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## RESEARCH ARTICLE

# An Energy-Aware, Self-Adaptive, Battery-Free Smart Wristband for Long-Term Health Monitoring

SHIHONG CHEN<sup>1</sup>, (Student Member, IEEE),  
AND ESTHER RODRIGUEZ-VILLEGAS<sup>1</sup>, (Fellow, IEEE)

Wearable Technologies Laboratory, Department of Electrical and Electronic Engineering, Imperial College London, SW7 2AZ London, U.K.

Corresponding author: Shihong Chen (shihong.chen19@imperial.ac.uk)

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**ABSTRACT** Continuous monitoring of physiological parameters, including heart rate and oxygen saturation, is important in healthcare applications. Modern wearables are expected to support wireless connectivity, be small and lightweight, and offer long-term use. These features introduce challenges in power consumption and management. As a result, battery-powered wearables often face trade-offs between size, energy storage, performance, and operating time. This research presents a self-sustainable, battery-free smart wristband for continuous heart rate monitoring. The wristband extends operational life by integrating solar energy harvesting with supercapacitor technology in an environmentally sustainable design. Power consumption is minimized through onboard processing, which reduces inefficient data transmission, and adaptive sensor sampling, which dynamically allocates energy based on heart rate, supercapacitor voltage, and harvesting conditions. Benefiting from hardware and software co-design, the proposed wearable device achieves self-sustainability at a sensor sampling rate of 50 Hz with only 1.45 hours of indoor light exposure (1000 lux) per day and at 200 Hz with 4.74 hours. The in-field experiments show that onboard processing reduces Bluetooth Low Energy (BLE) data transmission to essential information, saving about 2 J of energy. The system shortens supercapacitor charging time by 17 minutes per hour through its ability to automatically reduce the sampling frequency from 200 Hz to 50 Hz when harvesting energy is scarce. The proposed system can even operate effectively in around 200 lux of light, equivalent to a dimly lit living room. These results underscore the system's ability to dynamically balance power-performance trade-offs, offering a promising long-term solution for continuous health monitoring in various environments.

**INDEX TERMS** Adaptive sampling, battery-free, power management, energy-aware, onboard processing, indoor solar energy harvesting, supercapacitor, wearable devices.

## I. INTRODUCTION

Wearable health monitoring systems are emerging as important tools in modern healthcare because these devices enable continuous real-time measurement of vital physiological parameters, which help evaluate health conditions, detect early warning signs, and prevent hospital readmissions [1]. The non-invasive and easy-to-integrate photoplethysmography (PPG) technology is distinguished as an effective method

for monitoring vital signs, such as heart rate and oxygen saturation [2].

However, supporting the widespread adoption of autonomous wearable devices in healthcare requires systems that are compact, lightweight, and maintain high performance over long periods [3]. The main challenge is to balance these design requirements with reliability and user comfort, an essential factor for the advancement and adoption of wearable health technologies.

Due to the limited power density of traditional batteries [3], [4], [5], realizing compact form factors in wearables presents

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significant challenges. This limitation results in an inherent system design trade-off between device size, power capacity, system performance, and device lifetime [3]. To be specific, wearable devices must be small enough to remain unobtrusive, but this size reduction often limits the battery capacity; therefore, the available power is limited. Furthermore, approaches to improve performance, such as increasing data accuracy or enhancing the real-time processing capabilities, typically result in increased power consumption, which in turn reduces the device's operational lifetime unless a larger battery is used—contradicting the need for a compact form factor [3], [4].

Different methods have been developed to address these limitations by enhancing particular components of wearable devices. To enhance both device performance and operational lifetime without compromising size, researchers have proposed solutions, including energy harvesting [5], [6], improved energy storage [7], [8], [9], advanced power management techniques [10], [11], [12], [13], and on-board processing [14]. These strategies typically focus on solving one aspect of the problem at a time, rather than providing a comprehensive system-level solution.

To support the perpetual operation of wearable devices, the wearable system should be optimized from a systems perspective rather than optimizing individual subsystems in isolation. Energy efficiency is intended to be balanced for the energy harvester, storage unit, and sensor load to maintain functionality and extend operational lifetime. System performance, i.e., sensing accuracy and reliability, may degrade when power consumption is reduced at the component level. Therefore, system-level energy optimization remains imperative to balance power capacity, device size, and performance. To the best of our knowledge, no solution has yet integrated these technologies into an overarching framework that holistically manages the trade-offs among device size, energy capacity, and performance and offers extended autonomous operation.

This paper introduces a self-sustaining solar-powered wristband that operates without batteries to track heart rates in real time. The system combines solar energy harvesting with a supercapacitor technology, onboard processing, and real-time adaptive sampling to create a unified solution. The design considerations and key features in the proposed system are summarized below:

- Solar energy harvesting provides renewable power, enabling the wristband to function without a traditional battery.
- The supercapacitor extends operational life with significantly higher charge-discharge cycles and provides a more sustainable alternative by storing energy through electrostatic processes, rather than relying on chemical processes.
- Onboard processing minimizes power consumption by selectively processing relevant data, reducing the need for frequent Bluetooth Low Energy (BLE) transmission.

- Real-time adaptive sampling dynamically manages the system's power distribution, adjusting the sampling frequency of the PPG sensor based on solar energy availability, supercapacitor voltage, and heart rate data, ensuring optimal system performance under various conditions.

The rest of the paper is structured as follows. Section II reviews related work and summarizes various approaches to address the identified challenges. Section III presents the proposed system and details its implementation through hardware–software co-design. Section IV provides the experimental results and analysis. Finally, Section V concludes the paper.

## II. RELATED WORK

The field of energy harvesting has gained substantial interest because it enables wearable devices to operate longer by extracting power from the environment. The potential of wearable devices has been explored through different technologies, which include solar cells [7], [14], [15], [16], [17], [18], kinetic energy harvesters [19], [20], thermoelectric generators [21], [22], [23], and RF energy harvesting systems [24], [25]. Researchers have introduced hybrid power solutions that integrate multiple energy sources to boost both reliability and energy availability [26], [27], [28].

Among energy harvesting methods, solar energy is promising for miniaturized wearables due to its higher power density, enabling it to capture renewable energy from ambient light while maintaining a compact form factor [6]. However, the availability of solar energy harvesting depends on continuous light exposure, which is not ubiquitous; therefore, energy storage components must be included to compensate. The device size tends to increase when additional solar panels are added due to suboptimal design [7].

To optimize energy storage in wearable systems and decrease dependence on traditional batteries, supercapacitors have been proposed as a sustainable alternative. Supercapacitors offer significantly higher charge-discharge cycles and faster charging capabilities, which can extend the operational lifetime of wearable devices [8], [9]. These properties make them particularly well-suited for energy-harvesting-based BLE sensor devices. Their ability to withstand frequent charge-discharge cycles aligns well with the intermittent nature of energy harvesting. Their high current capability meets the instantaneous current demands of BLE communication and PPG sensors, which often require several milliamperes of current draw. This addresses a key limitation of conventional rechargeable batteries, which are less efficient at delivering high current bursts [7]. Although the integration of supercapacitors alleviates certain limitations of traditional batteries, key challenges remain. Notably, these include limited energy availability for harvesting and the trade-off between storage capacity and device form factor.

While supercapacitors improve energy storage capabilities, minimizing power consumption at the device load remains

essential. Onboard processing has been explored as an effective strategy to reduce load power consumption by processing data locally, thus decreasing the energy required for transmitting raw data [14]. In [14], onboard processing reduced power consumption by up to 53% compared to raw data transmission. However, despite this reduction, the system described in [14] still faces limitations for continuous, high-performance monitoring. Specifically, the system requires prolonged charging periods—up to 12 hours under 500 lux illumination—to maintain constant operation. This prolonged charging requirement highlights a critical limitation, underscoring the need for further improvement in energy efficiency beyond relying solely on onboard processing.

The onboard processing system reduces communication-related energy consumption, but further techniques are studied to optimize power usage at the energy harvesting and sensor load stages. In [26], the system combines solar and RF energy harvesting with Maximum Power Point Tracking (MPPT), allowing each source to track and maximize energy harvesting independently. Similarly, [28] incorporates MPPT and manual switching between solar and USB power sources for sensors. At the sensor level, [10] employs a duty-cycling method to reduce power consumption from the sensor load, while [17] discusses using sleep and wake-up modes to ensure continuous operation and prolong the node's lifetime.

The research has also investigated adaptive sampling as an energy optimization method. The sampling rate stands as a critical element that determines both sensor data resolution and energy usage in wearable systems according to [29] and [30]. The simplest method to save energy involves lowering the sampling rate because it reduces the number of data collection and transmission events. The approach requires finding a balance between maintaining application-specific accuracy and reducing the sampling rate. The dynamic adjustment of sampling rates according to monitored activities leads to improved energy efficiency, as reported in [31], [32], and [33]. The sampling rate needs to be elevated while running because this activity requires precise data acquisition. The system uses reduced sampling rates for sedentary activities to save energy without affecting performance. The adaptive approach represents a crucial requirement for wearable devices that use energy harvesting or operate with power limitations [33]. However, the solutions mentioned above typically address only one aspect of the system, such as user activity, without considering the availability of energy harvesting or the status of storage.

