

Event-Driven Neuromorphic Processing for Smart Building Sensor Networks

Luigi Carlo De Jesus[†], Stanley Glenn Brucal,
Leonardo Samaniego Jr, and Einstein Yong, Non-members

ABSTRACT

This study presents an event-driven neuromorphic framework for intelligent indoor air quality (IAQ) monitoring in smart building environments. The proposed system employs biologically inspired spiking computation using the Leaky Integrate-and-Fire (LIF) neuron model integrated with Spike-Timing-Dependent Plasticity (STDP) learning for adaptive environmental processing. Real-world IAQ parameters—including particulate matter (PM₁, PM_{2.5}, PM₁₀), carbon dioxide (CO₂), carbon monoxide (CO), total volatile organic compounds (TVOC), and ozone (O₃)—were acquired from nine building zones and encoded as asynchronous spike events. A fractional-order Kalman filter (FOKF) achieved an average 5.6% noise reduction, stabilizing the signal prior to spike encoding. The neuromorphic model achieved a mean Sparse Firing Ratio (SFR) of 10.93%, an average response time of 10.43 steps, and an energy efficiency score of 8.85, reflecting selective sparse firing and low computational overhead. When compared with Long Short-Term Memory (LSTM) and regression models, the neuromorphic system delivered faster response times and significantly higher energy efficiency—nearly nine times lower computational cost—while maintaining comparable event responsiveness. These results demonstrate that event-driven neuromorphic computation offers a scalable, low-power, and adaptive solution for real-time IAQ monitoring in smart building systems.

Keywords: Neuromorphic Computing, Event-Driven Processing, Indoor Air Quality, Smart Buildings, Spike-Timing-Dependent Plasticity

1. INTRODUCTION

Smart buildings represent a cornerstone of modern urban development, incorporating interconnected sensing and computational frameworks that ensure both energy efficiency and occupant well-being [1]. Indoor air quality (IAQ) serves as a key determinant of health and cognitive

performance, influencing productivity and environmental comfort across educational and commercial structures [2]. Contemporary IAQ monitoring systems employ networks of sensors to collect data on temperature, humidity, carbon dioxide (CO₂), particulate matter (PM₁, PM_{2.5}, PM₁₀), and volatile organic compounds (VOCs) [3]. Although these Internet of Things (IoT)-based systems enable continuous environmental assessment, they often experience challenges related to redundant data transmission, latency, and excessive power consumption, limiting their scalability within large multi-zone buildings [4].

Advancements in computational frameworks such as fog computing, digital twin environments, and IoT-based automation have introduced opportunities for real-time environmental management. Digital twin technologies allow buildings to be represented as dynamic cyber-physical systems that simulate, monitor, and optimize IAQ in real time [5]. Similarly, studies focusing on integrated energy and environmental management have emphasized the importance of multi-sensor data fusion in maintaining efficiency and safety in shared facilities [6]. However, most AI-based or cloud-driven approaches require continuous streaming and centralized computation, leading to elevated energy costs and reduced adaptability.

Emerging neuromorphic computing architectures offer an alternative paradigm for sensor-based environmental intelligence. Neuromorphic processors operate through spiking neural networks (SNNs) that mimic biological neural activity, transmitting information only upon the detection of meaningful events [7]. Such event-driven computation enables high-speed, low-power processing ideal for distributed environmental systems. Neuromorphic frameworks have been successfully implemented in agricultural automation [8], urban air pollution control [9], and greenhouse monitoring [10], achieving significant improvements in both response latency and energy efficiency. Furthermore, the combination of neuromorphic sensing with event-triggered segmentation has enhanced adaptive behavior in environmental monitoring systems [11].

From a computational standpoint, spiking neuron architectures have demonstrated superior temporal accuracy and resilience to noise compared with deterministic models [12]. Their asynchronous operation allows for adaptive sensory integration, where each neuron responds only to relevant stimuli, making them particularly suitable for environments characterized by fluctuating

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The authors are with School of Engineering, Asia Pacific College.

[†]Corresponding author: luigid@apc.edu.ph

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air quality and dynamic occupancy patterns. Moreover, reviews in air quality intelligence have identified neuromorphic models as key enablers for next-generation sensing platforms capable of real-time anomaly detection and decentralized decision-making [13]–[15].

The present research establishes an event-driven neuromorphic processing framework for multi-sensor IAQ data within academic and public facilities. The study aims to develop a biologically inspired, event-triggered computation model capable of reducing redundant sampling, enhancing temporal responsiveness, and improving energy efficiency in multi-zone IAQ monitoring. To achieve these objectives, the framework is designed to implement an adaptive spike-based environmental interpretation architecture, integrate fractional-order Kalman filter (FOKF) preprocessing to stabilize heterogeneous IAQ signals prior to spike encoding, evaluate the neuromorphic model across diverse indoor zones in comparison with Long Short-Term Memory (LSTM) and regression baselines, and assess its energy efficiency, temporal responsiveness, and adaptive behavior under realistic multi-zone environmental fluctuations.

