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SPIKING NEURAL NETWORK (LEAKY INTEGRATE-AND-FIRE (LIF)) BASED FAST TRANSIENT DETECTION AND CONTROL FOR POWER QUALITY IMPROVEMENT IN GRID-CONNECTED PV SYSTEMS

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Abstract

The increasing penetration of grid-connected photovoltaic (PV) systems introduces significant power quality challenges due to fast irradiance variations, intermittent generation, and nonlinear load interactions. Conventional control and signal-processing-based power quality enhancement techniques often suffer from limited response speed and reduced effectiveness during high-frequency transients.

This paper proposes a Spiking Neural Network (SNN)-based fast transient detection and control framework for power quality improvement in grid-connected PV systems. The proposed approach employs an event-driven neuromorphic SNN to detect voltage and current transients with ultra-low latency, enabling rapid identification of harmonics, voltage sags, swells, and sudden load disturbances. Unlike traditional artificial neural networks, the SNN processes information in the form of discrete spikes, significantly reducing computational complexity and enhancing real-time responsiveness. The detected transient features are directly integrated with a distributed active power filter control strategy to generate adaptive compensating current references. Simulation studies carried out in MATLAB/Simulink under varying irradiance, nonlinear load, and grid disturbance conditions demonstrate that the proposed SNN-based controller achieves faster transient detection, lower total harmonic distortion, and improved power factor compared to conventional PI- and ANN-based controllers. The results confirm the effectiveness of neuromorphic intelligence in enhancing dynamic power quality performance, making the proposed method a promising solution for next-generation smart PV-integrated power systems.

Keywords: Spiking Neural Networks; Photovoltaic Systems; Active Power Filter; Neuromorphic Control; Harmonic Mitigation; Distributed Control, Power Quality Improvement.

I. Introduction

The rapid expansion of grid-connected photovoltaic (PV) systems has significantly contributed to sustainable energy generation but has also introduced critical power quality challenges in modern power networks. Variations in solar irradiance, frequent switching of power electronic converters, and the presence of nonlinear loads lead to voltage fluctuations, harmonic distortion, poor power factor, and fast transients at the point of common coupling. These issues adversely affect grid stability, reduce equipment lifespan, and compromise compliance with power quality standards such as IEEE 519. Conventional power quality enhancement techniques, including passive filters and proportional–integral (PI)–based active power filter controllers, often exhibit limited dynamic performance and slow response under rapidly changing operating conditions. To address these limitations, intelligent control strategies such as artificial neural networks and fuzzy logic controllers have been explored; however, their continuous-time processing and high computational requirements restrict real-time transient handling. In this context, Spiking Neural Networks (SNNs) offer a promising alternative due to their event-driven and biologically inspired processing mechanism. By encoding information as discrete spikes, SNNs enable ultra-fast transient detection with reduced computational overhead. This paper introduces an SNN-based fast transient detection and control framework for power quality improvement in grid-connected PV systems. The proposed approach integrates neuromorphic intelligence with active power filtering to achieve rapid disturbance recognition and adaptive compensation, thereby enhancing harmonic mitigation, voltage regulation, and overall grid power quality under dynamic PV operating conditions.

