

# A Self-Calibrating, Energy-Autonomous Sensor Node for Long-Term Structural Health Monitoring Using Hybrid Piezo-Thermoelectric Harvesting

**Mr. T Ganeshdas, Associate Professor**

**Mr. Ashok Kumar, Assistant Professor**

**Department of Physical Science, Shadan Degree College for Boys**  
Affiliated to Osmania University, Khairtabad, Hyderabad, Telangana, India

## Abstract

Structural Health Monitoring (SHM) of infrastructure such as bridges, pipelines, and buildings is essential for safety, but long-term operation of sensor nodes is limited by power constraints and sensor drift. This paper presents the design and implementation of a fully **energy-autonomous wireless sensor node** using **hybrid piezo-thermoelectric energy harvesting**. The node combines vibration-based and thermal-gradient harvesting to ensure energy reliability under varying environmental conditions. An onboard microcontroller executes a **lightweight machine-learning-based drift-detection algorithm** that triggers **self-calibration** using an internal reference, maintaining long-term accuracy. Experimental results demonstrate that the system sustains continuous operation at a 5-minute sampling rate using harvested energy alone, with a net positive energy margin of 92 mWh/day. The self-calibration reduces drift error by over 90 % compared with static calibration. The prototype thus demonstrates a practical path toward decade-long, maintenance-free SHM deployments.

**Index Terms** Structural Health Monitoring (SHM), Energy Harvesting, Piezoelectric, Thermoelectric, Self-Calibration, Sensor Drift, LoRaWAN, Low-Power IoT.

## I. Introduction

### A. Background and Motivation

Aging infrastructure worldwide demands continuous condition monitoring to prevent catastrophic failures. Conventional SHM systems rely on wired or battery-powered sensors, which limit deployment scalability and require costly maintenance. Energy harvesting offers a self-sustaining alternative, yet most solutions depend on a single source such as solar radiation, which is intermittent or unavailable in many environments. Moreover, long-term sensor accuracy is degraded by **drift** caused by thermal and mechanical aging.

### B. Problem Statement

Two critical challenges restrict sustainable SHM sensor networks:

1. Ensuring sufficient, reliable energy from ambient sources for sensing, processing, and transmission.
2. Maintaining measurement accuracy autonomously through drift detection and calibration without human intervention.

### C. Proposed Solution

This work introduces a hybrid-harvested, self-calibrating sensor node featuring:

- **Hybrid Piezo-Thermoelectric Energy Harvesting:** simultaneous utilization of vibration and thermal-gradient energy to improve reliability.
- **Efficient Power Management:** employing MPPT-based PMU with combined battery-supercapacitor storage.
- **Intelligent Self-Calibration:** a microcontroller-based drift detection and correction routine that maintains precision over long durations.

## II. Related Work and Research Gap

### A. Energy Harvesting for SHM

Piezoelectric vibration harvesters have been used to power SHM sensors [4]. Hybrid energy systems combining piezoelectric and thermoelectric sources show improved power yield [1], [5].

### B. Low-Power IoT Communication

Low-power MCUs and LPWAN protocols (e.g., LoRaWAN) are established as viable technologies for distributed SHM nodes.

### C. Sensor Drift Compensation

Lightweight algorithms for MEMS drift correction (bias and scale) are proposed in [2] and [3].

### D. Gap Identified

No prior work integrates **multi-source energy harvesting** with **on-device self-calibration** validated for **long-term energy autonomy**. This integration constitutes the novelty of this paper.

## III. System Architecture

Subsystem	Function
Hybrid Energy Harvester	Piezoelectric + Thermoelectric modules scavenge vibration and temperature-gradient energy.
Power Management Unit (PMU)	MPPT, voltage boosting, and dual-stage storage (Li-ion battery + supercapacitor).
Sensing & Processing Core	Ultra-low-power MCU, MEMS accelerometer, temperature sensor, drift-detection logic.
Communication Module	LoRaWAN transceiver for low-data-rate, long-range communication.
Self-Calibration Block	Internal reference routine triggered automatically on drift detection.

## IV. Hardware and Software Implementation

### A. Energy Harvesting Subsystem

- **Piezoelectric Source:** PZT cantilever tuned to 30 Hz structural vibration, average 3.1 mW.
- **Thermoelectric Source:** Commercial TEG (TEC1-12706) mounted across 10 °C gradient, average 3.9 mW.
- **Combined Output:** 7 mW raw, 5.25 mW after PMU efficiency (75 %).

### B. Power Management Unit

- MPPT IC: Texas Instruments BQ25570.
- Storage: 3.7 V LiPo battery (40 mAh) + 0.33 F supercapacitor for burst current.
- Output: 3.3 V regulated rail.

### C. Sensing & Processing Core

- MCU: STM32L476 (Cortex-M4).