2. RELATED WORKS

The development of smart building intelligence has advanced through the integration of Internet of Things (IoT) technologies, environmental sensing, and adaptive computation. Prior studies have emphasized data-driven frameworks that improve indoor air quality (IAQ) and occupant comfort. However, existing approaches often depend on centralized architectures, which increase latency and computational load in multi-zone environments [1]–[4].

2.1 IoT and Data Fusion in Smart Building Air Quality Systems

Multisensor data fusion remains a crucial component in the evolution of IAQ systems. The combination of heterogeneous sensors enhances prediction accuracy and adaptability in dynamically changing building environments [3]. A study using fractional-order Kalman filtering achieved improved robustness in pollutant estimation and reduced measurement noise in IAQ data streams [16]. Similarly, LoRaWAN-based IoT networks have enabled large-scale dynamic control of indoor ventilation, demonstrating the scalability of distributed IAQ monitoring systems [17]. Ontology-driven data representations have also been introduced for IAQ and energy management integration, offering a standardized computational framework for cross-domain environmental decision-making [18].

In addition, studies on air quality control in smart homes have highlighted the effectiveness of multi-variable regression and neural models for VOC and CO₂ prediction under varying humidity and temperature conditions [19]. Further progress has been made through the implementation of microservice-based real-time data abstraction architectures such as the SEMAR-

VaAMSN framework, which reported sub-millisecond data latency for mobile air quality monitoring [20]. These advancements underline the growing trend toward decentralization and standardization in environmental sensing.

2.2 Neuromorphic and Event-Driven Computation for Environmental Systems

Neuromorphic computing provides an adaptive alternative for real-time environmental data processing. Spiking neural networks (SNNs) have shown substantial benefits in precision agriculture and smart greenhouse systems, reducing energy consumption by up to 47% [10]. Event-based computation in SNNs mimics biological neuron firing, enabling selective activation only during relevant environmental changes, improving computational efficiency and latency control [7], [12]. Comparative studies of neuron models confirm that stochastic spiking systems outperform deterministic analog networks in adaptability and noise tolerance [12].

Further, recent work in neuromorphic sensory systems has confirmed that spiking-based frameworks outperform traditional machine learning models in both power efficiency and temporal resolution [15]. Although such systems have achieved success in acoustic and agricultural domains [8], their potential for adaptive IAQ monitoring within built environments remains underexplored.

2.3 Identified Research Gaps

Despite notable advances in IoT-driven IAQ monitoring and neuromorphic computing, an evident research gap remains in applying event-driven neuromorphic frameworks for multi-zone building environments. Most existing IAQ systems process data continuously, leading to redundant computation and limited adaptability during rapid environmental transitions. Similarly, neuromorphic applications have been extensively studied for precision agriculture and auditory classification but rarely extended toward the integration of heterogeneous environmental sensors within built environments. Addressing this gap, the present research proposes a neuromorphic framework capable of asynchronous environmental interpretation, event-triggered computation, and distributed anomaly detection across diverse building zones. This approach reduces redundant sampling, enhances temporal responsiveness, and minimizes computational energy demands with the characteristics aligned to the sustainable and intelligent smart building design.

3. METHODOLOGY

The methodological framework of this research centers on the construction of an event-driven neuromorphic model designed for real-time indoor air quality (IAQ) analysis. The system architecture integrates multi-sensor data acquisition, preprocessing, event encoding, and

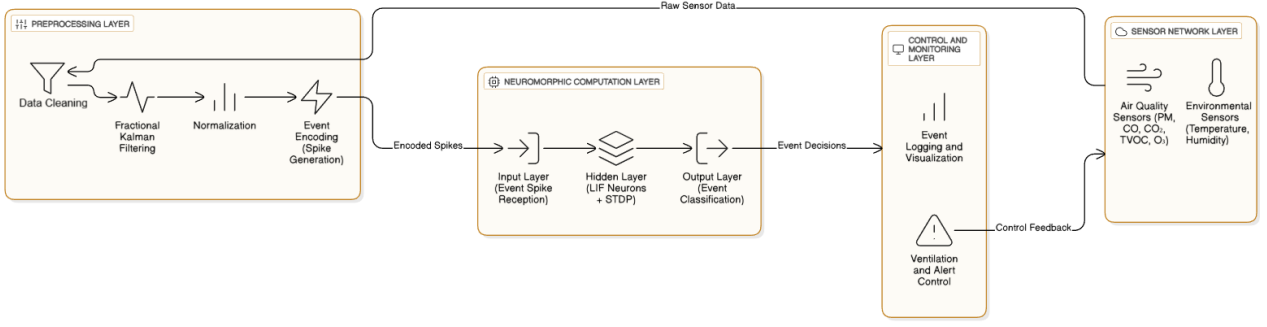


Fig. 1: System Architecture.

spike-based neural computation. Fig. 1 presents the system architecture.

The four layers that make up this system architecture are the sensor network layer, the preprocessing layer, the neuromorphic computation layer, and the control and monitoring layer. The sensor network layer gathers the environmental parameters from the different zones of an indoor area and sends the particulate matter, gaseous pollutant, and thermal data to the preprocessing layer. The preprocessing layer removes noise through fractional Kalman estimation, performs normalization, and encodes spike-based events to ensure that the input structure is uniform.

