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The Creation of Solar-Powered, Energy-Efficient Wireless Sensor Network Topologies That Use Advanced Algorithms, Artificial Intelligence for Energy Forecasting, And Machine Learning Techniques

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Abstract

Microgrids are miniature, decentralized power systems connected to the larger electrical grid, employing various components to monitor energy usage and environmental variables. Their adoption in residential areas has been limited due to installation and maintenance challenges. Integrating ambient-powered, wireless sensors could enhance their functionality, reducing energy waste by harvesting power from environmental sources. A combination of energy harvesting technologies and battery power is suggested for optimal performance, potentially utilizing everyday components for cost efficiency. Additionally, the thesis explores advancements in "smart agriculture," which incorporates renewable energy, automated systems, and innovative sensors to improve farming efficiency and sustainability. Key areas include soil quality monitoring, pest detection, and the application of AI and big data analytics, aiming to provide insights into agricultural innovation for academics and professionals.

Keywords: Wireless sensor, energy harvesting, energy prediction, SMS

Introduction

The widespread use of wireless sensor networks (WSNs) has gained attention in areas such as healthcare, smart cities, industrial automation, and environmental monitoring over the past decade. A central challenge in WSN deployment, especially in remote or harsh environments, is the limited power availability due to the finite lifetime of traditional sensor node batteries. Research into energy harvesting devices has emerged to address this issue. Machine learning (ML) offers a promising solution to enhance energy efficiency in WSNs by enabling real-time optimization and predictive adjustments for sensor nodes based on past and current energy data. Results from testing indicate that ML-driven energy management significantly outperforms traditional strategies, improving energy savings, extending network longevity, and maintaining data throughput in diverse energy harvesting scenarios. This highlights the feasibility of integrating ML algorithms into energy harvesting systems for more sustainable WSN operations.

Smart cities, healthcare, and environmental monitoring are just a few of the WSNs, which allow for the collection of information as it happens, have been very beneficial to several industries. One of their primary issues is the sustainable conduct of WSNs in low-power settings. The operating and maintenance costs of common battery-powered WSNs can go up due to their short lifetime. Integrating energy harvesting-a technique that allows wireless sensor networks (WSNs) to harness renewable energy sources including solar radiation, wind, vibrations, and radio frequency (RF) signals-into the system for the purpose of increasing its visibility and ensuring that wireless sensors can be continuously monitored. By "energy harvesting" (EH) for WSNs, we mean more than just solving problems with power consumption; we're also ushering in a new age of environmentally friendly, self-sufficient networking. Energy harvesting systems allow wireless sensor nodes to live longer and rely less on limited energy sources, thus researchers are moving quickly to find solutions.

Hybrid energy harvesting wireless sensor networks (EH-WSNs), integrated with cognitive and cooperative communication systems, enhance spectrum efficiency and network security, yet face significant challenges in energy management and security robustness. This research aims to provide an overview of best practices for EH solutions, addressing issues like scalability, energy efficiency, and security in long-life WSNs. It emphasizes the role of physical layer security (PLS) and advocates for advanced network routing algorithms. The review serves as a resource for researchers and industry professionals, exploring innovative techniques to overcome current limitations and the impracticality of traditional power sources, especially for long-term critical applications.

Literature Review

Shah, Jaymin. (2022) [1]. The rapid development of the ubiquitous nature of wireless sensor networks (WSNs) has rendered them crucial in several domains, including healthcare, smart cities, environmental monitoring, and industrial automation. When it comes to deploying WSNs, traditional power sources have their limitations, which may lead to operational inefficiencies and increase maintenance costs due to the increased frequency of battery recharges and replacements. In this research, we track the development of energy harvesting devices that aim directly at the power constraints of WSNs. By converting thermal energy, solar radiation, vibration, and other forms of natural energy into usable power, and electromagnetic radiation, these technologies provide a greener alternative for operating WSNs. In the long run, this increases their durability and reliability.

Goda, *et al*. (2019) [2]. This study evaluates energy harvesting technologies like solar, piezoelectric, and thermoelectric systems for wireless sensor networks (WSNs). It underscores solar energy's importance in reducing carbon emissions and presenting the benefits of ambient vibration energy harvesting. The analysis reviews these technologies based on operational longevity, energy conversion efficiency, and ease of integration. Findings suggest a shift towards sustainable, autonomous WSNs suitable for remote locations, alongside discussions on new energy management strategies to enhance IoT applications in an energy-aware society. It aims to address practical applications, integration challenges, and necessary policy considerations for successful self-powered sensor networks.

Sreedevi, Indu. (2020) [3]. The fundamental components of a network of wireless sensors are dispersed sensor nodes that draw electricity from a shared source. Constructing a solar power system that effectively extends the life of sensor nodes. The recommended the three primary components of a solar power system are solar panels, rechargeable batteries, and a control circuit. To charge a battery using solar power, one way to increase the voltage of the electrical energy generated by the panels. This system provides energy to several sensor nodes. In addition, inverters are made to work with alternating current. The whole system architecture, module designs, implementation details, and performance assessment procedures are detailed in this paper. This small, self-contained technology allows wireless sensor network nodes to function well in outdoor environments, according to the experimental findings.

