Politecnico di Torino

Energy Management for IoT
01UDGOV

Master's Degree in Computer Engineering

Report lab 3

Energy storage, generation and conversion

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CHAPTER 1

1.1 Introduction

The aim of this laboratory is to develop a comprehensive simulation of an IoT system, with a particular focus on energy management—namely, energy generation, conversion, and storage. From a power perspective, the project intends to assess:

- The appropriate capacity of the energy storage to support system loads;
- The ability of the generation sources to supply the necessary power;
- The losses incurred during energy conversion processes.

Modeling and pre-simulating the system is essential to validate and estimate the behavior of individual components as well as the overall system, especially in applications where long-term autonomy of the IoT device is required.

The system under study comprises:

- Four sensors (temperature, air quality, methane, and microphone);
- A memory and control unit (MCU);
- A data transmission module based on the ZigBee protocol (RF Radio);
- A battery with a DC-DC converter;
- A thin-film photovoltaic module operating at the Maximum Power Point (MPP) through a DC-DC converter.

1.1.1 Photovoltaic Module and Maximum Power Point (MPP)

The photovoltaic module in our system operates under varying irradiance conditions, making it critical to extract the maximum possible energy from available sunlight. The **Maximum Power Point (MPP)** is defined as the point on the I-V (current-voltage) curve at which the product of current and voltage—and hence the power output—is maximized.

In our simulation, the MPP is determined by digitizing the curves provided in the PV datasheet. These curves are used to populate lookup tables that relate different irradiance levels to the corresponding voltage and current values at the MPP. A DC-DC converter is then employed to ensure that the PV module operates at this optimal point.

Operating at the MPP is essential because:

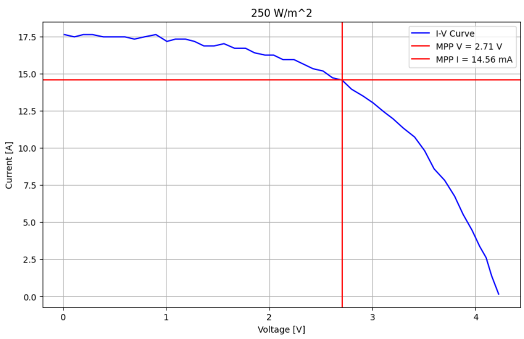
- It maximizes the energy harvested from the PV module, which is crucial in energy-constrained IoT applications.
- It enables the system to dynamically adapt to changing irradiance conditions, ensuring optimal performance at all times.
- It improves overall system efficiency by reducing conversion losses, since the output of the PV panel is better matched to the load requirements.

Thus, effective MPP tracking directly contributes to enhanced energy autonomy and system performance, a key aspect of our simulation study.

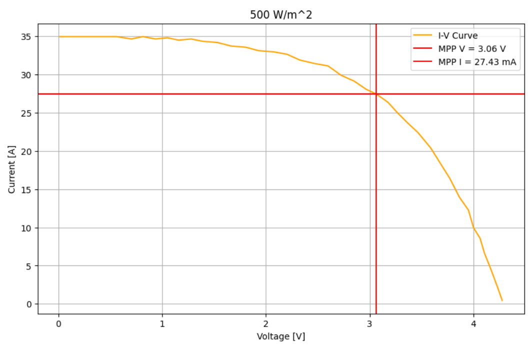
The simulation, implemented using *SystemC* and *SystemC-AMS*, employs a modular architecture that allows for the integration of dedicated models for each component. This approach enables a detailed analysis of converter efficiencies, battery dynamic behavior, and the impact of load scheduling on overall system performance.

The subsequent sections of this report will present and discuss the simulation results, addressing the main challenges and proposing potential solutions to optimize the system's autonomy within a sustainable and self-sufficient design framework.

