Design & evaluation of a Hybrid Energy-harvesting System for Wearable Health & Environmental Monitoring

An Honors Thesis Proposal

Samanvay Upadhyay

December 2025

Professor Jeremy Gummeson, Faculty Sponsor

Electrical and Computer Engineering Department

Professor Yeonsik Noh, Secondary Reader

Electrical and Computer Engineering Department

Introduction

This honors thesis explores the design, simulation and scheduling of a hybrid energy-harvesting system meant for battery-less wearable sensing. The system utilizes three ambient energy sources (photovoltaic, thermoelectric and kinetic) and uses energy-aware sensing and transmission scheduling to allow perpetual battery-less operation with a small energy buffer capacitor. Three validated simulation modules (SEH: PV model and IV fitting, TEH: transient/steady two-node thermoelectric solver with ambient weather matching, KEH: transient piezo models with rectifier + capacitor simulation) along with a scheduler simulator that uses per-session CSV/parquet outputs from those modules have been created for this project in my 499Y honors research. These simulation modules use publicly available datasets for these energy harvesters to build representative combined timebases for realistic use scenarios (outdoor exercise, indoor movement, rest), estimate achievable sensing uptime and data quality and maximize useful sensing and transmission while minimizing energy buffer size by exploring scheduling policies.

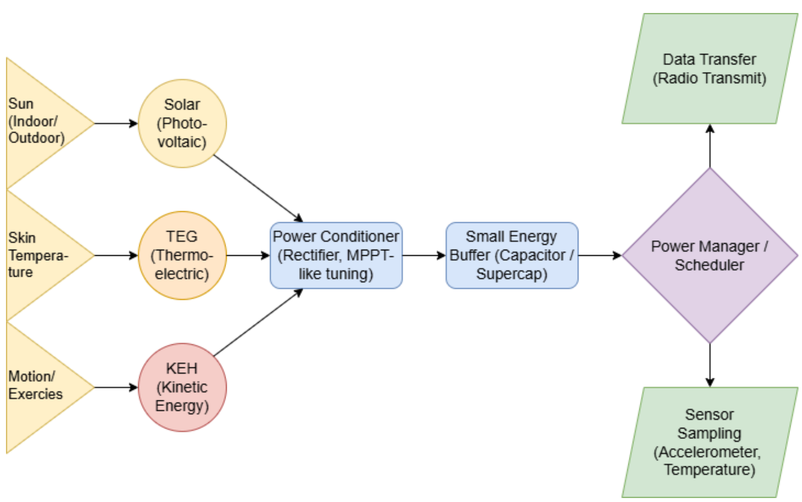

Figure 1: General overview of the Hybrid Energy-Harvester's system architecture setup.

Wearable health monitors are ubiquitous but constrained by batteries that affect the device's form factor, lifetime and environmental sustainability. Hybrid energy-harvesting intends to reduce, or even remove, this reliance on batteries by capturing power from multiple sources of ambient energy. However, creating a practical battery-less wearable device requires co-design between harvesters, power electronics and task scheduling, especially policies tailored to the intermittent and multi-modal nature of energy harvesting patterns in the real world. This research uses simulation and scheduling models at the system level to measure how well hybrid solutions perform, along with their limits, for real-time health monitoring and general sensing tasks.

Scientific Question

Is sustained periodic sensing and intermittent wireless reporting for a sensing system possible with a hybrid energy-harvesting system (solar + thermoelectric + kinetic) and to what extent? What scheduling strategies minimize energy storage requirements while maximizing the sensing uptime and data quality across realistic active and resting scenarios.

Objectives.

1. **Measure energy supply** from PV, TEG and KEH under realistic usage scenarios using the three simulation models. Generate stats per session (mean power, energy per session, duty factors, power quantiles) and compute resampled distributions across each scenario.
2. **Develop and test scheduling policies** (periodic, threshold, opportunistic, predictive) to maximize sensing uptime and data quality while lowering energy storage costs.
3. **Understand storage sizing tradeoffs** by determining the minimum energy buffer size to meet performance goals (sampling quality, transmission reliability) under each scenario.

4. **Produce a tested simulation based design framework and lookup table** for a battery-free wearable prototype such as expected sampling uptime outdoors and indoors, recommended buffer capacity and harvester sizes.

Deliverables.

1. Per-session statistics for PV, TEG and KEH datasets.
2. Scenario-based combined timeseries and bootstrap distributions.
3. Comparative scheduler evaluation based on performance and energy storage metrics.
4. Thesis manuscript, final presentation and hardware prototype of the hybrid energy-harvesting system.

Significance and relationship to literature

The literature review covers hybrid energy harvesters along with software/hardware frameworks necessary for batteryless devices. Recent reviews point to hybridization of energy harvesters as a way to reduce needed energy storage while improving dependability [4][5]; recent prototypes also show integrated harvest and storage and batteryless wearables [6][8]. My project advances this field by combining high-fidelity simulation models for the three harvester types and scheduler simulation to understand system-level tradeoffs. The area of my work remains under-quantified in the literature because prototype measurements are costly and environment dependent.

Importance to knowledge advancement.

1. **System-level insight:** Instead of one device, the research looks at multiple energy inputs and how they interact with energy-aware scheduling. This provides practical guidance to designers of battery-less wearables on sizing and policy choices.

2. **Methodological contribution:** The simulation and scheduler combined approach produces reproducible results of scenario-specific estimates for storage sizing and uptime which enables faster design iterations without testing on hardware first.
3. **Application relevance:** Results from this research will directly inform the feasibility of battery-less monitoring under typical real-world scenarios using hybrid energy-harvesting. It will also help huge practical harvesters and scheduler pairings.

Literature Review

Introduction

Wearable tech—fitness bands, smart glasses, and biomedical sensors—is increasingly being used owing to improvements made possible by flexible sensor technologies and microcircuit integration[1]. However, energy supply is a prime challenge for such devices. Traditional energy supply solutions tend to be hard and bulkier, thus limiting the overall usability and device design. Moreover, they tend to degrade with time and thus require periodic recharging and replacement[1][2]. The possibility of replacing them on a periodic basis for devices meant for use at a distance and for on-body use may be difficult and raise concerns for the environment[3][4]. To overcome these difficulties, various harvesting solutions for extracting ambient energy from various heat and chemical processes and for powering the device seamlessly have begun to emerge[5][6]. Hybrid energy harvesters that collect energy from various sources tend to be more efficient and reliable. Most current literature in this field still focuses on single harvester sources like piezo or light or lacks the long-term, multi-modal datasets that my research will be generating. Another recent advancement is batteryless

Internet-of-Things solutions that use small capacitors or supercapacitor storage for power and do not interrupt services even with varying energy supply through harvested energy[2][6][7][8]. This review provides insight into the advances from 2019 to 2025 for wearables with energy harvesting and batteryless design. These wearables function on the premise of power-harvesting methods instead of battery power and thus tend to be highly dependent on accessible ambient energy; therefore, they demonstrate highly dynamic behavior for task execution. Due to the constantly changing power conditions, the task scheduler needs to adapt at a highly accelerated rate for uninterrupted functioning of basic operations. Some wearables tend to forecast tasks for high-priority accomplishment when resources are limited. Energy harvesters for wearables harness the energy from motion, heat, and light and transform them into electrical energy for sensors and health monitors. A significant number of emerging wearables allow uninterrupted operations without the requirement for recharging from outside energy resources. Research from the literature suggests advancements mainly from experimentation-based approaches and solutions instead of proposals at the concept level and from recent publications within the current decade. A key factor missing from papers and physical prototypes in this field is the simulation-first approach present in my work that allows for testing corner cases (e.g., long periods of indoor inactivity).

