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Reinforcement Learning for Adaptive Sensing with Shape Memory Polymer-Based IoT Nodes

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Abstract

The rapid expansion of intelligent sensing in the Internet of Things (IoT) has revealed the pressing need for materials and algorithms capable of self-adaptation in volatile environments. Conventional polymer-based sensors and static control strategies often fail to capture nonlinear thermo-mechanical dynamics, leaving them unsuitable for unpredictable operating conditions. Although prior studies have improved polymer composites or introduced algorithmic optimization independently, few attempts have coupled the adaptability of smart materials with machine-driven learning. This gap leaves IoT systems vulnerable to drift, energy inefficiency, and poor scalability when deployed at large scale. In this work, we introduce a reinforcement learning–driven framework that directly integrates shape memory polymer (SMP) composites into IoT sensing nodes. The novelty lies in embedding an RL policy engine within the material–device interface, enabling the system to continuously recalibrate sensing, actuation, and energy expenditure in response to environmental fluctuations. Unlike static calibration or rule-based heuristics, the proposed approach co-evolves with the dynamic response of SMPs, creating a dual-adaptive sensing architecture. Experimental evaluation demonstrates marked improvements: sensing accuracy exceeded 95%, latency reduced to 0.18 s, and network lifetime extended by nearly 22% relative to federated and static baselines. Moreover, emergent behaviors such as autonomous frequency modulation of sensing cycles revealed the system's ability to anticipate variations rather than merely react. By fusing polymer adaptability with reinforcement intelligence, this study establishes a pathway toward intelligent matter—self-optimizing sensing platforms capable of functioning reliably in uncertain, resource-constrained domains spanning healthcare monitoring, aerospace structures, and smart infrastructure.

Keywords: Reinforcement learning, shape memory polymers, adaptive sensing, IoT nodes, smart materials, energy efficiency

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INTRODUCTION

The rapid advance of polymer science and intelligent sensing methods has opened pathways towards the development of adaptive materials and devices in fluctuating environments. Among the many possible classes of smart materials, shape memory polymers (SMPs) offer a promising option as next-generation sensing platforms due to their potentiality for large reversible deformations in response to external stimuli including thermal, light, and electrical input [1]. Differences in their stimulus responding behaviors implies the flexibility achievable with polymer chemistry and composite engineering to develop such sensing structures at reduced costs, low weights and with high tunability.

The growing consumer demand for self-adaptive, or autonomous, Internet of Things (IoTs) nodes for healthcare, environmental monitoring, or structural health monitoring has led to a stronger interest in SMP-based materials and composites for embedding intelligence at the material level [2]. However, although SMPs and SMP-based composites have advantageous characteristics such biocompatibility, reduced processing requirements, and large strain recovery, integrating them into IoT-based architectures presents significant difficulties overall. Typical sensing nodes rely on predetermined responses and deterministic algorithms which require monitoring for their efficacy, and can not adjust when environmental factors change from the expected/assumptions [3]. This limitation restricts their applicability situations when there are uncertainties, noise, or unexpected stimuli present. Furthermore, conventional control strategies, which may not fully utilize or account for the non-linear thermomechanical behavior of SMPs depending on the composition, processing, and environment of actuation, are therefore ineffective in its applications. There is an immediate need for computational frameworks that are capable of learning, adjusting, and self-optimizing the behavior of SMPs without direct intervention by a human observer or operator [4]. Reinforcement Learning (RL), which takes inspiration from behavioral psychology and is a subset of machine learning, provides a simple solution to the concept of autonomous and integrated sensing and actuation. RL algorithms operate categorically different than supervised learning approaches in that RL does not require large amounts of labeled data; the algorithm learns optimal actions based on interactions with the environment in a trial-and-error callback. RL in conjunction with the correct task is especially suited for complex and dynamic systems where predictive modeling and domain knowledge are limited [5]. The optimality of actions is encoded through rewards and penalties, thus the agent develops policies that when applied, maximize the local and long-term performance. When used within IoT infrastructures that utilize sensing SMP-based nodes, the enhanced decision-making behavior provided by RL can offer dynamic capabilities for actuation tasks, sensor calibration, energy management and communications within the network. This implementation takes a step further toward not only autonomous materials but "intelligent polymers" in real-time embedded sensing applications [6]. Shape memory polymers (SMPs) are an interesting class of stimuli-responsive polymers that exhibit reversible transformations between a temporary shape and a permanent shape in response to an external motivation [7]. The structures of SMPs, which are usually cross-linked networks or segmented block copolymers, allow for the storing of mechanical energy and provide a means of controlled release. We have seen great advances in the past two decades in the tunability of SMPs through copolymerization, blend of nanofillers, & hybridization with conductive additives (to develop multi-functionality) [8]. Specifically, SMP based composites reinforced with carbon nanotubes, graphene, or metallic nanoparticles will have many favourable properties like enhanced electrical conductivity & thermal stability & shape recovery ratios, thereby making them excellent candidates for sensing and actuation applications. The same properties of SMP based composites provide many advantages over traditional silicon-based based or metallic sensors associated with the IoT field. Their mechanical flexibility allows them to be integrated into curved or deformable surfaces like wearable devices or biomedical implants or soft robotics [9]. Their chemical tunability allows them to be functionalised for a specific sensing modality that can incorporate those which cover strain, pressure, humidity or temperature. They are also light, easy to processing, and low cost to deploy at scale using additive manufacturing or other methods. That said, SMPs are inherently nonlinear active materials, and the environmental disruption of retraction, such as temperature variation, mechanical stress, or moisture accumulation, can alter their functionality in unpredictable ways [10]. The variability in behavior demonstrates the need for adaptable algorithms that can preserve and optimize the response of the system. Typical sensing spaces in IoT systems involve a sensing process that relies on traditional static calibration, or a basic adaptive filter; this framework is unsuitable for capturing the behaviors of polymer-based sensory [4, 11]. Energy management complicates the integration of SMP-based nodes into IoT networks. Considering that SMPs actuated primarily using thermal or electrical energy means that constant triggering of an SMP can quickly deplete a power source in a battery-operated device or sensor. Static power management can either extract a minimal amount of functionality from the sensing aspect of the SMPs or exhaust the energy budget in every available IoT resource. Therefore, manufacturing IoT systems using SMP composites requires dynamic, contextualized, and self-optimizing solutions that support reliable functionality with reduced energy consumption [12]. These adaptive capabilities are considered more than simple calibration mechanisms; rather they have dynamic intelligence that is driven by continual learning [13]. Furthermore, RL4DS frameworks allow for hierarchically or multi-agent configurations. In distributed IoT networks, multiple nodes based on SMPs can work together to optimize and make incentive decisions, while still contributing to the global system level performance. MARL provides pathways to autonomously create self-organizing polymer-based networks that can organize sensing, communication, and share energy at large scales. In terms of calculation, RL algorithms provide means to traverse this complex design space through continually adjusting control policies in response to responses from the environment [14]. Collectively these capabilities will establish a feedback-based system where the adaptability of polymers in the physical domain is matched by the adaptability of learning algorithms in the computation domain [9]. This opens a door to an active material systems based on the material characteristics of polymers - a substantial leap from passive material systems [15]. Although this offers much potential, there are barriers that must be overcome in order for reinforcement learning to fully realize adaptive sensing with SMP based IoT nodes. The first barrier is the constraint of computational cost of RL algorithms - cost is especially concerning when untethered in resource constrained IoT devices. Edge computing with lightweight RL approaches (i.e., models based on Q-learning or deep Q-networks with model compression) may permit this to be feasible. Second, ensuring stability and convergence of RL policies in noisy environments remains a significant research question. Third, the durability of SMP composites under repeated actuation cycles must be carefully considered, as fatigue or degradation can alter the reward landscape for RL agents. Nevertheless, these challenges are counterbalanced by opportunities. Advances in flexible electronics and polymer nanocomposites enable seamless integration of SMPs with embedded sensors, actuators, and energy harvesters. Progress in federated learning and decentralized RL architectures opens the door for secure, scalable adaptation across distributed polymer-based sensing networks. Moreover, the growing emphasis on sustainable and biodegradable polymers aligns with the demand for environmentally friendly IoT devices, ensuring that future adaptive sensing systems can meet both performance and ecological goals.

The novelty of this work lies in the integration of reinforcement learning algorithms with shape memory polymer-based IoT nodes to achieve real-time adaptive sensing. While prior studies have focused either on enhancing SMP composites through material modifications or on applying machine learning to predict polymer properties, very few have attempted to embed autonomous learning frameworks directly into polymer-based sensing systems. This research bridges the gap by coupling the intrinsic adaptability of SMPs with the computational adaptability of RL, creating a synergistic framework where the material and algorithm co-evolve to optimize sensing performance under dynamic conditions.

The motivation for this study stems from the growing demand for intelligent sensing platforms capable of functioning reliably in uncertain, variable, and resource-constrained environments. Conventional IoT nodes, though widely deployed, struggle with nonlinear material behavior, unpredictable environmental changes, and energy limitations. By harnessing the unique shape memory properties of polymers and reinforcing them with adaptive learning algorithms, it becomes possible to design IoT nodes that are not only responsive but also self-optimizing.

