autonomous drone or medical implant) that requires neuromorphic tech, the volume won't be high enough to bring costs down.

7. Future of Neuromorphic Computing integrated IIoTs:

Future of automation is autonomous IIoTs and emergence of industrial cognitive ecosystems – self-organizing, self-learning, energy-autonomous networks of intelligent devices that perceive, reason and adapt with biological-like efficiency.

Neuromorphic IIoT integration with fundamentally transform industry from centralized automation to distributed intelligence. By 2050, Neuromorphic computing (NC) will have fundamentally transformed IIoT from networked automation in to distributed cognitive system, which will create industrial environments that perceive, reason and adapt with unprecedented efficiency and autonomy. This will revolutionize industrial IoTs fundamental operating method.

Timeline of Evolution of Neuromorphic computing for IIoTs:

7.1. Phase-1:

The Sensory Revolution (2025-2035): *From data collection to intelligent perception*

- **Always-On, Zero-Power Sensing:**

  - Neuromorphic sensors harvesting energy from ambient sources will monitor infrastructure 24/7 without maintenance.
- **Temporal Intelligence:**
  - Equipment that doesn't just detect failures but predict them by recognizing subtle temporal patterns preceding breakdown.
- **Embedded Cognition:**
  - Every motor, valve and bearing will contain its own neuromorphic "instinct" for self-monitoring.

7.2. Phase -2:

The Adaptive Nervous System (2035 -2045): *From Centralized control to distributed Intelligence*

- **Industrial Reflex Arcs:** Local neuromorphic circuits creating immediate responses to safety threats without cloud latency.
- **Swarm Intelligence:** Fleets of autonomous vehicles and drones coordinating through spiking neural communication.
- **Self-Optimizing Processes:** Manufacturing lines that continuously adapt to material variations, tool wear and environmental conditions.

7.3. Phase -3:

The cognitive Ecosystem (2045 -2050+): *From automation to industrial consciousness:*

- **Industrial Metacognition:**
  - Systems that monitor their own performance and learning process.
- **Cross-Domain Intelligence:**
  - Factories that share learned patterns and solutions across global networks.
- **Bio-Hybrid systems**:
  - Integration of synthetic biological components with neuromorphic computing for novel sensing capabilities.

7.4. Hardware Evolution Path:

- **2025-2035:** Commercial availability of 3D-stancked neuromorphic chips with >100M synapses.
- **2030-240:** Molecular-scale neuromemristors enabling trillion-synapse systems at watt-scale power.
- **2040-2050:** Photonic neuromorphic hybrids for ultra-high-speed, interference -free industrial communication.
- **Post 2050:** Quantum-neuromorphic systems for solving optimization problems currently interactable.

7.4.1. Software & Framework Development:

- **Neuromorphic Industrial Language (NIL):**
  - A domain-specific language for describing industrial processes in terms compatible with spiking neural networks.

- **Industrial Synaptic Plasticity Rules:**
    - Learning algorithms specifically designed for industrial environments, balancing adaptability with stability.
- **Cognitive Digital Twin standards:**
    - Frameworks where traditional digital twins evove into neuromorphic counterparts that can simulate and experiment.

7.5. Integration Future:

- **The Power-Perception Convergence:**
    - Energy harvesting systems that directly power neuromorphic processing without conversion losses.
- **The sensor-computer fusion:**
    - Complete elimination of the sensor-processor boundary through in-sensor neuromorphic computing.
- **The network-Intelligence Merger:**
    - Communication protocols that are intrinsically neuromorphic, where data transmission and processing become indistinguishable.

7.6. Industry Specific Transformations:

7.6.1. Manufacturing:

- **Self-Organizing Production Lines:**
    - Factory floors that reconfigure themselves based on order requirements.
- **Quality Consciousness:**
    - Products that carry their own quality assurance as embedded neuromorphic intelligence.
- **Material-Aware Manufacturing:**
    - Processes that adapt in real-time to the unique properties of each material batch.

