
IOT-ENABLED HYBRID SOLAR–RF ENERGY HARVESTING FRAMEWORK FOR BATTERYLESS AGRICULTURAL MONITORING NODES: A PATHWAY TO SUSTAINABLE RURAL DEVELOPMENT IN NIGERIA

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ABSTRACT

Nigeria's agricultural sector employs over a third of the national workforce yet remains largely rain-fed, poorly monitored, and vulnerable to climate variability, post-harvest loss, and inefficient input use. Precision agriculture built on the Internet of Things (IoT) has demonstrated potential to improve yield efficiency and reduce resource waste, but its adoption in rural Nigerian communities is constrained by unreliable grid electricity and the prohibitive cost of maintaining battery-powered sensor networks across dispersed farmland. This paper proposes and analyzes a hybrid solar-photovoltaic and radio-frequency (RF) energy harvesting framework that powers batteryless, edge-intelligent soil and microclimate sensor nodes for smallholder farms. The framework combines a low-power photovoltaic (PV) harvesting front end with an ambient RF/backscatter harvesting subsystem to sustain sensing, local inference, and long-range low-power wide-area network (LPWAN) transmission without disposable batteries or grid dependence. A lightweight edge-intelligence layer performs on-node anomaly detection to minimize radio duty cycling and reduce energy demand. A subsystem-level analytical energy budget, referenced to a 3.3 V rail, estimates an average node power draw of a few hundred microwatts, with supercapacitor leakage explicitly included. System architecture, energy-budget analysis, and a phased deployment methodology suited to Nigerian rural infrastructure are presented, alongside a discussion of manufacturing localization, cost, spectrum-regulatory compliance, and policy pathways. The framework is intended to support maintenance-light, indigenously buildable monitoring infrastructure with potential to improve data-driven farm management and create local technical employment in sensor assembly, calibration, and network operations.

Keywords: energy harvesting; batteryless IoT; RF backscatter; precision agriculture; edge intelligence; sustainable development

1. INTRODUCTION

Sustainable national development in Nigeria depends heavily on modernizing agriculture, which remains a major source of employment and a critical determinant of food security (National Bureau of Statistics [NBS], 2017). Despite this, smallholder farmers, who cultivate the majority of Nigeria's arable land, continue to rely on visual inspection and experience-based judgement rather than data-driven decision-making for irrigation timing, fertilizer application, and pest management. The consequence is chronic yield gaps, water waste, and avoidable crop loss that ripple through the national economy as food-price volatility and import dependence.

The Internet of Things (IoT) has repeatedly demonstrated, in both developed and developing agricultural economies, the capacity to close this information gap through networks of low-cost sensors that continuously report soil, weather, and crop-health parameters to a central platform for analysis and alerting (Ojha, Misra, & Raghuwanshi, 2021). The barrier to replicating this success in Nigeria is not sensing technology itself, but power. Grid electricity does not reliably reach the majority of Nigerian farmland, and disposable or rechargeable batteries impose a recurring cost and maintenance burden that is economically unworkable across the hundreds of nodes a meaningful monitoring network requires.

This paper addresses that constraint directly. It proposes an engineering framework in which each sensor node harvests its own operating energy from two locally abundant and complementary sources, ambient solar irradiance and ambient or dedicated radio-frequency (RF) energy, combined with an edge-intelligence layer that minimizes energy-hungry radio transmissions. The contribution of this work is threefold: (i) a hybrid harvesting architecture and voltage-referenced energy budget suited to Nigerian solar and RF conditions; (ii) an edge-intelligence duty-cycling strategy that reduces the energy cost of communication, the most power-intensive node function; and (iii) a phased deployment and local-manufacturing methodology designed around Nigeria's technical, economic, and infrastructural realities, so that the framework is a buildable national asset rather than a laboratory proof of concept.

2. BACKGROUND AND RELATED WORK

2.1 Energy Harvesting for Wireless Sensor Networks

Solar-powered wireless-sensor-network (WSN) nodes are well established for outdoor deployments, but single-source solar designs remain vulnerable to multi-day cloud cover, dust from harmattan conditions, and canopy shading (Williams, Torquato, Cameron, Fahmy, & Sienz, 2021; Sudevalayam & Kulkarni, 2011). Vullers, van Schaijk, Doms, Van Hoof, and Mertens (2009) showed that even centimetre-scale photovoltaic (PV) cells can sustain duty-cycled microcontroller loads provided the power-conditioning stage does not consume a large share of the harvested surplus, a decisive point for batteryless nodes whose sub-milliwatt load makes microampere-scale quiescent draw a first-order loss. RF energy harvesting, including ambient backscatter communication, has separately been shown capable of powering ultra-low-power sensing largely independent of weather (Liu et al., 2013), though reported ambient power in rural, tower-distant settings typically falls in the nanowatt-to-low-microwatt range (Kim et al., 2014; Zungeru, Ang, Prabakaran, & Seng, 2012), making RF a trickle complement rather than a primary supply.

