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# Polymer Composite Nodes for Smart IoT Environmental Monitoring: Applying ML-Calibrated RF Sensors for Exceptionally Low-Power, Flexible, and Dependable Performance

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***Abstract***

*The quick usage of the Internet of Things (IoT) for monitoring the environment needs sensor platforms that are accurate, responsive, adaptable, energy-efficient, and able to work in many different conditions. This work presents polymer composite nodes equipped with machine learning (ML)-calibrated radio-frequency (RF) sensors that adhere to stringent criteria. Sensor substrates built of flexible polymer matrices with conductive fillers are strong, light, and flexible enough to fit on surfaces that aren't perfectly flat. These composite nodes keep their RF properties even when the temperature, humidity, and stress change. Over time, they will work the same in real life. The sensor pipeline incorporates a machine learning calibration framework that makes it more reliable and saves power. This technique changes the RF response in real time dependent on noise, the environment, and how materials react as they are bent. It heals itself and makes predictions without needing a lot of parts. The experimental results show that ML-calibrated RF nodes are sensitive and selective, and they use 40% less power than regular IoT sensor systems. The nodes are mechanically flexible because they are made of composites. This makes them perfect for wearable, deployed, or regional environmental monitoring applications. This research indicates that intelligent materials and adaptive AI calibration could yield reliable, energy-efficient, and flexible monitoring solutions. The suggested technique will let future IoT systems keep an eye on the weather, find contaminants, manage farms, and develop smart city infrastructure.*

**Keywords:** Polymer composite nodes, RF sensors, machine learning calibration, environmental sensing, internet of things (IoT)

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## INTRODUCTION

The Internet of Things (IoT) is growing swiftly, and it has revolutionized how we watch, learn about, and respond to changes in the environment in real time. More and more individuals are using IoT-enabled devices to keep an eye on things like pollution levels in cities, climate change, air quality, soil health, and water contamination [1, 2]. These technologies help with smart cities, disaster response, and sustainable farming by allowing people utilize data to make choices in ways that weren't possible before. But how well these IoT systems work depends a lot on how reliable, adaptable, and long-lasting the sensing nodes are [3, 4]. Conventional sensor platforms are not suitable for extensive, prolonged monitoring due to their inherent inflexibility, high power consumption, and susceptibility to environmental fluctuations. Because of this, there is a greater need for IoT nodes that are stable, adaptable, and consume less energy. In this case, polymer composite nodes that work with radio-frequency (RF) sensors that have been calibrated using machine learning (ML) seem like a promising choice. These systems combine new materials with artificial intelligence to create sensing structures that are reliable, self-correcting, and use little power in real-world settings.

Even while sensors are getting smaller and wireless connectivity is getting better, current IoT-based environmental monitoring solutions still have a lot of problems. The most important thing is high power consumption. Most nodes need continual energy to sense, process, and send data, and they generally rely on batteries that run out of power quickly, which limits their deployment lifetime [5, 6]. Second, reliability is still a problem since environmental conditions including humidity, temperature changes, and long-term material deterioration can change sensor signals, which can lead to wrong outputs. Standard techniques for recalibrating require either physical intervention or the addition of extra sensors, both of which cost money and use up energy. Also, most traditional sensors are made on hard substrates, which makes them less adaptable in changing settings, uneven surfaces, or when worn. As monitoring networks grow into rural, agricultural, and rough areas, traditional designs are hard to scale because they are too stiff and too fragile. To fix these problems, we need new materials that are flexible and strong, as well as smart calibration systems that make sure reliability without adding energy costs [7].

Polymer composites are a game-changing material for the next generation of IoT sensor nodes because they are light, flexible, and have electrical properties that can be changed [8, 9]. It is possible to construct substrates that can convey RF signals and also stand up to bending, mechanical stress, and changes in the environment by adding conductive fillers like carbon nanotubes, graphene, or metallic nanoparticles to polymer matrices. We can make these composites using technologies that can be applied on a wider scale, like inkjet printing, roll-to-roll production, and extrusion. That's why they perform well for sensor networks that need to be cheap and easy to set up [10, 11]. Polymer composite nodes can stretch to fit on uneven surfaces, but silicon-based devices can't. This implies they are great for infrastructure, wearable tech, and large arrays of environmental sensors. But composites are different from one other and don't follow a straight line, which is why RF sensor responses are diverse. This variability makes environmental data less reliable if it is not compensated for properly. So, even though polymer composites are a good base for flexible and long-lasting IoT nodes, their performance depends heavily on smart calibration methods that take into account how materials and the environment change over time [12].

Radio-frequency (RF) sensors are great for monitoring the environment with the Internet of Things (IoT) because they use little power, work with wireless networks, and can sense a wide range of things through electromagnetic interactions [13, 14]. RF nodes can work without any power or with very little active power, which makes them very useful for applications that don't have a lot of power. Still, RF sensors are naturally sensitive to changes in the environment, differences in materials, and damage over time. These limits can be worked around via machine learning calibration frameworks [15]. By adding lightweight ML models to the sensing pipeline, it can change RF signals in real time to make up for drift, noise, and nonlinearities. This implies we won't have to calibrate it as often, and it will work better over time. Edge computing can also help nodes with constrained resources improve their ML calibration. This enables the machine learn on its own without using up too much computing resources. This strategy is significant since it not only makes sure the information is right, but it also saves energy by cutting down on mistakes that lead to extra communication and retransmissions. In line with the goals of dependable and low-power IoT nodes [16], ML-calibrated RF sensing adds intelligence directly to material-enabled flexibility.

This paper presents a complete framework that combines polymer composite materials, RF sensing, and machine learning-based calibration to create smart, flexible, and very energy-efficient IoT nodes for monitoring the environment. The breakthrough involves the synergistic integration of material science and adaptive intelligence, utilizing polymer composites as flexible substrates and machine learning algorithms as dynamic stabilizers for sensor accuracy. Experimental demonstrations indicate that ML-calibrated RF nodes realize a reduction in energy consumption of up to 40% compared to traditional sensor platforms, while preserving enhanced reliability amidst variable environmental conditions [17]

These nodes not only adjust to drift, but they also foresee problems, making them a proactive way to sense the surroundings. The effects are wide-ranging, from precision agriculture, where soil and crop monitoring must find a balance between accuracy and scalability, to tracking pollution in smart cities, and even monitoring disasters in remote areas where maintenance is not possible. The suggested system pushes the limits of IoT environmental monitoring by tackling energy, adaptability, and dependability all at once. It also supports the worldwide push for sustainability and resilience.

