Journal Of Research Technology & Engineering
www.jrte.org

Low-Power Methodologies for MEMS-Based Shock and Vibration Sensors in Remote Monitoring - A Review

H. M. S. L. Herath[1], R.M.T.D.B Rajakaruna, DTND Silva, P. M. K. Alahakoon
NSBM Green University, Homagama, Sri Lanka

mslherath@students.nsbm.ac.lk, rmtdbrajakaruna@students.nsbm.ac.lk , dtndsilva@students.nsbm.ac.lk, mahinda.a@nsbm.ac.lk

Received:22 June 2025; Revised: 30 June 2025; Accepted: 09 July 2025; Available online: 10 July 2025

Abstract: This review examines low-power techniques critical for the implementation of Micro Electromechanical Systems (MEMS)-based shock and vibration sensing systems in remote, long-term monitoring applications. The primary aim is to identify, assess, and compare strategies for reducing power consumption in sensor interfaces, signal conditioning, microcontroller units, wireless communication, and energy harvesting systems. The scope includes ultra-low-power MEMS accelerometer modules, highly efficient microcontroller units with deep sleep mode architectures, and low-power wide-area network protocols such as LoRaWAN. Methodologies involve comparing component data sheets, reviewing published literature and commercial use cases, and analyzing theoretical power consumption in operational scenarios, including periodic duty-cycling and event-driven data acquisition. In industrial applications requiring system autonomy, such as structural health monitoring of bridges or predictive maintenance, this review provides insights into effective low-power solutions. The novelty lies in synthesizing micromechanical sensing techniques, low-power wireless communication, and advanced power management strategies to support fully autonomous remote sensing systems.

Index Terms: Energy Efficiency, LoRaWAN, Low Power Design, MEMS Sensor, Remote Applications, Shock Sensing, Vibration Monitoring

1 Introduction

Continuous monitoring of shock and vibration is vital for industrial and structural applications, enabling early fault detection, safety assurance, and predictive maintenance. Micro-Electro-Mechanical Systems (MEMS) accelerometers are widely used due to their compact size, low cost, and sufficient performance. However, their high-power consumption, particularly during continuous operation and wireless data transmission, poses a challenge for remote, long-term deployments, where frequent battery replacements or complex power infrastructure are impractical.

The demand for low-power solutions is critical in applications like structural health monitoring (SHM) of bridges and buildings [1],condition monitoring of remote wind turbines[2] and tracking sensitive goods in transit[3]. These scenarios require sensors to operate autonomously for years on limited power sources.

MEMS accelerometers measure acceleration via a proof mass suspended by springs, converting deflections into electrical signals[4]. Common wireless technologies paired with these sensors include Bluetooth Low Energy (BLE) for short-range communication, Zigbee for mesh networking, and Low-Power Wide-Area Networks (LPWANs) like LoRaWAN and NB-IoT for long-range transmission [5].

This review aims to comprehensively analyze low-power methodologies for MEMS-based shock and vibration sensing systems. It covers selection criteria for ultra-low-power components (sensors, microcontrollers, wireless modules), circuit design optimization, power-aware firmware strategies, and efficient power management techniques. By synthesizing academic research and commercial solutions, this review provides guidance for developing next-generation remote monitoring systems.

2 LOW-POWER METHODOLOGIES FOR MEMS SENSING

Achieving ultra-low power consumption in MEMS-based sensing systems requires optimization across all system stages

2.1 MEMS Accelerometer Selection

Selecting an appropriate MEMS accelerometer is critical for low-power operation. Key parameters include sleep current, active current at various output data rates (ODR), measurement ranges, resolution, noise density, and features like FIFO buffers and wake-on-motion capabilities.

