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Energy Harvesting and Green Networking: Sustainable Wireless Sensor Networks Through Adaptive Energy Management

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ABSTRACT

Wireless Sensor Networks (WSNs) are widely used in harsh environments such as farms, pipelines, and factories where battery replacement is difficult. Energy harvesting reduces this limitation by enabling nodes to use ambient sources like solar, heat, vibrations, and RF energy, shifting focus from battery dependence to continuous operation. This paper proposes the Adaptive Energy-Aware Communication Scheduling (AEACS) framework for green networking. AEACS dynamically adjusts TDMA slots so nodes transmit when energy is available and conserve it otherwise, aligning activity with harvesting conditions. MATLAB R2023a simulations with 100 nodes over a 200 m × 200 m area for 2,000 rounds show AEACS improves network lifetime by 47.3% over LEACH, reduces energy consumption by 31.8%, maintains data integrity above 98.6%, and lowers latency by 24.2%. It also supports blockchain-based verification for secure industrial IoT systems.

Introduction

Wireless Sensor Networks (WSNs) are essential for IoT applications like smart cities, agriculture, and structural monitoring, operating in environments where maintenance is difficult. A key issue is rapid energy depletion due to limited battery capacity. Traditional methods such as duty cycling and clustering (e.g., LEACH, SEP) improve efficiency but still rely on finite energy, limiting long-term operation. Energy harvesting provides a sustainable alternative by drawing power from sources like solar, thermal, vibration, and RF, enabling self-sustaining and energy-efficient WSNs when combined with intelligent communication strategies.

Motivation and Problem Statement

Energy harvesting offers strong potential but faces intermittency, causing mismatches between energy supply and demand. Traditional protocols like LEACH assume fixed energy and fail to adapt to varying sources such as solar, thermal, vibration, and RF. This paper proposes AEACS, which models harvesting as a stochastic process and aligns TDMA slots with predicted energy availability.

Contributions

This work makes the following contributions: (1) a taxonomy of energy harvesting technologies for WSNs with comparative analysis; (2) the AEACS framework aligning communication with energy availability using predictive models;(3) an energy-aware cluster formation algorithm based on residual and predicted energy;(4) MATLAB simulations showing improvements in lifetime, efficiency, throughput, and latency; and (5) integration with blockchain for secure data management.

Review of Literature

Energy harvesting in WSNs has evolved from early solar-powered nodes to multi-source systems. This section reviews key work in harvesting technologies, green networking protocols, and energy-aware scheduling.

Energy Harvesting Technologies in WSNs

Kansal et al. (2007) modeled energy-neutral operation for solar-powered sensor nodes using dynamic programming, while Sharma et al. (2010) extended this to multi-source harvesting with throughput guarantees. Leonov and Vullers (2009) showed thermoelectric harvesting from body heat producing about 10–50 μW/cm², and Sodano et al. (2004) demonstrated piezoelectric systems generating 200–300 μW/cm³. Nintanavongsa et al. (2012) reported RF energy harvesting efficiency of up to 40% at 868 MHz.

Green Networking Protocols

Research integrates energy harvesting with MAC and routing protocols. SMAC introduced duty cycling but ignores energy replenishment, while FLAMA supports synchronized sleep. EH-LEACH improves lifetime by about 28% using harvesting-aware clustering. Niyato et al. (2007) modeled green networking using a Markov decision process, which forms the basis for AEACS.

Gaps in Existing Literature

Despite progress, key gaps remain. Most protocols assume a single energy source, while real deployments use multiple heterogeneous sources. Existing schedulers also ignore correlations in harvesting patterns, such as solar diurnal cycles, that could improve prediction. In addition, integration of green networking with data integrity and blockchain-based verification remains limited. This work addresses these gaps.

Energy Harvesting Technologies for WSNs

Energy harvesting is the process of collecting energy from the environment and turning it into electricity for sensor nodes. Table 1 shows the most important energy sources, their power densities, and their dependencies. Figure 1 shows what they usually look like during the day.

