BODOQUE: An Energy-Efficient Flow Monitoring System for Ephemeral Streams

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Effective environmental monitoring is crucial for managing global environmental challenges and providing the necessary data for Environmental Intelligence (EI). This discipline involves the integration of data from various sources to gain a comprehensive understanding of specific regions or processes. In this paper, we introduce *BODOQUE*, a hardware-software infrastructure to monitor water flows in ephemeral streams where the water rarely flows with great force. *BODOQUE* uses a low-power TinyML-based camera to detect the presence of water, activating a more complex system to measure flow only when the water flows, thereby optimizing energy consumption. This device is being deployed in the Segura basin, Murcia, Spain. This region is grappling with severe environmental issues that affect the Mar Menor, a unique saltwater lagoon. This paper focuses on the power-saving capabilities of *BODOQUE*, comparing the energy consumption of different edge devices running the code that measures water flow in the streams. Our goal is to determine the optimal hardware setup for the system based on our experiments, which involve performance and energy consumption tests. The results provide valuable information for future environmental monitoring systems, considering the best balance among the device's cost, performance, and energy consumption.

CCS Concepts: • **Human-centered computing → Ambient intelligence**; • **Computing methodologies → Machine learning algorithms**; • **Software and its engineering → Power management**.

Additional Key Words and Phrases: Edge Computing, Environmental Monitoring, Environmental Intelligence, TinyML, Energy Efficiency, IoT, Ephemeral Streams

1 INTRODUCTION

The escalating environmental challenges climate change poses underscore the critical need for robust environmental monitoring and intelligence. Rising temperatures, shifting weather patterns, and an increasing frequency of extreme weather events necessitate comprehensive understanding, prediction, and mitigation strategies to safeguard our planet for future generations [3].

Ephemeral streams, known as intermittent or seasonal streams, have emerged as a focal point in this context. These temporary watercourses, a vital component of Earth's hydrological system, are crucial in shaping landscapes, influencing nutrient cycling, supporting biodiversity, and providing numerous ecosystem services [6]. However, their sporadic nature and often remote locations present unique challenges for continuous monitoring, making traditional approaches inadequate and energy-intensive [8].

In light of these challenges, this paper presents *BODOQUE*, a system specifically designed for efficient and effective water monitoring of ephemeral streams. *BODOQUE* employs a low-power, TinyML-based camera to detect the presence of water, activating a more complex and power-consuming system only when water flows through the stream, thus helping conserve energy.

The relevance of such a system is exemplified in the context of the Mar Menor, a unique saltwater lagoon in Murcia, Spain, which is the focus of this work [5]. The Mar Menor has been facing an environmental crisis, with over 1500 tons of fish and shellfish perishing between 2016 and 2021 due to hypoxia events caused by eutrophication and human activities. The eutrophication is primarily caused by the inflow of nutrients from agricultural runoff into the Segura basin, which flows into the Mar Menor. This leads to excessive growth of algae and other aquatic plants, depleting oxygen levels in the water and creating lethal hypoxia conditions for marine life [11].

The intersection of environmental monitoring and energy efficiency has been the subject of numerous studies in recent years [12] [4] [7], underscoring the importance of developing innovative, cost-effective, and energy-efficient solutions for environmental challenges. This paper focuses on the power-saving capabilities of *BODOQUE*, comparing the energy consumption of different edge devices running a flow measurement code that measures the water flow in the streams and comparing the results to our previously implemented solution [2].

The paper is organized as follows: Section 2 introduces *BODOQUE*, our proposed solution for monitoring ephemeral streams in the Segura Basin. Section 3 presents some of the results of the evaluations we performed. Finally, Section 4 offers the conclusion and directions for future work.

2 PROPOSED SOLUTION

This section introduces our proposal for monitoring ephemeral water streams called *BODOQUE* (**B**imodal **O**bservational **D**evice for **O**ptimizing **QU**antification of **E**phemeral streams). We delve into the design and operation of the system, highlighting its bimodal operation and the key components contributing to its enhanced energy efficiency, cost-effectiveness, and sustainability.

