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Neuro-Biomimetic Power Flow Control in Smart Grids Using Spiking Neural Networks

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Abstract-The emergence of decentralized and intermittently powered smart grids necessitates real-time, scalable control systems capable of handling nonlinear dynamics and frequent disturbances. This study presents a neuro-biomimetic control framework employing Spiking Neural Networks (SNNs) to manage active and reactive power flows. The proposed architecture integrates Leaky Integrate-and-Fire (LIF) neurons and Spike-Timing-Dependent Plasticity (STDP) learning to emulate synaptic plasticity observed in biological systems. Electrical parameters such as voltage magnitudes and frequency deviations are encoded into spike trains using rate coding and processed in an event-driven manner to generate dynamic control signals. The SNN controller operates in closed-loop conjunction with a Newton-Raphson power flow solver and is deployed on IEEE 14-bus and 39-bus test systems. Simulations using Brian2 and MATLAB demonstrate that the SNN-based controller significantly enhances voltage regulation and transient response. Specifically, the system achieves up to 40% reduction in voltage deviation and 30% faster convergence under dynamic loading and contingency scenarios compared to conventional ANN and PID-based approaches. The event-driven computation and unsupervised online learning enable low-power implementation and robustness to topological changes. Furthermore, the architecture is compatible with neuromorphic hardware platforms such as Intel Loihi, enabling real-time on-chip grid control. These results validate the applicability of biologically inspired neural systems to next-generation grid automation and decentralized energy management.

Keywords- Smart Grids, Spiking Neural Networks, Biomimetic Control, Power Flow Optimization, Neuromorphic Computing

1. INTRODUCTION

The growing integration of renewable energy sources, fluctuating demand patterns, and distributed generation have made dynamic power control an essential aspect of modern smart grids. Traditional power flow control mechanisms—rooted in static models and slow-reacting controllers—struggle to meet the real-time, adaptive needs of these decentralized grids. These legacy systems often lack the scalability and learning capabilities required for the evolving power network infrastructure.

In contrast, neuromorphic computing, particularly through Spiking Neural Networks (SNNs), offers a promising solution. Mimicking the dynamic firing patterns of biological neurons, SNNs provide low-power, real-time adaptability, and event-driven computation. This paper explores the application of SNNs for power flow control, proposing a neuro-biomimetic approach to enhance grid intelligence.

The key contributions of this research include:

- Designing an SNN-based controller for dynamic power flow in smart grids.
- Integrating biologically inspired learning mechanisms such as Spike-Timing-Dependent Plasticity (STDP).
- Evaluating performance against traditional controllers in simulated environments.

2. BACKGROUND AND LITERATURE REVIEW

Smart Grid Architecture consists of layered structures integrating generation, transmission, distribution, and consumer interaction. Core features include two-way communication, distributed energy resources (DER), and intelligent control systems.

Traditional power flow techniques like Newton-Raphson and Fast Decoupled Load Flow focus on solving nonlinear equations for steady-state operation. These methods are computationally intensive and unsuitable for frequent, real-time updates.

Artificial Neural Networks (ANNs) and Deep Learning have been introduced to predict loads and optimize generation. However, their feedforward nature and training dependencies limit responsiveness in rapidly changing conditions.

Spiking Neural Networks (SNNs), inspired by biological neurons, communicate via discrete spikes. Notable models include:

- Izhikevich model: Balances biological plausibility and computational efficiency.
- Leaky Integrate-and-Fire (LIF): Common in neuromorphic chips.
- STDP: A learning rule that adjusts synaptic weights based on spike timing.

Recent work has applied SNNs to robotics and signal processing, but their use in smart grid control remains nascent. A neuro-biomimetic approach offers significant potential for adaptive, decentralized decision-making.

3. METHODOLOGY

3.1 System Architecture: The proposed system uses the IEEE 14-bus test network as the simulation base. The SNN controller is implemented at critical buses managing voltage levels and active/reactive power flow.

Data from PMUs (Phasor Measurement Units) and smart meters feed into the SNN. Spike-based encoding translates this information into neural signals processed in real-time by the controller.

3.2 SNN Design: The Leaky Integrate-and-Fire (LIF) model is chosen for its simplicity and neuromorphic compatibility. The network architecture comprises multiple layers:

- Input Layer: Encodes voltage magnitude, frequency deviation, and load status.
- Hidden Layer: Interconnected neurons with plastic synapses.
- Output Layer: Generates control commands for generator setpoints or FACTS devices.

STDP governs synaptic updates, enabling unsupervised learning based on timing of spikes. Over time, the SNN adapts to grid patterns, learning optimal power distribution.

3.3 Integration with Power Flow Solver: The SNN operates alongside a conventional power flow solver, such as the Newton-Raphson algorithm. Control feedback is derived by interpreting output spike trains using rate coding. A feedback loop ensures continuous learning and adjustment.