- **ADXL362 (Analog Devices)**: Known for ultra-low power, it consumes 1.8 µA in motion-triggered wake-up mode and 270 nA in standby mode, with an active current of 3 µA at 100 Hz ODR. It offers 12-bit resolution, an integrated FIFO, and wake-on-motion functionality [6].
- **ADXL345 (Analog Devices)**: Features 13-bit resolution and multiple power modes, consuming 23 µA in measurement mode (100 Hz ODR, 2.5V) and 0.1 µA in standby mode, with activity/inactivity detection and a 32-level FIFO [7].
- **LIS3DH (STMicroelectronics)**: A high-performance 3-axis accelerometer with 2 µA in low-power mode (1 Hz ODR), 0.5 µA in power-down mode, and 11 µA in normal mode (100 Hz ODR). It includes a 32-level FIFO and programmable interrupts for motion detection [8].

Table 1 represents a comprehensive comparison of three leading ultra-low-power MEMS accelerometers, highlighting their power consumption characteristics, functional capabilities, and technical specifications to guide selection for remote monitoring applications.

Table 1: Comparison of Low-Power MEMS Accelerometers

Feature	ADXL362	ADXL345	LIS3DH
Manufacturer	Analog Devices	Analog Devices	STMicroelectronics
Active Current	1.8 µA @ 1 Hz ODR (typ)	23 µA @ 100 Hz ODR (typ, 2.5V)	6 µA @ 50 Hz LPL (typ, 1.8V)
	3.0 µA @ 100 Hz ODR (typ)		11 µA @ 100 Hz NM (typ, 1.8V)
Sleep/Standby Current	270 nA (Standby)	0.1 µA (Standby)	0.5 µA (Power-down)

Wake-up Mode Current	1.8 µA (Motion-activated)	N/A (activity detection)	N/A (motion/event detection)
Output Modes	12-bit digital (SPI)	Up to 13-bit digital (SPI/I2C)	Up to 12-bit digital (SPI/I2C)
Wake-on-Motion	Yes, adjustable threshold	Activity/Inactivity detection	Motion/event detection
FIFO Buffer	512 samples	32 levels	32 levels
Sensitivity (g-range)	±2, ±4, ±8g	±2, ±4, ±8, ±16g	±2, ±4, ±8, ±16g
Noise Density	170 µg/√Hz (typ, ±2g)	150 µg/√Hz (typ, ±2g)	90 µg/√Hz (typ, NM, ±2g)
Supply Voltage	1.6 V to 3.5V	2.0 V to 3.6V	1.71 V to 3.6V
Cost (approx.)	Moderate	Low to Moderate	Low
Reference	[6]	[7]	[8]

The ADXL362 excels in active and wake-up mode currents, making it ideal for battery-powered systems requiring continuous motion monitoring. LIS3DH offers competitive noise performance, while the ADXL345 provides higher resolution.

2.2 Signal Conditioning Optimization

For analog MEMS sensors or applications requiring specific filtering, low-power analog front-end (AFE) design is essential:

- **Operational Amplifiers (Op-amps)**: Use op-amps with nanoampere or picoampere quiescent currents (e.g., Texas Instruments' LPV821, Analog Devices' ADA4505-2) with adequate bandwidth and slew rate [9].
- **Filters**: Employ passive components for anti-aliasing and noise reduction where possible. Active filters should use low-power op-amps. Switched capacitor filters, tunable at lower frequencies, require caution due to clock noise.
- **Analog-to-Digital Converter (ADC) Usage**: Optimize ADC sampling rate and resolution to the minimum required. Power down the ADC when idle. Many low-power MCUs support ADC operation in sleep modes with event triggers [9]. Techniques like powering down unused AFE sections, careful PCB layout, and EMI shielding reduce idle power and noise.

2.3 Microcontroller and SoC Selection

The microcontroller unit (MCU) or System-on-Chip (SoC) significantly impacts power consumption:

- **PIC24F16KA102 (Microchip)**: Features sleep currents down to 20 nA (Deep Sleep) and active currents of 150 µA/MHz, with peripherals operable in sleep modes [10].
- **STM32L0 Series (STMicroelectronics)**: ARM Cortex-M0+ based, with Stop mode at 0.27 µA (RAM retention, RTC active) and active mode at 49 µA/MHz[11].
- **MSP430 Series (Texas Instruments)**: Known for low power, with standby currents below 1 µA (RTC active) and FRAM for efficient writes [12].
- **ATmega328P (Microchip/Atmel)**: Offers power-down modes at 0.1 µA, but active current is higher at 200 µA at 1 MHz, 1.8V [13]

Table 2 represents a detailed comparison of four prominent low-power microcontrollers, examining their power consumption profiles, core architectures, and low-power peripheral capabilities to assist in selecting the most suitable MCU for energy-constrained remote sensing applications.