Our prior solution for monitoring ephemeral streams in the Segura Basin employed a system that combined an outdoor high-performance network camera and a small single-board computer (SBCs). The system was designed to transmit videos to a server only upon detecting rainfall in the surroundings, a determination made by consulting weather stations. While this approach was practical, it was burdened by several limitations. The system's continuous operation led to high power consumption, with the SBC requiring, on average, 2.53 W and the network camera around 12 W. Moreover, the system's dependence on transferring large volumes of data to a remote server for processing posed efficiency challenges.

The conception of *BODOQUE* was led by the need to develop a more efficient and sustainable solution for monitoring ephemeral streams. The system now operates bimodally, leveraging a low-power sensing module and a high-performance edge module, a design that allows for significant energy savings and increased operational efficiency. This bimodal operation allows the system to conserve energy by keeping the more complex and power-consuming part of the system inactive when not needed. The Edge Device, as a single-board computer, provides the necessary computational power for processing the video data, while the high-resolution camera captures high-quality video of the ephemeral streams. Combining these components in the high-performance edge module enables the *BODOQUE* system to perform its monitoring tasks effectively while optimizing energy consumption.

2.1 Low-Power Sensing Module

The low-power sensing module of the *BODOQUE* system consists of a low-power TinyML-based camera, a coordination unit, and a relay (see Figure 1). This module is designed to be energy efficient and primarily serves to detect the presence of water in the streams and control the activation of the high-performance module. The low-power TinyML-based camera is the primary sensor in this module. Upon detecting the presence of water, it sends a signal to the coordination unit. The coordination unit plays a crucial role in the system. It is connected to a relay that controls the power supply to the components of the High-Performance Edge Module. When the coordination

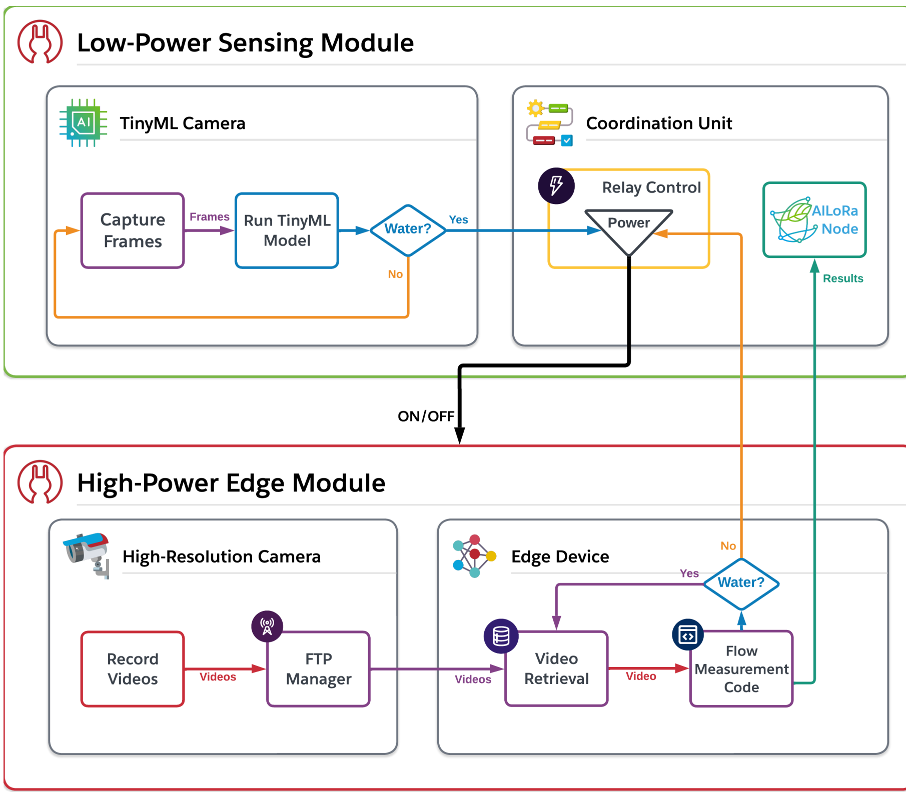

Fig. 1. *BODOQUE*'s Pipeline

unit receives the signal from the low-power TinyML-based camera, it activates the relay, powering on the Camera and the Edge Device.