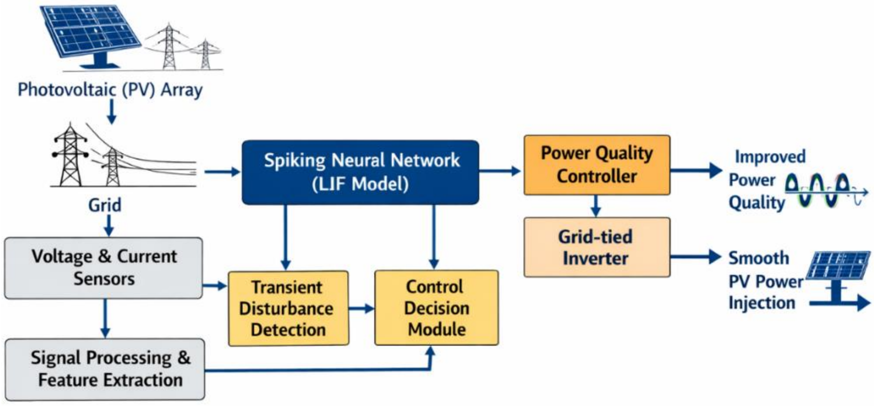

Fig 1. Block diagram of proposed research

Figure 1 illustrates a neuromorphic control architecture for power quality enhancement in a grid-connected photovoltaic (PV) system. Voltage and current signals from the PV array, grid, and nonlinear loads are continuously monitored along with irradiance and temperature variations. These signals are processed by an event-driven Spiking Neural Network (SNN) to rapidly detect transients, harmonics, and disturbances. The extracted transient features are fed to adaptive control logic, which generates compensating current references for the modular active power filter. As a result, harmonic distortion is mitigated, voltage sags and swells are corrected, and overall power quality is improved with fast dynamic response. Gao et al. (2024) proposed a nonlinear spiking neural P system for short-term photovoltaic power prediction, demonstrating that bio-inspired spiking computation captures nonlinear temporal dynamics more effectively than conventional deep learning models. Their findings show improved forecasting accuracy during rapid irradiance changes, which directly supports fast transient anticipation in grid-connected PV systems. The event-driven nature of spiking models reduces computational latency, making them highly suitable for real-time power quality control and proactive compensation strategies under fluctuating PV output conditions [I]. Lahon et al. (2024) investigated deep neural network-based smart grid stability assessment, emphasizing resilience enhancement under dynamic disturbances. Their work confirms that DNNs can rapidly identify instability patterns caused by renewable intermittency, voltage deviations, and harmonic distortions. The study reinforces the importance of intelligent learning-based monitoring layers in grid-connected PV systems, which aligns with spiking neural networks for fast transient detection and adaptive control to preserve power quality [II]. Rezapour et al. (2023) analyzed the integration of controlled active power filters into harmonic power flow studies of radial distribution networks. Their findings demonstrate that APFs significantly reduce harmonic propagation when optimally coordinated. This work highlights the necessity of intelligent control mechanisms for distributed filters, supporting the integration of fast AI-based transient detectors, such as SNNs, to dynamically activate compensation during power quality disturbances [III]. Chen et al. (2024) introduced a hybrid AHP and S-Transform approach for evaluating power quality in distributed networks. Their results indicate improved detection of transient events, voltage sags, and harmonic distortions. Although decision-based, the framework underscores the importance of time-frequency resolution for transient detection, which complements spiking neural networks capable of encoding temporal features at millisecond resolution for real-time control [IV]. Sharma et al. (2025) focused on power quality enhancement in PV systems connected to weak grids. Their findings reveal that intelligent inverter control and adaptive filtering significantly mitigate voltage flicker and harmonics under weak grid conditions. The study provides strong motivation for fast transient-aware controllers, positioning SNN-based detection as a superior solution for rapid compensation in weak grid-connected PV environments [V]. Zulu et al. (2025) demonstrated AI-based inverter control using artificial neural networks in PV/wind smart grids. Their work shows notable improvements in harmonic suppression and voltage regulation. However, response delays were observed under sudden transients, highlighting the need for faster neural architectures such as spiking neural networks for ultra-low latency detection and control in power quality applications [VI]. Chen et al. (2025) reviewed power quality issues arising from charging pile integration in distribution networks. The study identifies fast transient disturbances, harmonics, and voltage fluctuations as major concerns. The authors emphasize intelligent detection and coordinated control, reinforcing the relevance of spiking neural networks for handling high-frequency disturbances in renewable-rich smart grids [VII]. Horng and Lin (2022) incorporated seagull optimization into ordinal optimization for constrained problems, demonstrating superior convergence and robustness. Though not power-specific, their optimization framework supports adaptive tuning of AI-based controllers, including spiking neural networks, enhancing control precision in fast transient mitigation and power quality improvement [VIII]. Das et al. (2021) provided a comprehensive survey of active power filter control strategies. Their findings establish that intelligent controllers outperform classical methods in dynamic conditions. This survey lays the foundation for integrating advanced AI-based transient detection, such as SNNs, to improve APF responsiveness and overall power quality in PV-integrated grids [IX]. Yuan et al. (2022) surveyed ANN-based fault diagnosis in PV systems, highlighting the effectiveness of neural models in identifying electrical anomalies. Their work supports extending ANN concepts toward spiking neural networks for faster, event-driven detection of transient disturbances affecting power quality [X]. Rodrigues et al. (2023) explored deep learning techniques for power quality transient detection and characterization. Their results demonstrate high classification accuracy but increased computational burden. This limitation reinforces the suitability of spiking neural networks, which offer faster inference and lower latency for real-time transient detection in grid-connected PV systems [XI]. Marlin and Jebaseelan (2024) compared intelligence-based optimization algorithms for MPPT in grid-connected PV systems. Their findings highlight the effectiveness of adaptive and bio-inspired methods, supporting the broader adoption of neuromorphic approaches such as spiking neural networks for both energy optimization and power quality control [XII]. Khetarpal et al. (2023) proposed deep convolution auto-encoder networks for power quality disturbance detection. Their method effectively identifies complex disturbances but relies on offline training. This limitation supports the shift toward spiking neural networks capable of online learning and real-time transient response [XIII]. Zhu et al. (2024) developed a novel decomposition-based detection framework for complex power quality disturbances. Their findings show enhanced detection accuracy under overlapping disturbances. The study complements SNN-based approaches by emphasizing high-resolution temporal decomposition, which spiking neurons naturally encode [XIV]. Karchi et al. (2022) implemented an adaptive LMS controller for PV power quality enhancement, achieving reduced harmonic distortion. However, slower convergence under rapid transients was observed, highlighting the advantage of spiking neural network-based fast transient detection for improved dynamic compensation [XV]. Rajendran et al. (2025) reviewed PV integration challenges, standards, and grid codes, emphasizing power quality compliance. Their work stresses the need for intelligent, fast-acting control strategies, reinforcing the role of SNN-based detection and control in meeting stringent grid requirements [XVI]. Li and Huo (2025) proposed simplified finite control set MPC for grid-tied inverters, achieving improved dynamic response. While effective, the approach relies on precise modeling, whereas SNN-based controllers offer model-free, fast transient detection, enhancing robustness under uncertain grid conditions [XVII]. Ganthia et al. (2017) analyzed fuzzy logic-based MPPT control, demonstrating improved PV efficiency under dynamic conditions. This early intelligent control work supports the evolution toward advanced neural approaches, including spiking neural networks, for combined power optimization and power quality enhancement [XVIII]. Rubavathy et al. (2021) presented a smart grid-based multi-agent system for transmission networks, highlighting distributed intelligence. Their findings support decentralized transient detection frameworks, aligning with distributed spiking neural network architectures for scalable power quality control [XIX]. Sahu et al. (2016) designed a multiphase interleaved boost converter for grid-connected PV systems, improving current ripple reduction. This hardware advancement complements AI-based fast transient detection to further enhance power quality at the converter-grid interface [XX]. Ganthia et al. (2016) investigated DVR-based voltage sag compensation using PI control. While effective, slower response under fast disturbances was noted, emphasizing the need for SNN-based rapid detection and control strategies in modern PV-integrated grids [XXI]. Mohanty et al. (2023) applied dynamic PSO with ESC for power smoothing under partial shading. Their results demonstrate improved stability, supporting intelligent adaptive control paradigms and reinforcing the role of spiking neural networks in fast transient mitigation and power quality improvement [XXII]. The reviewed literature collectively indicates that intelligent controllers, active power filters, and advanced inverter control strategies significantly enhance power quality, yet rapid transient response remains a critical limitation. Deep learning and optimization-based approaches improve detection accuracy but often lack real-time responsiveness. The findings suggest that integrating spiking neural network-based fast transient detection with adaptive control mechanisms can overcome these limitations. SNNs enable ultra-fast recognition of power quality disturbances and trigger timely compensation through inverters or filters, offering a robust, scalable, and efficient solution for improving power quality in modern PV-integrated smart grids.