Hybrid Energy Harvesting

Hybrid energy harvesting combines various energy conversion processes and leverages the environment for simultaneous harnessing of various energy forms. The combination and integration of various energy types, such as solar and mechanical energies, increase overall energy and stabilize energy supply and flow rates [9][10]. Liu et al. describe the core aspects and elements of design for Hybrid Energy Harvesting (HEH) and cover aspects such as material properties and design aspects, structural design and integration approaches, and application areas and analysis for HEH and energy harvest integration and applications for various products and design types [11]. It is observed in various literature works that overall efficiency can be increased with simultaneous use and conversion and harnessing from multiple energy types and resources and combination and integration approaches such as joint solar and piezoelectric energy harnessing as well as joint harnessing and conversion from solar and thermoelectric energy types and resources and methods and approaches [9][11]. For example, harnessing and conversion from solar energy with thermoelectric and kinetic energy originating from various motion activities and events would increase overall net energy harvesting among various lighting and motion activities. Kang and Yeo point to specific hybrid implementations: Ren et. al made a flexible device that links an organic solar cell to a single-electrode TENG, improving the harvester's voltage and current by ~120% and 105% with respect to having them as individual devices[12][13]. Similarly, Zhao et al. showed a hybrid nanogenerator that captures piezoelectric (mechanical) and solar energy, delivering greater power density than standalone transducers [12]. The advantages of combined harvesting methods are starting to be measured more precisely. Simone et al. used actual climate records like sunlight and wind to analyse hybrid harvesting. Their findings indicate that well-structured integrated systems keep running steadily despite changing environments and need far less stored power. For example, their results "show that one of the main advantages of the hybrid solution is the reduction in the size of the storage device, enabling the replacement of rechargeable batteries with supercapacitors"[10][14]. In simple terms, hybrid energy systems may reduce the need for large buffers, making it easier to run devices without batteries. Liu et al. noted that synergetic hybrids like piezoelectric–pyroelectric films or tribo–photoelectric stacks can deliver high power output per area while maintaining flexibility [3].

Designing hybrid harvesters needs precise setup. Different transducers should match both electrically and mechanically and power-management circuits must handle multiple inputs[9]. Kang and Yeo highlight difficulties in handling power from various origins, pointing out that control logic is essential to match varying voltages or currents while also improving energy transfer efficiency[2][9]. Still, more studies now describe hybrid setups: Recent wearable prototypes have been combining organic photovoltaics with piezo/tribo generators or with thermoelectrics[6][9]. With better materials and flexible electronics, hybrids offer better power and dependability: pairing body-heat TEGs with small PV cells can supply better stable current both day and night; vibration harvesters can contribute additional power during peak motion periods. Overall, combined or multiple-energy sources are becoming a reliable way to increase usable power and maintain functionality in wearables[13][10].

Batteryless Sensor Systems and Intermittent Computing

Batteryless sensor nodes rely only on collected energy, using capacitors or tiny supercapacitors for short-term storage instead. To function, these transiently powered systems gather sufficient charge before activating for sensing or sending data. Consequently, such devices work in bursts: charging first, running briefly, then turning off until more energy is gathered[7]. Unlike conventional battery-driven units with steady power supply, their operation isn't continuous but cycles with available energy. Mosavat et al. point out that without batteries, devices usually run in short bursts because stored power is limited; as a result, steady performance becomes difficult compared to systems using batteries[7].In line with this, Ahmed et al. argue that scaling to more

IoT units requires designs that work reliably while avoiding both upkeep and reliance on traditional power sources [3][4].

When devices run on and off, it creates challenges for consistent operation. During outages, preserving the processor's condition becomes critical. Engineers apply nonvolatile storage like FRAM to save data before shutdowns. Alternatively, they organize code into repeat-safe blocks that handle resets without errors. Lukas et al. developed a working battery-free package system meant for wearable tech[2]. Their prototype includes an ultra-low-power SoC, FRAM (non-volatile boot memory), and a radio; it can sense and process data (at only ~1.02 μW average power) and recover from power loss without losing state[2][8]. Other works design software frameworks and compilers (e.g. Alpaca, Chain, Mementos) specifically to support intermittent execution. Ahmed et al. note that the community has indeed developed new energy-efficient programming languages, compilers, runtimes, and architectural mechanisms to enable practical batteryless IoT applications[3]. These advances include checkpointing libraries, loop invariants, and task scheduling mechanisms tailored to the on/off power pattern.

In networked sensing, running without batteries impacts communication. For example, Mosavat et al. explore ways to support wireless links between energy-limited, battery-free devices[7]. Since standard radios use too much power even while waiting, they suggest using wake-up receivers (WuRs), which monitor channels more efficiently. This reveals an essential design trade-off: adding functionality such as connectivity while respecting irregular, scarce energy supplies. As a result, batteryless wearables typically carry out basic actions intermittently, capture small data amounts, send them quickly, then enter low-power mode, timed according to available energy.

On the whole, moving to batteryless sensors means changing both hardware and software approaches. While microcontrollers need to run steadily on tiny amounts of power, usually through energy-harvesting circuits, peripherals should use as little energy as possible. Systems with fewer components, like direct wireless links or event-triggered data collection, work better here. Even so, there are working models of entirely battery-free wearables: one uses a flexible patch powered by sunlight[6], another runs a fabric-based pressure grid via a slim thermoelectric layer[2]. Altogether, smart engineering shows such devices can function well when active only briefly and occasionally.

Energy-Aware Scheduling in Batteryless Devices

Due to limited, unpredictable power, timing and resource handling matter greatly in devices without batteries. Tasks like sensing or sending data need alignment with available energy supply. In real use, smart scheduling appears in various ways. At minimum, a device tries an action once its internal charge reaches a threshold. Better methods assign fixed times or rank jobs by expected energy levels alongside how urgent they are.

Recent studies looked at timing methods for devices using harvested energy. Sabovic et al. showed a system that schedules jobs based on available power, considering both task links and incoming energy flow [3]. While approaches differ, they mainly aim to prevent situations where big tasks stop halfway due to low power. For example, the system could split heavy computations into chunks matching regular charging periods. Alternatively, it may postpone less urgent actions until more energy arrives, like sunlight powering solar sensors.