Sharma, *et al*. (2019) [4]. Wireless sensor networks (WSNs) are essential for various IoT applications, but traditional batteries pose limitations due to their non-rechargeable nature and capacity constraints. The operational lifespan of WSNs depends on several factors, including duty cycle and environmental conditions. A promising solution is to charge WSN batteries using ambient solar energy, which addresses energy availability challenges, despite facing issues like heat, conversion inefficiency, and environmental impacts. This research finds that solar energy harvesting can significantly extend WSN longevity from 5.75 days to 115.75 days at a 25% duty cycle, potentially achieving an infinite lifetime, while also enhancing network performance from 100 kbps to 160 kbps.

Qaragoez, *et al*. (2024) [5]. Solar and radio frequency energies collaboratively power self-sustaining sensor nodes in integrated systems, crucial for the growing demands of IoT applications. The Integrated Dual-Mode Backscattering Power Harvester (IDM-BEH) can autonomously convert electromagnetic radiation and light into power, negating reliance on batteries. It features a rectifier operating across 2.45-2.65 GHz and 3.45-3.55 GHz, along with a cooperative solar array for RF energy collection and communication. The IDM-BEH demonstrated resilience with 9.8 dB backscattering and a peak energy efficiency of 25.76%, successfully extracting 17.4 µW at a light intensity of 186.6 lx from a distance of 1.2 meters.

Harvesting Source Evaluation

This method allows for a better-informed evaluation of the best sources for harvesting.

RF: One way to overcome the problems that are limiting the use of WSNs is by using energy harvesting. Using radio frequency (RF) as a substitute for traditional power sources solves the problems caused by collecting sources that are only accessible sometimes, making it a practical choice for powering wireless sensor nodes. The area where people live and work is encircled by many RF signals, which are undetectable to the naked eye. An example of an RF signal would be a Wi-Fi, cellphone, radio, or television signal. A sinusoidal voltage may be obtained from radio frequency (RF) by using an antenna to block out a certain frequency. A rectifier circuit may transform this periodic voltage into a negligible quantity of direct current.

With L standing for the path loss factor, PR for the received The Friis equation uses the following variables to represent the received power: power, transmitting antenna gain (GT), receiving antenna gain (GR), wavelength (λ), and distance (d) between the two antennas from radio frequency (RF).

$$P_R = P_T \frac{G_T G_R \lambda^2}{(4\pi d)^2 L}$$

In this research, the ambient radio frequency (RF) levels in various residential locations were investigated rather than calculating potential power using the Friis equation. An AD8318 logarithmic amplifier and a tuned monopole whip antenna were employed to measure RF power, converting the captured sinusoidal voltage to DC voltage, expressed in decibels relative to one milliwatt (dBm). The results showed that while a Wi-Fi router can theoretically generate 20 dBm, the actual measured power received at a distance is significantly lower. Testing in a residential setting with high network load (4K video and large file downloads) revealed only a minor 3 dBm variation in RF readings, suggesting that this difference may not primarily stem from the router or load conditions.

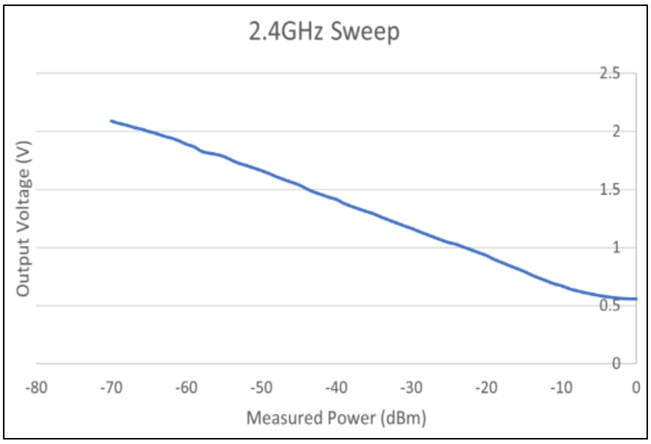

Fig 1: 2.4GHz power sweep for the AD8318 logarithmic amplifier

The logarithmic amplifier at Bucknell University recorded 1.811 V, translating to a power of -60 dBm (0.9 nW) in a crowded room. Nearby, a log amp measured 1.43 V (-40 dBm or 0.1 µW) close to a Wi-Fi router, while the Dana 303 classroom, located beneath a school radio station, showed 0.998 V (-25 dBm or 3.16 µW). Although radio frequency interference is not expected, an increase in radio frequency levels was noted. Harvesting ambient RF energy is inefficient; substantial power accumulation over time is required, with an M4 Express MCU needing 0.126 mWh for 10 seconds of operation. The maximum RF generation observed would take over 40 hours to charge this requirement. Lower-power devices, like the STM8L001j3 MCU, which consumes only 270 µW, show more feasibility for RF power use. Sensitivity, the minimum power required for a system to operate, plays a crucial role in energy harvesting viability.

$$\text{Sensitivity (dBm)} = 10\log_{10}\left(\frac{P}{1\ \text{mW}}\right)$$

P is the absolute lowest power needed by the system to carry out an operation. For its testing purposes, the feather M4 express needs 0.045 W of instantaneous power. If this is the case, then more than 16 dBm of power is needed to start up an RF harvester. This sensitivity is much greater than the accessible ambient RF, even if the Feather M4 express is a power-hungry device in comparison to certain alternatives. The STM8L001j3 needs just 150 µA/MHz, making it one of the most power-efficient microcontroller units available.