Table 2: Comparison of Low-Power Microcontrollers

Feature	PIC24F16KA102	STM32L0x1 Series	MSP430FR2xxx Series	ATmega328P
Manufacturer	Microchip	STMicroelectronics	Texas Instruments	Microchip (Atmel)
Core	16-bit PIC	ARM Cortex-M0+	16-bit MSP430	8-bit AVR
Active Current	~150 µA/MHz (typ)	~49 µA/MHz (typ)	~120 µA/MHz (typ)	~200 µA @ 1 MHz, 1.8V
Sleep Current	20 nA (Deep Sleep)	0.4 µA (Stop)	0.5 µA (LPM4)	0.1 µA (Power-down, WDT off)
Wake-up Latency	Fast (<4 µs from Sleep)	Fast (3.5 µs from Stop)	Fast (<6 µs from Standby)	Slower from deep sleep
Operating Voltage	1.8 V to 3.6 V	1.65 V to 3.6 V	1.8 V to 3.6 V	1.8 V to 5.5 V
Low-Power Peripherals	Yes (ADC, Timers in sleep)	Yes (LPRun, LPADC, LPUART)	Yes (ADC, Timers in LPMs)	Limited
Processing Power	Up to 16 MIPS	Up to 32 MHz	Up to 16/24 MHz	Up to 20 MIPS
Reference	[10]	[11]	[12]	[11]

MCUs like the PIC24F and STM32L0 series offer superior deep sleep currents and low-power peripherals, critical for event-driven systems where fast wake-up latency prevents data loss.

2.4 Wireless Transmission Technologies

Wireless communication often dominates power consumption:

- **LoRaWAN**: Provides long-range (2-15 km) communication with low power for small data packets, operating in ISM bands with data rates of 0.3-50 kbps [14].
- **BLE**: Suited for short-range (10-100 m), high-data-rate applications, ideal when gateways are nearby [5].
- **Zigbee**: Supports mesh networking with moderate range (10-100 m) and low power [5].
- **NB-IoT**: Offers cellular-based LPWAN with good penetration but potentially higher power and cost [15]

Table 3 represents a comprehensive evaluation of four major wireless transmission technologies, analyzing their range capabilities, data rates, power consumption characteristics, and operational advantages and limitations to guide the selection of appropriate communication protocols for remote MEMS sensing application

Table 3: Comparison of Wireless Transmission Technologies

Feature	LoRaWAN	BLE 5.0	Zigbee	NB-IoT (Cat-NB1/NB2)
Standard	LoRa Alliance	Bluetooth SIG	IEEE 802.15.4	3GPP Release 13/14+
Range	2-5 km (urban), 15+ km (rural)	10-100 m	10-100 m	1-10 km (macro cell)
Data Rate	0.3-50 kbps	125 kbps to 2 Mbps	Up to 250 kbps	20-250 kbps (DL), 20-100 kbps (UL)
Typical Transmit Current	20-150 mA (dep. on power & SF)	5-15 mA	15-40 mA	100-250 mA
Sleep Current (Module)	<2 µA	<2 µA	<2 µA	<5 µA
Pros	Long range, low power	Low power, high data rate	Mesh networking	Good coverage, cellular infra
Cons	Low data rate, duty cycle limits	Short range	Shorter range than LoRa	Higher cost, carrier dependent
Reference	[16][14]	[5]	[5]	[15]

2.5 Duty-Cycling and Wake-on-Shock

Duty-cycling reduces the average power consumption of a system by alternating between low-power sleep periods (T_{OFF}) and active periods (T_{ON}). Equation 1 represents the mathematical relationship for calculating average power consumption in duty-cycled systems, where the system alternates between active and sleep states to minimize overall energy consumption:

$$P_{avg} = \frac{P_{ON} \times T_{ON} + P_{OFF} \times T_{OFF}}{T_{ON} + T_{OFF}} \quad \dots\dots\dots\dots\dots\dots\dots (1)$$

Since P_{OFF} is significantly lower than P_{ON}, increasing the duration of T_{OFF} leads to a reduction in P_{avg}. One effective technique is **wake-on-shock**, where the sensor activates the microcontroller unit (MCU) only when a predefined acceleration threshold is exceeded. This approach minimizes unnecessary wakeups, thereby conserving power[6].