One application of adaptive sampling in PPG-based wearables is to adjust the sample rate of PPG sensors. The sampling rate of PPG sensors is an important factor in balancing power consumption, maintaining an adequate signal-to-noise ratio (SNR), and ensuring the accuracy of physiological measurements [34], [35], [36], [37], [38], [39], [40]. In [34] and [35] stated that a sampling rate of at least 50 Hz is adopted for the correct analysis of

heart rate variability (HRV) metrics but for more accurate metrics like Root Mean Square of Successive Differences (RMSSD) and Percentage of successive NN (normal-to-normal) intervals that differ by more than 50 milliseconds (pNN50%), sampling rates of more than 100 Hz are recommended. The analysis of pulse rate variability (PRV) does not require interpolation when the sampling rate is 100 Hz. However, when the sampling rate is 250 Hz, time-domain HRV metrics such as Standard Deviation of Normal-to-Normal Intervals (SDNN) and RMSSD are well captured. Sampling rates above 250 Hz do not contribute much unless the environment is very noisy [35], [36]. The results of the studies show that PRV metrics from sampling rates of 100–200 Hz have a bias of less than 2%, while those from sampling rates of 40–50 Hz have a bias of 20% [37]. Nevertheless, the higher sampling frequency significantly increases power consumption, especially in the LED components of the PPG sensors, as they need to be activated more frequently [40]. Furthermore, higher sampling rates require higher storage and processing capacities, which is a big concern in resource-limited systems [34]. To overcome these problems, methods such as compressive sampling, event-driven sampling, and aggressive duty cycling have been proposed to reduce power consumption without significantly sacrificing the SNR [40], [41]. However, these methods require sophisticated edge algorithms for signal reconstruction and, as such, consume more power, and in some cases, require customized circuits [42], [43], [44]. Interpolation techniques, such as cubic splines [38], can enhance the accuracy of the signal at lower sampling rates, but at the cost of higher computational complexity and, consequently, increased power consumption by the system [36], [40]. In paper [38], it was shown that applying spline interpolation to “upsample” the PPG signal allows for a much lower base rate (e.g., 10 Hz) to be used while still preserving the HRV metrics. In their controlled simulation, a 10 Hz sampled PPG (with cubic spline refinement) produced almost identical HRV results to those of a raw 200 Hz signal. However, this is only possible if advanced offline processing is carried out. Reference [38] noted that if no interpolation is applied, the native sampling rate (200 Hz) must be high enough on its own. Therefore, in practical wearable applications (where real-time processing and power constraints limit the use of extensive interpolation), it is better to use a higher native sampling frequency rather than post-processing techniques. Therefore, the activation timing of LEDs at the system level must be optimized to find the best compromise between power efficiency and accuracy. Thus, the correct selection and optimization of the sampling rate for PPG sensors will enable a suitable trade-off between power consumption and accuracy, thus enabling long-term health monitoring.

To complete the proof of concept, this paper proposes an adaptive PPG sampling mechanism in a solar harvesting system, where the sampling frequency dynamically adjusts

between 50 Hz and 200 Hz based on three key parameters: the MPPT voltage from the solar cell, the voltage on the supercapacitor, and the measured heartbeat. These parameters reflect the availability of environmental energy, the energy conservation status within the system, and the application's requirements for accurate physiological monitoring.

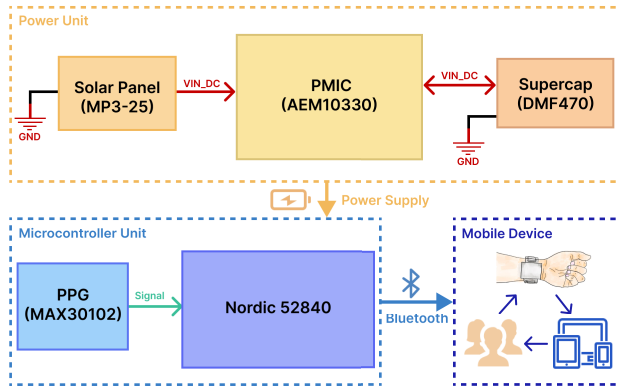


FIGURE 1. Block diagram of the flexible solar energy harvesting system.

### III. PROPOSED SYSTEM DESIGN

Figure 1 presents a comprehensive system diagram of the proposed smart wristband, with critical efficiency points highlighted for design considerations. The architecture of this system can be broadly divided into three subsystems: the power source unit, the processing unit, and the sensing unit. To achieve optimized end-to-end efficiency, the efficiency of each subsystem must be optimized, and the compatibility between subsystems must also be ensured.

The power source unit serves as an energy reservoir and consists of three main components: a flexible solar panel for capturing energy, a power management unit (PMU) for regulating voltage, and a supercapacitor for storing energy. These components work together to ensure maximum energy harvesting and efficient conservation of excess energy for future use. As shown in Figure 1, the first critical efficiency point occurs at the harvester. The solar cell captures light energy (both solar and indoor artificial light) and converts it into an unregulated voltage and current output. To maximize the harvested energy, an MPPT circuit is implemented to maintain the solar cell at its Maximum Power Point (MPP), typically using impedance matching. This circuit dynamically adjusts the operating conditions to optimize energy extraction. The second efficiency point ensures that the harvested energy is delivered to the load in a stable and reliable manner. To achieve this, a regulated circuit, such as a boost or buck converter, is required to convert the voltage from the harvester's output to the appropriate voltage level for the load. Because the light source is not ubiquitous, and solar energy can only be harvested when light is present, energy storage via a supercapacitor is essential. The supercapacitor not only stores surplus energy but also acts as a current buffer, managing sudden high current demands from components

like the BLE module or sensors. The third efficiency point is ensuring that the maximum harvested energy is safely transferred into the storage device without damaging it. This is achieved by incorporating overvoltage and undervoltage protection mechanisms into the charging circuit.

The processing unit manages the operational states of the different components and enables effective data acquisition by the sensor node. As one of the power-hungry components in the system, MCU are configured into sleep mode for the majority of the time, drawing an average current of approximately  $1.5 \mu\text{A}$  with the peripherals of the Real-time counter (RTC) module and the low-frequency clock source (LFCLK) running. Thanks to these peripherals, not only save lots of energy but also keep checking the state of the rest of the system so that a duty-cycling manner can be achieved by enabling the MCU only when the counter initiates an event.

The sensing unit is responsible for collecting physiological signals in a non-invasive manner. To validate this proof-of-concept, the sampling frequency of the PPG sensor is chosen to be adaptive due to its significant impact on power consumption and resource usage stated in the aforementioned section II.

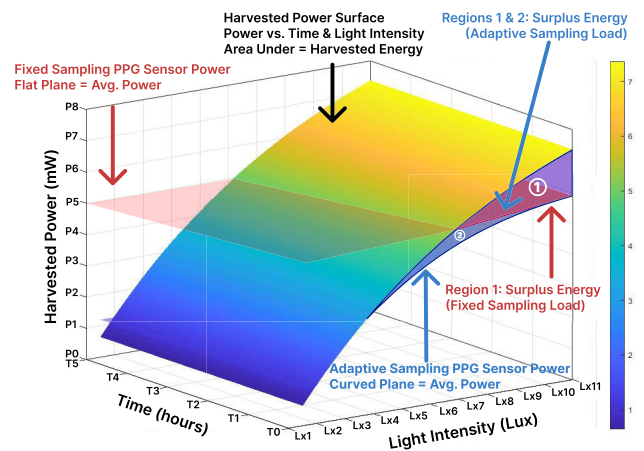


FIGURE 2. Illustration of adaptive and fixed sampling rate sensor power profiles under varying illumination levels. 3D surface plot representing harvested power (mW) as a function of light intensity and time. The surface is generated under idealized conditions assuming constant light intensity over time at each illumination level. In real-world scenarios, light intensity is variable due to environmental and user-related factors. This plot serves as a conceptual illustration to compare harvested power trends with sensor power demands under fixed and adaptive sampling schemes.

To illustrate the adaptive sampling strategy's functionality in the proposed system for achieving power conservation on the load side, a 3D surface plot is provided in Figure 2.

While the 3D surface plot assumes constant light intensity over time for each illumination level, this simplification reflects an idealized scenario. In realistic settings, light intensity — especially in wearable contexts — fluctuates due to motion, environmental changes, and user activity. This figure is intended primarily as a conceptual tool to illustrate the interaction between illumination, time, and harvested

power, and to highlight periods where energy surplus or deficit may occur with respect to system load. Actual harvested energy would require integrating a time-varying power profile, which is considered in the system's dynamic energy-aware design and validated in the experimental results.

The power consumption of two distinct sensor configuration methods is compared. The x-axis represents light intensity (lux), marked as  $Lx0$  to  $Lx11$ ; the y-axis is time (hours), marked as  $T0$  to  $T5$ ; and the z-axis is harvested power (mW), marked as  $P0$  to  $P8$ .