The active operation of the MCU consumes 270 µW while running in an extremely low-power mode (limited to 1MHz). Although this procedure reduces the sensitivity to -5.7 dBm, it is still far lower than the RF levels seen in most residential areas.

Although this figure was used, research has shown that passive RF-DC converters may be made more efficient, leading to a much lower sensitivity. A rectifier that allows energy harvesting with sensitivity levels as low as -40 dBm for a resistive load of 50 kΩ was conceived and constructed in one research. This sensitivity is far more in line with the quantity of RF energy that might be realistically used.

Piezoelectric

A method known as piezoelectricity involves the use of crystals to transform electrical current from mechanical energy. The possibility of using the energy of footfall by combining floor tiles with piezoelectric elements. In areas where individuals are continually on the move, this kind of energy collecting will work well. I counted the number of individuals coming and going via one entry at the Elane Langone center at Bucknell to get a feel for the potential energy harvesting from human footprints.

Table 1: Number of People That Traveled Through a Single Entrance in the ELC

Time	Number of People
12:55-1:00	22
1:00-1:15	51
1:15-1:30	91
1:30-1:45	31
1:45-2:00	97
2:00-2:05	15

In a one-hour window on a weekday from 1:00 to 2:00 PM, 270 individuals passed through a student area entry. Research indicates that a small piezoelectric tile, composed of 20 disc-type transducers connected in series and parallel, can harvest energy at a rate of 60.4 mW per step. This design could generate 1.63 Wh of electricity during that period, significantly exceeding the 45 mWh consumed by a testing Feather M4 Express device. Although the energy from individual steps is immediate, it can be stored for use with portable electronics, making this approach effective in areas with moderate foot traffic, though less suitable for narrow residential zones.

Heat

Thermoelectric generators (TEGs) use converting heat into electricity is possible via the See beck effect, which is based on the relationship between temperature and the voltage generated between two semiconductors. The TEG's power output is proportional to the temperature differential between the material's hot and cold surfaces. To estimate the TEG's power output, it's necessary to measure the heat output of standard smart grid equipment. I recorded the thermal characteristics of several everyday items using a FLIR E6xt thermal imaging camera. I calculated the heat gradient by subtracting the ambient temperature from the heat output of each device, given that all measurements were collected at a constant 21 °C.

Table 2: Temperature of Common Devices

Device	Location	Temperature	Gradient
Sensor Controller System	Dana 147	31.8 °C	10.8 °C
Computer Monitor	Dana 147	40.9 °C	19.9 °C
Coffee Machine	Dana Lobby	41.3 °C	20.3 °C
TV Cable Box	Dana Lobby	38.3 °C	17.3 °C
Back of TV	Apartment	33.3 °C	12.3 °C
Projector Input Panel	Maker E	46.9 °C	25.9 °C
Security Camera	Maker E	39.3 °C	18.3 °C
Wi-Fi Router	Apartment	36.0 °C	15.0 °C

With these details, I tested the SP1848, a little Peltier tile, to see how well it might work. In a Peltier thermoelectric generator, equation represents the open circuit potential difference between two junctions. The equation includes both the temperature differential (ΔT) where the tile's hot and cold surfaces meet and where Seebeck coefficient (Ÿ), which estimates the amount of thermoelectric voltage generated for a specific dispersion of heat through a substance. A temperature-dependent measurement of the SP1848's open-and short-circuit voltages and currents 20, 40, 60, and 80, and 100 degrees Celsius are provided by the manufacturer. With these data, the SP1848 Peltier tile's Seebeck coefficient may be determined.

$$V_{oc} = \alpha \, \Delta T$$

Based on the manufacturer's specifications, a temperature gradient of 20 °C generates 0.95 volts as the open circuit voltage. The Seebeck coefficient (α) approaches 0.0475 as a result of this. Take a look at Equation to see how much current a TEG can produce. Factors that influence it include the linked load's resistance and the temperature gradient ŔT, which affects the TEG's internal resistance.

$$I = \frac{V}{R+R_L}$$

The Seebeck coefficient, temperature gradient, load resistance, and internal resistance are used in Equation to predict the amount of power that a TEG may generate.

$$Power,\ P_L = \left(\frac{\alpha\Delta T}{R+R_L}\right)^2 \times R_L$$

As the temperature rises, so does the TEG's internal resistance. In order to find the resistance across the tile at different temperature gradients, I heated one side of the Peltier tile until it reached the target temperature and set it against a container of water at 0 °C. I used an appropriately combined container of ice water to keep the cold side at 0 °C during the heating process. I double-checked the temperature gradient with the thermal imaging camera as well. I finished by taking a multimeter reading of the Peltier tile's internal resistance. I used these numbers to create a model that pits the load's resistance against the power that might be generated. The output voltage is proportional to the microcontroller unit's (MCU) internal resistance. In theory, for a TEG to produce its maximum power, The load resistance ought to be in sync with the device's internal resistance.