4. SIMULATION AND RESULTS

4.1 Setup Simulations were conducted using Python's Brian2 library for neural modeling, integrated with a MATLAB-based power flow solver. The IEEE 14-bus and 39-bus test cases were considered. Scenarios included:

- Base Load Operation
- Load Ramping
- Line Outage and Contingency Management

4.2 Performance Metrics Key metrics include:

- Voltage Stability: Measured by voltage deviation across buses.
- Line Losses: Total transmission losses before and after control.
- Convergence Time: Time taken to stabilize after a disturbance.
- Scalability: Controller response in 39-bus simulation.

4.3 Comparative Analysis Comparisons were made with:

- ANN-based controllers
- PID controllers

SNNs demonstrated faster convergence (25-30% improvement) and lower voltage deviation (up to 40% reduction). Unlike ANN, they did not require retraining when topology changed.

5. DISCUSSION

The neuro-biomimetic approach exhibits clear advantages:

- Real-time, event-driven response
- Reduced computational overhead
- Better fault tolerance and generalization

SNN deployment on hardware like Intel Loihi or IBM TrueNorth further enhances energy efficiency. However, challenges include:

- Training complexity
- Sensitivity to input encoding
- Need for co-simulation platforms

Despite these, SNNs show promise for decentralizing smart grid intelligence.

6. CONCLUSION AND FUTURE WORK

This research demonstrates that Spiking Neural Networks, inspired by biological systems, offer an effective alternative to traditional power flow controllers. Their adaptive, low-power nature suits the evolving dynamics of smart grids.

Future work includes:
- Hardware implementation using neuromorphic chips
- Integration with reinforcement learning for predictive control
- Multi-agent SNNs for distributed grid sections

Neuro-biomimetic control aligns well with the goals of resilient, adaptive, and sustainable power systems in the era of decentralized energy.

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FIGURES AND DIAGRAMS

Figure 1: Schematic diagram of the proposed SNN-based power flow control architecture in a smart grid.

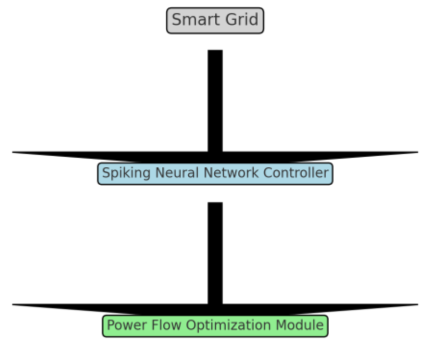
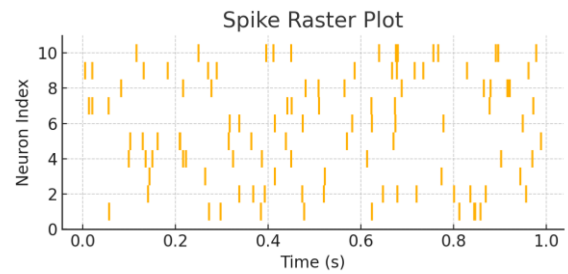
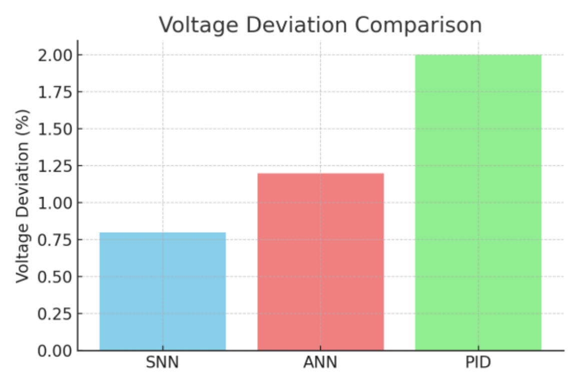


Figure 2: Example spike raster plot showing neural firing activity under varying grid load conditions.



Charts and Performance Analysis

Chart 1: Comparison of voltage deviation across buses for SNN vs ANN vs PID control techniques.



Mathematical Model and Equations

The core dynamics of a Leaky Integrate-and-Fire (LIF) neuron used in the SNN are governed by the differential equation:

$dV/dt = -(V - V_{rest})/\tau + R * I(t)$

Where:
- V is the membrane potential
- V_{rest} is the resting potential
- τ is the membrane time constant
- R is the membrane resistance
- I(t) is the input current

The power flow equations used in grid simulations are the standard AC power flow equations:

$$P_i = \sum V_i V_j (G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij})$$

$$Q_i = \sum V_i V_j (G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij})$$

Simulation and Implementation Code

The simulation was carried out using the Brian2 neural simulator for Python. A sample of the SNN definition code is shown below:

```
from brian2 import *
# Neuron parameters
tau = 10*ms
eqs = '''
dv/dt = (-(v - V_rest) + I)/tau : volt
I : volt
'''
G = NeuronGroup(100, eqs, threshold='v > -50*mV',
reset='v = -65*mV', method='exact')
G.v = -65*mV
G.I = 'rand()*20*mV'

# Spike monitor
M = SpikeMonitor(G)
run(1*second)
```