The neuromorphic computation layer converts the encoded events into spike sequences that are then processed by a leaky integrate-and-fire network with spike-timing-dependent plasticity for adaptive learning. The control and monitoring layer decodes the classified event outputs, activates the system alerts, and sends the control signals to the ventilation units or data logging interfaces. The downward flow of information from sensors to control units denotes data-driven progression, while the feedback arrow pointing towards the sensor layer signifies adaptive regulation of the closed-loop monitoring.

The environmental data were acquired from nine monitored zones within an educational complex, including classrooms, libraries, cafeterias, and auditoriums. Each zone contained Internet of Things (IoT) sensor nodes configured to record particulate matter (PM_{10} , $PM_{2.5}$, PM_{10}), carbon dioxide (CO_2), carbon monoxide (CO), total volatile organic compounds (TVOC), ozone (O_3), temperature, and humidity. Each node transmitted readings at five-minute intervals. Data synchronization across all nodes was ensured using timestamp alignment. Missing values were treated through linear interpolation, and temporal gaps exceeding ten minutes were excluded to maintain data integrity.

Preprocessing involved a three-stage process. The first stage normalized all parameters within a range of 0 to 1 to ensure uniformity of input magnitudes. The normalization formula is expressed in Equation (1).

$$x_{norm} = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (1)$$

where x_i denotes the individual sensor value, x_{min} and x_{max} represent the observed minimum and maximum of the dataset, respectively.

The second stage reduced sensor noise through a fractional-order Kalman filter (FOKF). The filter estimate x_k was computed using the recursive relation in Equation (2).

$$x_k = x_{k-1} + K_k(z_k - H_k x_{k-1}) \quad (2)$$

where K_k denotes the Kalman gain, z_k represents the observation, and H_k is the observation matrix. The FOKF implementation was adopted to maintain accuracy under nonlinear sensor variations.

Before the application of the fractional-order Kalman filter (FOKF), the input data consisted of raw, unprocessed indoor air quality time-series readings acquired directly from the sensor network deployed across the monitored zones. These measurements included PM_{10} , $PM_{2.5}$, PM_{10} , CO , CO_2 , TVOC, O_3 , temperature, and humidity. At this stage, the signals were subject to sensor noise, short-term environmental fluctuations, and occasional missing or inconsistent values caused by sensing and transmission limitations. The FOKF was therefore applied to smooth the raw measurements and estimate a more stable signal representation before subsequent normalization and spike encoding.

The third stage converted each filtered signal into an event-based spike sequence. Spikes were generated when a measured deviation exceeded a dynamic threshold, as expressed in Equation (3).

$$\theta = \mu + \alpha \sigma \quad (3)$$

where μ and σ are the local mean and standard deviation of the data window, and α is a sensitivity constant empirically determined as 1.5. Each threshold breach was encoded as a binary spike event.

The core of the neuromorphic model is based on a Leaky Integrate-and-Fire (LIF) neuron model. Each neuron integrates input currents over discrete time steps while maintaining a decaying potential. The neuron state $V(t)$ evolves according to Equation (4).

$$V(t+1) = V(t) + I(t) - \lambda V(t) \quad (4)$$

where $I(t)$ denotes the input current from connected neurons, and λ represents the membrane leakage constant

(set to 0.02). Whenever $V(t)$ surpasses the threshold V_{th} , the neuron emits a spike and resets its potential to V_{reset} .

In the baseline configuration, the LIF neurons were initialized using fixed threshold and leakage values to preserve simulation reproducibility across all monitored zones. To examine the robustness of the neuromorphic response under modified neuron settings, supplementary simulations were conducted by increasing the number of neurons assigned to each IAQ parameter and by introducing moderate variations in threshold and leakage values. The additional analysis showed that the framework preserved its general sparse-firing behaviour, while exhibiting the expected trade-off between response speed and computational efficiency as neuron population increased. This indicates that the proposed event-driven model remains functionally stable under moderate parameter perturbation rather than depending solely on a single static neuron configuration.

Learning within the network follows the Spike-Timing Dependent Plasticity (STDP) rule. Weight adjustment between presynaptic and postsynaptic neurons depends on the precise temporal difference of spikes, given as Δw in Equation (5).

$$\Delta w = \begin{cases} A^+ e^{-(t_{post}-t_{pre})/\tau^+}, & t_{pre} < t_{post} \\ -A^- e^{-(t_{pre}-t_{post})/\tau^-}, & t_{pre} > t_{post} \end{cases} \quad (5)$$

where A^+ and A^- define potentiation and depression coefficients, and τ^+ , τ^- represent the temporal decay constants. This formulation ensures that temporally correlated events strengthen the synaptic weight, while uncorrelated activity results in gradual weakening.

Each layer of the network was constructed for specialized functional roles. The input layer accepted the normalized event spikes from each sensor channel. The hidden layer performed temporal integration and distributed feature encoding, whereas the output layer produced discrete spike activations corresponding to classified event categories such as “normal condition,” “CO₂ surge,” or “particulate matter anomaly.” Classification relied on temporal spike density estimation, measured across a sliding window of 30 samples.