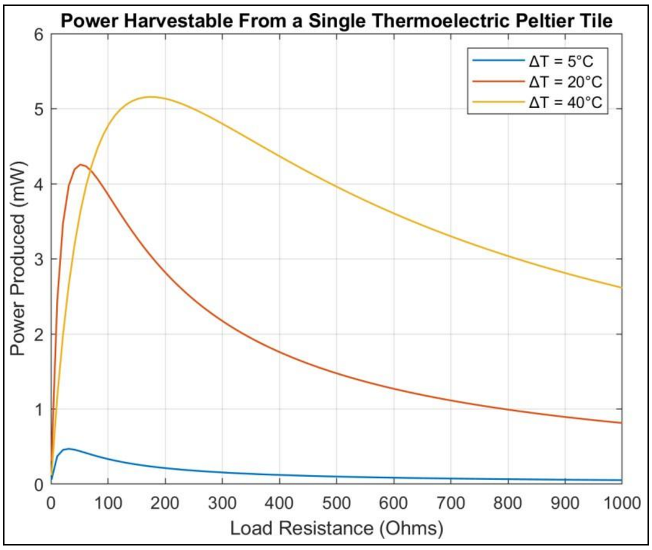

Fig 2: Power producible by a single Peltier TEG

A power curve wasn't made for every single device's temperature gradient, but a lot of the ones that were tested showed a difference of around 20 °C. This much heat can be converted into 4 mW by a single Peltier tile. The M4 Express won't be able to use this much juice, but the other low power MCUs we discussed before will have no problem.

Light: The electricity production process of solar photovoltaic cells starts with sunlight absorption, typically measured in W/m². Peak power output occurs around midday due to high solar intensity. Indoor solar power generation is less efficient, as artificial light levels are significantly lower than daylight, although energy collection is possible through window-mounted PV cells. Research by C. A. Reynaud highlights three key differences between indoor and outdoor light, including variability in light spectrum, lower irradiance levels (0.1 to under 100 mW/cm²), and distinct light components impacting indoor solar cell performance. For experimental data, a compact 25 cm² monocrystalline PV cell was used to measure performance under varying illumination, with baseline readings taken at 80.6 kLUX on a sunny day, nearing optimal conditions of 1000 W/m².

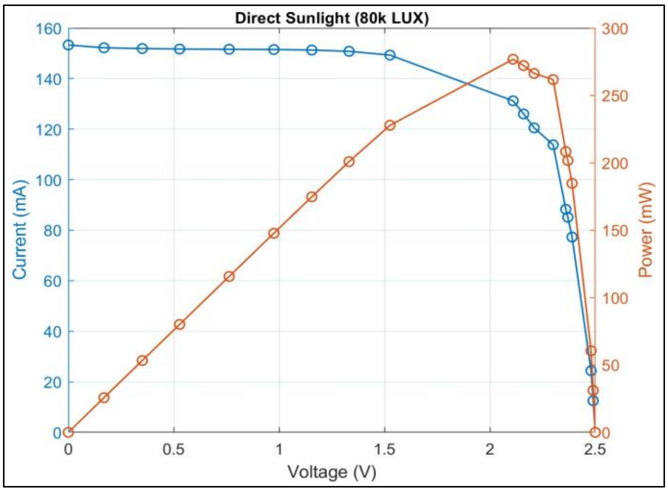

Fig 3: Curve in direct sunlight

The next step was to design an indoor IV curve for the cell by attaching it to a window facing south. Because the sun's rays reach most windows on Earth that face south since most people live in the northern hemisphere, where 80% of the population dwells. Using the cell in a south-facing window yields almost half of the power provided by direct sunlight, which is not surprising.