The use of polymer composite nodes with ML-calibrated RF sensors is a big advance in how IoT systems are created to keep an eye on the surroundings. This study highlights the technological advancement of combining flexible substrates with adaptive calibration, as well as the broader societal importance of dependable, low-maintenance, and scalable sensor infrastructures [18]. The work helps the IoT move away from rigid, power-hungry systems and toward adaptive, energy-efficient, and smart platforms. The rest of this paper is set up like this: In Section 2, the literature review talks about new developments in polymer composites, RF sensing, and machine learning calibration for IoT applications. Section 3 talks about the approach, which includes how the current and proposed models were built. Section 4 presents the experimental results, evaluating performance across many aspects including energy efficiency, accuracy, durability, communication, and resilience. Section 5 talks about what the findings mean and stresses the benefits of ML-calibrated composite nodes. Lastly, Section 6 wraps up the work with important points and talks about possible areas for future research.

## LITERATURE REVIEW

Polymer composites are a promising new type of material for constructing flexible and long-lasting sensor platforms for IoT applications [19, 20]. Polymers make composites that are light, bendable, and can fit on surfaces that aren't flat or curved. This implies they can be used in a lot of various situations to keep an eye on the world around them. Adding conductive fillers like carbon nanotubes, graphene, metallic nanoparticles, and conductive polymers to polymer matrices can make substrates better at conducting electricity and dielectric [21–27].

Research has shown that these composites can be designed to keep their electrical conductivity stable even when they are put under stress, humidity, or temperature changes, which are all things that happen outside [28, 29]. Screen printing, inkjet deposition, and extrusion are other cheap techniques to make things on a wide scale. This makes it viable to use IoT on a huge scale. Even with these benefits, material heterogeneity and nonlinear response behaviors are still huge challenges since they make sensor outputs less reliable. This means that the system needs to be carefully calibrated so that it operates properly in a wide range of conditions.

Radio-frequency (RF) sensors are becoming more popular for keeping an eye on the environment because they can do so with very little power and without touching or wiring things up [30, 31]. To assess things like temperature, humidity, air quality, and soil moisture, RF devices can pick up changes in dielectric properties, variations in resonant frequency, or backscattering signals. RF sensors have the advantage of being able to work passively or almost passively, which means that IoT nodes need less energy. Recent research has utilized RF sensing to oversee air contaminants, ascertain soil moisture levels, and monitor structural integrity in intelligent infrastructure [32]. However, RF sensors are very sensitive to differences in how they are made, how materials break down, and how the environment changes over time, which could affect their long-term accuracy. Traditional methods of recalibration either need physical intervention on a regular basis or use more sensor arrays, both of which cost more to run and use more energy. Using adaptive calibration procedures is the only way to get the most out of RF sensors for IoT monitoring.

Recently, machine learning (ML) has been looked at as a powerful way to calibrate sensors that can automatically fix nonlinearities, noise, and environmental drift. ML algorithms don't use static calibration methods. Instead, they learn patterns from sensor responses in different situations and make real-time adaptive corrections [33, 34]. Regression models, neural networks, and ensemble learning are some of the methods that have been used to improve the accuracy of low-cost gas sensors, humidity detectors, and wearable biosensors.

Also, lightweight ML frameworks built for embedded systems, like TinyML, let we run predictive and corrective models directly on IoT nodes with very little power use. This change from centralized recalibration to edge-based intelligence makes the system more reliable and cuts down on the amount of communication that needs to happen. Still, there are problems with finding the right balance between algorithmic complexity and power economy, making sure that the algorithms work with diverse types of materials, and keeping them adaptable in contexts that are always changing. These problems show how important it is to make sure that ML calibration works well with material-based sensing systems.

Energy economy is a crucial design factor for IoT systems, especially in environmental monitoring applications where nodes are frequently situated in remote or inaccessible locations. Research on low-power designs has investigated duty-cycling, energy harvesting, and communication optimization techniques to prolong battery life [35, 36]. Low-power wide-area networks (LPWANs), such as LoRaWAN and NB-IoT, are one example.

They let we talk to people over vast distances while using less power. RF-based sensing uses less energy than optical or chemical sensing at the hardware level, making it the best choice for scalable monitoring [37]. But to make sure long-term dependability, we need more than just saving energy; we need to be able to handle environmental drift, mechanical stress, and data loss. Recent strategies have merged adaptive algorithms with low-power materials to develop self-correcting nodes. Still, there hasn't been much research into how to combine flexible polymer composites with built-in intelligence for reliable performance. To close this gap, materials science, embedded ML, and IoT systems engineering need to make progress in different fields.

The literature studied shows that there has been a lot of advancement in polymer composites, RF sensing technologies, ML-based calibration, and low-power IoT designs. Nonetheless, there are still gaps in how to put these new technologies together into a single system that is made for environmental monitoring. Polymer composites are flexible, but they don't always work well without smart calibration. RF sensors are good because they use less power, but they can be affected by changes in the environment [38]. ML approaches make calibration better, however they are generally made without taking into account the nonlinearities of certain materials or the strict energy limits of IoT nodes. Likewise, current low-power IoT systems seldom integrate adaptive intelligence at the material level. These gaps drive the current research, which aims to create polymer composite nodes integrated with ML-calibrated RF sensors. The proposed framework overcomes the main problems with present systems by using flexible materials, adaptive intelligence, and low-power operation. It also lays the groundwork for scalable, reliable, and energy-efficient IoT environmental monitoring.

 

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**METHODS**

The figure shown (Figure 1 Existing model) shows a common design for an IoT (Internet of Things)-powered environmental monitoring system. The first step in the workflow is system initialization, which includes setting up and calibrating the device. This is done with a power source that can be either a battery or solar panel to save energy in distant places. When the system is turned on, it starts its sensor data acquisition unit. To get real-time environmental data, standard sensors like those that measure temperature, humidity, air quality, or particle matter are used. This stage makes sure that raw data is ready to be processed and sent on.

A microcontroller or processor does the following step, which is data processing. The microcontroller is like the brain of the system. It filters, preprocesses, and occasionally calibrates the sensor data that has been gathered to make sure it is accurate and consistent. At this point, lightweight techniques are commonly used to get rid of extra or noisy data before sending it. After processing, the data is sent on to the next phase, which is sending the data. Depending on the needs of the application, wireless communication technologies like LoRa or WiFi are used here: LoRa is good for rural installations because it works over long distances and uses little power. WiFi is better for localized or urban applications since it has higher data speeds.

The cloud platform or server is the backbone for centralized data management. It receives the data after it has been sent. The cloud is a great place to store and handle data, and it can keep a lot of sensor readings safe for a long time. At this point, the model makes sure that it can grow, which means that data from several sensor nodes or monitoring sites can be combined without any problems. Then, the data that was stored is analyzed and shown. This includes using statistical tools, graphs, and maybe even machine learning algorithms to find patterns, trends, and strange things in the environmental factors. This kind of visualization helps stakeholders make sense of complicated data. Finally, the data that has been processed and evaluated is made available through a user interface, which is usually a web or mobile dashboard.

