Final Degree Project

Biomedical Engineering Degree

Energy Optimization in Research Infrastructure: A Data-Driven Analysis of the CEK Building

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Abstract

This thesis presents a bottom-up energy audit of the Esther Koplowitz Centre (CEK) building at IDIBAPS, Barcelona, to guide targeted energy-saving actions. Due to the absence of permanent metering, this study combined a detailed equipment inventory, short-term monitoring campaigns, and statistical modeling of hourly electricity data from 2023–2024. The calibrated model explains 97% of measured weekly demand, with a relative error of 3%, and captures seasonal variation with a Mean Absolute Percentage Error (MAPE) of 6.8%. Disaggregation reveals a concentrated energy profile, with HVAC systems responsible for ~52% of annual use, followed by laboratory equipment (~36%) and the Data Processing Center (CPD; ~9%). Regression analysis further shows that outdoor temperature and daily occupancy explain 83% of day-to-day energy variability, with summer temperatures strongly influencing seasonal peaks. Three high-impact interventions emerge, ranked by estimated savings: (i) submetering and recommissioning HVAC subsystems; (ii) raising set-points of ultra-low temperature (ULT) freezers from -80 °C to -70 °C; and (iii) increasing the CPD cooling set-point from 24 °C to 26 °C. Together, these measures would cut consumption by ≈ 0.43 GWh per year (about 8.1 MWh per week)—11 % of today's 3.87 GWh annual load. Despite limited metering infrastructure, this approach demonstrates how a data-informed audit can reliably uncover savings opportunities and provide a scalable audit framework applicable to comparable biomedical research infrastructures.

Keywords: energy audit, bottom-up modeling, HVAC optimization, laboratory freezers, data processing center, biomedical research buildings, energy efficiency.

Resum

Aquesta tesi presenta una auditoria energètica *bottom-up* de l'edifici Esther Koplowitz Centre (CEK) d'IDIBAPS, a Barcelona, amb l'objectiu de guiar accions concretes d'estalvi energètic. Davant la manca de monitorització permanent, l'estudi combina un inventari detallat d'equipaments, campanyes de monitoratge esporàdiques i modelització estadística de dades horàries d'electricitat del període 2023–2024. El model calibrat explica el 97% de la demanda setmanal mesurada, amb un error relatiu del 3%, i recull la variabilitat estacional amb un error percentual mitjà absolut (MAPE) del 6,8%. La desagregació mostra un perfil de consum concentrat: els sistemes HVAC representen aproximadament el 52% del consum anual, seguits pels equips de laboratori (~36%) i el Centre de Processament de Dades (CPD; ~9%). L'anàlisi de regressió mostra que la temperatura exterior i l'ocupació diària expliquen el 83 % de la variabilitat diària de consum, amb un impacte destacat de les temperatures estivals. S'identifiquen tres mesures prioritàries segons el potencial d'estalvi: (i) submesura i reoptimització dels subsistemes HVAC; (ii) elevació dels punts de consigna dels congeladors ULT de -80 °C a -70 °C; i (iii) augment del punt de consigna de refrigeració del CPD de 24 °C a 26 °C. En conjunt, aquestes mesures reduirien el consum aproximadament en 0,43 GWh l'any (uns 8,1 MWh per setmana), és a dir, un 11 % de la càrrega anual actual de 3,87 GWh. Malgrat la infraestructura de mesura limitada, aquest enfocament demostra que una auditoria informada per dades pot identificar de manera fiable oportunitats d'estalvi i proporcionar un marc d'auditoria escalable aplicable a infraestructures biomèdiques similars.

Paraules clau: auditoria energètica, modelització bottom-up, optimització HVAC, congeladors de laboratori, centre de processament de dades, edificis biomèdics, eficiència energètica.

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Glossary of Abbreviations

AHU	Air Handling Unit
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
BMS	Building Management System
CEK	Esther Koplowitz Centre
CPD	*Centre de Processament de Dades* (Data Processing Center)
DCIM	Data Center Infrastructure Management
HVAC	Heating, Ventilation, and Air Conditioning
IDIBAPS	Institut d'Investigacions Biomèdiques August Pi i Sunyer
kW	Kilowatt
kWh	Kilowatt-hour
LED	Light Emitting Diode
LSB	Laboratori de Seguretat Biològica (Biological Safety Laboratory)
MAPE	Mean Absolute Percentage Error
OLS	Ordinary Least Squares
PERT	Program Evaluation and Review Technique
PUE	Power Usage Effectiveness
RMSE	Root Mean Square Error
SARIMAX	Seasonal Autoregressive Integrated Moving Average with eXogenous variables
SIME	*Sistema d'Informació i Monitorització Energètica*
SIRENA	*Sistema d'Informació dels Recursos Energètics i l'Aigua*
SuRe-Cat	Sustainable Research Catalonia Network
SWOT	Strengths, Weaknesses, Opportunities, Threats
UAB	Universitat Autònoma de Barcelona
UCLM	Universidad de Castilla-La Mancha
ULT	Ultra-Low Temperature (freezer)
UPC	Universitat Politècnica de Catalunya
WBS	Work Breakdown Structure

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1. Introduction

1.1. Motivation and Aim of the Project

In light of escalating environmental concerns and the global imperative for sustainable development, energy efficiency has emerged as a paramount challenge. Buildings are responsible for approximately 40% of global energy consumption and over one-third of carbon dioxide emissions, underscoring their significant impact on the environment. Within this sector, healthcare and research facilities, such as biomedical research centers, are notably energy-intensive due to their continuous operation and the specialized equipment they house.

The International Energy Agency's Energy Efficiency 2024 report emphasizes that improving building-level efficiency is one of the most effective and immediate strategies for reducing both energy use and carbon emissions. It highlights the urgent need for smarter energy monitoring and operational improvements, not just as an environmental necessity, but as a practical step toward economic resilience and sustainability [1].

This project arises from a personal and professional commitment to energy sustainability, providing an opportunity to apply engineering methodologies to real-world energy systems. The motivation is twofold: to contribute meaningfully to global energy efficiency efforts, and to gain a deeper technical understanding of how data, modeling, and system analysis can be used to improve energy performance.

1.2. Objective

The main objective of this thesis is to analyze and quantify the energy consumption of the CEK building at IDIBAPS in order to identify the most energy-intensive areas and systems within the facility. This knowledge will serve as the foundation for proposing specific, targeted, and intelligent solutions that can effectively contribute to improving the building's energy efficiency, reducing operational costs, and reinforcing the center's commitment to environmental sustainability.

At the outset of the project, the only available information consisted of the center's global electricity consumption data extracted from utility bills. Therefore, a key focus of this work is the disaggregation of total energy usage into distinct categories and equipment groups. This bottom-up approach aims to reconstruct the building's energy profile by estimating consumption across various time scales, from daily to annual, and understanding the contribution of individual systems to the overall demand.

By achieving this level of detail, the project seeks to support data-driven decisions and highlight opportunities for energy optimization in a way that is feasible, scalable, and aligned with the operational needs of a biomedical research environment.

1.3. Structure and Methodology

The methodology followed in this project was designed to progressively build a detailed understanding of the energy consumption patterns of the CEK building at IDIBAPS, starting from a limited dataset and advancing toward a structured decomposition by systems and equipment.

At the beginning of the project, the only available data consisted of monthly electricity invoices, which provided a global figure for the building's total energy consumption. In order to extract meaningful insights from this information, the first step involved processing and visualizing the data using Python. Through this preliminary analysis and basic plots, an average daily consumption pattern was established, revealing two distinct behaviors: a constant and significant baseline consumption during nighttime hours, and a noticeable increase during the day, coinciding with standard working hours. This finding suggested the existence of systems operating continuously, regardless of occupancy, and prompted further investigation into their origin.

Based on these observations, a hypothesis was formulated suggesting that the building's total energy demand could be attributed to several subsystems functioning independently. After conducting an initial investigation and gaining a better understanding of the building's context, the most likely contributors were identified as laboratory equipment, HVAC and building infrastructure, and the Data Processing Center (CPD), which, although initially undocumented, was suspected to be a significant energy consumer.

To evaluate this hypothesis, the main areas were analyzed separately, and theoretical energy-consumption values were calculated using a bottom-up approach and subsequently aggregated by main category. This procedure enabled an estimation of the building's overall energy profile, broken down into specific systems within each category. The resulting theoretical model was then compared against the actual consumption reported in the energy invoices in order to assess the accuracy of the decomposition. In cases where discrepancies appeared, additional refinements were made to improve estimation accuracy and better reflect the real operational context.

This structured approach, beginning with raw global data, formulating hypotheses, performing bottom-up estimations, and validating them against real figures, provided a solid foundation for identifying the most energy-intensive systems in the building. The insights derived from this analysis subsequently informed the examination of optimization opportunities and contributed to the final discussion of sustainability measures and efficiency-enhancement strategies applicable to the CEK building.

1.4. Limitations and Scope

This project is focused on the analysis and estimation of energy consumption within the CEK building at IDIBAPS, with the aim of identifying major consumption areas. The scope of the study is limited to this specific building and does not extend to other facilities or departments within the institution.

The analysis is based primarily on global electricity consumption data obtained from utility bills, complemented by a bottom-up estimation approach in which energy usage is broken down by system and equipment type. The categories analyzed include laboratory equipment, HVAC and building infrastructure, and the Data Processing Center (CPD). Consumption estimates were generally derived from available technical data and usage assumptions, although in specific cases, such as isolated areas with defined electrical feeds like the CPD, direct measurements were used to improve accuracy.

Due to the absence of a comprehensive real-time monitoring system or sub-metering at the equipment level, several limitations apply to the precision of the results. In many instances, assumptions had to be made regarding operating hours, load profiles, and usage patterns, particularly for equipment without logging or telemetry. Additionally, limited access to certain technical documentation or historical performance data introduced some uncertainty into the modeling process.