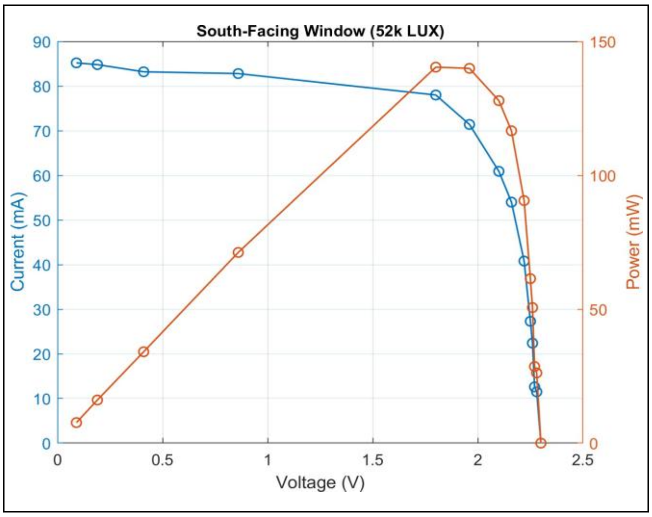

Fig 4: IV curve for south-facing window

Based on the statistics, installing a high-efficiency monocrystalline cell in a south-facing window seems to be the most feasible way to execute PV harvesting in a microgrid. It is possible to power several low-power MCUs with only one 25 cm2 cell, as it can generate more than 100 mW. On the other hand, as compared to a north-facing window or even lower interior illumination conditions, the electricity generated drops by over 98%.

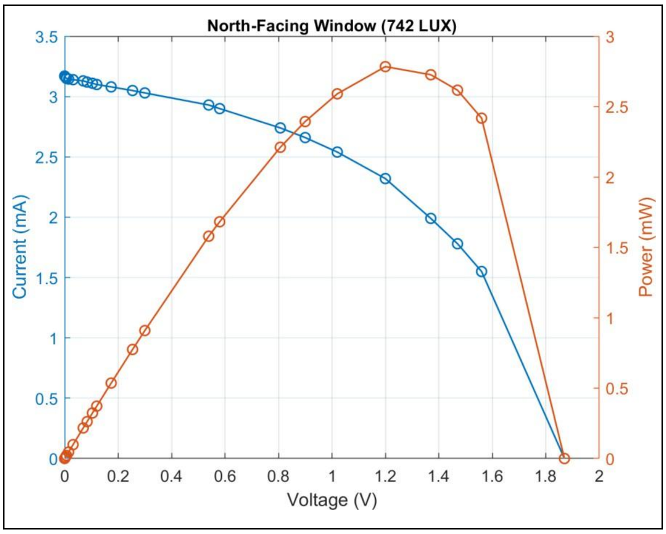

Fig 5: IV curve for north-facing window

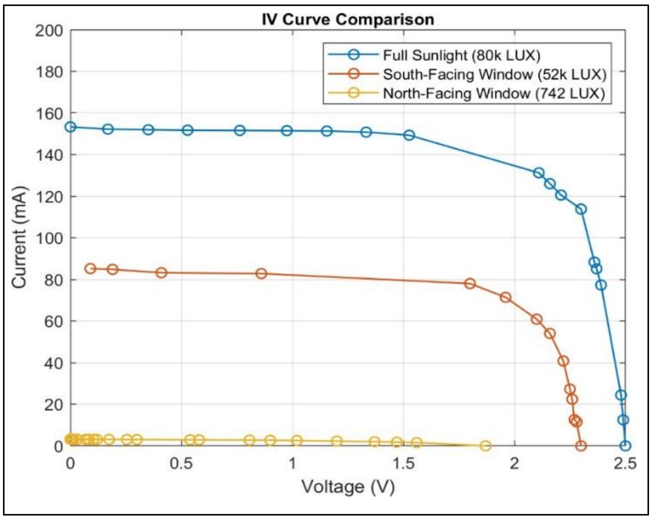

Fig 6: IV curve in different lighting conditions

A south-facing window can effectively collect solar energy, potentially powering devices like the Arduino through compact monocrystalline cells. The M4 Express can derive ample energy from a single photovoltaic cell in such a location. While this energy is primarily available during daylight, it represents a viable long-term power source. Conversely, alternative approaches like harvesting indoor light energy can be considered, although they yield less power due to narrower light wavelengths compared to sunlight. Factors affecting energy generation include the distance from the light source and the panel's angle, as explored in related research.

To Solar-Powered Wsns Ensure Scalability and Reliability in Smart Cities, Farms, And Real-Time Environmental Monitoring Through Advanced Power Management Algorithms Like Adaptive Allocation And MPPT, Influenced by Ai-Driven Energy Forecasting and Machine Learning: A primary driver of wireless sensor networks (WSNs) market growth is the potential for new, cost-effective sensing applications. However, average system lifetimes are significantly below industry expectations due to energy limitations. Energy harvesting (EH) systems, drawing power from environmental sources like solar and wind, have gained traction as a solution to this energy challenge. Although EH integration could extend WSN lifespans, the development of complete EH-WSN nodes is hindered by resource requirements and cost. Consequently, simulation is preferred over hardware prototyping to accurately analyze system components and their interactions under various conditions. Tools like COOJA and MSPSim facilitate code reuse and simulation for the MSP430 MCU, while the case study of a solar-equipped WSN application in a road tunnel illustrates the variability of energy density collection and reconciles findings between real-world and simulated results.