The coordination unit is also connected to the Edge Device. This connection allows the Edge Device to provide the coordination unit with the processing results, which the coordination unit then sends using a low-power, long-range and mesh-capable communication protocol based on LoRa (namely, AlLoRa protocol) [1], to a gateway for further processing and analysis. Moreover, the coordination unit receives a signal from the Edge Device when the processing is complete and no more water is left to measure the streamflow. Upon receiving this signal, the coordination unit waits until the Edge Device is off and then deactivates the relay, powering off the High-Performance Edge Module's components. This action restarts the process, with the low-power TinyML-based camera resuming its monitoring for the presence of water.

While the high-performance edge module is off, the coordination unit continues to send the results. It can store them, eliminating the need to keep the more power-consuming part of the system active while the results are being transmitted. This bimodal operation allows the system to conserve energy by keeping the more complex and power-consuming part inactive when not needed.

2.2 High-Performance Edge Module

BODOQUE's high-performance edge module is a more complex subsystem that includes a high-resolution camera and a single-board computer (SBC) serving as the Edge Device (see Figure 1). This module is activated only when the low-power sensing module detects the presence of water.

The Edge Device runs a discharge measurement code (described in Section 2.3) that measures water flow in the streams. The data collected is then transmitted to the coordination unit, which sends it over LoRa using the AlLoRa protocol to a gateway for further processing and analysis.

When the system detects no more water flowing in the ephemeral stream, it stops requesting videos from the camera. After finishing the transfer of all the results to the coordination unit (for it to store them and transmit them later using the AlLoRa protocol), the Edge Device signals the coordination unit that it can be deactivated. The coordination unit waits for the Edge Device to turn itself off before shutting down the relay, halting the high-performance edge module.

2.3 Discharge measurement code

The discharge measurement code, central to our system, is based on the principles of image-based methodologies for discharge measurements. Over the past two decades, various methods have been developed, e.g., Large-Scale Particle Image Velocimetry (LSPIV), Particle Tracking Velocimetry (PTV), Space Time Image Velocimetry (STIV), among others. Herein we used the system developed by [10], which is based on a cross-correlation image velocimetry technique but overcomes some of the known factors that compromise LSPIV performance, such as glare, shadows, and lack of traceable features in the flow.

First, a short video must be acquired, captured by the High-performance Edge module's camera. The frames are subdivided into interrogation windows, and the cross-correlation algorithm is applied to each window, yielding a displacement field. Erroneous vectors due to wrong matching patterns are filtered out, and a surface velocity profile is fitted to the stream-wise components of the velocity vectors. The discharge is then calculated by estimating the bulk velocity based on the surface velocity.

Initially developed for traditional computing architectures, the code has been successfully adapted in this study to run on devices powered by ARM processors, enabling the system's deployment at the edge. This adaptation opens up new possibilities for using energy-efficient and cost-effective appliances in environmental monitoring systems.

In the next section, we compare several edge devices tested for use in *BODOQUE*'s High-performance edge module, focusing on their power-saving capabilities and performance in executing the discharge measurement code.

3 EXPERIMENTS, RESULTS, AND DISCUSSION

The primary objective of our experiments was to evaluate the performance and energy efficiency of different edge devices when running the discharge measurement code. We aimed to identify the device that offers the best balance between processing speed, energy consumption, and cost. This information is crucial for optimizing the *BODOQUE* system and ensuring its sustainability and effectiveness in monitoring ephemeral streams. Additionally, we sought to compare *BODOQUE*'s overall power consumption with our previous system, considering the frequency and duration of rain events in the specific region we are considering.

3.1 Evaluated Prototype Devices

For our prototype, we used an Arduino Nicla Vision[1] as the low-power TinyML-based camera, which is equipped with a 2MP color camera that supports TinyML, a smart 6-axis motion sensor, an integrated microphone, and a distance sensor.