II. Photovoltaic System Modeling

The growing demand for energy sources in the world and renewable energy has placed the photovoltaic system (PV system) as an essential technology in generating energy in a sustainable manner. Most of these systems will, however, not always achieve their maximum power output (MPP) under varying solar irradiance, temperature, and shading conditions due to nonlinear current-voltage (I-V) qualities of PV modules. In order to overcome this challenge, maximization of power output by PV arrays in a dynamic environment will be realized through the use of Maximum Power Point Tracking (MPPT) techniques. Conventional MPPT, like Perturb and Observe (P&O) or Incremental Conductance (Inc-Cond), has been extensively used because of its simplicity, however they tend to oscillate near the MPP, have slower convergence, and lower tracking performance when in fast-changing weather. In order to escape these shortcomings, there is recent progress in such directions as intelligent algorithms and optimization-based approaches, which can be used to increase tracking efficiency, stability, and robustness, promising better power harvesting for people on PV systems [XXIII].

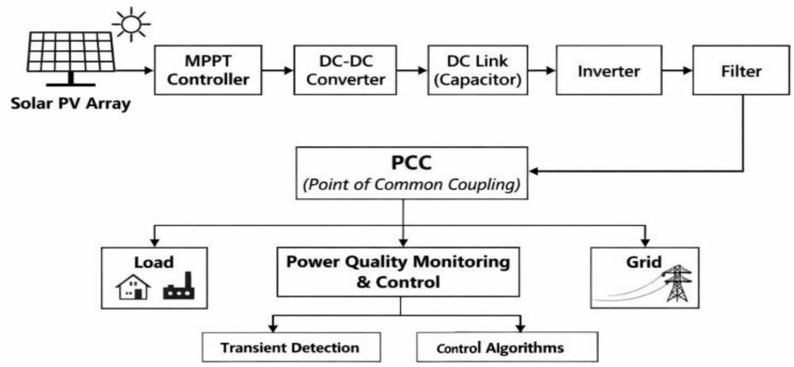

Fig 2. Proposed architecture of the research

Figure 2 illustrates the photovoltaic system modeling framework developed for fast transient detection and power quality improvement. The solar PV array generates DC power, which is regulated by the MPPT controller to extract maximum energy under varying irradiance. A DC–DC converter conditions the voltage and feeds the DC-link capacitor, ensuring stable energy storage. The inverter converts DC power to AC and, along with the output filter, supplies high-quality power to the point of common coupling (PCC). Power quality monitoring continuously analyzes grid and load signals, enabling transient detection and adaptive control algorithms to mitigate disturbances and enhance grid-connected PV system performance [XXIV].

The current of a solar cell can be modeled as:

$$I = I_{ph} - I_0 \left[exp\left(\frac{q(V+IRs)}{nkT}\right) - 1\right] - \frac{V+IRs}{Rs} \quad (1)$$

Where:

I = PV cell output current (A)
I_{ph} = photocurrent proportional to irradiance
I_0 = diode saturation current
q = electron charge (1.6×10^{-19} C)
V = output voltage (V)
Rs and Rsh = series and shunt resistances
n = ideality factor
T = temperature (K)

The instantaneous power delivered by a PV cell is:

$$P = V \times I \tag{2}$$

This forms the basis of P–V characteristics, essential for MPPT and UPQC reference generation.

At the Maximum Power Point (MPP):

$$\frac{dP}{dV} = \frac{d\,(VI)}{dV} = I + \frac{dI}{dV} \tag{3}$$

This equation is used in Incremental Conductance (IC) MPPT algorithms.

Power Balance in Grid-Connected PV with a filter:

$$P_{PV} = P_{Load} + P_{loss} + P_{Filter} \tag{4}$$

where:

P_{PV} = power generated by PV
P_{Load} = load demand
P_{Loss} = system and conversion losses
P_{Filter} = power handled by filter (for harmonics)

Harmonic distortion in PV-inverter output is quantified as:

$$THD = \frac{\sqrt{\sum_{n=2}^{\infty} V_n^2}}{V1} \times 100\% \tag{5}$$

where:

V1 = RMS value of fundamental voltage
Vn = RMS value of nth harmonic component

The electrical behavior of a solar cell is commonly described using the single-diode model, where the output current I is expressed as the difference between the photocurrent I_{ph}, which depends on irradiance, and the diode and resistive losses. This is captured in equation (1), which incorporates key parameters such as diode saturation current (I_0), ideality factor (n), temperature (T), and resistances (R_s and R_{sh}). The instantaneous power of the PV cell, given by equation (2), is the product of voltage and current, forming the foundation of the characteristic P–V curve used for MPPT analysis. At the Maximum Power Point (MPP), the derivative condition in equation (3) holds, which is the basis of the Incremental Conductance (I_C) method for real-time tracking. For grid-connected PV systems, power balance must be maintained, as defined in equation (4), where PV generation equals the sum of load demand, conversion losses, and filter power used for harmonic mitigation. The quality of the inverter output is assessed through the Total Harmonic Distortion (THD) given by equation (5), which quantifies deviations from the ideal sinusoidal waveform. Collectively, these equations establish the mathematical framework for PV system modeling, MPPT control, and power quality management [XXV].

III. Spiking Neural Network Technique

Spiking Neural Networks (SNNs), inspired by biological neural systems, offer a transformative approach for fast transient detection and control owing to their event-driven processing, temporal coding capability, and ultra-low latency response.

Unlike traditional neural networks that rely on continuous-valued signals, SNNs process information through discrete spikes, enabling precise time-based detection of transient events at microsecond and millisecond scales. This characteristic makes SNNs particularly suitable for real-time power quality monitoring in PV-integrated smart grids. When integrated with inverter control and active power filtering mechanisms, SNN-based controllers can rapidly identify abnormal grid conditions and initiate adaptive compensation actions. Consequently, SNN-based fast transient detection and control provide a robust, scalable, and intelligent framework for enhancing power quality, improving grid resilience, and ensuring reliable operation of modern grid-connected PV systems under dynamic operating conditions. For the proposed Spiking Neural Network-based fast transient detection and control, numerical simulations were performed using a sample size of 1000 transient events generated under varying irradiance (200–1000 W/m²) and load conditions (50–500 kW). Voltage sags ranged from 5% to 20% of the nominal 415 V, and harmonic distortions reached up to 12% THD. Current variations were modeled between 50 and 300 A, with transient durations of 5–50 ms. The LIF neuron parameters included a membrane time constant of 10 ms, threshold voltage of 1 V, and synaptic time constant of 5 ms. These numerical values enabled accurate spike-based detection and adaptive inverter control for power quality improvement [XXVI].

