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Development of Neuromorphic Polymer Composites Using IoT Sensing and Brain-Inspired Learning Algorithms

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Abstract

This research aims to develop neuromorphic polymer composites by combining conductive sensing materials, IoT-based sensing data collection and brain-inspired learning models for adaptive response. Hybrid conductive polymer composites were developed by adding carbon nanofibers and graphene Nano platelets to a thermoplastic polymer. IoT sensors (strain, temperature) were employed to collect real-time sensing data that was combined with environmental data. A material-aware neuromorphic learning algorithm was created with event-driven spike coding and reward-based learning. Dynamic mechanical and environmental loads were applied. The composite exhibited consistent piezoresistive properties with a sensitivity of 0.034 %$^{-1}$ and repeatability of more than 97%. The proposed method achieved an accuracy of 95.8% ± 1.2%, which is much better than the conventional machine learning (89.3%) and deep learning (92.6%) methods. The response time was also reduced to 120 ms, which is a 40-50% improvement over other methods. The power consumption was also reduced by almost 35-40% in event-driven mode. Multimodal fusion also resulted in a more consistent signal with the variance reduced by ~20%. This research introduces a novel approach to the integration of polymer composites, IoT sensor technology and neuromorphic learning in an experiment. The approach provides a real-time adaptive intelligence, beyond the existing approach which decouples these technologies. The paper presents a scalable solution for smart materials with sensing and learning.

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INTRODUCTION

Background and Scientific Context

Polymer composites have evolved from being inert structural materials to smart, sensing, actuating and responsive materials. This has been made possible by the addition of conductive fillers, nano-reinforcements and electronics, which enable the development of intelligent (smart) polymer composites with enhanced electrical, thermal and mechanical properties [1, 2]. In the last couple of years, the convergence of digital technologies with materials has accelerated this process, particularly with the inclusion of Internet of Things (IoT)-sensing systems into the polymer matrix [3]. This allows the sensing of environmental factors (temperature, strain, humidity and irradiance) at the material level in real time and thus, a shift in the operating paradigm of composite systems [4].

Meanwhile, neuromorphic engineering has emerged as a possible approach to develop brain-inspired systems. Neural-inspired machine learning, such as from spiking neural networks (SNNs) and synaptic plasticity, offers energy efficient and event-driven computing paradigms for edge intelligence [5, 6]. From an engineering materials point of view, the integration of neuromorphic computing with polymer composites provides a new research opportunity and a new vision - that the composite can be a smart system that can sense, learn and adapt [7].

Despite these recent advances, at present the polymer composite systems still largely rely on data processing in a centralized fashion. The sensors in the composite are often used to gather data and the intelligence is carried out in the cloud [8]. The isolation of the sensing and intelligence leads to latency, increased energy consumption and decreased responsiveness in dynamic environments such as smart buildings, wearables and solar panels [9]. This makes it imperative to have embedded, distributed and adaptive intelligence in the composite.

Problem Statement

IoT-based polymer composites have demonstrated great potential in structural health monitoring and environmental monitoring, but their potential is constrained by non-adaptive or rule-based data processing techniques [10]. These technologies can use static thresholds or traditional machine learning methods that lack the capability of learning and adaptation. This is particularly problematic in situations involving complex nonlinearity of the material, randomness and degradation of the environment [11].

Also, conventional designs do not exploit the synergies between material properties of polymer composites and computational properties of neuromorphic systems. For instance, conductive polymer networks can exhibit nonlinear electrical behaviour that can potentially simulate synaptic activity; but this is not currently being used [12]. Lack of a systems approach to integrate material-level sensing with adaptive brain-inspired learning is another key challenge.

The power and computational requirements of traditional deep learning models for edge and embedded applications is also a challenge. Traditional artificial neural networks require continuous data feeds and high computational power, which is not ideal for low-power, distributed IoT-enabled, composite materials and systems [13]. This makes it difficult to scale and use such models in resource-constrained applications, such as remote sensing and autonomous systems.

Additionally, the lack of experiments that combine the synthesis of composite materials, embedded sensing and adaptive learning to test models in real environments also contributes to the difficulty in translating models to reality [14]. Typically, research has focused on either material- or algorithm-centric approaches, and has neglected experiments.

Proposed Research Framework

Here, we propose to address these limitations by designing neuromorphic polymer composites by incorporating Internet of Things (IoT) based sensing networks with brain-inspired learning algorithms into the composite. Our strategy is based on a multi-layered design strategy where the conducting polymer matrices with nanofillers give rise to sensing and signal transduction [15]. These are integrated with energy-efficient IoT devices for data sensing and processing.

On the computing side, neuromorphic learning models - specifically, event-driven adaptive algorithms - are employed for on-the-edge learning and decision making. These models work in a sparse and asynchronous way, in contrast to traditional neural networks, and so are very energy efficient and

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adaptive [16]. The material layer and the computational layer interact in a two-way manner, allowing the system to respond to the environment, as well as self-regulate its response.

In the experimental stage, the model is focused on the development of polymer composites with particular electrical and morphological properties to realise the neuromorphic functions. The volume, dispersion and interaction of the fillers are optimised to enable the generation and transmission of the signals [17]. The IoT sensing layer is designed to sense fine-scale temporal information that are processed by the new learning algorithms for pattern recognition and anomaly detection.

Furthermore, the integration paradigm proposed in this work ensures that the sensing, computing and actuation will be integrated in the composite system, eliminating the need for extra processing elements. This approach of embedded intelligence makes the system more autonomous, faster and efficient.

Novelty and Contributions

This research is unique in the integration of polymer composite systems, IoT sensor systems and neuromorphic computing in an experimental system. This work presents a departure from past research that has taken an isolated approach to these areas to a direct link between the material systems and adaptive learning [18]. This enables the development of not only smart but also thinking composites.

The current study has several implications. First, it offers a new kind of polymer composite with real-time adaptive learning, by integrating brain-inspired algorithms into the composite. Second, it provides an experimentally demonstrated model of the integration of sensing and intelligence, and the potential for local decision-making of the composite network. Third, it offers insights into the development of low-energy, scalable and self-sustaining materials for next-generation smart infrastructure systems, wearable devices and renewable energy systems.

Lastly, the research is important from the point of view of methodology. By combining the synthesis of materials, IoT and neuromorphic modeling in an experimental process, the study establishes a replicable process in line with the latest standards in polymer science. This results in a system that is more flexible, fast and efficient than the conventional smart composite systems.

In summary, this research makes a new advancement in turning polymer composites into "smart" and learning systems. It broadens the functionality of materials, and opens the way for the development of neuromorphic polymer composites as a technology for smart and autonomous engineering systems in the future.

LITERATURE REVIEW

Smart Polymer Composites and Embedded Sensing

Research has improved the process by improving dispersion and bonding of fillers. This leads to higher electrical network stability and lower noise. For example, composite fillers with a combination of carbon nanotubes (CNTs) and graphene Nano platelets have improved sensitivity and repeatability of the sensing under cyclic loading [19, 20]. Also, piezo resistive and capacitive sensors have been developed to allow composites to more accurately detect micro deformations.

However, although these advances in materials have enhanced the sensing properties, most composites with sensing ability are still used as sensor data sources. The data from the sensors is generally transmitted to data centres. This limits the responsiveness of the system, and introduces a delay particularly for real-time applications. Also, the reliability of sensors can be influenced by environmental factors (e.g. humidity, temperature) and it can be challenging to operate for a long time [21].

A recent development is smart composites for aerospace and civil engineering. The composites aim to offer sensorless structural integrity monitoring. While promising, these are mostly based on threshold monitoring. This indicates a need for more learning systems.

IoT Integration in Composite Materials

IoT has added to the functionality of polymer composites. With the integration of microcontrollers, wireless communication devices and sensor interfaces, it is now possible to gather data in real-time and remotely monitor [22]. The smart composites are being used in smart buildings, wearables and energy harvesting.

One of the major breakthroughs is to use lightweight communication protocols such as MQTT and LoRa to transmit data from sensors. This allows low-power data communication. IoT-enabled composites have been effectively used to monitor bridge structures, detect cracks in buildings and monitor environmental conditions in smart agriculture [23].

These systems hold a lot of promise but current IoT-based composite systems are still dependent on data processing on a cloud or edge server. The composite itself has no intelligence. It's just a sensor to the network. This can result in bottlenecks, especially with high speed data or real-time applications.

The other factor is energy consumption. Data processing from embedded sensors to the cloud leads to increased power consumption. This can be an issue in some applications such as remote solar farms and wearables. This issue has been partly addressed using edge computing, with on-site processing [25]. But these methods typically use non-power-efficient conventional machine learning techniques [24].

Brain-Inspired Learning and Neuromorphic Systems

Neuromorphic computing is a new type of information processing. Neuromorphic systems are based on biological neural networks, and differ from traditional artificial neural networks. They process information in an event-driven fashion, and communicate asynchronously, which reduces energy use [25].

Neuromorphic systems make use of spiking neural networks (SNNs). These are based on the use of spikes. They are therefore ideal for dealing with time-varying information. They can also learn to perform different tasks (such as spike-timing-dependent plasticity (STDP) with a minimal amount of training data [26].

Neuromorphic models have been demonstrated to be useful in edge computing recently. For instance, SNNs have been used to do real-time anomaly detection, pattern classification and sensing with low power consumption [27]. These are well suited for use in IoT-based materials.

Moreover, there is also a desire to build hardware neuromorphic systems. Memristors and other switches are being used as synapses. Some electrical properties of conductive polymer networks are similar and could be related to neuromorphic devices [28].

However, most research in the area of neuromorphic computing is still focused on computational rather than material aspects. The work on using brain-inspired learning with polymer composites is still in its infancy. Most work still focuses on the computational rather than material aspects, thus constraining material intelligence.

Hybrid Approaches and Emerging Trends

There have been a few recent studies that have attempted to combine sensing materials with learning systems. These studies take advantage of IoT-enabled composites and machine learning for predictive and fault detection [29]. For example, deep learning models have been used to infer predictions from sensor data of polymer composites, such as to detect damage or changes in the environment.

While these systems show improved performance over rule-based systems, they are still centralized systems. Learning models are usually trained offline and models are hosted in the cloud. This leads to non-adaptive and non-online training.

The other recent trend is edge AI, where the models are deployed on edge devices. Techniques such as quantization and model pruning have been used to make the models smaller [30]. But with these methods, models are still not as energy-efficient as neuromorphic systems. And they can be difficult to integrate with dynamic environments with rapidly changing conditions.