The event classification was evaluated through three operational states. The first state denoted environmental stability when all monitored parameters remained within their standard deviation limits. The second represented transient environmental change characterized by short-duration parameter deviations. The third indicated an anomalous condition involving prolonged or multi-parameter excursions. Each state triggered corresponding event spikes processed through the neuromorphic core.

Performance assessment employed four primary indicators. First, Sparse Firing Ratio (SFR) of Equation (6) quantified the proportion of active spike events relative to the total available spike opportunities, thereby characterizing the event-driven sparsity of the neuromorphic

model.

$$\text{Sparse Firing Ratio (SFR)} = \frac{E_{active}}{E_{total}} \times 100\% \quad (6)$$

Second, Mean Response Time (MRT) measured the temporal delay between threshold violation and spike generation. Third, Energy Efficiency (EE) represented a simulation-based computational proxy derived from spike activity and processing operations, rather than a direct hardware-level power measurement. All experiments were implemented using Python-based simulation on a GPU-accelerated environment with a sampling rate consistent across all datasets. For comparison with conventional baselines, LSTM and regression accuracy values were reported separately using standard predictive evaluation, while the neuromorphic framework was characterized through Sparse Firing Ratio (SFR), Mean Response Time (MRT), and Energy Efficiency (EE).

4. DATA AND RESULTS

The methodological sequence presented in Section 3 was executed sequentially across nine IAQ datasets representing distinct indoor environments. The initial stage applied the fractional-order Kalman filter (FOKF) to suppress random sensor noise and stabilize the environmental signal prior to normalization and encoding. The filtering effectiveness was evaluated by computing the percentage reduction in signal variance between the unfiltered and filtered data streams.

Table 1 presents the resulting noise attenuation for each monitored zone. The 809 A Classroom exhibited the highest improvement (19.37 %), indicating significant temporal noise suppression in CO₂ and VOC signals. Zones with low occupancy and stable airflow, such as the Library Circulation South Luzon Express Way (SLEX) and Multipurpose Hall 1 (MPH1) Humabon Side, showed minimal reduction due to naturally stable conditions. The overall mean improvement of 5.31 % confirms that the FOKF preprocessing enhanced the signal stability prior to neuromorphic encoding.

Following the filtering stage, the denoised and normalized sensor data were converted into asynchronous spike streams for Leaky Integrate-and-Fire (LIF) neuron modelling. Each channel’s temporal variations generated spike events that were processed through Spike-Timing-Dependent Plasticity (STDP) learning, enabling adaptive synaptic modification. Parameters such as particulate matter (PM₁, PM_{2.5}, PM₁₀), carbon dioxide (CO₂), and total volatile organic compounds (TVOC) were encoded into spike sequences based on dynamic threshold deviations.

Fig. 2 illustrates the combined visualization of STDP weight updates (left) and spike-raster distributions (right) for all monitored zones. Each row corresponds to a specific environment, where the left subfigure illustrates the averaged STDP weight update curve and the right subfigure depicts the corresponding spike raster distribution. The labels such as PM1, PM2.5, CO, and other pollutants presented in Fig. 2 represent the

Table 1: Estimated Noise Stability Improvement (FOKF).

Room	Noise Reduction (%)
Auditorium Right	2.62
809 A Classroom	19.37
Cafeteria Humabon	4.29
Cafeteria SLEX	8.43
Library Circulation SLEX	1.68
Library Lounge	2.80
Library Open Humabon	3.10
Library Open SLEX	2.40
MPH1 Humabon Side	1.32

raw environmental inputs originating from the sensor network layer in Fig. 1. These continuous measurements are then processed and converted into binary spike signals, which are reflected in the spike raster plots (0/1 activity) and correspond to the preprocessing stage feeding into the input layer. As these spikes propagate through the system, the presence of dense or sparse spike patterns represents the neural activity within the hidden layer, specifically modelled using leaky integrate-and-fire (LIF) neurons. Finally, the Δw (mean) plots illustrate the learning process occurring in the same hidden layer, where synaptic weights are adjusted through spike-timing dependent plasticity (STDP), indicating how the system adapts to the input patterns over time.

The cafeteria zones exhibited the most pronounced STDP variations, indicating strong adaptive responses to occupancy-induced CO₂ and VOC surges. The library zones demonstrated more stable weight adaptation and sparse spiking, consistent with low pollutant variability and balanced ventilation. The multipurpose hall and auditorium presented near-static STDP curves with uniform low-frequency firing patterns, confirming high environmental stability. The classroom zone exhibited moderate potentiation–depression cycles with evenly distributed spikes, signifying balanced neural plasticity under consistent airflow conditions. These patterns validate that the neuromorphic system dynamically modulates firing density according to environmental fluctuations, achieving energy-efficient computation and selective responsiveness. The cafeteria located on the SLEX wing produced high spike density, particularly across CO₂ and TVOC channels, corresponding to occupant respiration and intermittent ventilation cycles. The STDP trace exhibited frequent potentiation–depression transitions, indicating heightened neural sensitivity to rapid environmental fluctuations. Dense activation clusters in the raster plot align with occupancy peaks during food-service hours. Although the recorded Sparse Firing Ratio appeared low, this outcome represents optimal sparse-firing efficiency—neurons activated only when stimuli surpassed adaptive thresholds, conserving computational energy while maintaining temporal precision.