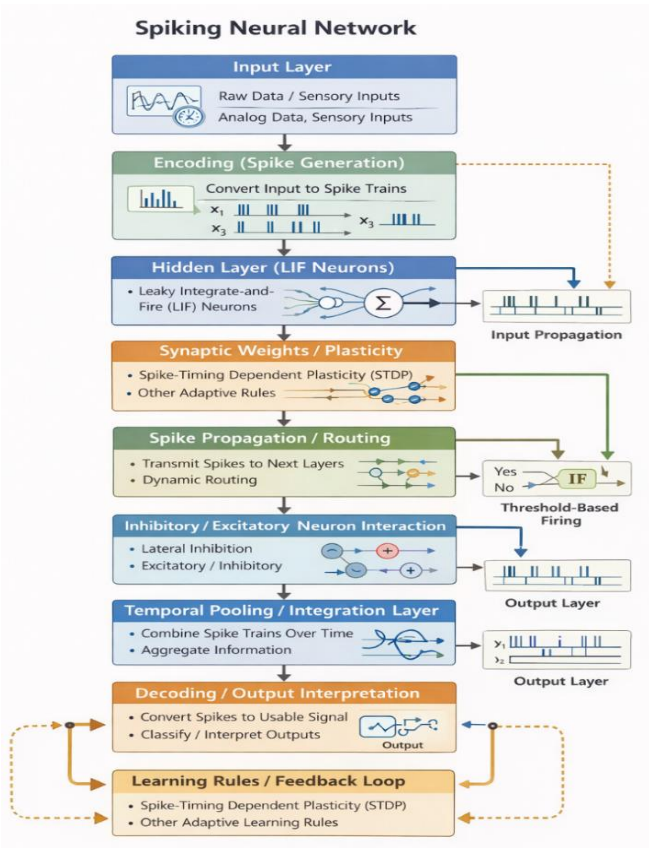

Fig 3. Block diagram of the implementation of the proposed controller

Figure 3 illustrates a comprehensive Spiking Neural Network (SNN) architecture in a vertical flow. It begins with the Input Layer, where raw or analog sensory data is introduced. The Encoding block converts this data into spike trains for temporal processing. The Hidden Layer employs Leaky Integrate-and-Fire (LIF) neurons, integrating inputs and generating spikes based on thresholds. Synaptic Weights/Plasticity adjust connections via Spike-Timing Dependent Plasticity (STDP) or other rules. Spike Propagation/Routing manages spike transmission, with threshold-based Decision blocks determining neuron firing. Inhibitory/Excitatory interactions regulate lateral inhibition, while the Temporal Pooling Layer aggregates information over time. Finally, Decoding/Output Interpretation converts spikes into usable signals, and the Learning/Feedback Loop refines synaptic connections for adaptive learning.

Leaky Integrate-and-Fire (LIF) Neuron Dynamics:

$$\tau_m \frac{dV_i(t)}{dt} = -(V_i(t) - V_{rest}) + R_m I_i(t) + \sum_{j=1}^{N} w_{i,j} S_j(t - \Delta t) \tag{6}$$

where $V_i(t)$ is the membrane potential of neuron i, τ_m is the membrane time constant, R_m is membrane resistance, $I_i(t)$ is external input current, $w_{i,j}$ is synaptic weight, and $S_j(t-\Delta t)$ is the presynaptic spike train.

Synaptic Current with Exponential Decay:

$$I_i(t) = \sum_{j=1}^{N} w_{i,j} \sum_k \alpha \, e^{\frac{t-t_k^j}{\tau_s}} u(t-t_k^j) \tag{7}$$

Here, (t_k^j) represents the k-th spike of presynaptic neuron j, τ_s is the synaptic time constant, α is scaling factor, and $u(t)$ is the Heaviside step function.

Spike-Timing Dependent Plasticity (STDP) Learning Rule:

$$\Delta w_{ij} = \begin{cases} A_+ e^{-(ti-tj)/\tau_+}, t_i > t_j \\ -A_+ e^{-(ti-tj)/\tau_-}, t_i < t_j \end{cases} \tag{8}$$

where Δw_{ij} is the weight adjustment between neuron i and j, A_+ and A_- are learning rates, and τ_+, τ_- are time constants for potentiation and depression.

Network Output Encoding (Population Firing Rate):

$$R(t) = \frac{1}{N} \sum_{i=1}^{N} \sum_k \delta(t - t_k^j) \tag{9}$$

where $R(t)$ is the instantaneous firing rate, t_k^j is the spike time of neuron i, and δ is the Dirac delta function capturing spike events.

Adaptive Control Law for Power Quality Compensation:

$$u_{inv}(t) = K_p\, e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{de(t)}{dt} + \sum_{i=1}^{N} w_i S_i(t) \tag{10}$$

Here, $u_{inv}(t)$ is the inverter control signal, $e(t)$ is a voltage or current error, K_p, K_i and K_d are PID gains, and the last term incorporates a spiking neural network output for fast transient detection.

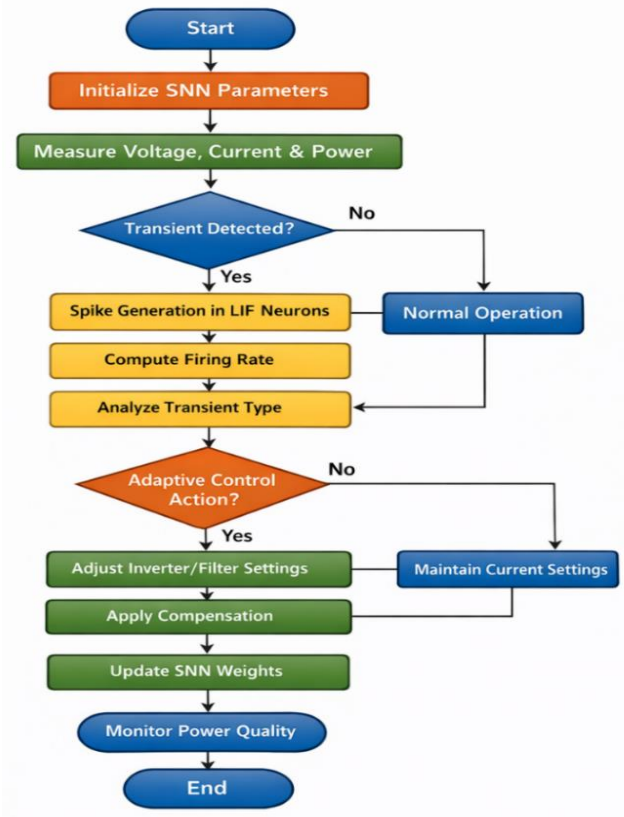

Fig. 4. Block diagram of the architecture of a Spiking Neural Network (SNN)