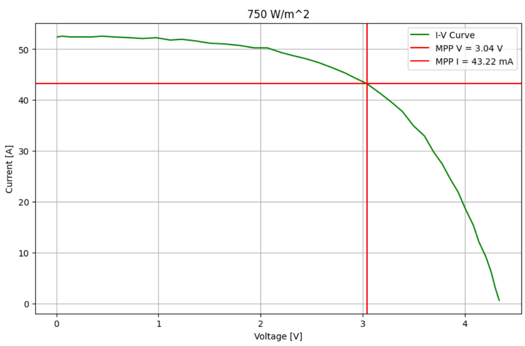
In advance these are the graphics of our MPP point that we inserted into the LUT:



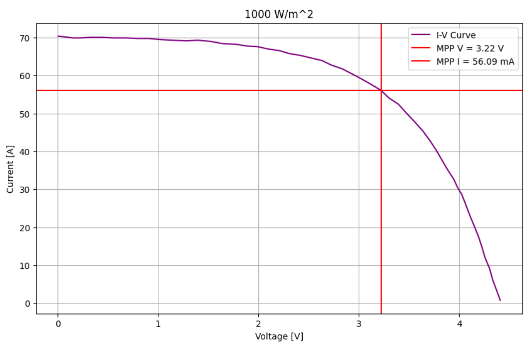
(a) 250W/m2



(b) 500W/m2



(c) 750W/m2



(d) 1000W/m2

1.2 System Overview and Simulation Setup

In this chapter, we provide an in-depth description of the simulation environment and the architecture of the IoT system under study. The system is designed to manage energy flow through generation, conversion, and storage components, ensuring reliable operation of the IoT device.

1.2.1 Simulation Environment

The simulation is implemented using *SystemC* and *SystemC-AMS*, which offer a modular framework for energy simulation. The setup requires:

- A C++ compiler and *make* for compiling the simulation code.
- *SystemC* and *SystemC-AMS* libraries, whose paths are set via the `SYSTEMC_HOME` and `AMS_HOME` environment variables.
- Additional tools such as MATLAB and Python for data analysis and visualization.

1.2.2 Component Modeling

The IoT system comprises several key components, each modeled to capture its dynamic behavior:

Photovoltaic Module

The photovoltaic module is modeled using lookup tables that relate irradiance to the voltage and current at the Maximum Power Point (MPP). The data for these tables is obtained by digitizing the curves provided in the datasheet. The module thus simulates the variability in power production due to changing irradiance conditions.

DC-DC Converters

Two DC-DC converters are modeled:

- The converter for the photovoltaic module, which adjusts the voltage and current from the PV panel.
- The battery converter, whose efficiency is characterized by curves digitized from the datasheet.

Battery Model

The battery is modeled using a circuit-based approach that captures both its lifetime and dynamic behavior. The model includes:

- A left branch that estimates the available capacity and state of charge (SOC).
- A right branch that relates the battery voltage to the SOC, taking into account internal resistance and load current.

Load Modeling and Scheduling

Load behavior is modeled through periodic activation profiles, distinguishing between active and sleep states. The scheduling of sensor activations (temperature, air quality, methane, and mic sensors) is defined by a JSON configuration file, which orchestrates the sequence of load activations and their timing.

1.2.3 Simulator Setup and Configuration

The simulator setup involves:

- Cloning the repository containing the simulation code.
- Installing and configuring the required libraries and tools.
- Setting up simulation parameters such as the simulation step (1 second) and determining which signals are to be traced during the simulation.

This detailed setup ensures that the simulation accurately reflects the real-world behavior of the IoT system and provides a robust framework for further analysis of energy management and system autonomy.

CHAPTER 2

Implementation

2.1 Part 1 - Model of the photovoltaic module

In this section, we present the main features of the simulation utilizing parallel scheduling. As a result of the simulation, the system operates for approximately 16 days (378 hours) before the battery is completely discharged.