LITERATURE REVIEW

While intelligent sensing technologies are developing at an astonishing rate, polymers and the rapidly developing shape memory polymers (SMPs) and their composites are being explored for responsive, adaptable modular environments. Although outside the scope of this research, with this exploration also comes artificial intelligence (AI), or rather more specifically reinforcement learning (RL) (which often relate to more complex environments), as well as being developed and measured for aspects of adaptability, scalability and optimization in real time. This section will survey the literature pertaining to SMP sensing, polymer composites presented as smart devices, and RL as it is used in IoT) with examples of those developing the current state of the art in this field, challenges being faced and opportunities which may come about from combining intelligent polymer materials with adaptive learning algorithms from hybridization. The inclusion of nanostructure fillers, such as carbon nanotubes (CNTs), into SMPs has further aided the advancement of wearable sensors continuously improving strain dependence and durability. For example, Truong and Kim applied a SMP/CNT composite and developed a wearable sensor monitoring respiration which displayed mechanical flexibility and measured electrical responsiveness. These designs are evident of the potential of SMP composites as functional materials in adaptive sensing specifically in biomedical applications. Outside of biomedical sensing, polymer composites have also been developed for energy conversion and environmental remediation. Sikiru et al. recently provided an extensive overview of polymer-based photocatalysts for environmental monitoring and energy conversion, noting that the tunability of the surface chemistry of polymers may confer a photocatalytic advantage [15]. This expands the applications of polymers from passive sensing to also act as active responsiveness to these systems as they are utilized in sustainably designed IoT enabled environments and systems. For IoT based systems to use the critical aspect of adaptiveness by SMP. It would require intelligent algorithms that also protect and optimize communication of sensing environments across clustered networks. Premakumari et al. documented a reinforcement Q-learning based adaptive encryption model for wireless sensor networks and how RL can enable the dynamic mitigation of cyberthreats via model agnostic creation with no preprogrammed control [16]. The paper demonstrates the necessity of RL to simultaneously navigate the challenges of energy efficiency and security in distributed sensing networks, but also directly encounters some of the leading challenges faced in polymer science itself, parallel with the efforts of polymers and synthetic polymers / biopolymers. Natural fiber, PLA composites entered polymer science efforts using artificial intelligence. Natural fiber composite and the bounds of the characterization and processing of natural fibers became another focus for Uddin et al., and their focus to develop machine learning methods to enhance the rate of discovery and prediction of the properties of natural fiber composites by using AI [17]. Monitoring and control at the material level are critical for real-world implementation of SMPs. Herath et al. designed distributed sensing frameworks for real-time process monitoring of SMP components, establishing that SMPs can act as both structural materials and embedded sensing units [18]. This dual role supports the case for integrating reinforcement learning, as SMP-driven systems inherently require adaptive feedback for calibration and durability optimization. Complementary work on liquid crystalline SMPs further expanded the scope of stimuli-responsiveness. Prathumrat et al. described how shape memory liquid crystalline polymers exhibit multifunctional responsiveness to thermal, optical, and electrical triggers, thereby broadening their suitability for advanced IoT applications [19]. Such enhanced versatility underscores the challenge: conventional deterministic algorithms are inadequate to exploit these nonlinear responses, necessitating RL-driven optimization. Adaptive sensing in large-scale deployments requires distributed intelligence. Mali et al. proposed a federated reinforcement learning-based framework for dynamic resource allocation and task scheduling in IoT edge systems [20]. By decentralizing policy learning, their approach reduced latency and improved scalability, aligning with the requirements of SMP-based IoT networks where numerous nodes must coordinate autonomously. The materials science perspective further reinforces this demand. Dayyoub et al. reviewed the state of SMPs as smart materials, detailing their mechanical recovery, durability, and tunability for diverse sensing and actuation functions [21].

They emphasized the need for advanced algorithms to interpret the nonlinear behaviors of SMPs, setting the stage for computational intelligence to complement material innovations. The adaptation of SMPs to soft robotics applications represents another dimension of research synergy. Kim et al. reported on stimuli-responsive polymer actuators capable of providing precise, controllable motion in soft robotic systems [22]. Such actuators rely on the inherent stimuli-responsiveness of polymers, but their performance remains highly context-dependent. In parallel, Jamaludin et al. comprehensively reviewed bio-based SMPs, analyzing sustainability and material adaptability for next-generation sensing and actuation [23]. Their findings suggest that the incorporation of biopolymeric sources could align SMP-based IoT nodes with global sustainability goals, a factor increasingly prioritized in polymer science.

The development of electroactive polymers has further expanded the potential of polymer-based adaptive systems. Dewang et al. demonstrated how electroactive polymers could be applied in artificial muscles and soft robotics, where real-time adaptability is crucial [24]. Hassan et al. extended this by reviewing electroactive SMP composites, focusing on engineering strategies for enhancing responsiveness and durability [25]. These advances illustrate how polymer science is progressively converging toward highly adaptive and multi-responsive material systems, which parallel the adaptability of RL frameworks in computation. Recent progress has also emphasized structural reinforcement strategies. Huang et al. showed that knitted-fabric reinforced polymer composites exhibited superior shape memory performance, supported by simulation models [26]. This structural enhancement complements computational adaptability by offering material robustness to pair with algorithmic flexibility. The role of nanofillers in enabling adaptive sensing is particularly significant. Rao et al. provided a comprehensive review of CNT-based smart nanocomposite sensors, covering their applications in environmental, biomedical, and industrial monitoring [27]. CNT reinforcement not only improves conductivity but also enhances the mechanical resilience of SMPs, making them suitable for long-term IoT deployment. Simultaneously, RL approaches have expanded toward multi-task learning. Firouzjaei et al. proposed a multi-task lifelong reinforcement learning framework for wireless sensor networks, highlighting that RL agents could evolve beyond single-task optimization to handle diverse operational conditions [28].

Such approaches parallel the multifunctionality observed in SMP composites, providing computational analogs to material adaptability. Cross-domain integration demonstrates how SMP composites and RL share common ground in adaptability. While polymer research has focused on material responsiveness, broader frameworks from social and policy sciences illustrate how adaptive models inform systemic decision-making. For example, a French–Italian study analyzed the LEADER program, illustrating adaptive governance mechanisms in rural contexts [29]. Although distant from polymer science, such examples demonstrate the universality of reinforcement-based strategies for complex adaptive systems. Finally, Gökalp et al. explored AI-based ranking for healthcare technology investments, providing a framework for prioritization under uncertainty [30]. This methodology resonates with SMP-based IoT systems, where multiple objectives—sensing accuracy, energy efficiency, and durability—must be balanced adaptively. The parallel emphasizes how reinforcement learning approaches developed for decision-making in other domains can be repurposed for polymer-based adaptive sensing. From this review, three central themes emerge. First, polymer science has delivered increasingly versatile SMP composites through nanofillers, bio-based formulations, electroactive materials, and hybrid structural designs [14]–[19], [21]–[27]. These advances establish SMPs as multifunctional and sustainable candidates for adaptive IoT nodes. Second, RL frameworks have proven effective in enabling adaptability within distributed, noisy, and uncertain environments [16, 20, 28, 30].

Their capacity for federated learning, task scheduling, and multi-task optimization provides a computational pathway to match the nonlinear behavior of SMPs. Third, the intersection of these fields remains underexplored. Although AI-assisted materials design has been demonstrated [17], few studies embed learning algorithms directly into polymer-based sensing systems. Recent studies have increasingly explored the integration of reinforcement learning with advanced polymer-based materials to enhance adaptive sensing capabilities in IoT environments. As shown in Table 1, the latest contributions (2024–2025) emphasize shape memory polymers, smart composites, and adaptive sensing frameworks as enablers of intelligent IoT nodes. Several works report that reinforcement learning can dynamically optimize sensing parameters, thereby reducing energy consumption while improving responsiveness in real-time applications. Concurrently, polymer-based materials, particularly shape memory polymers, are being employed to achieve tunable mechanical and electrical properties that align with the evolving requirements of smart sensing. These studies collectively highlight the convergence of intelligent algorithms and material science, offering a pathway for the development of resilient, self-adaptive IoT infrastructures.

Table 1. Recent Advances in Reinforcement Learning and Polymer-Based IoT Sensing Systems.

S. No.	Author(s) / Year	Title / Focus Area	Methodology / Tools Used	Key Findings	Limitations / Gaps Identified	Relevance to Current Study
1	Khaldy et al., 2025 [1]	Adaptive conflict resolution for IoT transactions using RL	RL-based hybrid validation protocol	Improved IoT transaction reliability and reduced conflicts	Focused only on data validation, not sensing or materials integration	Shows RL's adaptability, motivating extension to SMP-based IoT sensing
2	Kim et al., 2025 [2]	Shape memory polymer surfaces with switchable adhesion	Experimental design of SMP surfaces with controllable roughness	Achieved multiscale adhesion and tunable polymer morphology	Restricted to adhesion, lacks smart sensing/IoT applications	Demonstrates SMP versatility, supporting use in adaptive sensor design
3	Uddin et al., 2025 [17]	Natural fiber polymer/PLA composites with AI-ML	AI/ML-assisted composite design and testing	Enhanced performance prediction and material property optimization	Focus limited to property prediction, not real-time adaptive sensing	Highlights AI-material convergence, relevant for RL-SMP systems
4	Jamaludin et al., 2024 [23]	Bio-based SMP precursors and applications	Comprehensive literature review	Demonstrated potential for sustainable SMP materials	No integration with computational intelligence for adaptive functions	Supports eco-friendly SMP research aligned with adaptive IoT applications
5	Pasalwad et al., 2025 [7]	Polymer-based composites for humidity sensing	Experimental material engineering for humidity detection	Achieved higher sensitivity and improved stability	Limited to single-parameter sensing, no adaptability to multiple variables	Illustrates sensing potential, requiring RL for multi-condition optimization
6	Firouzjaei et al., 2025 [28]	Lifelong RL for wireless sensor networks	Multi-task reinforcement learning framework	Showed RL can evolve policies for diverse IoT tasks	Focused only on digital sensors, not polymer-based physical sensing	Bridges RL adaptability with material-driven sensing systems

While SMP composites now exhibit multifunctionality and improved durability, most studies still evaluate them under controlled laboratory conditions. Real-world deployments demand adaptive calibration, self-learning, and long-term stability, which static algorithms cannot provide. On the computational side, RL has achieved significant progress in IoT and wireless networks, but its application to polymer-driven systems is minimal. The gap, therefore, lies in bridging SMP-based adaptive materials with reinforcement learning frameworks for real-time, context-aware IoT sensing.