The TinyML model used in the Arduino Nicla Vision was trained using the Edge Impulse[2] platform with videos from the camera used on our previous solution, which are converted into pictures of the frames, scaled down to 96x96 pixels, and used to train the model with a CNN optimized for running on TinyML devices. The registered power consumption of the Nicla Vision was 0.67 W on average while capturing frames and running the TinyML model and 0.49 W on average while idle. The energy consumption of the Arduino Nicla Vision is minimal, making it an excellent choice for our power-efficient system.

For the coordination unit, we selected a LoRa-enabled ESP32 module (LILYGO LoRa32[3]) that is compatible with the AlLoRa protocol, has TF card support for storing the results and the needed pins for managing the communication between devices. The power consumption of the selected coordination unit was 0.107 W.

Lastly, for the high-resolution camera present in the High-Power Edge module, we used the Vivotek IB9367-HT camera[4] running at 30 fps (1920x1080), which is the same one used for our previous solution.

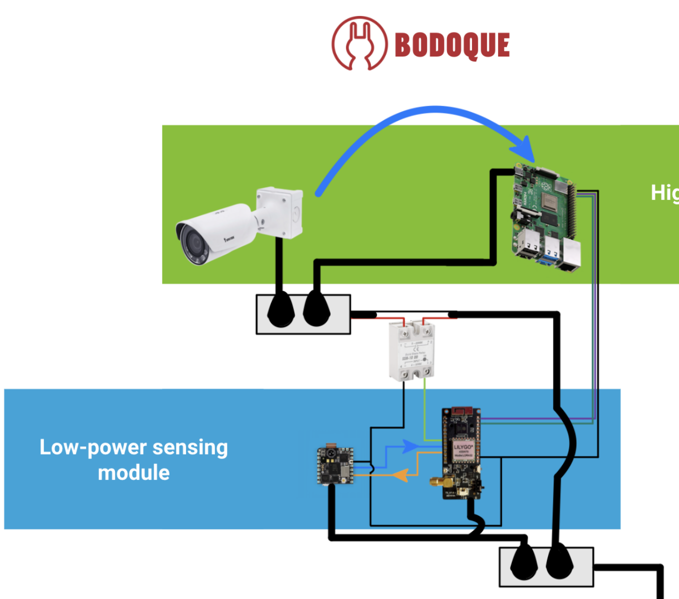

Fig. 2. BODOQUE's Hardware Setup

For the edge devices evaluated in this study, the factors considered for comparison include their hardware features, compatibility with various software, and their respective costs. The devices used were:

[1]https://store.arduino.cc/products/nicla-vision
[2]https://edgeimpulse.com
[3]https://www.lilygo.cc/products/lora3
[4]https://www.vivotek.com/ib9367-ht