In networked settings, managing power use ties into how messages are sent. According to Mosavat et al., deciding to use wake-up radios counts as timing control: rather than staying active nonstop (an inefficient approach), the device remains in deep sleep until a separate WuR trigger activates it briefly[7]. Other protocols similarly incorporate knowledge of each node's energy state. The goal is to maximize forward progress, the total useful work done (sensing or transmitting data) while avoiding wasted attempts when a device is energy-starved.

These approaches follow a simple rule: use no more energy than what is gathered over time. For example, in battery-free IoT systems using tinyML, tasks might run locally or be sent elsewhere depending on available power at the moment. Instead of frequent writes, smart caching helps save resources when electricity is scarce - recent studies point this out. According to Ahmed et al., progress continues here; researchers are building easier tools for developers, such as code environments and timing controls that adjust themselves if power drops suddenly[2].

In conclusion, energy-aware scheduling in batteryless wearables involves dynamically prioritizing or fragmenting tasks to fit within available energy, leveraging low-power hardware features to minimize idle losses and co-designing system software to checkpoint and recover state. These approaches together help ensure that batteryless wearables can perform their sensing and communication tasks reliably even under unpredictable power input.

Wearable Harvesters and Applications

A variety of energy-harvesting devices have appeared on wearables. Sunlight is easily available outdoors, making solar cells common. Thin organic and perovskite solar units are now built into flexible tech or clothes. Jinno et al. developed soft, waterproof organic solar films for smart textiles[6], working well even when bent around body shapes. Some tiny fiber-shaped solar elements are already woven directly into cloth structures [7].

Thermoelectric devices convert body heat into electrical energy by applying the Seebeck effect. Since skin runs at roughly 34°C and ambient air sits near 22°C, just a narrow thermal gradient emerges - so power levels usually stay in the microwatt range per cm^2. Still, flexible TEG units work well in wearable formats like wristbands or adhesive patches. Wang's team in 2020 linked ultra-thin thermoelectric layers with sensors to make garments that sense touch while generating their own current[10]. As long as there's a temperature contrast, these units deliver consistent direct current, unlike motion-driven systems prone to fluctuations.

Mechanical harvesters using piezoelectric, triboelectric, or electromagnetic principles capture energy from movement. When deformed, materials such as PVDF generate electric charge through piezoelectric effect. TENGs create power via surface contact and separation, often using fabric layers that exchange electrons. Zhao et al. built a hybrid nanogenerator combining piezoelectric and photovoltaic elements to scavenge light and motion[12]. Piezo/tribo generators can output pulses in the 10–100 μW range during active motion (e.g. walking or bending), but generate no energy at rest which is why they are extremely relevant in hybrid designs.

Integrated harvesters and energy storage combine the above methods. For example, Sun et al. wove a textile "solar-mechanical" cable that simultaneously generates electricity from light (organic PV) and motion (triboelectric layers)[4]. Such multifunctional fabrics can power small sensors continuously in real-life use. These smart harvesters provide steady power to tiny sensors during everyday activities. Because they capture energy in multiple ways, such materials support various body-worn devices. While individual designs suit specific scenarios, mixed approaches should deliver steadier output for upcoming wearable technologies.

Methods

The research is divided into a two-stage methodology:

1. **Simulation stage (completed and reproducible):** generate modality and timestamp-based harvested power traces using PV cells, TEG and KEH. Align and

combine the traces into representative scenario timeseries, understand power generation based on these scenarios and evaluate scheduler policies on an energy-buffer model. These steps were implemented in the provided python codebase and produced bootstrap numbers and sampling-rate feasibility estimates used in this proposal.

2. **Harvester prototype stage:** implement lab bench tests and wearable prototype experiments to compare actual harvester outputs to simulation results and measure actual per-event energy costs on a target hardware platform. Refine the simulation models based on hardware results.

Preliminary Research

Simulation models:

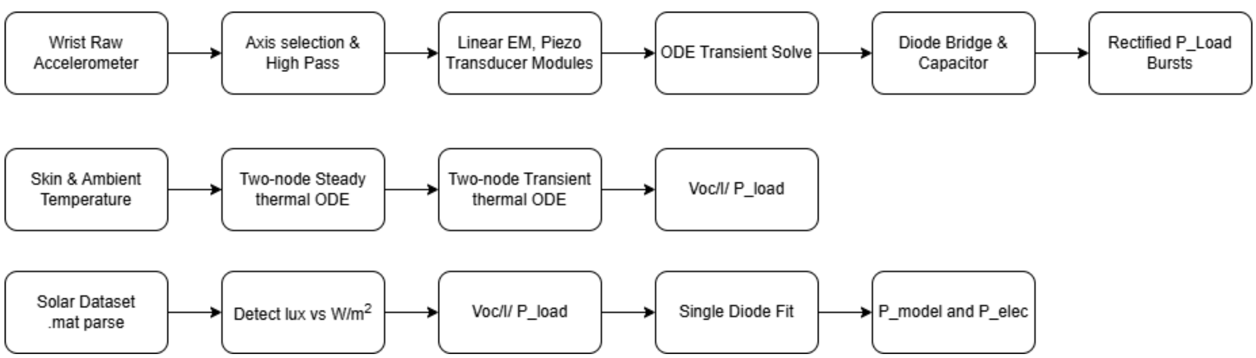

Figure 2: Simulation Model Overview for KEHs, TEGs and PV cells respectively.

1. PV pipeline

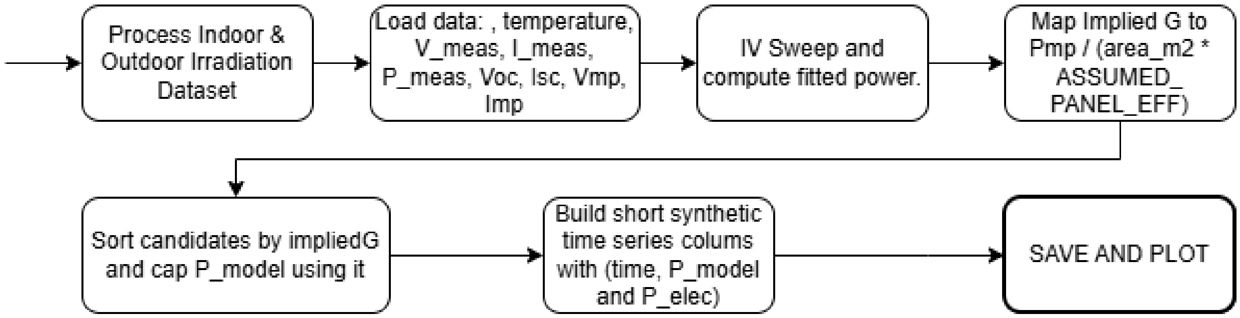

Figure 3: Simulation Model for Photovoltaic cells

The dataset used for PV cell simulation comes pre-processed with measured power collected from the harvester [15]. The simulation model confirms the data by mapping the computed power to an Implied G to detect implausible fit results. The model also uses an assumed panel efficiency (based on the efficiency of Hi-Tronic ZW 86x82 solar panels used in the dataset) to determine actual harvestable energy from the PV panel.

a. Input .mat filetype datasets of irradiance and V/I sweeps, convert lux to W/m^2 heuristic, NOCT temperature estimate, single-diode least-squares fit and datasheet fallback.

b. Output per sample P_model_W and P_elec_W (after booster efficiency).