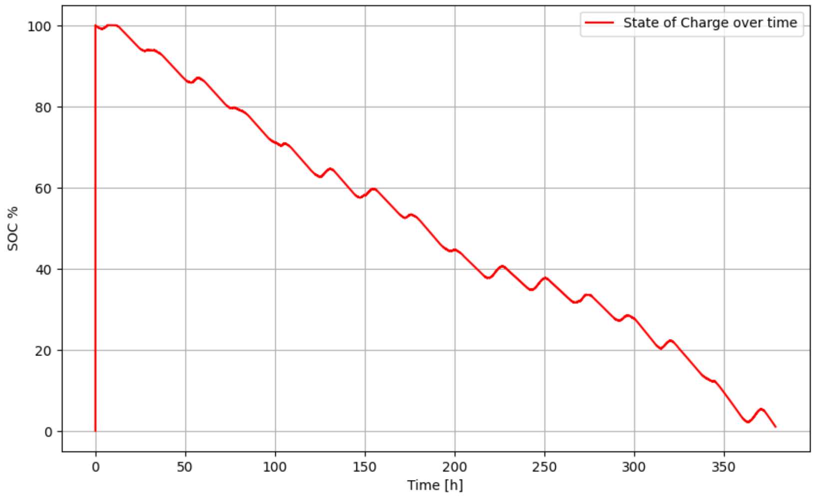


Figure 2.1: Battery discharge over time.

The following figures illustrate the workload, as well as the current and power demand from the sensors and MCU, which are required for proper system operation. As per system specifications, all sensors, the MCU, the bus, and the RF radio operate at 3.3V. Since parallel scheduling is implemented, the system exhibits a high instantaneous power demand due to the concurrent execution of tasks.

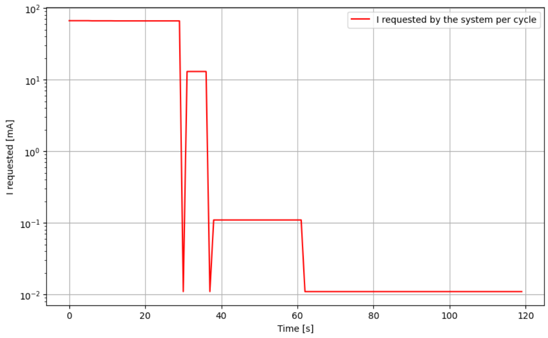


Figure 2.2: Current requested by the load

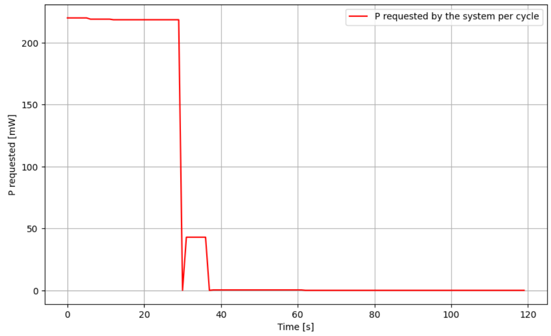


Figure 2.3: Power requested by the load

Unfortunately, the PV panel alone is not capable of supplying the total power required by the system. Due to irradiance conditions, the maximum power output of the panel is approximately 175 mW under optimal conditions.

2.1.1 Efficiency of the PV Panel DC-DC Converter

Another critical factor to consider is the efficiency of the DC-DC converter connected to the PV panel. The graph on the right in the following figure presents the voltage distribution from the PV panel and the corresponding efficiency of the converter. As shown, the converter operates within an efficiency range of 78% to 90%, which is considered a satisfactory performance for the system.