Table 3: SENSEH: Transitioning Between Realism and Simulation and Back Again

Harvester	WSN nodes	Environment	Interface
Simulated	Simulated Real	Simulated or real	Memory
Simulated real	Simulated real	Simulated real	PINS

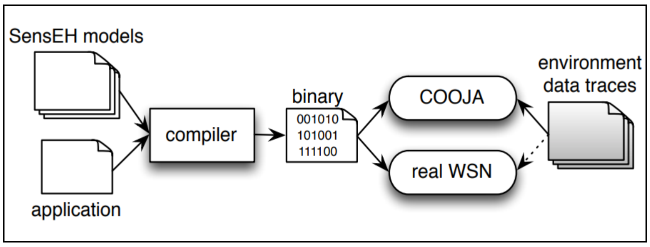

Fig 7: SENSEH tool chain optimized for memory utilization

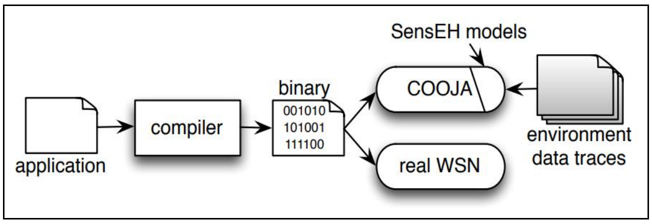

Fig 8: Toolchain for SENSEH in PINS mode

Applications; but, by combining COOJA With MSPSim, an MSP430-based mote hardware emulator, it is possible to emulate both TinyOS and Contiki. But none of them can foretell when power use, energy harvesting, or battery deterioration will occur. The literature that we examined is summarized in Table 4, which also compares and contrasts it with SENSEH. Similar to previous modeling approaches, SENSEH incorporates COOJA's emulation capabilities with models for power consumption, batteries, and harvesters, as shown visually in the chart. What follows is an explanation of how developers might make use of this flexible instrument to transition between in-field and simulated testing. Our research indicates that SENSEH is the first comprehensive software framework to provide this functionality.

Table 4: SENSEH vs. cutting-edge

	Harvester	Energy Storage	Power Consumption	Emulation
Wu *et al.*		C	C	
Sanchez *et al.*	C	C	C	
HarvWSNet	C	C	C	
Green Castalia	C	C		
WSNsim	C	C	C	
Jeong & Culler	C	C	C	
SIVEH	C	C		
PASES	C	C	C	
TOSSIM				C
COOJA/MSPSim				C
SENSE	C	C	C	C

Results: So that we may evaluate The WSN In order to find out how much electricity each node in the network uses on average and the number of nodes that can remain operational with zero power consumption. Then, we calculate the expected improvement throughout the lifespan of our tunnel WSN.

Energy that is consumed as opposed to energy that is harvested: Looking at the nodes' average daily power usage. This was computed as an average of several COOJA simulations in an attempt to replicate the tunnel's radio propagation conditions to the best of our ability. In these studies, we determined that a node needs Self-sufficiency requires 72 J/day; hence, the harvester should continuously provide an average of 0.834 mW throughout the day. However, as expected, our light dataset shows that a large amount of energy cannot be generated in this configuration. Eight out of forty nodes cannot reach self-sufficiency use a solar cell array that has less than 10 panels, according to our calculations of the daily energy production of an AM-1816 solar panel. Their energy consumption is outstripped by the other nodes' ability to provide sufficient electricity. Consequently, we provided 10 solar panels to every self-sufficient node, resulting in an enormous array of 20 × 30 cm.

Admiring for a lifetime

We evaluate the starting and remaining battery voltages as the WSN evaluates the performance in order to illustrate the simulated energy harvester's impact both anticipated increase in node lifespan. On top of that, we evaluate the

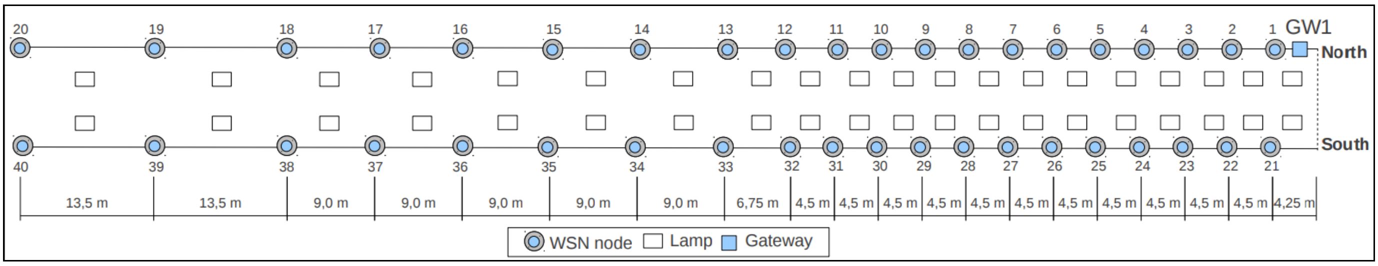

Fig 9: Tunneling WSN nodes into physical position

The COOJA simulations and indoor testbed experiments compare outcomes over a 48-hour period while considering light datasets. Both use the same binary code for SENSEH nodes but differ in injecting light values. Node 1 depletes its battery first in the COOJA simulation, consuming 76 J/day without a harvester but achieving energy neutrality with one. Node 8, however, cannot reach energy neutrality due to limited light absorption in the tunnel's transition zone. While daily energy usage decreases from 88 J to 28 J with the harvester, nodes deep within the tunnel face challenges from low-intensity artificial lighting. The relevance of costs and benefits in practical WSN use remains a compelling topic following the findings from the indoor testbed.