2. TEG pipeline

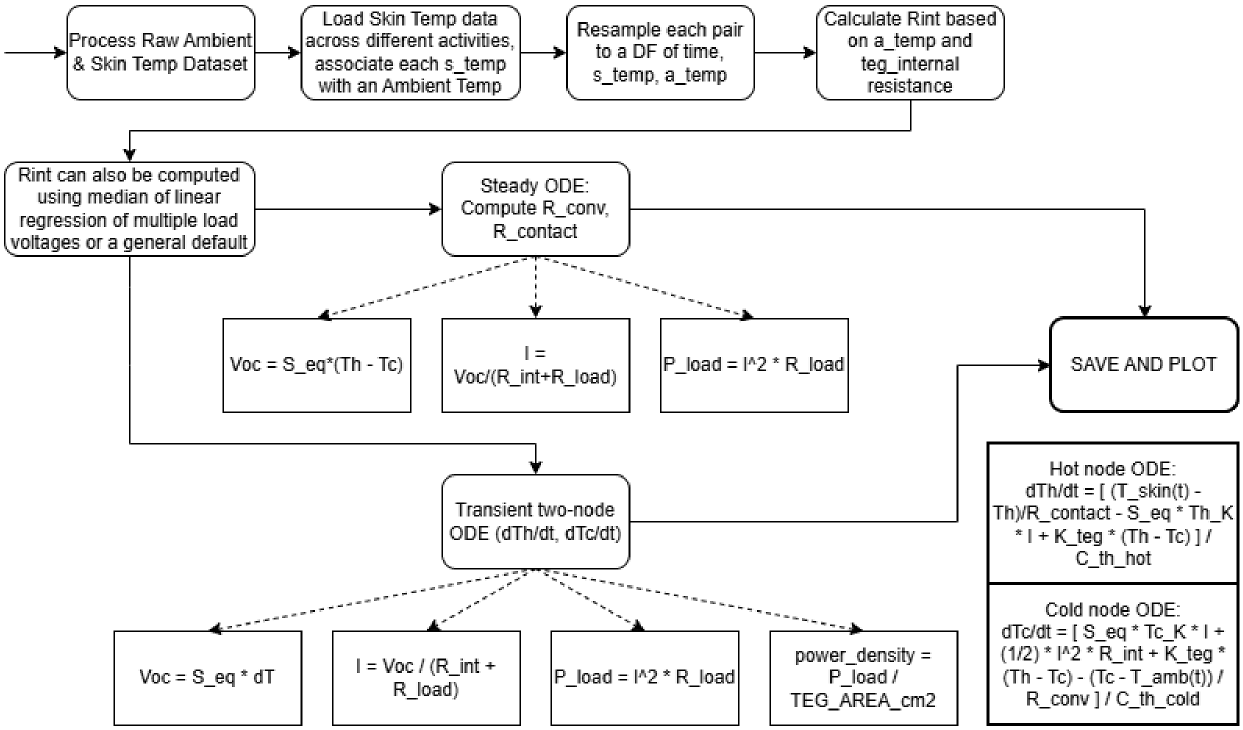

Figure 4: Simulation Model for Thermo-electric generators

The dataset used for thermo-electric generators does not come pre-computed with measurable power[16]. The dataset does provide meaningful insight into body temperature across various activities like aerobic work like walking and resting and anaerobic work like running and exercising. The simulation code uses a two-node thermoelectric model for both steady state and transient solvers. It uses wearable TEMP.csv sessions from the dataset and the Meteostat library for ambient temperature values. The code maps a module-level thermal resistance to the simulation area, calculates per-area convective and radiative coefficients and converts the legacy contact / convective resistance inputs to per-area conductances. The steady-state function (teg_steady_df) deals with a nonlinear two-equation problem at every time step (concerning the temperatures of hot and cold nodes) and uses scipy.optimize.root with a least squares fallback, if necessary. The transient function (teg_transient_df) generates interpolators for the skin and ambient temperatures, initializes with the steady state, solves the ordinary differential equations for Th and Tc with solve_ivp, and finally transforms the obtained solutions back into the original temporal order.

a. Input: wearable TEMP.csv and ambient Meteostat temperature
b. Output: per-sample P_load_W, T_h_C, T_c_C and energy using two-node transient and steady thermal models.

