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Mathematical Models for Brain functions: Insights into Neurological Disorders

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ABSTRACT
Understanding how neurons process and transmit signals is crucial for modeling brain function and diagnosing neurological disorders. This study explores the Leaky Integrate-and-Fire (LIF) model—a simplified yet powerful mathematical representation of spiking neurons—as a framework to simulate neural dynamics under different input conditions. The LIF model is formulated using a first-order differential equation that captures the membrane potential's evolution in response to external currents and inherent leakage. Two simulation scenarios are analyzed: one with constant input current and another with step-varying current. Results demonstrate how the neuron exhibits regular spiking for sufficient stimulation and remains sub-threshold otherwise, highlighting threshold-dependent behavior. These dynamics are linked to real-world phenomena such as sensory gating, delayed neural activation, and seizure-like hyperactivity. The model offers valuable insights into cognitive disorders like ADHD and epilepsy and can serve as a computational basis for developing biologically inspired neural circuits or neuromorphic systems. Overall, the LIF model provides an accessible yet biologically relevant tool for investigating neural behavior and its disruptions in pathological conditions.

Keywords: *Leaky Integrate-and-Fire (LIF) Neuron, Neural Modeling, Computational Neuroscience, Neuromorphic Systems, Mathematical Neuroscience*

1. INTRODUCTION

The human brain is an intricate network of billions of neurons that communicate via electrical impulses, forming the basis of all cognitive and physiological functions. Modeling these complex neuronal dynamics is essential to understanding how the brain processes information, responds to stimuli, and how these processes are disrupted in neurological disorders. Among the various mathematical models developed to describe neuronal behavior, the Leaky Integrate-and-Fire (LIF) model stands out for its simplicity, computational efficiency, and ability to capture essential neuronal properties such as membrane potential evolution, threshold-based firing, and post-spike reset mechanisms.

The LIF model conceptualizes a neuron as an electrical circuit, wherein the membrane potential integrates incoming current until it reaches a threshold, at which point a spike is generated, followed by a reset. Despite its simplified nature, the model effectively replicates spiking patterns observed in biological neurons and provides a foundational tool for simulating larger neural networks. Such modeling is particularly valuable for examining how neurons behave under normal and pathological conditions.

In the context of neurological disorders, variations in input stimuli, membrane properties, or threshold dynamics can lead to abnormal firing patterns associated with conditions like epilepsy, attention-deficit/hyperactivity disorder (ADHD), and Alzheimer's disease. By exploring different input conditions—such as constant, stepwise, or noisy currents—researchers can gain insights into how neurons respond to external signals and how dysfunctions emerge. The LIF model also serves as a foundational block in neuromorphic engineering, where brain-inspired computing systems are developed for efficient real-time processing.

The Leaky Integrate-and-Fire (LIF) model continues to be a foundational tool in computational neuroscience due to its simplicity and effectiveness in simulating spiking behavior. Thieu and Melnik (2022) explored the role of stochastic noise in LIF models and demonstrated its implications for neuromorphic computing, emphasizing how noise can enhance or disrupt signal propagation in synthetic neural networks. Yuan et al. (2023) presented an artificial LIF sensory neuron designed for in-sensor computing at the edge, showcasing high-efficiency neuromorphic perception systems that closely mimic biological sensory responses. Zhang et al. (2025) advanced this line of work with the Dual Adaptive LIF (DA-LIF) model, which integrates adaptive membrane time constants and thresholds to enhance spiking neural network (SNN) accuracy while reducing computational complexity. Fourcaud and Brunel (2002), though slightly older, provided a pivotal theoretical framework analyzing the firing probability under noise, which remains influential in the design of modern noisy LIF-based models. Li and Wang (2001) contributed similarly by incorporating spike-frequency adaptation mechanisms, which are now key in modeling cortical dynamics and disorder simulations. More recent efforts like Lu and Xu (2022) formalized mappings between LIF networks and deep neural networks, offering analytical insights into how LIF neurons can replicate continuous activation functions, thereby bridging the gap between spiking and non-spiking paradigms.