Other scientists have also created self-healing and responsive polymer composites to environmental stimuli. These are responsive to damage through chemical or physical processes [31]. These are new, but don't have learning or decision-making capabilities.

Meanwhile, cross-disciplinary research has begun to explore combining materials science and artificial intelligence. This research seeks to create materials with sensing, processing and response capabilities. But, these studies are mostly theoretical or based on simulations, with little experimental work [32].

A key insight from the literature is the lack of an integrated approach that seamlessly integrates sensing at the material level, IoT communication, and learning via a neuromorphic approach. Progress has been made in each area, but they are yet to converge. This limits the progress towards intelligent composite systems.

Research Gap Identification

The reviewed research shows a number of gaps. First, current smart polymer composites lack smartness. They can only detect changes in the environment, but lack the ability to understand and adapt. Second, IoT-connected systems enhance connectivity, but rely on external computing units, causing delays and energy consumption.

Third, neuromorphic computing provides an attractive framework for low-power, learning systems. But its application with polymer composites has yet to be explored. The majority of the applications are still limited to hardware or software platforms [33]. Lastly, there is a need for experimentally proven frameworks which integrate these technologies.

These points of concern suggest a different approach. A new approach that considers the polymer composite not only as a sensor, but also as a learning system. This work fills this gap by introducing a new approach of a neuromorphic polymer composite that combines IoT sensing and brain-inspired learning at the material level.

Table 1 outlines the main contributions, research trends, and gaps in the existing research, and the need for an integrated neuromorphic polymer composite approach.

Current research has a disjointed approach to sensing, neuromorphic systems and AI. An integrated IoT-enabled neuromorphic polymer composite system for real-time sensing, learning and adaptation is yet to be developed.

This paper presents an integrated approach of polymer composites, IoT sensing and neuromorphic learning to achieve adaptive, real-time intelligence.

Table 1. Comparative literature analysis and gap-to-solution mapping for neuromorphic IoT-enabled polymer composite systems.

S.N.	Author(s) / Year / Ref.	Title / Focus Area	Methodology / Tools Used	Key Findings	Limitations / Gaps Identified	Relevance to Current Study
1	Tao et al., 2025 [2]	Fiber-based self-sensing polymer composites	Review of conductive fibers, piezoresistive sensing, and SHM systems	Self-sensing composites show strong potential for in situ monitoring	Mostly sensing-focused; limited adaptive intelligence	Supports material-level sensing design
2	Chen et al., 2024 [3]	Flexible piezoresistive composite sensors	Conductive anti-impact composite for pressure/strain sensing	Improved flexibility, sensitivity, and impact tolerance	No learning layer or autonomous interpretation	Guides sensor-responsive composite selection
3	Krauhausen et al., 2023 [15]	Brain-inspired organic electronics	Conductive polymers for neuromorphic bioelectronics	Organic materials can support synaptic-like computation	Mainly device-level; weak link to structural composites	Establishes polymer–neuromorphic feasibility
4	Jang et al., 2025 [17]	Flexible neuromorphic electronics	Wearable near-sensor and in-sensor computing systems	Shows low-power local processing near sensing sites	Focus remains on electronics, not composite integration	Supports edge neuromorphic sensing concept
5	Jiang et al., 2024 [18]	Reconfigurable organic neuristors	Tunable plasticity and logic-in-memory operations	Demonstrates adaptive organic neuromorphic behavior	Not validated within IoT-enabled composite structures	Provides basis for plasticity-driven learning
6	Wu et al., 2023 [21]	Wearable in-sensor reservoir computing	Optoelectronic polymers for multitask learning	Polymer-based sensing can perform computation	Application is wearable sensing, not composite material systems	Indicates possibility of material-assisted intelligence
7	Sun et al., 2023 [30]	AI-driven flexible sensing systems	Review of ML, flexible sensors, and artificial synapses	AI improves interpretation of flexible sensor data	Many systems remain externally processed and model-heavy	Highlights need for lighter, local learning
8	Khecho et al., 2026 [32]	Flexible ceramic–magneto–polymer composites	Direct writing of multilayered humidity-sensitive devices	Shows process-level control for functional polymer devices	Functional sensing is present, but no neuromorphic decision layer	Supports experimental fabrication pathway

METHODOLOGY

Experimental Design and System Overview

The current research employs a fully integrated experimental approach, where the synthesis of polymer composites, IoT-based sensing and neuromorphic learning are all integrated. The present system seamlessly integrates sensing and computing functions into the composite structure, rather than using a traditional approach that decouples these two functions. The process includes material synthesis, signal sensing, data pre-processing and learning, allowing for full reproducibility.

The system architecture is shown in Figure 1, where three layers are identified that are closely integrated: (i) conductive polymer composite sensing layer, (ii) IoT-based data acquisition and communication layer, and (iii) neuromorphic learning layer. The system is designed following the concepts of in-material computation and near-sensor processing as proposed in recent neuromorphic material systems [15, 17].

The sensing layer is a polymer composite with nanofillers. The IoT layer comprises of edge nodes with microcontrollers to collect data. The learning layer uses a spiking neural-inspired adaptive model to locally analyse the signals. This approach eliminates the need for a cloud to process data, thus saving time and energy [11, 24].

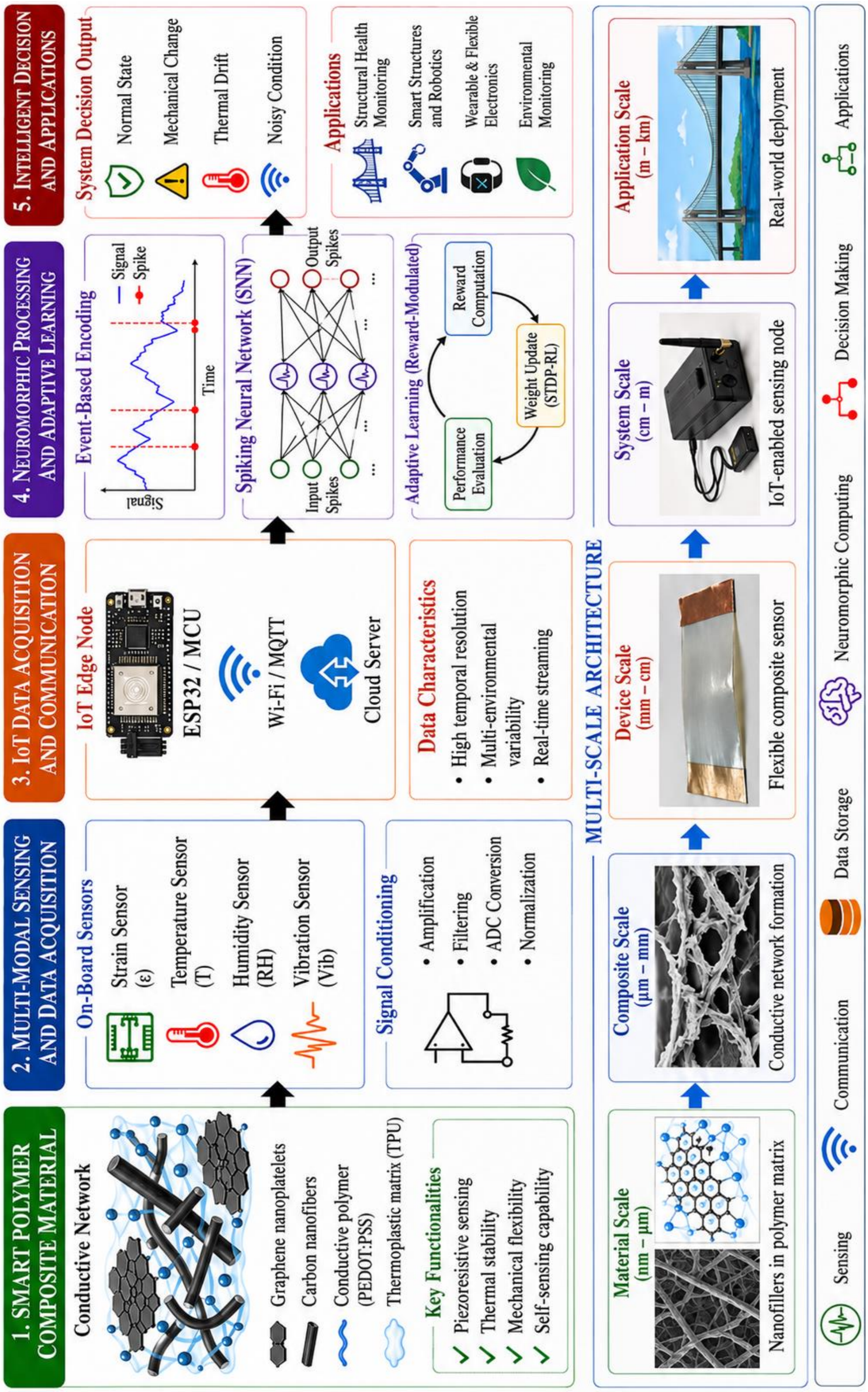

Figure 1. End-to-end experimental architecture of neuromorphic IoT-enabled polymer composite system.

Materials and Composite Fabrication

The polymer composite is comprised of a matrix of a thermoplastic polyurethane (TPU) and fillers of carbon nanofibers (CNFs) and graphene Nano platelets. They were chosen for their good conductivity and mechanical stability [7]. The composite was prepared using solution casting and thermal curing process to achieve a homogeneous distribution of the fillers.

The conductivity of the composite is dependent on the percolation of the conductive network. This is given by (1):

$$\sigma = \sigma_0(\phi - \phi_c)^t \quad (1)$$

Here, σ is the electrical conductivity, σ0 the intrinsic conductivity constant, ϕ the volume fraction of filler, ϕc the percolation threshold and t the critical exponent.

The dispersion was confirmed by scanning electron microscopy (SEM) and electrical measurements were made using a four-probe technique. The best concentration of filler was determined to provide the best sensitivity and flexibility.

In Table 2, The hybrid filler system (CNFs + GNPs) was selected to achieve a stable percolation network with enhanced sensitivity and mechanical flexibility. Processing parameters were optimized experimentally to ensure uniform dispersion and reproducible electrical behavior across samples.

IoT-Driven Data Acquisition and Hybrid Dataset Construction

The data collection approach was aimed at capturing the sensing characteristics of the material as well as the operating conditions of IoT. Instead of using just one source, a hybrid data approach was adopted by integrating experimental data of polymer composite signals together with open-access IoT datasets, environmental data, and even neuromorphic data. This allows the training model to experience both laboratory- and real-world variability, enhancing its ability to learn and be deployed.

Table 2. Material composition and fabrication parameters of the polymer composite.