The plot assumes that, under ideal conditions, if light intensity is maintained over a duration of time, the power harvested per unit time is also constant. The equation to compute this diagram is shown below:

$$E = \int_{Lx0}^{Lx11} \int_{T0}^{T5} P(t, I) dt dI \quad (1)$$

where  $E$  is the total harvested energy (in milliwatt-hours, mWh). This integral measures the accumulated energy over time and varying light intensity, and is interpreted as the volume under the surface.

The surface represents the harvested power  $P(t, I)$  in milliwatts (mW), as a function of  $t$ , time (hours), and  $I$ , light intensity (lux). The level of harvested power is represented by the color bar, ranging from dark blue (low) to yellow (high).

The flat, red, semi-transparent plane in the center is the average power consumption of the PPG sensor driven at a constant sampling rate (traditional approach) at  $P5$ . This allows visualizing the relationship between the power consumption of a constant sampling rate load and the harvested power as the interaction between two planes: the harvested power surface and the flat red plane.

At  $Lx7$ , the intersection point marks where the two planes meet. As the light intensity increases above this point, the harvested power is greater than the average power consumption of the constant sampling load. This creates Region 1, the space between the red plane and the harvested power surface, which is surplus energy that can be stored in the energy storage unit.

Likewise, the semi-transparent blue curved plane beneath the harvested power surface represents the average power consumption of the PPG sensor when it is operating at an adaptive sampling rate. Since light intensity is used as a parameter to adjust the sampling rate, the adaptive power surface decreases with decreasing light intensity. The area between the adaptive power surface and the harvested power surface forms Region 1 and Region 2. Region 1 represents the saved excess energy, and Region 2 represents the additional energy savings achieved by using the adaptive sampling approach compared to the traditional fixed-rate sampling scheme.

The benefits of adopting an adaptive sampling scheme extend beyond power conservation. As indicated in the figure 2, the average power consumption of the fixed-configuration PPG sensor remains constant, irrespective

of the harvested energy status. This configuration relies heavily on the energy storage element to store excess energy during periods of surplus and provide energy during shortages. However, this approach risks either energy wastage during surplus periods or insufficient power during shortages if the storage capacity is not ideally matched to the system's requirements. Conversely, when the PPG sensor's sampling frequency adapts to the availability of environmental energy, the system can dynamically optimize power consumption. By adjusting the frequency based on the energy available, the overall system performance and power efficiency are more effectively balanced. This adaptive approach ensures the system can intelligently manage energy, toggling between power conservation and performance boost modes as needed. For example, when harvested energy is abundant but the energy stored in the storage element is low, the system can prioritize recharging the supercapacitor by reducing the sensor's power consumption. If the user's heart rate is relatively low, which may indicate a resting state, the system can lower the PPG sensor's sampling frequency. This reduction in sampling frequency will decrease power consumption while still maintaining acceptable measurement accuracy. Meanwhile, the power management integrated circuit (PMIC) can allocate more energy to recharge the supercapacitor, ensuring quicker energy recovery. This context-aware decision-making enables the system to automatically balance performance and energy efficiency, depending on both the user's physiological state and the available energy. The system is extensible so that additional sensors or peripherals can be incorporated, provided that the total power consumption remains within the defined energy constraints.

#### A. HARDWARE IMPLEMENTATION

To maximize overall system power efficiency, a system-level approach must be applied. It is not only crucial to select optimal individual components but also to engineer them to function cohesively. These components can be categorized into three subsystems: the Power Harvesting Unit, Central Processing Unit, and Sensing Unit. The goal of the Power Harvesting Unit is to extract the maximum available energy from the environment. The Central Processing Unit focuses on reducing transmission power through



**FIGURE 3.** Overview of the solar-powered wristband prototype, weighed on an electronic scale with a total mass of 31.76 g.

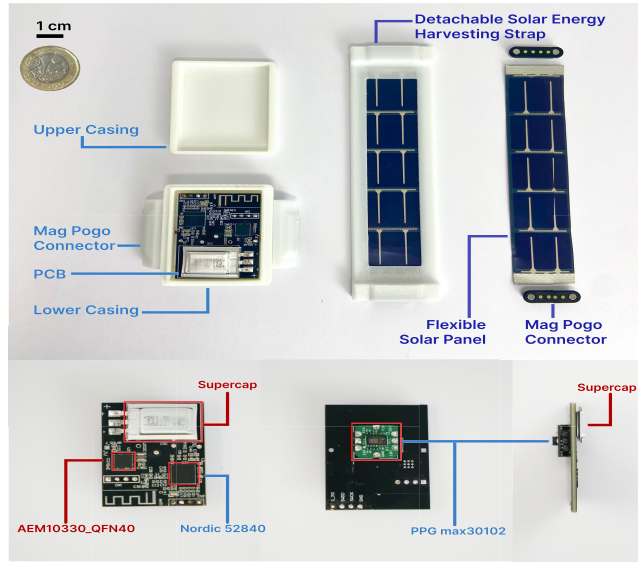


**FIGURE 4.** Detailed illustration of the wristband prototype structure and components.

on-board data processing. Finally, the Sensing Unit adapts its operations to make the system context-aware, enabling dynamic adjustments based on environmental and operational conditions.

### 1) POWER HARVESTING UNIT

Within the power harvesting unit, the power management unit (PMU) plays a crucial role in maximizing and effectively managing harvested energy. The PMU is responsible for performing MPPT to ensure the solar cell consistently operates at its optimal power output. Furthermore, it regulates the harvested energy to deliver rated voltage and current levels according to load requirements and provides essential protection against Undervoltage and overvoltage conditions, thus enabling safe and efficient charging of the energy storage elements. Therefore, the selection of an appropriate PMU significantly impacts the overall efficiency and performance of the power harvesting system.

A wide variety of PMICS are available for energy harvesting applications, each offering distinct capabilities and specifications, illustrated in Table 1. Selecting an appropriate PMIC involves careful consideration of several key factors, including input voltage range, MPPT effectiveness, compatibility with different types of energy storage elements, startup voltage requirements, dynamic power distribution mechanisms, and built-in safety features such as supercapacitor balancing circuits and voltage protections. The ability of a PMIC to initiate charging from a fully depleted supercapacitor is particularly crucial, as some PMICS may misinterpret a fully discharged supercapacitor as a faulty battery (bq25504), or require specific configurations to activate charging mechanisms, which could complicate system integration and operation (bq25570) [28]. Additionally, dynamic power distribution capabilities enable efficient energy allocation

between the storage element and the load, significantly enhancing overall system efficiency and performance. For illustrative purposes in this study, the AEM10330 PMIC was selected due to its notably low startup voltage requirement of 275 mV (equivalent to 3  $\mu$ W), integrated dynamic power control mechanisms, and built-in supercapacitor balancing circuit suitable for dual-cell configurations, as specified in its datasheet [45]. Additionally, as indicated in Table 1, the AEM10330 PMIC has two current drive capability ( $I_{out,max}$  range) options: 30 mA in low-power mode and 60 mA in high-power mode. The selection between these two depends on the input and output range of the DC-DC converter to optimize converter efficiency for the AEM10330 [45]. The proposed system is configured with a low-power mode to achieve optimal conversion efficiency, tailored to the input and load requirements.

To align with the concept of wearability in hardware design, the selection of a solar panel should prioritize minimal intrusiveness regarding weight, shape, and flexibility. Thus, initial design considerations should address physical parameters, including solar panel type and materials. Solar panels, categorized based on the silicon form, can be classified into three main types: amorphous, mono-crystalline, and polycrystalline silicon [46]. Although rigid solar cells generally offer cost-effectiveness and higher conversion efficiency, they tend to be bulkier, heavier, and inflexible, potentially compromising wearable comfort and integration. In addition to physical characteristics, electrical parameters significantly influence the overall system design. Essential electrical parameters include current-voltage (I-V) and voltage-power (V-P) characteristics, which guide the selection and design of accompanying components in the solar power system. The open-circuit voltage ( $V_{oc}$ ) is another critical parameter, which must align with the input voltage range of the power PMIC to guarantee optimal functionality. Accurately characterizing the maximum available power under varying illumination intensities is also essential, as it defines the energy budget and influences the PMIC's conversion efficiency, ultimately affecting end-to-end system performance. Furthermore, programming the open-circuit voltage MPPT algorithm in the PMIC to the correct percentage of the MPP is vital for achieving optimal energy harvesting efficiency. Typically, this percentage falls within the range of 60% to 90%, and precise determination requires empirical in-field measurements for specific solar panels. The accurate calculation of the MPP percentage for PMIC programming necessitates determining both  $V_{oc}$  and  $V_{max}$ , as illustrated by equation (2).

$$MPP (\%V_{oc}) = \frac{V_{max}}{V_{oc}} \quad (2)$$

whereas the  $V_{max}$  represents the voltage at which the solar panel outputs the maximum power, the  $V_{oc}$  refers to the open-circuit voltage. For illustrative purposes in this study, the MP3-25 solar panel from PowerFilmsSolar<sup>®</sup> was selected for this work due to its physical specifications and adequate output power. This flexible solar module is