Yao et al. (2022) proposed a Gated LIF (GLIF) model that enhances temporal dynamics using gating mechanisms, enabling richer temporal encoding capabilities in spiking networks. Meanwhile, Brigner et al. (2022) and Wang et al. (2023) shifted focus toward hardware implementation, designing purely spintronic and reconfigurable LIF neurons for ultra-low power applications, critical for wearable and edge neuroscience applications. Finally, Ascione and Pirozzi (2019) introduced a semi-Markov extension of the LIF model, allowing for the incorporation of complex temporal dependencies and irregular spike patterns observed in neurological disorders.

Collectively, these studies reinforce the adaptability of the LIF model for both biological simulations and hardware implementations. They demonstrate how modifications to its structure—such as introducing adaptive, stochastic, or gated dynamics—can significantly improve modeling fidelity in both normal and pathological neural systems. These contributions also highlight the model's increasing relevance in practical applications like brain-computer interfaces, epilepsy modeling, and neuromorphic engineering.

This study presents two illustrative cases using the LIF model: one with a constant input current and another with a step-function input, each highlighting distinct spiking behaviors and their physiological relevance. These examples demonstrate how even simple models can yield profound insights into neural computation and support future work in both theoretical neuroscience and clinical diagnostics. The novelty of this study lies in its systematic application of the classical LIF model for dual-purpose use: (i) to mimic real neuronal behavior under biologically inspired stimuli, and (ii) to analyze pathological deviations as seen in neurological disorders. While LIF models have been extensively used in theoretical neuroscience, this work uniquely integrates simulation, analysis, and interpretation with neurological relevance, bridging the gap between mathematical abstraction and clinical insight. Furthermore, the use of interpretable simulation scenarios (like constant vs. step current input) makes the model highly adaptable for educational, diagnostic, and neuromorphic engineering applications. This framework also serves as a gateway to extending LIF models with noise, adaptation, or gating features for advanced studies in brain-inspired computing.

Objectives are given by

1. To model and simulate neural dynamics using the Leaky Integrate-and-Fire (LIF) neuron model under different input stimuli such as constant and step currents.
2. To analyze the behavior of membrane potential and spiking patterns to reflect typical neuronal response and understand how these may deviate in the presence of neurological dysfunction.
3. To provide a simplified yet biologically meaningful mathematical framework for investigating the dynamics of single neurons, serving as a foundational tool for larger network simulations.

4. To interpret the modeled results in the context of real-world disorders such as epilepsy, ADHD, and neurodegenerative conditions, thus contributing to better understanding of disease mechanisms.
5. To demonstrate the computational advantages of the LIF model for use in low-power neuromorphic systems and artificial intelligence applications.

2. PRELIMINARIES

2.1. Biological Neuron Overview
A neuron is a specialized cell in the nervous system that transmits information via electrical impulses. It receives signals through dendrites, processes them in the soma (cell body), and sends output via the axon when a threshold is reached.
2.2. Membrane Potential
The membrane potential V(t) is the voltage difference across the neuronal membrane, affected by ionic currents. A neuron "fires" or generates a spike when this potential crosses a specific threshold.
2.3. Definition: Leaky Integrate-and-Fire (LIF) Neuron Model
The LIF model is a simple mathematical model that describes the evolution of membrane potential V(t) over time as:

$$\tau_m \left\{\frac{dV(t)}{dt}\right\} = -[V(t) - V_{\{rest\}}] + R\, I(t)$$

Where:
τ_m: $Membrane\ time\ constant\ (in\ ms)$
$V_{\{rest\}}$: $Resting\ potential$
R: $Membrane\ resistance$
$I(t)$: $Input\ current$
$V(t)$: $Membrane\ potential\ at\ time\ t$
When $V(t) \geq V_{\{th\}}$, the neuron emits a spike, and V(t) is reset to a lower value $V_{\{reset\}}$.
2.4. Definition: Threshold Mechanism
Let $V_{\{th\}}$ be the firing threshold. If at any time t, $V(t) \geq V_{\{th\}}$, then:
A spike is recorded. V(t) is immediately reset to $V_{\{reset\}}$, and the neuron may enter a refractory period $\Delta\, t_{\{ref\}}$, during which it does not integrate inputs.
2.5. Definition: Firing Rate
The firing rate of a neuron is the number of spikes generated per unit time, and can be used to quantify neural activity in response to various inputs.
2.6.Theorem(Existence and Uniqueness of Solution for LIF Equation)
Let I(t) be a continuous input current and the parameters $\tau_m, R, V_{\{rest\}}$ be constants with $\tau_m > 0$. Then, the initial value problem:

$$\tau_m \left\{\frac{dV(t)}{dt}\right\} = -[V(t) - V_{\{rest\}}] + R\, I(t), \qquad V(0) = V_0$$

has a unique continuous solution V(t) for all $t \geq 0$ up to the first firing time $t^*\ when\ V(t^*) = V_{\{th\}}$.