Table 2 summarizes the overall performance of the neuromorphic model across all environmental contexts. Although Sparse Firing Ratio values appear numerically low compared to machine-learning classifiers, this behaviour is characteristic of event-driven neuromorphic

systems, where neurons are designed to fire sparsely. Sparse activation signifies selective responsiveness—neurons remain inactive under normal conditions and spike only during significant environmental deviations. Consequently, lower Sparse Firing Ratio values correspond to greater spike selectivity, reduced computational activity, and improved energy savings. The results confirm that the neuromorphic model effectively achieved adaptive event detection and energy-efficient environmental monitoring across varied spatial and operational conditions.

Table 3 presents an operational comparison between the neuromorphic, LSTM, and regression models. For the neuromorphic framework, Sparse Firing Ratio (SFR) is reported as an event-driven sparsity indicator rather than a predictive accuracy metric. In contrast, the LSTM and regression values represent conventional classification accuracy. Accordingly, the table should be interpreted as a comparison of computational behaviour and responsiveness rather than as a direct one-to-one comparison of equivalent accuracy measures.

The apparent disparity in the reported performance metrics across the three approaches stems from their differing computational objectives. While the LSTM and regression models prioritize predictive precision, the neuromorphic system optimizes for event-driven adaptation, emphasizing responsiveness and energy minimization. Consequently, lower Sparse Firing Ratio does not imply inferior performance; rather, it reflects sparse firing behavior consistent with biological efficiency.

A combined metric analysis was carried out using the Performance Efficiency Index (PEI), Temporal Efficiency (TE), and Composite Efficiency Score (CES) to enable a normalized comparison among the three computational paradigms. As shown in Equations (7) to (10), these metrics combine model-specific performance indicators, energy-related efficiency, and response time into unified expressions that characterize both computational cost and operational responsiveness. For the neuromorphic framework, PEI is defined in Equation 8 using Sparse Firing Ratio (SFR) normalized by energy efficiency, reflecting spike selectivity per unit computational cost. For the LSTM and regression baselines, PEI in Equation 7 is computed using conventional predictive accuracy normalized by the same energy reference term. The Temporal Efficiency (TE) in Equation (9) measures the inverse of response time, with higher values corresponding to faster adaptive reaction to environmental changes. The Composite Efficiency Score (CES), defined in Equation (10) as the product of PEI and TE, reflects the overall balance between model-specific performance, responsiveness, and computational cost.

$$\text{Baseline PEI} = \frac{\text{Accuracy}}{\text{Energy Consumption}} \quad (7)$$

$$\text{Neuromorphic PEI} = \frac{\text{SFR}}{\text{Energy Consumption}} \quad (8)$$