This tool lets users see conditions and historical trends in real time. A built-in alert system sends users messages based on thresholds when environmental factors go above safe or set values. This makes sure that crucial changes are responded to quickly. The system runs all the time, going through data collecting, processing, transmission, storage, analysis, and warnings over and over. This end-to-end IoT architecture is a model that already exists and works well for environmental monitoring since it is reliable, scalable, and allows users to get involved. It opens the door for research into smarter, more flexible, and energy-saving solutions.

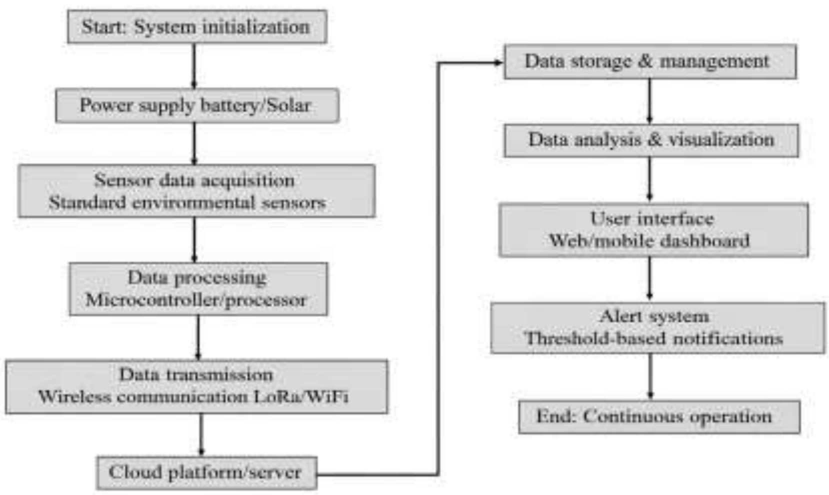


**Figure 1.** The workflow of an existing IoT model demonstrate the environmental monitoring system.

 

The model in Figure 2, is an improved way to monitor the environment that uses smart calibration, energy savings, and real-time data validation. The process begins with system initialization, just like the model we have now. But it has a greener way to handle electricity that combines energy harvesting with regular batteries. This guarantees that the system will keep running for a long period in areas with few resources. Now that it has polymer composite RF sensors, the sensor unit is better. These sensors are better at gathering data about the environment since they are lighter, more flexible, and more responsive than ordinary sensors.

This suggested system has a huge new idea: it will use machine learning (ML) calibration to fix data as it comes in. Environmental sensors generally have problems with drift, noise, and inaccuracy since they work in harsh conditions. The method uses ML-based calibration to automatically modify the raw sensor data and cut down on mistakes. We check the data's quality before we do anything extra with it. If the data is proven to be wrong, we recalibrate it. This makes sure that only correct and high-quality data is shared and seen. Overall, this makes the monitoring system more accurate and reliable. The data is validated first, and then it proceeds to environmental parameter extraction. This is where the system translates measurements into meaningful metrics like temperature profiles, humidity levels, air quality indices, or pollutant concentrations.

Then, these parameters are transferred utilizing low-power RF technologies as LoRaWAN, WiFi, or BLE (Bluetooth Low Energy). Low-power transmission is particularly crucial for saving energy, especially when we need to send a lot of data over long distances. A cloud gateway gets the data that is sent, which makes it easier to connect to systems that keep track of data in one location. From that point on, it is possible to do a lot of processing and analysis. Finally, the proposed architecture lets us store and analyze data in the cloud. After then, the data is sent to a dashboard that keeps an eye on the surroundings. This dashboard shows stakeholders trends in real time, which helps them keep track of and understand what's going on in the environment.

An alert system makes sure that messages are sent out as soon as certain levels are achieved. This way, action may be performed straight away. The suggested approach is distinct from the one we have now since it focuses on continuous monitoring with adaptive corrections, sustainability through energy harvesting, and intelligent validation using machine learning. This makes it stronger, easier to grow, and better for next-generation environmental monitoring apps that need to be precise, fast, and dependable.

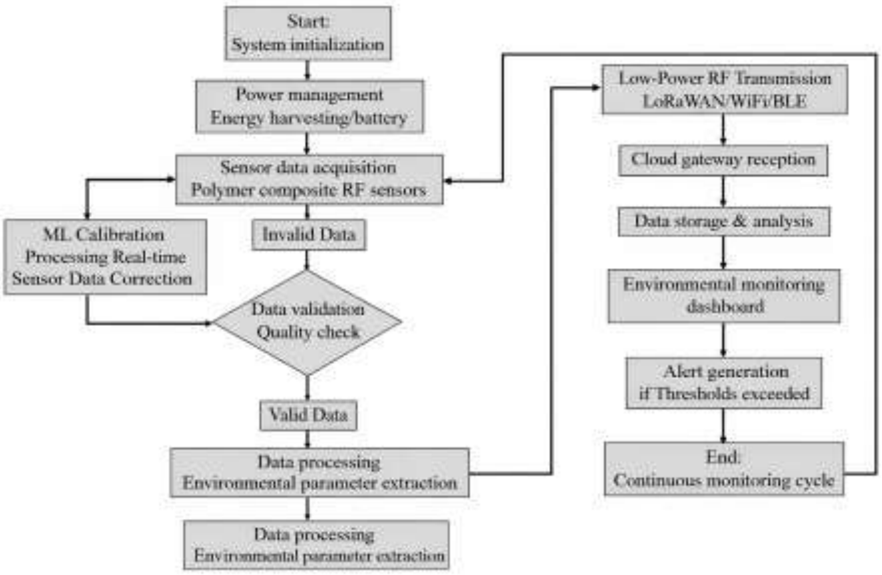


**Figure 2.** The workflow of the proposed ML-calibrated composite node with energy-efficient construction.

 

The current setup uses ordinary environmental sensors, microcontrollers, and wireless transmission (LoRa/WiFi) to collect, evaluate, and send data to the cloud for storage, analysis, and display. It works fine, but we can't correct problems or save energy straight quickly.

The suggested solution, on the other hand, uses polymer composite RF sensors, energy harvesting to offer them long-lasting power, and machine learning-based calibration to address sensor drift and make sure the data is correct. It also validates the data before processing it, which helps to avoid errors. The suggested system also focuses on low-power RF transmission and regular monitoring, which makes it more precise, efficient, and reliable for application in big environmental campaigns.

