Proceedings of CONF-CIAP 2026 Symposium: Applied Mathematics and Statistics
DOI: 10.54254/2753-8818/2026.CH30863

# *Simulating Synaptic Transmission and Learning Mechanisms in Spiking Neural Networks: From Biology to Neuromorphic Computing*

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***Abstract.*** Synapses are fundamental units of communication within the nervous system, enabling electrical and chemical signal transmission between neurons. This paper explores the structure and function of biological synapses, with particular emphasis on their role in information processing, learning, and memory through synaptic plasticity. Using a comparative methodology that examines biological fidelity, computational efficiency, and hardware feasibility, this paper investigates how synaptic mechanisms such as Short-Term Depression (STD) and Spike-Timing-Dependent Plasticity (STDP) are modeled in artificial systems, particularly in Spiking Neural Networks (SNNs) and neuromorphic computing. Pulse integrators—analog circuits designed to simulate synaptic signal integration—are introduced as core components bridging neuroscience and hardware implementation. This research highlights the increasing relevance of biologically inspired learning rules and hardware in the development of low-power, efficient AI systems. The conclusion emphasizes the potential of synaptic models to advance neuromorphic architectures and improve the adaptability of intelligent machines, with promising applications in edge computing, autonomous systems, and adaptive sensory processing.

***Keywords:*** Synapse, Spiking Neural Network, Synaptic Plasticity, Pulse Integrator, Neuromorphic Computing

## 1. Introduction

Synapses form the communication junctions between neurons, essential for the proper functioning of the nervous system. Since their conceptual introduction by Charles Sherrington in 1897, synapses have remained central to the current understanding of how the brain processes, stores, and reacts to information [1]. Recent developments in microelectronics and neuroscience have made possible the emulation of synaptic behaviors in artificial systems, particularly within the field of neuromorphic computing.

This paper focuses on the simulation of biological synapses and their learning mechanisms within Spiking Neural Networks (SNNs), a model of neural computation that uses discrete events or "spikes" to process information [2,3]. Specifically, we explore the design and function of analog pulse integrators and their role in mimicking neuronal integration and synaptic plasticity.

Our research aims to address the following questions: How do biological synaptic behaviors influence artificial learning models? What role do circuits like pulse integrators play in enabling such models? Can synaptic plasticity, including mechanisms such as STDP and STD, be effectively implemented in hardware?

By answering these questions, this study aims to contribute to the development of energy-efficient, real-time learning systems and indicates the potential of synapse-inspired circuits for future intelligent technologies.

## 2. Basic structure and function of neural synapses

### 2.1. Definition and historical background

A synapse is a specialized junction that allows neurons to pass electrical or chemical signals to other neurons, muscles, or glands. The term was first introduced by Sir Charles Sherrington in 1897, who described it as the point where one neuron connects to another. His work laid the foundation for modern neurobiology and earned him the Nobel Prize in Physiology or Medicine in 1932.

Sherrington's discovery was revolutionary because it provided the first clear explanation of how nerve cells communicate. Before his work, the mechanism of signal transmission in the nervous system was largely unknown. His research revealed that synapses are not merely physical connections but dynamic structures that regulate the flow of information.

In addition to chemical synapses, electrical synapses were later identified, where ions flow directly between neurons via gap junctions, allowing faster signal transmission [4]. Modern studies continue to reveal the complexity of synaptic communication, including the role of glial cells and neuromodulators.

### 2.2. Structural components

A typical chemical synapse consists of three main parts: Presynaptic Neuron: The neuron that sends the signal. It contains synaptic vesicles filled with neurotransmitters. Synaptic Cleft: A narrow gap between the presynaptic and postsynaptic neurons. Postsynaptic Neuron: The neuron that receives the signal. It has receptors on its membrane that bind to neurotransmitters.

The process of synaptic transmission involves the release of neurotransmitters from the presynaptic terminal, their diffusion across the synaptic cleft, and binding to receptors on the postsynaptic membrane, leading to ion channel opening and potential change. Ultrastructural studies reveal active zones, vesicle docking sites, and postsynaptic densities as critical for efficient transmission. As shown in Figure 1, the structure of a chemical synapse highlights these key components and their spatial organization.