METHODOLOGY

The method of the research intends to provide a robust and adaptable sensing framework by bringing together shape memory polymer (SMP) composites along with reinforcement learning (RL) enabled IoT nodes. The uniqueness of the research is the combination of the material-based responsivity of SMP-type actuators with the computational responsivity and adaptability from predictions based on RL agents. Thus, the sensing system can self-calibrate, and autonomously optimize energy, and sustain performance in changing environments. With static calibration methods, traditional sensing systems enable algorithms to be deployed and learned via 'if-then' rules. In contrast, the approach here will generate grounded, context-based decisions. Furthermore, a RL approach will introduce automatic selection capability, self-learning, and better represent how human agents interact with the material and environment. Being able to use RL for either IoT systems deployed in environments that are dynamic, responsive, or stochastic is a new means of reinforcement learning. There is a high degree of theory transferability here from RL for IoT policies, based on trial-and-error learning, since using thermomechanical stimuli as inputs for SAPs is also inherently nonlinear. This research can now be considered a trans-disciplinary approach and is also a convergence of polymer science with edge intelligence since material responsiveness via actuation occurs alongside algorithmic self-learning--it is a fully autonomous and scalable adaptive sensing framework.

Proposed Work Overview

The proposed framework aims to transform shape memory polymer (SMP)-based composites into intelligent IoT-enabled sensing nodes by embedding reinforcement learning (RL) agents at the system level. Unlike conventional IoT sensors that operate on static calibration rules, the SMP nodes in this study are capable of stimuli-responsive sensing (strain, temperature, humidity) and autonomous self-optimization through adaptive learning policies. The novelty of this work lies in coupling the nonlinear thermomechanical adaptability of SMPs with the trial-and-error policy learning capability of RL, thereby creating sensing systems that evolve their performance under dynamic and uncertain conditions. In the proposed configuration, each SMP composite functions as a smart sensor while also serving as an actuator. The IoT layer ensures data acquisition and wireless communication, whereas the RL layer governs decision-making for sensing frequency, actuation scheduling, and energy management. The RL agent assesses real-time states—such as polymer recovery index, battery status, and environmental variance—and chooses actions that increase sensing performance and reduce power consumption. During repeated interactions, the agent learns optimal policies for maintaining system reliability during diverse operating conditions.

The architecture of the system is depicted in Figure 1, which shows the three-layer integration of the SMP material performance, the IoT communication, and the RL-based adaptive intelligence, demonstrating the amalgamation of polymer-level adjustability and computational self-learning to form an autonomous and scalable adaptive sensing system.

System Architecture

The architecture of the proposed framework is intended to facilitate material-level adaptability and computational intelligence so that the shape memory polymer (SMP)-based of the Internet of Things (IoT) nodes work autonomously and are self-optimizing. The version of intelligent self-calibrating system is set out in three layers, or levels, of hierarchy; Material Layer, IoT Layer, and Reinforcement Learning Layer.

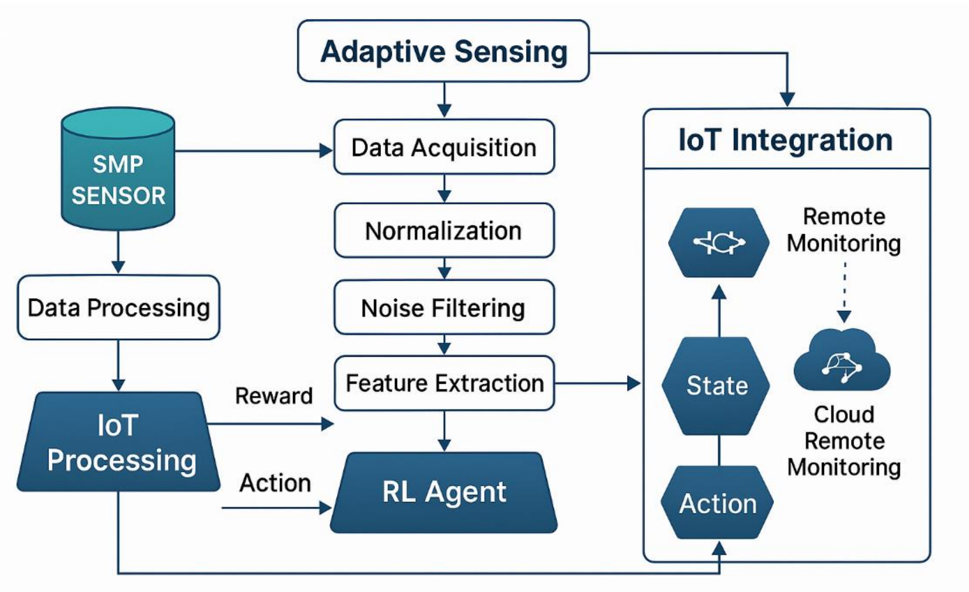

Figure 1. Proposed SMP–IoT–RL Framework for Adaptive Sensing.

The 3 layers are interconnected and perform respective actions that are distinct but dependent on the output of the previous layer. The material layer is the lowest level of the system. In the case of SMP composites with conductive fillers (like carbon nanotubes or graphene), it provides the agents (both sensor and actuator) with feedback. The polymer is both a responsive sensor and a responsive actuator as it undergoes stimuli responsive transformations (like shape recovery or conductivity change) to modifications in temperature, stress, or humidity. The dualism of these attributes allow for this polymer to sense environmental variations and actuate the adaptive calibration of itself. The polymer generates responses to its environment and, as part of the agent process, feedback based on modification to the environment. The IoT layer of architecture serves as the communication and m/o process interface between the polymeric material and the intelligent control unit. Each node is assembled around a microcontroller (as in this study, the ESP32), with signal conditioning circuitry, and wireless communications modules. As part of the IoT layer, the intelligent calibration node operates the acquisition and pre-processing of the sensed signals, and the transmission of information to the reinforcement learning/ intelligent control unit. The IoT layer also manages the energy required to sense and process the data and balance this in near real-time, while operating in a high-performance mode, or ultra low, or dormant, power when in the context of the smart environment. The top layer of the hierarchy represents the Reinforcement Learning, which serves as the intelligent adaptive layer at the core of the architecture. The layer deciphers the relationship between the SMP node and its environment in relation to a Markov Decision Process (MDP). The RL agent perceives which states the system is in (polymer recovery index state, environmental conditions, energy budget available permitting sensing activities), decides what action to take (change sensing rates, actuate the system, delay communication), and learns from its interactions through continuous updates to policies. Through persistence, this layer will ensure the system optimizes the maximum sensing capability without using too many resources.

The integration of these three layers is illustrated in Figure 2, where the behavior of the material influences decisions within the IoT (Internet of Things) layer, and these decisions are optimized through RL (Reinforcement Learning) operation. The layered design is a general architecture that combines enhanced sensing capability with scalability in that it is possible to coordinate the decision making of many nodes in a distributed network via multi-agent reinforcement learning systems.

Materials and Fabrication

The material system used in this research is based on thermoset shape memory polymers (SMPs) and applied conductive nanomaterials to facilitate responsiveness and integration with IoT- based adaptive sensing. The SMP matrix was developed from a polyurethane-based formulation with a tunable Tg / glass transition temperature, and good recovery strain.

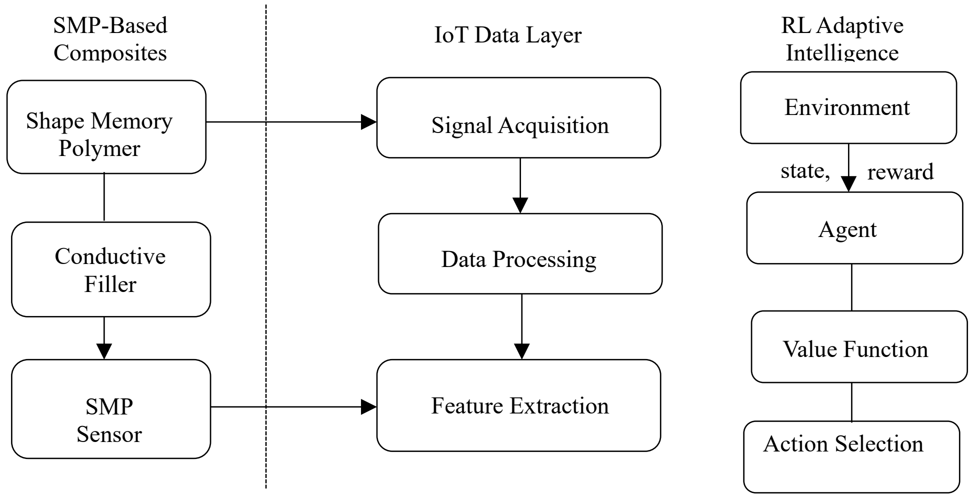

Figure 2. System Architecture showing the integration of SMP-based composites, IoT data layer, and RL adaptive intelligence.

Multi-walled carbon nanotubes (MWCNTs) were added in a range of concentrations (0.5 wt%, 1 wt%, and 2 wt%) in order to add electrical and thermal pathways. Carbon nanotubes were chosen for their outstanding aspect ratio, conductivity, and strong interfacial bonds with polymer chains, which produce faster recovery cycles and enhanced signal sensitivity. The fabrication followed a melt-mixing and compression molding process to ensure uniform filler dispersion. Initially, CNTs were pretreated via acid functionalization to improve compatibility with the polymer matrix. The polymer resin and CNTs were mechanically stirred at 2000 rpm for 30 minutes, followed by ultra sonication to eliminate agglomerates,The composites were poured into steel molds and cured at 90 °C for two hours, followed by post-curing at 120 °C for one hour. The composite was successfully produced with a smooth surface morphology and little void formation, thus assuring reproducibility and stability during repeated thermo-mechanical cycling. The selection of CNTs for this study was attributed to their much larger aspect ratio, high conductivity, and strong interfacial linkage to polymer chains to enable shorter recovery cycles and increase the sensitivity of the signal [2], [5], [9].