3. KEH pipeline

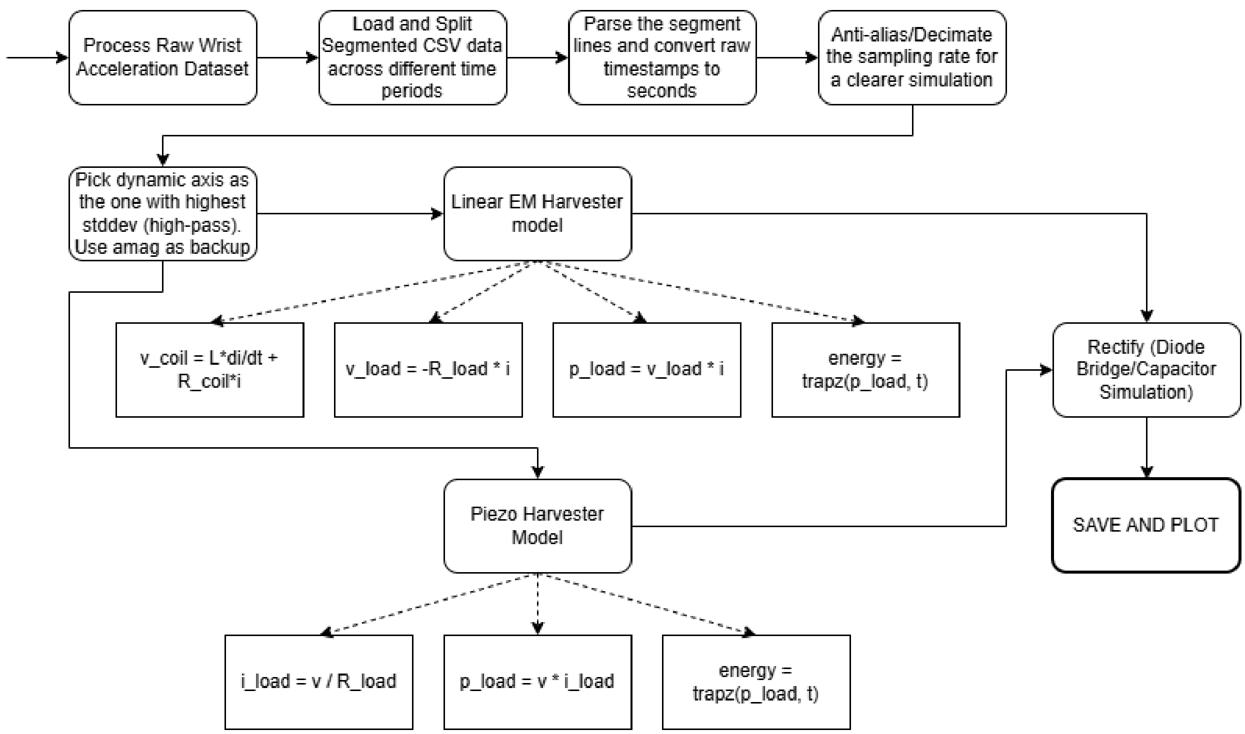

Figure 5: Simulation Model for Kinetic Energy-Harvesters

The dataset used for KEH simulation consists of wrist accelerometer data across various physical activities [17]. The script KEH takes raw acceleration logs, transforming them into rectified harvester power traces, modeled with physics-based transient solutions for linear electromagnetic harvesters and piezoelectric harvesters, together with a heuristically derived transient solution for a rectifier and a capacitor charger. The script reads nanosecond-timestamped acceleration logs, splitting them into monotonic chunks, which are then optionally resampled at a specified rate. The script also optionally selects a dynamical axis, high-pass filtering all three axes to remove the effects of gravity, then picking the axis with the highest dynamical variance. There are two harvester models with solutions for transients. In LinearEMHarvester, a three-state system (displacement, velocity, coil current) is modeled with a solution for an initial value problem, while a coupled mechanical-electrical state with piezoelectric capacitance is modeled with a solution in PiezoHarvester. Following the solution of the transients, a stable simulation for a diode bridge with a capacitor (diode_bridge_cap_simulate) is run to derive Vcap, Iload, and rectified Pload for specified charging resistance and capacitance.

a. Input: Raw wrist accelerometer logs
b. Output: P_load parquets using transient piezo solver and diode-bridge & capacitor simulation produce rectified traces.

4. **Scheduler**

The scheduler analyzes the statistics of a given session by resampling with a specified time unit dt, as well as metrics like mean, median and percentiles, together with the probability of exceeding certain thresholds, followed by a bootstrap resampling on the mean of sessions to acquire a distribution per scenario, where the bootstrap technique is used to compare the scenarios irrespective of the size of the time series. The scheduler makes policy evaluation by generating a representative, aggregate timebase for a particular situation. This is done by picking a reference series, scaling the alternative modalities within the same temporal horizon with reference, center, and scale modes, after which the corresponding power columns are aggregated to obtain the total harvest W. The energy simulator itself simulates a capacitor buffer with the equation $E = 0.5CV^2$, with specified Vmin and Vmax, leakage, and booster efficiency. The eta_simple function is employed to simulate the efficiency of power conversion, which depends on the input power. The energy simulator also considers different cost models, such as E_wake, E_sample, E_proc, E_tx_session, and per byte E_tx, which are used in different policy types: periodic, threshold, opportunistic, EWMA, event-driven, and batch.

a. Input: Processed files from previous simulation pipelines.
b. The scheduler classifies these files into the three categories of PV, TEG and KEH, resamples and aligns the files to build scenario combined timebases, compute scenario distributions and policy simulation using an energy-buffer model and operation costs: E_wake = 2.0e-3 J; E_sample = 1.0e-3 J; E_proc = 0.5e-3 J; E_tx_session = 10e-3 J; per byte = 0.01e-3 J; bytes_per_sample = 4.
c. Output: Power availability in different scenarios.

Simulation Results:

1. Representative harvester simulations:

a. KEH

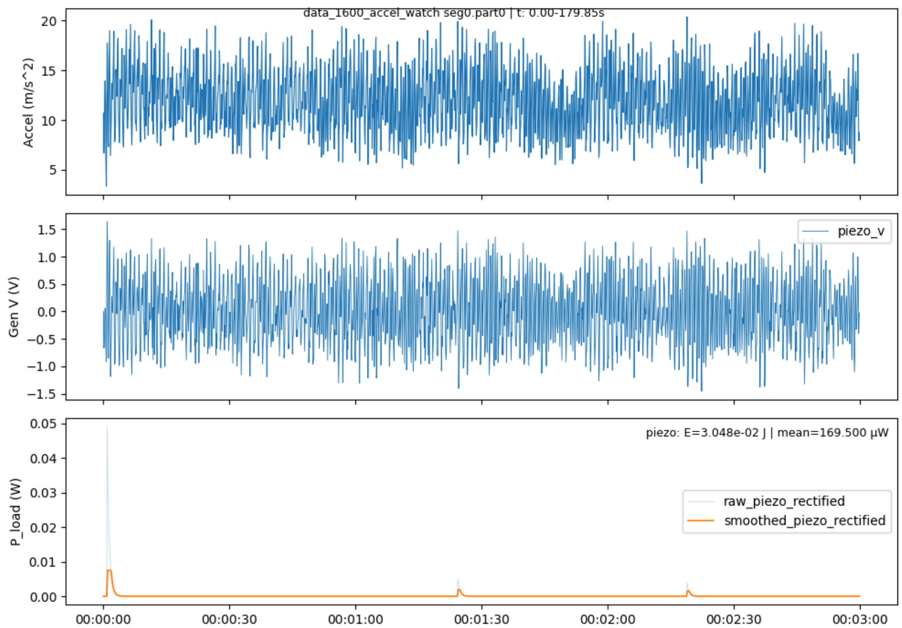

Figure 6: Representative KEH while general resting

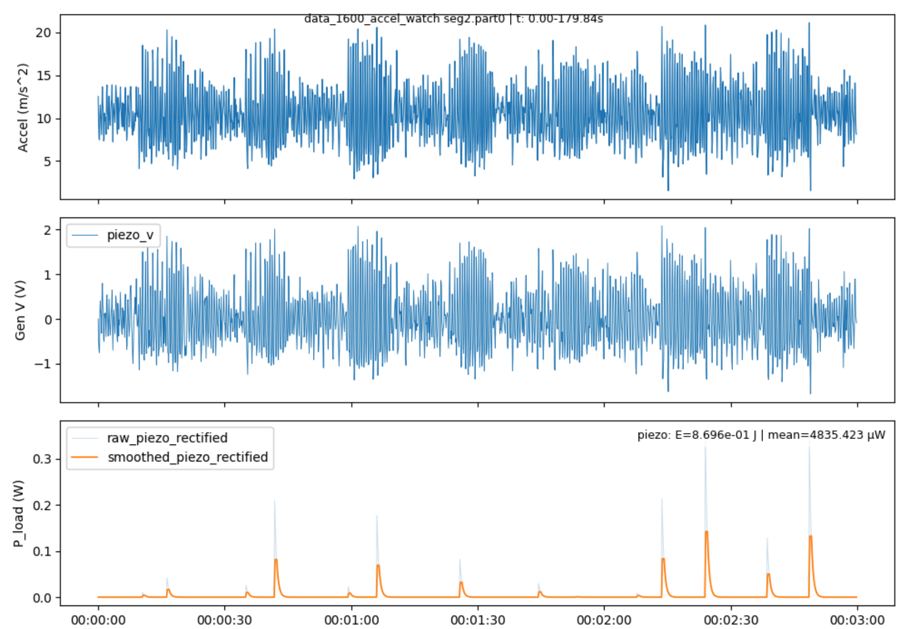

Figure 7: Representative KEH while exercising

b. TEG

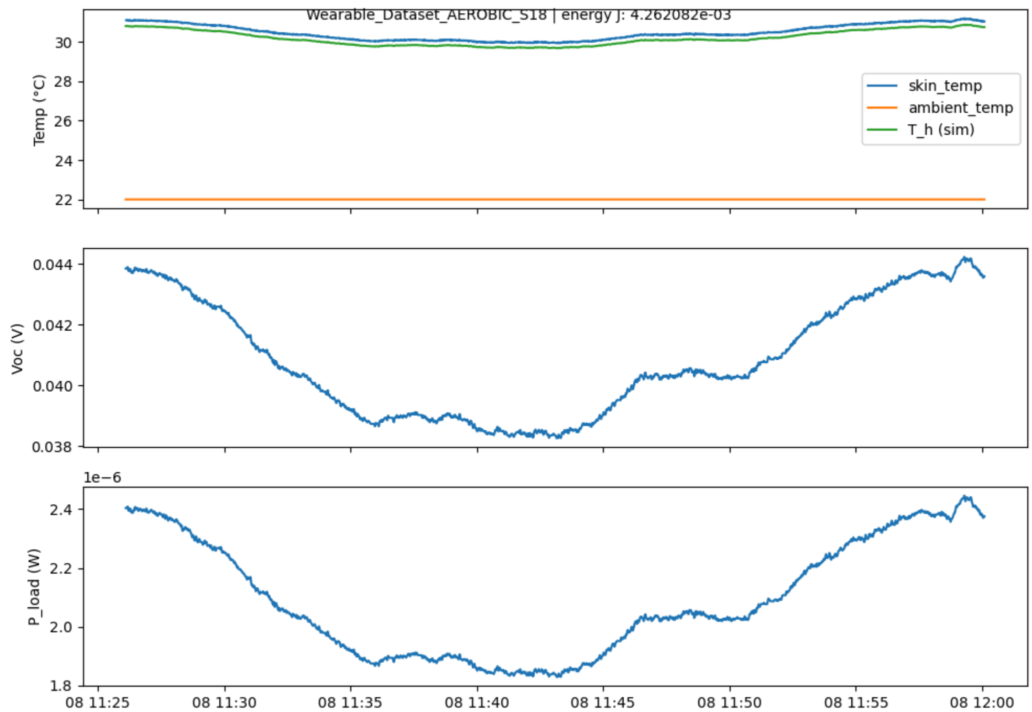

Figure 8: Representative TEG while resting

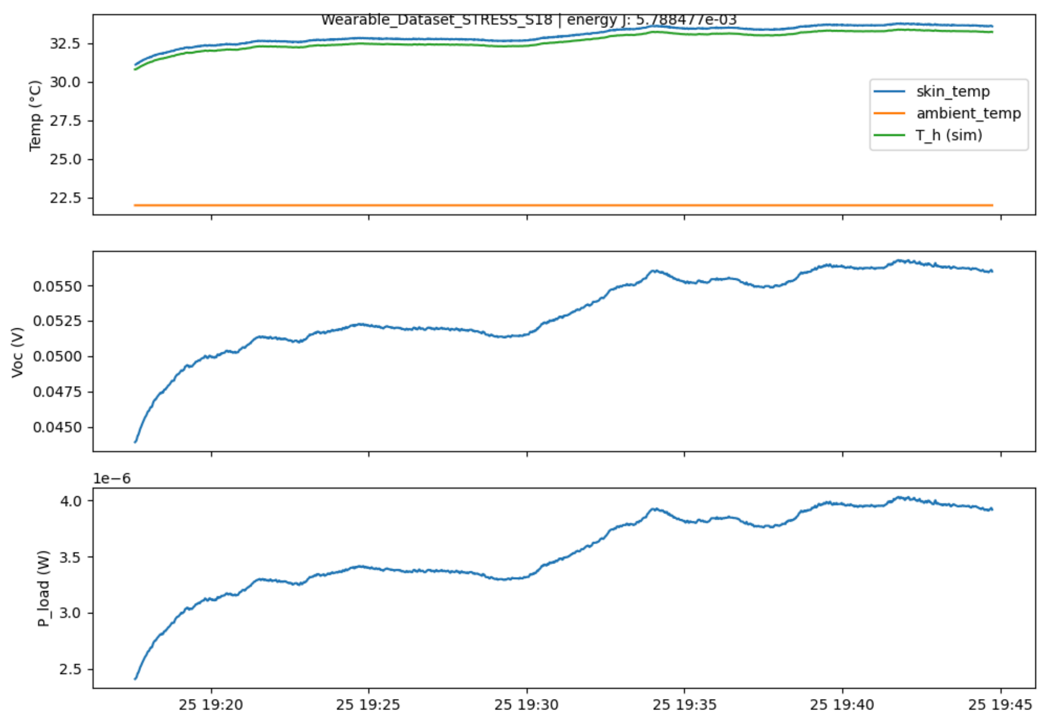

Figure 9: Representative TEG while exercising

c. PV

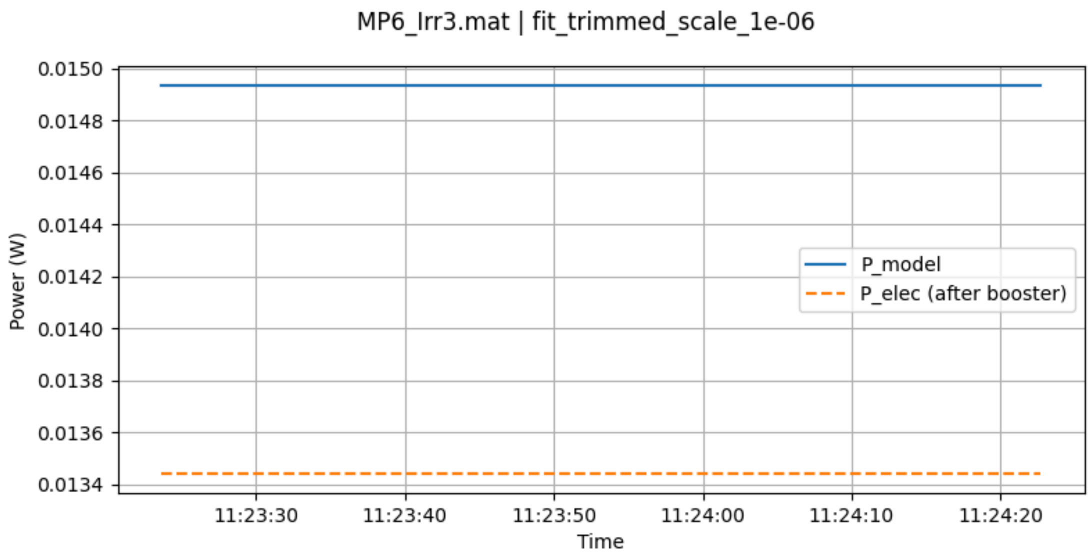

Figure 10: Representative PV harvest outdoors (immobile)