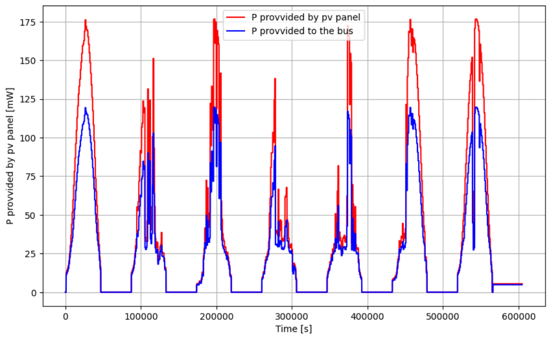


Figure 2.4: Current requested by the load

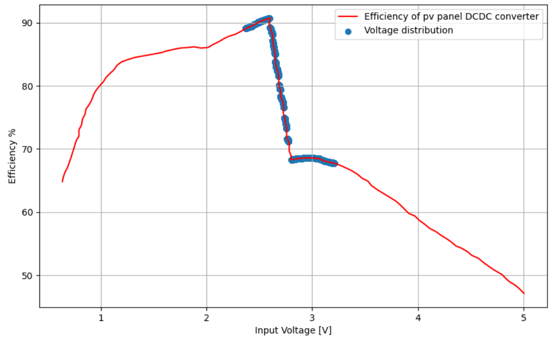


Figure 2.5: Power requested by the load

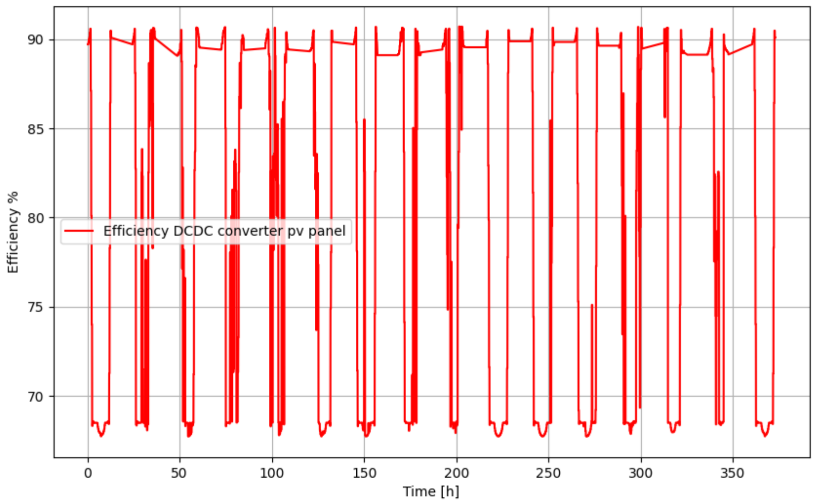


Figure 2.6: Overall efficiency of the PV panel's DC-DC converter.

The figure above illustrates the overall efficiency of the PV panel's DC-DC converter throughout the entire simulation period. Notably, efficiency drops during nighttime when the panel ceases to generate power. The estimated average efficiency of the converter is approximately 80.12%.

2.1.2 Efficiency of the Battery DC-DC Converter

Another important metric to evaluate is the efficiency of the battery's DC-DC converter. In this analysis, we focus solely on the discharge efficiency, as the battery can either supply power to the bus when the PV panel output is insufficient or store energy when the panel generates excess power. The observed mean efficiency of the battery's DC-DC converter throughout the simulation is approximately 67.84%.