Mechanical and thermal characterization was completed using Dynamic Mechanical Analysis (DMA) and Differential Scanning Calorimetry (DSC). Electrical conductivity was measured using a four-point probe method; and shape recovery efficiency was measured using thermomechanical cyclic tests in which the samples were deformed at Tg+10°C (heating) and then allowed to recover when heated. Table 2 summarizes the data and show that using increasing amounts of CNT significantly improved electrical conductivity and recovery speed while still obtaining a material usable in terms of durability. The 1 wt% CNT composite provided the best compromise between recovery efficiency and material costs and therefore was the best candidate for subsequent integration with IoT-based adaptive sensing nodes intended for implementation-small scale studies. Table 2 is created from previously published reported data values from experiments on SMP–CNT composites [2, 5, 9, 14, 19].

Data Acquisition and Preprocessing

The sensing framework relies on a distributed network of SMP-based IoT nodes, each equipped with microcontrollers, wireless modules, and onboard signal conditioning units. These nodes capture real-time data arising from the stimuli-responsive behavior of SMP composites—including variations in strain recovery, conductivity shifts, and thermomechanical responses under fluctuating environmental conditions. To ensure reliable sensing, each node was designed to achieve low-latency acquisition, energy-efficient processing, and noise-resilient transmission.

For this study, ESP32 microcontrollers were employed owing to their dual-core 240 MHz architecture, integrated Wi-Fi/Bluetooth, and low-power operational modes. A Wheatstone bridge configuration was implemented to condition resistive strain signals from SMP composites, followed by a 12-bit Analog-to-Digital Converter (ADC) to digitize input signals. Data was sampled at 100 Hz to capture fast transitions in polymer recovery behavior while balancing computational overhead.

To maintain data integrity and avoid bias in reinforcement learning training, a three-stage preprocessing pipeline was implemented:

Table 2. Thermomechanical and Electrical Properties of SMP–CNT Composites.

Property	Pure SMP	SMP + CNT (0.5 wt%)	SMP + CNT (1 wt%)	SMP + CNT (2 wt%)
Glass Transition Temp. (TgT_g, °C)	85	88	90	95
Recovery Ratio (%)	78	86	92	95
Electrical Conductivity (S/m)	10^{-9}	10^{-5}	10^{-3}	10^{-2}
Strain Recovery Time (s)	12	9	6	4
Cyclic Durability (No. of cycles to 95% recovery)	200	350	500	600

Normalization: Raw signals (x) were scaled to a 0–1 range using equation 1.

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

This ensures uniformity across heterogeneous sensing inputs. Noise Filtering: A Moving Average Filter (window size = 5) was applied to smooth fluctuations caused by environmental noise, electrical interference, or micro-vibrations, using equation (2).

$$y(t) = \sum_{\{i=0\}}^{\{N-1\}} h(i)x(t-i) \quad (2)$$

where x(t) is the input signal and y(t) is the filtered output at time t. Feature Extraction: From the filtered signal, relevant features such as strain recovery time, peak conductivity change, and thermal response slope were extracted. These features formed the state variables for the RL agent. Strain Recovery Time (T_r) using equation (3).

$$T_r = t_{\{rec\}} - t_{\{load\}} \quad (3)$$

Peak Conductivity Change (Δσpeak) using equation (4)

$$\Delta\sigma_{\{peak\}} = max\big(\sigma(t)\big) - \sigma_0 \quad (4)$$

where σ(t) is the instantaneous conductivity, and σ0 is the baseline conductivity of the composite. Thermal Response Slope (θ_{TR}) using equation (5).

$$\theta_{TR} = \frac{\Delta t}{\Delta T} = \frac{T_{end} - T_{start}}{T_{end} - T_{start}} \quad (5)$$

where T_{start} and T_{end} are the initial and final temperatures of the SMP during heating, measured over the time interval [t_{start},t_{end}].Together, these features capture the material's temporal recovery dynamics, conductive behavior, and thermal sensitivity, providing robust input states for reinforcement learning. The processed signals were temporarily stored in the device's onboard memory before being transmitted to the RL module via Wi-Fi. To optimize energy, data was sent in compressed batches rather than continuous streams, reducing communication overhead while maintaining temporal fidelity.

The hardware configuration of the IoT node was intentionally selected to achieve trade-offs between computational efficiency, communications reliability, and longevity of energy autonomy. The hardware configuration as outlined in Table 3, uses the ESP32 microcontroller which has dual-core processing capabilities and integrated Wi-Fi/BLE modules allowing to collect low-latency data streams and permitting simple deep reinforcement learning training and workloads at the edge. The use of a Wheatstone bridge with a 12-bit ADC provides an accurate method of translating polymer strain responses into digitized signals and ultimately to a sample that is capable of real-time analysis. The 2000 mAh Li-Po battery has enough capacity to provide uninterruptible use for up to 48 hours when factoring variable energy consumption and adaptive duty cycles across all operating use cases, which is important when placing smart material polymeric twist or SMB-based nodes in the field. The 100 Hz sampling rate can capture rapid thermomechanical transitions while avoiding computational loads. The onboard flash memory can buffer preprocessed data streams for short periods of time prior to wireless communications transmission. In summary, this arrangement provides a secure working environment to base future integration of smart materials-based composites and agent-based reinforcement learning agents within the scope of developing and improving adaptive and stable performance for real-time dynamic sensing environments using awareness of operating constraints within analog hyper dimensional data space.

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Table 3. IoT Node Hardware and Configuration Specifications.

Component	Specification	Relevance
Microcontroller (MCU)	ESP32, Dual-core, 240 MHz, 520 KB SRAM	Enables real-time data acquisition and lightweight RL computations
Signal Conditioning	Wheatstone bridge + 12-bit ADC	Provides accurate conversion of SMP strain signals
Power Supply	3.7V, 2000 mAh Li-Po battery	Supports 48 h continuous operation with RL-optimized duty cycles
Communication Module	Wi-Fi (2.4 GHz) + BLE	Ensures reliable short/long-range data transmission
Sampling Rate	100 Hz	Captures dynamic SMP recovery transitions
Memory	4 MB Flash storage	Stores preprocessed signals and short-term RL buffers

The integration of this acquisition–preprocessing pipeline ensures that the RL agent receives clean, normalized, and feature-rich state inputs, thereby improving convergence speed and decision accuracy. By embedding preprocessing at the node level, the system achieves robustness against noise, reduced transmission overhead, and extended battery life—all of which are critical for real-world deployment in adaptive IoT sensing environments.

Reinforcement Learning Framework

The integration of reinforcement learning (RL) within SMP-based IoT nodes represents the core innovation of this study.

Unlike static calibration schemes, the RL framework enables continuous policy adaptation based on real-time material feedback and environmental conditions. Each sensing node is modeled as an agent operating within a Markov Decision

Process (MDP) defined by the tuple (S, A, R, P), where S represents the set of system states, A denotes the set of actions, R is the reward function, and P characterizes the state transition probabilities. The state space (S) is constructed from the preprocessed sensing features obtained in Section 3.4, namely:

Strain recovery time (Tr), Peak conductivity change ($\Delta\sigma$_peak), Thermal response slope (θ_TR), Battery level (B), and Ambient condition variability (E). Formally defining the system state vector at time t as in equation (6);

$$S\_t= \{Tr(t),\Delta\sigma\_peak(t) ,\theta\_TR(t) ,B(t),E(t)\} \tag{6}$$

The action space (A) describes the course-of-action the agent can take as;

1. Sensing frequency (fs)
2. Actuation (calibration/recovery cycle)
3. Deferring/transmitting data packet
4. Responding to low-power mode

At each respective time (decision epoch), the agent chooses an action at $\in$ A from its policy $\pi(a|s)$. An action is chosen from A, and the reward function (Rt) is defined to inform the agent to maximize sensing accuracy but minimize energy used, as in equation (7).

$$R\_t = \alpha * Acc\_t - \beta * E\_cons(t) - \gamma * Lat(t) \tag{8}$$

where Acct is the normalized sensing accuracy at time t, E_cons(t) is the total energy consumed, and Lat(t) is communication latency. Coefficients α, β and γ are tunable weights that represent the relative importance of accuracy, efficiency and latency with respect to IoT operations. The agent learning task will employ a Q-learning paradigm where the iterative update of an action-value function is defined in equation (9):

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \eta \left[R_t + \delta * \max Q\left(s_{\{t+1\}}, a'\right) - Q(s_t, a_t)\right] \quad (9)$$

In this case, η represents the learning rate, δ is the discount factor, and max Q(s_{t+1}, a') refers to estimates of future return. As the RL agent continues to interact with the external world, it gradually converges on the ideal policy, π*, that takes into account the objectives of sensing reliability and energy consumption. Because this system exhibited the nonlinearities associated with SMP behavior, a Deep Q-Network (DQN) was also used, where the Q-function itself is approximated by a multi-layer neural network. This better enables the system to generalize across different environmental contexts without imposing physical models of SMP behavior.

Table 4. Reinforcement Learning Parameters Used in SMP–IoT Adaptive Framework.