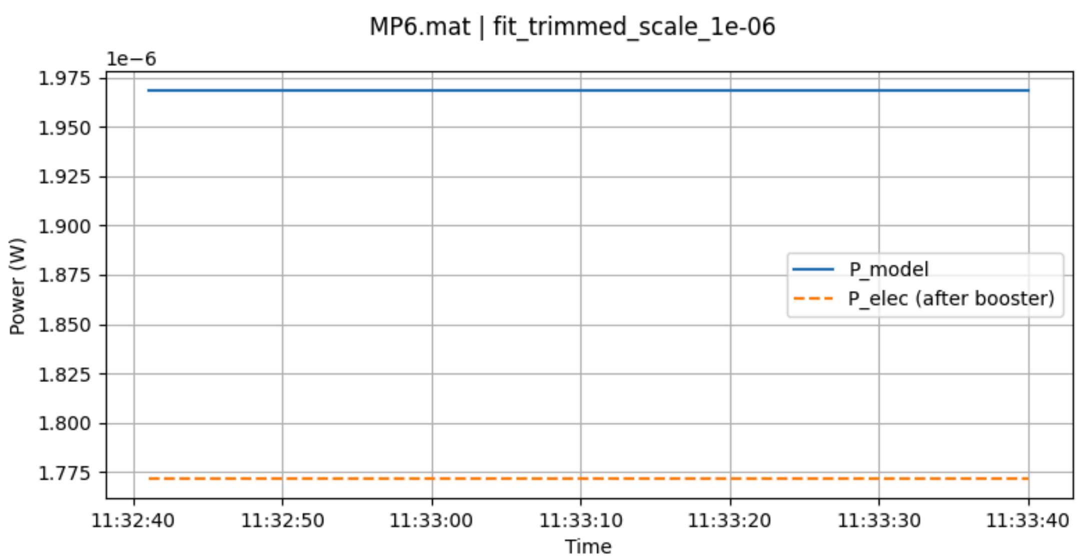

Figure 11: Representative PV harvest indoors (negligible)

2. **Analysis of harvester simulations:**

   a. **KEH**

      i. Segment 0: piezo energy ≈ 3.048×10^{-2} J; mean rectified ≈ 169.5 μW.

      ii. Segment 2: piezo energy ≈ 8.696×10^{-1} J; mean rectified ≈ 4.8 mW

      iii. Pattern: short, high-power spikes; long intervals of near-zero harvest.

      iv. Implications: KEH is best used opportunistically during physical activity; a small buffer is necessary to store energy for immediate transmit or local processing.

   b. **TEG**

      i. Voc ranges ~0.028 – 0.06 V depending on trial

      ii. P_load on the order of 1 - 4 μW

      iii. STRESS: mean P_load ≈ ~3–4 μW, AEROBIC: smooth 1.8–2.4 μW trend.

      iv. Pattern: TEG can provide a steady low-power baseline; transient solver captures thermal inertia and changes during activities.

      v. Implications:TEG is suitable for background low-rate tasks (temperature logging, occasional keepalive, etc.)

   c. **PV**

      i. Outdoor: P_model is approximately 14.62 mW with 0.9 efficiency on the PV panel

      ii. Indoor: Negligible power in the magnitude of 10-12.

      iii. Implication and Pattern can’t be determined due to lack of wearable PV datasets though the present simulation suggests PV being used opportunistically like KEH when outdoors.

3. **Key measured values from scheduler sim:**
    a. outdoor_solar ≈ 0.01057 W (≈ 10.57 mW).
    b. indoor_solar ≈ 1.47e-06 W (≈ 0.00147 mW, negligible).
    c. keh_only ≈ 0.013033 W (≈ 13.03 mW).
    d. exercise_only (KEH + active TEG) ≈ 0.018588 W (≈ 18.59 mW).
    e. rest_only ≈ 0.000030 W (≈ 0.03 mW, negligible).
    f. Outdoor exercise (solar + exercise) ≈ 0.029158 W (≈ 29.16 mW).
    g. Indoor exercise ≈ 0.0185895 W (≈ 18.59 mW).

    Using operation costs provided above, one regular sample event consumes about 3.5e-3 J. Therefore, some representative sampling numbers are as follows:

    - Outdoor exercise ≈ 8.3 samples/sec
    - Exercise_only ≈ 5.3 samples/sec
    - KEH_only ≈ 3.7 samples/sec
    - Outdoor_solar alone ≈ 3.0 samples/sec
    - Rest_only ≈ 1 sample every two minutes

High-duty but low-bandwidth tasks (outdoor exercise, exercise_only, keh_only):

- Possibility of Periodic ECG snapshots though raw ECG sampling is still infeasible.
- Any of the lower duty tasks mentioned below.

Moderate duty tasks (outdoor solar alone):

- Step counting, environmental logging, coarse heart rate estimation.

- On-body environmental monitors (temperature, humidity, etc.) that sample slowly.

Low energy / opportunistic tasks (rest, indoor solar):

- Low duty activities and intermittent monitoring
- Passive health tagging like storing a timestamped event when something triggers motion.

Hardware Prototype

Hardware Design

1. **Primary goal:** Confirm the simulation-derived predictions on real hardware and refine the simulation parameters based on the necessary overheads of the hardware I use for my prototype.
2. **Components:**
   a. **Harvesters:**
      i. **PV:** Small flexible cells for both indoor and outdoor solar harvesting. Specific cells will be identified based on availability, parameters on simulation models can be updated based on different devices.
      ii. **TEG:** Micropelt module TGP-651, Small footprint (1.5 cm2), S_eq = 0.006 V/K. Parameters on simulation model can be updated if final prototype uses a different module.
      iii. **KEH:** Small piezo harvester for wrist mounting. Other mounting areas like ankle or shoe can be determined based on dataset availability.
   b. **Power Management IC** (specifically suited for Energy Harvesting) and **Energy Buffer** (supercapacitor bank of configurable capacitance)

c. **Low-Power Microcontroller** (for scheduling and processing), **Radio** (small BLE transceiver), **Sensors** (Accelerometer, skin thermistor, optional ECG)

3. **Measurement instruments:**
    a. **Oscilloscopes** to measure instantaneous harvester currents and general PMIC activity
    b. **Solar simulator, Temperature-controlled hotplate, Shaker Actuator & Accelerometer**
4. **Experiments:**
    a. Verify best scheduler strategies by running experiments with the hardware prototype
    b. Run targeted workloads based on determined use-case and buffer capacity for comparing scheduling
    c. Move on to scenario tests like outdoor exercise (solar+kinetic), indoor movement (kinetic), resting (thermal)
    d. Measure uptime, sensing quality, energy budgets.
    e. Confirm metric between simulation and real-world

Evaluation

Measurable goals.