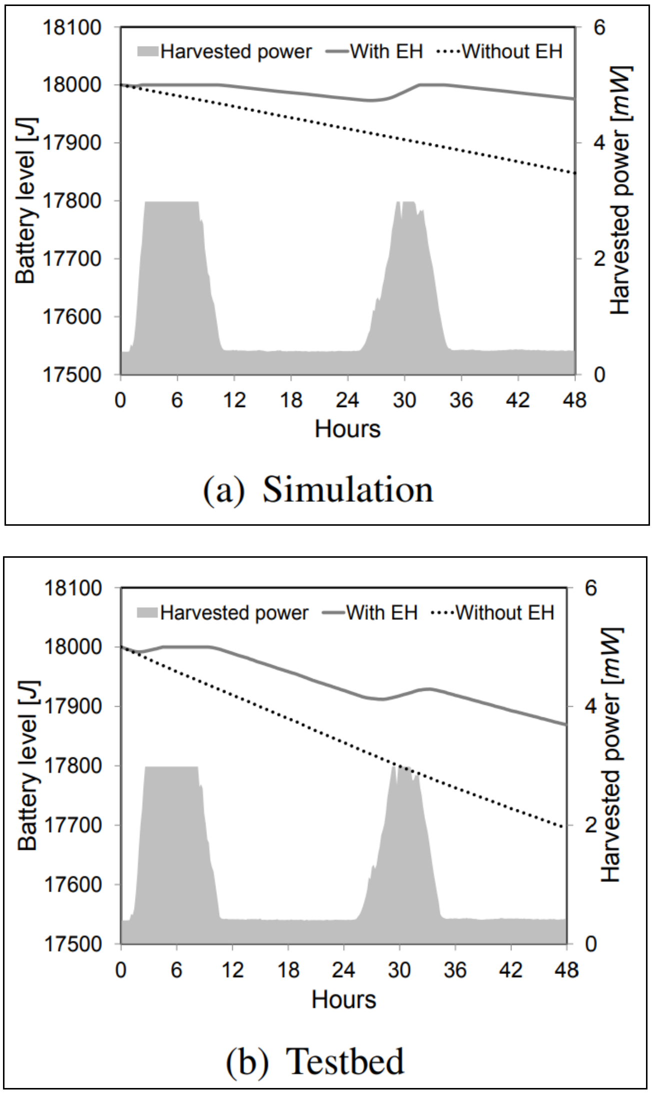

Fig 10: Information on the node's battery life and energy harvesting at the entrance.

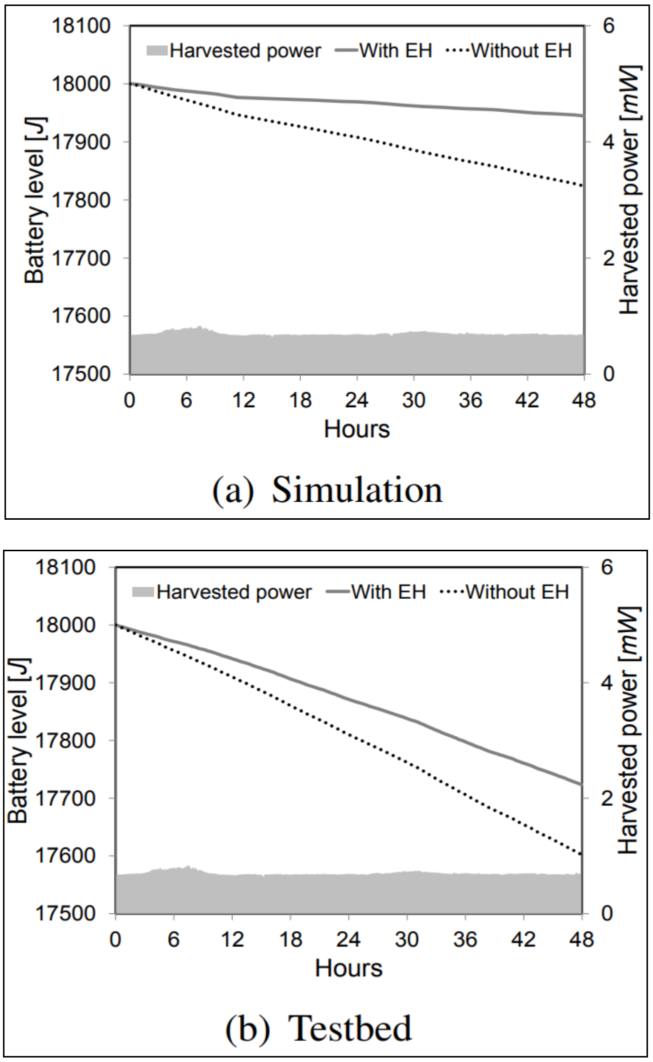

Fig 11: Data about a node's energy harvest and battery life in the transition zone