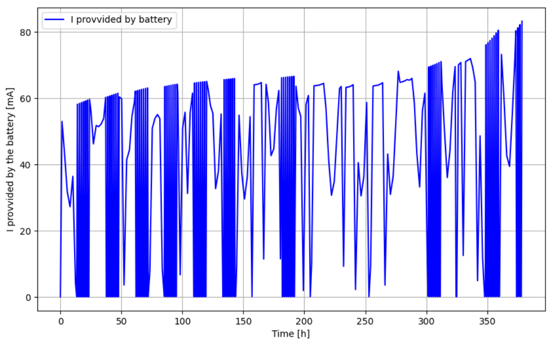


Figure 2.7: Current provided by the battery

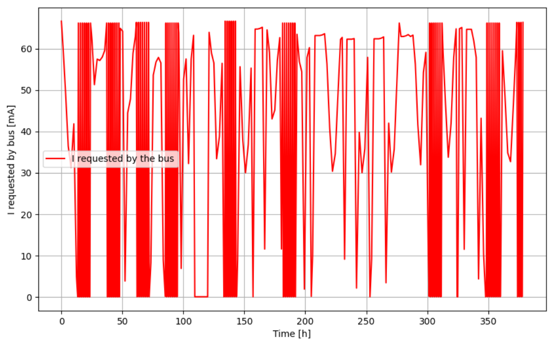


Figure 2.8: Current requested by the load

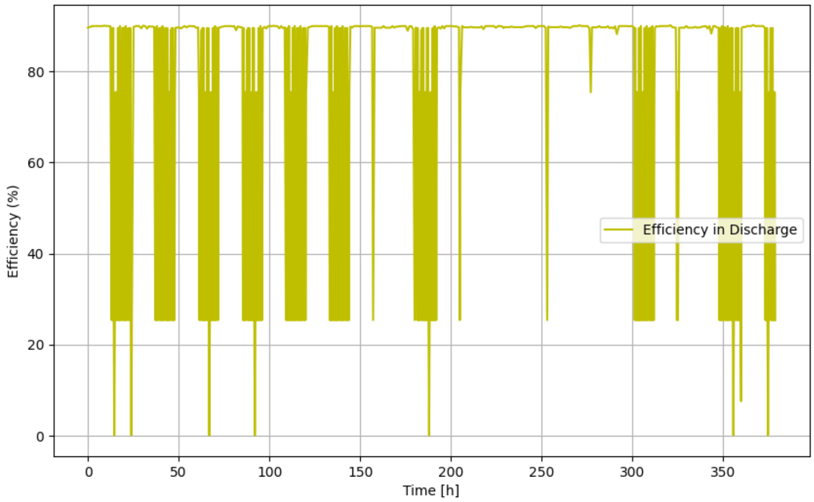


Figure 2.9: Overall efficiency of the battery's DC-DC converter.

2.1.3 Battery Usage

As observed, the maximum current provided by the PV panel during peak irradiance periods is never sufficient to meet the system's load demand. Consequently, the battery plays a crucial role in compensating for the PV panel's energy deficit. Even if maximum irradiance conditions improve, a single PV panel would still be unable to supply all the necessary current. The estimated battery utilization throughout the simulation is approximately 48.47%.