1. Create cleaned per-session statistics for at least 10 sessions per modality (PV, TEG, KEH) with summary parquets and plots
2. Evaluate different scheduling policies across all scenarios and create a comparative table of different metrics like sampling rate, sampling transmission, uptime fraction.
3. Produce a thesis manuscript and hardware prototype for the research.

Assessment criteria:

1. Technical correctness like fidelity of simulation, justification of modeling assumptions and clarity in scheduler algorithmic logic.
2. Ability to reproduce combined timeseries and scheduler runs on similar datasets.
3. Interpretation and analysis of tradeoffs and design choices like policy choice and energy storage size.
4. Writing quality of manuscript, figures and tables. Effectiveness of final presentation.

Communication

Communication for next semester will be similar to this semester. I will be having weekly 30-minute meetings with Professor Gummeson. We will understand the data derived from the hardware prototype, discuss results, identify obstacles and plan next steps. All design, additional simulation, and hardware work will be conducted individually and no additional technician assistance will be expected.

Timeline

The timeline for next semester is as follows:

- Have access to all hardware parts - February 4
- Confirm component-level characterization and ensure all parts work as intended - February 11 (if not the follow the fallback plan)
- Compare hardware lab tests with simulation results and fine-tune simulation models if necessary - February 17th
- Finish running hybrid workloads based on different use-cases (mentioned above) and buffer capacity for comparing scheduling (Bench test) (if not the follow the fallback plan) - March 3rd
- Complete scenario tests like outdoor exercise (solar+kinetic), indoor movement (kinetic), resting (thermal) - March 17th
- Measure uptime, sensing quality, energy budgets and confirm metrics between simulation and real-world - March 31st
- Thesis 1st draft submission - April 3rd
- Thesis 2nd draft submission - April 10th
- MassURC Exhibition - April 17th
- Thesis final submission - April 17th
- ECE Honors Exhibition - April 23rd

Fallback options: If specific parts become unavailable, use discrete development boards and modules that are immediately available off the shelf. If discrete breakouts become necessary for different harvesters, ensure the hybrid approach remains relevant by expanding on the bench test instead of moving on to scenario tests by creating realistic scenario parameters in the lab itself. If hardware fails completely, produce an expanded simulation validation report that uses high-quality component curves measured from supplier datasheets and justify the results from the simulation using those values.

References

[1] C. Xu *et al.*, *"Portable and wearable self-powered systems based on emerging energy harvesting technology," Microsystems & Nanoengineering*, vol. 7, article 25, 2021. doi:10.1038/s41378-021-00248-z.

[2] M. Kang and W.-H. Yeo, *"Advances in energy harvesting technologies for wearable devices," Micromachines*, vol. 15, no. 7, p. 884, 2024. doi:10.3390/mi15070884.

[3] S. Ahmed *et al.*, *"The Internet of Batteryless Things," Commun. ACM*, vol. 68, no. 2, pp. 28–37, Feb. 2024.

[4] H. Liu, H. Fu, L. Sun, C. Lee, and E. Y. Yeatman, *"Hybrid Energy Harvesting Technology: From Materials, Structural Design, System Integration to Applications," Renew. Sust. Energy Rev.*, vol. 137, p. 110473, 2021. doi:10.1016/j.rser.2021.110473.

[5] A. Simone, P. Marino, R. Greco, and A. Lo Schiavo, *"Quantifying the Benefits of Hybrid Energy Harvesting from Natural Sources," Electronics*, vol. 14, no. 7, p. 1400, 2025. doi:10.3390/electronics14071400.

[6] S. Saifi *et al.*, *"An ultraflexible energy harvesting-storage system for wearable applications," Nat. Commun.*, vol. 15, article 6546, 2024. doi:10.1038/s41467-024-50894-w.

[7] S. Mosavat, J. Göpfert, B.-C. Renner, and M. Zimmerling, *"CATO: Wake-Up reCeiver-based communicaTiOn for Batteryless Devices," Sensors (Basel)*, vol. 25, no. 2, p. 582, 2025.

[8] C. J. Lukas *et al.*, *"A 1.02 µW Battery-Less, Continuous Sensing and Post-Processing SiP for Wearable Applications," IEEE Trans. Biomed. Circuits Syst.*, vol. 13, no. 2, pp. 271–281, Apr. 2019. doi:10.1109/TBCAS.2019.2894775.

[9] J. Yuan and R. Zhu, *"A fully self-powered wearable monitoring system with systematically optimized flexible thermoelectric generator," Appl. Energy*, vol. 271, p. 115250, 2020. doi:10.1016/j.apenergy.2020.115250.

[10] Y. Wang *et al.*, *"Self-Powered Wearable Pressure Sensing System for Continuous Healthcare Monitoring Enabled by Flexible Thin-Film Thermoelectric Generator," Nano Energy*, vol. 73, p. 104773, 2020. doi:10.1016/j.nanoen.2020.104773.

[11] Y. Wang *et al.*, *"Hierarchically patterned self-powered sensors for multifunctional tactile sensing," Sci. Adv.*, vol. 6, no. eabb9083, 2020. doi:10.1126/sciadv.abb9083.

[12] X. Zhao *et al.*, *"Hybridized Nanogenerators for Effectively Scavenging Mechanical and Solar Energies," iScience*, vol. 24, p. 102415, 2021. doi:10.1016/j.isci.2021.102415.

[13] H. Jinno *et al.*, *"Stretchable and Waterproof Organic Photovoltaics for Washable Electronic Textile Applications," Nat. Energy*, vol. 2, pp. 780–785, 2017. doi:10.1038/s41560-017-0009-8.

[14] J. Min *et al.*, *"An Autonomous Wearable Biosensor Powered by a Perovskite Solar Cell," Nat. Electron.*, vol. 6, pp. 630–641, 2023. doi:10.1038/s41928-023-01010-7.

[15] B. J. Restrepo-Cuestas, A. Ortiz-Pasos, and M. Durango-Flórez, “Electrical behavior dataset of photovoltaic mini panels under indoor and outdoor conditions,” Data in Brief, vol. 60, p. 111607, Jun. 2025, doi: https://doi.org/10.1016/j.dib.2025.111607.

[16] A. Hongn, F. Bosch, L. E. Prado, José Manuel Ferrández, and M. P. Bonomini, “Wearable Physiological Signals under Acute Stress and Exercise Conditions,” Scientific Data, vol. 12, no. 1, Mar. 2025, doi: https://doi.org/10.1038/s41597-025-04845-9.

[17] G. Weiss. "WISDM Smartphone and Smartwatch Activity and Biometrics Dataset ," UCI Machine Learning Repository, 2019. [Online]. Available: https://doi.org/10.24432/C5HK59.