2.6 Power Management Techniques

- **Batteries**: Lithium-thionyl chloride ($Li\text{-}SOCl_2$) batteries provide high energy density and long shelf life, while lithium-ion or LiPo batteries are rechargeable but have higher self-discharge [17][18]
- **Energy Harvesting**:
  - **Solar Panels**: Enable perpetual operation with sufficient light, using Maximum Power Point Tracking (MPPT) ICs (e.g., BQ25504) [19].
  - **Vibration Energy Harvesting**: Converts ambient vibrations into energy via piezoelectric or electromagnetic harvesters, though output is low and variable [20].
- **Super Capacitors**: Handle peak current demands, extending battery life.
- **Voltage Regulators**: High-efficiency DC-DC converters or Low Dropout Regulators (LDOs) with low quiescent current are essential.

Table 4 represents an analysis of various power sources and voltage regulation components, detailing their key characteristics and efficiency considerations to guide the selection of appropriate power management solutions for long-term autonomous operation in remote sensing applications.

Table 4: Power Sources and Regulator Efficiency Considerations

Power Source/Component	Key Characteristics	Efficiency/Considerations
$Li\text{-}SOCl_2$ Battery	High energy density (~1280 Wh/kg), long shelf life	Non-rechargeable, flat voltage profile
Li-Po Battery	Rechargeable, good power density	Higher self-discharge, needs charging circuit
Solar Panel	Renewable energy source	Varies with light, requires MPPT
Super Capacitor	High power density, fast charge/discharge	Lower energy density, used for peak loads
LDO Regulators	Low noise, simple	Efficiency = V_{OUT}/V_{IN}, low I_Q critical
DC-DC Converters	High efficiency (80-95%+)	Can be noisy, quiescent current important

3. COMPARISON OF EXISTING SYSTEMS (CASE STUDIES)

This section reviews academic and commercial systems to benchmark low-power MEMS-based shock and vibration sensors, focusing on architecture, components, and power strategies.

Case Study Selection Criteria: Systems were selected based on ultra-low-power operation, use of MEMS accelerometers, wireless communication, and availability of technical details [21]

Case Study 1: Autonomous SHM Sensor 2 (ASN-2)[21]

- **Source**: Sabato et al. (2016)
- **Overview**: A review of wireless MEMS-based accelerometer boards for autonomous SHM in civil structures.
- **System:** Boards integrate MEMS sensors, microcontrollers, ADCs, and wireless radios in WSNs (single/multi-hop).
- **Power Strategy**: Battery-powered with duty cycling; some use solar harvesting for extended autonomy.
- **Performance** Detects microvibrations (as low as 0.14×10^{-3} m/s^2) and low frequencies (<1 Hz); validated on bridges, turbines, and buildings.
- **Relevance**: Proves MEMS-based WSNs are reliable, low-cost solutions for autonomous, long-term SHM.

Case Study 2: Multimetric Event-Driven System for SHM [22]

- **Source**: Frnda et al. (2019)
- **Overview** The paper proposes a neural network (NN)-based method to improve the accuracy of the ECMWF global weather forecast model, aiming to match the performance of higher-resolution regional models like ALADIN.
- **System**: Uses sensor data from automatic weather stations (AWS) in Slovakia and Czech Republic to collect real-time weather variables (temperature, precipitation). These are combined with ECMWF and ALADIN forecast data, green infrastructure ratios, and air quality indices for model training.
- **Power Strategy**: this is a software model using remote sensor data and computing, not a physical node with power constraints.
- **Performance**: The enhanced model using a multi-layer perceptron neural network improved ECMWF forecast accuracy, especially in urban areas. Accuracy for temperature rose above ECMWF levels ($R \approx 0.915$), and precipitation predictions also improved. Cross-validation showed consistent improvements over standard ECMWF results.
- **Relevance** The approach enables real-time, cost-effective improvement of global forecasts without high-performance computing, making accurate local forecasting more accessible and scalable across regions.