2.2 Hybrid Harvesting and Edge Intelligence

Hybrid harvesting, combining two or more ambient sources through a shared power-management integrated circuit (PMIC), smooths the intermittency of any single source because solar and RF availability are largely decorrelated in time (Williams et al., 2021). The practical cost is power-management complexity: a dual-input PMIC must arbitrate sources of very different voltage and current characteristics while keeping its own quiescent overhead low (Vullers et al., 2009; Kansal, Hsu, Zahedi, & Srivastava, 2007). Separately, radio transmission is consistently identified as the largest energy cost in a WSN duty cycle (Williams et al., 2021; Kansal et al., 2007), motivating edge intelligence, in which lightweight inference models run directly on constrained microcontrollers so that only actionable results are transmitted; the tinyML community has formalized benchmarking practice for exactly this class of workload (Banbury et al., 2020, preprint). Combining hybrid harvesting with on-node inference, rather than treating them as separate research threads, is the specific gap this paper addresses.

2.3 IoT-Enabled Precision Agriculture and the Research Gap

Precision agriculture built on networked sensing has an extensive evidence base in developed economies, where grid power and technician access are largely assumed rather than engineered around (Ojha et al., 2021; Friha, Ferrag, Shu, Maglaras, & Wang, 2021). A joint assessment by the Food and Agriculture Organization and International Telecommunication Union (2022) across 47 Sub-Saharan African countries found digital-agriculture adoption concentrated in donor-funded pilots rather than sustained, farmer-financed deployments, with unreliable rural electricity and recurring battery-replacement cost named among the most common reasons pilots fail to scale. Reviewed individually, solar harvesting, RF/backscatter harvesting, hybrid power management, and edge intelligence are each reasonably mature; what is missing, and what this paper contributes, is their combination into a single, voltage-referenced, leakage-inclusive design specifically budgeted for the solar and RF conditions, cost constraints, and deployment logistics of Nigerian smallholder farmland.

3. PROPOSED SYSTEM AND METHODOLOGY

3.1 System Architecture

The proposed node architecture comprises four functional layers: a dual-source energy-harvesting front end, a power-management and storage stage, a sensing and edge-intelligence compute stage, and a low-power wide-area communication stage, as shown in Fig. 1.

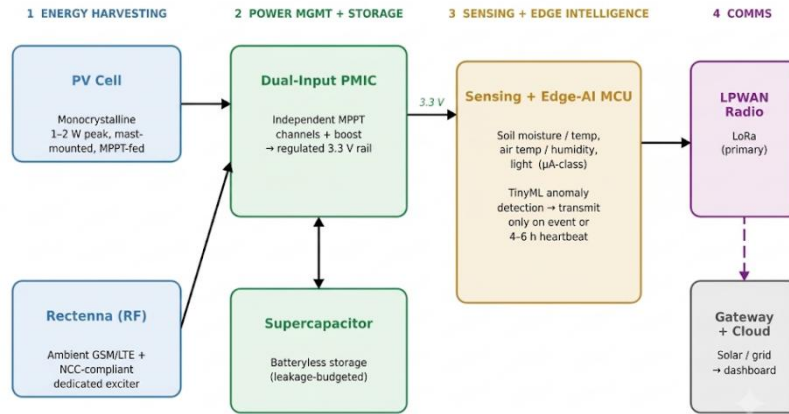


Figure 1: Batteryless hybrid solar–RF agricultural monitoring node: dual-source harvesting, supercapacitor storage, on-node edge inference, and event-driven LPWAN uplink.

The solar subsystem uses a small monocrystalline PV cell (1–2 W peak) mounted above the crop canopy, feeding a maximum-power-point-tracking (MPPT) charge stage chosen for low quiescent current; a simpler direct-charge path serves as a fallback where MPPT overhead would approach the harvested surplus under low irradiance. The RF subsystem uses a rectenna tuned to ambient GSM/LTE bands as a supplementary trickle source; in low-signal areas, a low-cost dedicated exciter co-located at the gateway provides a supplementary RF source, operating within the equivalent-isotropically-radiated-power limits and licence-exempt conditions set by the Nigerian Communications Commission (NCC, 2003). Both sources are merged through a dual-input PMIC into a regulated 3.3 V rail feeding a supercapacitor rather than a chemical battery, eliminating replacement and disposal; supercapacitor self-leakage is included explicitly in the energy budget rather than neglected.