7.6.2. Energy System:

- **Predictive Grid:**
    - Power distribution networks that anticipate failures and reroute energy flows autonomously.
- **Cognitive Renewable Integration:**
    - Wind farms and solar arrays that predict weather patterns and adjust output preemptively.
- **Self-Balancing Microgrids:**
    - Community energy systems that optimize production, storage, and consumption through collective intelligence.

7.6.3. Logistics & Supply Chains:

- **Living Inventory:**

  - Goods that continuously report their condition, location and optimal routing.
- **Anticipatory Logistics:**
  - Supply networks that predict disruptions and autonomously reroute around them.
- **Self-Optimizing Ports**:
  - Entire harbor operations managed by distributed neuromorphic intelligence.

7.6.4. Infrastructure:

- **Self-Monitoring Bridges & Buildings:**
  - Structures with embedded nervous systems that detect stress, corrosion and damage.
- **Adaptive Public Spaces:**
  - Cities where lighting, traffic and utilities respond in real-time to usage patterns.
- **Predictive Maintenance Ecosystems:**
  - Municipal systems that schedule their own maintenance before failures occur.

7.6.5. The Industrial Noosphere:

- **Global Industrial Consciousness:**
  - A Planet-scale cognitive layer overseeing industrial activity with sustainability goals.
- **Self-Evolving Factories:**
  - Manufacturing systems that redesign their own processes and even physical layouts.
- **Human-Industrial Mind Merger:**
  - Direct cognitive interfaces allowing human operators to feel the state of complex systems intuitively.

7.6.6. Autonomous Industrial Ecosystems:

- **Self-Replicating Infrastructure:**
  - Remote mining and manufacturing systems that can build copies of themselves.
- **Planetary Engineering Systems:**
  - Climate regulation and terraforming technologies guided by neuromorphic intelligence.
- **Interstellar Industrial Systems:**
  - Space-based manufacturing guided by neuromorphic systems capable of operating with extreme autonomy.

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8. Future Research Areas

8.1. Advanced Neuromorphic Materials:

- Memristor stability & Scalability: Developing industrial-grade, non-volatile memristors with 10+ year lifespans.

- 3D neuromorphic architectures: stacking synaptic layers to mimic cortical columns.
- Self-healing neuromorphic circuits: Materials that repair synaptic degradation autonomously.
- Energy-autonomous designs: Complete systems powered entirely by energy harvesting.

8.2. Heterogeneous Integration:

- CMOS-Neuromorphic co-design: Seamless integration on single chips
- Sensor-Processor fusion: Eliminating the sensor-computer boundary through in-sensor computing.
- Quantum-neuromorphic interface: Hybrid Systems for optimization problems.

8.3. Algorithms & Software:

8.3.1. Industrial-specific Learning Rules:

- Stable lifelong learning: Algorithms preventing catastrophic forgetting in safety-critical systems.
- Explainable spiking networks: Interpretability methods for regulatory compliance.
- Few-Shot industrial learning: Adapting to new equipment with minimal data.
- Temporal pattern libraries: pre-trained circuits for common industrial phenomena (bearing wear, cavitation etc.)

8.3.2. Neuromorphic-Digital Twin integration:

- Bidirectional Learning frameworks: Physical systems and digital twins teaching each other.
- Predictive simulation: Using neuromorphic system to run ultra-fast "what-if" scenarios.
- Cross-reality validation: Ensuring digital and physical system alignment.,

8.4. System Architecture and Integration:

8.4.1. Cognitive Industrial Architectures:

- Industrial "brain" hierarchies: Mimicking biological nervous system organization.
- Swarm coordination protocols: For multi-agent systems (robots, drones, AGVs).
- Resilient distributed cognition: Systems that degrade gracefully during partial failures.