**TABLE 1.** Comparison of PMICs for energy harvesting applications.

| PMIC Model | MPPT | $I_{outmax}$       | Storage Element           | Input Voltage Range             | Converter Type | $I_{Quiescent}$ |
|------------|------|--------------------|---------------------------|---------------------------------|----------------|-----------------|
| bq25570    | Yes  | 110mA              | Li-ion, Li-Poly, SuperCap | 100mV (600mV cold start) - 5.1V | Buck and Boost | 488nA           |
| bq25504    | Yes  | 130mA              | Li-ion, Li-Poly, SuperCap | 80mV (330mV cold start) - 5.5V  | Boost          | 330nA           |
| ltc3105    | Yes  | 70mA               | Li-ion, Li-Poly, SuperCap | 250mV to 5V                     | Boost          | 24μA            |
| ltc4071    | No   | 50mA               | Li-ion, Li-Poly           | down to 0.5V                    | Diode          | 550nA           |
| max17710   | No   | 100mA              | Li-ion, Li-Poly           | 6V                              | Boost/LDO      | 625nA           |
| Aem10330   | Yes  | up to 30mA or 60mA | Li-ion, Li-Poly, SuperCap | 100mV (274mV cold start) - 4.5V | Buck-Boost     | 875nA           |

composed of thin-film amorphous silicon that is laminated with standard-duty PET and features foil tape contact terminals [45]. It also features compact dimensions of  $114\text{ mm} \times 24\text{ mm} \times 0.22\text{ mm}$  and weights only 0.85g [47], which make it an optimal selection for wearable technology. The combination of its lightness and flexibility offers users a comfortable and unobtrusive experience. Moreover, the MP3-25 is well-suited to capture both direct sunlight and indirect light in shady areas. Furthermore, it has a lifetime of up to 30 years and under full sun conditions can generate a power output of 93mW [45].

Due to the inherent characteristics of the solar cell, an energy storage device is required, which not only backs up the surplus energy but also buffers the sudden draw of current by the BLE and optical sensor. The capacity of the supercapacitor should balance between size and adequacy. With these considerations, the storage component employed in this research was a Murata Electronics DMT334R2S474M3DTA0 supercapacitor [49]. With a capacitance of 470 mF, a voltage rating of 5.5 V, and an ESR of 130 mΩ, this device measures  $21\text{ mm} \times 14\text{ mm} \times 3.5\text{ mm}$  and operates within a broad temperature range of  $-40^\circ\text{C}$  to  $85^\circ\text{C}$ .

## 2) CENTRAL PROCESSING

The central processing part of the system was implemented using Nordic Semiconductor's nrf52840, which integrates various hardware sub-systems for data processing, control, sensing, and communication within a chip of  $7\text{ mm} \times 7\text{ mm}$ . The microcontroller features a 32-bit ARM Cortex-M4 core with a floating-point unit (FPU), operating at 64 MHz, hence assuring high computational capabilities while executing sophisticated signal processing tasks [50]. It also integrates a collection of autonomous peripherals, including the Easy-DMA, ADC, and SPI/I2C interfaces, which can be used for efficient acquisition and communication of sensor data with minimal CPU intervention, further optimizing overall power consumption [51]. The nrf52840's programmable peripheral interconnect (PPI) system facilitates direct communication between peripherals without CPU involvement, optimizing energy efficiency in repetitive tasks like sensor data sampling and control. Additionally, the nRF52840 integrates a powerful, ultra-low-power radio supporting Bluetooth 5.2, Thread, and Zigbee, offering robust communication capabilities with a current consumption as low as 4.8 mA in transmission mode at 0 dBm and as low as around 1.5 μA in system ON idle mode

with no RAM retention and Real-time counter (RTC) on from low-frequency clock source [52].

## 3) HEALTH-RELATED SENSING

The sensing module chosen to illustrate the system design decisions (Heart rate in this proof-of-concept) was the MAX30102, a small IC designed for pulse oximetry and heart rate monitoring. This sensor module provides an integrated solution by cooperating with Red and Infrared LEDs, photodetectors, and ambient light cancellation modules, all working in conjunction with advanced low-noise circuitry. The measured raw data can be stored in its internal 186-byte FIFO and later can be read out via I2C by MCU [53].

The MAX30102 can be configured into three modes—Heart Rate mode, SpO<sub>2</sub> mode, and Multi-LED mode—which are selected by enabling either the red LED or both LEDs. The LED current is programmable from 0 to 50 mA with an appropriate supply voltage. Additionally, the LED pulse width can be programmed from 69 μs to 411 μs, allowing the algorithm to optimize SpO<sub>2</sub> and heart rate (HR) accuracy, as well as power consumption, based on different use cases. The sampling rate can be selected from 50 to 3200 samples per second. To validate this proof of concept, the sampling rate of the PPG sensor was engineered to be reconfigurable between 50 Hz, 100 Hz, and 200 Hz, based on feedback from the measured heart rate, the availability of harvested ambient energy, and the level of stored energy.

To ensure that each selected sampling rate is both meaningful and sufficient to yield valid results, equations 3 are used to illustrate the relationship between sampling frequency, heart rate, and signal quality, where signal quality is quantified by the number of samples acquired per cardiac cycle.

$$\begin{aligned}
 N_{\text{samples per beat}} &= \frac{T_{\text{beat}}}{T_s} = f_s \cdot T_{\text{beat}} = f_s \cdot \left( \frac{60}{\text{HR}_{\text{bpm}}} \right) \\
 &= \frac{60 \cdot f_s}{\text{HR}_{\text{bpm}}} \quad (3)
 \end{aligned}$$

whereas:

- $T_{\text{beat}}$  — Duration of one cardiac cycle (heartbeat) in seconds.
- $\text{HR}_{\text{bpm}}$  — Heart rate in beats per minute (bpm).
- $f_s$  — Sampling frequency in hertz (Hz).
- $T_s$  — Sampling interval in seconds (time between samples).
- $N$  — Number of samples collected per heartbeat.

This equation shows that the number of samples per heartbeat is directly proportional to the sampling frequency  $f_s$ , and inversely proportional to the heart rate in beats per minute ( $HR_{bpm}$ ). With the help of this equation 3, the Least number of samples that can be collected per beat can be calculated to capture a clean waveform of a heartbeat using a PPG sensor.

Heart rate (HR) was selected as an adaptive parameter for adjusting the PPG sampling rate, as HR estimation imposes minimal constraints on sampling frequency. Studies have demonstrated that HR can be reliably computed with sampling rates as low as 5–10 Hz, requiring only a few samples per cardiac cycle [38]. In practice, wearable devices often use 20–30 Hz for accurate pulse detection [37]. Thus, all sampling rates employed in this study are sufficient for robust HR estimation.

This study focuses on enhancing power efficiency in wearable systems, and the use of different PPG sampling rates serves illustrative purposes. However, sampling resolution becomes critical for more complex cardiovascular metrics, such as HRV, RMSSD, pNN50, and SDNN. These metrics demand higher temporal precision to ensure accuracy.

For general HRV analysis, a minimum sampling rate of 50 Hz is recommended, with 100 Hz or more preferred for robust measurement [37], [39]. Specifically, RMSSD and pNN50 are susceptible to signal attenuation below 100 Hz, requiring sampling rates in the 100–200 Hz range for accurate representation [34], [37]. According to [38], SDNN—a metric representing the standard deviation of normal heartbeats [39]—can be accurately captured at 50 Hz under typical variability (0.23 Hz with 0.05 Hz deviation). However, in scenarios with subtle, high-frequency variations (0.11 Hz with 0.01 Hz deviation), a sampling rate of 200 Hz is required to avoid interpolation errors and maintain fidelity [39].

HR also reflects the user's physiological state, which influences the required number of samples per beat. Under resting conditions (60–80 bpm), HRV is typically high, and variability can be captured effectively with 50–100 Hz sampling [39]. During exercise or high-stress states (120–180 bpm), HRV decreases, necessitating higher sampling frequencies (100–200 Hz) to ensure accurate detection of beat-to-beat variations [37], [38].

Leveraging HR to control the sampling frequency dynamically enables a context-aware system without requiring additional sensors, such as accelerometers. This approach simplifies hardware complexity while improving energy efficiency. In the proposed system, the sampling frequency is adaptively adjusted based on HR, while maintaining a fixed sampling window of 4 s, with an LED current of 6 mA and a pulse width of 411  $\mu$ s.