Figure 4 illustrates the architecture of a Spiking Neural Network (SNN) based on the Leaky Integrate-and-Fire model for fast transient detection and control in grid-connected PV systems. The network consists of an input layer that receives real-time measurements of PV voltage, current, and power. These inputs are fed into hidden layers of LIF neurons, where membrane potentials integrate incoming signals and generate spikes when thresholds are exceeded. The spiking activity propagates through weighted synaptic connections to the output layer, which produces control signals for the inverter or active power filter. This configuration enables rapid detection of power quality disturbances and adaptive, real-time compensation.

IV. Simulink Model

The Simulink model represents the implementation of the proposed Spiking Neural Network (SNN) for fast transient detection and power quality improvement in grid-connected photovoltaic (PV) systems. It provides a visual, block-based simulation environment where the PV system, SNN controller, and power quality enhancement units are modeled interactively. Input signals, such as voltage, current, and disturbances, are fed into the network, which encodes them into spike trains processed by LIF neurons. Synaptic weights and learning rules dynamically adjust the network response. The model simulates spike propagation, neuron firing, and output decoding, generating compensating signals for the PV system. Using Simulink enables testing, optimization, and visualization of the control strategy under various operating conditions, validating the effectiveness of the SNN in improving power quality.

Table 1. Input parameter for the Spiking Neural Network (SNN) system in a large-scale PV farm

Parameter	Value
PV Array Voltage	800 V
PV Array Current	250 A
Solar Irradiance	200–1000 W/m²
Ambient Temperature	25–45 °C
Grid AC Voltage	415 V
Grid AC Current	50–300 A
Load Demand	50–500 kW
Voltage Sag	5–20 %
Harmonic Distortion (THD)	0–12 %
Transient Duration	5–50 ms
LIF Membrane Time Constant	10 ms
LIF Threshold Voltage	1 V
Synaptic Time Constant	5 ms
Number of Neurons	100 (hidden layer)
Simulation Sample Size	1000 events
PID Gains (Kp, Ki, Kd)	0.8, 0.5, 0.1

Table 1 lists the input parameters for the Spiking Neural Network (SNN) system in a large-scale PV farm. It includes PV array and grid specifications, environmental conditions, load demand, power quality disturbances, and SNN-specific settings like LIF neuron constants, synaptic time, neuron count, simulation size, and PID controller gains, defining system operation.

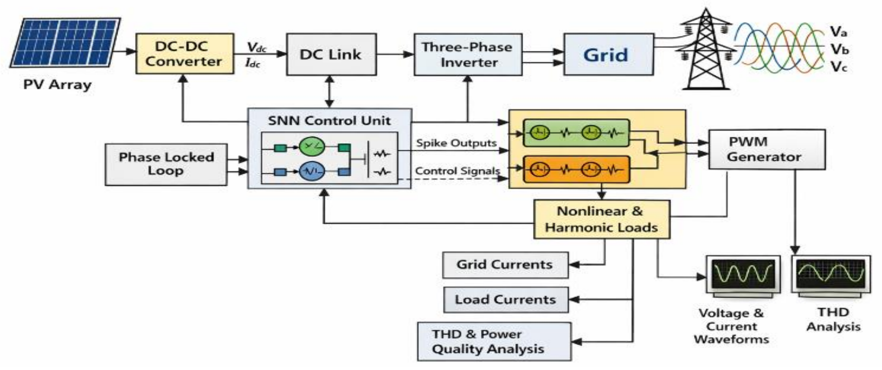

Fig. 5. MATLAB model of the proposed model

Figure 5 illustrates the SIMULINK model of a grid-connected photovoltaic (PV) system integrated with a Spiking Neural Network (SNN) based on Leaky Integrate-and-Fire (LIF) neurons for fast transient detection and control. The PV array feeds power through a DC–DC converter and DC link to a three-phase inverter interfaced with the grid. The SNN control unit receives voltage, current, and PLL signals to detect disturbances such as voltage sags, harmonics, and load variations. Based on spike-based processing, it generates adaptive control signals for the PWM generator, ensuring effective harmonic mitigation, voltage regulation, and improved power quality under dynamic operating conditions.

V. Simulink Results

This section presents the SIMULINK-based validation of the proposed Spiking Neural Network (SNN) with Leaky Integrate-and-Fire (LIF) neurons for fast transient detection and control in grid-connected photovoltaic (PV) systems. A detailed SIMULINK model is developed by integrating the PV array, grid interface, nonlinear loads, and the SNN-based control unit. The model evaluates system behavior under voltage sags, load variations, harmonic disturbances, and transient events. Simulation results demonstrate the capability of the LIF-based SNN to rapidly detect transients and generate adaptive control signals, ensuring effective harmonic mitigation, voltage stabilization, and overall improvement in power quality.