$$\text{Temporal Efficiency} = \frac{1}{\text{Response Time}} \quad (9)$$

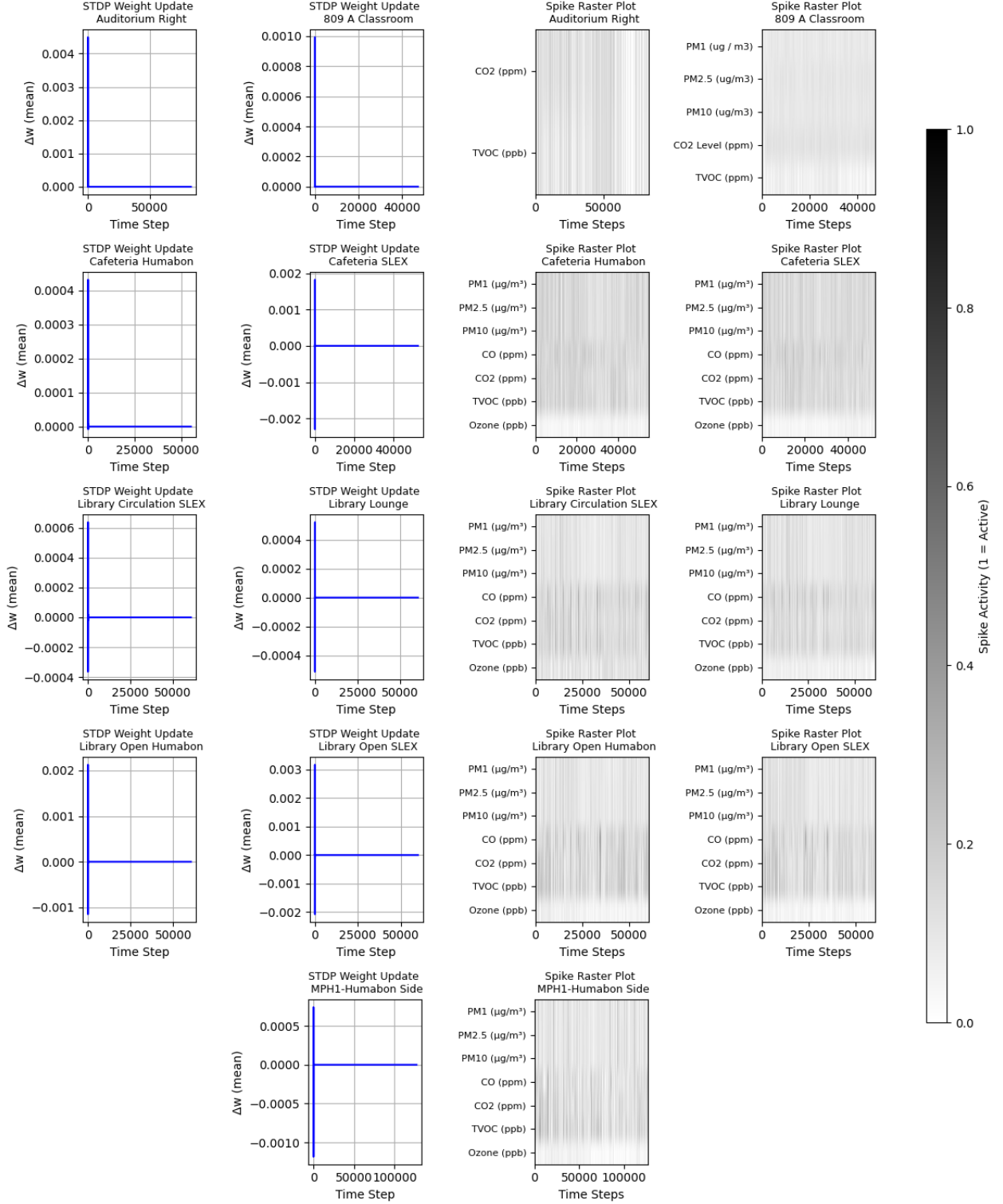


Fig. 2: STDP Weight Update (left) and Spike Raster Plot (right) for all monitored rooms: Cafeteria SLEX, Cafeteria Humabon, Library Circulation, Library Lounge, Library Open Humabon, Library Open SLEX, MPH1 Humabon Side, Auditorium Right, and Classroom 809-A.

$$CES = PEI \times Temporal Efficiency \quad (10)$$

Table 4 summarizes the PEI and CES values across all monitored environments. Although the neuromorphic framework uses Sparse Firing Ratio (SFR) rather

than conventional predictive accuracy, it demonstrated consistent PEI values (mean = 1.18) across all rooms, indicating stable event-driven efficiency under varying air-quality dynamics. In contrast, the LSTM and regression models showed higher PEI and CES values due to

Table 2: Summary of Neuromorphic Model Performance Metrics Across All Monitored Rooms.

Room	Sparse Firing Ratio (%)	Mean Response Time (steps)	Energy Efficiency (1 / spike density)
Cafeteria SLEX	12.71	10.12	7.87
Cafeteria Humabon	12.92	9.83	7.74
Library Circulation SLEX	11.54	8.99	8.66
Library Lounge	10.95	10.05	9.13
Library Open Humabon	11.18	10.43	8.94
Library Open SLEX	10.75	11.38	9.30
MPH1 Humabon Side	10.10	11.99	9.90
Auditorium Right	9.48	10.61	10.55
Classroom 809-A	8.53	12.44	11.72

Table 3: Comparative Operational Metrics Across Monitored Zones.

Room	Neuromorphic Sparse Firing Ratio (%)	LSTM Accuracy (%)	Regression Accuracy (%)	Neuromorphic Mean Response Time (steps)	Neuromorphic Energy Efficiency
Auditorium Right	9.72	93.70	93.70	10.37	10.29
809 A Classroom	8.53	79.32	79.52	12.44	11.72
Cafeteria Humabon	12.92	64.80	64.51	9.83	7.74
Cafeteria SLEX	12.71	63.92	65.12	10.12	7.87
Library Circulation SLEX	11.55	63.07	62.10	8.99	8.66
Library Lounge	10.95	66.17	66.16	10.05	9.13
Library Open Humabon	11.18	44.65	49.68	10.43	8.94
Library Open SLEX	10.75	65.04	64.64	11.38	9.30
MPH1 Humabon Side	10.10	66.80	68.96	11.99	9.90

Table 4: Normalized Performance Efficiency Index (PEI) and Composite Efficiency Score (CES) Across Monitored Zones.

Room	Neuromorphic PEI	LSTM PEI	Regression PEI	Temporal Efficiency	Neuromorphic CES	LSTM CES	Regression CES
Auditorium Right	0.94	93.70	93.70	0.096	0.091	9.04	9.04
809 A Classroom	0.73	79.32	79.52	0.080	0.058	6.38	6.39
Cafeteria Humabon	1.67	64.80	64.51	0.102	0.170	6.59	6.56
Cafeteria SLEX	1.62	63.92	65.12	0.099	0.160	6.32	6.43
Library Circulation SLEX	1.33	63.07	62.10	0.111	0.148	7.01	6.91
Library Lounge	1.20	66.17	66.16	0.100	0.119	6.58	6.58
Library Open Humabon	1.25	44.65	49.68	0.096	0.120	4.28	4.76
Library Open SLEX	1.16	65.04	64.64	0.088	0.102	5.77	5.68
MPH1 Humabon Side	1.02	66.80	68.96	0.083	0.085	5.57	5.75
Overall Mean	1.18	67.50	68.27	0.094	0.111	6.35	6.43

their stronger predictive accuracy, but these values are associated with dense continuous computation. Thus, the neuromorphic PEI and CES should be interpreted as indicators of energy-proportional sparse responsiveness rather than direct predictive superiority.