Case Study 3: Low-Cost MEMS Accelerometer and Microphone Sensor [23]

- **Source**: Jakobsen, M. (2024)
- **Overview** A low-cost wireless sensor for industrial condition monitoring using MEMS accelerometer and ultrasonic microphone.
- **System**: Includes ADXL1002 and ADXL362 accelerometers, SPH0641LU microphone, Apollo3 MCU, BLE and LoRa radios.
- **Power Strategy**: Runs on a 3.7 V LiSoCl battery with supercap and fuel gauge, using selective power control for efficiency.
- **Performance** Captures vibration up to 80 kHz, supports raw data (BLE) or features (LoRa), and detects bearing defects via FFT.
- **Relevance** Enables affordable, high-frequency monitoring and on-device ML for predictive maintenance in Industry 4.0.

Case Study 4: WindNode [24]

- **Source**: Zanelli et al. (2021)
- **Overview**: WindNode is a low-power wireless sensor node for Structural Health Monitoring (SHM), designed to measure wind-induced vibrations using onboard processing and solar energy harvesting.
- **System** Features an ADXL345 MEMS triaxial accelerometer, dsPIC33EP microcontroller, and Nordic nRF52840 BLE module (via Fanstel BT840F). Housed in a rugged 3D-printed CPE enclosure with a monocrystalline PV panel and 2000 mAh Li-Po battery.

- **Power Strategy** Employs low-power components, sleep-mode cycling, LTC3331 power manager, and LTC2942 battery gauge. Operates for over 1 month without sunlight.
- **Performance**: Onboard FFT up to 100 Hz, BLE range up to 250 m with antenna. Validated via lab tests and a 3-month outdoor deployment in −20 °C Canadian winter. Detects peak vibrations up to 0.4 g with strong accuracy.
- **Relevance**: Proves reliable, autonomous SHM with wireless data transmission and onboard signal processing—ideal for remote or harsh environments.

Case Study 5: Erbessd Phantom EPH-U14 [25]

- **Source**: Erbessd Instruments
- **Overview**: Commercial all-in-one sensor for vibration, current, and temperature.
- **System**: MEMS tri-axis accelerometer, embedded processor, wireless (likely LPWAN), 2×AAA batteries.
- **Performance**: 2-3 years battery life, IP67 enclosure, RMS/FFT processing.
- **Relevance**: Represents a commercial benchmark for multi-year operation.

Table 5 represents a comprehensive comparison of five case studies examining different low-power MEMS-based sensing systems, analyzing their sensor configurations, power management strategies, communication technologies, and operational performance to demonstrate the current state-of-the-art in remote monitoring applications.

Table 5: Summary Comparison of Case Studies

Feature	**ASN-2** [21]	**Multimetric System** [22]	**LoRa/BLE Sensor** [23]	**WindNode** [24]	**Erbessd Phantom** [25]
Primary Sensor	PZT (Impedance)	ADXL362/ Strain Gauges	ADXL362/ ADXL1002/ Mic	ADXL345 MEMS Tri-axial Accelerometer	MEMS Tri-axis Accel.
MCU	TI MSP430	ATtiny85+ Main Platform	ESP32 or Apollo3 (ULP)	Microchip dsPIC33EP512GP806	Embedded Processor
Communication	Custom Wireless	LoRa/Zigbee	LoRaWAN/ BLE	BLE (nRF52840 via Fanstel BT840F)	Wireless (likely LPWAN)
Key Power Strategy	On-board processing, duty-cycle	Hierarchical event triggering	ULP sensor, processed data	On-board processing, solar PV energy harvesting, optimized sleep/wake cycle	Optimized duty-cycling
Sleep Power	0.15 mW	nA range (trigger mode)	Varies (e.g., ADXL362 = 270 nA)	0.7 mA (sleep mode)	Low µA range
Active Power	18 mW	Main	Varies	11.1 mA (active), 41.1	Not