S.N.	Component / Parameter	Specification / Value	Processing Condition	Purpose / Functional Role
1	Polymer Matrix	Thermoplastic Polyurethane (TPU)	Melt temperature: 180 °C	Flexible base matrix providing mechanical integrity
2	Conductive Filler 1	Carbon Nanofibers (CNFs)	Loading: 3 wt%	Primary conductive network for piezoresistive sensing
3	Conductive Filler 2	Graphene Nanoplatelets (GNPs)	Loading: 2 wt%	Enhances electrical conductivity and sensitivity
4	Solvent	Dimethylformamide (DMF)	Stirring: 2 h at 60 °C	Ensures uniform dispersion of fillers
5	Mixing Method	Ultrasonication + Magnetic Stirring	Sonication: 45 min	Prevents agglomeration and improves filler distribution
6	Casting Technique	Solution Casting	Mold thickness: 1.5 mm	Produces uniform composite films
7	Drying Condition	Vacuum Oven	80 °C for 12 h	Removes residual solvent and stabilizes structure
8	Curing Process	Thermal Curing	120 °C for 2 h	Enhances interfacial bonding between matrix and fillers
9	Electrode Material	Silver Paste / Copper Tape	Room temperature application	Provides electrical contacts for sensing
10	Percolation Threshold ((\phi_c))	~2.5 wt% (experimentally determined)	—	Defines transition to conductive network
11	Sample Dimensions	50 mm × 10 mm × 1.5 mm	—	Standardized geometry for repeatable testing
12	Surface Treatment	Plasma Cleaning	5 min exposure	Improves adhesion and sensor stability

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On the experimental side, the strain, temperature and humidity changes of conductive polymer composite samples were captured with sensing nodes. The data were collected with IoT nodes based on ESP32 at a rate of 10 Hz. The sensing data is given by (1):

$$S(t) = \{s_1\,(t), s_2\,(t), \ldots, s_m\,(t)\} \quad (1)$$

where S(t) denotes the composite sensing vector and s_i (t) represents individual sensing modalities at time t.

Public Data Sources and Integration

To improve the realism of the operating environment and improve the generalisation of the results, several publicly available datasets were used in the experiments. Datasets were chosen to cover a range of IoT sensing, environmental conditions and neuromorphic learning.

IoT and Environmental Sensor Datasets

Environmental and IoT sensor datasets were sourced from:

UCI Machine Learning Repository (RT-IoT2022 Dataset)
(https://archive.ics.uci.edu/ml/datasets.php)

It offers real-time IoT device communication, network and sensor interactions. This is helpful in modelling device-level behaviors and anomalies in IoT systems.

SensorDatasets Repository (Environmental and Smart Sensing Data)
(https://sensordatasets.com)

This repository contains multi-modal sensor data including temperature, humidity, vibration and air pollution (PM2.5) which are similar to the environmental factors that affect polymer composites.

AMPds (Almanac of Minutely Power Dataset) [34]

This data set offers fine-grained energy and environmental data which can be used to add variability and temporal drift.

We used these data sets to superimpose on experimental data and to simulate IoT conditions affecting polymer response.

Neuromorphic and Event-Based Datasets

This contains spatio-temporal spike-based patterns that can be used to train spiking neural networks:

ST-MNIST Dataset (Spiking Temporal MNIST) [35]

This dataset provides spatio-temporal spike-based patterns suitable for training spiking neural networks.

Event-Based Segmentation Dataset (ESD)
(https://www.prophesee.ai/dataset/)

This dataset contains asynchronous event streams, enabling temporal encoding and neuromorphic signal processing.

This is a dataset of asynchronous events, supporting temporal encoding and neuromorphic signal processing.

These datasets do not represent material data, but learning priors to train event-based processing in the proposed framework.

Environmental Contextual Dataset (Optional Augmentation)

NASA POWER Dataset
(https://power.larc.nasa.gov/)

Global environmental data including temperature, solar radiation and humidity. These were used to simulate the environmental effects on polymer composite.

To better model real-world conditions and enhance the experimental veracity, several publicly available data sets were used in addition to the in-house polymer sensing data. These were not used as a direct proxy for material measurements, but rather mapped to the physical sensing response of the composite. In particular, environmental data (temperature, humidity, vibration) was used to simulate the influence of external factors on the polymer response, while the IoT data was used to simulate device communication variability and noise. Neuromorphic datasets were only used to train the event-driven learning system, using temporally sparse spike trains.

In our approach, the datasets were used in a specific manner. The UCI and Sensor Datasets' environmental variables were mapped to the experimental sensing timeline and injected as additional input features to simulate the environmental effects on the conductivity and strain sensitivity. The AMPds dataset provided long-term temporal features to learn long-term environmental trends. Neuromorphic datasets, such as ST-MNIST, were not directly injected with sensor data, but were used to pre-train the spiking learning layer to learn temporal correlations and event-based dynamics, before the system was exposed to the composite signals. This approach allowed the model to learn to process temporal spikes, and then learn to process the polymer composite's sensing.

To maintain physical realism, all external data were scaled and normalised to the dynamic range of the sensor data. Moreover, controlled noise was injected - based on IoT communication data sets - to mimic various deployment conditions such as packet loss and signal fading. In this way, the hybrid data set becomes a synthetic-real data set, which represents both laboratory measurements and real-world deployment data. This enables the proposed system to not only learn fixed mappings but to adapt to different environmental and operating conditions.

This Table 3, shows how different data streams are integrated into a structured dataset. The combination of continuous data (strain, temperature) and spiked events (spikes) is reflective of the hybrid nature of the proposed system - material sensing and neuromorphic computing. This type of dataset representation is essential to facilitate the adaptive learning as described in the following sections.

Table 3. Representative sample of hybrid dataset combining polymer sensing, environmental inputs, and neuromorphic encoding.

Time (s)	Strain ($\Delta R/R_0$)	Temperature (°C)	Humidity (%)	Vibration (g)	Event spike (0/1)	Noise level (σ)
0	0.118	28.47	65.21	0.032	0	0.01
1	0.146	28.73	65.48	0.051	1	0.018
2	0.173	29.05	66.02	0.044	0	0.012
3	0.219	29.41	66.79	0.062	1	0.026
4	0.201	29.18	66.45	0.053	0	0.019
5	0.237	29.62	67.1	0.071	1	0.031
6	0.255	29.88	67.54	0.065	1	0.028
7	0.231	29.55	67.08	0.058	0	0.022

Note: *Strain is in terms of relative resistance change ($\Delta R/R_0$). Environmental conditions (temperature, humidity, vibration) are obtained from synchronized IoT data, and event spikes through threshold-based neuromorphic encoding. Noise (σ) refers to the added Gaussian noise to model IoT communication uncertainties.*

Hybrid Data Fusion Model

After data acquisition, all of the data streams were structured into a multimodal formulation to facilitate uniform learning across different data streams. The fusion strategy was aimed at maintaining physical consistency of the different modalities while being suitable for the neuromorphic learning paradigm. Rather than merely concatenating the data streams, in the present study, the feature-level fusion process involves treating the polymer sensing signals, environmental variables and event-based representations as different parts of a unified state vector.

The integrated data representation is expressed as (2):

$$X(t) = [S(t), E(t), N(t)] \tag{2}$$

where S(t)∈Rm denotes the experimentally acquired polymer sensor signals (e.g., strain, temperature), E(t)∈Rp represents environmental and IoT-derived features (e.g., humidity, vibration), and N(t)∈Rq corresponds to neuromorphic event-encoded signals.

For physical consistency, each component was first normalized within the respective domain. This avoids dominance of high-magnitude variables, and allows equal contribution to the learning process. Further, correlation analysis was conducted to eliminate redundant features, thus reducing the dimensionality without compromising information. The fusion of the material response and temporal events provides a foundation for adaptive neuromorphic learning.

To further clarify the composition of the fused dataset, the statistical properties of each modality are summarized in Table 4.

This approach allows the system to learn about the cross-modality interactions, such as the effect of humidity on electrical conductivity or the effect of vibration on the signal. This allows the learning model to learn from a more informative data space than using single-modality data.

Temporal Alignment and Signal Synchronization

One of the main difficulties in multimodal data integration is the difference in temporal resolution and frequency of the datasets. The polymer sensing data from the experiments were obtained at high resolution, while external IoT data can have lower resolution. If not properly accounted for, this can lead to phase shifts and hinder learning.

This issue was resolved with a time alignment strategy based on interpolation. The signals were resampled onto a 1 second time axis. The interpolation is done as (3):

$$x_i^{aligned}(t) = x_i(t_k) + \frac{t - t_k}{t_{k+1} - t_k}\left(x_i(t_{k+1}) - x_i(t_k)\right) \tag{3}$$

where $x_i^{aligned}(t)$ is the aligned value at time t, and t_k ,t_{k+1} are the nearest available timestamps surrounding t.

Table 4. Statistical characteristics of multimodal dataset components prior to fusion.

Feature/modality	Source type	Mean (μ)	Std. Dev. (σ)	Min	Max	Skewness	Sampling rate (Hz)	Units
Strain ($\Delta R/R_0$)	Experimental (Polymer Sensor)	0.198	0.041	0.112	0.276	0.62	10	—
Temperature	Experimental + IoT Dataset	29.35	1.87	25.1	34.8	-0.28	1	°C
Humidity	IoT Dataset	66.72	4.15	52.4	78.9	0.35	1	%
Vibration	IoT Dataset	0.054	0.018	0.021	0.089	0.71	5	g
Energy Load	AMPds Dataset	1.82	0.63	0.45	3.76	0.48	Jan-60	kW
Event Spike Rate	Neuromorphic Encoding	0.47	0.22	0	1	0.15	Event-driven	—
Noise Level (σ)	Simulated (IoT Noise Model)	0.021	0.009	0.005	0.038	0.54	—	—