- The NVIDIA Jetson AGX Xavier Developer Kit; a robust edge AI platform tailored for robotics and autonomous machines. It has an 8-core NVIDIA Carmel ARM v8.2 64-bit CPU, a 512-core Volta GPU with Tensor Cores, and 32 GB of LPDDR4x memory. The device operates on an Ubuntu-based NVIDIA JetPack SDK and is compatible with a broad spectrum of AI frameworks and libraries. The NVIDIA Jetson AGX Xavier Developer Kit is priced at approximately $1,300[5].
- The NVIDIA Jetson AGX Orin Developer Kit; another high-performance AI platform designed for robotics and autonomous machines. An Orin SoC powers it with 12 ARM Cortex-A78AE CPU cores, 2048 CUDA cores, 64 Tensor cores, and 8 GB of LPDDR5 memory. Like the Xavier, the Orin runs on the Ubuntu-based NVIDIA JetPack SDK and supports various AI frameworks and libraries. The NVIDIA Jetson AGX Orin Developer Kit is priced at approximately $2,000[6].
- The NVIDIA Jetson Orin Nano Developer Kit; a compact and cost-effective AI and edge computing device. It is equipped with a 6-core Arm Cortex-A78AE v8.2 64-bit CPU, a GPU based on the NVIDIA Ampere architecture with 1024 CUDA cores and 32 Tensor Cores, and 8 GB of LPDDR5 memory. It also supports the Ubuntu-based NVIDIA JetPack SDK. The Jetson Orin Nano Developer Kit is priced at $500[7].
- The Raspberry Pi 4 Model B; a popular choice for various computing projects due to its affordability and extensive community support. The version we used for this study has a quad-core ARM Cortex-A72 CPU, a Broadcom VideoCore VI GPU, and 4 GB of LPDDR4 memory, although other versions with different memory capacities are also available. It supports various operating systems, including Raspberry Pi OS, Ubuntu, and others. The Raspberry Pi 4 Model B is priced at $110[8].
- The Google Coral Dev Board Mini; a compact single-board computer designed for rapid prototyping of on-device machine learning products. A MediaTek 8167s SoC powers it, with a quad-core Arm Cortex-A35 and an integrated IMG PowerVR GE8300 GPU. It comes with 2 GB of LPDDR3 memory. The device also features an Edge TPU coprocessor, which can perform 4 trillion operations per second (TOPS) using only 0.5 watts for each TOPS. It runs on Mendel, a derivative of Debian Linux, and is compatible with TensorFlow Lite models. The Google Coral Dev Board Mini is priced at around $100[9].

The choice of the edge device to use in our implementation will significantly impact the performance and energy efficiency of BODOQUE.

3.2 The Dataset

The dataset employed in this study comprises videos of four-second duration captured from various locations. These locations, denoted as `site1`, `site2`, `site3`, and `site4`, present unique environmental conditions, thereby enabling a comprehensive evaluation of the discharge measurement code's performance across diverse scenarios on edge devices. The diversity of the dataset, in terms of river width, pixel dimension, and environmental conditions, makes it particularly relevant for our experiments, as it allows us to assess the robustness and versatility of our system under different real-world conditions.

[5]https://developer.nvidia.com/embedded/jetson-agx-xavier-developer-kit
[6]https://www.nvidia.com/en-us/autonomous-machines/embedded-systems/jetson-orin/
[7]https://developer.nvidia.com/blog/develop-ai-powered-robots-smart-vision-systems-and-more-with-nvidia-jetson-orin-nano-developer-kit/
[8]https://www.raspberrypi.org/products/raspberry-pi-4-model-b/specifications/
[9]https://coral.ai/products/dev-board-mini/

Table 1. Description of monitoring sites

Site	River width (m)	Pixel dimension	Comments
site1	41	0.02	Multi-view system
site2	1	0.002	Concrete canal
site3	48	0.015	Medium river
site4	18	0.009	Small river

The main parameters influencing the processing time are the pixel dimension and the river width since this will determine the number of sub-windows where the calculations will be done. Additionally, `site1` is a multi-view site [9]; this site has two views. When more views are processed, the calculations are done in parallel; hence the time will also depend on the structure of the different platforms.

3.3 Experiments Set-up

Each example was run ten times on each evaluated edge device introduced in Section 3.1. Experiments were conducted with the dataset presented in Section 3.2.

During each run, we recorded the execution time of the discharge measurement code and the device's power consumption during that period. To calculate the average energy consumption per example, we integrated the power over time for each example and then divided by 10. This method allowed us to obtain each device's average energy consumption per example.

Finally, we conducted a comparative analysis of the overall power consumption of the *BODOQUE* system and our previous system during a year of operation. This analysis considered the power consumption of the low-power sensing module and the high-performance edge module, using two of the best-performing devices selected after the Energy evaluations. We based our calculus on weather data from the Murcia region, specifically the number of rainy days per year and the average duration of each rain event.

3.4 Results Analysis

The execution times of the discharge measurement code varied significantly across the tested devices and examples. As shown in Figure 3, the NVIDIA Jetson AGX Orin Developer Kit and NVIDIA Jetson AGX Xavier Developer Kit (32 GB) demonstrated the fastest execution times, while the Google Coral Dev Board Mini had the longest execution times. The Raspberry Pi 4 Model B (4 GB) had intermediate execution times.