Although the primary focus of the project is on technical systems, some attention was also given to the potential correlation between human occupancy patterns and energy consumption, in order to better understand daily and weekly demand variations.

This project does not include the detailed design, implementation, or evaluation of energy-saving strategies, nor does it attempt to model complex behavioral impacts in detail. Also does not include accurate modelling or predictive modelling. Instead, the study focuses on the technical decomposition of global consumption figures, offering a structured estimation that serves as a foundation for a conclusion and broad proposal of future steps that could be made on that for future improvements in energy monitoring and management.

Despite these limitations, the methodology provides a coherent and scalable framework for understanding energy distribution within the CEK building, and it offers actionable insights for identifying optimization priorities in similar research environments.

2. Background

2.1. Institutional and Building Context

The August Pi i Sunyer Biomedical Research Institute (IDIBAPS) is a prominent biomedical research institution located in Catalonia. Established in 1996, it is part of the CERCA network (Research Centers of Catalonia) and operates as a public consortium made up of the Government of Catalonia, the Hospital Clínic de Barcelona, the Faculty of Medicine and Health Sciences of the University of Barcelona, and the Institute of Biomedical Research of Barcelona (CSIC) as an associated partner [3].

IDIBAPS brings together approximately 2,000 professionals, organized into 97 research groups distributed across five main scientific areas:

- Biological aggression and response mechanisms
- Respiratory, cardiovascular, and renal pathobiology and bioengineering
- Liver, digestive system, and metabolism
- Clinical and experimental neurosciences
- Oncology and hematology

In addition, three transversal groups focus on Primary Care, Nursing and Pharmacology, and Clinical Trials.

In recent years, IDIBAPS has reinforced its commitment to sustainability and environmental responsibility. Recognizing that scientific research involves substantial resource consumption, the Sustainability Committee was established within the institution in mid-2022. This committee has initiated various actions to reduce the environmental impact of the institution, including the development of a sustainability manual aimed at promoting more sustainable practices within the research environment [2].

Research activity at IDIBAPS is mainly concentrated in two key facilities: the Esther Koplowitz Centre (CEK) and the CELLEX Biomedical Research Centre. Other auxiliary buildings include other locations as depicted in Figure 1.

Figure 1. Aerial view of IDIBAPS facilities. Numbered markers indicate: (1) Esther Koplowitz Centre (CEK), C. Rosselló 149–153; (2) CELLEX Biomedical Research Centre (CELEX), UB, C. Casanova 143; (3) Maternity building, C. Sabino Arana 1; (4) C. Mallorca 183; (5) C. Urgell 216; (6) C. Còrsega 176; and (7) C. Còrsega 180. [4].

As outlined in Section 1.4, the present study is exclusively focused on the CEK (Esther Koplowitz Centre), located at Carrer Rosselló, 149–153, in Barcelona. Inaugurated in 2010, the CEK encompasses approximately 5,000 m² of laboratory space distributed across five floors, and an additional 2,500 m² in the basement level. Figure 2 presents a schematic representation of the CEK building, showing the distribution of floors, technical areas, and underground levels.

Figure 2. Schematic illustration of the CEK building, illustrating the distribution of laboratory floors (P1–P5), ground floors (PB, PA), and basement levels (S-1 to S-3), including areas allocated to research activities and technical infrastructure. Diagram produced by the author.

The building operates daily from 6:00 a.m. to 12:00 a.m., and access is restricted to authorized personnel only, with minors prohibited from entering both the CEK and CELLEX buildings.

The laboratory areas are organized by research focus as follows:

- First Floor: Diseases related to poverty and immunology
- Second Floor: Hematology and oncology
- Third and Fourth Floors: Digestive system and liver diseases
- Fifth Floor: Metabolism, diabetes, and obesity

Each floor features a consistent layout, including a 4°C cold room (1.75 m²), one or two -20°C freezer rooms (4.60 m² each), culture rooms, work areas, and specialized laboratory equipment necessary for experimental procedures. See Annex 12.1 for a typical floor plan.

The basement (S-1) houses various critical support facilities for research: the Biobank, Cytometry, Genomics, and Imaging Units, along with the Sterilization Service. It also includes a Category 2 radioactive facility (IRA-3029), authorized for work with unsealed radioactive sources, and a Level 3 Biological Safety Laboratory (LSB-3), registered under notification number A/ES/13/1-11. Moreover, the basement contains additional freezer rooms and the Data Processing Center (CPD), which plays a key role in handling and storing large volumes of research data. This room requires continuous cooling to maintain optimal operating conditions, making it one of the building's most energy-intensive areas due to its constant power demand and high heat output.

Understanding the functional and architectural layout of the CEK building is fundamental to accurately analyzing its energy consumption. The nature of its operations, the diversity of research equipment, and the need for strict environmental controls all contribute to a complex energy profile. This context frames the technical and methodological approach used throughout this study.

2.2. General Concepts

This section introduces key concepts and equations used in the estimation and analysis of energy consumption within the CEK building. The goal is to provide the necessary theoretical background to support the methodology and calculations described in later sections.

2.2.1. Energy and Power

Electric energy consumption is typically expressed in kilowatt-hours (kWh), which represents the amount of power used over time. The basic formula for calculating energy consumption is:

Equation 1. Energy Consumption formula

$$\mathrm{E} = \mathrm{P} \cdot t$$

Where:

- E is the energy consumed (kWh)
- P is the active power (kW)
- t is the duration of consumption (hours)

In electrical systems, power can be supplied through single-phase or three-phase configurations. While single-phase power is common in residential environments, buildings such as the CEK use three-phase systems to efficiently supply energy to high-demand equipment like laboratory devices, HVAC systems, and data servers. In a three-phase system, the active power consumed can be estimated using:

Equation 2. Three-phase active power formula

$$P = \sqrt{3} \cdot V \cdot I \cdot cos\theta$$

Where:

- V is the line-to-line voltage (V)
- I is the average current across the three phases (A)
- $\cos\theta$ is the power factor, which reflects the efficiency of the load. In AC systems, the power factor $\cos\theta$ reflects the efficiency with which electrical power is converted into useful work. For typical IT and server equipment, the power factor usually ranges from 0.85 to 0.95, and modern infrastructure is generally designed to meet regulatory standards requiring power factor correction [5].

This expression allows for the calculation of active power based on electrical current measurements, which is essential when direct power data is not available. Once power is known, total energy consumption can be estimated by multiplying it by the time of operation.

3. Market Analysis

Energy efficiency and sustainability have become core priorities across all sectors, with particular urgency in energy-intensive environments such as biomedical research centers. Laboratories typically house high-consumption equipment including centrifuges, ultra-low temperature (ULT) freezers, fume hoods, and advanced HVAC systems. As awareness grows regarding their environmental impact, these facilities are increasingly the focus of institutional and policy-driven initiatives to reduce energy consumption and carbon emissions. Some examples are *Green Labs Austria* [6], *Labconscious* [7] i *Sustainable Labs by Harvard* [8].

3.1. Market Drivers and Opportunities

The market for energy optimization in research buildings is driven by several key factors:

- Regulatory pressure and institutional mandates, especially under frameworks such as the European Green Deal, national energy transition plans, and carbon neutrality goals by 2030–2050 [9, 10]
- Rising operational costs, particularly electricity costs, which incentivize facilities to explore energy-saving technologies [11] .
- Reputation and accreditation schemes, such as LEED or My Green Lab certification, which influence funding, partnerships, and research attractiveness [12, 13].
- Technological maturity of building management systems (BMS), real-time energy monitoring tools, and IoT-enabled lab equipment, which enable granular diagnostics and optimization [14, 15].
- Availability of funding programs, including Horizon Europe and national innovation grants supporting energy transition in the research and healthcare sectors [16].
- Increased knowledge dissemination and awareness, driven by academic publications and scientific conferences, is accelerating the adoption of energy-efficient solutions:
    - Academic journals, such as *Energy and Buildings*, regularly publish peer-reviewed research on best practices, simulation studies, and experimental findings related to building energy performance in laboratory environments [17].
    - International conferences, such as the International Conference on Sustainable Energy Engineering (ICSEE), offer platforms for the exchange of innovative approaches, case studies, and emerging technologies in sustainable building design and energy efficiency [18].

These drivers collectively shape a growing and diversifying market for energy efficiency solutions in the biomedical research infrastructure. The convergence of policy mandates, technological readiness, cost pressures, and knowledge transfer mechanisms is fostering an increasingly supportive environment for energy optimization initiatives across the sector.

3.2. Benchmarking and Case Studies

To assess the applicability of energy optimization strategies at IDIBAPS, it is essential to examine how comparable institutions have approached similar challenges. This benchmarking exercise includes both biomedical research centers and academic institutions with broader sustainability mandates. The aim is to identify effective practices, tools, and strategies that may inform future actions at IDIBAPS in the context of laboratory energy performance and institutional sustainability.

3.2.1. Research Institutions

Institute for Bioengineering of Catalonia (IBEC)

IBEC has obtained the My Green Lab certification and adopted multiple sustainability measures, including LED lighting retrofits, laboratory equipment optimization protocols, and user training programs. These initiatives are aligned with the institution's objective to extend certification across all research groups by 2024, as stated in institutional press releases and official documentation [19].

Centro Nacional de Investigaciones Oncológicas (CNIO)

CNIO has prioritized the optimization of energy-intensive biobank operations, particularly in relation to ultra-low temperature (ULT) freezers. Although specific energy-saving actions are not publicly detailed, institutional communications emphasize operational standards aimed at preserving biological samples under controlled conditions, suggesting an implicit focus on energy efficiency [20].