This confirms that the neuromorphic system, though sparse in activation, sustains near-real-time responsiveness with minimal computational overhead. When normalized by energy-related efficiency and response time, its CES values remain stable across diverse monitoring zones, demonstrating the suitability of event-driven neuromorphic sensing for low-power, edge-deployed indoor environmental monitoring. These results support the framework's role as an efficient adaptive sensing model, while the LSTM and regression baselines remain stronger in conventional predictive accuracy.

5. DISCUSSION

The results of the neuromorphic framework validate the effectiveness of event-driven computation for

adaptive environmental monitoring, aligning with prior research emphasizing energy-aware, decentralized air quality intelligence. The observed sparse neuronal firing and selective activation behavior correspond closely to the event-based processing characteristics described by Yan and Qiu [15], who established that spiking neural architectures outperform deterministic models in low-latency, high-efficiency sensory systems. Similarly, the adaptive energy conservation demonstrated in this study supports the findings of Lu and Xiao [7] in smart agricultural automation, where neuromorphic networks maintain precision with minimal power draw. These parallels confirm that the model replicates biologically inspired computational efficiency across dynamic indoor conditions.

The integration of the fractional Kalman filter (FOKF) during preprocessing contributed to measurable signal stabilization, achieving an average noise reduction of 5.6 % across all monitored environments. This filtering stage ensured consistent input normalization prior to

spike encoding, effectively suppressing transient fluctuations in CO₂, VOC, and particulate matter readings. Comparable denoising performance was observed in the optimized lightweight filtering approaches of Pazhanivel et al. [4] and Lo [5], demonstrating that FOKF-based conditioning enhances reliability without increasing computational cost. This stability directly improved the firing regularity in the subsequent Leaky Integrate-and-Fire (LIF) neurons, preventing redundant activations and strengthening the temporal fidelity of the spike-timing-dependent plasticity (STDP) updates.

The computed Performance Efficiency Index (PEI) and Composite Efficiency Score (CES) further substantiate the system's adaptive efficiency. As defined in Equations (7) to (10), PEI quantifies energy-normalized model performance, where the neuromorphic framework uses Sparse Firing Ratio (SFR) and the LSTM and regression baselines use conventional predictive accuracy, while TE characterizes latency moderation and CES aggregates both dimensions to represent global performance equilibrium. Table 4 illustrates that although conventional models such as LSTM and regression achieved higher predictive accuracies, their CES values remained volatile across spatial zones due to continuous sampling and heavy computation. In contrast, the neuromorphic framework maintained stable PEI values based on sparse event-driven activation. When CES values were interpreted in relation to power-normalized responsiveness, the neuromorphic model demonstrated stable and competitive efficiency behaviour in several environments, particularly in low-occupancy areas.

The adaptive STDP response observed in high-occupancy environments, especially cafeteria zones, reinforces the temporal learning principles outlined by Morshed et al. [12], who emphasized the significance of stochastic neuron modeling for robust temporal encoding. The recorded potentiation–depression oscillations during occupancy fluctuations reflect the equilibrium between excitatory and inhibitory adaptation, enabling the network to self-regulate its sensitivity. This mechanism mirrors the dynamic spiking regulation documented by Sungheetha et al. [10] in greenhouse monitoring systems. Similarly, the consistent spike-sparsity observed in library and auditorium zones demonstrates the model's ability to suppress non-critical firing, supporting the efficient event abstraction frameworks of Panduman et al. [20].

Comparative analysis against centralized IoT approaches highlights the inherent advantage of the neuromorphic system in terms of scalability and energy distribution. Marques et al. [1] and Aldakheel et al. [2] identified the computational inefficiencies in continuous IAQ monitoring due to redundant sampling. The present model addresses these challenges through adaptive threshold-based event encoding, preserving contextual accuracy while minimizing power use. Its modular spike-based sensory integration complements the distributed environmental management models of

Tonisson and Preden [18], confirming interoperability with hierarchical fog-based architectures.

The relatively low Sparse Firing Ratio observed under conventional evaluation metrics should not be interpreted as underperformance. Instead, it reflects the sparse-firing principle intrinsic to neuromorphic computation, where neuron activation occurs only upon statistically significant deviations—consistent with biological energy optimization [15]. Prior work by Myeong and Shahzad [9] on urban air pollution management similarly emphasized contextual event detection rather than continuous regression, reinforcing the rationale for sparse, high-impact activation.