In some applications, faster execution times are crucial. For instance, in real-time systems where immediate response is required, a device with faster execution times would be more suitable. However, in the case of *BODOQUE*, real-time results were not a necessity. The system is designed to monitor ephemeral streams over time, and the data collected is sent over LoRa using the AlLoRa protocol for further processing and analysis. As such, the system can afford longer execution times without compromising its effectiveness.

The average power consumption of the devices is vastly different; see Figure 4, with the NVIDIA Jetson AGX Orin Developer Kit and NVIDIA Jetson AGX Xavier Developer Kit (32 GB) consuming the most power and the Google Coral Dev Board Mini consuming the least. The Raspberry Pi 4 Model B (4 GB) had intermediate power consumption.

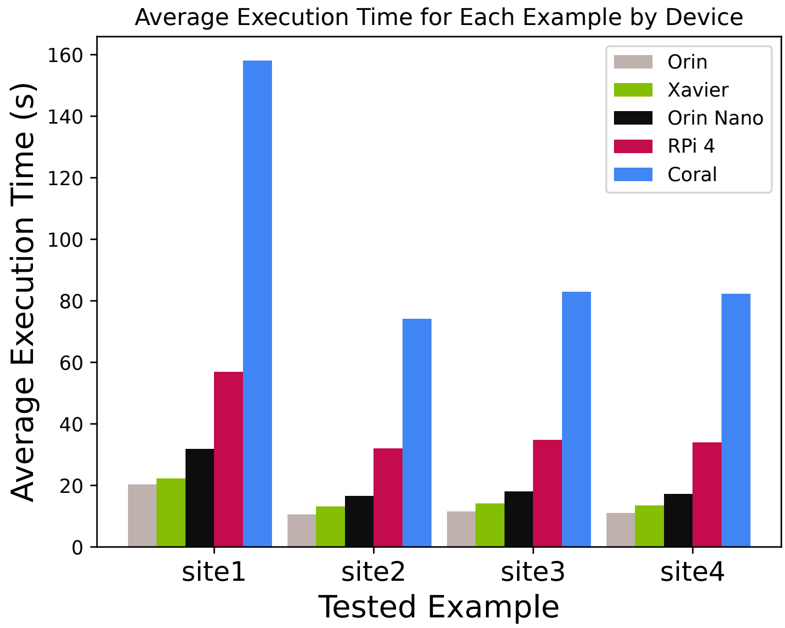

Fig. 3. Average execution time per example in different devices

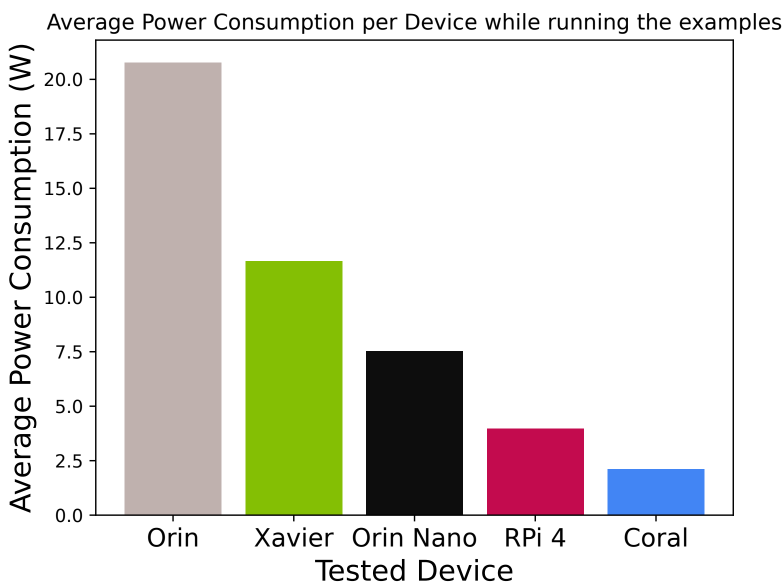

Fig. 4. Average power consumption while executing the examples in different devices

High power consumption can be a concern in continuously running systems, leading to increased energy costs and potential overheating issues. However, with BODOQUE, the high-performance edge module is activated only when needed, helping mitigate the impact of high power consumption.