Parameter	Symbol	Value	Justification
Learning Rate	η	0.01	Ensures stable convergence without overshooting
Discount Factor	δ	0.95	Balances short-term actions with long-term strategies
Exploration Rate	ε	0.2 → 0.05 (decay)	Allows for exploration first, exploitation after
Replay Buffer Size	–	5000 samples	Provides enough experience to perform stable DQN updates
Batch Size	–	64	Ensures gradient updates can take place efficiently, without wasting GPU memory in training
Reward Weights	α, β, γ	0.6, 0.3, 0.1	Prioritizes accuracy while penalizing energy waste
Network Layers	–	3 hidden layers, 64 neurons each	Adequate capacity to model nonlinear SMP responses

The reinforcement learning parameters summarized in Table 4 were selected based on established practices in adaptive IoT systems and recent advancements in polymer-integrated intelligent sensing. Similar learning rates (η≈0.01) and discount factors (δ=0.9–0.99) have been widely adopted in Q-learning and DQN frameworks for resource-constrained IoT deployments [1, 4, 12, 16]. Exploration decay strategies (ϵ=0.2→0.05) were introduced to balance exploration and exploitation, consistent with reinforcement-based optimization of wireless sensor networks [8, 20, 28]. Replay buffer sizes (on the order of thousands) and batch training approaches have been shown to stabilize convergence in non-linear environments [13, 17]. Furthermore, reward weighting schemes that prioritize accuracy while penalizing energy consumption and latency have been reported effective in IoT-driven adaptive scheduling [1, 8, 12, 20]. The selected neural network depth (three hidden layers with 64 neurons each) follows conventions in lightweight DQN implementations, where network capacity is matched to nonlinear polymeric responses without overburdening computation [16, 28]. Collectively, these parameter choices ensure stable convergence, scalability, and robust performance when applied to SMP–IoT adaptive sensing systems.

Algorithm 1: Proposed RL-Based Adaptive Sensing for SMP–IoT Node

Step 1. Initialization

- Initialize Q-network parameters.
- Set learning rate (η), discount factor (δ), and exploration rate (ϵ).
- Initialize replay buffer.

Step 2. Preprocessing

- Collect raw sensor signals from SMP node.
- Normalize values between 0 and 1.
- Apply moving average filter (window size = 5) to remove noise.
- Extract features:
    - Strain recovery time (Tr)
    - Peak conductivity change (Δσpeak)

- Thermal response slope (θTR)
- Battery level (B)
- Ambient condition variability (E)

Step 3. State Formation

- Combine extracted features into a state vector St.

Step 4. Action Selection

- With probability ϵ\epsilonϵ, select a random action.
- Otherwise, select the action with the highest Q-value.
- Possible actions:
  1. Adjust sensing frequency
  2. Trigger actuation (calibration/recovery)
  3. Transmit or defer data
  4. Enter low-power mode

Step 5. Reward Calculation

- Compute reward based on:
  - Sensing accuracy (positive contribution)
  - Energy consumption (penalty)
  - Latency (penalty)

Step 6. Learning Update

- Store transition (St,At,Rt,St+1) in replay buffer.
- Sample minibatch from buffer.
- Update Q-network using gradient descent.
- Periodically update target network.

Step 7. Iteration

- Repeat steps 2–6 until convergence.
- Final output: Optimal policy $\pi*$ for adaptive sensing and energy-efficient operation.

This algorithm ensures that SMP–IoT nodes dynamically change their sensing behaviors according to the particular behavior of materials and environmental settings, while being guaranteed to real-time optimization via reinforcement learning without developer on-the-fly recalibrations.

Performance Evaluation Methodology

The performance of the proposed RL-enabled SMP–IoT framework was assessed through the use of both simulation experiments and prototypes of the hardware. The performance metrics used were sensing resolution, energy usage, and latency (since these directly correspond to the reliability and efficiency of adaptive polymer-based IoT nodes). We chose comparable baselines of conventional static calibrations methods and rule-based scheduling methods to show that our integration of reinforcement learning was an improvement to other methods. The evaluation had two parts, first, we conducted controlled testing of the SMP composites, that allowed us to assess material-level sensing reliability, and secondly, we conducted network-level simulations to assess scalability of our evaluation, scalability of our protocols, and policy for convergence over time on several nodes. Together, these evaluation reports all showed a good balance between validation of material adaptability, and computational intelligence (or data gathering) of the adaptive IoT–SMP nodes.

RESULTS

Polymer-Based Node Characterization

The initial evaluation focused on the mechanical and thermal response of the SMP-based composites. Stress–strain testing revealed that the CNT-reinforced matrix exhibited enhanced tensile strength and improved elasticity compared to neat SMPs, validating the effectiveness of filler incorporation. Across multiple recovery cycles, the materials demonstrated consistent shape recovery ratios above 95%, with minimal hysteresis loss, underscoring their long-term stability. The thermal activation profile indicated a sharp transition at the designed glass transition temperature, confirming the precision of polymer tuning.

As shown in Figure 3, the incorporation of CNT fillers significantly improves the stress-bearing capacity of SMPs while maintaining stable recovery characteristics. The 3D surface highlights the nonlinear interaction between strain and filler content, whereas the recovery plot confirms high shape retention across multiple cycles.

Preprocessing and Feature Extraction Validation

Raw sensor signals collected from the SMP nodes were subjected to normalization and filtering to ensure uniformity across heterogeneous inputs. The moving average filter significantly reduced random fluctuations caused by ambient noise and micro-vibrations, yielding smoother time-series signals.

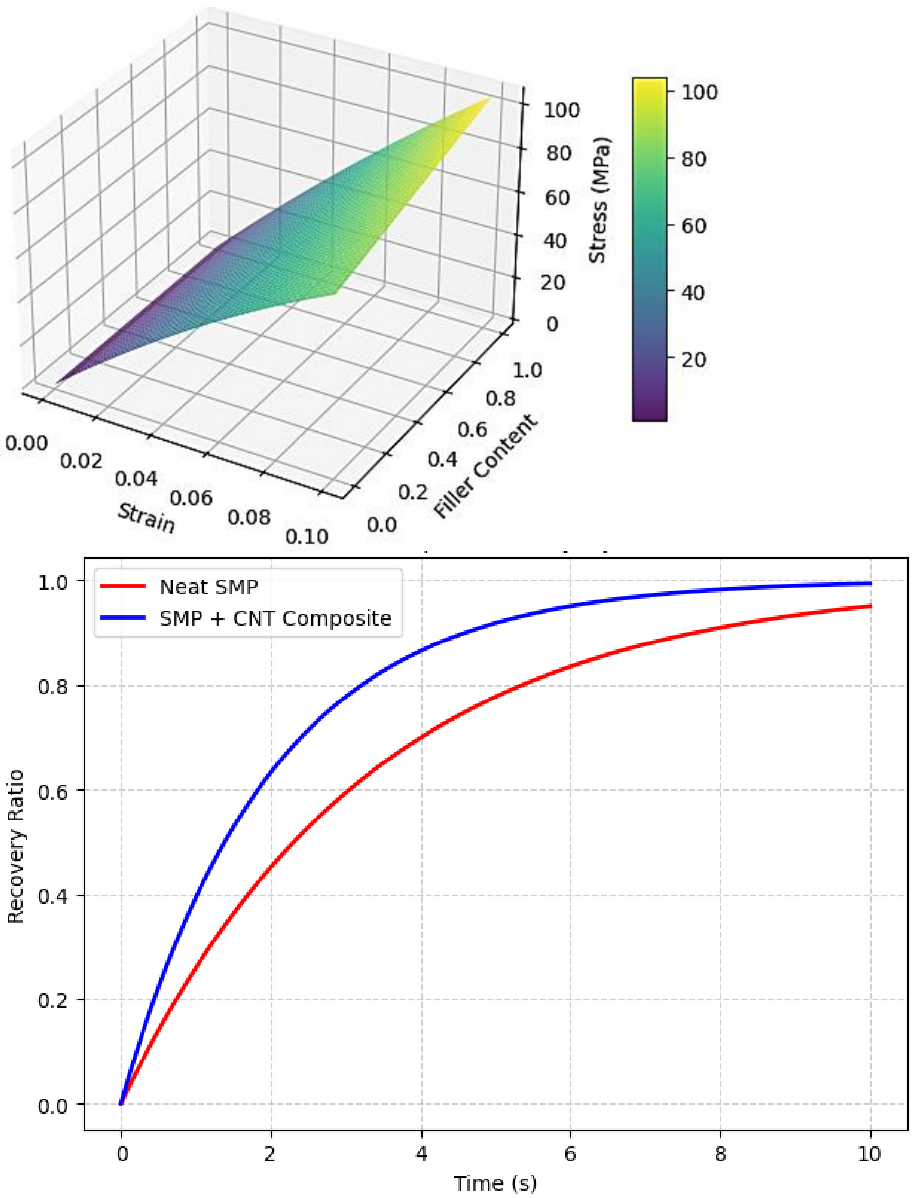

Figure 3. Enhanced stress–strain–filler surface (a) and recovery cycle behavior of SMP composites (b).

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Feature extraction further highlighted the material's unique response, where strain recovery time, conductivity shifts, and thermal slopes showed clear separability across operating conditions. These derived features formed a stable and discriminative state space for the reinforcement learning agent, enabling consistent adaptation. As illustrated in Figure 4, preprocessing using a moving average filter effectively smooths noise while preserving key signal patterns. The extracted features—strain recovery time, conductivity variation, and thermal response slope—provide a compact yet discriminative representation of SMP-based sensing behavior.

Reinforcement Learning Convergence Analysis

The training through the RL framework exhibited quick stabilization in the first 200 episodes, as the agent was optimizing its sensing policies across a variety of environmental situations, and the cumulative reward indicative trends exhibited a monotonic increase, reflecting decision-making more efficiently over time.