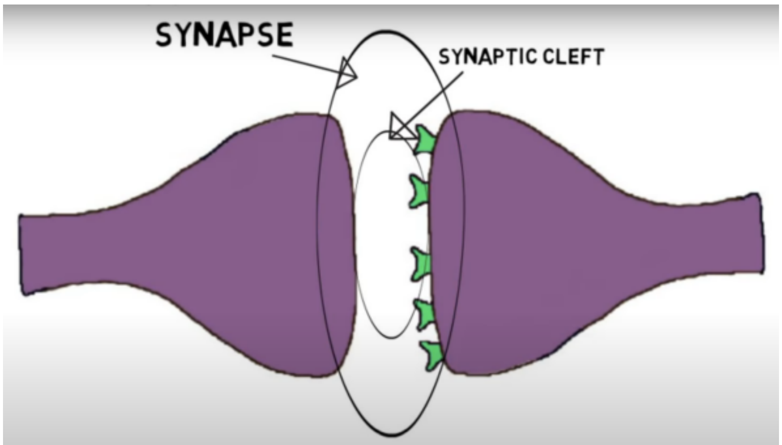


Figure 1. Structure of a chemical synapse

### 2.3. Excitatory and inhibitory synapses

Synapses can be classified based on their effect on the postsynaptic neuron: Excitatory Synapses: These use neurotransmitters like glutamate to depolarize the postsynaptic membrane, making it more likely to generate an action potential. Inhibitory Synapses: These use neurotransmitters like GABA to hyperpolarize the membrane, reducing the likelihood of firing.

This balance between excitation and inhibition is crucial for maintaining neural stability and enabling complex computations. Additionally, neuromodulatory synapses release substances such as dopamine or serotonin, which modulate synaptic efficacy over broader timescales and influence learning and behavior [5].

## 3. Synaptic transmission and plasticity

### 3.1. Process of neurotransmitter release and reception

When an action potential reaches the presynaptic terminal, voltage-gated calcium channels open, allowing $Ca^{2+}$ ions to enter. This influx triggers synaptic vesicles to fuse with the presynaptic membrane and release neurotransmitters into the synaptic cleft. These chemicals then bind to receptors on the postsynaptic neuron, leading to changes in its membrane potential. As shown in Figure 2, this sequence of events illustrates the dynamic nature of synaptic transmission.

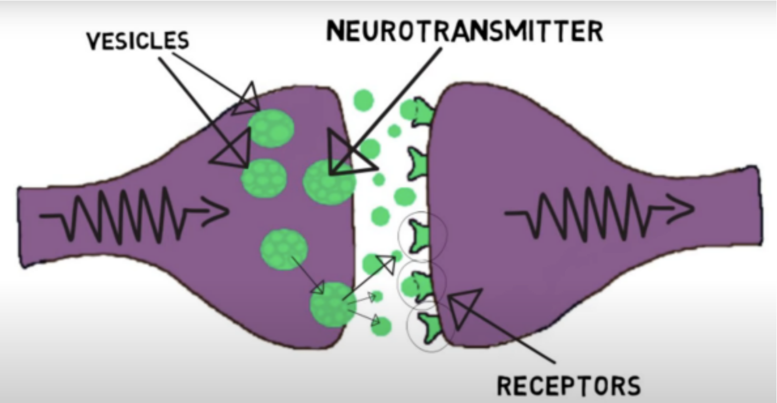


Figure 2. Synaptic transmission process

### 3.2. Synaptic plasticity and learning mechanisms

Synaptic plasticity refers to the ability of synapses to strengthen or weaken over time in response to activity. This is the biological basis of learning and memory [5,6].

Two key forms include: Long-Term Potentiation (LTP): A long-lasting increase in synaptic strength, often involving NMDA receptor activation, calcium influx, and downstream signaling pathways that lead to increased receptor expression and structural changes. Long-Term Depression (LTD): A long-lasting decrease, typically triggered by low-frequency stimulation and involving different calcium dynamics and phosphatase activation. These mechanisms allow the brain to adapt to new information and experiences.

### 3.3. Biological mechanism and significance of Short-Term Depression (STD)

Short-Term Depression occurs when high-frequency stimulation leads to a temporary decrease in synaptic strength. This is often due to the depletion of synaptic vesicles or desensitization of receptors. STD helps prevent neural overexcitation and filters out redundant stimuli, allowing the brain to focus on relevant information.