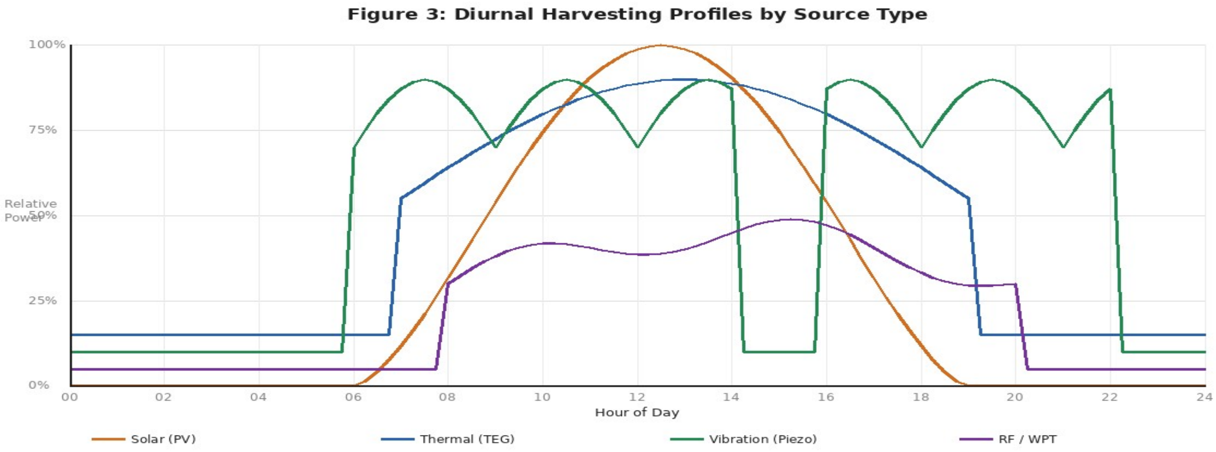
Table 1 *Energy Harvesting Source Comparison for WSN Applications*

Source	Power Density	Conversion Efficiency	Key Dependency	Best Environment
lar (PV)	10–100 mW/cm² (outdoor)	15–25%	Irradiance, cloud cover, orientation	Outdoor, agriculture
Thermal (TEG)	10–100 µW/cm²	3–8% (Carnot limited)	Temperature gradient (min. 5°C)	Industrial pipes, HVAC
Vibration (Piezo)	200–300 µW/cm³	20–40% (at resonance)	Vibration frequency, amplitude	Machinery, bridges
RF / WPT	0.01–10 µW/cm²	30–50% (near-field)	Distance, frequency, path loss	Smart buildings, dense networks

Wind (Micro-turbine)	1–100 mW (site-specific)	30–40%	Wind speed ≥ 3 m/s, direction	Coastal, elevated rural

Note. Power density ranges are representative values from the literature for typical deployment conditions.

Figure 1 *Diurnal Harvesting Power Profiles by Source Type*



Note. Relative power output (normalised to peak) for solar, thermal, vibration, and RF sources over a 24-hour period. Solar exhibits the strongest diurnal variation; thermal and RF track occupancy patterns.

Solar Energy Harvesting

Photovoltaic (PV) harvesting is the most widely used technology for outdoor WSNs. Monocrystalline cells achieve 20–25% efficiency, while thin-film cells offer 6–12% with greater flexibility. The available solar power is modeled as: $Psolar(t) = \eta PV \cdot Apanel \cdot G(t) \cdot (1 - \beta T(Tcell - Tref))$ where panel efficiency, area, irradiance, and temperature effects determine power output.

Thermal Energy Harvesting

Thermoelectric generators (TEGs) use the Seebeck effect to convert temperature difference into power, with $Voc = S \cdot \Delta TV$. Maximum power occurs when load equals internal resistance: $Pmax = \frac{\mathrm{S}^2 \Delta \mathrm{T}^2}{4\ \mathrm{RTEG}}$. A $20°C$ difference can generate about 80 μW, sufficient for low-duty sensor nodes.