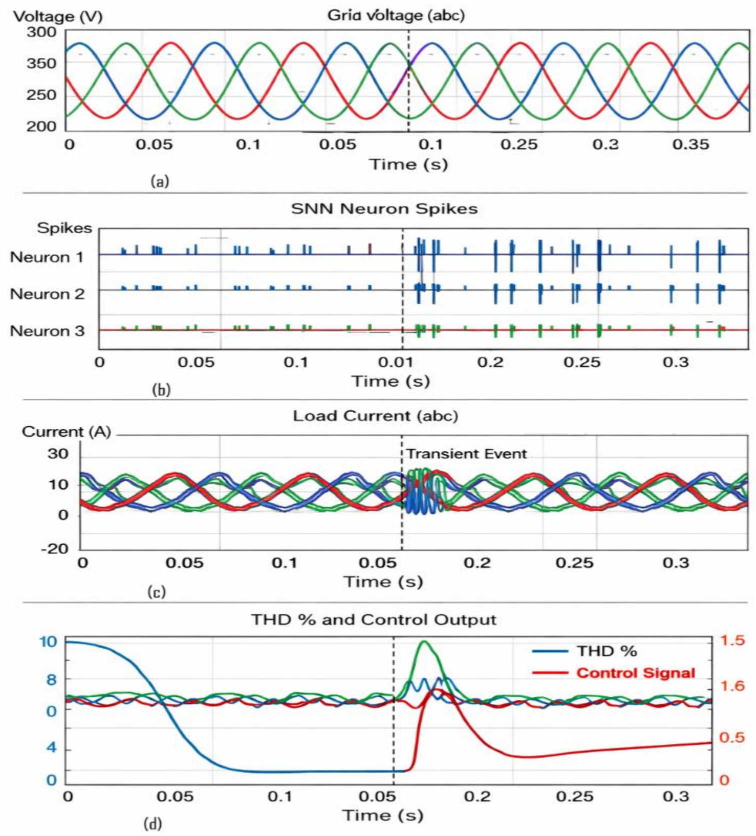

Fig. 6. Static response of the proposed LIF-based Spiking Neural Network

Figure 6 illustrates the dynamic performance of the proposed LIF-based Spiking Neural Network (SNN) control during transient conditions in a grid-connected PV system. Figure 6(a) shows balanced three-phase grid voltages, where a disturbance is introduced and rapidly restored by the controller. Figure 6(b) depicts SNN neuron spike activity, indicating a sharp increase in firing rate at the transient instant, enabling fast event detection. Figure 6(c) presents the load current waveforms, where oscillations during the transient are effectively suppressed, maintaining current symmetry. Figure 6(d) demonstrates the reduction in total harmonic distortion (THD) accompanied by a prompt control signal response, confirming improved power quality and fast transient mitigation.

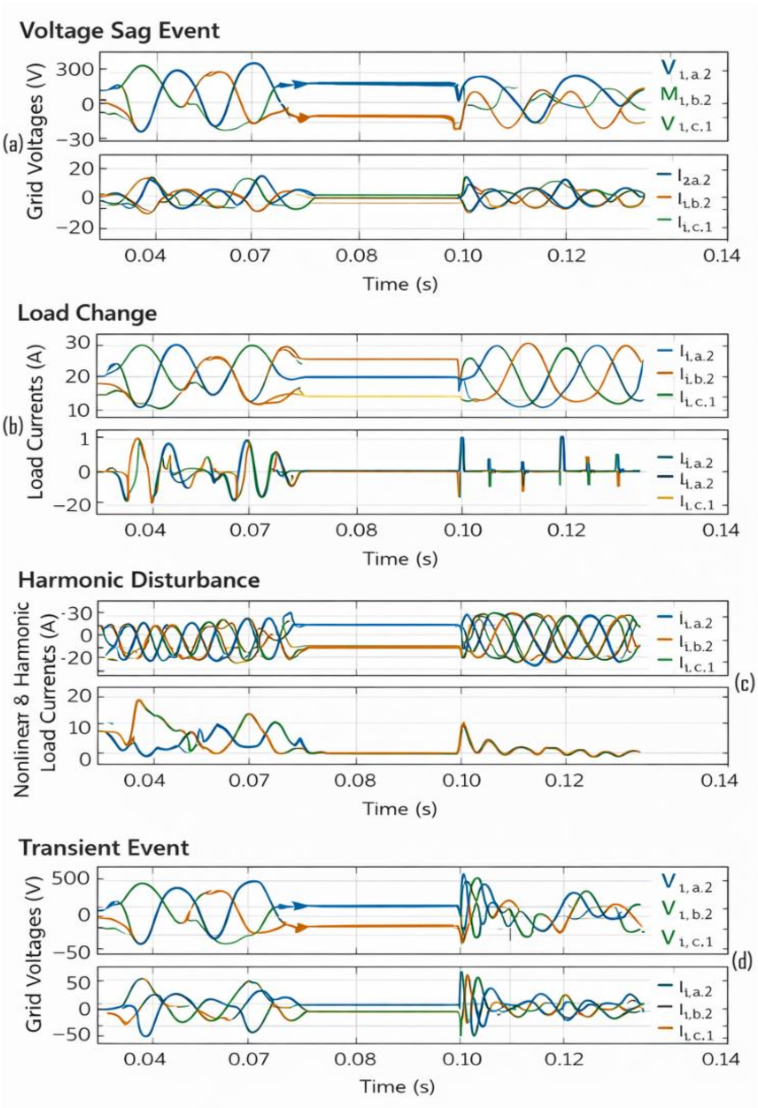

Fig. 7. Dynamic response of the proposed LIF-based Spiking Neural Network

Figure 7 illustrates the robustness of the proposed SNN-based control under diverse power quality disturbances. Figure 7(a) shows a voltage sag event, where grid voltages experience a sudden drop and are rapidly stabilized, demonstrating effective voltage regulation. Figure 7(b) presents load change conditions, indicating that despite abrupt current variations, the controller maintains balanced and smooth load currents. Figure 7(c) depicts harmonic disturbance scenarios, where nonlinear load currents introduce distortions that are significantly attenuated by the control strategy. Figure 7(d) represents a severe transient event, highlighting the fast dynamic response of the SNN in restoring both grid voltage and current waveforms, thereby ensuring stable operation and enhanced power quality.