## B. SOFTWARE IMPLEMENTATION

### 1) OVERALL SYSTEM FIRMWARE FLOW

Figure 5 presents the flowchart of the adaptive heart rate measurement system firmware, which incorporates solar

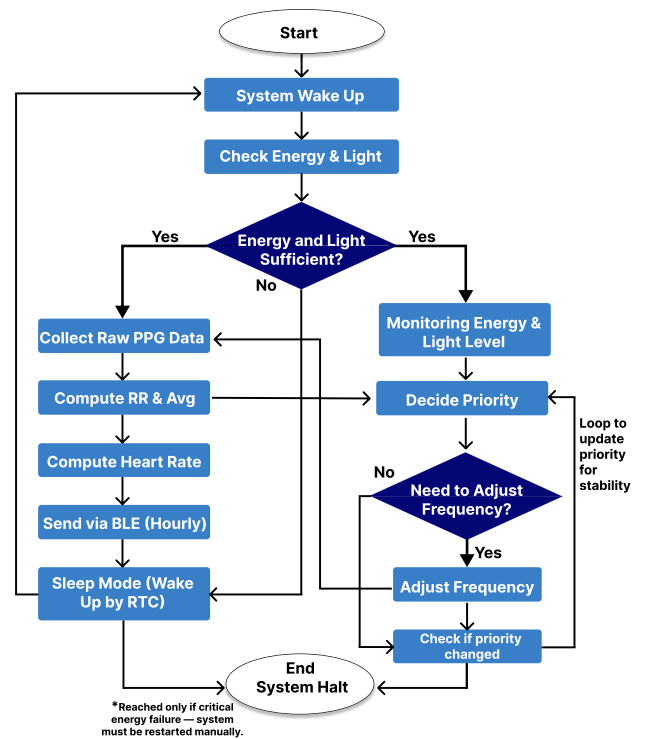


FIGURE 5. Firmware flow diagram for adaptive sensing in a solar-powered wristband system.

energy harvesting to optimize energy consumption. The firmware is primarily designed to duty-cycle between **Active** and **Idle** modes to ensure efficient power management. In the **Idle** mode, the central processing unit (CPU), which is the most power-intensive component, enters a sleep state. Meanwhile, low-power peripherals, such as the Real-Time Clock (RTC) and the Low-Frequency Clock (LFCLK), remain operational to maintain essential system functionality. During the **Active** mode, the photoplethysmography (PPG) sensor, energy monitoring unit, and Bluetooth Low Energy (BLE) module are initialized and activated to perform data acquisition and communication tasks. Additionally, various peripherals of the Nordic nrf52840 microcontroller, including the Two-Wire Interface (TWI/I2C), Successive Approximation Analogue-to-Digital Converter (SAADC), RTC, and LFCLK, are appropriately initialized to support system operations in this mode.

During this Active mode, the system acquires preliminary parameters such as heart rates, supercapacitor energy levels, and ambient light intensity to establish baseline values for RR intervals, which represent the temporal spacing between successive heartbeats, and to assess the potential for energy harvesting. Based on these measurements, priorities are assigned to each of the three parameters. These priorities are used by the 'Dynamic Adjustment Algorithm' to determine how to adjust the sampling frequency of the PPG sensor and to decide which power source—solar cell or supercapacitor—should be used to power the load. The assigned priority signals are also sent to the AEM10300 Power PMIC to

internally decide if the storage element (STO) should take precedence over the load (LOAD). At startup, the PMIC must choose between charging the storage element first to accumulate energy before the application circuit becomes operational or charging the load decoupling capacitor first to expedite application startup. Later, these priorities are also used to configure interrupt priorities, particularly during the **Idle** mode, to ensure optimized system behavior that aligns with the available energy and operational requirements.

A sampling window size of 4 s was chosen for heart rate measurement to ensure measurement accuracy while minimizing power consumption. The raw data are stored using the EasyDMA module, allowing the CPU to stay inactive until it is required to calculate the RR intervals. Subsequently, the system transitions into a continuous monitoring state, performing periodic measurements of energy levels and light intensity. In this state, the CPU remains in sleep mode, with only the RTC, LFCLK, and SAADC modules remaining operational. Thanks to the EasyDMA and PPI modules, the system can access RAM and trigger events for other peripherals without involving the CPU [50]. The SAADC module also features event monitoring on specific channels using limit-based triggers. This allows the system to break the monitoring loop by initiating an event in case of a sudden, unexpected drop in energy levels. Depending on the scenario, this mechanism prioritizes either charging or utilizing backup energy stored in the supercapacitor.

To ensure accurate heart rate estimation, the system implements an exponentially weighted moving average (EWMA) of the RR intervals, using a sliding window of the last 4 to 10 readings. This approach mitigates transient fluctuations and reduces noise in the data. The averaged RR interval is then processed by a dynamic adjustment algorithm that continuously evaluates real-time heart rate, energy levels, and ambient light conditions. Based on these inputs, the algorithm dynamically adjusts the PPG sensor's sampling frequency in real-time. To further conserve power, the updated sampling frequency is applied only at the beginning of each measurement phase. For example, if the system detects a significant reduction in the RR interval—exceeding a predefined threshold of 20%—the sampling frequency is increased to capture more detailed heart rate information. Conversely, an increase in the RR interval, a drop in supercapacitor energy, or diminished ambient light leads to a reduction in sampling frequency to conserve power.

When conditions necessitate further energy conservation, the PPG sensor, alongside the energy and light intensity monitoring units, is deactivated, and the microcontroller transitions into a low-power **Idle** mode. In this state, the duration of the Idle period is dynamically adjusted based on current energy and light conditions to optimize power management. Once the Idle period ends, the microcontroller reactivates all sensors, resuming the monitoring cycle.

This adaptive algorithm, implemented in the C programming language, allows the system to perform real-time adjustments to sampling frequency and power management,

thereby achieving an optimal balance between measurement accuracy and energy efficiency for prolonged operation.

## 2) SENSOR PROCESSING

Heart rate (HR) was calculated for a wrist-worn PPG with windows of 4 seconds. To measure heart rates ranging from 40 to 150 beats per minute (bpm), a 4-second measurement window is sufficient to capture 2–3 heartbeats for analysis. The raw PPG signals were then pre-processed and a high-pass Filter was implemented to remove DC component, before employing a peak detection algorithm to identify the systolic peaks of the PPG pulses.

The heart rate HR was calculated in bpm as:

$$\text{HR (bpm)} = \frac{60}{\text{RR}_{\text{interval}}} \quad (4)$$

where 60 represents the duration of 60 s and RR represents the average timestamp difference of two adjacent detected systolic peaks in the PPG:

$$\text{RR}_{\text{interval}} = \frac{1}{N} \sum_{i=1}^N (\text{Peak}_{T_{i+1}} - \text{Peak}_{T_i}) \quad (5)$$

where  $N$  is the total number of inter-beat time differences.

## C. ENERGY BUDGET CALCULATION

In combination with the aforementioned hardware-software co-design, the maximum and minimum power that can be harvested from the ambient environment (e.g., under specific illumination conditions) can be experimentally determined. As shown in Figure 6, the V-I and V-P curves of the solar cell under various light conditions were obtained through in-field experiments, allowing for an accurate estimation of the anticipated power output. The flexible solar panel was worn in orientations representative of typical user activity. As a result, the angle of light incidence was not explicitly fixed or controlled but was inherently determined by the ambient light environment and the natural orientation of the device. This approach prioritizes realism over idealization and aligns with evaluating self-sustainability in common indoor settings. The experiment evaluated the performance of solar cells under a range of lighting conditions that are typical of the indoor application environment, where lighting intensity and characteristics can significantly differ. The study focused on four specific light intensities: 200 lux, indicative of the ambient light in a typical living room; 500 lux, which corresponds to the illumination found in well-lit office spaces; 1000 lux, reflecting bright indoor conditions; and 2000 lux, akin to the minimal sunlight that might penetrate indoors through a window. Measurements were conducted using the Agilent N6705B DC Power Analyzer. The analyzer supports sourcing and measuring DC voltage and current. Therefore, a voltage sweep was performed while measuring the current produced by the solar panel. The input voltage was adjusted in consistent increments from 0 V up to the open-circuit voltage (when the measured current approached

zero). At each step, steady-state current and voltage were recorded under constant illumination. The step size was approximately 0.1 mV, and the total duration of each sweep was under 50 seconds. This controlled approach allowed for accurate characterization of the cell's electrical behavior under steady-state conditions, supporting reproducibility and traceability of the results.

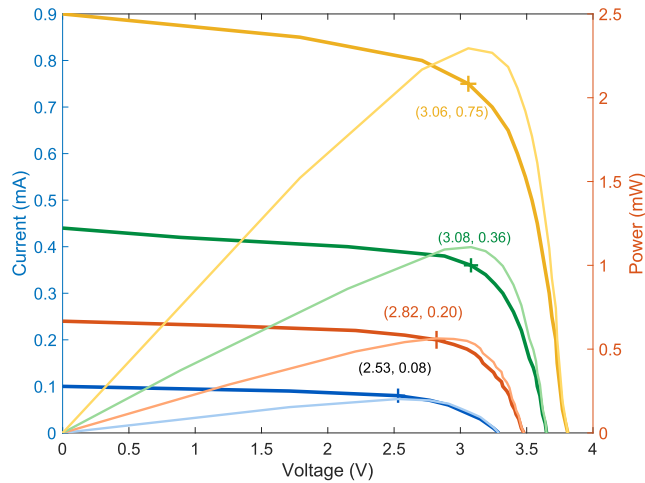


**FIGURE 6.** IV and PV curves of a solar panel MP3-25 for different illumination levels.

From Figure 6, the current-voltage (I-V) and power-voltage (P-V) characteristics of the solar cell under various light intensities can be observed. Different colors represent different illumination levels, and MPPS on the I-V curves are marked accordingly. The product of the corresponding current and voltage at each MPP yields the maximum power. As shown, the maximum power output from the solar cell ranges approximately from 0.2 mW to 2.3 mW, depending on the light intensity.