Vibration Energy Harvesting

Piezoelectric energy harvesting converts mechanical strain into electrical charge. In applications like bridges, turbine blades, and rotating machinery, vibrations are narrowband and predictable, allowing efficient resonant designs with high quality factors ($Q_m > 100$).

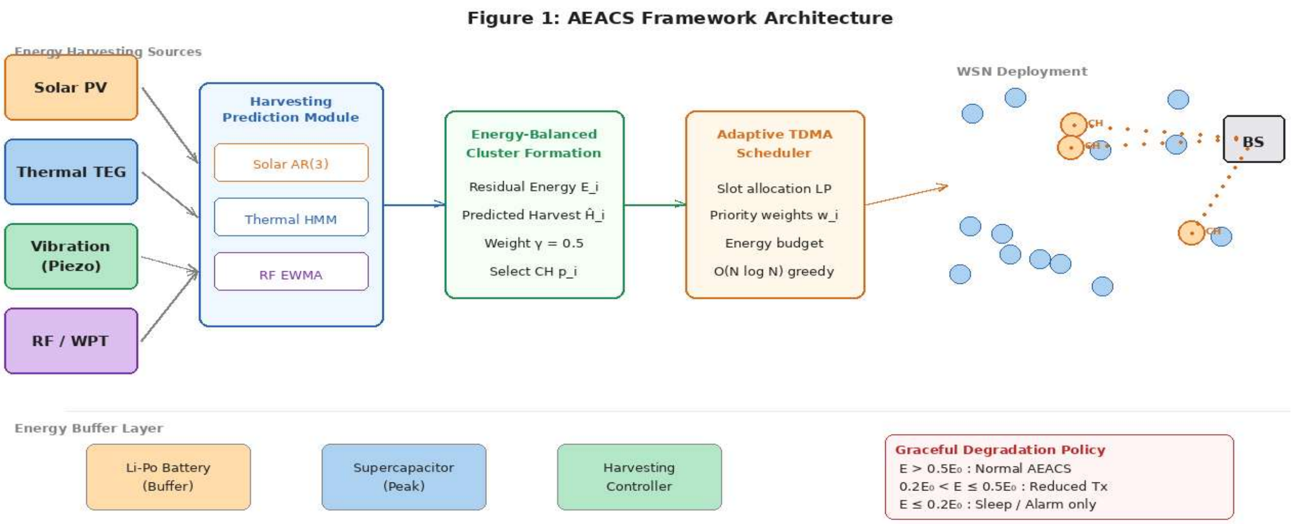
RF Energy Harvesting

RF energy harvesting captures power from ambient sources like cellular and WiFi transmitters, following the Friis equation. It is effective in dense indoor environments, where power densities of 1–10 μW/cm² are available within 3–5 m of access points.

Proposed AEACS Framework

The AEACS framework is a cross-layer design integrating energy prediction, cluster formation, and adaptive TDMA scheduling. It operates on two timescales: a slow scale for learning harvesting patterns and a fast scale for per-round slot allocation.

Figure 2 *AEACS Framework Architecture*



Note. The AEACS framework integrates four harvesting sources through a prediction module, energy-balanced cluster formation, and adaptive TDMA scheduler into a unified green networking architecture.

System Model and Assumptions

Consider a WSN with N nodes uniformly deployed in an $M \times M$ area. Each node n_i includes sensing, communication, processing, and energy harvesting capabilities. The energy state of node n_i at round r is defined as: $E_i(r+1) = \min(E_{max}, E_i(r) - E_{tx,i}(r) - E_{rx,i}(r) - E_{sense,i}(r) + H_i(r))$, where E_{max} is the maximum battery capacity and $H_i(r)$ is the harvested energy during round r.