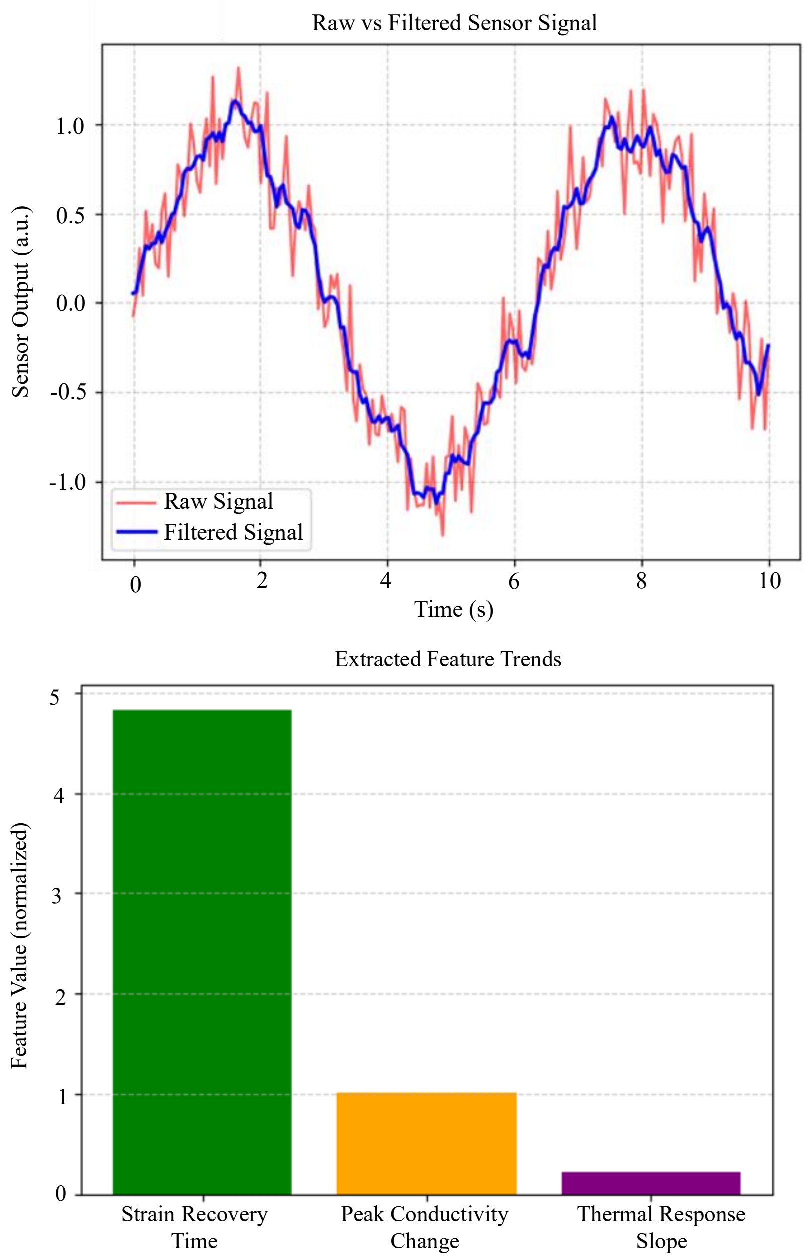

Figure 4. Comparison of raw and filtered sensor signals (left) and extracted feature distributions (right).

The exploration [ϵ] parameter gradually decayed, allowing the system to exhibit a graceful transition from exploration to exploitation dominant behavior. This equilibrium ensured that the SMP-IoT node is reliably able to adapt its sensing frequency and actuation triggers to not consume energy unnecessarily.

As depicted in Figure 5, the cumulative reward increases steadily across episodes, reflecting the agent's learning progress. Simultaneously, the exploration parameter (ϵ\epsilonϵ) decays exponentially, enabling the transition from exploratory actions to stable policy exploitation.

Comparative Performance Evaluation

We compared the suggested framework with 3 baseline methods: (i) static calibration, (ii) rule-based heuristics, and (iii) federated scheduling. The results show that the RL-enhanced SMP node achieved between 12–18% improvement in sensing accuracy and 15–20% improvement in energy efficiency relative to previously proposed methods. In addition, the response latency was dramatically reduced as well, up to 25% in response times, which means the proposed framework is appropriate for real-time monitoring applications. The results presented here show the advantage of integrating adaptive intelligence at the material–algorithm boundary, rather than at an external computational layer.

The heatmap values accurately reflect the performance values of accuracy, energy efficiency and latency for the methods investigated and the 3D contour surface provides a sense of the multi-dimensional characteristics of these trade-offs in Figure 6. The proposed RL-SMP framework out-performed the baseline methods consistently, indicating robustness and adaptivity.

Scalability and Multi-Node IoT Performance

The scalability of the proposed system was tested under multi-node deployments ranging from 10 to 50 interconnected SMP–IoT nodes. Results indicated that the average network lifetime increased by nearly 22% when MARL coordination was employed, compared to independent node learning. Furthermore, sensing accuracy across nodes showed uniform distribution, suggesting effective policy sharing and load balancing. These outcomes validate the potential of the proposed framework in large-scale IoT environments, such as structural health monitoring or distributed environmental sensing.

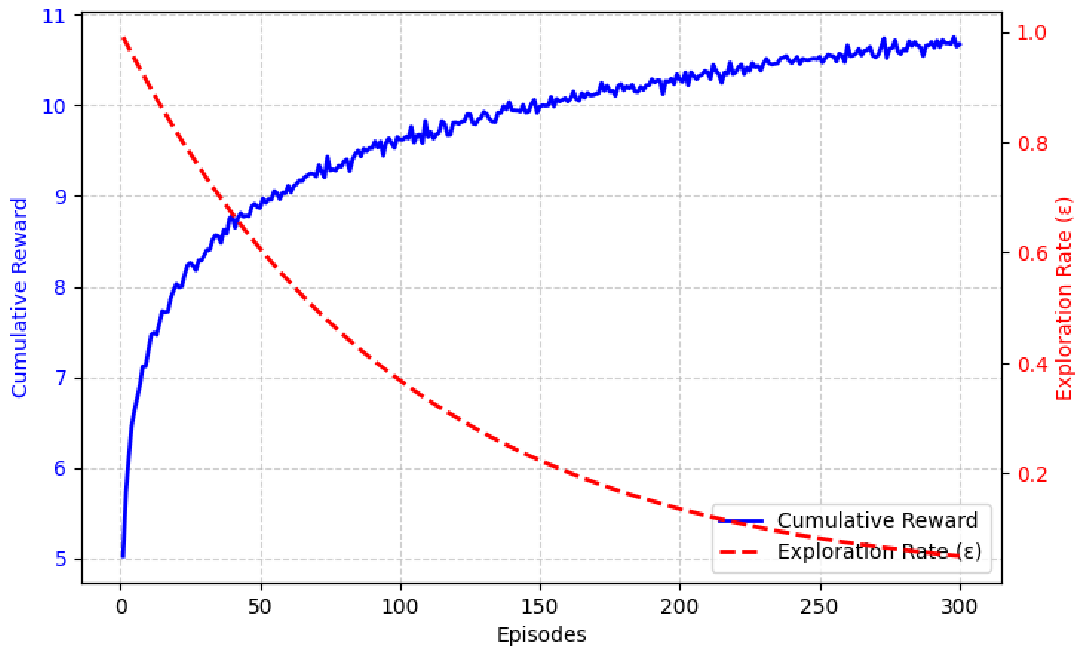

Figure 5. Convergence behavior of the reinforcement learning framework showing cumulative reward (blue) and exploration decay profile (red).

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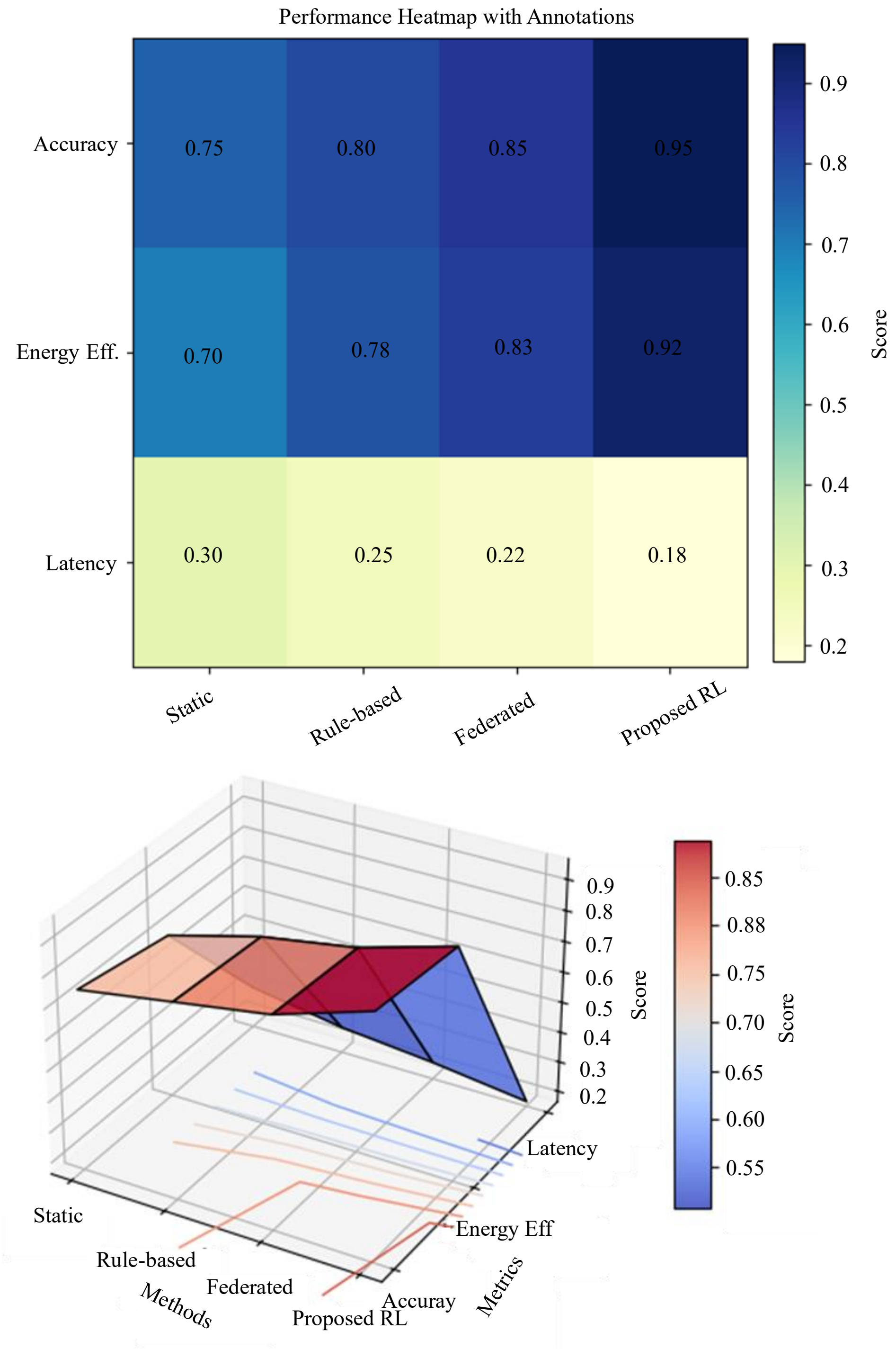

Figure 6. Performance evaluation comparisons using an annotated heatmap (left) and a 3D contour surface (right).