Although, from the Figure 6, the harvested energy can be as much as around 2.3 mW, the power from the solar cell is unregulated and the conversion efficiency from the solar cell to the rest of the system are not taken into account. Therefore, a further field experiment was conducted to examine the efficiency of the AEM10330 PMIC in capturing and storing solar energy in laboratory settings. These tests were designed to measure the real-world capability of the PMIC in terms of energy harvesting. The outcomes of these experiments are presented in a bar chart Figure 7, which outlines the maximum power from the harvester ( $P_{\text{solar}}$ ) and the net power can be stored in the supercapacitor ( $P_{\text{sto}}$ ) at various light intensities. The efficiency noted in between the two bars represents the power conversion efficiency of the PMIC. The equipment used for this analysis was the DC Power Analyzer N6705B from Agilent Technologies®.

There are multiple configuration modes available in the AEM10330. To achieve the maximum voltage swing from the storage device, the system was configured to operate between 4.65 V and 1 V. The supercapacitor deployed in this system has a maximum capacity of 470 mF. Therefore, the maximum

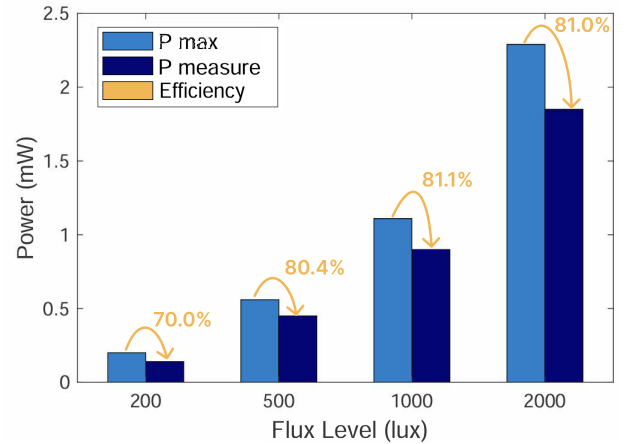


**FIGURE 7.** Harvested power and PMIC efficiency under different illumination levels.

energy that can be stored in the system is determined by the following equation 6:

$$E_{\text{Supercap}} = \frac{1}{2} \times C_{\text{Supercap}} \times (V_{\text{OVCH}}^2 - V_{\text{CHRDY}}^2) \quad (6)$$

where,  $E_{\text{Supercap}}$  is the maximum energy that can be stored in the system and  $V_{\text{OVCH}}$  is the maximum voltage this PMIC can charge to and  $V_{\text{CHRDY}}$  is the minimum voltage this PMIC can distribute the stored energy to the load. Based on this equation 6, the maximum energy that can be supplied to the load without the Solar harvester is: 4.84 J.

#### IV. EXPERIMENT RESULTS AND ANALYSIS

A series of in-field experiments were conducted to validate the proposed proof-of-concept. First, the reliability and stability of the overall system were evaluated by verifying that raw PPG signals could be consistently acquired under varying, dynamically reconfigured sampling frequencies. Second, system-level power consumption was measured across different operational scenarios to assess self-sustainability and to demonstrate how the proposed methods collectively enhance energy efficiency on the system level.

##### A. VALIDATION MEASUREMENTS

In the proposed system, the sampling frequency of the PPG sensor is adaptively adjusted based on the user's heart rate, the availability of harvested energy, and the level of stored energy. To validate the effectiveness of this adaptive approach, raw PPG signals were measured to assess signal clarity and stability as the sampling rate dynamically changed.

A controlled test condition was selected to evaluate the system's behavior. As shown in Figure 8 (a) and (b), raw PPG signals were recorded while the user was at rest, with a heart rate of approximately 75 bpm. The PPG sensor was securely positioned on the tester's wrist to minimize motion artifacts and ambient light interference. During the test, the supercapacitor was half-charged (approximately 3 V), and

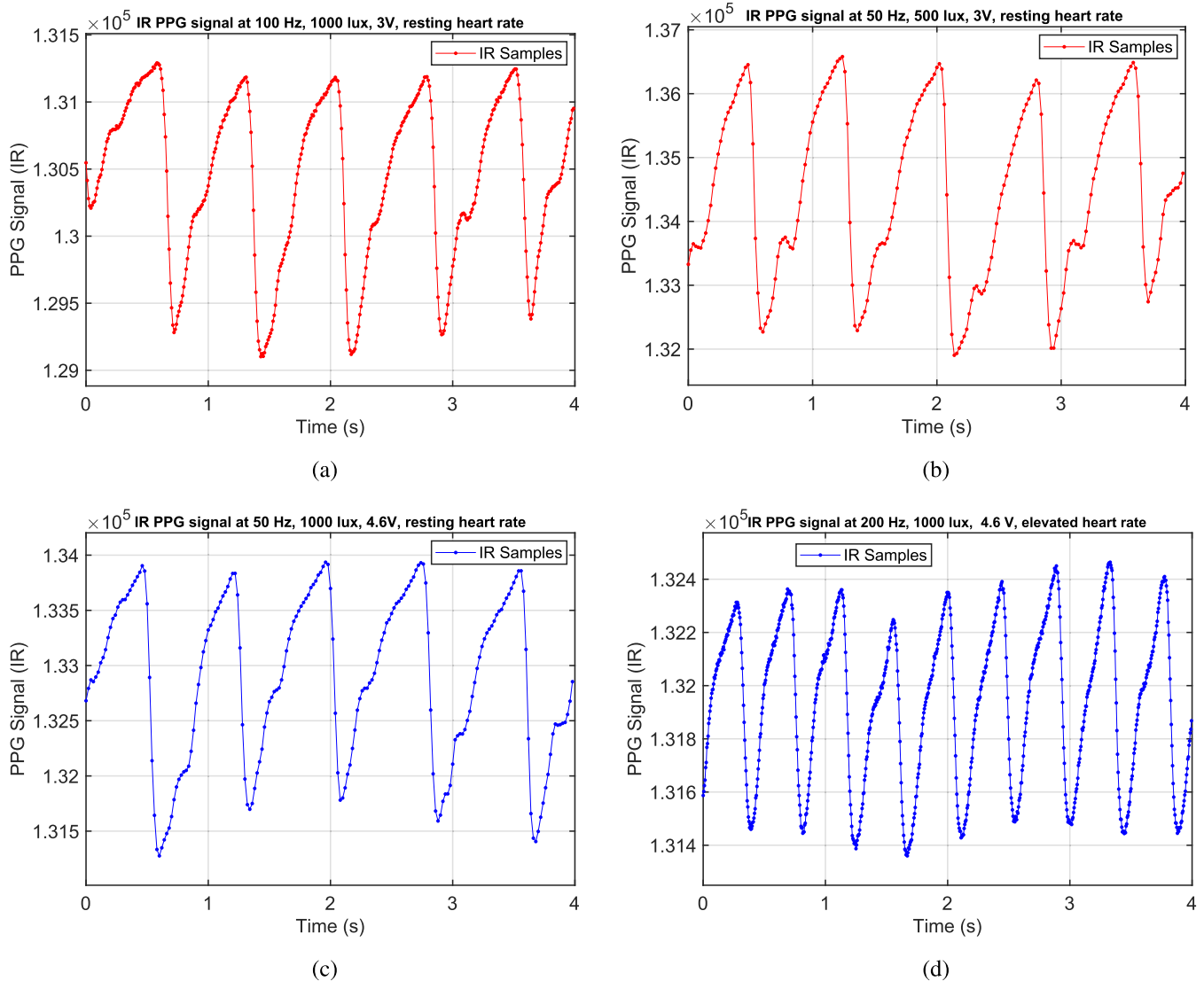


**FIGURE 8.** IR PPG signals captured by the adaptive sampling algorithm under various physiological and environmental conditions. Group (a)–(b): Effect of illumination change under constant physiological state and 3 V supercapacitor voltage. (a) IR signal captured at 100 Hz under 1000 lux. (b) IR signal captured at 50 Hz after a drop in illumination from 1000 lux to 500 lux. Group (c)–(d): Effect of heart rate variation under constant illumination (1000 lux) and supercapacitor voltage of 4.6 V. (c) IR signal captured at 50 Hz during resting heart rate. (d) IR signal captured at 200 Hz after an elevated heart rate was detected.

ambient illumination was reduced from 1000 lux to 500 lux to simulate a typical environmental change.