European Molecular Biology Laboratory (EMBL – Heidelberg)

EMBL has established a sustainability strategy that integrates building-level energy management. According to internal correspondence with Brendan Rouse, the Head of Sustainability at EMBL, the Heidelberg campus employs a Building Management System (BMS) to monitor electricity usage at 15-minute intervals. Consumption data are analyzed monthly using regression techniques based on degree-days for heating and cooling, normalized against campus area, full-time equivalent staff (FTEs), and publication output. The analysis is conducted using spreadsheet-based tools. However, the granularity of monitoring is currently limited to the whole-building scale; asset-level data for laboratory infrastructure—such as ULT freezers and fume hoods—are not yet available [21].

3.2.2. Academic Institutions with Broader Energy Strategies

Universitat Politècnica de Catalunya (UPC)

UPC has implemented a comprehensive energy strategy under its 2030 Sustainable Campus Plan. Central to this is the SIRENA (Sistema d'Informació dels Recursos ENergètics i l'Aigua) platform, which enables real-time monitoring of electricity, gas, and water consumption at 15-minute intervals across campus buildings. The system supports advanced diagnostics—such as harmonic distortion and reactive power analysis—via PowerStudio software. Complementary infrastructure upgrades, including BMS systems, photovoltaic installations (649 kWp as of 2023), and large-scale LED retrofits, led to an 18.7% reduction in energy use in the first half of 2023 [22]. Recent investigations made by stuents have highlighted the practical implementation of these systems. Morcillo conducted detailed consumption monitoring of the Omega CPD, showing that incremental increases in cooling setpoints (from 24 °C to 26 °C) led to a 3.6% improvement in the Power Usage Effectiveness [23]. In parallel, Muscolo identified key limitations in CPD energy management, notably the lack of data transparency and the absence of a Data Center Infrastructure Management (DCIM) system, despite institutional sustainability commitments [24]. These findings highlight the critical role of high-resolution telemetry and integrated monitoring platforms in optimizing energy performance in complex technical infrastructures such as data centers.

Universitat Autònoma de Barcelona (UAB)

UAB's energy strategy encompasses building retrofitting, LED lighting upgrades, and the installation of over 677 kWp of solar photovoltaic capacity. The university has established centralized monitoring for renewable energy production and implemented real-time submetering across its facilities. These efforts have resulted in a 39% reduction in total energy use from 2010 to 2023, as reported in UAB's sustainability documentation [25].

University of Castilla-La Mancha (UCLM)

UCLM provides a noteworthy case of methodological transparency in energy monitoring. A study conducted on its Albacete campus by Bastida-Molina et al. included both the analytical framework and open-source code for energy evaluation. The analysis identified the biomedical building as the largest energy consumer, underscoring the high demand associated with research-intensive infrastructures. In contrast to other European institutions—such as Bordeaux, Melbourne, or Politecnico di Milano—UCLM's approach distinguishes itself by the reproducibility and rigor of its methodology, as emphasized in the authors' own comparative review [26].

Table 1. Benchmarking of energy strategies in research institutions and universities.

Institution	Focus Area	Main Strategies	Monitoring System	Reported Results
IBEC	Labs	LED lighting, equipment optimization	Manual monitoring	Achieved My Green Lab certification
CNIO	Biobanks	Optimized ULT freezer operations	Not specified	Enhanced energy efficiency in storage
EMBL	Buildings	BMS implementation, regression analysis	15-minute interval data collection	Improved energy tracking
UPC	Campus-wide	SIRENA system, infrastructure upgrades	Real-time monitoring	18.7% reduction in energy consumption (2023)
UAB	Campus-wide	Retrofitting, renewable installations	Centralized monitoring	39% reduction in total energy use (2010–2023)
UCLM	Biomedical Building	Transparent energy analysis	Published methodology and code	Identified highest energy consumer on campus

4. Concept Engineering

The development of this project required an in-depth understanding of the energy context at the CEK building within the IDIBAPS research center. To define a viable implementation strategy, it was essential to explore the current literature, assess the available infrastructure, and evaluate different approaches for carrying out an energy consumption analysis.

This chapter outlines the methodology chosen for the implementation of the energy analysis, exploring alternative approaches and justifying the final selection based on technical, economic, and logistical considerations.

4.1. Data Acquisition Strategies

Accurate energy analysis requires access to both global and partial electricity consumption data. For this project, the first step consisted in securing real-time global consumption records from the main electrical system of the CEK building.

In institutional buildings with high-voltage installations (above 15 kV), one common method involves direct fiscal monitoring through the utility meter. This approach consists of connecting directly to the official utility meter (installed by the energy provider). The setup typically involves using a GPRS modem equipped with a SIM card to transmit data at 15-minute intervals, connecting an electrical probe (clamp or sensor) directly to the utility meter's output and configuring the system and registering it with a cloud-based energy monitoring platform such as DexCell Energy Manager, enabling real-time data access and historical storage [27].

Alternatively, consumption data can be obtained through internal building energy management systems or external portals provided by distribution companies. In the case of CEK, data access is provided by Datadis, a centralized platform developed by Spain's electricity distributors. Access is managed through the SIME system of the Generalitat de Catalunya, allowing automated downloads via both web interface and API without requiring on-site hardware installations.

To obtain a breakdown of consumption by subsystem or area, two methodological approaches are considered: an empirical strategy based on real-time monitoring instrumentation, and a theoretical strategy relying on estimated energy usage derived from equipment specifications and operational patterns.

4.1.1. Empirical Strategy: Real-Time Monitoring

The empirical approach is based on the direct measurement of electrical parameters through physical instrumentation installed at various points in the CEK building's distribution system. This strategy enables the collection of high-resolution, real-time data to facilitate subsystem-level analysis and continuous performance supervision.

A typical monitoring architecture is illustrated in Figure 3. Measurement devices (1) capture electrical variables such as voltage, current, and power. The data is then transmitted to a local data concentrator (2), which forwards it to a remote server (3) via an internet connection. Finally, users can access and visualize the data through any internet-connected interface (4), such as a laptop, tablet, or smartphone.

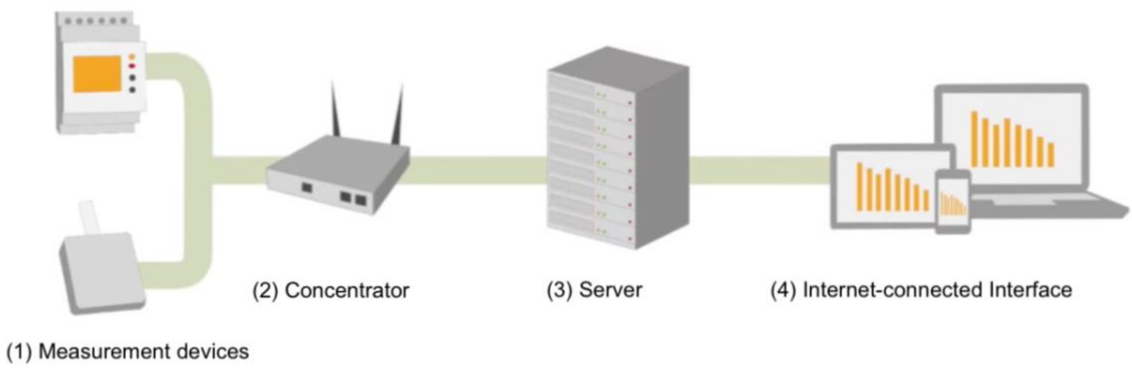

Figure 3. Typical architecture for real-time electrical consumption monitoring [27].

To assess partial consumption at floor or room level, network power analyzers can be installed in each electrical distribution panel. These analyzers continuously monitor parameters such as voltage, current, active power, reactive power, and energy, providing detailed insight into electrical behavior. When implementing that system, key design considerations include the type of electrical connection (single-phase or three-phase), mounting requirements (DIN-rail or panel-mounted), and the physical space available in the panel [28].

For a more granular analysis, such as evaluating specific high-consumption machines, additional measurement options may be used:

- **Clamp meters**: Portable devices used for manual spot measurements, commonly employed for short-term diagnostics [29].
- **Current transformers**: Fixed components that encircle live conductors to step down the current for safe and continuous monitoring. When paired with data loggers or analyzers, enable detailed energy tracking at the device or subsystem level [30].
- **Integrated power analyzers**: Standalone units installed on individual machines, for comprehensive parameter tracking.

According to the International Energy Agency, direct measurements provide the most accurate method for analyzing energy consumption by end-use and equipment type. The IEA emphasizes that while such instrumentation involves higher upfront costs and logistical complexity, it is indispensable for identifying behavioral patterns, temporal variations, standby loads, and inefficiencies not observable through estimation-based strategies [31].

4.1.2. Theoretical Strategy: Estimation-Based

The second strategy considered for obtaining a detailed breakdown of energy consumption within the CEK building is the theoretical approach. This method avoids the need for physical measurement devices by estimating partial energy consumption based on technical specifications and expected usage patterns.

The first step is the creation of a detailed inventory of the equipment of all equipment in the building, categorized by floor or operational area. For each device relevant technical data would have to be collected such as model, manufacturer, and functionality power (W).

Subsequently, the typical operating hours of each piece of equipment are assessed. This can be done through consultations with users, manual usage logs, or automated tracking systems where available. For critical equipment or where greater accuracy is required, sensors or hour meters can be installed to monitor actual operation time.

Finally, the total theoretical energy consumption is calculated for each device by multiplying its power rating (W) by the number of operating hours (h). These values are then aggregated by equipment type, or operational zone to provide a comprehensive overview of the building's partial energy usage. Additionally, consumption estimates can be summarized over different timeframes such as weekly, monthly, or annually, to support broader trend analysis.