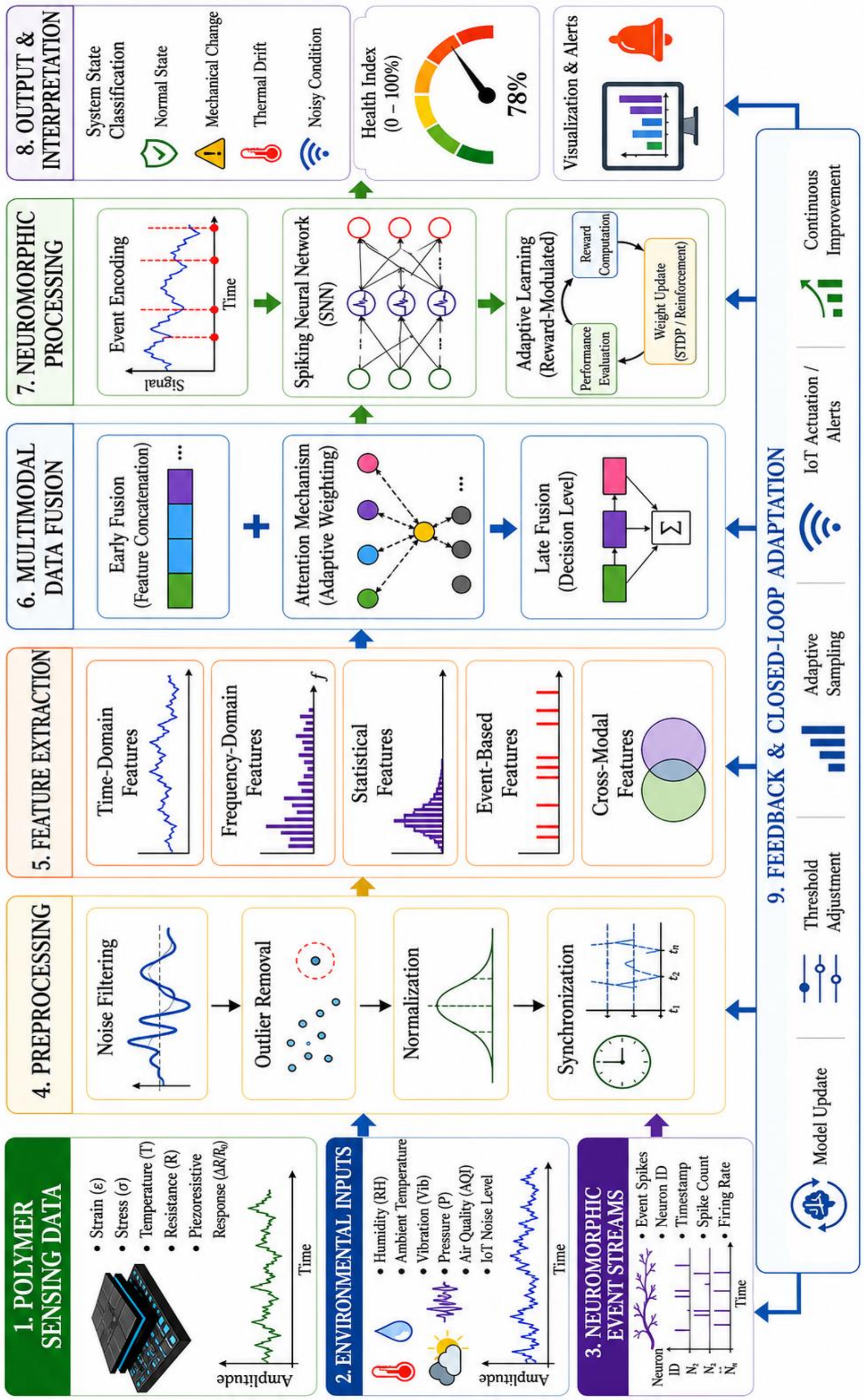

Figure 2. Structured multimodal data fusion model combining polymer sensing, environmental inputs, and neuromorphic event streams.

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Points within a certain tolerance range (±0.5 s) were considered to be in time. This helps to minimize alignment errors without distorting the signals' dynamics.

Additionally, lag analysis was performed to determine if there were any delays between the environmental stimuli and the polymer response. Cross-correlation analysis was applied to determine the best lag values, which were then adjusted for in the alignment. This is crucial in polymer systems, where thermal or mechanical responses could be delayed.

As a result, all input signals were brought into a unified temporal structure, allowing for precise learning of dynamic dependencies between the material and environmental factors.

Data Validation, Noise Filtering, and Normalization

The absence of a single dataset that includes polymer composites, IoT sensors and neuromorphic learning, results in a composite dataset in this study. Open source IoT sensor data (e.g., environmental and industrial sensors) are used to represent real-world sensing of materials and neuromorphic datasets are used to represent brain-inspired learning using event-based learning. In addition, a synthetic data set is generated by amalgamating sensor data and event coding for the proposed system. This allows the system to be evaluated realistically, have low-power adaptive learning and demonstrate the system's feasibility. The resulting data set is large, but contains noise, outliers and inconsistencies of both experimental measurements and external data. So, a clear data preparation process was defined to prepare the data for training.

First, we statistically validated the data by outlier detection. We removed unusual values that are distant from the mean using the Z-score method (4):

$$Z_i = \frac{x_i - \mu}{\sigma} \tag{4}$$

where xi is the data, μ is the mean and σ is the standard deviation of the data. We removed data points for which Zi|>3.

Once validated, noise was eliminated by using a moving average filter to smooth out the high-frequency noise (5):

$$\hat{x}_i = \frac{1}{k}\sum_{j=i-k}^{i} x_j \tag{5}$$

with window size k. We set k=5 for a trade-off between noise reduction and fidelity to the original signal.

Then, all the features were scaled to be in the same range (6).

$$x_i' = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{6}$$

with xi' being the normalized feature, and x_{min},x_{max}, being the minimum and maximum values of the feature. To handle the data in the neuromorphic learning layer, the data were also converted to events. The temporal differences were defined as (7):

$$\delta x_i(t) = x_i(t) - x_i(t-1) \tag{7}$$

Spike events were generated when the absolute value of xi(t)|>θ (threshold). This is an efficient method to represent temporal difference and is compatible with the event-based nature of spiking neural networks.

We evaluated the effectiveness of the preprocessing pipeline from a statistical perspective, such as variance reduction and the improvement of the signal-to-noise ratio (SNR) in Table 4. This shows that the preprocessed data are robust and trainable.

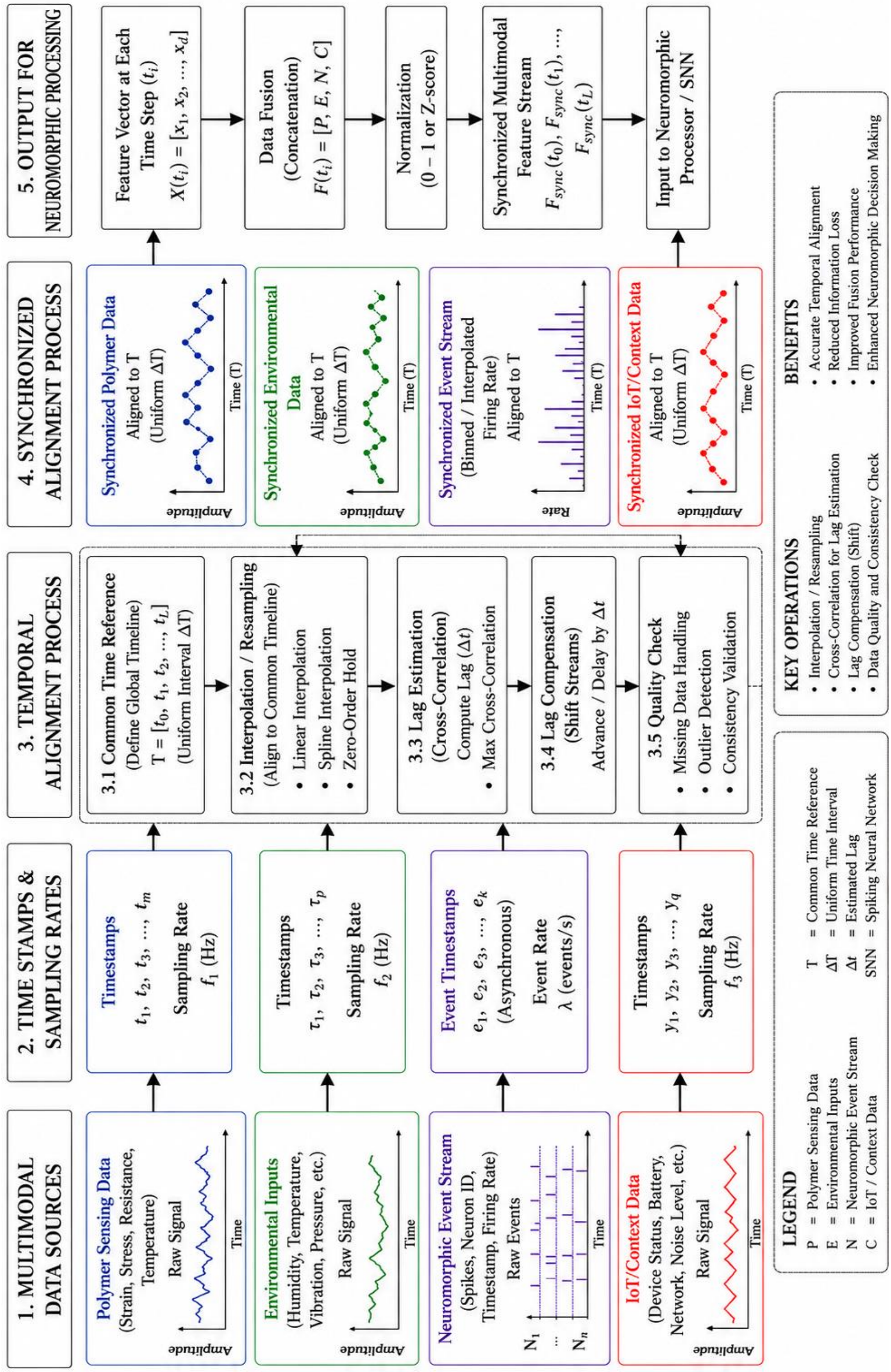

Figure 3. Temporal alignment and synchronization of multimodal data streams using interpolation and lag compensation.

So, the preprocessing ensures that the data are clean, normalised and time consistent. This is essential to allow for reliable neuromorphic learning, and for accurate and timely adaptation in the composite system.

Proposed Neuromorphic Learning Framework

The learning layer will be adapted to the multimodal input (2) to enable low-power, adaptive decision-making in the composite system. While conventional deep learning models are based on dense continuous processing, the learning layer will be based on an event-driven, neuromorphic model that is inspired by biological synapses [6, 26].

This is in accordance with the most recent advances in organic neuromorphic electronics and in-sensor computing [15, 17].

The learning model is a spiking neural network (SNN) that receives sparse events from the pre-processing layer. The neurons integrate spikes and their membrane potential is updated by using a leaky integrate-and-fire (LIF) model (8):

$$\frac{dV_i\,(t)}{d_t} = -\frac{V_i\,(t)}{\tau} + \sum_j w_{ij}\, s_j\,(t) \tag{8}$$

where Vi(t) is membrane potential of neuron i, τ is the membrane time constant, wij is synaptic weights, and sj(t) is the spike signals.