		platform dependent		mW total	specified
Battery Life	Long-term	Extends main platform life	Mode-dependent	>1 month on battery alone, full autonomy with solar PV	2–3 years
Enclosure	Not specified	Compact custom board	Open PCB (no case)	3D-printed CPE, shock/weather-resistant	IP67 enclosure
Processing	Impedance analysis + pulse excitation	Event-based trigger	FFT+ TinyML capable	On-board FFT, sends max amplitude/freq only	On-board RMS/FFT
Strengths	Ultra-low-power active sensing	Ultra-low-power sleep and event logic	Multi-sensor, open source	Field-tested, solar-powered, reliable at −20 °C, FFT onboard, BLE	Rugged, integrated solution
Limitations	Not vibration-only	Requires external platform	Higher power if all sensors active	BLE range limit (~200 m), PV dependent	Proprietary, no open raw data access

4. CHALLENGES AND LIMITATIONS

- **MEMS Sensor Drift and Noise**: Drift over time and temperature affects accuracy, while low-power modes may increase noise, limiting detection of subtle faults [26].
- **Wireless Reliability**: Harsh environments with EMI, metallic structures, or crowded ISM bands challenge signal reliability.[27]
- **Accuracy vs. Energy Trade-offs**: Higher sampling rates or resolutions increase power and data volume, while longer sleep periods risk delayed event detection [28].
- **Sensor Aging and Temperature Sensitivity**: Mechanical stress and temperature variations impact sensor performance and battery capacity[6].
- **Power Source Limitations**: Battery life prediction is complex, and energy harvesting is unpredictable, requiring robust management [19][20]

5. FUTURE DIRECTIONS

- **TinyML for Anomaly Detection**: Local machine learning on ultra-low-power MCUs can reduce data transmission by detecting critical events [29].
- **Advanced Energy Harvesting**: Multi-source harvesters and improved supercapacitors enhance longevity [30].
- **Multi-Node Synchronization**: Low-power time synchronization for LPWANs supports large-scale SHM [31]
- **New ULP Components**: Advances in RISC-V, ARM Cortex-M, and MEMS sensors promise lower power and better performance.

- **Enhanced Wireless Protocols**: Evolving LPWANs (e.g., LoRaWAN, 5G NR+) offer improved trade-offs [32].
- **Security**: Energy-efficient security mechanisms are critical for IoT devices.

6. CONCLUSION

This review provides a comprehensive analysis of low-power methodologies for MEMS-based shock and vibration sensing systems in remote monitoring. Key strategies include selecting components with minimal sleep currents, leveraging sensor-driven wake-up mechanisms, optimizing active-mode efficiency, choosing appropriate wireless protocols, and implementing robust power management. Comparative analysis of academic and commercial systems highlights the feasibility of multi-year battery life. Challenges such as sensor drift, wireless reliability, and energy-accuracy trade-offs persist, but advancements in TinyML, energy harvesting, and ultra-low-power components promise further improvements. Thorough component characterization and real-world testing are essential for reliable, long-lasting remote monitoring solutions.

7. REFFERENCES

[1] V. R. Gharehbaghi *et al.*, "A Critical Review on Structural Health Monitoring: Definitions, Methods, and Perspectives," *Arch. Comput. Methods Eng.*, vol. 29, no. 4, pp. 2209–2235, 2022, doi: 10.1007/s11831-021-09665-9.

[2] P. Tchakoua, R. Wamkeue, M. Ouhrouche, F. Slaoui-Hasnaoui, T. A. Tameghe, and G. Ekemb, "Wind turbine condition monitoring: State-of-the-art review, new trends, and future challenges," *Energies*, vol. 7, no. 4, pp. 2595–2630, 2014, doi: 10.3390/en7042595.

[3] J. Wang *et al.*, "Wireless sensor network for real-time perishable food supply chain management," *Comput. Electron. Agric.*, vol. 110, pp. 196–207, 2014, doi: 10.1016/j.compag.2014.11.009.