- Sensors: ADXL355 (MEMS accelerometer), foil strain gauge, TMP36 (temperature).
- Average sleep current: 5  $\mu$ A.

#### D. Software and Algorithms

1. **Drift Detection:** one-class SVM trained on reference data; triggers recalibration if deviation  $> 2\sigma$ .
2. **Self-Calibration Routine:** measures reference orientation or zero strain, recomputes offset and scale coefficients, stores to NVM.
3. **Duty-Cycle Scheduling:** 5-minute interval (sleep  $\approx 295$  s, sensing  $\approx 4$  s, transmission  $\approx 1$  s).

#### V. Experimental Setup and Characterization

##### A. Energy Harvesting Test Bench

- Piezo tested on shaker table (0.5 g @ 30 Hz).
- TEG evaluated with controlled 10  $^{\circ}$ C gradient.
- Combined output recorded using Keysight DAQ 970A.

##### B. Power Profiling

Measured using Nordic Power Profiler Kit II.

Mode	Current	Duration	Energy (J)	Description
Sleep	5 $\mu$ A	295 s	0.0049	MCU + sensor deep sleep
Sensing	1.5 mA	4 s	0.0198	Sensor acquisition
Transmission	120 mA	1 s	0.396	LoRa uplink
<b>Total / cycle</b>	—	300 s	<b>0.4207 J</b>	5-minute cycle

Average power  $P_{avg}=0.4207/300=1.4\text{mWP}$

Daily consumption = 33.65 mWh/day.

##### C. Harvested Energy

Source	Raw (mW)	Net after PMU (mW)	Daily (mWh)
Piezo	3.1	2.33	55.8
TEG	3.9	2.93	70.2
<b>Combined</b>	<b>7.0</b>	<b>5.25</b>	<b>126.0</b>

Net positive margin =  $126 - 33.65 = 92.35$  mWh/day.

##### D. Storage Sizing

Battery for 24-h autonomy (80 % DoD):

$E_{req}=33.65/0.8=42.07\text{mWh}=11.4\text{mAh}@3.7\text{V}$ .

→ Select  $\geq 40$  mAh Li-ion

Supercapacitor for LoRa burst:

$E=0.396J$ ;  $V1=3.3V$ ,  $V2=2.7V$   
 $C=0.244F \Rightarrow$  choose  $0.33 F$ .

### E. Calibration Energy

$10 s @ 15 mA \rightarrow 0.495 J = 0.137 mWh$ . Weekly calibration adds only  $7 mWh/year (< 0.02 mWh/day)$ . Negligible.

### F. Degraded Scenarios

Scenario	Raw Power (mW)	Net (mW)	Harvest (mWh/day)	Energy Balance
Piezo only	3.1	2.33	55.8	+22.1 mWh surplus
TEG only	3.9	2.93	70.2	+36.5 mWh surplus
Weak harvest (0.5 + 1.0 mW)	1.5	1.13	27.0	-6.6 mWh deficit $\rightarrow$ needs solar assist or larger storage

### G. Self-Calibration Efficacy

Thermal chamber test ( $-10^{\circ}C \rightarrow +60^{\circ}C$ ):

- Uncalibrated MEMS bias drift:  $\pm 27\%$ .
- After self-calibration:  $\pm 2.3\%$ .

$\rightarrow 91.5\%$  drift reduction.

## VI. Results and Discussion

- Energy autonomy:** harvested power exceeds consumption by  $\approx 2.6\times$  under normal conditions, proving continuous operation possible.
- Storage optimization:** minimal battery (40 mAh) + 0.33 F supercap ensures  $> 24 h$  autonomy with minimal size/weight.
- Accuracy maintenance:** calibration algorithm maintains measurement fidelity with negligible energy overhead.
- Scalability:** LoRaWAN enables multi-node deployment across kilometers with centralized data collection.

## VII. Conclusion and Future Work

A self-calibrating, hybrid energy-harvesting sensor node for SHM has been developed and experimentally validated. The prototype achieves full energy autonomy at 5-minute duty cycles, with substantial energy surplus and long-term measurement stability.

Future research will:

- Integrate a photovoltaic micro-harvester for low-vibration environments.
- Extend ML-based drift detection via federated learning across nodes.
- Conduct year-long field trials on bridge structures to assess endurance.
- Develop ruggedized encapsulation for outdoor deployment.

**References (IEEE Style)**

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**Appendix A – Summary of Quantitative Results**

Parameter	Symbol	Value	Unit
Energy per cycle	E_cycle	0.4207	J
Average power	P_avg	1.4	mW
Daily consumption	E_day	33.65	mWh
Harvested energy	E_harv	126	mWh/day
Net surplus	—	92.35	mWh/day
Battery capacity	C_bat	40	mAh
Supercap	C_sc	0.33	F
Drift reduction	—	91.5 %	—