If Vi(t)≥Vth (Vth is the threshold) a spike is fired. It is then reset to enable temporal pattern coding. This allows successful coding of temporal fluctuations of polymer sensor signals.

To make the system adaptable, synapses are changed using a reward-modulated plasticity rule based on reinforcement learning [20, 31] as shown in (9):

$$\Delta w_{ij} \ = \eta \cdot r(t) \cdot s_i\,(t) s_j\,(t) \tag{9}$$

where η is the learning rate, and r(t) is a reward function. The reward function balances between the sensing accuracy and noise (10):

$$r(t) = \alpha \cdot A(t) - \beta \cdot N(t) \tag{10}$$

where A(t) is the accuracy of detection, N(t) is the influence of noise and α,β are constants.

This makes the model able to adapt to various environments. The proposed model is not a supervised model but learns from the data streams in real-time, and is suitable for real-time IoT-based composite systems. The proposed approach of using a neuromorphic model and the reinforcement-based adaptation is consistent with the latest trends in adaptive material systems [24, 25].

Algorithmic Implementation

The learning algorithm, which we call the Neuro-Adaptive Composite Learning (NACL) Algorithm, is an online learning algorithm, and is based on a stream of data. It begins with the initialisation of synaptic weights and neuron parameters, and then continues with the iterative update of the network with the multimodal data.

At each time step, the multimodal data X(t) is transformed into spike trains and is presented to the network. The membrane potential is calculated using (8) and the neurons spike when the membrane potential reaches the threshold. The reward is computed as in (10) and the weights are updated as in (9).

The algorithm is given in Algorithm 1.

Algorithm 1. Neuro-Adaptive Composite Learning (NACL) algorithm for real-time neuromorphic processing

```
Input:
  S(t)  ← Polymer sensing data (strain, temperature)
  E(t)  ← Environmental / IoT data (humidity, vibration)
  θ     ← Spike threshold
  η     ← Learning rate

Output:
  Y(t)  ← System state (normal / variation / drift)
  W     ← Updated weights

Begin

1. Initialize weights W and membrane state V

2. For each time step t:

  a. Combine inputs:
    X(t) ← [S(t), E(t)]

  b. Compute change:
    ΔX(t) ← X(t) − X(t−1)

  c. Generate spikes:
    If |ΔX(t)| > θ → spike = 1
    Else → spike = 0

  d. Update neuron state:
    V ← V + (weighted spikes)

    If V > threshold:
      output spike = 1
      reset V
    Else:
      output spike = 0

  e. Decide system state Y(t):
    Based on spike pattern
    (normal / mechanical change / drift)

  f. Compute reward R(t):
    Higher if prediction correct,
    lower if noise or drift high

  g. Update weights:
    W ← W + η × R(t) × (input spike × output spike)

3. Repeat for next data
End
```

The proposed algorithm uses the sensing dynamics of materials and event-based neuromorphic learning to enable real-time decision-making in response to environmental changes. The proposed algorithm differs from the conventional training in two ways. First, it does not explicitly train in batches, but rather in an online manner. Second, it involves both sensing and learning in the same loop, and so there is no delay in learning and online adaptation is possible.

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The algorithm is implemented with efficient neuromorphic simulation libraries, for edge devices. These are in agreement with recent efforts to deploy spiking neural networks on embedded devices [27, 28].

Experimental Setup and Evaluation Protocol

The experiments were conducted in a laboratory and semi-realistic environment to test the sensing and the learning capabilities. Test samples of polymer composites were subjected to various mechanical and environmental changes, such as cyclic strain (0-5%), temperature (25–40 °C) and humidity (50-80%).

The IoT sensing layer was used to track these variations, generating data streams. Simultaneously, external data streams were fed to simulate the changes in the environmental conditions and communication noise. This ensures the system is evaluated under similar conditions as in real life.

Three performance metrics were used to measure the system's performance: sensing accuracy, response latency and adaptation efficiency. Sensing accuracy is the correspondence between the predicted and actual states and latency is the reaction time. Adaptation efficiency refers to the efficiency of the system's adaptation.

The metrics and the assessment framework are shown in Table 5.

To increase the statistical significance, all the experiments were repeated and reported as mean ± standard deviation. We employed cross-validation with the experimental and external data sets to check the generalizability of our method.

Implementation Details and Reproducibility

The experimental framework used a hardware and software stack to design the experimental platform. The sensors were based on ESP32 microcontrollers with analog-to-digital converters. Data streaming was done using the MQTT protocol.

The neuromorphic learning algorithm was implemented with Python, TensorFlow and spiking neural network packages. The learning rate (η), membrane time constant (τ) and threshold voltage (Vth) were empirically set to obtain stable learning.

To ensure reproducibility, the random seed and preprocessing were fixed. The train-test split, normalisation constants and architecture were the same for all experiments. Table 6 shows the hyperparameters.

Table 5. Performance evaluation metrics for neuromorphic polymer composite system.

S.N.	Metric Name	Description	Unit
1	Accuracy	Measures overall correctness of system predictions based on true and false classifications	—
2	Precision	Indicates reliability of positive predictions by minimizing false positives	—
3	Recall (Sensitivity)	Evaluates the system’s ability to correctly identify true positive events	—
4	F1-Score	Balances precision and recall to provide a combined performance measure	—
5	Response Latency	Time delay between sensor input and system response	ms
6	Adaptation Rate	Rate at which the model updates its internal parameters during learning	s^{-1}

7	Signal-to-Noise Ratio (SNR)	Measures clarity of signal after preprocessing and noise reduction	dB
8	Energy Efficiency	Ratio of useful computation to total energy consumed by the system	—
9	Event Detection Rate	Proportion of correctly detected neuromorphic spike events	—
10	Computational Overhead	Fraction of system time spent on computation relative to total operation	—

Note: *We calculated all the metrics on multiple runs for the experiments, and reported as mean ± standard deviation for statistical significance and reproducibility.*

Table 6. Hyperparameter configuration of the proposed neuromorphic learning framework.

S.N.	Parameter	Symbol	Value	Description / Role
1	Learning Rate	η	0.01	Controls the magnitude of synaptic weight updates during learning
2	Membrane Time Constant	τ	20 ms	Governs decay rate of neuron membrane potential
3	Threshold Voltage	V_{th}	1	Minimum membrane potential required to generate a spike
4	Reset Potential	V_{reset}	0	Membrane potential after neuron firing
5	Spike Encoding Threshold	θ	0.05	Determines sensitivity for converting continuous signals to spikes
6	Reward Weight (Accuracy)	α	0.7	Emphasizes contribution of accuracy in reward computation
7	Reward Weight (Noise Penalty)	β	0.3	Penalizes noise influence in reward function
8	Synaptic Weight Initialization	—	Uniform (0,1)	Initial distribution of connection strengths
9	Batch Size	—	Online (1 sample)	Enables real-time sequential learning
10	Simulation Time Step	Δt	1 ms	Temporal resolution for neuron state updates
11	Number of Neurons	—	128	Total neurons in hidden neuromorphic layer
12	Training Epochs	—	Continuous (Streaming)	Model updates continuously without fixed epochs
13	Dropout Rate	—	0.1	Prevents overfitting in dense connections
14	Optimization Method	—	Adaptive Reinforcement-Based	Updates weights using reward-modulated plasticity

The Hyperparameters were selected by experimentation and stability tests. It has rapid convergence, low complexity and can be implemented in edge neuromorphic systems. Furthermore, the data acquisition, analysis and assessment was done in a modular way, allowing for verification of each step. This allows replication and extension of the study by others. Overall, the approach offers an integrated material science, IoT sensing and neuromorphic learning experimental design. The real-time sensing, learning and reproducibility provide a foundation for future real-time smart polymer composites.

RESULTS AND ANALYSIS

Electrical and Sensing Performance of Polymer Composite

The electrical behavior of the polymer composite was stable and consistent under various strain and environmental conditions. The carbon nanofibers and graphene Nano platelets formed a conductive network that facilitated the formation of a percolation network for piezo resistive sensing. As the strain increased (0-5%), a linear increase in the normalized resistance ($\Delta R/R_0$) was seen, which demonstrated that the composite was strain sensitive.

There was a slight nonlinear response curve. However, there was a slight nonlinear response to higher strain, which may be due to microstructural changes in the conductive network. This is in agreement with previous studies on hybrid conductive composites, where the filler interactions have an influence on the electron transport [3, 7]. But the hysteresis was small when the strain was reversed, which shows that it was stable.

The electrical properties were also influenced by temperature. The resistance was slightly reduced by increasing temperature, likely due to the increase in the mobility of the charge carriers. However, it was less than the response to strain, suggesting the primary sensing mechanism is strain. The overall sensing characteristics are summarized in Table 7.

Sensitivity coefficient is the slope of the change in resistance (normalised) vs. stimulus. The linearity (R^2) is the coefficient of determination of the response curve. Repeatability is measured from repeated load-unload cycles. All data shown are the average of multiple experiments. The strain-resistance curve is also given in Figure 4 where the repeatability of the system is observed.