## 4. Bio-inspired mechanisms and classification of pulse integrators

### 4.1. Basic principle of pulse integrators

A pulse integrator is an analog circuit that mimics the way biological neurons integrate incoming postsynaptic potentials (PSPs). Its core function is to accumulate input current or charge pulses over time and generate an output signal—typically a voltage—when a predefined threshold is exceeded, simulating the firing mechanism of a neuron. This temporal integration abstracts the spatial and temporal summation of excitatory and inhibitory inputs in dendrites. In biological terms, the integrator approximates the membrane capacitance's charging and discharging dynamics, where the time constant of integration determines the persistence of the input signal's effect. Basic implementations often use a capacitor as the primary storage element, with reset mechanisms to mimic refractory periods. The design of these circuits must carefully balance biological plausibility, silicon area, and power consumption [7].

### 4.2. Nonlinear integrator

Nonlinear integrators process input pulses in a manner that is not strictly proportional to the input amplitude or frequency, enabling them to model complex neural behaviors such as saturation, adaptation, and thresholding. These circuits often incorporate transistors operating in subthreshold regime to achieve exponential or sigmoidal response functions, closely matching the nonlinear input-output relationships observed in biological neurons. For instance, a nonlinear integrator can model synaptic saturation—where high-frequency inputs lead to diminished increments in postsynaptic response—by intentionally limiting the maximum voltage on the integration capacitor. Another application includes modeling active dendritic compartments, where localized nonlinear boosts occur due to voltage-gated ion channels. Such integrators are particularly useful for simulating synaptic plasticity rules like STDP under realistic conditions, where the weight update depends nonlinearly on the membrane potential or local calcium concentration. Their design often involves feedback elements or translinear loops, providing tunable parameters that control the degree and type of nonlinearity [5,7].

### 4.3. Log-domain integrator

Log-domain integrators use logarithmic compression to handle a wide range of input intensities. This makes them ideal for modeling sensory systems, such as vision or hearing, where neurons respond logarithmically to stimulus intensity.

### 4.4. Differential Pair Integrator (DPI)

The Differential Pair Integrator (DPI) is a widely adopted circuit in neuromorphic design, known for its ability to accurately compute the temporal integral of the difference between two input currents. At its core, the DPI uses a differential pair of transistors to split a bias current between two branches, effectively performing a continuous-time subtraction. The resulting current is then integrated on a capacitor, producing an output voltage that represents the cumulative difference between excitatory and inhibitory inputs. This architecture makes the DPI exceptionally suitable for modeling the balanced excitation and inhibition observed in cortical circuits, which is critical for maintaining network stability and enabling selective response patterns. Furthermore, the DPI's transfer function can be configured to implement linear or nonlinear integration, and its time constant is easily tunable via the bias current. This flexibility has led to its extensive use in neuromorphic chips that implement learning rules such as STDP, where the precise timing between pre- and postsynaptic events needs to be converted into analog weight updates. As shown in Figure 3, the compact and symmetric structure of the DPI facilitates dense integration in large-scale arrays [7,8].

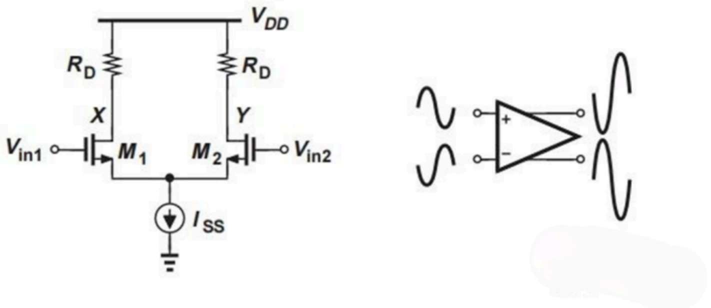


Figure 3. Circuit diagram of a differential pair integrator

## 5. Brain-inspired learning mechanisms in Spiking Neural Networks (SNNs)

### 5.1. Basic concepts of Spiking Neural Networks

Spiking Neural Networks (SNNs) represent the third generation of neural network models, distinguished by their use of discrete, asynchronous spike events for information encoding and transmission [2]. Unlike traditional artificial neural networks (ANNs) that rely on continuous activation values, SNNs incorporate temporal dynamics into their computational framework, closely mimicking the information processing mechanisms of biological neural systems. This biological fidelity grants SNNs several significant advantages: remarkable energy efficiency due to event-driven computation, inherent temporal information processing capabilities, and sparse activity patterns that reduce computational overhead [3]. The fundamental computational unit in SNNs is the spiking neuron model, with the leaky integrate-and-fire (LIF) model being widely adopted for its balance between biological plausibility and computational efficiency. More complex models, such as the Hodgkin-Huxley and Izhikevich models, offer greater biological accuracy at the cost of increased computational resources [2,3].