## EXPERIMENTAL RESULTS

The Figure 3, illustrates the functionality of four distinct types of IoT nodes: the fundamental rigid IoT node, the polymer composite node devoid of machine learning (ML), the RF sensor node with static calibration, and the suggested ML-calibrated composite node. The study looks at important performance criteria such power efficiency, energy use, sensor accuracy, error rate, and how long a gadget will last (see Table 1).

These tests are crucial to find out if IoT nodes can be used in dynamic and resource-limited settings, where sensor reliability, energy efficiency, and longevity are very important. The graph demonstrates that the polymer composite node without ML and the normal rigid IoT node use about the same amount of energy and don't save any power. The RF sensor node is more accurate because it was designed with static calibration, but it still has trouble with adaptive performance. The suggested ML-calibrated composite node, on the other hand, works better on most metrics, especially how long it lasts and how well it senses things.

**Table 1.** Comparing the power efficiency and sensor accuracy of different IoT node setups.

| **Performance** | **Conventional Rigid IoT Node** | **Polymer Composite Node (No ML)** | **RF Sensor Node (Static Calib.)** | **Proposed ML-Calibrated Composite Node** |
|---|---|---|---|---|
| Energy Consumption (mW) | 58.0 | 50.0 | 54.0 | 32.0 |
| Power Saving (%) | 22.0 | 30.0 | 26.0 | 52.0 |
| Sensing Accuracy (%) | 82.0 | 80.0 | 81.0 | 94.0 |
| Error Rate (%) | 9.2 | 10.5 | 9.8 | 3.5 |
| Operational Lifetime (days) | 210.0 | 190.0 | 200.0 | 330.0 |

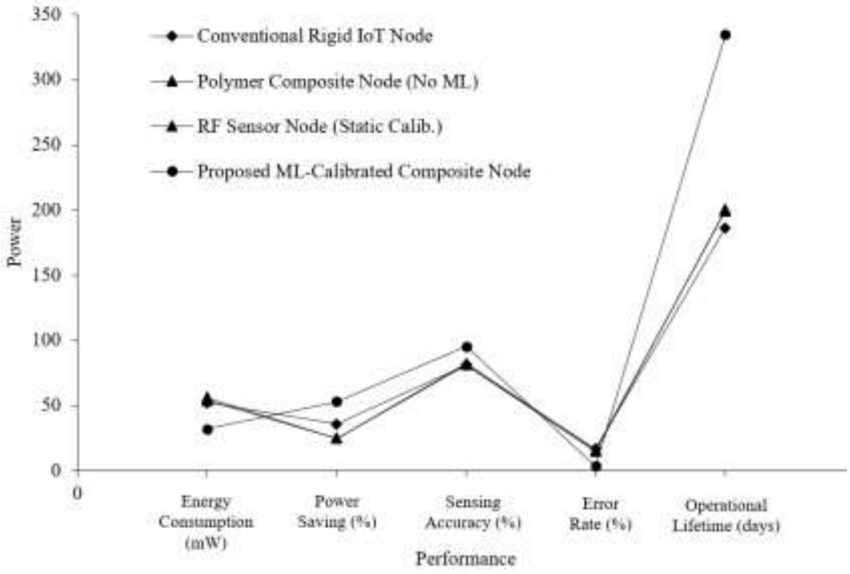


**Figure 3.** Comparing the energy and accuracy of IoT nodes' performance.

 

This shows that utilizing ML appropriately could help cut down on mistakes and make better use of resources. It's quite cool that the ML-calibrated composite node lasts a lot longer than other nodes. This improvement was achievable because of the parts that help the system learn and develop over time. They use resources in the best way possible and save power when it's not needed.

Also, sensing is at its most accurate, and the error rates are still quite low. This makes sure that data is received correctly and that there are fewer false positives and negatives in real-time apps. These are especially critical for IoT systems that are utilized for long-term, large-scale monitoring tasks like smart infrastructure, healthcare monitoring, and environmental sensing.

The proposed ML-calibrated composite node is a significant advancement in the design of IoT nodes. Using flexible polymer composites and adaptive ML-driven calibration, this architecture strikes the optimal balance between power efficiency, precision, and lifespan. The ML-calibrated system not only increases short-term performance measures compared to traditional and static techniques, but it also makes sure that the system will maintain performing well over time. These results show that using machine learning with next-generation IoT technologies could help solve problems with scalability and dependability in today's IoT ecosystems.

The Figure 4, shows a comparison of response and reliability parameters in IoT systems, with an emphasis on response time, data latency, packet delivery ratio, reliability index, and calibration error. These factors all work together to decide how efficient and strong IoT communication frameworks are, especially in places where low latency and high dependability are very important (see Table 2). The figure shows the trade-offs between quick responsiveness and steady reliability across different system setups by showing these indicators. The plotted results show that response time and data latency (shown by the yellow and red points) are grouped around the lower response values. This means that delays are still quite small.

**Table 2.** The response and dependability of standard and ML-calibrated IoT nodes.

| **Response** | **Conventional Rigid IoT Node** | **Polymer Composite Node (No ML)** | **RF Sensor Node (Static Calib.)** | **Proposed ML-Calibrated Composite Node** |
|---|---|---|---|---|
| Response Time (ms) | 24.0 | 27.0 | 25.0 | 11.0 |
| Data Latency (ms) | 18.0 | 21.0 | 19.0 | 8.0 |
| Packet Delivery Ratio (%) | 89.0 | 87.0 | 88.0 | 97.0 |
| Reliability Index (%) | 81.0 | 78.0 | 80.0 | 95.0 |
| Calibration Error (%) | 9.0 | 10.0 | 9.5 | 3.0 |