As a final validation step, the sum of all estimated consumption values is compared against the global energy consumption data obtained from invoices or monitoring systems. This comparison helps to confirm the accuracy of the estimations and identify any significant discrepancies or anomalies in the dataset.

4.1.3. Strategy Selection

After evaluating both the empirical and theoretical approaches, the theoretical strategy has been selected for this project. While the empirical method offers more precise, real-time data, its high initial cost, logistical complexity, and the need for continuous equipment maintenance make it less feasible within the scope and resources of a final degree project. In contrast, the theoretical strategy allows for a cost-effective and scalable analysis of partial energy consumption by leveraging equipment specifications and estimated usage patterns. Despite offering lower precision and relying on estimations rather than direct measurements, it allows for the identification of high-consumption zones and systems without the need for additional hardware or infrastructure. A detailed comparison of the two approaches is presented in Table 2, highlighting their respective advantages and limitations.

Furthermore, this strategy allows for the selective integration of empirical measurements, such as temporary installation of power analyzers or clamp meters in critical locations. These targeted interventions can serve to validate or refine theoretical estimates, ensuring that the overall methodology remains robust and adaptable to future improvements.

Table 2. Comparison of empirical vs theoretical energy monitoring strategies.

Option	Advantages	Disadvantages
Empirical Strategy	• Provides direct and accurate real-time data. • Continuous and automatic monitoring.	• Requires a significant initial investment in equipment and installation. • Involves logistical and equipment management challenges. • Requires regular maintenance and calibration of equipment.
Theoretical Strategy	• No need for additional equipment installation. • Lower initial investment. • Reduced installation and maintenance costs. • No additional installation space required.	• Relies on theoretical calculations and estimates. • Less precise compared to empirical monitoring. • Lack of real-time data may limit responsiveness. • Requires more time and human involvement.

4.2. Data Processing

In the conceptual phase of this project, it is also essential to assess the available tools for processing and analyzing energy consumption data. The selection of appropriate tools depends on factors such as project complexity, available resources, and specific analytical objectives.

1. **Microsoft Excel and PivotTables**
Microsoft Excel is a widely used tool for data analysis due to its versatility and user-friendly interface. PivotTables allow for interactive summarization and analysis of large datasets, facilitating the creation of customized reports and visualizations. Excel's widespread availability and ease of use make it a practical choice for initial data exploration and reporting.

2. **Business Intelligence (BI) Platforms**
Power BI, Tableau, and QlikView are BI platforms that offer advanced data visualization capabilities, allowing the creation of interactive dashboards and detailed reports. These platforms support real-time monitoring, multi-source data integration, and automated KPI generation, making them suitable for energy efficiency analysis [32].

3. **Python and Data Analysis Libraries**
Python is a programming language renowned for its data analysis capabilities, supported by libraries such as pandas, NumPy, and matplotlib. These libraries facilitate efficient data manipulation, statistical analysis, and visualization. Python's flexibility allows for the development of customized workflows tailored to specific project needs, making it a valuable tool for in-depth energy consumption analysis.

4. **Specialized Energy Management Software**
Dedicated energy management platforms offer advanced tools for monitoring, auditing, and optimizing energy use in large or complex facilities. Key examples include:

- **Spacewell Energy (Dexma):** Cloud-based system for real-time monitoring, benchmarking, anomaly detection, and energy auditing [33].
- **Atrius Energy (formerly BuildingOS):** Centralizes data from multiple sources for performance optimization and sustainability reporting [34].
- **EnergyCAP:** Enterprise-grade platform for utility tracking, benchmarking, and automated reporting, with ENERGY STAR integration and KPI management [35].

A comparative overview of the tools described is provided in Table 3, summarizing their respective strengths and limitations in the context for this energy analysis.

Table 3. Comparison of data processing tools for energy analysis.

Tool or Method	Advantages	Disadvantages
Microsoft Excel	Easy to use, widely available, PivotTables allow for interactive data analysis.	Limited scalability for large datasets, fewer advanced visualization options, less automation compared to other tools.
Python and Data Libraries	Highly customizable, powerful for data analysis and prediction, , with access to advanced visualization tools.	Requires programming knowledge, less intuitive for non-technical users.
Business Intelligence (BI) Platforms	Advanced visualizations, interactive dashboards, integration with multiple data sources.	High cost, steep learning curve, less flexible than Python when it comes to data wrangling.
Specialized Energy Management Software	Tailored functionalities for energy analysis, automatic KPI generation.	High cost, may require specific training or enterprise access.

After evaluating the various tools available for energy data analysis during the conceptual phase of the project, the most appropriate and feasible options selected were Microsoft Excel and Python with data analysis libraries.

Microsoft Excel was chosen due to its wide accessibility, ease of use, and powerful functionalities such as PivotTables, which allow for rapid data filtering, aggregation, and visualization. Excel is especially valuable in the early stages of analysis, where it serves as an intuitive platform to organize large datasets and make quick approximations of theoretical consumption based on inventory and usage patterns. In parallel, Python was selected for its greater flexibility and its ability to manage more complex data workflows. This includes merging and processing multiple datasets, generating advanced visualizations, and automating repetitive calculations. Its extensive ecosystem of libraries, including pandas, matplotlib, and openpyxl, provides an adaptable and efficient framework tailored to the specific characteristics of the building's energy systems. Python will be particularly useful in the final stages of analysis for producing accurate, high-quality plots and cross-validating results.

While Business Intelligence tools such as Power BI and Tableau offer advanced visualization capabilities and interactive dashboards, they were not prioritized for this project. These platforms often require paid licenses, have a steeper learning curve, and may lack the data manipulation flexibility provided by Python—especially when dealing with raw, unstructured data. Lastly, enterprise-level energy management platforms such as Dexma, EnergyCAP, and Atrius were acknowledged as robust industry solutions. However, due to their high cost, integration complexity, and limited accessibility in an academic setting, they were excluded from this project's implementation. These platforms may be better suited for large-scale or institutional energy management initiatives and remain valuable references for future applications.

4.3. Data Analysis and Interpretation

For the analysis and interpretation of energy consumption data, various methodological approaches can be employed depending on the available data and project objectives. The following strategies were considered for their potential to offer valuable insights into the building's energy performance:

1. **Temporal Trend Analysis**: Examines energy consumption over time (daily, weekly, or monthly) to identify patterns or deviations. This helps reveal the impact of operational schedules, weather, and seasonal factors, and is useful for establishing baselines and detecting time-based inefficiencies.
2. **Comparison Between Major Consumption Sources**: Evaluates energy use across system categories such as laboratory equipment, HVAC, and the data center. This method helps prioritize high-consumption areas for developing targeted energy-saving measures, where actions would have a greater impact.
3. **Equipment-Specific Consumption Analysis**: Involves estimating or measuring energy use of individual devices or equipment groups. Particularly relevant in lab environments like IDIBAPS, this strategy supports decisions such as replacing inefficient equipment or optimizing operation schedules.
4. **Detection of Anomalous Patterns**: Uses statistical or predictive methods to flag irregular energy usage, potentially indicating equipment faults or unnecessary standby loads. However, effective implementation requires continuous, high-resolution data.
5. **Segregation by Floor or Research Group**: Analyzes energy consumption by physical area or research unit to detect disparities and support behavioral or policy-based interventions.
6. **Occupancy-Based Consumption Correlation**: Cross-references energy data with occupancy levels using access logs. This can be estimated with a simple regression. Has the potential to reveal opportunities to adjust HVAC or lighting schedules during low-occupancy periods, improving overall energy efficiency.

Among the methods considered, comparing measured consumption to source-based estimates is selected as the primary analytical strategy because it directly aligns with the project's objective of decomposing the building's overall energy use into its principal subsystems.

Temporal trend analysis is indispensable for validating and contextualizing this decomposition. Examining consumption patterns over daily, weekly, and monthly intervals confirms whether the peaks and troughs suggested by subsystem estimates coincide with known activity periods (e.g., weekday laboratory use) and baseline loads (e.g., overnight operation).

Occupancy-based correlation can be implemented via statistical regression using access-control records to assess whether variations in building use correspond to measurable changes in total energy consumption.

Segregation by floor or research group is excluded from the core analysis, given the homogeneous design and equipment layout across levels 1–5, spatial disaggregation would add complexity without further insight into primary drivers of energy use.

Equipment-specific analysis is performed only for devices exhibiting exceptionally high power ratings or standby draws. A fully granular, piece-by-piece inventory is unnecessary except for those few devices whose ratings justify focused attention.

Although anomaly detection represents a valuable tool when continuous, high-frequency metering is available, it is not adopted as a central element of this study. The framework relies predominantly on theoretical estimations, monthly billing, statistical flagging of irregular usage events is neither reliable nor directly relevant to the bottom-up decomposition objective.

Taken together, these methodological choices ensure that the analysis remains tightly focused on reconciling source-based estimates with measured consumption, while using temporal and occupancy data only as complementary validation in line with the project’s scope.

5. Detail Engineering

This chapter constitutes the analytical core of the project, encompassing the acquisition, processing, and interpretation of energy-related data within the CEK building at IDIBAPS. Building upon the conceptual framework outlined in Chapter 4, a bottom-up estimation methodology was employed as the primary analytical strategy. This choice reflects a balance between feasibility, scalability, and analytical rigor in the absence of direct submetering.

The analysis begins with the identification and quantification of energy consumption in three principal subsystems:

1. Laboratory Equipment
2. HVAC and Auxiliary Systems
3. Data Processing Center (CPD)

For each, a tailored approach was adopted—inventory modeling and usage estimation for laboratory devices; capacity-based seasonal profiling for several HVAC components; and empirical measurements for the CPD via targeted instrumentation campaigns.