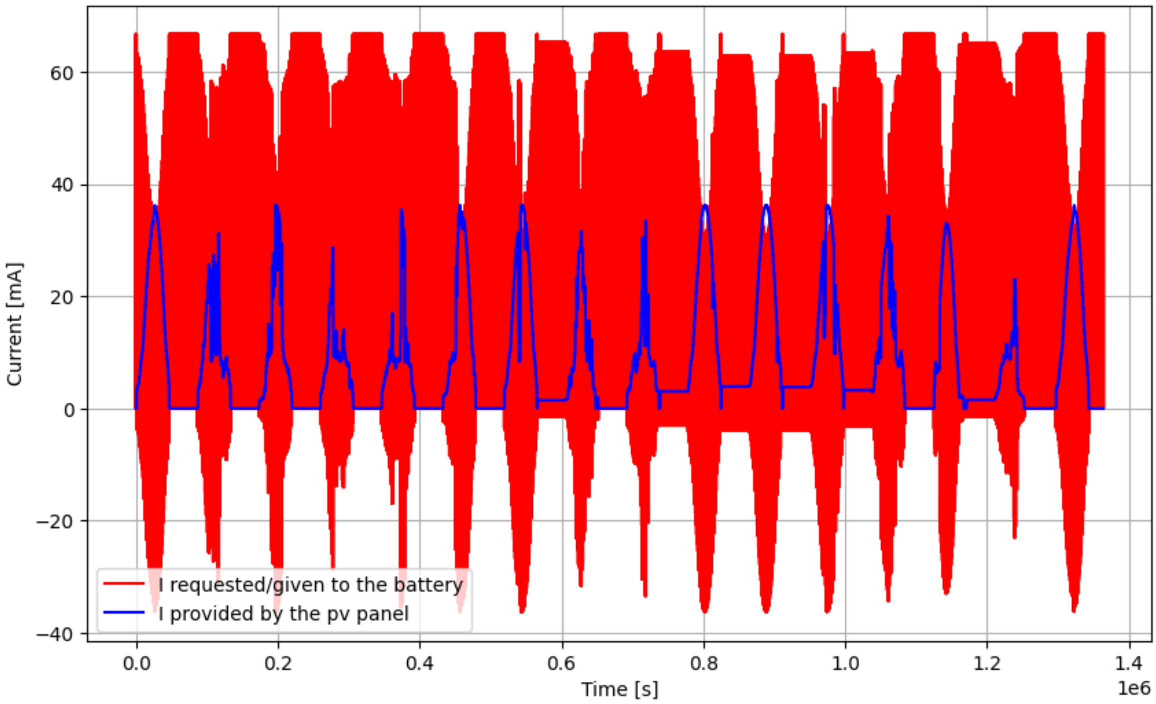


Figure 2.10: Current harvested and provided by the battery

2.2 Part 2 - Parallel vs Serial Simulation Scheduling

2.2.1 Simulation Results and Discussion

In this study, we investigate the energy autonomy of our IoT system under different workload scheduling strategies. The system is composed of a PV panel, a DC bus, an MCU, and a battery (with the associated DC-DC converters). Loads are modeled as two-state (active and sleep) Power State Machines (PSMs) supplied with a fixed voltage. Critical simulation parameters—such as simulation length, time step, reference voltage, and battery self-discharge factor—are defined in dedicated JSON configuration files, which also specify the activation modes and intervals of the various loads. (see Figs.2.11)

2.2.2 Parallel Simulation

A first set of simulations was conducted using the `parallel.json` configuration file. In this configuration, all sensors are activated simultaneously within a periodic cycle of $T = 120$ s, with each load (including the MCU and the RF module) having its own distinct *ON* period. The PV panel supplies voltage and current to its DC-DC converter based on irradiance data from the `gmonths.mat` file.

After running the simulation, we focused on key quantities such as the battery state of charge (SOC) and battery voltage (V_{batt}). The results (see Figs. 2.12) showed that, with this configuration, the system remained operative for approximately 16 days.

2.2.3 Serial Simulation

An alternative simulation was performed using a different JSON configuration to achieve a serial execution of the loads. In the serial simulation, sensor activations are staggered so that each sensor begins its *ON* period immediately after the previous sensor's *ON* time has ended.

Two distinct serial scheduling strategies were investigated:

1. **High-Consumption First:** In this configuration, sensors with the highest current consumption were scheduled at the beginning of the cycle. The rationale behind this approach is that executing high-current tasks while the battery is fully charged can help mitigate the rate-dependent capacity loss, leading to a more gradual discharge profile.

2. **Reversed Order:** In a second serial experiment, the order was inverted so that low-consumption sensors were activated first, followed by the high-consumption ones. This ordering delays the onset of high current draws until the battery is partially depleted, resulting in a steeper discharge curve when the high-current tasks are executed.

Although the current output from the PV panel remained consistent across both parallel and serial simulations (since the same irradiance data was used), the battery voltage and SOC trends varied. The serial configuration with high-consumption tasks scheduled first yielded a more favorable discharge profile, with a narrower gap between the SOC and V_{batt} curves, compared to the reversed order configuration.

2.2.4 Discussion

Our simulation results clearly demonstrate that the parallel configuration, in which all loads are activated simultaneously, leads to a faster battery discharge. The high peak current drawn in parallel operation stresses the battery and exacerbates rate-dependent losses, as noted in battery-aware DPM studies. In contrast, serial scheduling can improve battery longevity by spreading the load over time. In particular, executing high-current tasks when the battery is fresh (i.e., a non-increasing discharge current profile) is optimal for maximizing the energy extracted from the battery. Conversely, delaying high-current tasks (as in the reversed order serial simulation) results in a more rapid decline of battery capacity.

- For the parallel configuration, the operating time amounts to: 1,363,944 s.
- For the serial configuration (LLHH), the operating time amounts to: 1,367,788 s.

Thus, a gain of 3,844 s (approximately 1 h) is achieved. Overall, the experiments highlight the importance of workload scheduling in energy-constrained systems. While parallel activation leads to rapid battery depletion, serial configurations—especially when high-consumption tasks are prioritized—can significantly enhance battery endurance.