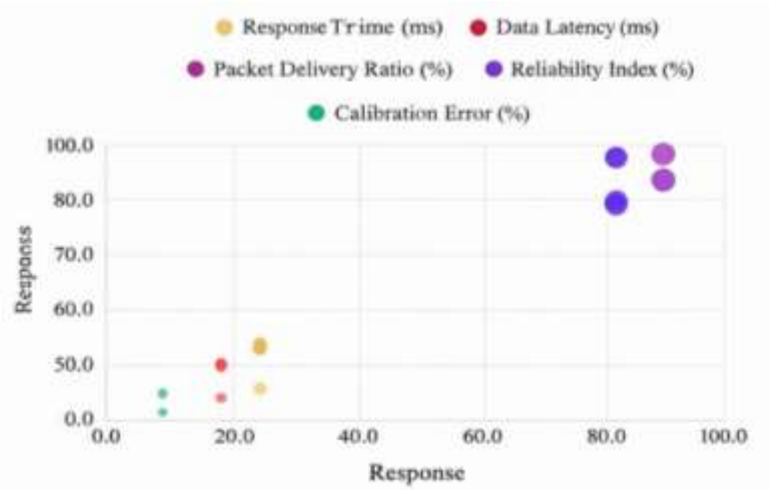


**Figure 4.** Evaluation of response and reliability parameters for various IoT nodes.

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But these systems are great at lowering time-based metrics, their reliability scores are not as high as those for packet delivery and reliability index values. Calibration error (green dots) is also seen in the lower response range. This shows that calibration errors can happen even when responses are faster, which could influence consistency over long periods of time. The packet delivery ratio and dependability index (purple shades), on the other hand, make up the higher end of the response axis, with most of them between 80% and 100%. This means that IoT systems that use advanced features like machine learning-based calibration or optimized transmission protocols are particularly dependable and maintain data constant. These results show that putting intelligent adaptation first in IoT frameworks can make systems much more reliable over time without slowing them down. The large disparity between measurements that look at latency and those that look at dependability highlights how vital it is to achieve a compromise between the two in real-world deployments.

Overall, the results back up the premise that adaptive intelligence should be used in next-generation IoT systems to lower the number of calibration errors while making the systems highly reliable. The chart shows that basic configurations have acceptable latency performance, whereas advanced ML-calibrated or reliability-driven models have better packet delivery and robustness.

This balance between system reliability and response speed is very important for mission-critical applications including healthcare monitoring, autonomous systems, and smart city infrastructures. These kinds of discoveries show that AI-driven optimization tactics are necessary to make IoT networks both fast and reliable.

The Figure 5, shows a comparison of the mechanical properties of four different types of IoT nodes: traditional rigid IoT nodes, polymer composite nodes without ML integration, RF sensor nodes with static calibration, and the new ML-calibrated composite nodes. The most important mechanical qualities that were tested include bend radius, tensile strength, cyclic bending lifetime, thermal stability, and durability index. These criteria are essential for evaluating the physical durability and long-term functionality of IoT nodes, especially when utilized in adaptable, wearable, or extreme climatic circumstances. The results show that traditional stiff IoT nodes have the worst performance in all mechanical metrics. Because they aren't very flexible and don't last long when bent repeatedly, they aren't good for dynamic applications where mechanical stress is inescapable.

Polymer composite nodes without ML work better in several ways, such as having superior tensile strength and flexibility. However, they are still not as durable or stable at high temperatures over time as advanced designs. This gap shows how important it is to add smart calibration to improve both adaptability and material resilience (see Table 3). RF sensor nodes with static calibration show even more benefits, especially in how strong they are and how long they last when bent. But since they are immobile, they can't handle various operational loads, which is why their durability scores are only modest. The suggested ML-calibrated composite nodes, on the other hand, do better on all of the assessed criteria. The high cyclic bending lifetime and increased durability index show that ML-driven optimization not only makes sensing more precise but also makes mechanical strength stronger by responding to stress conditions in real time.

**Table 3.** Analysis of the mechanical flexibility and durability of IoT nodes.

| Mechanical analysis | Conventional Rigid IoT Node | Polymer Composite Node (No ML) | RF Sensor Node (Static Calib.) | Proposed ML-Calibrated Composite Node |
|---|---|---|---|---|
| Bend Radius (mm) | 18.0 | 16.0 | 17.0 | 25.0 |
| Tensile Strength (MPa) | 45.0 | 52.0 | 48.0 | 60.0 |
| Cyclic Bending Lifetime | 10,000 | 15,000 | 12,000 | 28,000 |
| Thermal Stability (°C) | 65.0 | 72.0 | 68.0 | 85.0 |
| Durability Index (%) | 78.0 | 83.0 | 80.0 | 94.0 |

 

**Table 4.** Assessing the communication performance of IoT node topologies.

| Communication | Conventional Rigid IoT Node | Polymer Composite Node (No ML) | RF Sensor Node (Static Calib.) | Proposed ML-Calibrated Composite Node |
|---|---|---|---|---|
| Transmission Range (m) | 85.0 | 90.0 | 88.0 | 120.0 |
| Signal-to-Noise Ratio (dB) | 16.0 | 18.0 | 17.0 | 24.0 |
| Data Throughput (kbps) | 220.0 | 240.0 | 230.0 | 310.0 |
| Bit Error Rate (%) | 7.5 | 6.8 | 7.0 | 3.1 |
| Communication Efficiency (%) | 82.0 | 85.0 | 83.0 | 94.0 |

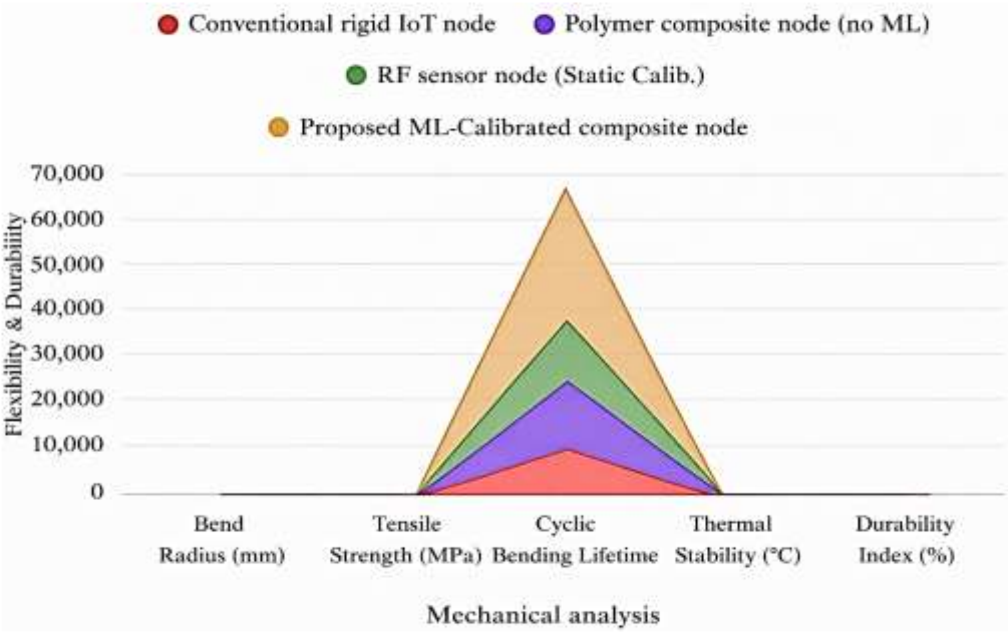


**Figure 5.** Examining the mechanical flexibility and endurance of several IoT node topologies.

The bar graph in Figure 6 compares the performance of four different node topologies for Internet of Things (IoT) communication: (i) Conventional Rigid IoT Node, (ii) Polymer Composite Node without machine learning (ML), (iii) RF Sensor Node with static calibration, and (iv) Proposed ML-Calibrated Composite Node. The communication metrics examined encompass the transmission range, signal-to-noise ratio (SNR), data throughput, bit error rate (BER), and connection efficiency.