These subsystem-level estimations were then contrasted against historical electricity data, enabling partial validation and refinement of the reconstructed energy profile. Furthermore, the chapter explores temporal consumption patterns over hourly to seasonal scales (2023–2024), revealing structural trends in daily load behavior. Finally, a statistical regression analysis is conducted to quantify the influence of key explanatory variables—outdoor temperature and building occupancy—on global consumption using OLS modeling.

Collectively, the chapter offers a comprehensive and multi-resolution assessment of electricity demand within the CEK building, forming the empirical foundation for the strategic discussion and optimization proposals developed in Chapter 10.

5.1. Laboratory Equipment in the CEK building

The objective of this section is to develop a standardized and representative inventory of laboratory equipment for quantifying the energy consumption of the CEK research center at IDIBAPS. An initial equipment list was provided by the institution, covering floors 1 to 5 and floor -1. Given the distinct functional role of floor -1 (biobank, citometry, genomics), its analysis was conducted separately, while floors 1 through 5, sharing similar architectural and operational characteristics, were examined collectively.

5.1.1. Data Acquisition: Equipment Inventory

The preliminary database, provided in Excel format, consisted of 3,916 entries, corresponding to all equipment units registered along with the model, series number and location inside the building on floors 1 through 5. This raw dataset exhibited inconsistencies in naming conventions, formatting, and spelling, resulting in the identification of approximately 463 unique equipment labels. Consequently, a comprehensive cleaning and standardization process was conducted to ensure consistency and analytical reliability.

Non-electrical or low-consumption items, such as manual tools, were excluded in consultation with laboratory staff. Equipment labels were corrected, translated where necessary, and consolidated using Excel-based tools to unify variant entries under standardized identifiers. This process reduced the initial pool to 126 unique equipment names. Functionally and energetically similar devices were subsequently grouped into 52 core equipment types. To more accurately reflect their operational behavior, particularly for continuously running categories such as cell culture systems, certain entries were duplicated or disaggregated, resulting in a final analytical dataset comprising 66 distinct entries.

A hierarchical classification scheme was adopted, consisting of three levels: specific equipment type (e.g., agitador magnetic calefactor, -20 freezer), functional subcategory (e.g.,centrifugues, agitation, freezers), and general category (e.g., sample analysis and processing, cooling and refrigeration). The complete classification table is available in Annex 12.2.

5.1.2. Usage Estimation and Energy Calculation

Nominal power consumption (W) for each equipment type was obtained from technical datasheets, official manuals, or direct manufacturer inquiries. For equipment with multiple variants, the most frequently observed or technically representative model was selected. Equivalent substitutions were used when exact specifications were unavailable.

Weekly usage hours were estimated using two complementary approaches: qualitative and quantitative. Qualitative data was obtained through interviews with laboratory personnel and managers, who provided estimated weekly usage (in hours) for the selected equipment. Quantitative data was collected from equipment linked to the *Agendo* reservation system, which logs usage for specific shared equipment. To calculate average weekly usage times from the quantitative data, booking records from May 1, 2023, to February 15, 2024, were analyzed. Final weekly usage estimates for each equipment type were determined by averaging the data from floors 2, 3, and 4, which were considered representative of floors 1 through 5 due to comparable activity types, usage patterns, and architectural layout. Further detail of these calculations can be found in Annex 12.5 (Folder 1: 1_Equipment_Inventory/Agendo), which contains the full booking dataset, processing spreadsheets, and estimation methodology.

The weekly timeframe was selected to smoothen daily fluctuations and to provide a scalable unit for projecting monthly or annual consumption. The energy consumed per week was calculated using the previously introduced energy formula (Equation 2.1):

$$E_{weekly} = \mathrm{P} \cdot t$$

Where P denotes the equipment power (W) of the device and t he estimated weekly operating time (h). The resulting energy values were expressed in kilowatt-hours (kWh) and aggregated by equipment category.

5.1.3. Results

The analysis of weekly energy consumption distribution across floors 1 to 5 revealed three dominant categories: Cooling and Refrigeration Equipment (38%), Cell Culture Equipment (34%), and Sample Analysis and Processing Equipment (23%), as presented in the right chart in Figure 4. Together, these three categories account for over 90% of the total laboratory equipment consumption. Their dominance is largely due to continuous operation, particularly for refrigeration and cell culture devices. Sample Analysis Equipment, despite variable usage and power intensity, remains a major contributor due to its large number of equipment per this category. In contrast, Heat and Pressure Equipment (3%) and Safety and Air Flow Equipment (2%) had minor contributions.

On floor -1, which functions, mainly as the Biobank, Cytometry, Genomics, the consumption profile shifts significantly. As shown in the left chart in Figure 4, Cooling and Refrigeration Equipment alone represents 82% of the total weekly consumption, reflecting the presence of 91 refrigeration devices, including ultra-low freezers at -150°C and -80°C, standard freezers at -20°C, refrigerators, and combined units. These units support long-term preservation of biological samples collected throughout the building. Device-level details and calculations for both systems are provided in Excel sheets in Annex 12.5 (Folder 1: 1_Equipment_Inventory).

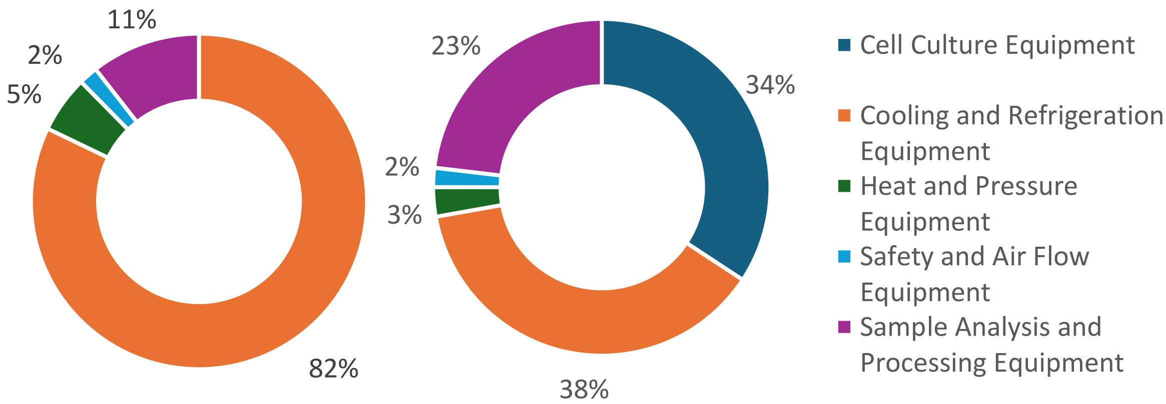

Figure 4. Energy consumption by equipment type. Left: Floor -1; Right: Floors 1-5.

When aggregated across the entire CEK building, Cooling and Refrigeration Equipment remains the primary contributor (61%), followed by Cell Culture Equipment (17%) and Sample Analysis Equipment (16%). Other categories each represent less than 5%, as depicted in Figure 5. A detailed tabular breakdown of this distribution, including absolute consumption values and relative shares for Floors 1–5, Floor -1, and the total building, is provided in Annex 12.2, Table 18. The **total weekly consumption** for all laboratory equipment is estimated at **26,761.04 kWh**, projecting to over 1.39 GWh annually.

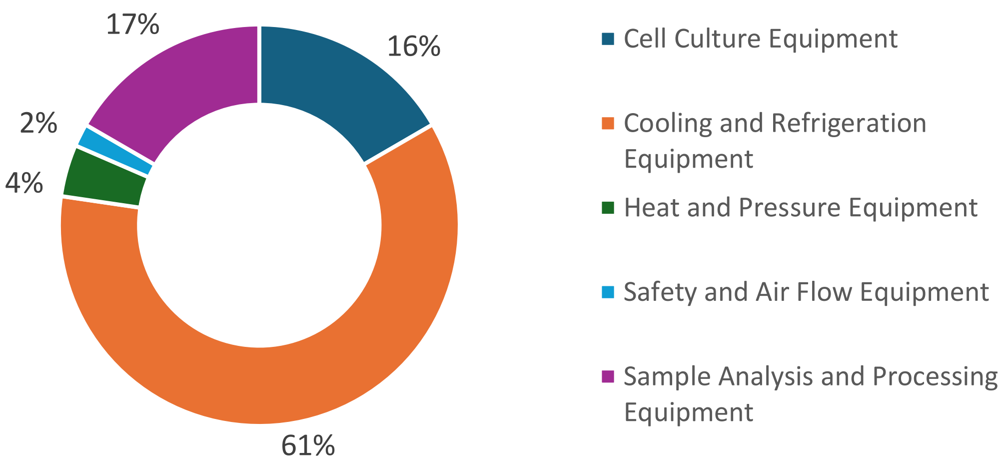

Figure 5. Weekly energy consumption distribution by laboratory equipment category across the CEK building.

A deeper analysis was conducted to examine the relationship between equipment prevalence and energy share. As shown in Figure 6 and detailed in Annex 12.2, Sample Analysis Equipment represents nearly half of the total device inventory (48.45%) but contributes only 16.66% of energy use. Conversely, refrigeration units comprise only 24.41% of devices but account for 60.68% of consumption.

This imbalance is especially pronounced on floor -1, where only 6.9% of building-wide devices are located, yet they account for 42.27% of total energy use. Similarly, Cell Culture Equipment, absent on floor -1, is responsible for 34.27% of energy use on floors 1 to 5 while comprising only 13.23% of equipment.