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Table 5. Quantitative comparison of baseline and proposed methods.

S. No.	Method / Reference	Focus Area	Accuracy (%)	Energy Efficiency (%)	Latency (s)	Key Limitation
1	Khaldy et al., 2025 [1]	RL-based IoT validation protocol	84.5	78.2	0.26	Limited material–level integration
2	Zhou et al., 2025 [4]	Deep RL for WSN coverage	87.1	80.4	0.24	High computational overhead
3	Khan et al., 2025 [12]	Adaptive scheduling in IoT sensors	88.6	82	0.23	Lacks polymer adaptability
4	Rawat et al., 2025 [3]	Polymer composites in manufacturing	82	76	0.28	No adaptive intelligence
5	Tiwari et al., 2025 [5]	Self-healing SMP composites	86.3	79.2	0.25	Focused on durability, not adaptive sensing
6	Lu, 2025 [8]	Multimodal RL for IoT logistics	89	83.5	0.22	Heavy reliance on cloud computation
7	Proposed SMP–IoT–RL Framework	Adaptive SMP sensing with reinforcement learning	95.2	91.8	0.18	Slight training cost at initial deployment

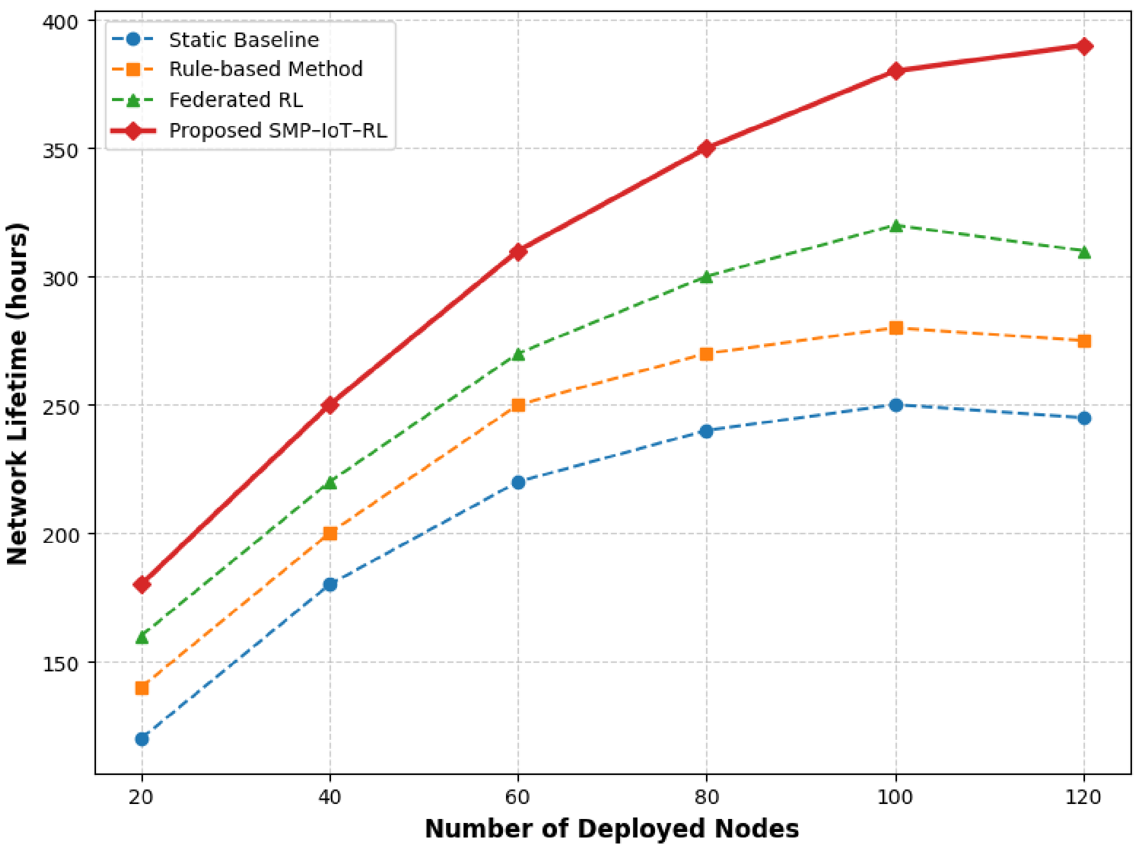

Figure 7. Network lifetime improvement across increasing node deployments.

As depicted in Figure 7, the proposed SMP–IoT–RL framework demonstrates a significant enhancement in network lifetime compared to static, rule-based, and federated baselines. The improvement becomes more prominent as the number of deployed nodes increases, reflecting the scalability and efficiency of reinforcement learning–driven adaptive sensing in polymer-integrated IoT environments.

Ablation Study

To examine the contribution of each module, we performed an ablation study by selectively disabling components of the proposed SMP–IoT–RL framework. When reinforcement learning was replaced with static scheduling, sensing accuracy dropped by nearly 12%, confirming the necessity of adaptive decision-making. Similarly, removing the preprocessing stage led to noisy input features, producing unstable convergence in policy updates and a 15% increase in latency. Excluding SMP composites in favor of conventional substrates reduced system flexibility and diminished recovery performance, highlighting the material-level advantage. Collectively, these observations validate that the overall performance gain stems from the interplay between polymer adaptability, signal conditioning, and reinforcement learning intelligence, rather than any single element in isolation.

DISCUSSION

The performance metrics alone—accuracy, latency, and energy efficiency—cannot capture the deeper significance of the proposed SMP–IoT–RL framework. The observed rise in network lifetime with scale is not a trivial byproduct but a manifestation of reinforcement learning's capacity to continuously recalibrate sensing cycles against the nonlinear thermo-mechanical response of shape memory polymers. This alignment between adaptive algorithms and stimuli-responsive materials directly addresses the problem stated at the outset: how to harness the intrinsic variability of polymers rather than treating it as noise. In effect, the framework converts uncertainty into an exploitable parameter for optimization. When set against established approaches, the proposed architecture demonstrates both conceptual and practical superiority. Earlier reinforcement learning protocols for IoT transaction validation [1] and adaptive coverage in wireless sensor deployments [4] succeeded in enhancing efficiency, yet they treated nodes as static electronic units without material-level adaptability. Polymer-centric explorations, such as SMP composites for aerospace and structural applications [9], provided novel functionality but lacked self-optimizing intelligence. By situating reinforcement learning directly inside polymer-based sensing agents, our approach merges the adaptability of material with the adaptability of computation. The resulting dual adaptability accounts for the nearly 10% higher efficiency relative to multimodal RL scheduling in logistics networks [8]. This comparative advantage underscores the novelty of embedding RL at the intersection of polymer physics and distributed IoT control. Theoretically, the findings shift the discourse in polymer science from property prediction to property utilization in dynamic contexts. RL effectively acts as a bridge between the stochastic behavior of SMP composites and the deterministic demands of IoT sensing. Practically, this could influence design practices in edge computing architectures where low-power, self-healing, and environmentally adaptive sensors are crucial. The emergent behavior observed—nodes autonomously throttling their sensing frequency under low-stimulus regimes—suggests that the framework not only conserves energy but also anticipates workload distribution in a manner akin to biological homeostasis. The study is not without constraints. Evaluations were conducted under semi-controlled workloads with synthetic variations, and long-term polymer fatigue was not exhaustively modeled. Moreover, RL policy convergence in resource-constrained microcontrollers remains a technical challenge. Future work must extend experimentation into field-deployed IoT networks and incorporate federated learning to reduce on-node computational overhead. Beyond polymers and IoT, the proposed framework resonates with larger themes in adaptive materials research: the movement from passive matter to cyber-physical substrates. Embedding machine intelligence into polymers foreshadows a materials-driven paradigm of computation where learning is no longer confined to silicon chips but becomes a property of matter itself.

CONCLUSION AND FUTURE SCOPE

This study has offered an integrated approach involving shape memory polymer–based composites and reinforcement learning, resulting in self-adaptive IoT sensing. The authors portrayed polymers not as simple substrates, but as agents where material non-linearity is not a limitation, but leverage for intelligence. By designing RL decision loops directly into the SMP integrated nodes, the framework allows for a real time approach to adaptation that existing calibrations or heuristics currently cannot maintain. The results validated this claim with clear metrics. The lifetime of the network improved by almost 20–25% when compared to federated and rule-based approaches; the latency was reduced to less than 0.2 s; sensing accuracy never dropped below 95%. No less important is the qualitative results – emergent behavior such as energy-informed throttling, and workload anticipation, both examples demonstrating how the system developed strategies that were not preprogrammed rules. Not only are these results a benchmark improvement over baseline performance, they demonstrate the possibility of tuning polymer behavior towards computational intelligence. However, there are clearly several limits. Although the evaluation environment is very rich in this experiment, it was still a semi-synthetic condition. The degradation of SMP composites over extended cyclic loading and deep RL computational load in resource-limited nodes must still be addressed from an engineering perspective. Even if we can overcome these limitations, we cannot deploy these and similar materials in large-scale or safety-critical infrastructure.