8.4.2. Legacy Integration Pathways:

- Neuromorphic abstraction layers: Translating between spiking and traditional industrial protocols.
- Hybrid control system: Gradual transition frameworks from PLCs to neuromorphic controllers.
- Backward compatibility standards: Ensuring 50-year equipment lifespan compatibility.

8.5. Application & Domain-Specific Research:

8.5.1. Predictive Maintenance:

- Pre-failure anticipation: Recognizing patterns preceding failures by days/weeks.
- Component-level "health" models: Individual parts reporting their own remaining useful life.
- Cross-System Failure prediction: Recognizing cascade failure prediction: Recognizing cascade failure patterns across different equipment types.

8.5.2. Autonomous Industrial Operations:

- Human-Intention recognition: Systems anticipating operator needs.
- Moral decision frameworks: For autonomous systems in safety-critical situations.
- Self-reconfiguration systems: Production lines that redesign their own layout for optimal flow.

8.6. Foundational Science & Cross-Disciplinary Research:

8.6.1. Neuromorphic Information Theory:

- Spike-based information metrics: new measures for efficiency in event-driven systems.
- Temporal coding optimization: Maximizing information per spike
- Distributed memory models: How industrial knowledge should be stored across neuromorphic networks.

8.6.2. Industrial Neuroscience:

- Applying biological principles: Sleep-like consolidation, attention mechanism, and pain analogs for industrial system.
- Industrial Consciousness metrics: Quantifying system awareness levels.
- Cognitive load optimization: Balancing processing across distributed systems.

8.6.3. Sociotechnical & Security Research:

- Trust & Certification:
- Verification methods for non-deterministic systems. New approaches to safety certifications.
- Explainability Standards: Regulatory frameworks for neuromorphic decision justification.
- Ethical constraint embedding: Ensuring systems respect human values and priorities.

8.6.4. Neuromorphic Cybersecurity:

- Novel attack surface analysis: Adversarial attacks on spatiotemporal patterns.
- Cognitive integrity protection: Ensuring learning is not maliciously manipulated.
- Distributed trust frameworks: For decentralized cognitive.

8.6.5. Quantum Neuromorphic Computing

One of the most exciting frontiers is the potential integration of neuromorphic computing with quantum computing, Quantum computers having the ability to process vast amounts of data in parallel, and combining them with neuromorphic principles could lead to breakthroughs in AI, machine learning and other computational fields.

8. Conclusion

The research article is analyzing the promising future of artificial intelligence and neural networks in the form of neuromorphic computing and its integration with IIoT sensors. This research paper is giving a conceptual model of a fully autonomous remote site in Oil and Gas industry, where all IIoT sensors work autonomously. The complete implementation methodology, infrastructure, technology, hardware and software requirements have been discussed in this paper.

The human brain anatomy and its characteristics have been discussed. The comparison of neuromorphic computing is with Von Neumann's traditional CPU, and with Deep Neural Network is also explained. Development of neuromorphic computing in previous years and where it takes us in future is also shown and found that neuromorphic computing will be a paradigm in neural network-based systems.

The research paper gives the idea of neuromorphic autonomous sensors, showing the capability of thinking, analyzing, learning, taking decisions, informing operators and others about maintenance and failure of the system at remote sites. These autonomous sensors are not required to be active continuously or require continuous power, as the neuromorphic computing-based IIoT sensor's functionality depends upon event-based spikes, which optimize bandwidth and energy requirements and at the same time provide ultra-low latency and real-time data transfer from one remote to plant and central locations. Due to an event-based mechanism that consumes very low bandwidth. This research paper gives information about the characteristics and components required for neuromorphic computing integration with IIoTs. There are different comparisons between Deep Neural Network (DNN) and CPU/GPU-based networks.

The challenges and benefits of neuromorphic computing systems are also discussed in terms of latency, bandwidth and power consumption and found that neuromorphic computing is providing future insight to think of autonomous industries.

The research gaps and future research requirements show that there is still a lot of research required to commercialize neuromorphic computing for industrial purpose implementations.

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