### 5.2. Implementation of STDP learning rule in SNNs

Spike-Timing-Dependent Plasticity (STDP) serves as the cornerstone of unsupervised learning in most SNN implementations. This Hebbian-like learning rule adjusts synaptic weights based on the precise temporal relationship between pre- and postsynaptic spikes: if the presynaptic spike precedes the postsynaptic spike (causal relationship), the synapse is potentiated; conversely, if the presynaptic spike follows the postsynaptic spike (anti-causal relationship), the synapse is depressed [5,6]. Hardware implementation of STDP typically employs a pair of cross-coupled circuits that detect and integrate the timing differences between spikes, generating appropriate weight update signals. Several variations of basic STDP have been developed to enhance its functionality and biological realism. These include triplet-STDP, which considers patterns of three spikes to better replicate experimental data; reward-modulated STDP, which incorporates global reward signals to enable reinforcement learning; and homeostatic STDP, which maintains network stability through mechanisms like synaptic scaling and sliding thresholds [3,5]. These advanced STDP implementations have demonstrated remarkable capabilities in feature extraction, pattern recognition, and temporal sequence learning.

### 5.3. Role of Short-Term Depression in neural network learning

Short-Term Plasticity (STP), particularly Short-Term Depression (STD) and Short-Term Facilitation (STF), introduces dynamic temporal filters to SNNs, significantly enhancing their computational capabilities. STD, characterized by a temporary decrease in synaptic efficacy during high-frequency stimulation, primarily results from the depletion of readily releasable neurotransmitter vesicles in biological synapses [4]. In SNNs, this mechanism is implemented through dynamic variables that track neurotransmitter availability or receptor desensitization. The functional benefits of STD in SNNs are multifaceted: it prevents network saturation during burst inputs, implements adaptive gain control that enhances dynamic range, facilitates temporal filtering that emphasizes novel stimuli, and contributes to working memory through transient activity patterns [4,5]. When combined with long-term plasticity mechanisms like STDP, STD enables more stable and efficient learning by preventing runaway dynamics and promoting balanced network activity. Furthermore, the interplay between STD and STF creates rich temporal dynamics that support complex information processing tasks, including speech recognition, motion detection, and temporal pattern classification [3,9].

## 6. Applications of pulse integrators and synaptic mechanisms in neuromorphic hardware

### 6.1. Event-driven computing and low-power implementation

Neuromorphic hardware leverages the event-driven nature of SNNs to achieve unprecedented energy efficiency in intelligent computing systems. Unlike conventional von Neumann architectures that operate on fixed clock cycles, neuromorphic systems employ asynchronous, event-driven processing where computations are triggered only by incoming spikes [7,10]. This approach eliminates the energy waste associated with clock distribution and idle computation, making it particularly suitable for power-constrained applications. Several key strategies enable this low-power operation: the use of analog and mixed-signal circuits for biological fidelity with minimal power overhead; memristive crossbar arrays that combine memory and computation to avoid the von Neumann bottleneck; and subthreshold CMOS designs that exploit the exponential current-voltage relationship of transistors to achieve biological time constants with nanoampere-level currents [7,8,10]. These implementations typically achieve energy consumption in the range of picojoules per spike, representing orders of magnitude improvement over traditional digital approaches for equivalent temporal processing tasks.

### 6.2. Applications in pattern recognition and dynamic signal processing

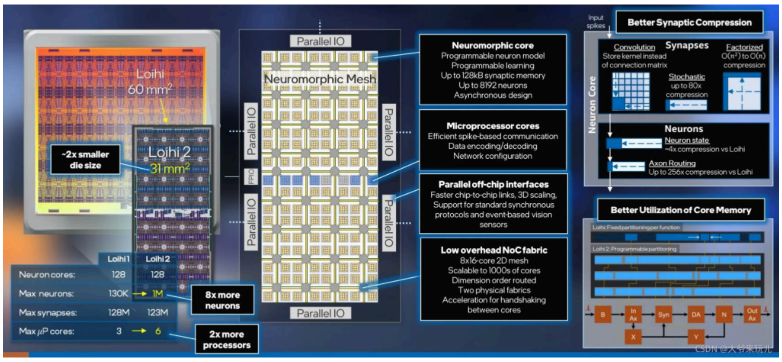
The unique temporal processing capabilities of SNNs, enabled by pulse integrators and synaptic plasticity mechanisms, have led to breakthrough applications in real-world signal processing domains. In visual processing, SNNs integrated with dynamic vision sensors (DVS) demonstrate exceptional performance in high-speed object tracking and gesture recognition, processing sparse event-based data with minimal latency and power consumption [9]. For auditory processing, silicon cochleas coupled with SNN classifiers achieve robust speech recognition in noisy environments and sound source localization, leveraging the inherent temporal structure of audio signals. Additional applications include tactile sensor processing for robotics, where SNNs classify texture and slip detection; olfactory sensing with electronic noses that identify complex odor patterns; and multimodal sensor fusion that integrates visual, auditory, and tactile information for autonomous systems [3,9,10]. These applications benefit particularly from the SNNs' ability to process non-stationary signals with varying time scales, a capability that stems directly from the combination of pulse integrators and synaptic plasticity mechanisms.