The experiment reveals that the node, receiving identical light trails, cannot operate in an energy-neutral way due to significant battery consumption, primarily because of testbed conditions. The power consumption of the node without an energy harvester is about 152 J/day, nearly double that in simulations. Despite this, a 60% improvement in lifespan is predicted with 65 J/day depletion during energy harvesting simulations. The SENSEH toolchain allows monitoring of battery voltage drop over time, offering insights into lifespan predictions, which was unavailable in the original COOJA simulator. This feature aids in both virtual and physical environments, and similar simulations can estimate the voltage drop and lifetime of NiMH batteries.

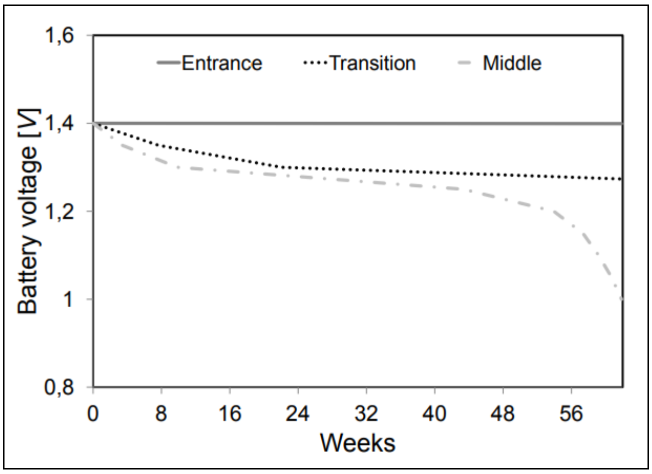

Fig 12: Various locations inside the tunnel show the gradual drain of NiMH batteries' voltage.

Figure 12 shows the results for different tunnel node positions. Since the quantity of energy used to recharge the battery at night is equal to the amount used during the day, the voltage at a node at the tunnel entrance is almost constant and full. Nodes in the transition zone see a decline in battery voltage over time due to energy use outpacing generation. Because there is a finite amount of energy that can be gathered environmental factors, nodes situated in the tunnel also encounter this problem. Similar to what would happen without a harvester, these nodes become close to 1 V after 62 weeks of operation, when the battery expires.

Conclusion

This study demonstrates that energy harvesting can enhance the installation and longevity of wireless sensor nodes (WSNs) in residential microgrids, highlighting photovoltaic (PV) cells and thermoelectric generators (TEGs) as the most effective methods due to their cost-effectiveness and efficiency. An experimental hybrid energy harvesting sensor developed can collect energy from as low as 40 µW. Despite the increasing interest in energy harvesting for achieving energy neutrality in WSNs, developers face challenges due to the limited availability of simulators and the need to switch programming languages for real-world deployments. The SENSEH framework unifies simulation and deployment, allowing users to test applications in a realistic manner. The research explored solar panels' viability for energy-neutrality in WSNs used for adaptive lighting, leveraging SENSEH's MEMORY mode. Furthermore, advancements in smart agriculture, integrating renewable energy and IoT technologies, are essential to address challenges posed by climate change and resource depletion. Smart agriculture aims to enhance sustainability and resilience by employing AI and ML for improved pest detection and resource management. Affordable and scalable technologies, like communication networks utilizing LoRaWAN and ZigBee, are vital for empowering resource-constrained farmers. The envisioned innovations support the global aims of Zero Hunger and Climate Action, contributing to sustainable development and environmental resilience.

References

1. Shah, Jaymin. (2022). Development of Energy Harvesting Technologies for Wireless Sensor Networks Environmental Monitoring. International Journal Science and Technology. 13. April-June 2022. 10.71097/IJSAT.v13.i2.3069.
2. Goda, Dileep Reddy & Surarapu, Pavani. (2019). Innovations in Energy Harvesting Technologies for Wireless Sensor Networks: Towards Self-Powered Systems. Asia Pacific Journal of Energy and Environment. 6. 101-112. 10.18034/apjee.v6i2.727.
3. Sreedevi, Indu. (2020). An efficient solar energy harvesting system for wireless sensor network nodes. Journal of Information and Optimization Sciences. 41. 10.1080/02522667.2020.1714182.
4. Sharma, Himanshu & Haque, Ahteshamul & Jaffery, Zainul. (2019). Maximization of Wireless Sensor Network Lifetime using Solar Energy Harvesting for Smart Agriculture Monitoring Maximization of Wireless Sensor Network Lifetime using Solar Energy Harvesting for Smart Agriculture Monitoring. Ad Hoc Networks. 10.1016/j.adhoc.2019.101966.
5. Qaragoez, Yasser & Pollin, S. & Schreurs, Dominique. (2024). Integrated Dual-Mode Energy Harvesting for Self-Sustaining Sensor Nodes: Synergy of Solar and RF Energies.