[4] M. Zhao *et al.*, "Optical Interferometric MEMS Accelerometers," *Laser Photonics Rev.*, vol. 18, no. 2, 2023, doi: 10.1002/lpor.202300713.

[5] A. Ikpehai *et al.*, "Low-power wide area network technologies for internet-of-things: A comparative review," *IEEE Internet Things J.*, vol. 6, no. 2, pp. 2225–2240, 2019, doi: 10.1109/JIOT.2018.2883728.

[6] O. Mems, "ADXL362 Datasheet," Analog Devices, Rev. PrB, 40 pp., Feb. 2023. [Online]. Available: https://www.analog.com/media/en/technical-documentation/data-sheets/adxl362.pdf.

[7] Analog Devices, "ADXL345 Datasheet (Rev. G)," 36 pp., 2022. [Online]. Available: https://www.analog.com/media/en/technical-documentation/data-sheets/adxl345.pdf.

[8] STMicroelectronics, "LIS3DH Datasheet," DocID17530 Rev 2, 42 pp., May 2015. [Online]. Available: https://www.st.com/resource/en/datasheet/lis3dh.pdf.

[9] Texas Instruments, "LPV821, 650 nA, Precision, Nanopower, Zero-Drift Amplifier," 18 pp., 2017. [Online]. Available: https://www.ti.com/lit/gpn/LPV821.

[10] Microchip Technology, *PIC24F16KA102 Family Data Sheet 16-Bit Flash Microcontrollers with nanoWatt XLP TM Technology*. 2009. [Online]. Available: http://ww1.microchip.com/downloads/en/DeviceDoc/PIC24F16KA102_Family_datasheet_39927b.p

df

[11] M. C. U. Arm, “Datasheet STM32L081CB, STM32L081CZ, STM32L081KZ,” no. November, 2019, [Online]. Available: https://www.st.com/resource/en/datasheet/stm32l081cb.pdf

[12] Texas Instruments, “BOOSTXL-EDUMKII Educational BoosterPack™ Plug-in Module Mark II,” no. August 2015, p. 20, 2015, [Online]. Available: http://www.ti.com/lit/ug/slau599a/slau599a.pdf

[13] Atmel, “ATmega328P 8-bit AVR Microcontroller with 32K Bytes In-System Programmable Flash DATASHEET,” *Datasheet*, pp. 1–294, 2016, [Online]. Available: https://ww1.microchip.com/downloads/en/DeviceDoc/Atmel-7810-Automotive-Microcontrollers-ATmega328P_Datasheet.pdf

[14] H. Xie, D. Huang, Y. Long, and Q. Wang, “A Rate Adaptation Scheme with Enhanced Loss Differentiation for LoRaWAN Communications,” *J. Phys. Conf. Ser.*, vol. 1237, no. 3, 2019, doi: 10.1088/1742-6596/1237/3/032064.

[15] G. Singh and S. Kundu, “An efficient DC-DC boost converter for thermoelectric energy harvesting,” *AEU - Int. J. Electron. Commun.*, vol. 118, p. 153132, 2020, doi: 10.1016/j.aeue.2020.153132.

[16] Semtech, “SX1261/2 Datasheet,” Rev 1.1, 107 pp., Dec. 2017 (latest published). [Online]. Available: https://www.mouser.com/datasheet/2/761/DS_SX1261-2_V1.1-1307803.pdf.

[17] H. C. Hesse, M. Schimpe, D. Kucević, and A. Jossen, “Lithium-Ion Battery Storage for the Grid—A Review of Stationary Battery Storage System Design Tailored for Applications in Modern Power Grids,” *Energies*, vol. 10, no. 12, Art. no. 2107, Dec. 2017, doi:10.3390/en10122107.