Initially, under 1000 lux, the sampling frequency was set to 100 Hz, and the raw data was plotted to validate the sampling rate and the signal quality as shown in Figure 8 (a). When the illumination decreased to 500 lux, the adaptive algorithm automatically reduced the sampling frequency to 50 Hz in response to the lower energy harvesting conditions, as shown in Figure 8 (b). A four-second raw PPG measurement under these conditions is shown in both Figure 8 (a) and (b). The peaks in the diagrams are clearly distinguishable, and the effect of reduced resolution—fewer samples per beat—is evident in Figure 8 (b). These results demonstrate that the system maintains a stable and clear signal acquisition across

varying ambient conditions and energy states, validating the robustness of the adaptive sampling strategy.

A second signal validation experiment was conducted under constant ambient illumination of 1000 lux, with the supercapacitor fully charged to approximately 4.6 V. This scenario simulates optimal operating conditions, with both sufficient harvested energy and ample stored reserves. The PPG sensor was securely attached to the tester's wrist to minimize motion artifacts throughout the experiment.

Initially, the tester was at rest with a heart rate of approximately 75 bpm. The heart rate was then intentionally elevated to approximately 135 bpm to evaluate the system's ability to adaptively adjust the sampling frequency based on physiological feedback. As shown in Figure 8 (c) and (d), the

raw PPG signals correspond to the resting and elevated heart rate conditions, respectively. These results confirm that the system dynamically increases the sampling rate in response to increased heart rate, as dictated by the adaptive algorithm.

**TABLE 2.** Measured current consumption in different operational modes.

| Mode                                   | Voltage (V) | Average Current Draw (mA)                               |
|----------------------------------------|-------------|---------------------------------------------------------|
| Sample Acquisition                     | 3.3         | 0.14 mA (50 Hz)<br>0.32 mA (100 Hz)<br>0.62 mA (200 Hz) |
| Processing Calculation Reconfiguration | 3.3         | 3.6 mA                                                  |
| Sleep Mode                             | 3.3         | 2.58 $\mu$ A                                            |
| BLE                                    | 3.3         | 4.6 mA                                                  |

## B. SYSTEM POWER CONSUMPTION AND AUTONOMOUS OPERATION

### 1) ADAPTIVE SAMPLING

As only the IR LED was enabled in Max30102, each raw sample of data comprises three bytes. The sampling rate was configured to adapt based on the user's heart rate, ambient light intensity, and stored energy. An in-field experiment evaluating the power consumption across different operational modes was conducted and is presented in Table 2, and an example of power measurement in idle mode is presented in Figure 9. As anticipated, during the sample acquisition mode, the current drawn by the system was proportional to the increase in the PPG's sampling rates, which directly affects the active duration of the PPG LED current. Higher sampling rates result in more samples taken per unit time, hence increasing the current draw. Additionally, with EasyDMA enabled in the MCU's TWI, it is possible to transfer data from the PPG to its RAM without activating the CPU, significantly reducing the average current draw. After data collection, onboard processing was performed to process the raw data. The RR intervals were not only instrumental in calculating the heart rate but also reused as a parameter to adjust the sampling rates, thereby avoiding additional power consumption. During this period, the heart rate was calculated, and the sampling frequency was adaptively adjusted. The average current draw was approximately 3.6 mA since the CPU was active throughout. An increase in PPG sampling frequency leads to a rise in raw data volume, which theoretically should elevate processing power consumption as CPU cycles for data retrieval from RAM and processing increase. However, during the power measurement, no significant increase in power consumption was observed. This is attributed to the fact that with the CPU operating at 64 MHz, the additional computational time required due to an increase in sample size from 250 to 1000 samples was minimal. The overall processing time took around 0.23 ms. This efficiency demonstrates that adaptive power management, in combination with onboard processing,

is highly effective. Validation of this approach will be presented in subsequent sections. Finally, all the processed data (2)-byte Heart rate) is transmitted via BLE once per hour. Therefore, hourly and daily energy consumption can be computed by following equations (7), (8) and (9):

$$\begin{aligned}
 E_{\min} &= E_{\text{sample}} + E_{\text{proc}} + E_{\text{sleep}} \\
 &= V \times I_{\text{sample}} \times t_{\text{sample}} \\
 &\quad + V \times I_{\text{proc}} \times t_{\text{proc}} \\
 &\quad + V \times I_{\text{sleep}} \times t_{\text{sleep}}
 \end{aligned} \quad (7)$$

where  $E_{\min}$  represents the average energy consumption per measurement per minute. The  $E_{\text{sample}}$  was calculated at different sampling rates of the PPG sensor accordingly. Then, an average hourly energy consumption can be calculated by including the energy used by BLE in equation (8).

$$E_{\text{total\_hour\_BLE}} = E_{\text{total\_hour}} + E_{\text{BLE}} \quad (8)$$

$$E_{\text{total\_day}} = E_{\text{total\_hour\_BLE}} \times 24 \quad (9)$$

**TABLE 3.** Measured energy consumption at different sampling frequencies.

| Sampling Frequency (Hz) | Energy per Hour (J) | Energy per Day (J) |
|-------------------------|---------------------|--------------------|
| 50                      | 0.168               | 4.03               |
| 100                     | 0.346               | 8.31               |
| 200                     | 0.643               | 15.4               |

**TABLE 4.** Minimum exposure time (in minutes) required per hour to achieve self-sustainability at different sampling rates and illumination levels.

| Illumination (lux) | 50 Hz | 100 Hz | 200 Hz |
|--------------------|-------|--------|--------|
| 200                | 19.93 | 41.17  | N/A    |
| 500                | 6.21  | 12.81  | 23.83  |
| 1000               | 3.10  | 6.40   | 11.90  |
| 2000               | 1.51  | 3.12   | 5.80   |

**TABLE 5.** Minimum exposure time (in Hours) required per day to achieve self-sustainability at different sampling rates and illumination levels.

| Illumination (lux) | 50 Hz | 100 Hz | 200 Hz |
|--------------------|-------|--------|--------|
| 200                | 7.98  | 16.47  | 30.61  |
| 500                | 2.48  | 5.12   | 9.52   |
| 1000               | 1.24  | 2.56   | 4.76   |
| 2000               | 0.61  | 1.25   | 2.32   |

Finally, A total energy consumption per day  $E_{\text{total\_day}}$  can be computed by equation 9. The calculation results are summarized and presented in Table 3.

Combining the energy budget available from the solar harvesting node, the hourly and daily time required to achieve self-sustainability can be estimated by equation (10):

$$\text{Time Required} = \frac{\text{Energy Consumption (J)}}{\text{Harvested Power (J/h)}} \quad (10)$$

**TABLE 6.** Comparison of energy harvesting wearable systems.

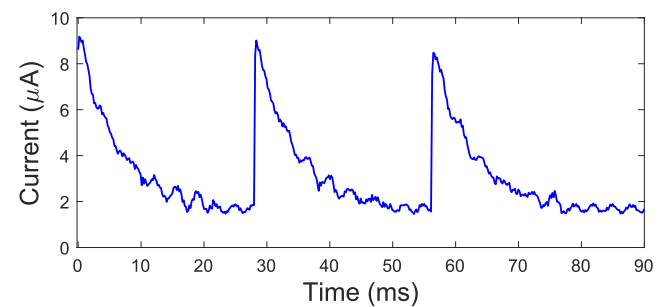
| Parameter                            | Paper 1 [15]                                                                   | Paper 2 [27]                                               | Paper 3 [14]                                                                                             | Paper 4 [26]                                               | Proposed System                                                                                          |
|--------------------------------------|--------------------------------------------------------------------------------|------------------------------------------------------------|----------------------------------------------------------------------------------------------------------|------------------------------------------------------------|----------------------------------------------------------------------------------------------------------|
| <b>Energy Harvested Type</b>         | Photovoltaic energy harvesting                                                 | Hybrid energy harvesting (photovoltaic and thermoelectric) | Photovoltaic energy harvesting                                                                           | Hybrid energy harvesting (photovoltaic and thermoelectric) | Photovoltaic energy harvesting                                                                           |
| <b>Type of Storage and Capacity</b>  | Lithium polymer battery, 135 mAh, 1798.2 J                                     | Dual supercapacitors, 50 F total, 352.8 J                  | Lithium-ion battery, 40 mAh, 532.8 J                                                                     | Lithium battery, 300 mAh, 3996 J                           | Supercapacitor, 470 mF, 4.8 J                                                                            |
| <b>Operational Lifetime</b>          | Self-sustaining under 6 h of direct sunlight                                   | 46 h without energy harvesting                             | Self-sustaining after 64 min sunlight or 12 h under indoor lighting                                      | 18 h without energy harvesting                             | Self-sustaining after 2 h under indoor lighting                                                          |
| <b>Power Management Strategy</b>     | BQ25570 IC with maximum power point tracking (MPPT)                            | DC–DC boost converter with MPPT                            | BQ25570 IC with MPPT, achieving up to 90% efficiency                                                     | BQ25504 DC–DC boost converter with MPPT                    | AEM10330 IC with MPPT                                                                                    |
| <b>Area of Harvester</b>             | Rigid solar cells, 60 mm × 45 mm                                               | TEG: 40 mm × 40 mm; Solar: 72 mm × 60 mm                   | Flexible solar panel, 10 mm × 50 mm                                                                      | Solar: 1840 mm <sup>2</sup> ; TEG: 1024 mm <sup>2</sup>    | Flexible solar panel, 114 mm × 24 mm                                                                     |
| <b>Onboard Processing Capability</b> | Not supported; measured state-of-charge (SoC) transmitted via BLE every second | Not supported; raw sensor data transmitted via BLE         | Supported; ARM Cortex-M3 microcontroller processes data onboard, transmitting only processed information | Not reported                                               | Supported; ARM Cortex-M4 microcontroller processes data onboard, transmitting only processed information |

If the calculated time exceeds 3600 seconds (1 hour), it is marked as N/A since self-sustainability cannot be achieved within one hour under that condition. The results are presented in table 4.