When considering the total energy consumption, which is the integration of power over time, the NVIDIA Jetson Orin Nano Developer Kit demonstrated marginally superior energy efficiency compared to the Raspberry Pi 4 Model B (4 GB). Despite not being the least power-consuming device at any given moment, its faster execution times resulted in lower total energy consumption, as reflected in Figure 5. In contrast, while having the lowest power consumption at any given moment, the Google Coral Dev Board Mini took longer to run the examples. Consequently, its total energy consumption was almost as high as that of the power-hungry NVIDIA Jetson AGX Orin Developer Kit.

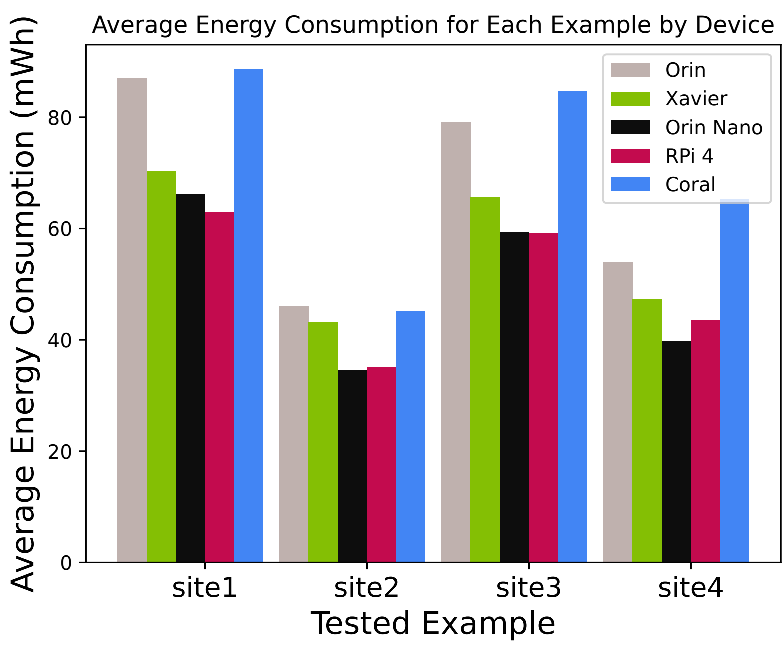

Fig. 5. Average Energy consumption per example in different devices

These findings underscore the importance of considering both execution time and power consumption when evaluating the energy efficiency of a device. A device that consumes less power but takes longer to execute a task may use more energy overall.

Eventually, we conducted a simulated year-long energy consumption analysis to evaluate the energy efficiency improvements of the *BODOQUE* system over our previous system. This analysis was based on the actual weather conditions of the Murcia region, precisely the number of rainy days and the duration of each rainy period.

In the previous system, the PCB device and the camera were always on, resulting in a static power consumption of 14.53 W and a total energy consumption of 127.28 kWh over a year. With our proposed *BODOQUE* system, we obtain a variable power consumption ranging from 0.78 W (when only the low-power sensing module is active) to 16.52 W (when the high-performance edge module and the camera are also functional using the Raspberry Pi 4) and 20.12 W (when using the Jetson Orin Nano).

To estimate the active duration of the high-performance edge module and the camera throughout the year, we began by determining the total annual rainfall hours in Murcia. This was achieved by utilizing the average yearly rainfall data (362.9 mm) and estimating the rainfall rate from a specific rain event. This particular event was marked by a surge in rainfall to 15 mm within the first 40 minutes, succeeded by a nearly linear decline over the next 40 minutes until it ceased. These observations inferred an average rainfall rate of 7.5 mm per hour. This led us to an estimated total of 48.4 hours of rainfall annually in Murcia, which we denote as T_{rain} in our calculations.