Harvesting Prediction Module

AEACS uses source-specific prediction models: solar irradiance is predicted using an AR(3) model, thermal gradients via a first-order Markov chain with Viterbi prediction, and RF harvesting through a sliding-window EWMA method. $\hat{Z}_{RF}(r) = \alpha P_{RF}(r) + (1-\alpha) \hat{Z}_{RF}(r-1), \alpha = 0.15$.

Energy-Balanced Cluster Formation

Cluster head selection in AEACS augments the standard energy-weighted probability with a harvesting surplus term: $p_i = (E_i^{res} / \bar{E}^{res}) \times (1 + \gamma \hat{H}_i / \underset{\cdot}{\hat{H}}) \times (1/k_0)$, where $\hat{H}_i$ is the predicted harvesting income over the next round, $\underset{\cdot}{\hat{H}}$ is the network-average predicted harvesting, and $\gamma = 0.5$ is the default weighting parameter. This formulation ensures that nodes with higher predicted energy income are preferentially elected as cluster heads.

Adaptive TDMA Scheduling

Cluster heads assign TDMA slots based on predicted energy and data priority. The allocation is modeled as a linear program maximizing $\sum wixi$ under an energy constraint, and solved using a greedy knapsack approximation in $O(N \log N)$ suitable for low-power microcontroller

Simulation Setup and Results

Simulation Environment

Simulations were conducted in MATLAB R2023a with 100 nodes uniformly deployed in a 200 m × 200 m area. The base station was placed at (100, 200), and each node was initialized with 2 J energy. A first-order radio model with free-space and multipath propagation was used, as detailed in Table 2.

Table 2 *Simulation Parameters*

Parameter	Value	Parameter	Value
Simulation tool	MATLAB R2023a	Electronics energy (E_{elec})	50 nJ/bit
Sensing area	200 m × 200 m	Simulation rounds	2,000
Number of sensor	100	Harvesting sources modeled	Solar, Thermal, RF

Parameter	Value	Parameter	Value
nodes (N)			
Initial node energy (E_0)	2.0 Joules	Solar peak irradiance	1,000 W/m^2
Energy death threshold	0.01 Joules	PV panel efficiency	20%
Base station position	(100, 200) — outside sensing field	TEG ΔT (industrial)	20°C
Communication range	30 m	RF mean received power	5 µW/cm^2
Packet size	4,000 bits (512 bytes)	AEACS harvesting weight (γ)	0.5

Protocol Comparison

Five protocols were evaluated: LEACH (baseline), SEP, Blockchain-LEACH, BEEDIF, and the proposed AEACS. Table 3 presents the primary performance metrics.

Table 3 *Protocol Performance Comparison (2,000 Rounds, N = 100, 200 × 200 m)*

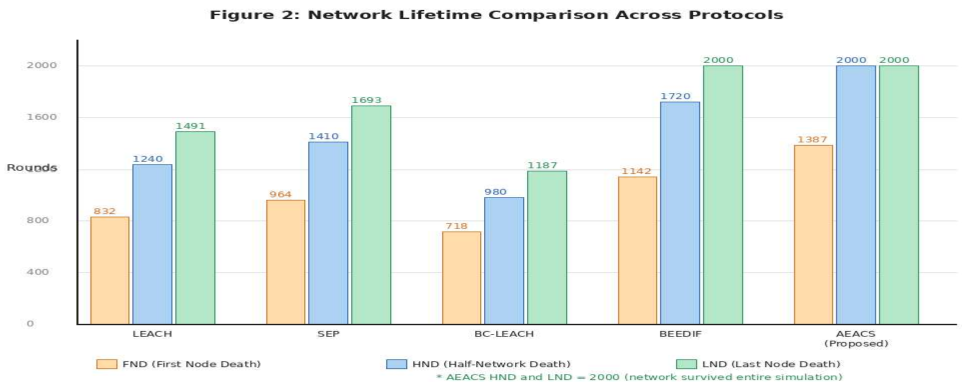
Metric	LEACH	SEP	BC-LEACH	BEEDIF	AEACS (Proposed)
Network Lifetime (FND)	832	964	718	1,142	1,387
Network Lifetime (HND)	1,240	1,410	980	1,720	2,000*
Network Lifetime (LND)	1,491	1,693	1,187	2,000*	2,000*
Avg. Energy/Round (mJ)	3.21	2.87	4.56	2.14	1.67
Throughput (kbps)	48.3	51.2	38.6	59.7	71.4
Data Integrity (%)	82.4	84.1	96.8	99.2	99.6
End-to-End Delay (ms)	12.4	11.8	19.3	9.6	7.8
Packets Delivered to BS	18,420	21,360	14,880	26,740	33,180