Each node integrates capacitive soil-moisture, soil- and ambient-temperature, humidity, and light sensors selected for microampere-range operating currents. A microcontroller with a low-power neural-network accelerator runs a lightweight tinyML anomaly-detection model that flags soil-moisture stress or abnormal microclimate signatures; the node transmits only when the model flags a condition, or on a coarse scheduled heartbeat, which is the principal mechanism keeping average power draw within the harvestable budget. The 4–6 h heartbeat interval shown in Fig. 1 is chosen as a conservative upper bound on the time between updates an extension officer needs for irrigation and pest-risk decisions under normal conditions; because the heartbeat, rather than the event-triggered path, sets the guaranteed minimum transmit rate, it is also the primary lever for keeping the LPWAN radio-transmit contribution in Table 1 near its lower bound, with event-triggered transmissions adding to that baseline only when the edge model flags a condition. Communication uses LoRa for its low transmit-energy per message; a solar-plus-optional-grid gateway, far fewer in number than the nodes, aggregates data over cellular backhaul to a dashboard accessible to extension officers and cooperative managers.

3.2 Energy Budget Analysis

The core constraint of a batteryless design is that average harvested power must meet or exceed average consumed power, including storage leakage, over a representative operating cycle. Because the present study is at the framework and design stage, the budget below is an analytical estimate based on component-level operating ranges rather than the output of a completed simulation or prototype. Table 1 summarizes the node energy budget, referenced to the regulated 3.3 V rail.

Table 1: *Node energy budget (referenced to a 3.3 V rail).*

Node Subsystem	Active Current	Duty Cycle	Avg. Power @3.3 V
Sensor suite (soil, temp/humidity, light)	0.3–1.0 mA	~1%	~10–33 μ W
Edge-inference MCU (active compute)	4–8 mA	<0.5%	~66–132 μ W
MCU sleep/idle state	2–5 μ A	~98%	~7–16 μ W
LPWAN radio transmit burst	30–120 mA	<0.1%	~100–400 μ W
Harvesting/PMIC quiescent overhead	10–20 μ A	Continuous	~33–66 μ W
Supercapacitor leakage	10–50 μ A	Continuous	~33–165 μ W
TOTAL (average)	~75–245 μ A	—	~250–810 μ W

Based on the component-level ranges and engineering assumptions summarized in Table 1, the projected average node power consumption is approximately 0.25–0.8 mW at the regulated 3.3 V rail. The estimate includes sensor, processing, radio, power-management, and supercapacitor-leakage contributions. On an engineering-estimate basis, this projected load is substantially below the nominal peak output of the proposed 1–2 W PV source; however, actual energy sufficiency will depend on irradiance, canopy shading, dust, conversion losses, RF-harvesting yield, and storage losses. The ambient RF subsystem is therefore treated as a supplementary source rather than the primary energy supply. These values represent a design-stage energy budget and have not yet been experimentally validated. Because leakage is comparable to the load, the supercapacitor is sized from the net (harvest-minus-leakage) surplus rather than from nominal harvest current alone.

3.3 Phased Deployment Methodology

Deployment proceeds in four phases. Phase 1, bench validation, characterizes the harvesting front end and trains the edge model on locally collected soil and microclimate data at a university research farm. Phase 2, pilot cluster, deploys 10–20 nodes across a single cooperative farm cluster, paired with extension-officer dashboard training, to validate energy sufficiency and inference accuracy across a full cropping season. This range is selected as a practical pilot size that permits deployment across a single cooperative farm cluster while remaining sufficiently large to observe node-to-node variation in canopy shading, soil type, and RF signal strength within the cluster, providing a spread of operating conditions for validating inference accuracy before committing to the larger capital and logistics outlay of Phase 3. Phase 3, cooperative-scale rollout, expands to a full cooperative or local government area, incorporating feedback on mechanical housing durability, livestock interference, and gateway placement. Phase 4, local manufacturing transition, partners with Nigerian electronics-assembly capacity, including university engineering workshops, to localize PCB assembly, antenna fabrication, and enclosure production, reducing per-node cost and import dependence.

4. DISCUSSION AND IMPLICATIONS

4.1 National Impact and Alignment with the Conference Theme

Continuous, low-cost soil and microclimate monitoring closes the information gap identified in Section 1: the precision-agriculture literature consistently associates timelier, data-informed irrigation and input decisions with reduced water waste and improved yield consistency relative to calendar-based scheduling (Ojha et al., 2021; Friha et al., 2021). Because the proposed framework reduces dependence on grid electricity and recurring battery replacement, it could extend digital-agriculture monitoring to

smallholder cropland where conventional powered networks are difficult or costly to maintain, with implications for national food-price volatility and import dependence that scale with the phased rollout of Section 3.3.