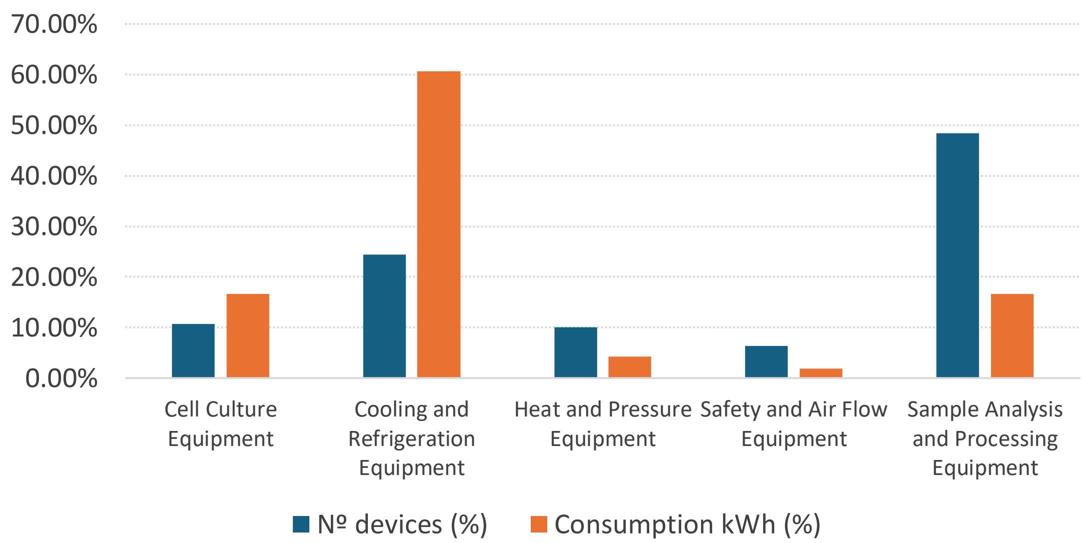

Figure 6. Comparison between device count and energy share, categorized by equipment type.

These results confirm that energy planning must prioritize categories with high per-unit intensity and continuous operation. Refrigeration and cell culture systems are particularly critical targets.

5.1.4. Detailed Analysis of Refrigeration Equipment

To further dissect the impact of the refrigeration category, a subtype breakdown was conducted. As shown in Table 4 and visualized in Figure 7, -80°C freezers are the most energy-intensive, consuming 87.99% of refrigeration-related energy despite representing only 36.96% of the refrigeration inventory. -20°C freezers, though nearly as numerous, contribute significantly less due to lower power demand. Refrigerators and combined units together represent under 7% of refrigeration energy use.

Table 4. Breakdown of refrigeration equipment by energy consumption and unit quantity, showing both absolute values and relative shares (%).

Refrigeration Type	Consumption (kWh)	Share (%)	Units	Share (%)
-150 °C Freezer	184.8	1.14%	1	0.31%
-80 °C Freezer	14,288.37	87.99%	119	36.96%
-20 °C Freezer	666.32	4.10%	107	33.23%
Refrigerators	629.61	3.88%	80	24.84%
Combined Units	470.4	2.90%	14	4.35%
Total	16,239.50	100.00%	322	100.00%

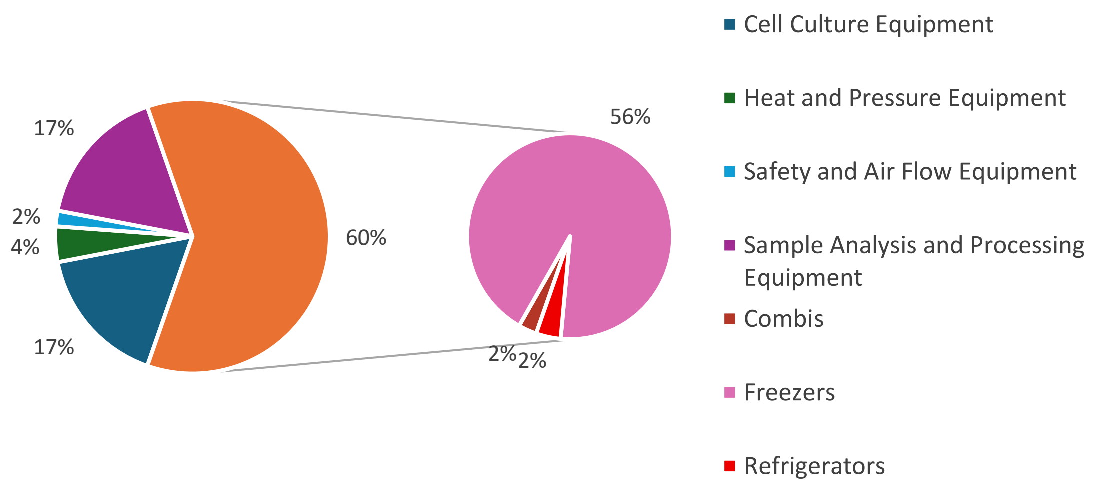

Figure 7. Energy consumption of the laboratory equipment category, with detailed breakdown of Cooling and Refrigeration Equipment in the CEK building.

These findings highlight the disproportionate impact of -80°C freezers and support targeted focus for optimization strategies for this device class.

5.1.5. Methodological Considerations and Limitations

Although the methodology offers a systematic approach for estimating energy use, several limitations must be acknowledged. Firstly, the weekly usage estimates rely on interviews and booking data, which may not fully reflect real-world operating conditions. Secondly, manufacturer-provided power specifications may differ from actual device behavior, particularly during idle or partial-load operation. Finally, the lack of real-time monitoring restricts the ability to capture transient or irregular usage patterns, especially for intermittently used equipment.

Despite these constraints, the methodology provides a reliable framework for assessing energy consumption and identifying priority areas for energy efficiency. The insights gained serve as a solid foundation for future interventions aimed at reducing the building's energy footprint, particularly through targeted improvements in refrigeration management.

5.2. HVAC and Auxiliary Systems of the CEK Building

The HVAC and auxiliary systems of the CEK building provide critical environmental control to support biomedical research activities. These include functions such as temperature regulation, air purity, humidity control, and pressure differentials, which are necessary for maintaining biosafety and experimental integrity. Due to their continuous operation and system complexity, HVAC components constitute a significant portion of the building's total energy consumption.

To estimate energy demand, a bottom-up methodology was implemented. Nominal absorbed electrical power values were obtained from manufacturer datasheets and validated through on-site inspections. These values were used to compute theoretical energy demand under continuous full-load operation. Seasonal load factors were then applied based on functional analysis and expert consultation, yielding refined estimates that approximate actual usage in the absence of real-time submetering.

Unless otherwise indicated, the data sources for all subsystems are derived from verified datasheets and technical inspections. Detailed equipment breakdowns, model sheets, and supporting calculations are provided in Annex 12.5 (Folder 2: 2_HVAC_Data). Seasonal operation assumptions and aggregated consumption calculations appear in Tables 6 and 7.

5.2.1. Chillers (Cooling Units)

Chillers form the core of the building's cooling infrastructure, supplying chilled water to air handling units (AHUs), fan-coils, and other terminal devices. Located on the rooftop, these units operate within a redundancy configuration, where typically only one chiller is active while others remain on standby to ensure uninterrupted service.

The primary chiller in use is the Trane RTAC 200, a helical-rotary air-cooled unit operating on the vapor-compression cycle with HFC-134a refrigerant. The system is integrated into the Building Management System (BMS), which oversees its performance and safety.

Based on the equipment nameplate (Serial No. EKS3551), the unit has a nominal electrical power of 160 kW. This corresponds to a theoretical maximum consumption of 1,120 kWh/day under full-capacity continuous operation. However, HVAC professionals confirm that actual load varies with ambient conditions and system demand, particularly across seasons and daily cycles.

5.2.2. Air Handling Units (AHUs)

Air Handling Units (AHUs) are responsible for maintaining indoor air quality and thermal comfort by controlling temperature, humidity, and air pressure throughout the facility. These systems are especially critical in laboratory zones, where controlled environments are essential for biosafety and experimental reliability.

The CEK building operates a total of eighteen AHUs. Units typically include dual electric motors for supply and return air flows, both managed by variable frequency drives (VFDs) to adapt performance to occupancy and thermal loads in real time.

Absorbed electrical power data for each AHU was sourced from manufacturer technical documentation and verified through direct on-site inspection. Calculations considered both supply and return fan motors where applicable. Assuming continuous operation, the total instantaneous demand was estimated at approximately 142.1 kW.

5.2.3. Ventilation Fans

Approximately twenty-seven ventilation fans are installed across the CEK building to ensure air renewal and contaminant extraction in specific zones, such as restrooms, gas storage rooms, emergency stairwells, and biosafety labs. These fans contribute significantly to maintaining indoor air safety and are frequently integrated with gas detection systems that modulate fan speed in response to real-time sensor input.

Due to the lack of comprehensive inventory data for all fan models, the Soler & Palau CVTT-12/12 was selected as a representative unit based on on-site inspection. With an absorbed power of 1.5 kW, and assuming uniform characteristics across the installed units, the aggregated nominal power was estimated at 40.5 kW. This value represents a theoretical upper-bound scenario under full-load continuous operation. Actual consumption is addressed through seasonal and temporal adjustment factors.

5.2.4. Cold Storage Chambers

Cold storage infrastructure spans five levels of the building (from 1 to 5), with one chamber per laboratory floor. Each chamber maintains two separate temperature zones: +4 °C for refrigeration and –20 °C for freezing. These are supported by five Bitzer semi-hermetic compressors (model 4GC-6.2Y-40S), each with an electrical input of approximately 5.44 kW, resulting in a combined nominal capacity of 27.2 kW.

These systems are critical for biomedical sample conservation and are generally operated with minimal modulation year-round. The theoretical full-load consumption corresponds to 652.8 kWh/day, but actual usage is presumed stable and less variable than other HVAC systems.