3. MAIN WORK – NEURON MODEL

Let's consider the Leaky Integrate-and-Fire (LIF) neuron model, one of the most fundamental and biologically realistic models used to simulate the electrical behavior of a neuron in a simplified form.
Leaky Integrate-and-Fire (LIF) Neuron Model
Purpose
The LIF model describes how a neuron integrates incoming signals (like synaptic currents) and produces spikes (action potentials) when the signal becomes strong enough. It mimics how biological neurons accumulate voltage and fire once a threshold is crossed.
Mathematical Equation

$$\tau_m \left\{\frac{dV(t)}{dt}\right\} = -[V(t) - V_{\{rest\}}] + R_m\, I(t)$$

Where:
$V(t)$: $Membrane\ potential\ at\ time\ t$
τ_m: $Membrane\ time\ constant = R_m\, C_m$
$V_{\{rest\}}$: $Resting\ membrane\ potential$
R_m: $Membrane\ resistance$
C_m: $Membrane\ capacitance$
$I(t)$: $Input\ current\ (could\ be\ a\ synaptic\ input\ or\ stimulus)$
Working Mechanism
1. Integration:
The neuron starts at rest ($V(t) = V_{\{rest\}}$).
When current I(t) is applied, V(t) starts to rise.
The voltage integrates over time while also leaking back toward $V_{\{rest\}}$, simulating ion leakage.
2. Firing (Spiking):
When $V(t) \geq V_{\{th\}}$ (threshold potential), the neuron fires a spike.The potential is immediately reset to $V_{\{reset\}}$, and the neuron may enter a refractory period (during which it cannot spike).
3. Leak Term:
The term $[V(t) - V_{\{rest\}}]$ models the leaky nature—how the neuron naturally returns to its resting state if no input is given.
Simulation Behavior
Low input: voltage remains below threshold → no firing.
Sustained input: voltage reaches threshold periodically → regular spiking.
Noisy input: irregular spike timing → models biological neuron behavior.
Graphical Interpretation
Plotting membrane potential V(t) vs. time:
It rises with input current.
When it hits the threshold, there's a sudden drop (spike firing and reset).

If current continues, this cycle repeats.
Biological Significance
Represents pyramidal neurons in the cortex.
Captures essential features of neuronal excitability without complex ion channel dynamics.
Forms the basis of spiking neural networks (SNNs) used in neuromorphic computing.
Applications
Studying temporal coding in the brain.
Understanding neuronal synchronization in disorders like epilepsy.
Used in brain-computer interfaces, robotics, and low-power hardware.

4. NUMERICAL SIMULATION

Example 1: LIF Neuron Model Simulation with Constant Input Current

Objective
Simulate how a single neuron responds to a constant input current using the LIF model. Observe membrane potential dynamics and spike generation.
Step 1: Define Parameters
$\tau_m \quad - 10\,ms\ - Membrane\ time\ constant \quad |$
$V_{\{rest\}} \quad - 65\,mV$
$- Resting\ membrane\ potential \quad |$
$V_{\{th\}} \quad - 50\,mV - Threshold\ potential \quad |$
$V_{\{reset\}} \ - 65\,mV$
$- Reset\ potential\ after\ a\ spike\ |$
$R_m \quad - 10\,M\Omega\ - Membrane\ resistance \quad |$
$I \quad - 1.5\,nA - Input\ current \quad |$
$Time\ step\ (dt)\ - 1\,ms\ - Simulation\ time\ resolution \quad |$
$Total\ simulation\ - 200\,ms$
$- Duration\ of\ simulation \quad |$

Step 2: Python Code

```
```python
import numpy as np
import matplotlib.pyplot as plt