Reliable grid electricity does not reach most Nigerian farmland, and the Rural Electrification Agency's own capital-project reporting indicates that closing this gap through conventional grid extension remains a multi-year, capital-intensive undertaking rather than a near-term certainty (Rural Electrification Agency [REA], 2024). Because the proposed node requires neither grid connection nor battery replacement, it decouples digital-agriculture adoption from the pace of electrification rollout, consistent with the energy-access priorities documented jointly by the Food and Agriculture Organization and International Telecommunication Union (2022). The framework also touches several Sustainable Development Goals simultaneously: affordable and clean energy (SDG 7) through reliance on ambient renewable sources; responsible consumption and production (SDG 12) through reduced dependence on recurring battery use and associated waste; industry, innovation, and infrastructure (SDG 9) through the local-manufacturing pathway of Section 3.3; and zero hunger (SDG 2) through anticipated yield and input-efficiency gains.

4.2 Economic Scalability and Local Capacity

The phased local-manufacturing transition is the primary lever for reducing per-node cost over time, compressing the import duties, shipping, and currency-conversion overheads on imported sensor and radio modules as production scales from tens of units in Phase 2 toward hundreds or low thousands in Phase 3. Eliminating recurring battery-purchase and replacement logistics further shifts the node's cost profile from a recurring operating expense toward a one-time capital expense, easier for cooperatives and financing partners to plan around. Localizing PCB assembly, antenna fabrication, and enclosure production also builds domestic RF, photovoltaic, and embedded-systems expertise transferable well beyond agriculture, and each deployment phase creates rural technical employment in calibration, maintenance, and assembly. As a rough order-of-magnitude planning estimate rather than a costed bill of materials, imported-component sourcing at Phase 2 pilot volumes is estimated at approximately \$25–35 (about ₦33,750–₦47,250 at a reference planning rate of ₦1,350/\$) per node, inclusive of estimated freight, applicable duties and import charges, and currency-conversion costs, with the local-manufacturing transition of Phase 4 projected to reduce this toward approximately \$15–20 (about ₦20,250–₦27,000) per node as deployment scales beyond Phase 3 volumes by substituting domestically assembled PCBs, antennas, and enclosures for imported equivalents; these figures should be treated as planning estimates to be refined once Phase 2 procurement data and applicable Nigerian import tariff classifications are available, not as validated costings. The estimate does not constitute a detailed bill of materials and excludes project-level costs such as gateway infrastructure, installation, field labour, testing equipment, software development, and long-term maintenance.

4.3 Limitations

The energy budget in Section 3.2 is derived from component-level datasheet ranges and engineering estimates rather than from a simulated, prototyped, or field-measured system, so the projected multi-day autonomy remains an unvalidated design target rather than a demonstrated performance result. RF harvesting yield is highly location-dependent and marginal far from cellular infrastructure, necessitating the NCC-compliant exciter fallback of Section 3.1, which adds gateway-side cost. Supercapacitor storage exhibits self-leakage comparable to the node load and capacitance fade at elevated ambient temperatures common in Nigeria, so multi-year node lifetime is bounded by temperature-derated ageing rather than open-ended. Mechanical durability of externally mounted PV and antenna elements against dust, humidity, livestock, and theft requires robust, low-cost enclosure design, and edge-model accuracy depends on training data representative of local soil types and crop varieties. Sustained adoption also depends on extension-service capacity to act on the data produced; the technology is necessary but not sufficient without complementary agricultural-advisory infrastructure.

5. CONCLUSION

This paper has proposed a hybrid solar–RF energy-harvesting framework for batteryless, edge-intelligent agricultural monitoring nodes designed around the infrastructural and economic conditions of rural Nigeria. A voltage-referenced analytical energy budget suggests an average node draw of a few hundred microwatts when radio bursts and supercapacitor leakage are included. This projected load is substantially below the nominal peak rating of the proposed 1–2 W PV source, but actual energy sufficiency remains to be established through simulation, prototype testing, and field measurements. By combining complementary harvesting sources with on-node inference intended to reduce the energy cost of communication, the framework is designed to reduce the recurring power and maintenance burden associated with conventional battery-dependent precision-agriculture IoT deployments. The phased deployment and local-manufacturing methodology further provides a pathway for the technology to mature from a research prototype into a domestically buildable national asset, supporting food security, energy justice, local industrial capacity, and rural technical employment simultaneously. Key limitations include the absence of prototype and field validation of the energy budget, location-dependent RF yield, temperature-related supercapacitor ageing, and dependence on complementary extension-service capacity. Future work will report field-validated energy-harvest yields, supercapacitor-ageing data, and edge-model accuracy from the Phase 1–2 deployments described in Section 3.3.

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