5.2.5. Pumping Systems

The pumping network supports both HVAC water loops and sanitary circuits, with multiple in-line centrifugal pumps of various sizes installed across technical areas. The total installed capacity of identified pumps sums to 66.4 kW, based on nameplate values. However, to better reflect realistic operating conditions, such as alternating duty cycles, redundancy strategies, and partial load operation, a correction factor of 0.5 was conservatively applied. This results in an adjusted nominal demand of 33.2 kW, which corresponds to an estimated daily consumption of 796.8 kWh under full daily use.

5.2.6. Other Auxiliary Systems

Additional systems include firefighting pumps, motorized dampers, wastewater pumps, and specific lab-related units such as millipores, gas cabinets, and digesters. These systems operate either intermittently or under low electrical loads. Given their limited contribution to total energy demand and the irregularity of their usage, these auxiliary systems were excluded from aggregated modeling. Their estimated impact remains below 5% of overall consumption.

5.2.7. Aggregated Load Estimation and Seasonal Profiles

The estimation of total HVAC energy demand was carried out using a top-down methodology based on the installed nominal electrical capacity of each major subsystem and the application of seasonal load profiles. The approach involves two primary steps: (1) identifying the nominal absorbed power (kW) of each subsystem through manufacturer datasheets and on-site verification, and (2) adjusting these values using estimated operational load percentages for each season.

While this method does not reflect direct measurements, it offers a reasoned approximation of consumption patterns in the absence of submetering. Seasonal adjustments are informed by technical knowledge of system behavior and environmental demand. For example, maintaining a constant chilled water supply at 7 °C with a return temperature near 12 °C imposes greater load on chillers during summer, due to higher internal and ambient thermal inputs. In contrast, lower external temperatures during winter reduce compressor effort, resulting in lower energy demand. This operational logic underpins the higher seasonal load factors assigned to cooling units and pumping systems during warmer periods.

Tables 5, 6, and 7 summarize the results of this estimation process: Table 5 details the nominal installed capacities of the HVAC subsystems; Table 6 presents the corresponding seasonal load factors; and Table 7 provides the resulting seasonal energy demand in kWh, derived from the adjusted operational profiles.

Table 5. Nominal capacity of major HVAC systems.

System	kWh
Cooling Units	160.00
Air Handling Units	142.09
Ventilation Fans	40.50
Cold Chambers	27.20
Pumping Systems	33.20

Table 6. Estimated seasonal load (%) by subsystem.

System	Winter (Q1)	Spring (Q2)	Summer (Q3)	Autumn (Q4)
Cooling Units	20%	40%	50%	25%
Air Handling Units	30%	65%	75%	40%
Ventilation Fans	75%	80%	85%	80%
Cold Chambers	90%	100%	100%	90%
Pumping Systems	50%	65%	75%	60%

Table 7. Estimated seasonal energy demand [kWh].

System	Winter (Q1)	Spring (Q2)	Summer (Q3)	Autumn (Q4)
Cooling Units	32.00	64.00	80.00	40.00
Air Handling Units	42.63	92.36	106.57	56.84
Ventilation Fans	30.38	32.40	34.43	32.40
Cold Chambers	24.48	27.20	27.20	24.48
Pumping Systems	16.60	21.58	24.90	19.92
Totals (sum)	146.08	237.54	273.09	173.64

The following figures provide a visual synthesis of the tabulated results. Figure 8 illustrates the proportional distribution of installed nominal capacity across the main HVAC subsystems. Figure 9 presents the estimated seasonal energy demand by subsystem, based on the load-adjusted values introduced in Tables 5 through 7.

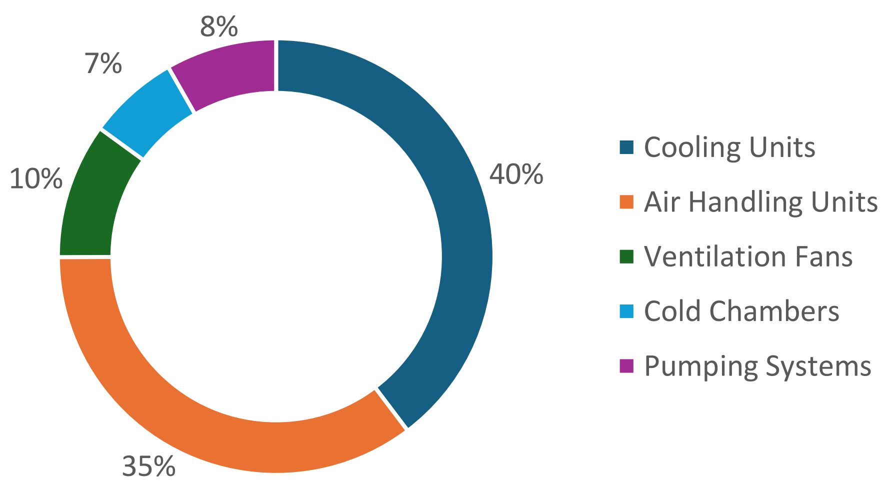

Figure 8. Nominal capacity breakdown shares by HVAC system.

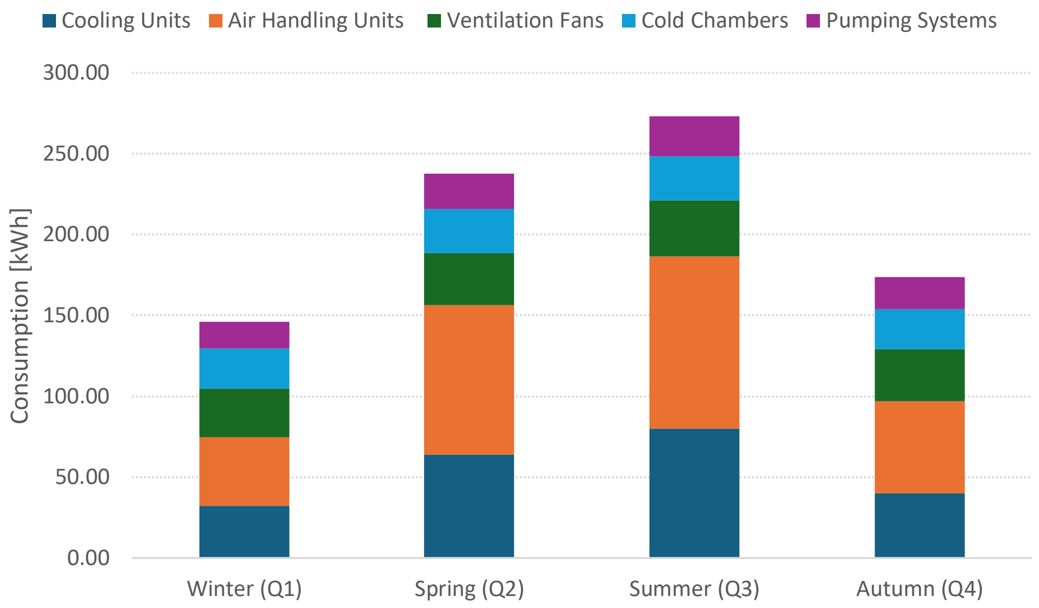

Figure 9. Seasonal energy demand by HVAC subsystem [kWh].

5.3. Data Processing Center (CPD)

The Data Processing Center (CPD) is located on floor -1 of the CEK building and functions as the technological core of the institution. It hosts critical IT infrastructure, including high-performance servers that operate continuously and generate substantial thermal loads. Due to these operating conditions, the CPD requires both an uninterrupted power supply and permanent cooling to prevent thermal runaway and system instability.

To meet the continuous cooling demand, the facility is equipped with three Uniflair CPS precision cooling units operating 24 hours a day. These systems ensure temperature stability, particularly in the rear zones of the server racks, where heat generation is most intense. Consequently, a detailed characterization of the CPD's energy footprint, including both computational and cooling loads, was essential to the present analysis.

5.3.1. Data Collection

Two targeted measurement campaigns were conducted to quantify the CPD's electrical consumption. Data was collected using a Fluke 430 Series II Power Quality Analyzer, a professional-grade portable instrument designed for high-resolution monitoring of three-phase systems [36]. The analyzer was installed directly on the main electrical distribution panel of the CPD, which supplies both the IT equipment and the associated cooling units. This installation point ensured that all relevant consumption (both computational and HVAC-related) was captured.

The analyzer recorded RMS current per phase (L1, L2, L3), neutral current (N), and timestamps at the following resolutions:

- **February 2024 Campaign**: 5-minute interval (February 2–9, 2024)
- **May 2025 Campaign**: 1-minute interval (April 30–May 7, 2025)

The measurement files, exported in CSV format, included minimum, maximum, and status values for each channel. For the purposes of this study, only average current values were retained, as they provide a stable and interpretable metric for estimating energy consumption over time. The raw and processed data are included in Annex 12.5 (Folder 3: 3_CPD_Measurements).

5.3.2. Electrical Consumption Calculation

As direct power measurements were unavailable, the active energy consumption was estimated using the standard three-phase power formula introduced in Section 2.2.1 (Equation 2.2), Where V was assumed to be 400 V, $cos(\theta) = 0.9$, and $\mathrm{I_{avg}}$ represents the mean current across the three phases.

$$\mathrm{P_{active}} = \sqrt{3} \cdot V \cdot \mathrm{I}_{avg} \cdot cos(\theta)$$

The corresponding energy consumption for each recorded interval was then computed using Equation 2.1:

$$\mathrm{E} = \mathrm{P_{active}} \cdot \Delta t$$

With:

- $\Delta t = \frac{5}{60} = 0.08333\ \mathrm{h}$ for February 2024
- $\Delta t = \frac{1}{60} = 0.0167\ \mathrm{h}$ for May 2025

The resulting time series of energy consumption was post-processed using Microsoft Excel. Pivot tables were employed to aggregate consumption by hour and by day, enabling temporal trend analysis.