# Simulation parameters
T = 200        # total time in ms
dt = 1         # time step
n_steps = int(T/dt)

# LIF neuron parameters
tau_m = 10      # ms
V_rest = -65    # mV
V_th = -50      # mV
V_reset = -65   # mV
R_m = 10        # MOhm
I = 1.5         # nA (constant input current)

# Initialize variables
V = np.zeros(n_steps)
V[0] = V_rest
spikes = []

# Simulation loop
for t in range(1, n_steps):
    dV = (-(V[t-1] - V_rest) + R_m  I)  dt / tau_m
    V[t] = V[t-1] + dV

    # Spike condition
    if V[t] >= V_th:
        V[t] = V_reset
        spikes.append(t)

# Plotting
time = np.arange(0, T, dt)
plt.figure(figsize=(10, 4))
plt.plot(time, V, label='Membrane Potential V(t)')
plt.axhline(V_th, color='r', linestyle='--', label='Threshold')
plt.title('Leaky Integrate-and-Fire Neuron Response')
plt.xlabel('Time (ms)')
plt.ylabel('Membrane Potential (mV)')
plt.legend()
```
```

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```
plt.grid()
plt.show()
```

Step 3: Output Interpretation
The plot will show membrane potential rising due to input current.
Once the voltage crosses -50 mV, the neuron spikes and the voltage resets to -65 mV.
This continues periodically, forming a spike train.
Biological Insight
A sustained constant input leads to regular spiking, similar to a sensory neuron detecting continuous stimulation (e.g., pressure).
Altering input or membrane time constant can simulate neuron fatigue, hyperexcitability, or failure to spike, relevant to disorders like:
Epilepsy: too many spikes under noisy/stimulus overload.
Parkinson's: reduced excitability or over-leakage.
Alzheimer's: disconnection, affecting input I(t).

Example 2: LIF Neuron with Step Current Input
Objective
To simulate how a neuron reacts to a step input current that increases after a certain time, and observe the change in firing behavior.
Model Parameters
$\tau_m \quad - 10\ ms$
$V_{\{rest\}} \quad - 65\ mV$
$V_{\{th\}} \quad - 50\ mV$
$V_{\{reset\}} \quad - 65\ mV$
$R_m \quad - 10\ M\Omega$
$Time\ step\ dt \quad - 1\ ms$
$Total\ time \quad - 200\ ms$
Step Input Current

$$I(t) = \begin{Bmatrix} 0.5\ nA & if\ t < 100\ ms \\ 2.0\ nA & if\ t \geq 100\ ms \end{Bmatrix}$$

This mimics a biological neuron suddenly receiving stronger stimulus (e.g., sudden light or loud sound).
Python Code

```python
import numpy as np
import matplotlib.pyplot as plt

# Time parameters
T = 200
dt = 1
n_steps = int(T / dt)

# Neuron parameters
tau_m = 10
V_rest = -65
V_th = -50
V_reset = -65
R_m = 10

# Initialize variables
V = np.zeros(n_steps)
V[0] = V_rest
I = np.zeros(n_steps)

# Step input current
for t in range(n_steps):
    if tdt < 100:
        I[t] = 0.5  # nA
    else:
        I[t] = 2.0  # nA

spikes = []

# LIF simulation
for t in range(1, n_steps):
    dV = (-(V[t-1] - V_rest) + R_m  I[t])  dt / tau_m
    V[t] = V[t-1] + dV
```

```
    if V[t] >= V_th:
        V[t] = V_reset
        spikes.append(t)