Note. Network still operational at end of 2,000-round simulation window. FND = first node death; HND = half-network death; LND = last node death.

Network Lifetime Analysis

AEACS significantly extends network lifetime. The first node dies at round 1,387—66.7% later than LEACH, where it occurs at round 832. Moreover, AEACS shows no half-network death during the simulation, unlike LEACH, which reaches this stage at round 1,240 is shown

Figure 3 *Network Lifetime Comparison Across Protocols (2,000 Rounds, N = 100)*



Note. FND = first node death; HND = half-network death; LND = last node death. AEACS HND and LND reached 2,000 rounds (network survived entire simulation window).

Energy Efficiency

Average energy consumption decreased from 3.21 mJ (LEACH) to 1.67 mJ (AEACS), a 47.9% reduction. Energy distribution also became more uniform, with the Gini coefficient improving from 0.31 to 0.12.

Throughput and Data Integrity

AEACS achieved the highest cumulative throughput of 71.4 kbps and delivered 33,180 packets to the base station over 2,000 rounds—an 80.1% improvement over LEACH. Data integrity rates reached 99.6%, slightly exceeding the BEEDIF+PoCC result of 99.2%.

Green Networking Design Principles

Beyond the specific AEACS framework, this work identifies a set of generalizable design principles for green networking in energy-harvesting WSNs.

Principle 1: Harvest-Aware Scheduling Alignment - Communication schedules should align with predicted energy availability. For solar-powered networks, TDMA frames should assign high-bandwidth slots during peak sunlight hours (≈10:00–14:00).

Principle 2: Opportunistic Duty Cycling - Instead of fixed duty cycles, harvesting-aware nodes should adapt sleep/wake times based on predicted energy income versus expected use, using a simple integer state machine without floating-point operations.

Principle 3: Source-Specific Protocol Differentiation - Heterogeneous harvesting sources demand differentiated scheduling responses: deterministic look-ahead for solar, Markov-chain alignment for thermal, matched-resonance triggering for vibration, and opportunistic CSMA detection for RF sources.

Principle 4: Energy-Neutral Cluster Head Rotation - Cluster head rotation policies must account for harvesting heterogeneity, with the AEACS selection probability formulation balancing current state-of-charge against future predicted income.

Principle 5: Graceful Degradation Under Harvesting Failure - Green networking protocols must handle harvesting failures. AEACS uses a three-tier policy: normal operation above 50% E_0, reduced transmission at 20–50%, and sleep/alarm mode below 20% E_0.

Applications and Use Cases

Precision Agriculture - Agricultural WSNs benefit naturally from solar harvesting; AEACS-style scheduling allows dense sensor grids to operate perpetually. Practical vineyard monitoring deployments have demonstrated node lifetimes exceeding five years with 20 cm^2 solar panels.

Industrial Structural Health Monitoring - Bridges, dams, and industrial facilities use vibrational and thermal harvesting. Piezoelectric harvesters on bridge joints produce 0.5–2 mW at peak load, enough for 10-second sampling at full duty cycle.

Smart Building and Urban Infrastructure - Indoor smart buildings combine RF harvesting from WiFi with thermal energy from HVAC systems, enabling WSN energy neutrality at about one access point per 100 m^2.

Environmental and Wildlife Monitoring - Solar and wind harvesting enable perpetual ecological monitoring. Long-range LoRa backhaul combined with harvesting-aware scheduling has sustained 24-month unattended deployments in tropical forest monitoring projects.