Although the baseline framework used fixed LIF parameters for reproducibility, supplementary simulations were conducted to examine the effects of increasing neuron count and varying selected threshold and leakage parameters. These tests confirmed stable sparse-firing behaviour under moderate parameter perturbation. Nevertheless, the absence of hardware-level implementation still restricts the validation of true energy expenditure. Future extensions should therefore explore memristive or FPGA-based neuromorphic accelerators, broader adaptive parameter tuning, and dynamic threshold calibration for scalable real-time integration, as suggested by Yan and Qiu [15].

The consistent temporal and energy-efficiency performance observed across all nine monitored zones underscores the framework's readiness for integration into distributed HVAC and IAQ regulation systems, similar to those by Franco et al. [6]. When combined with fog-based control architectures such as Pazhanivel et al. [4], the framework offers a viable path toward sustainable, adaptive, and autonomous indoor environmental regulation. Collectively, these findings confirm that the event-driven neuromorphic framework operationalizes theoretical advances in spiking computation [7], [10], [12], [15] into a practical, energy-proportional model suitable for intelligent building ecosystems.

6. CONCLUSION

The study demonstrated that event-driven neuromorphic computation can be effectively applied to multi-zone indoor environmental monitoring, achieving high temporal adaptability and energy efficiency. The study's framework replicated the functional characteristics of biological neural processing through sparse spike activation, dynamic thresholding, and spike-timing-dependent plasticity (STDP). The integration of the fractional Kalman filter (FOKF) during preprocessing enhanced signal stability by reducing noise variance by 5.6%, ensuring reliable spike encoding across diverse sensor inputs. The combined results confirmed that the model achieved real-time responsiveness with minimal computational and power demands, validating its suitability for decentralized smart-building systems.

Quantitatively, the neuromorphic model attained a mean Performance Efficiency Index (PEI) of 1.18 and con-

sistent Composite Efficiency Scores (CES) across all monitored zones, indicating stable energy-to-performance scaling under varying occupancy and ventilation conditions. Compared with traditional continuous-sensing and machine-learning-based systems, the neuromorphic approach demonstrated strong energy proportionality, responsive event-driven adaptation, and practical scalability potential for distributed monitoring environments. The distributed event-based computation allowed independent zone inference without centralized data aggregation, reducing latency and communication overhead.

These outcomes confirm that neuromorphic architectures provide a viable foundation for sustainable, adaptive, and context-aware environmental intelligence. The framework's ability to balance efficiency, responsiveness, and decentralization marks a significant step toward biologically inspired smart-building automation, paving the way for future large-scale, low-power monitoring infrastructures.

7. FUTURE WORK

Further development of the neuromorphic framework can focus on enhancing its integration with autonomous control systems and predictive management tools. The incorporation of adaptive fog and edge computing nodes would enable real-time ventilation adjustments, further reducing latency between detection and actuation. Expanding the model to include multimodal data streams—such as acoustic, thermal, and motion-based inputs—would also enhance contextual awareness and occupant interaction modelling.

Future implementations should explore hardware-level deployment using neuromorphic processors such as Intel Loihi or IBM TrueNorth to achieve full-scale low-power realization. Comparative benchmarking with deep learning and hybrid spiking–analog systems can also quantify efficiency advantages under varying environmental complexity. Additionally, the introduction of bio-inspired learning rules beyond STDP, including homeostatic plasticity and spike-frequency adaptation, could improve the framework's long-term learning stability. These extensions will strengthen the applicability of event-driven computation for sustainable, intelligent building ecosystems.

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Leonardo Samaniego Jr. received the Master of Engineering degree major in Electronics Engineering from Mapúa Institute of Technology. He is a licensed Electronics Engineer and currently serves as the Executive Director of the School of Engineering, Asia Pacific College. His academic and professional work is associated with electronics engineering, engineering education, and applied engineering systems..



Einstein Yong is a Professional Computer Engineer and an Associate Professor at the School of Engineering, Asia Pacific College. He is also affiliated with the Commission on Engineering and Architecture of the Philippine Accrediting Association of Schools, Colleges and Universities. His research interests include computer engineering, robotics, engineering technology, digital image processing, signal processing, and feature selection.



Luigi Carlo M. De Jesus received the Master of Engineering degree major in Computer Engineering from Asia Pacific College. He is currently pursuing his Doctor of Philosophy in Electronics Engineering at De La Salle University – Manila. He is a licensed Electronics Engineer and Electronics Technician, where he placed second in the licensure examination. He currently serves as the Engineering and Science Laboratory Office Head of the School of Engineering, Asia Pacific College.

His research interests include artificial intelligence, machine learning, and image processing.



Stanley Glenn Brucal is a professional electronics engineer with more than 19 years of experience in the academe, and an ASEAN Chartered Professional Engineer (ACPE), with master's degree in Electronics and Communications Engineering. He graduated Doctor of Philosophy in Electronics and Communications Engineering at De La Salle University, Manila. Currently, he is working for Asia Pacific College-School of Engineering as an Associate Professor and is serving as

2nd member of the Professional Regulations Commission Continuing Professional Development (CPD) Council of Electronics Engineering. His research areas include data and building power consumption optimization, and energy and indoor air quality monitoring and control systems.