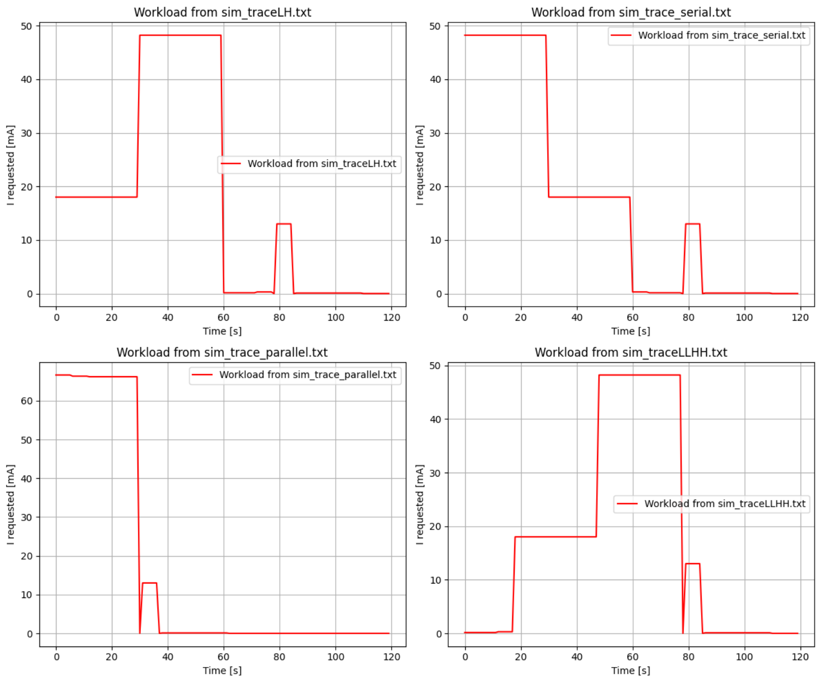


Figure 2.11: workloads

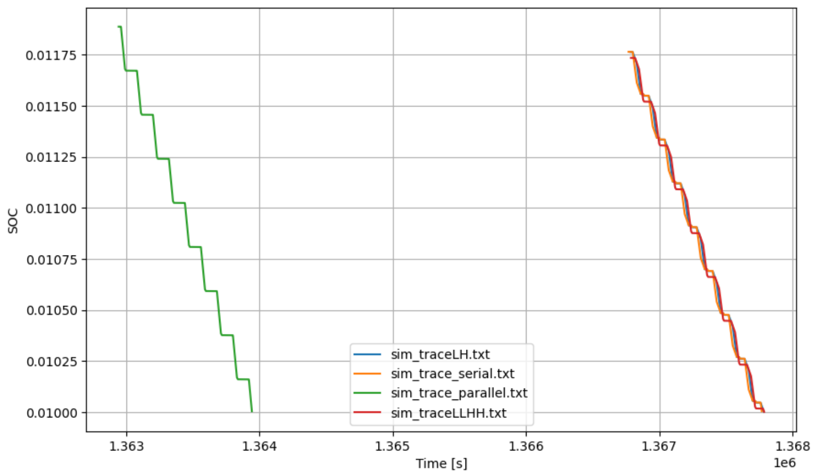


Figure 2.12: Discharge comparison

2.3 Part 3 - System Lifetime Improvements

In this section, we investigate potential strategies to extend the system lifetime by considering realistic budget constraints and hardware costs. Specifically, we analyze a scenario with a maximum available budget of $11. The cost of one battery is $4.99, while a single photovoltaic (PV) module costs $5.50. In addition, two hypothetical configurationa using **three batteries** and **two PV modules and two batteries** was considered to explore the potential benefits of increased storage capacity, assuming a higher budget was available. Based on these cost constraints, we evaluated the following configurations:

1. **Two PV Modules in parallel:** This configuration maximizes energy generation by deploying two PV modules.
2. **Two PV Modules and Two Batteries:** This option provides a balanced approach between energy generation and storage, potentially stabilizing system performance. Moreover, it is the best solution in terms of discharge time, as it clearly outperforms the other configurations analyzed—yielding nearly 2 months of possible lifetime.
3. **Two Batteries in parallel:** With a total cost of $9.98, this configuration emphasizes energy storage over generation, which may be beneficial under certain load conditions.
4. **Three Batteries in parallel:** With this configuration, we can further improve the discharge time. Ideally, if we could add n batteries, our system would gain an additional n days of lifetime, as demonstrated in Figure 2.13.