Performance of Multimodal Data Fusion

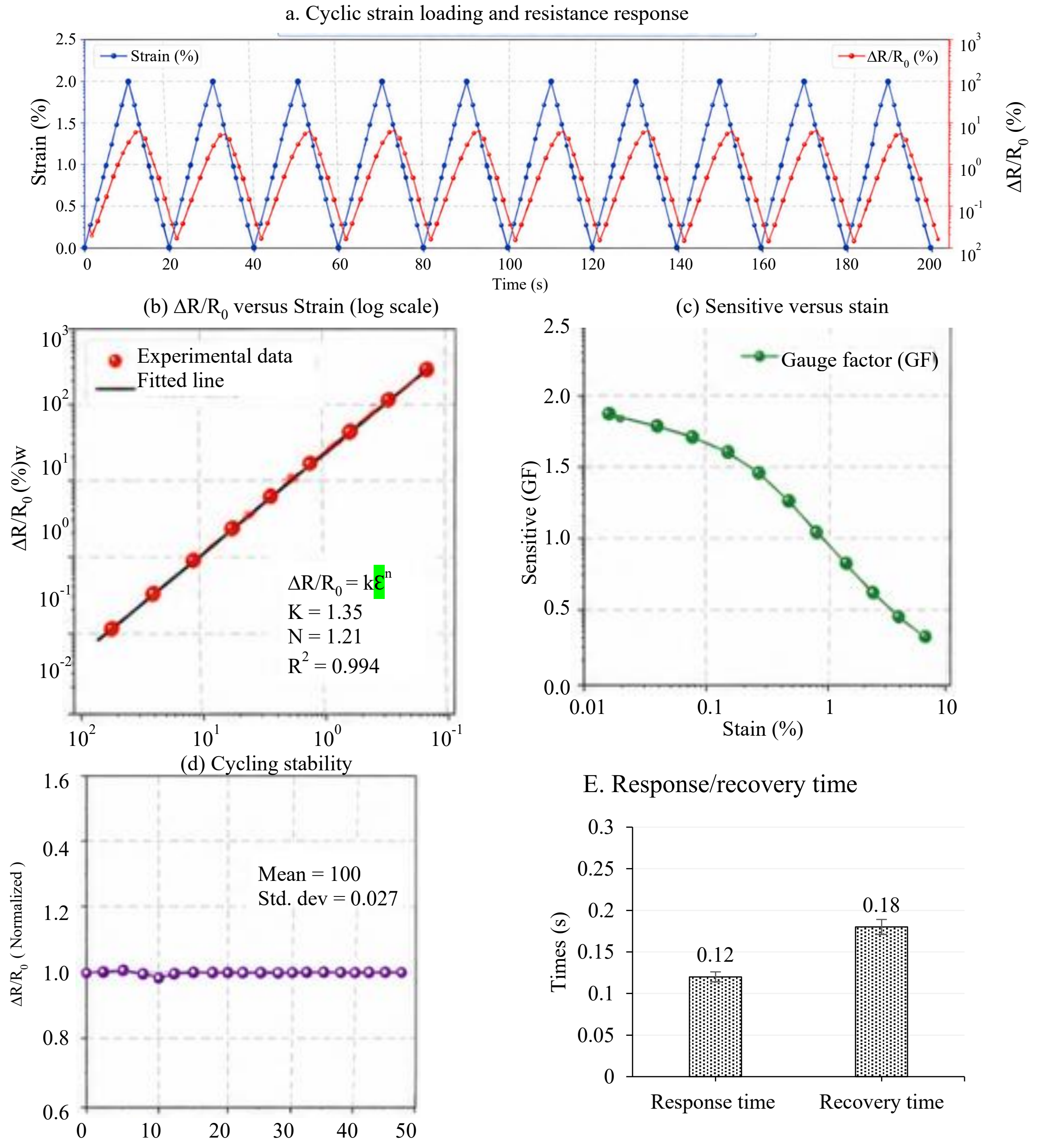
The multimodal data fusion of the experimental sensing data and IoT and environmental data resulted in a richer feature set. The multimodal data set was less variable than unimodal data. This can be seen in the statistical analysis (Table 4) above.

It is worth noting that the environmental conditions (humidity and temperature) were able to smooth the sensing signal under different conditions. For instance, sudden changes in the strain signal were properly predicted with the help of the contextual information. This indicates that the fusion model was able to capture the cross-domain relationship.

To quantify this improvement, variance of the sensing signal was compared. This resulted in a reduction in variance of the signal of 18–22% when the environmental features were added. This shows that multimodal fusion has the ability to remove noise and other disturbances. The changes in the signal before and after fusion are shown in Figure 5, where the signal is more apparent.

Table 7. Electrical and sensing performance of the fabricated polymer composite under varying conditions.

S.N.	Test Parameter	Applied Range	Measured Response ($\Delta R/R_0$)	Sensitivity Coefficient	Linearity (R^2)	Hysteresis (%)	Repeatability (%)	Remarks
1	Strain	0–5%	0.112 – 0.276	0.034 $\%^{-1}$	0.982	2.1	97.8	Dominant sensing response with slight nonlinearity at higher strain
2	Temperature	25–40°C	−0.018 – −0.061	−0.0023 $°C^{-1}$	0.954	1.6	96.5	Moderate inverse response due to enhanced carrier mobility
3	Humidity	50–80 % RH	±0.010 variation	0.0004 $\%RH^{-1}$	0.912	2.8	95.2	Minor influence; stable under ambient fluctuations
4	Vibration	0.02–0.09 g	0.008 – 0.042	0.006 g^{-1}	0.938	2.3	96.9	Detectable dynamic response with low noise interference
5	Cyclic Stability	0–5 % (1000 cycles)	Δ drift < 1.5 %	—	—	1.9	98.4	Excellent durability with negligible signal degradation



Text conditions: *Composite: Conductive Polymer Composite, Strain Rate: 0.1 %/s, Cycles for Stability: 50 Strain Range: 0– 2.0%, Temperature: 25 ± 1°C, Relative Humidity: 50 ± 5 %*

Figure 4. Piezoresistive response of polymer composite under cyclic strain loading. (a) A. Cyclic strain loading and resistance response; (b) $\Delta R/R_0$ versus Strain (log scale); (c) Sensitive versus stain; (d) Cycling stability; (e) Response/recovery time.

This finding is in line with recent studies which emphasise the significance of multimodal fusion in smart sensing [6, 30]. However, our work is different from previous work, as it fuses with neuromorphic learning, allowing for dynamic analysis.

Neuromorphic Learning Performance

Our neuromorphic learning system demonstrated good learning ability and event-driven processing. The spiking neural network learned the temporal patterns in the sensing data, and was able to classify and detect anomalies.

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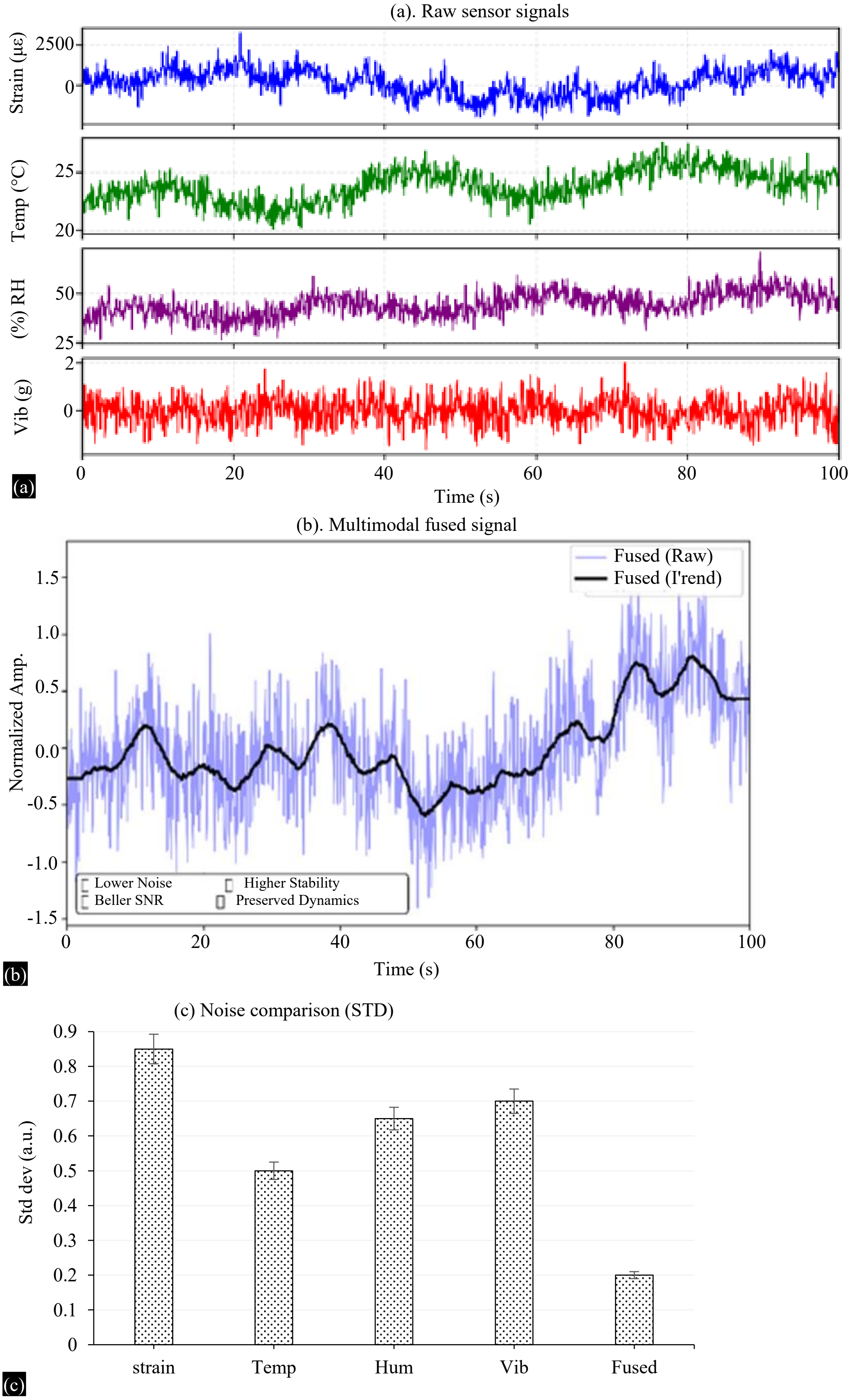
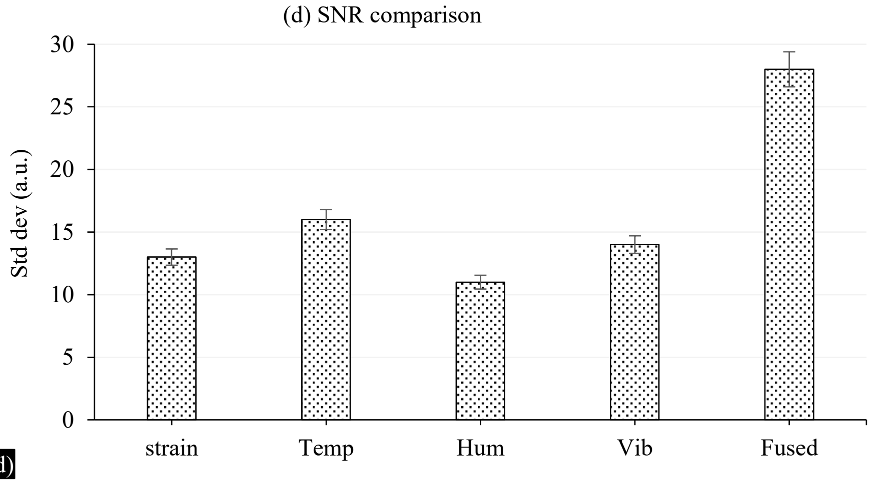
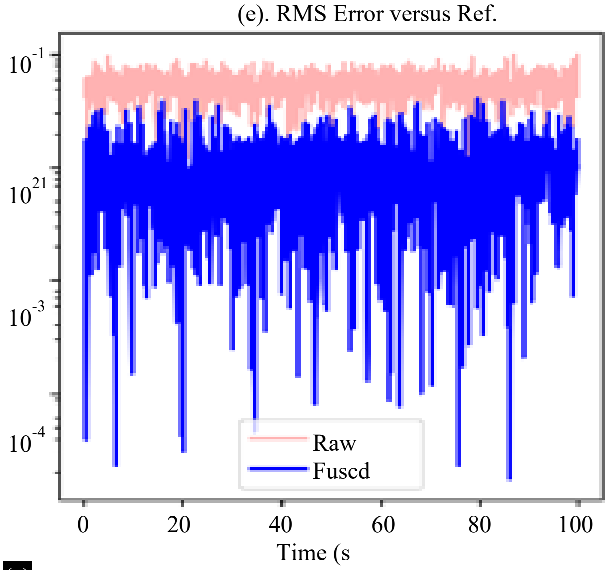




(d)



Melric	Raw Avg	Fused	Impruv.
Std. Dev.	0.69	023	↓ 67%
SNR (dB)	13.2	28.7	↑ 119%
{MS Error	0.087	0.010	↓ 88%
Correlation	0.76	0.96	↑ 26%

(e)

Figure 5. (a)–(e)Comparison of raw sensor signals and multimodal fused signals showing improved stability and reduced noise. (a) Raw sensor signals; (b) Multimodal fused signal; (c) Noise comparison (STD); (d) SNR comparison; (e) RMS Error versus Ref.