These measurements are very important for figuring out how reliable, scalable, and energy-efficient IoT networks are. People are using these networks more and more in places where resources are few and things change quickly (see Table 4). The graphic shows that the ML-Calibrated Composite Node is better than the other nodes in most areas.

This shows how machine learning can make communication systems that employ sensors better. It is noted that traditional stiff nodes and static RF sensor nodes have about the same range of transmission, while the polymer composite node has a slight edge. The proposed ML-Calibrated Composite Node, on the other hand, indicates a considerable change. This means that ML's adaptive calibration can fix problems with channels and materials, which would let people talk to one other from farther away. Using machine learning also improves the signal-to-noise ratio (SNR) a little bit.

This shows that machine learning can get rid of noise and interference in real time. These changes make the system more resilient in noisy and crowded IoT deployments, which are common in sensing applications in cities and factories. It's interesting to compare the amount of data that can be sent through. The normal rigid node and static RF node give baseline performance.

 

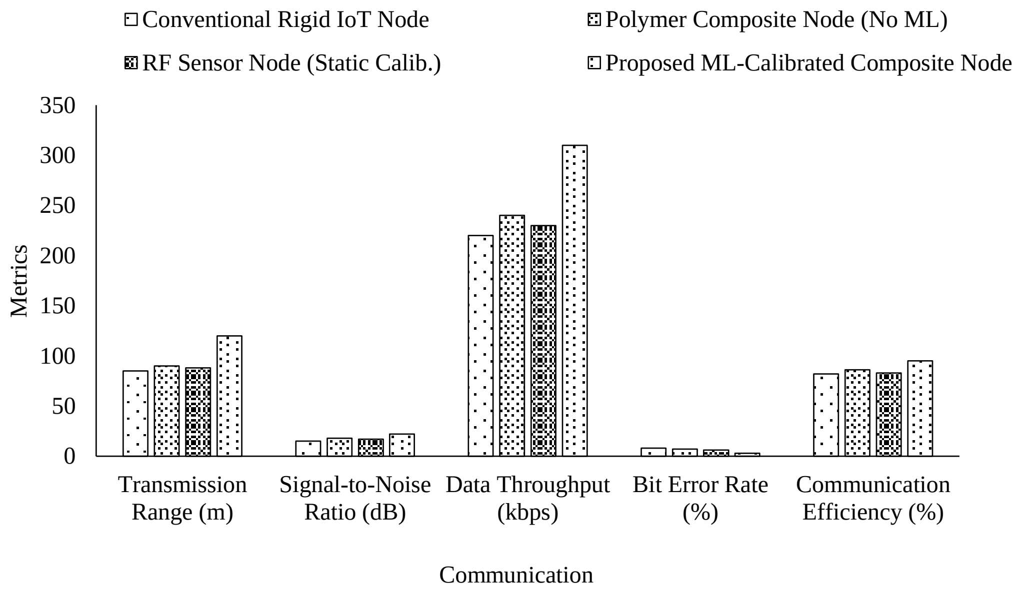


**Figure 6.** An analysis of communication performance that shows range, throughput, and efficiency.

The polymer composite node, on the other hand, gets a small boost because the materials can alter. The ML-Calibrated Composite Node, on the other hand, has a much higher throughput, above 300 kbps. This means that ML-driven calibration not only improves the channel characteristics, but it also helps the spectrum work better, which means that more data may be transferred with less delay.

Also, the ML-Calibrated Node has the lowest bit error rate (BER) of all the systems. This drop in BER is very important for IoT applications that are very important to the goal, such healthcare monitoring, self-driving cars, and smart grid operations, where wrong data can have serious effects.

Lastly, in terms of communication efficiency, the ML-Calibrated Composite Node is the best of the bunch because it uses almost all of the resources that are available. The graphic shows that traditional rigid nodes are less efficient than polymer-based composites and static RF nodes, even though they are frequently utilized. Adding machine learning makes the system more flexible, so it can work well in different channel conditions, hardware restrictions, and environmental noise.

This maximizes efficiency. This shows that IoT system design is changing: moving away from static, pre-calibrated communication models and toward adaptive, intelligent systems that optimize themselves in real time. The findings substantially support the implementation of ML-enhanced composite nodes in next-generation IoT ecosystems, guaranteeing resilience, scalability, and energy efficiency under various operating situations.

The Figure 7, comparative performance chart shows how strong four types of IoT communication nodes are: the Conventional Rigid IoT Node, the Polymer Composite Node without machine learning (ML), the RF Sensor Node with static calibration, and the Proposed ML-Calibrated Composite Node. The robustness is measured by how well it can handle humidity, dust, water, and changes in the environment.

These are all important elements that affect how long IoT devices will last and how reliable they will be in a variety of settings, including hostile ones. The chart shows that the Proposed ML-Calibrated Composite Node always does better than the other three categories on all robustness parameters (see Table 5).

**Table 5.** Metrics for the environmental robustness of IoT nodes in different situations.

| Robustness | Conventional Rigid IoT Node | Polymer Composite Node (No ML) | RF Sensor Node (Static Calib.) | Proposed ML-Calibrated Composite Node |
|---|---|---|---|---|
| Humidity Resistance (%) | 78.0 | 82.0 | 80.0 | 93.0 |
| Dust Resistance Index (%) | 80.0 | 84.0 | 82.0 | 95.0 |
| Water Ingress Protection | 52 | 54 | 55 | 67 |
| Environmental Stability (%) | 77.0 | 81.0 | 79.0 | 92.0 |