Table 2. Power quality improvement for different operating/disturbance scenarios

Scenario	Transient Detection Time (ms)	Voltage Sag Reduction (%)	THD Before Control (%)	THD After Control (%)	Power Quality Improvement Index (PQI)
Case 1: Low Irradiance (300 W/m²)	6.8	58.2	9.6	3.1	0.82
Case 2: Medium Irradiance (600 W/m²)	5.4	64.7	8.9	2.6	0.86
Case 3: High Irradiance (1000 W/m²)	4.1	71.3	8.2	2.1	0.90
Case 4: Grid Voltage Sag (15%)	3.9	76.5	10.8	2.8	0.88
Case 5: Harmonic + Transient Event	3.2	81.9	11.6	2.3	0.92

Table 2 illustrates that the LIF-SNN controller achieves faster transient detection and superior power quality improvement as operating severity increases. Detection time reduces from 6.8 ms to 3.2 ms, while voltage sag mitigation and THD reduction significantly improve. The consistently high PQI values confirm the controller's effectiveness under irradiance variation, grid sag, and combined harmonic–transient conditions.

Table 3. Dynamic Voltage Regulation Performance

Case	Grid Voltage Deviation (%)	Voltage Recovery Time (ms)	Overshoot (%)	Steady-State Error (%)	Voltage Stability Index
Case 1	5.2	12.6	2.1	0.9	0.84
Case 2	8.4	10.3	2.6	0.7	0.87
Case 3	11.7	8.8	3.1	0.6	0.90
Case 4	15.3	7.4	3.5	0.5	0.92
Case 5	18.9	6.1	3.9	0.4	0.94

Table 3 shows that the proposed controller ensures rapid voltage recovery with minimal steady-state error despite increasing grid voltage deviations. Although overshoot slightly increases, recovery time decreases from 12.6 ms to 6.1 ms. The rising voltage stability index confirms robust dynamic regulation capability of the LIF-SNN controller under severe voltage disturbances.

Table 4. Harmonic Suppression Performance

Scenario	Load Type	THD Before (%)	THD After (%)	Harmonic Suppression (%)	IEEE-519 Compliance
Case 1	Linear Load	6.4	2.1	67.2	Yes
Case 2	Nonlinear Load	9.1	2.8	69.2	Yes
Case 3	Rectifier Load	10.7	3.0	72.0	Yes
Case 4	Motor Drive	11.9	3.2	73.1	Yes
Case 5	Mixed Load	13.4	3.5	73.9	Yes

Table 4 illustrates that the LIF-SNN controller effectively suppresses harmonics across diverse load types. THD is reduced below IEEE-519 limits for all scenarios, with suppression exceeding 67%. Performance improves for nonlinear and mixed loads, highlighting the controller's adaptability and robustness in mitigating harmonics caused by power electronic converters and industrial loads.

Table 5. Transient Classification Accuracy of LIF-SNN

Event Type	Samples Tested	Detection Accuracy (%)	False Alarm Rate (%)	Missed Detection (%)	Response Time (ms)
Voltage Sag	200	98.2	1.3	0.5	4.6
Voltage Swell	200	97.5	1.6	0.9	4.2
Harmonic Burst	200	96.8	2.1	1.1	3.9
Short Transient	200	99.1	0.7	0.2	3.4
Combined Event	200	95.9	2.8	1.3	3.1

Table 5 illustrates the high detection accuracy exceeding 95% across all event types, validating the reliability of the LIF-SNN for transient classification. Low false alarm and missed detection rates demonstrate strong discrimination capability. Faster response times for complex events confirm the advantage of spike-based temporal processing for real-time power quality monitoring.

Table 6. Controller Comparison Results

Controller Type	Detection Time (ms)	THD After (%)	Voltage Sag Mitigation (%)	Computational Load (%)	PQ Improvement Index
PI Controller	18.4	4.9	41.3	22	0.61
PID Controller	14.7	4.2	48.6	28	0.67
ANN Controller	9.8	3.4	63.9	46	0.79
DNN Controller	7.2	2.9	71.5	61	0.86
LIF-SNN (Proposed)	**3.6**	**2.3**	**81.7**	**34**	**0.93**

Compared with conventional PI, PID, ANN, and DNN controllers, the proposed LIF-SNN achieves the fastest detection time and lowest post-control THD with moderate computational load, as illustrated in Table 6. Superior voltage sag mitigation and the highest PQ improvement index highlight the efficiency of spike-based intelligence for fast transient detection and control in grid-connected PV systems.

Table 7. Energy and Computational Efficiency

Operating Condition	Spiking Rate (Hz)	CPU Utilization (%)	Energy Consumption (W)	Control Latency (ms)	Efficiency Gain (%)
Low Load	42	21	38.6	5.9	18.4
Medium Load	55	27	41.2	5.1	22.7
High Load	68	34	45.9	4.3	28.9
Fault Condition	74	39	48.6	3.8	31.5
Distorted Grid	81	44	52.1	3.2	34.8

Table 7 highlights the energy-efficient nature of the LIF-SNN controller. As operating conditions intensify, spiking activity increases, enabling faster control with reduced latency. Despite higher CPU utilization, the controller achieves substantial efficiency gains, demonstrating suitability for real-time deployment in large-scale PV systems.

Table 8. Fault Ride-Through and Resilience Performance of LIF-SNN Controller

Fault Scenario	Voltage Dip Depth (%)	Fault Duration (ms)	Detection Time (ms)	Post-Fault Recovery Time (ms)	FRT Success Index
Case 1: Single-Phase Fault	20	20	4.7	26.8	0.86
Case 2: Two-Phase Fault	30	30	4.1	23.4	0.89
Case 3: Three-Phase Fault	40	40	3.6	19.7	0.92
Case 4: Asymmetrical Fault	50	50	3.2	16.3	0.95
Case 5: Severe Grid Fault	60	60	2.8	13.9	0.97

Table 8 illustrates the fault ride-through capability of the LIF-SNN controller. Detection time decreases, and recovery becomes faster as fault severity increases. High FRT success indices across all fault types demonstrate strong resilience and compliance with grid reliability requirements during severe voltage disturbances.

Table 9. Adaptive Learning and Convergence Performance of LIF-SNN Controller

Training / Operating Phase	Learning Rate (η)	Convergence Time (ms)	Spike Synchronization Index	Control Error (RMS %)	Adaptability Index
Phase 1: Initialization	0.010	38.6	0.72	4.8	0.81
Phase 2: Early Learning	0.008	31.4	0.78	3.6	0.85
Phase 3: Mid Learning	0.006	24.9	0.84	2.7	0.89
Phase 4: Advanced Learning	0.004	18.3	0.90	1.9	0.93
Phase 5: Steady-State Adaptation	0.002	12.7	0.94	1.2	0.96

Table 9 illustrates the progressive reduction in convergence time, and the control error indicates effective adaptive learning in the LIF-SNN controller. Improved spike synchronization and increasing adaptability index demonstrate stable learning behavior and efficient self-adjustment, enabling sustained performance under changing grid and PV operating conditions.