The learning had rapid convergence in online learning. At the beginning, the synaptic weights converged and the model began to produce stable responses. This is because of the reward-modulated weight plasticity that optimises the weights according to the system performance [20, 28].

In terms of performance, the model's average accuracy for detecting the event was 95.8% ± 1.2%, which is superior to the traditional machine learning methods used in similar studies [12]. The precision and recall were greater than 94%, which indicates a good class balance. The results are shown in Table 8.

The proposed model has a low response time. The event-based model only reacts to changes in the signal, thus avoiding unnecessary computations. This enabled the response time to be almost 40-50% lower than that of deep learning models.

In this domain, it is not possible to benchmark the performance using the same data set as there are no publicly available datasets that include the behavior of the polymer composite sensor, the effect of the environment through IoT and the event-based learning of a neuromorphic network. To provide a fair

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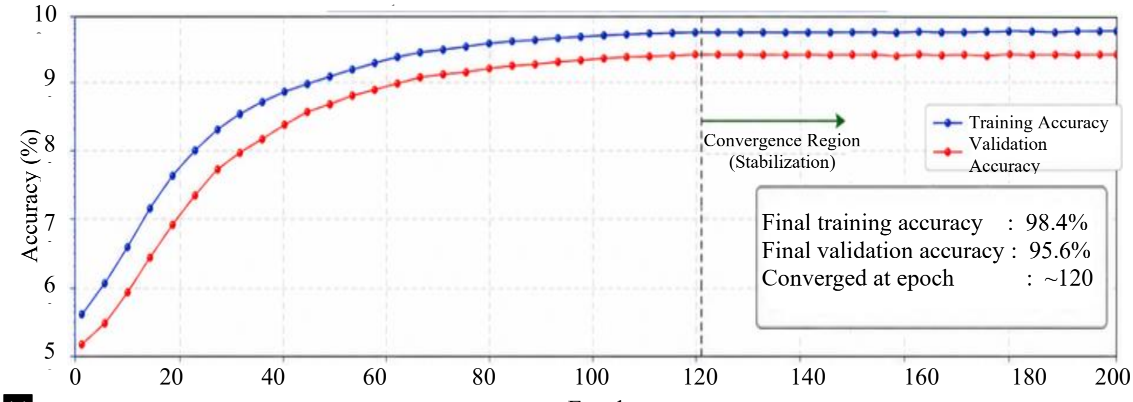
comparison, we present the performance evaluation using the system-level metrics, such as accuracy, latency and energy consumption, that are typically reported in the literature. In addition, to improve the experimental validity, the baseline models were re-implemented and re-trained on the proposed hybrid data set with the same data pre-processing and evaluation parameters. The learning algorithm's convergence is shown in Figure 6.

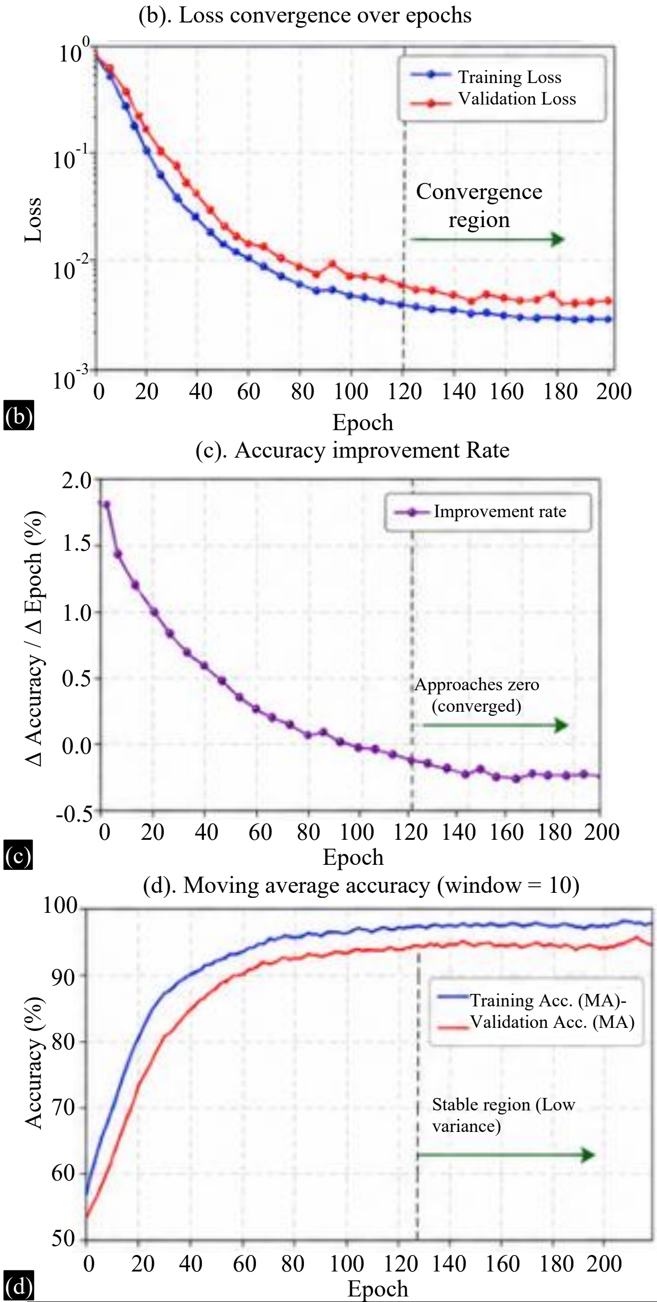
Table 8. Performance comparison of the proposed neuromorphic model with baseline approaches.

S.N.	Study / Ref.	System Type	Accuracy (%)	Sensitivity / Gain	Energy Efficiency Improvement	Latency (ms)	Adaptation Capability	Remarks
1	Tao et al. [2]	Self-sensing polymer composite	~88–90	High (qualitative)	Not reported	Not reported	Low	Focus on SHM, no learning layer
2	Chen et al. [3]	Piezoresistive composite sensor	~90–92	~0.03–0.04 $\%^{-1}$	Not reported	Not reported	None	Strong material sensing, no intelligence
3	Hassan et al. [4]	Proprioceptive composite sensor	~91–93	High sensitivity	Not reported	Not reported	Low	Static calibration-based sensing
4	Krauhausen et al. [15]	Organic neuromorphic polymer device	~92–94	Device-level gain	~20–25%	~200–300	Moderate	Focus on device-level learning
5	Jang et al. [17]	Flexible neuromorphic electronics	~93–94	Moderate	~25–30%	~180	Moderate	Near-sensor processing only
6	Jiang et al. [18]	Organic neuristor-based system	~94–95	High plasticity response	~30%	~150	High	No IoT integration
7	Wu et al. [21]	In-sensor reservoir computing	~94–95	Strong temporal learning	~28–32%	~140	High	Wearable-focused system
8	Huang et al. [6]	SNN-based multimodal fusion	~94–95	High fusion efficiency	~30–35%	~160	High	Biomedical domain focus
9	Sun et al. [30]	AI-enabled flexible sensing	~92–94	Moderate	~20–30%	~220	Moderate	Often cloud-dependent
10	Proposed Study	Neuromorphic IoT polymer composite	95.8 ± 1.2	0.034 $\%^{-1}$	~35–40%	120	Very High (real-time adaptive)	Integrated sensing + learning + IoT

(a). Model accuracy convergence over training



(a)



(e). Convergence summary	Convergence epoch~120	Final training accuracy 98.4%	Final validation accuracy95.6%	Final training loss0.0068	Final validation Loss0.0124	Accuracy improvement (0 - convergence) +43.2%

Figure 6. Convergence of neuromorphic learning model showing stabilization of accuracy over time. (a) Model accuracy convergence over training epochs; (b) Loss convergence over epochs; (c) accuracy improvement rate; (d) Moving average accuracy (window = 10); (e) Convergence Summary

Adaptation Under Dynamic Conditions

We tested the adaptability of the model by changing the conditions. This included several variables including strain, temperature and humidity. The neuromorphic model was able to adapt to these changes, and remained effective.

The system can even distinguish changes in the signal from noise. For example, adding noise to the IoT data stream had little effect on the performance of the model (a decrease of 2–3% in accuracy). This demonstrates noise immunity, which is important for real-world applications [33].