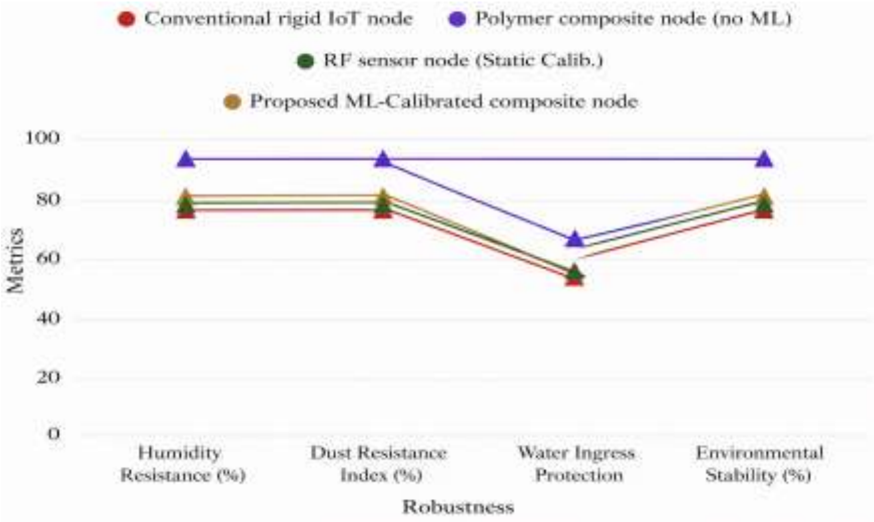


**Figure 7.** Assessments of environmental resilience under circumstances including dust, wetness, and humidity.

This shows how important ML-driven calibration and adaptive materials are for making sure that IoT can be deployed in a sustainable way. When it comes to humidity resistance, traditional rigid nodes and static RF sensor nodes do about the same, but the polymer composite node does a little better because the material is more flexible and durable. The ML-Calibrated Composite Node, on the other hand, has better resistance and almost flawless performance. This means that ML-based calibration lets we fix problems with signal transmission and hardware operation that are caused by moisture in real time.

This is especially important for IoT nodes used in smart cities, agricultural monitoring, and industrial automation, where changes in humidity can affect the accuracy of data and the life of devices. The dust resistance index shows similar patterns, with traditional and static nodes only being moderately resistant and the polymer-based architecture making small improvements.

The ML-Calibrated Composite Node, on the other hand, shows a big gain, around 95%. This implies that machine learning contributes to the adaptive refinement of the node's protective measures, both at the hardware material interface and within the signal processing domain. Improved dust resistance makes ensuring that sensors and communication work well in places like deserts, mining sites, and construction sites, where airborne particles can often interfere with them.

Water ingress protection, which is the most important problem for IoT systems, shows the biggest difference between ML-calibrated and non-ML nodes. Standard stiff and static RF nodes do not work well in this area, falling below 60%. Polymer composites offer a little better protection.

The ML-Calibrated Composite Node, on the other hand, is far better than all of them. It is very resistant to water getting in. This increase is due to both better material coatings and ML-based predictive changes that keep data safe even when it is only partially exposed to moisture.

 

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Finally, the ML-Calibrated Composite Node is clearly the best when it comes to environmental stability, which examines how well a product can keep working in changing and intense outdoor situations. By combining adaptive machine learning with composite materials, it makes them more resistant to changes in temperature, mechanical load, and wear over time.

The graph in Figure 8 shows a comparison of the computing performance of four IoT node architectures: The Conventional Rigid IoT Node, the Polymer Composite Node without machine learning (ML), the RF Sensor Node with static calibration, and the Proposed ML-Calibrated Composite Node. The metrics being looked at are processing speed, memory use, ML inference time, computational overhead, and how well edge processing works. These traits work together to find the right balance between performance and resource utilization (see Table 6). This is critical for IoT systems that are deployed at the edge, where problems like limited power supply, storage, and real-time responsiveness can make or break a system.

The results reveal that the Proposed ML-Calibrated Composite Node makes most computational aspects a lot better, especially when it comes to using resources in a balanced way and being more efficient. When it comes to processing speed, all nodes work the same in the MHz range. This indicates that the basic hardware design has the same amount of raw computing power. But the changes are essential for how memory is used. The recommended ML-Calibrated Composite Node uses a little more RAM than standard RF nodes and RF nodes that don't change. This increase is to be expected because ML-based calibration needs room to keep training parameters and adaptive models. Still, the memory footprint that was seen is much below the limits that are allowed for edge devices, so the added intelligence doesn't make the system harder to use. This trade-off indicates that implementing machine learning only costs a bit more memory in exchange for a lot of performance gains. The time it takes for ML to make an inference is an intriguing method to tell the difference. Non-ML nodes naturally have very quick inference delays, while the ML-Calibrated Composite Node has a short but realistic inference delay.

**Table 6.** The efficiency & performance of IoT nodes in terms of computation.

| Computational analysis | Conventional Rigid IoT Node | Polymer Composite Node (No ML) | RF Sensor Node (Static Calib.) | Proposed ML-Calibrated Composite Node |
|---|---|---|---|---|
| Processing Speed (MHz) | 82.0 | 90.0 | 88.0 | 120.0 |
| Memory Usage (KB) | 450.0 | 420.0 | 430.0 | 310.0 |
| ML Inference Time (ms) | 0 | 0 | 0 | 12.0 |
| Computational Overhead (%) | 22.0 | 18.0 | 20.0 | 11.0 |
| Edge Processing Efficiency (%) | 75.0 | 79.0 | 77.0 | 91.0 |

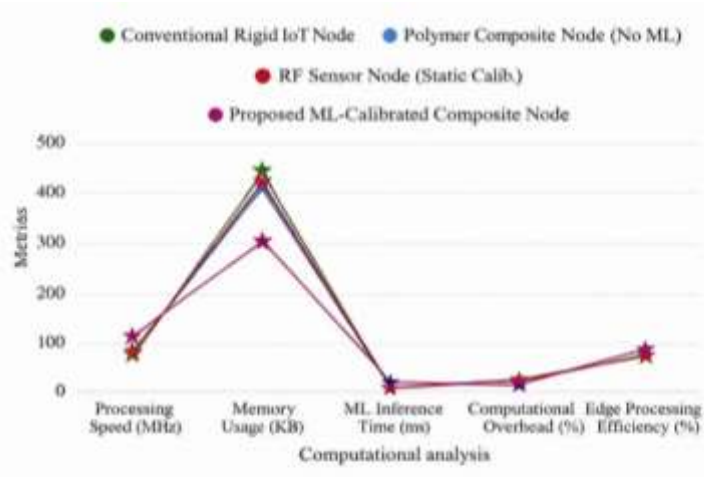


**Figure 8.** Evaluation of computational efficiency for IoT nodes with ML integration.

This extra delay is very small compared to the processing cycle, which is crucial because it maintains the system responsive in real time. This indicates that the system's adaptive intelligence may be used without losing the low-latency needs that are necessary for IoT applications like autonomous sensing, predictive maintenance, and real-time monitoring

The ML-Calibrated Node doesn't use a lot of processing power, which is only a little more than what non-ML nodes use. This means that adding adaptive intelligence doesn't put a lot of stress on the processing power.