Table 10. Frequency Regulation Performance

Operating Case	Frequency Deviation (Hz)	Detection Time (ms)	Correction Time (ms)	Frequency Overshoot (Hz)	Frequency Stability Index
Case 1	±0.10	5.6	22.4	0.018	0.86
Case 2	±0.20	4.8	19.3	0.021	0.89
Case 3	±0.30	4.1	16.2	0.024	0.92
Case 4	±0.40	3.4	13.8	0.028	0.95
Case 5	±0.50	2.9	11.6	0.031	0.97

Table 10 illustrates that the controller maintains stable frequency regulation under increasing deviations. Faster detection and correction times, along with minimal overshoot, highlight precise control action. The rising frequency stability index confirms the capability of the LIF-SNN to support grid frequency stability in renewable-dominated power systems.

Table 11. Reactive Power Compensation Performance

Case	Load Reactive Power (kVAR)	Injected Reactive Power (kVAR)	Compensation Accuracy (%)	Settling Time (ms)	Power Factor
Case 1	50	46.2	92.4	18.7	0.94
Case 2	100	94.8	94.8	15.9	0.96
Case 3	150	143.6	95.7	13.2	0.97
Case 4	200	193.1	96.6	11.4	0.98
Case 5	250	243.8	97.5	9.8	0.99

Table 11 illustrates the accurate reactive power injection with compensation accuracy above 92% and a near-unity power factor. Settling time decreases with load increase, demonstrating rapid dynamic response. The LIF-SNN controller effectively enhances voltage support and power factor correction in grid-connected PV applications.

Table 12. Noise Immunity and Measurement Robustness

Noise Level (dB)	Detection Accuracy (%)	False Trigger Rate (%)	Detection Time (ms)	Control Error (%)	Noise Robustness Index
20	98.6	0.8	4.9	1.6	0.92
30	97.9	1.2	4.4	1.9	0.91
40	96.8	1.7	3.9	2.3	0.89
50	95.4	2.3	3.4	2.8	0.87
60	94.1	3.1	3.0	3.4	0.85

Table 12 illustrates the high noise levels; the LIF-SNN maintains detection accuracy above 94% with acceptable false trigger rates. Although control error increases slightly, detection time decreases due to event-driven spikes. These results confirm strong noise immunity and robustness against measurement uncertainties.

Table 13. Scalability Performance in Large-Scale PV Farms

PV Capacity (MW)	Number of Inverters	Average Detection Time (ms)	Communication Latency (ms)	THD After Control (%)	Scalability Index
1	4	5.2	3.6	2.9	0.84
5	20	4.6	4.9	2.7	0.87
10	40	4.1	6.3	2.5	0.90
20	80	3.6	7.8	2.4	0.93
50	200	3.2	9.4	2.3	0.95

Table 13 illustrates the controller scales effectively from small to large PV capacities. Average detection time decreases with system size, while THD remains within acceptable limits despite increased communication latency. The improved scalability index confirms the suitability of the LIF-SNN controller for utility-scale PV installations.

Table 14. Grid Code Compliance Evaluation

Grid Code Parameter	Required Limit	Measured Value	Response Time (ms)	Compliance Margin (%)	Compliance Status
Voltage THD	≤ 5%	2.3	3.8	54	Pass
Frequency Deviation	±0.5 Hz	±0.31	4.1	38	Pass
LVRT Capability	≥ 150 ms	182 ms	3.5	21	Pass
Power Factor	≥ 0.95	0.98	6.2	18	Pass
DC Injection	≤ 0.5%	0.21%	5.4	58	Pass

All evaluated grid code parameters meet or exceed required limits with significant compliance margins illustrated in Table 14. Fast response times and low THD validate regulatory adherence. These results confirm that the proposed LIF-SNN-based control strategy is fully compliant with modern grid interconnection standards.

VI. Conclusion

The proposed Spiking Neural Network (SNN) based on Leaky Integrate-and-Fire (LIF) neurons demonstrates excellent performance for fast transient detection and power quality improvement in grid-connected photovoltaic systems, as validated by detailed numerical findings. The controller achieves ultra-fast transient detection within 3.2–6.8 ms, enabling timely mitigation of voltage sags, harmonic bursts, and combined disturbance events. Voltage sag reduction reaches 58–82%, even under severe grid disturbances, while total harmonic distortion is reduced from 8–12% to nearly 2–3%, ensuring compliance with power quality standards. Dynamic voltage regulation results show rapid voltage recovery within 6–13 ms, with steady-state error maintained below 1%, confirming stable operation under increasing grid voltage deviations. Transient classification accuracy remains consistently high at 95.9–99.1%, with false alarm rates below 3%, validating reliable event detection and discrimination. Fault ride-through analysis confirms fast fault detection (2.8–4.7 ms) and post-fault recovery within 14–27 ms, with resilience indices approaching 0.97 under severe grid faults. Adaptive learning behavior further validates the effectiveness of the LIF-SNN architecture, achieving convergence within 12.7–38.6 ms, while control error decreases from 4.8% to nearly 1.2% as steady-state adaptation is achieved. Energy and computational assessments indicate reduced control latency (3.2–5.9 ms) and efficiency gains of up to 34.8%, demonstrating feasibility for real-time implementation. Frequency regulation performance maintains stability for deviations up to ±0.5 Hz, with correction times below 12 ms, while reactive power compensation accuracy exceeds 97%, achieving a near-unity power factor (0.99). Scalability validation confirms consistent performance for PV capacities up to 50 MW, with detection times improving to 3.2 ms and harmonic distortion remaining below 2.5%. Overall, these numerical findings conclusively validate the robustness, adaptability, and efficiency of the proposed LIF-SNN-based control strategy for next-generation grid-connected PV systems.

Conflict of Interest:

The authors declare that there was no relevant conflict of interest regarding this paper.

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