### 6.3. Case studies: TrueNorth and Loihi neuromorphic chips

IBM TrueNorth: This pioneering neuromorphic chip employs a digital architecture with 1 million programmable neurons and 256 million configurable synapses, organized in a scalable crossbar network. TrueNorth implements a serial, time-multiplexed approach where each physical core emulates multiple neurons through rapid reconfiguration. While this design achieves remarkable energy efficiency (approximately 26 pJ per synaptic operation), it sacrifices some biological realism for scalability. TrueNorth has demonstrated compelling applications in real-time video analysis, multi-object tracking, and constrained optimization problems, typically consuming less than 100 milliwatts for complex classification tasks [10].

Intel Loihi: Representing the state-of-the-art in research neuromorphic systems, Loihi features a novel asynchronous spiking architecture that supports programmable synaptic learning rules, including STDP and its variants [8]. The second-generation Loihi 2 introduces significant enhancements: finer-grained programmability, wider dynamic range for synaptic weights, and improved neuron models that support multi-compartment dynamics. A distinctive feature of Loihi is its support for on-chip learning, enabling autonomous adaptation without external computation. Research applications include olfactory pattern recognition, adaptive robotic control, and sparse coding, with demonstrated energy efficiency improvements of up to 1000× compared to conventional approaches for specific temporal processing tasks [8]. As you can see in Figure 4.

BrainScaleS: This European neuromorphic system adopts a different approach, using analog emulation to achieve 1000× acceleration compared to biological real-time [7]. The analog neuron and synapse circuits of BrainScaleS faithfully reproduce the continuous-time dynamics of biological neurons, while digital components handle spike routing and plasticity rule implementation. This hybrid approach enables extremely fast simulation of neural networks for scientific research, particularly in studying learning dynamics and network plasticity. BrainScaleS-2, the current generation, incorporates plastic synapses with enhanced programmability, making it suitable for both neuroscience experimentation and machine learning applications [7].



| | Loihi1 | Loihi 2 |
|---|---|---|
| Neuron cores: | 128 | 128 |
| Max neurons: | 130K → | 1M |
| Max synapses: | 128M | 123M |
| Max $\mu$P cores: | 3 → | 6 |

Figure 4. Architecture of Intel Loihi neuromorphic chip

## 7. Conclusion

This paper has systematically explored the fundamental mechanisms of biological synapses and their hardware emulation through pulse integrators in Spiking Neural Networks (SNNs). We have demonstrated how synaptic plasticity mechanisms—particularly Spike-Timing-Dependent Plasticity (STDP) and Short-Term Depression (STD)—can be effectively modeled in neuromorphic hardware to enable efficient, low-power learning systems. The integration of neuroscience principles with microelectronics has established promising pathways for developing intelligent systems that are both scalable and energy-efficient.

Our analysis confirms that pulse integrators serve as crucial interfaces between biological principles and hardware implementation. Differential Pair Integrators have proven particularly valuable for implementing balanced excitation-inhibition and supporting STDP learning rules, while nonlinear and log-domain integrators offer distinct advantages for specific neuromorphic applications.

However, significant challenges remain in training deep SNNs due to the non-differentiable nature of spike events, and current hardware faces limitations in connectivity and dynamic range. Most existing synaptic models also oversimplify the rich molecular machinery of biological synapses.

Future research should prioritize developing more biologically plausible learning algorithms, enhancing hardware capabilities through emerging technologies like memristive devices, and exploring novel applications in adaptive edge computing and autonomous systems. The convergence of brain-inspired computing with artificial intelligence promises to overcome limitations of conventional architectures, potentially enabling machines that learn and adapt with unprecedented efficiency.

With continued interdisciplinary collaboration, synapse-inspired computing is poised to transform artificial intelligence, enabling autonomous systems that rival biological intelligence in efficiency and adaptability.

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