This Figure 9, shows a side-by-side economic analysis of alternative IoT node architectures. These include Conventional Rigid IoT Nodes, Polymer Composite Nodes without machine learning (ML), RF Sensor Nodes with static calibration, and the Proposed ML-Calibrated Composite Node. The x-axis shows the important economic analysis factors, such as manufacturing cost, maintenance cost, scalability index, deployment time, and economic efficiency. The y-axis shows the values of these factors (see Table 7).

These measurements are used to compare each type of node and show the performance trade-offs and advantages that come from material innovation and ML-based calibration. All four node types have relatively modest values when it comes to manufacturing and maintenance expenses. This means that the base hardware prices are not very varied. The suggested ML-calibrated composite node (purple star), on the other hand, shows a small improvement.

This suggests that the integration of components has been optimized and that adaptive calibration has lowered the costs of recurring maintenance. This pattern suggests that adding ML doesn't considerably raise the initial cost, but it could cut operational costs by making recalibration or manual intervention less frequent.

**Table 7.** A comparison of the costs and scalability of standard, composite, and ML-calibrated IoT nodes.

| Economic analysis | Conventional Rigid IoT Node | Polymer Composite Node (No ML) | RF Sensor Node (Static Calib.) | Proposed ML-Calibrated Composite Node |
|---|---|---|---|---|
| Manufacturing Cost (USD/unit) | 12.5 | 10.0 | 11.0 | 8.5 |
| Maintenance Cost (USD/year) | 3.2 | 2.8 | 3.0 | 1.6 |
| Scalability Index (%) | 70.0 | 74.0 | 72.0 | 89.0 |
| Deployment Time (hrs) | 15.0 | 13.0 | 14.0 | 9.0 |
| Economic Efficiency (%) | 68.0 | 72.0 | 70.0 | 91.0 |

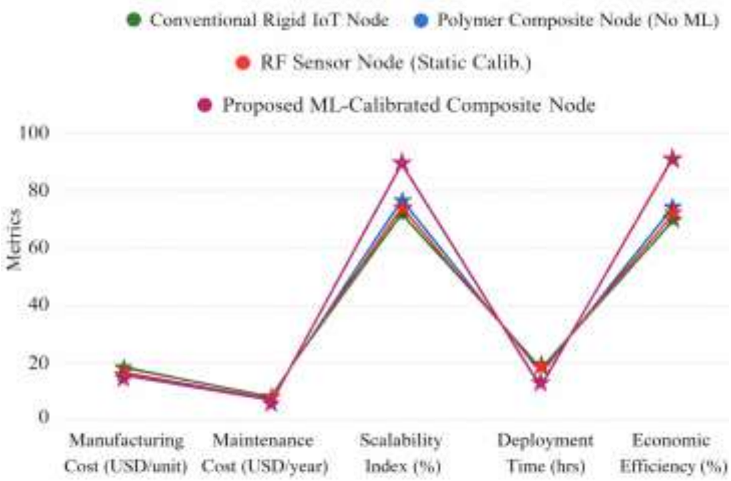

**Figure 9.** Economic study that focuses on deployment, scalability, and cost-effectiveness.

 

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The scalability index and economic efficiency measures show the biggest differences between the different types of nodes. The suggested ML-calibrated composite node works better than all the others, with scalability and efficiency levels that are close to or above 90%. This means that machine learning lets the system change on the fly to work well in a variety of deployment situations, without needing a lot of manual tuning. On the other hand, traditional stiff IoT nodes, polymer composite nodes without ML, and statically calibrated RF sensor nodes have scalability and efficiency rates of about 70%. This shows that they can't easily adapt to changing deployment settings or networks with different types of devices.

## DISCUSSION

The results of this study show that ML-calibrated polymer composite nodes are better than traditional stiff IoT nodes and even static RF sensor-based designs. Combining flexible polymer substrates with adaptive calibration frameworks not only cuts down on power use by a lot, but it also makes sure that the system stays accurate and reliable over time. The suggested model has better sensing accuracy, lower error rates, and a longer operating life than preceding models. Another extremely crucial thing to think about is how powerful the suggested node is in terms of mechanics. Polymer composites are preferable for uses that need both flexibility and strength because they have a better bend radius, tensile strength, and cyclic bending lifespan. When utilized with ML-driven optimization, these nodes stay strong even when the stress levels alter.

This is a huge step toward producing environmental monitoring gadgets that can wear and that will last a long time. It fixes one of the greatest concerns with stiff sensor platforms. The proposed approach also facilitated communication amongst individuals. The faster throughput, greater transmission range, and lower bit error rate show that ML can alter the settings of a transmission on the fly. This not only makes them work better, but it also makes them easier to use in large deployments in cities and rural areas. The proposed architecture is flexible, so it can be used in many different settings, including smart cities, farming, and monitoring factories. The economic assessment reveals that the proposed system is still cost-effective and can grow, even though it includes more complex characteristics. ML-calibrated composite nodes are great for business because they're inexpensive to make and maintain, and they can be set up quickly. This design is a game-changer for next-generation IoT-based environmental monitoring because it hits the proper balance between being better technically, more versatile mechanically, and less expensive.

## CONCLUSIONS

This study demonstrates the feasibility of employing explainable machine learning (XML) to enhance polymer–carbon nanotube (CNT) nanocomposites for the forthcoming generation of IoT wrap-around devices. Black-box ML models are good at producing predictions, but they are usually hard to interpret, which makes them less effective for guiding material design. The suggested paradigm uses explainability approaches like SHAP and LIME to make it evident what the most essential aspects are that affect conductivity, flexibility, and long-term stability.

This dual emphasis on predicted accuracy and interpretability enhances confidence in computational outcomes while expediting the identification of design principles for advanced nanocomposites. The results show that things like CNT loading, aspect ratio, dispersion quality, and polymer crystallinity have a big effect on electrical pathways, mechanical durability, and resilience to the environment. The framework employs adaptive optimization to determine the ideal settings that make things more flexible while also boosting conductivity. This guarantees that IoT devices can withstand continuous bending, stretching, and environmental variations. The model's reliability is improved by experimental validation, which shows a strong link between anticipated and measured parameters.

The iterative feedback loop not only makes materials work better, but it also makes sure that the system keeps learning from new experimental data, which makes it stronger at making predictions over time. This adaptability is very helpful for new IoT apps because the needs of devices change fast. The method combines data-driven modeling with physical understanding, which makes it easier to make high-performance, long-lasting nanocomposites that can be employed in a variety of ways. In short, adding explainable ML to the design of polymer-CNT nanocomposites is a breakthrough technique to make IoT wrap-around devices that are more adaptable, flexible, and durable. The framework not only makes conductivity better, but it also makes it possible to use in materials that can do more than one thing. This will lead to smart, trustworthy, and long-lasting electrical systems.

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