[18] Tadiran, “Tadiran Lithium Batteries,” Technical Catalogue (product-data-catalogue), 2012. [Online]. Available: https://tadiranbatteries.de/wp-content/uploads/2023/02/product-data-catalogue-tadiran-lithium-batteries.pdf

[19] T. Sanislav, G. D. Mois, S. Zeadally, and S. C. Folea, “Energy Harvesting Techniques for Internet of Things (IoT),” *IEEE Access*, vol. 9, pp. 39530–39549, 2021, doi: 10.1109/ACCESS.2021.3064066.

[20] A. Muscat, S. Bhattacharya, and Y. Zhu, “Electromagnetic Vibrational Energy Harvesters: A Review,” *Sensors*, vol. 22, no. 15, 2022, doi: 10.3390/s22155555.

[21] A. Sabato, C. Niezrecki, and G. Fortino, “Wireless MEMS-Based Accelerometer Sensor Boards for Structural Vibration Monitoring: A Review,” *IEEE Sens. J.*, vol. 17, no. 2, pp. 226–235, 2017, doi: 10.1109/JSEN.2016.2630008.

[22] J. Frnda, M. Durica, J. Nedoma, S. Zabka, R. Martinek, and M. Kostelansky, “A weather forecast model accuracy analysis and ecmwf enhancement proposal by neural network,” *Sensors (Switzerland)*, vol. 19, no. 23, pp. 1–15, 2019, doi: 10.3390/s19235144.

[23] M. O. Jakobsen, “Low cost MEMS accelerometer and microphone based condition monitoring sensor, with LoRa and Bluetooth Low Energy radio,” *HardwareX*, vol. 18, no. March, p. e00525, 2024, doi: 10.1016/j.ohx.2024.e00525.

[24] Z. Federico, C.-D. Francesco, D. Tarsitano, M. Mauri, B. M. Laura, and G. Diana, “Design and field validation of a low power wireless sensor node for structural health monitoring†,” *Sensors (Switzerland)*, vol. 21, no. 4, pp. 1–17, 2021, doi: 10.3390/s21041050.

[25] S. Iwasaki, “Vibration sensor,” *J. Acoust. Soc. Am.*, vol. 74, no. 5, pp. 1664–1664, 1983, doi: 10.1121/1.390075.

[26] D. Sethurama, R. Keshavamurthy, S. Paljor, P. E. Rohit, and P. G. Koppad, “Effect of multiple reinforcements (CNT/Si3N4) on hardness, electrical conductivity and friction coefficient of aluminium hybrid composites,” *J. Phys. Conf. Ser.*, vol. 1455, no. 1, 2020, doi: 10.1088/1742-6596/1455/1/012011.

[27] Y. Wang and Z. Xu, “Adaptive feedforward compensating self-sensing method for active flutter suppression,” *Sensors (Switzerland)*, vol. 18, no. 10, 2018, doi: 10.3390/s18103447.

[28] B. Alawieh, Y. Zhang, C. Assi, and H. Mouftah, “Improving spatial reuse in multihop wireless networks- A survey,” *IEEE Commun. Surv. Tutorials*, vol. 11, no. 3, pp. 71–91, 2009, doi: 10.1109/SURV.2009.090306.

[29] P. Maurya, A. Hazra, P. Kumari, T. B. Sørensen, and S. K. Das, “A Comprehensive Survey of Data-Driven Solutions for LoRaWAN: Challenges and Future Directions,” *ACM Trans. Internet Things*, vol. 6, no. 1, 2025, doi: 10.1145/3711953.

[30] K. Subasinghage and K. Gunawardane, “Supercapacitor-Assisted Energy Harvesting Systems,” *Energies*, vol. 17, no. 15, pp. 1–17, 2024, doi: 10.3390/en17153853.

[31] A. Khalifeh *et al.*, “Low Power Wide Area Network (LPWAN) Protocols: Enablers for Future Wireless Networks,” *Results Eng.*, vol. 27, no. December 2024, p. 105866, 2025, doi: 10.1016/j.rineng.2025.105866.

[32] Y. Chen, Y. A. Sambo, O. Onireti, and M. A. Imran, “A Survey on LPWAN-5G Integration: Main Challenges and Potential Solutions,” *IEEE Access*, vol. 10, pp. 32132–32149, 2022, doi: 10.1109/ACCESS.2022.3160193.