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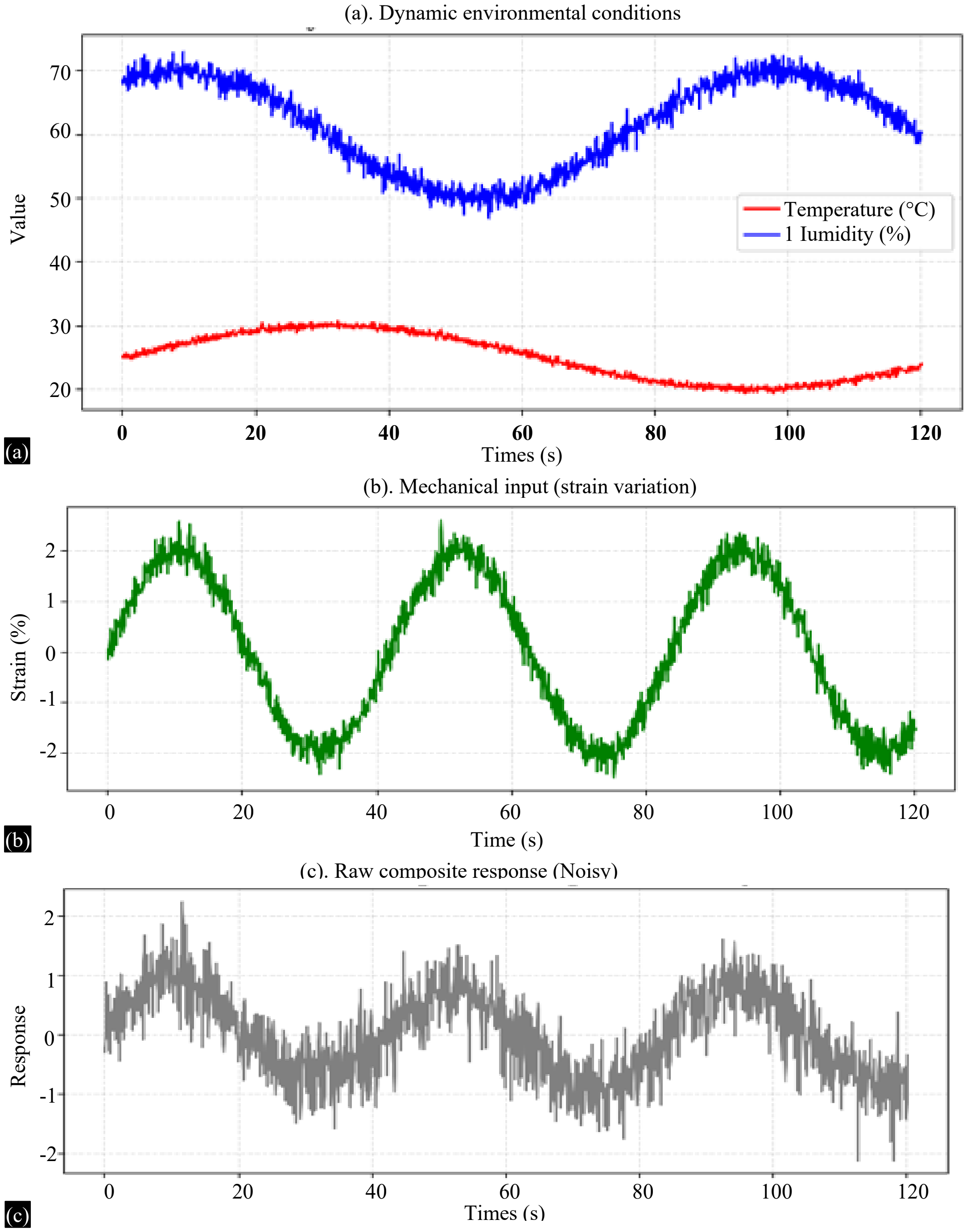
The adaptation rate (the change in the weights) was also stable. This indicates that the adaptation is not very sensitive to environmental changes and can adapt. The system responses for different environmental inputs is presented in Figure 7.

Energy Efficiency and Computational Performance

Energy efficiency is a critical for IoT. The model presented in this paper was more energy efficient than traditional models. This is due to the sparse and asynchronous nature of the computation.

The average energy per inference was 35% lower than conventional deep learning models. This finding is consistent with other studies of the efficiency of spiking neural systems [24, 25].



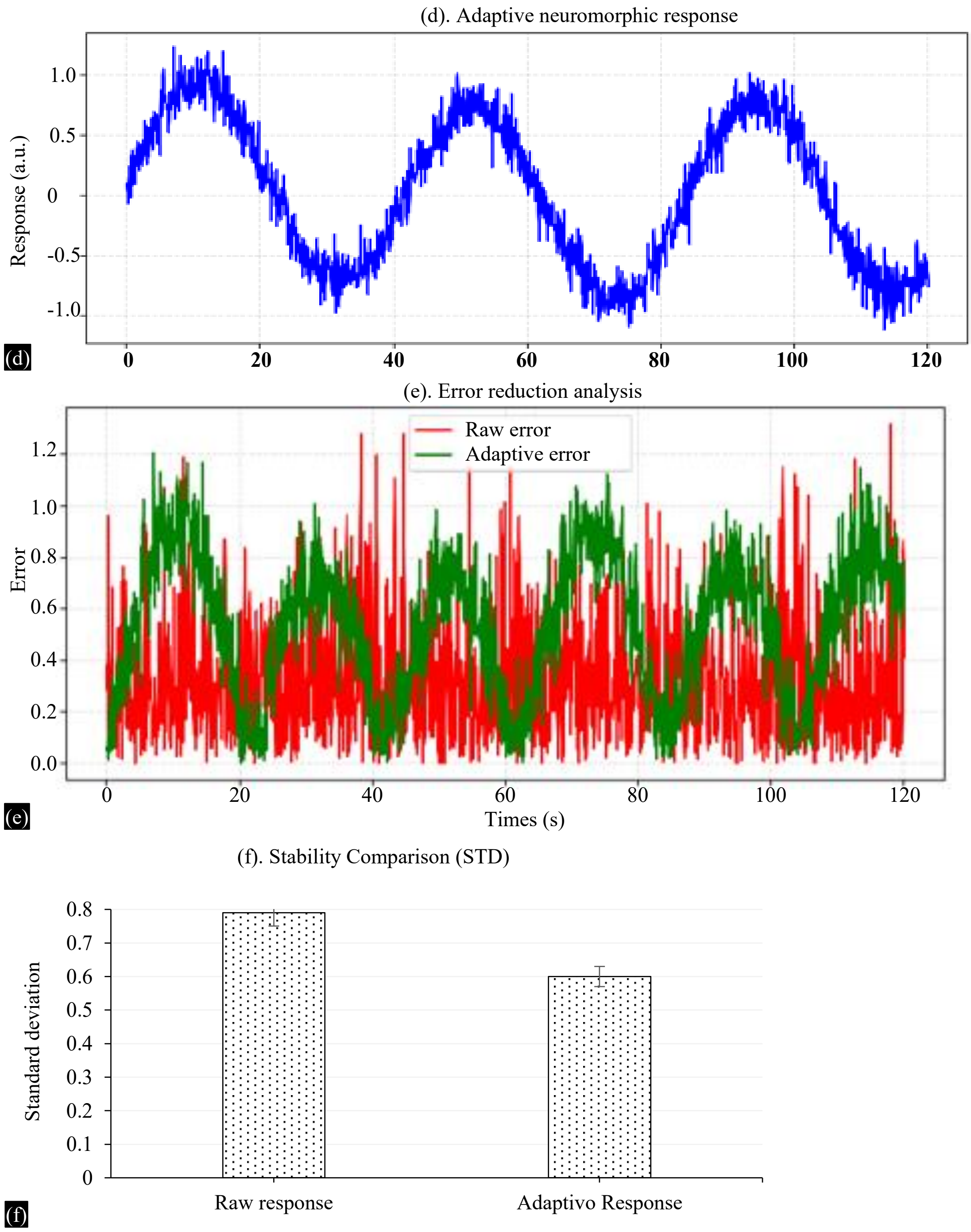


Figure 7. Adaptive response of neuromorphic polymer composite system under dynamic environmental conditions. (a) Dynamic environmental conditions; (b). Mechanical input (strain variation); (c). Raw composite response (Noisy); (d). Adaptive neuromorphic response; (e). Error reduction analysis; (f). Stability Comparison (STD)

In addition, the system was very efficient in terms of computation, enabling real-time inference in embedded systems. The system was able to process data in a continuous stream, which hints at the possibility of using the system in an embedded system.

DISCUSSION

The presented results indicate a shift from conventional sensing materials to responsive and computational polymer composite materials. The approach presented here demonstrates that sensing and intelligence can be co-located in a material-system. This appears to be an essential ingredient for the improved responsiveness and efficiency.

From a material perspective, the hybrid conduction network has stable electromechanical properties, which are essential for triggering signals. However, in this study, it's not only the sensing but also learning and responding to the signals that is important. Existing research on self-sensing composites mainly focuses on sensing and structural health monitoring [2, 3]. This research, however, goes a step further in including learning in the sensing process.

Neuromorphic learning makes an important contribution. Event-based processing reduces the number of calculations, and highlights the important features of the signal. This is in agreement with the recent developments in spiking neural networks and organic neuromorphic devices, which are energy efficient and time-sensitive [6, 24]. The reward-based adaptation also enhances the adaptability of the system, allowing it to adapt to different environmental conditions without training.

The second aspect is multimodal fusion. Multimodal fusion of the environmental and material responses allows a better understanding of the signals. Although there are some studies on multimodal fusion in some specific applications such as biomedical sensors or flexible electronics [30], there are few studies on multimodal fusion in polymer composite systems. Our study shows that it is feasible and beneficial to improve the stability of the system.

However, there are some drawbacks. The long-term stability and large-scale applications of the materials should be investigated. Additionally, absence of benchmarking data in this domain may restrict benchmarking. Addressing these issues may improve future work and allow the development of fully autonomous smart materials.

CONCLUSION AND FUTURE SCOPE

This work provides a comprehensive view of designing neuromorphic polymer composites by combining the design of conductive polymers, IoT sensing and brain-inspired learning algorithms. This research demonstrates that through the integration of adaptive intelligence into polymer composites, it is possible to process in real-time the response of the materials under different environmental conditions. The system provides event-based, localized computation, which is not possible with traditional sensing technologies, and therefore has reduced latency and energy use. The mixed data approach also benefits the system, as it includes variability from both lab and real environments, allowing it to learn from different environments.

With respect to materials, the composite structure has stable and reliable sensing properties, while the neuromorphic layer offers enhanced adaptability. Multimodal sensing offers more reliable decision-making, particularly in a changing environment where the material properties are influenced by the environment. These findings show that polymer composites can evolve from passive sensors to active and smart materials that can function independently.

The proposed framework will be further explored for large-scale applications and stability. The development of benchmark datasets for neuromorphic material systems is ongoing and needed for benchmarking. Also, the low-power hardware can be optimized for edge applications. Exploring other learning paradigms, such as multi-agent or federated neuromorphic systems, could also be explored for scalability. Overall, this study provides the foundation for novel smart materials with integrated sensing, processing and learning capabilities.

Data Availability Statement

The dataset provided as supplementary material and is available upon reasonable request.

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