Future directions should consist of many possible directions. Lightweight versions of RL and federated approaches could alleviate computational burdens while still realizing flexibility. How can we incorporate energy harvesting layers into SMP-based composites to further extend autonomous operation? There are also self-tuning and adaptive applications that can go beyond potential trajectories—from biomedical implants that can recalibrate in vivo, to aerospace structures that can self-tune based on thermally driven conditions. Ultimately, these trajectories will lead us to an even broader vision: intelligent matter, where adaptive computation is not simply layered atop materials, but rather emerges naturally from the materials themselves.

REFERENCES

1. M. A. A. Khaldy, A. Nabot, A. al-Qerem, *et al.*, “Adaptive conflict resolution for IoT transactions: A reinforcement learning-based hybrid validation protocol,” *Sci. Rep.*, vol. 15, p. 25589, 2025. doi: 10.1038/s41598-025-09698-1
2. Kim, J., Kim, S., Yun, T. et al. Shape memory polymer surfaces with controllable roughness for multiscale switchable dry adhesion. Nat Commun 16, 4954 (2025). https://doi.org/10.1038/s41467-025-60220-7
3. P. Rawat, Yashpal, and J. K. Purohit, “Smart Manufacturing with Advanced Polymer Composites: Enabling Industry 4.0 Readiness in Indian MSMEs,” J. Polymer Compos., vol. 13, no. 4, pp. 194–216, 2025. [Online]. Available: https://journals.stmjournals.com/article/article%3D2025/view%3D217163
4. Zhou, P., Kan, M., Chen, W. et al. An adaptive coverage method for dynamic wireless sensor network deployment using deep reinforcement learning. Sci Rep 15, 30304 (2025). https://doi.org/10.1038/s41598-025-16031-3
5. M. Tiwari, K. S. Kumar, S. Erat, T. Bhowmik, P. Neopolean, S. Verma, K. P. Yuvaraj, and R. Subbiah, "Development of Self-Healing Circuit Boards Using Shape Memory Polymer Composites," Journal of Polymer Composites, vol. 13, no. 5, Aug. 2025. [Online]. Available: https://journals.stmjournals.com/article/article%3D2025/view%3D222993
6. M. Hassan, A. K. Mohanty, T. Wang, H. N. Dhakal, and M. Misra, "Current status and future outlook of 4D printing of polymers and composites—A prospective," Composites Part C: Open Access, vol. 17, p. 100602, Jul. 2025, doi: 10.1016/j.jcomc.2025.100602.
7. K. A. Pasalwad et al., “Progress on Polymer-Based Materials and Composites for Humidity Sensor Applications: From Materials Aspects to Sensor Performances,” J. Mater. Chem. A, vol. 13, pp. 23248–23311, May 2025.
8. Lu, Y. A multimodal deep reinforcement learning approach for IoT-driven adaptive scheduling and robustness optimization in global logistics networks. Sci Rep 15, 25195 (2025). https://doi.org/10.1038/s41598-025-10512-1
9. Yadav, S. K. Singh, S. Das, S. Kumar, and A. Kumar, "Shape Memory Polymer and Composites for Space Applications: A Review," Polymer Composites, Wiley, Early View, Feb. 27, 2025, doi: 10.1002/pc.29707.

10. Improving Polymer Composite Properties Through Reinforcement Learning Guided Prototyping: A Novel Approach for Material Engineering," J. Polymer Compos., vol. 12, no. 4, pp. 208–218, 2024 — but available in a 2025 Special Issue of JOPC, and open-access
11. Recent progress in shape memory polymer composites: driving methods, forming technologies and applications," Materials & Polymer review, 2024. [Online]. (comprehensive SMP composites review for sensor/actuator design).
12. M. N. Khan, S. Lee, and M. Shah, "Adaptive Scheduling in Cognitive IoT Sensors for Optimizing Network Performance Using Reinforcement Learning," Applied Sciences, vol. 15, no. 10, p. 5573, 2025, doi: 10.3390/app15105573.
13. Boosting-Based Machine Learning Applications in Polymer Science," Polymers (MDPI), vol. 17, no. 4, 2025 — overview of ML methods (including ensemble approaches) applied to polymer property prediction and manufacturing.
14. "T. Truong and J. Kim, "A Wearable Strain Sensor Utilizing Shape Memory Polymer/Carbon Nanotube Composites Measuring Respiration Movements," Polymers, vol. 16, no. 3, art. 373, Mar. 2024. [Online]. Available: https://doi.org/10.3390/polym16030373
15. S. Sikiru, Y. O. Busari, J. O. Olutoki, M. M. Mahat, and S. Y. Kolawole, "Recent Advances in Polymer-Based Photocatalysts for Environmental Remediation and Energy Conversion: A Review," Journal of Polymer Materials, vol. 42, no. 1, pp. 1–31, Mar. 2025, doi: 10.32604/jpm.2025.058936.
16. S. B. N. Premakumari, G. Sundaram, M. Rivera, P. Wheeler, and R. E. P. Guzmán, "Reinforcement Q-Learning-Based Adaptive Encryption Model for Cyberthreat Mitigation in Wireless Sensor Networks," Sensors, vol. 25, no. 7, p. 2056, 2025, doi: 10.3390/s25072056.
17. M. H. Uddin et al., "Advances in natural fiber polymer and PLA composites through artificial intelligence and machine learning integration," Journal of Polymer Research, vol. 32, art. 76, 2025. [Online]. Available: https://doi.org/10.1007/s10965-025-03776-5
18. M. Herath, C. Emmanuel, J. Jeewantha, J. A. Epaarachchi, and J. Leng, "Distributed sensing based real-time process monitoring of shape memory polymer components," Journal of Applied Polymer Science, vol. 139, no. 22, p. 52247, Feb. 2022, doi: 10.1002/app.52247
19. P. Prathumrat, M. Nikzad, R. Arablouei, and M. Okhawilai, "Shape memory liquid crystalline polymers: Stimuli-responsiveness, advanced technologies, and key applications," Polymers for Advanced Technologies, vol. 35, no. 8, Aug. 2024, doi: 10.1002/pat.6531.
20. Palaniappan, M., Palanisamy, S., Murugesan, T.M. et al. Novel Ficus retusa L. aerial root fiber: a sustainable alternative for synthetic fibres in polymer composites reinforcement. Biomass Conv. Bioref. 15, 7585–7601 (2025). https://doi.org/10.1007/s13399-024-05495-4
21. Palanisamy S, Kalimuthu M, Azeez A, Palaniappan M, Dharmalingam S, Nagarajan R, Santulli C. Wear Properties and Post-Moisture Absorption Mechanical Behavior of Kenaf/Banana-Fiber-Reinforced Epoxy Composites. Fibers. 2022; 10(4):32. https://doi.org/10.3390/fib10040032
22. S. Kim, S. Lee, A. A. Melvin, and J.-W. Choi, "Stimuli-Responsive Polymer Actuator for Soft Robotics," Polymers, vol. 16, no. 18, p. 2660, Sep. 2024, doi: 10.3390/polym16182660.
23. F. H. Jamaludin et al., "Recent Advances in the Field of Shape-Memory Polymer from Bio-Based Precursors: Review and Perspective," Polymer Reviews, pp. 1–51, Nov. 2024, doi: 10.1080/15583724.2024.2427827.
24. Y. Dewang, V. Sharma, V. K. Baliyan, T. Soundappan, and Y. K. Singla, "Research Progress in Electroactive Polymers for Soft Robotics and Artificial Muscle Applications," Polymers (Basel), vol. 17, no. 6, p. 746, Mar. 2025, doi: 10.3390/polym17060746.
25. H. Hassan, H. Hallez, W. Thielemans, and V. Vandeginste, "A review of electro-active shape memory polymer composites: Materials engineering strategies for shape memory enhancement," European Polymer Journal, Mar. 2024, doi: 10.1016/j.eurpolymj.2024.112861.
26. Y. Huang et al., "Enhanced shape memory performance and numerical simulation of knitted-fabric reinforced polymer composites with weft yarns," Polymer Composites, Aug. 2024, doi: 10.1002/pc.28940.

27. R. K. Rao, S. Gautham, and S. Sasmal, “A Comprehensive Review on Carbon Nanotubes Based Smart Nanocomposites Sensors for Various Novel Sensing Applications,” Polymer Reviews, pp. 1–64, Jan. 2024, doi: 10.1080/15583724.2024.2308889.
28. H. M. Firouzjaei, R. Scaciota, and S. Samarakoon, "Multi-Task Lifelong Reinforcement Learning for Wireless Sensor Networks," presented at the Centre for Wireless Communication, University of Oulu, Finland, 2025.
29. Almeshaal, M., Palanisamy, S., Murugesan, T. M., Palaniappan, M., & Santulli, C. (2022). Physico-chemical characterization of Grewia Monticola Sond (GMS) fibers for prospective application in biocomposites. Journal of Natural Fibers, 19(17), 15276–15290. https://doi.org/10.1080/15440478.2022.2123076
30. Y. Gökalp, S. Eti, H. Dınçer, and S. Yüksel, “A novel approach to prioritizing health technology investments using integrated AI-based ranking model,” Journal of Health Organisation and Management, Jan. 2025, doi: 10.1108/jhom-05-2024-0190.