Table 4 presents exposure times in minutes required under various light intensities to achieve self-sustainability, based on measured energy input and system power consumption. This is the minimum light exposure needed per hour to balance the system's energy budget — ensuring energy harvested from ambient light equals or exceeds energy consumed.

When the solar cell supplies energy to the system, the energy is distributed along two primary paths: one directly powers the system load, while any surplus energy is stored in the supercapacitor. Therefore, reducing energy consumption at the load end increases the amount of surplus energy available for storage, resulting in faster charging of the supercapacitor. As observed in table 4, this system can achieve self-sustainable even under 500 lux room lighting across all frequency ranges. Under a 500 lux level, by reducing the sampling frequency from 200 Hz to 50 Hz, an additional 17.6 minutes of charging time can be saved, allowing the supercapacitor additional time to replenish the power reservoir. Under 200 lux, corresponding to dim indoor lighting typical of a low-lit living room or early morning light indoors, reducing the sampling rate from 200 Hz to 50 Hz enables the system to achieve perpetual operation within 19 minutes, down from 1.27 hours. Therefore, this adaptive power management strategy effectively manages power distribution by balancing performance and power consumption according to the application and environmental context. Similarly, the time in hours required to achieve self-sustainability per day is presented in Table 5. As shown in Table 5, if the proposed wristband is operating at 50 Hz, and the ambient light is 200 lux, then it requires only

7.98 hours a day to be continuously on without dissipating the stored energy in the supercapacitor. At 500 lux, 100 Hz operation is supported with just 5.12 hours of exposure to light, which is within reach for daily workplace wearables under bright lighting conditions. At 1000 lux, high-frequency 200 Hz operation becomes feasible with 4.76 hours/day, which happens to overlap with typical daytime activity cycles in high-brightness settings. At 2000 lux, even high-frequency 200 Hz operation becomes self-sustaining with just 2.32 hours of exposure — a negligible amount that is easily achieved during normal outdoor activities like walking, exercising, or commuting.

**FIGURE 9.** System current consumption during idle mode, measured using the Nordic Power Profiler Kit II (NRF-PPK2).

## 2) ONBOARD PROCESSING

Onboard processing not only enhances the power efficiency of BLE transmission but also improves data efficiency. This functionality allows the hardware to selectively transmit only the most relevant values for subsequent analysis.

The analysis below demonstrates that onboard processing can significantly enhance the power efficiency of BLE transmissions and coordinate well with the proposed adaptive

sampling frequency strategy for the PPG sensor. With consistent BLE settings, the window size remains at 4 seconds for PPG sampling. Each raw data sample in Heart Rate mode requires at least 3 bytes. The transmission times required to transmit all raw data collected by the sensor per hour are approximately 1.45 seconds for a 50 Hz sampling rate, 2.84 seconds for 100 Hz, and 5.631 seconds for 200 Hz. However, if only the processed heart rate value (2 bytes) is transmitted hourly, the time is merely 0.96 ms. As indicated in the table, with an average BLE transmission power of about 15 mA, the energy savings during BLE transmission can be calculated as follows:

$$\begin{aligned} E_{\text{saved}} &= E_{\text{raw}} - E_{\text{optimised}} \\ &= V \times I_{\text{raw}} \times t_{\text{raw}} \\ &\quad - V \times (I_{\text{proc}} \times t_{\text{proc}} + I_{\text{procdata}} \times t_{\text{procdata}}) \quad (11) \end{aligned}$$

By applying the values in equation 11 accordingly, the BLE transmission energy savings per day are calculated as follows: 0.506 Joules for a 50 Hz sampling rate, 1.01 Joules for 100 Hz, and approximately 2.03 Joules for 200 Hz. Onboard processing complements the adaptive PPG strategy effectively, as the high clock speed of the MCU ensures that even if the sample size increases from 250 to 1000, the increase in processing time and the additional current draw are negligible.

## V. DISCUSSION AND CONCLUSION

This work introduces a self-sustainable wearable sensing architecture that combines ambient light energy harvesting, supercapacitor-based energy storage, and adaptive sampling, with the PPG signal as an example physiological signal. The smart wristband demonstrated that a compact form factor device could operate autonomously to overcome traditional battery-powered wearable limitations. The system optimizes power usage and operational capabilities through dynamic sampling frequency adjustments between 50 and 200 Hz based on real-time heart rate measurements, solar power availability, and stored energy reserves. The system becomes energy self-sufficient with only 2 hours of average indoor lighting per day, indicating its viability for real low-power biomedical applications.

The emphasis of this study is system architecture — power management, energy harvesting, and adaptive sampling — rather than physiological signal variability. Therefore, the testing was on a single subject to allow reproducible and controlled power profiling conditions. While this approach isolates system-level performance, we recognize that real-world deployment will encounter skin tone variability, vascular physiology, and user motion. Such parameters may influence PPG signal quality and acquisition efficiency. With consideration of this limitation, we outlined the need for future testing in a more diverse population to obtain robustness and broader applicability.

Compared to state-of-the-art systems shown in Table 6, the proposed system achieves competitive energy autonomy

using flexible energy harvesters and a minimal power budget. In particular, it distinguishes itself through the use of a flexible solar cell that conforms to the body, enhancing comfort and energy harvesting area, and through onboard processing, which reduces communication overhead by improving data transmission efficiency. Additionally, by monitoring solar energy availability and supercapacitor voltage levels, the proposed system determines the power budget from the environment and the energy conservation status within the system. It also reuses the measured heart rate as another factor to adjust the system's sampling rate to meet the application's requirements for physiological monitoring. Therefore, through software-hardware co-design, the proposed system achieves context awareness and maintains system performance in response to changing environmental and operational conditions.

Nonetheless, some limitations remain. The system proposed is on a single-signal modality (PPG), and while the architecture is modular, as yet the system has not been tested for multi-sensor arrangements or in varying levels of ambient light in uncontrolled conditions.

Looking ahead, the architecture is designed for scalability. The complementary nature of adaptive sampling and energy-conscious design can be extended to include additional sensors (e.g., accelerometers, temperature, or SpO<sub>2</sub>) without violating energy constraints. The integration of alternative energy harvesting modalities, such as thermoelectric or kinetic energy, will further enhance system autonomy. Implementing lightweight on-device machine learning to predict user activity patterns or anticipate future energy availability will be the focus of future research, along with evaluating long-term performance across diverse users and environments.

Overall, this work establishes a power-efficient and adaptable framework for low-power wearable sensing. It offers a path to non-invasive physiological monitoring in real-world environments in a sustainable way, using a combined strategy of energy consumption and harvesting.

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**ESTHER RODRIGUEZ-VILLEGAS** (Fellow, IEEE) is currently a Professor (the Chair) of low-power electronics with Imperial College London, originally known for her engineering techniques to drastically reduce power in integrated circuits. She subsequently focused her research on life-science applications, founding the Wearable Technologies Laboratory. This laboratory specializes in both creating innovative wearable medical technologies to improve the management and diagnosis of chronic diseases and neural interfaces to facilitate brain research, whilst improving animal welfare. She is also the Founder and the CEO/CSO of Acurable, a medical device company, as well as the Co-Founder of TainiTec, which commercializes miniature brain monitoring systems. In 2020, she was elected as a fellow of U.K. Royal Academy of Engineering. She has served in many prestigious international technical committees, including, but not limited to the Administrative Committee of the IEEE Solid-State Circuit Society, IEEE ISSCC, IEEE ISCAS, and IEEE ESSCIRC. She has received many international recognitions and awards, including the IET Innovation Award, in 2009, the Global XPRIZE-Award, in 2014, the AAALAC 3Rs Award, in 2018, and the Silver Medal from U.K. Royal Academy of Engineering, in 2020. She was also named the top Scientist/Engineer in Spain under the age of 36, in 2009 (Complutense Award).

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**SHIHONG CHEN** (Student Member, IEEE) received the B.Eng. degree (Hons.) in electronic engineering from The University of Manchester, England, in 2019, and the M.Sc. degree in analogue and digital integrated circuit design from the Department of Electrical and Electronic Engineering, Imperial College London, London, U.K., in 2020, where he is currently pursuing the Ph.D. degree. His current research interests

include the Internet of Things (IoT), micro-scale solar energy harvesting, healthcare smart wearable devices, low power system design, power management unit integrated circuit design, machine learning, and signal processing.