All those configurations have been choosed because of the previous results given by the parallel scheduling, in fact the main problem was that the system is so current demanding and the actual power generator are not able to sustain the load for too much time. So as consequences we choose to point our focus on increase the battery capacity and increasing current produced by the panels.

2.3.1 Comparison

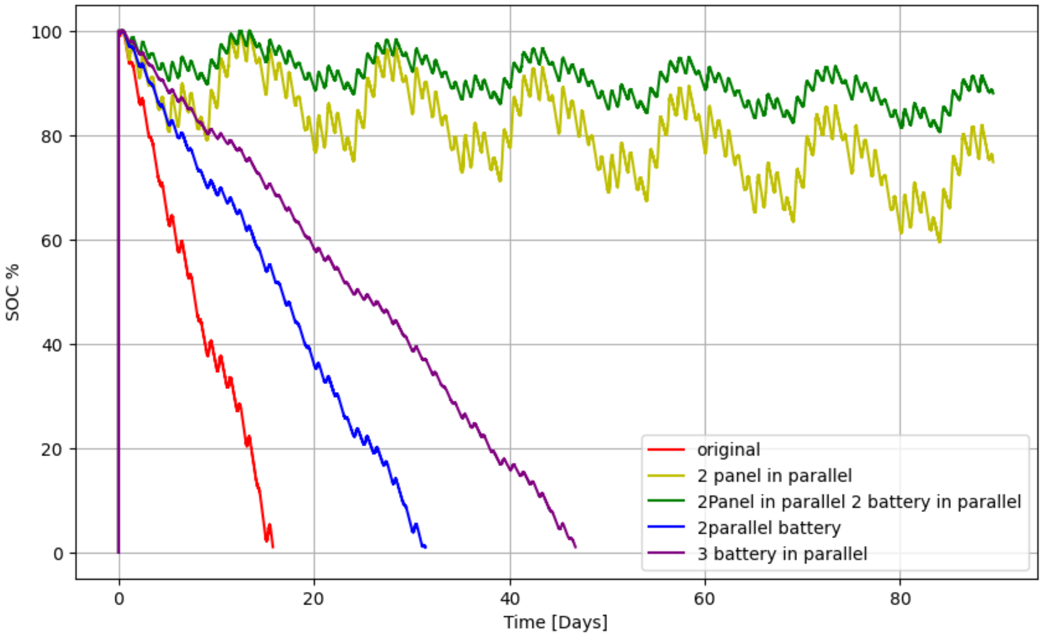


Figure 2.13: Discharge of the improvements

2.4 Conclusion

In this study, we evaluated various configurations and scheduling strategies for a battery-powered IoT system, focusing on the interplay between energy generation, load management, and storage efficiency. Our simulation results clearly demonstrate that:

- **Parallel vs. Serial Scheduling:** Parallel activation of all loads produces a high instantaneous current draw, which accelerates battery discharge. In contrast, serial scheduling—particularly when high-current tasks are executed first—leads to a more gradual discharge, extending the overall battery lifetime.

- **Optimal Configuration under Budget Constraints:** Among the tested configurations, the combination of two PV modules and two batteries provided the best balance between energy generation and storage, resulting in nearly thirteen months of potential operational lifetime. Configurations emphasizing storage (such as using additional batteries in parallel) further improve discharge time, with each additional battery ideally contributing to an extended operational period.

These findings underscore the critical role of workload scheduling and battery-aware power management strategies in extending system lifetime. By carefully tailoring the activation sequence of loads and selecting the appropriate hardware configuration, it is possible to optimize the energy autonomy of IoT systems, even under strict budget constraints.