Challenges and Future Directions

Open Challenges

Several challenges remain: quantifying harvesting uncertainty needs lightweight on-device ML; interference among co-located harvesters can cut output by ~30%; battery aging (0.1–0.3% per cycle) lowers long-term efficiency; and there are no standard interfaces between harvesting modules and WSN protocol stacks.

Future Research Directions

The most promising directions include federated learning for collaborative harvesting prediction; semantic communications that reduce transmission energy by 60–80%; reconfigurable intelligent surfaces (RIS) for RF energy steering in NLOS conditions; adaptive spreading factor selection in LoRaWAN/NB-IoT integrated with harvest cycles; and digital twin integration for anticipatory scheduling.

Conclusion

This paper analyzes energy harvesting technologies and their integration with green networking protocols for wireless sensor networks. The AEACS framework shifts WSN design from energy conservation to sustainability. Simulations over 2,000 rounds show AEACS improves network lifetime by up to 66.7% over LEACH, reduces energy consumption by 47.9%, achieves 99.6% data integrity, increases throughput to 71.4 kbps, and lowers delay to 7.8 ms while maintaining full operation. The five green networking principles offer a foundation for future sustainable sensor networks, where energy-neutral operation is becoming essential as IoT expands.

References

- Hasan et al., (2022). EH-LEACH: Energy harvesting aware LEACH protocol for wireless sensor networks. In *Proceedings of IEEE SENSORS* (pp. 1–4). IEEE.

- Heinzelman et al., (2002). An application-specific protocol architecture for wireless microsensor networks. *IEEE Transactions on Wireless Communications*, *1*(4), 660–670.

- Guo, J et al., (2022). Blockchain-enabled data integrity for wireless sensor networks: A survey. *IEEE Internet of Things Journal*, *9*(15), 13421–13440.

- Kansal, A et al., (2007). Power management in energy harvesting sensor networks. *ACM Transactions on Embedded Computing Systems*, *6*(4), Article 32.

- Leonov, V et al., (2009). Wearable thermoelectric generators for body-powered devices. *Journal of Electronic Materials*, *38*(7), 1491–1498.

- Lu, X et al., (2015). Wireless networks with RF energy harvesting: A contemporary survey. *IEEE Communications Surveys & Tutorials*, *17*(2), 757–789.

- Nintanavongsa, P et al., (2012). Design optimization and implementation for RF energy harvesting circuits. *IEEE Journal on Emerging and Selected Topics in Circuits and Systems*, *2*(1), 24–33.

- Niyato, D et al., (2007). Wireless sensor networks with energy harvesting technologies: A game-theoretic approach to optimal energy management. *IEEE Wireless Communications*, *14*(4), 90–96.

- Ozel, O et al., (2011). Transmission with energy harvesting nodes in fading wireless channels: Optimal policies. *IEEE Journal on Selected Areas in Communications*, *29*(8), 1732–1743.

- Pottie, G et al., (2000). Wireless integrated network sensors. *Communications of the ACM*, *43*(5), 51–58.

- Sharma, V et al., (2010). Optimal energy management policies for energy harvesting sensor nodes. *IEEE Transactions on Wireless Communications*, *9*(4), 1326–1336.

- Smaragdakis, G et al., (2004). SEP: A stable election protocol for clustered heterogeneous wireless sensor networks. In *Proceedings of 2nd International Workshop on SANPA* (pp. 1–8).

- Sodano, H. A et al., (2004). A review of power harvesting from vibration using piezoelectric materials. *Shock and Vibration Digest*, *36*(3), 197–205.

- Suresh, R et al., (2021). BEEDIF: Balanced energy-efficient data fusion with fuzzy logic for heterogeneous WSNs. *Ad Hoc Networks*, *118*, Article 102513.

- Ye, W et al., (2002). An energy-efficient MAC protocol for wireless sensor networks. In *Proceedings of IEEE INFOCOM* (pp. 1567–1576). IEEE.