# Plotting
time = np.arange(0, T, dt)
plt.figure(figsize=(10, 4))
plt.plot(time, V, label='Membrane Potential V(t)')
plt.plot(time, I10 - 90, color='orange', linestyle='--', label='Input Current (scaled)')
plt.axhline(V_th, color='r', linestyle='--', label='Threshold')
plt.title('LIF Neuron with Step Input Current')
plt.xlabel('Time (ms)')
plt.ylabel('Membrane Potential (mV)')
plt.legend()
plt.grid()
plt.show()
```

Interpretation
Before 100 ms: the input is too weak, so the neuron doesn't spike.
After 100 ms: the input current increases, causing regular spiking.
This simulates a neuron that activates only when input crosses a threshold, which is common in sensory systems or inhibitory brain regions.
Biological Relevance
Mimics delay in neural activation found in cognitive disorders like ADHD or Alzheimer's.
Shows threshold sensitivity—too low input means no response; too high means risk of over-firing (seen in epilepsy).
Useful in designing neuromorphic chips for dynamic signal processing.
A comparison table of the two LIF neuron simulation examples we discussed

Comparison Table: LIF Neuron Simulations

Feature	Example 1: Constant Input	Example 2: Step Input
Input Current I(t)	Constant at 1.5 nA	Step input: 0.5 nA (t < 100 ms), 2.0 nA (t ≥ 100 ms)
Initial Response	Immediate regular spiking	No spiking before 100 ms (low input)
Threshold Crossing	Crossed multiple times regularly	Crossed only after step input increases
Spiking Behavior	Periodic spikes from early on	Delayed spikes starting after 100 ms
Rest Phase	Voltage resets to -65 mV after spike	Same
Interpretation	Models consistent sensory input (e.g. pressure)	Models delayed activation (e.g. sensory awareness)
Neurological Insight	Normal neural response or seizure-prone	Decision threshold, signal gating, ADHD-like delay
Application	Sensory modeling, steady state response	Signal detection, attention, and gating dynamics

5. RESULTS, AND DISCUSSION

Example 1: Constant Input Current
The membrane potential V(t) increases exponentially due to constant input. It reaches the threshold (-50 mV}) periodically, generating spikes. After each spike, the potential resets to -70 mV, and this cycle continues.

Interpretation:
This behavior mimics a regular spiking neuron, such as a cortical pyramidal neuron under sustained excitation. It shows that even with a constant stimulus, the LIF model generates periodic spiking, which is biologically relevant and consistent with experimental recordings from real neurons.

Discussion:
The model demonstrates rate coding, where the firing frequency is directly proportional to the input current.
The regularity of spiking can represent normal cognitive function, such as consistent motor output or sensory perception.
This simulation establishes a baseline pattern of activity useful for detecting deviations due to disease states.

Example 2: Step Input Current
From t = 0 to 10 ms: no input → the neuron stays at rest, no spike occurs.

After t = 10 ms: input switches on → the membrane potential rises rapidly and begins to spike regularly.

Interpretation:

The LIF neuron responds sharply to stimulus onset, resembling neurons in the visual or auditory cortex that respond to sudden changes. The delay in response before t = 10 \, \text{ms} shows how the neuron remains inactive without sufficient input, modeling sensory thresholds in real systems.

Discussion:

This example models event-driven or stimulus-driven firing, useful in explaining reaction to external triggers (e.g., light flashes, sound pulses).

It is significant in studying epileptic seizures, where sudden abnormal stimuli may cause bursts of spiking.

The timing of spikes and their rate can help differentiate normal vs. pathological neural processing.

Observations

Firing frequency is sensitive to both magnitude and timing of input current.

The LIF model, though simple, captures important qualitative behaviors of real neurons, such as adaptation, threshold firing, and reset behavior.

These examples validate the model's application in understanding normal brain function and serve as a benchmark to compare abnormal conditions like epilepsy, Parkinson's, or multiple sclerosis, where spiking patterns are disrupted.

6. Conclusion

In this study, we explored the Leaky Integrate-and-Fire (LIF) model as a fundamental mathematical framework for simulating neuronal activity and understanding brain dynamics. The model's simplicity yet biological relevance makes it a powerful tool for capturing the essential characteristics of spiking behavior, such as membrane potential evolution, threshold-based firing, and refractory dynamics. Through two illustrative examples—constant and step input currents—we demonstrated how the LIF model can replicate regular and stimulus-driven firing patterns observed in real neurons. These patterns are foundational to interpreting both healthy and disordered neural behaviors.

The results indicate that the LIF model effectively simulates neuronal response to varying stimuli, thereby offering insight into physiological processes like sensory response and pathological conditions such as epilepsy, ADHD, or Parkinson's disease. By adjusting input and model parameters, it becomes possible to simulate different neuron types and analyze deviations in firing behavior linked to neurological dysfunction.

Extend the model to include excitatory and inhibitory synaptic currents using conductance-based models for more biologically accurate simulations.

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