However, *BODOQUE* must be active during the rain and the streamflow that follows the rain. To account for this, we introduced the Stream Flow Duration Factor (F_{stream}). Based on our observations from our previous work, we estimated that the streamflow continues for about 1.8 times the duration of the rain.

Additionally, the time it takes to process the videos also affects the active time of the high-performance edge module. We introduced the Video Process Factor (F_{video}) to account for this. Based on our measurements, considering the single-video examples (`site2`, `site3` and `site4`), the Raspberry Pi 4 took on average 33.38 seconds to process a 4-second video, leading to a process factor of 8.35. For the Orin Nano, the process factor was 4.31.

Therefore, the total active time of the high-performance edge module and the camera over a year (T_{high}) can be calculated as:

$$T_{high} = T_{rain} \times F_{stream} \times F_{video} \tag{1}$$

The total hours when only the low-power sensing module is active (T_{low}) is then:

$$T_{low} = T_{year} - T_{high} \tag{2}$$

where T_{year} is the total hours in a year.

Therefore, the total energy consumption of *BODOQUE* over a year (E_{year}) would be:

$$E_{year} = ((P_{high} + P_{low-idle}) \times T_{high}) + (P_{low-run} \times T_{low}) \tag{3}$$

where P_{high} is the power consumption when the high-performance edge module is active, $P_{low-idle}$ is the power consumption of the low-power sensing module when idle, and $P_{low-run}$ is the power consumption of the low-power sensing module while running the TinyML model.

Using these formulas, we can estimate *BODOQUE*'s total energy consumption over a year. When using the Raspberry Pi 4, the estimated energy consumption is 18.25 kWh, and when using the Jetson Orin Nano, the estimated energy consumption is 14.06 kWh. These values represent a significant reduction in energy consumption compared to the previous system, with a reduction of 85.66% and 88.96%, respectively, over the previous implementation, demonstrating the energy efficiency improvements of *BODOQUE*.

Lastly, the *BODOQUE* system, with its bimodal operation, offers a vastly more energy-efficient solution for environmental monitoring. By activating the high-performance edge module only when necessary, the system can significantly reduce its power consumption, leading to a lower environmental impact. This makes *BODOQUE* a sustainable and reliable solution for long-term environmental monitoring.

4 CONCLUSIONS AND FUTURE WORK

BODOQUE represents a substantial leap forward in environmental monitoring, particularly emphasizing ephemeral streams. Its dual-mode operation only triggers the high-performance edge module when necessary and significantly saves energy. This energy-conscious approach is cost-effective and encourages sustainable stewardship of the Mar Menor ecosystem. The ability of the system to process videos on-site rather than sending them for distant processing further enhances its efficiency.

This study evaluated a range of edge devices, each exhibiting a distinct balance of performance, energy consumption, and cost. The Raspberry Pi 4 Model B (4 GB) emerged as a standout contender, demonstrating a remarkable synergy of processing power, energy efficiency, and affordability. However, despite its higher price point, the Jetson Orin Nano exhibited superior energy efficiency to the Raspberry Pi 4. This result suggests that, for future projects where GPU-accelerated code execution is expected, the Jetson Orin Nano could potentially deliver more efficiency than the Raspberry Pi 4. Our extensive, year-long energy consumption analysis, based on rainfall data from the Murcia region, illustrates that the *BODOQUE* system - regardless of whether it utilizes the Raspberry Pi 4 or the Jetson Orin Nano - would markedly improve upon the energy consumption of our previous systems.

These results highlight *BODOQUE*'s energy efficiency and potential for sustainable environmental monitoring. Our future research efforts will focus on optimizing the discharge measurement code to harness the GPU of edge devices, provided they support this feature. We anticipate this improvement will increase the system's speed and potentially further decrease power consumption. Our continued efforts to refine and enhance the *BODOQUE* system underscore our commitment to delivering a robust, sustainable solution to meet environmental monitoring challenges in an era of climate change and uncertainty.

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