5.3.3. Results and Interpretation

Figure 10 display the aggregated average hourly energy consumption profiles for February 2024 and May 2025, respectively. Both profiles reveal a stable load across the 24-hour period, with a mild increase observed between 10:00 and 18:00, coinciding with working hours. This daytime rise likely reflects either increased IT activity or intensified cooling demand due to higher internal or ambient temperatures.

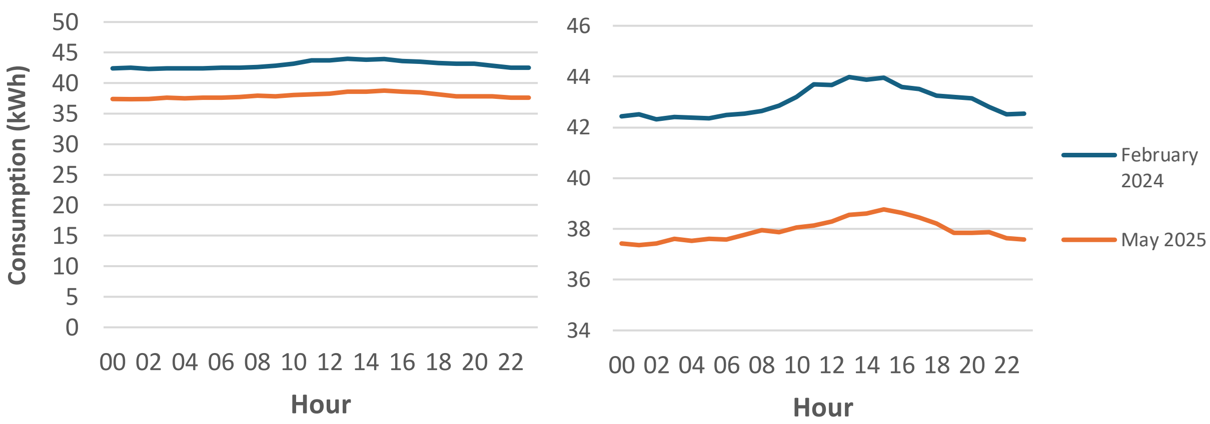

Figure 10. Hourly average energy consumption profile of the CEK building's CPD. Left: Full scale; Right: Zoomed-in view to highlight intra-day variation.

Overall, the May 2025 data consistently reflects lower hourly consumption values than February 2024. While the magnitude of this reduction is evident, no operational changes were reported between the two campaigns. As such, the observed differences are acknowledged but not analyzed further, since they fall outside the scope of the present study.

To further contextualize the CPD's energy profile, a comparative benchmark was referenced from the *Vertex Building CPD* at the *UPC Campus Nord*, as visualized through the SIRENA energy monitoring platform (see Figure 26 in Annex 12.6). Although the UPC facility hosts more computational infrastructure and operates at higher absolute capacity, its hourly energy baseline during early May 2025 remains within the 72-74 kWh range, comparable in scale to the CEK building's CPD, which maintains a baseline near 38-39 kWh throughout the day and same dates. This consistency across facilities of different institutional sizes supports the plausibility of the CEK CPD's measured values, lending credibility to the empirical findings obtained through the Fluke analyzer. It also affirms that despite differences in operational scale, the characteristic flat load profile and the magnitude of energy demand remain structurally similar across research-based data centers with continuous cooling requirements [37].

5.4. Temporal Patterns in Energy Consumption at CEK (2023-2024)

After disaggregating energy demand across the building's major subsystems, this section broadens the analytical scope by examining the temporal dynamics of total electricity consumption in the CEK building using aggregated data at multiple time scales. From hourly to seasonal patterns, the following visualizations offer a comprehensive overview of when energy usage is most intense and how it varies across the year.

The dataset was obtained from *Datadis*, Spain's national electricity data platform. The monitored supply point corresponds to the CEK building of the Fundació Clínic per a la Recerca Biomèdica (CUPS: ES0031408437474001AR0F), located at Rosselló 153, Barcelona. As a public institution, the foundation is registered with the *Sistema d'Informació i Monitorització Energètica* (SIME), which provides authorized access to detailed consumption records. Energy data was downloaded quarterly in CSV format with hourly resolution and was processed to derive hourly, daily, weekly, monthly, and seasonal averages. All scripts used for data processing and plotting are available in Annex 12.5 (Folder 4: 4_GlobalLoad_StatisticalModeling).

Figure 11 shows the average hourly electricity consumption throughout 2024. A sharp increase is observed between 07:00 and 09:00, with values rising from approximately 358 kWh to a peak of 522 kWh, an increase of nearly 46%. This elevated consumption persists until around 16:00, forming a stable daytime plateau. After this period, demand gradually declines toward evening levels. Notably, the baseline remains consistently high, but remains stable, with minimal variation (σ = 2.37 kWh) with no hourly average falling below 350 kWh. This reflects a continuous operational load maintained across the 24-hour cycle.

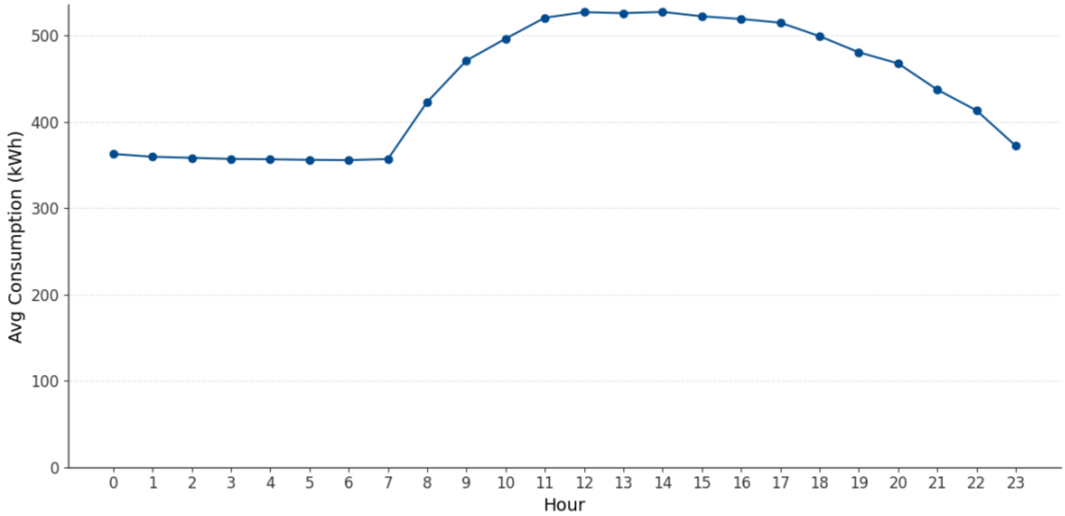

Figure 11. Average hourly energy consumption throughout the day at the CEK building (2024). Daily view.

Figure 12 depicts hourly consumption profiles across five weeks from late January to mid-February. All profiles exhibit a recurring weekday pattern, with peaks between 08:00 and 18:00. During nights and weekends, consumption drops but does not fall below 330 kWh, confirming the presence of a high and stable baseline. Small yet consistent peaks on Saturdays and Sundays are clearly visible, reflecting a recurring pattern of weekend activity despite reduced demand compared to weekdays.

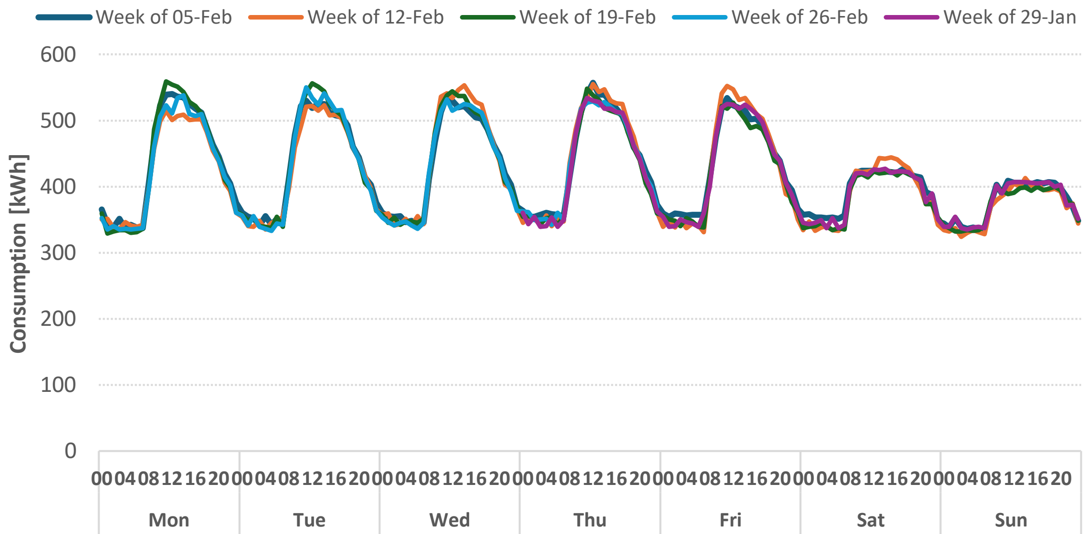

Figure 12. Hourly electricity consumption across five winter weeks (Jan–Feb 2024). Weekly view.

Figure 13 presents the same hourly resolution across four consecutive weeks in April 2024. The consumption profile maintains the same diurnal structure, with visible weekday peaks and partial reductions at night and during weekends. The magnitude of the weekend peaks is slightly more pronounced than in winter, but the baseline remains consistently above 350 kWh, reinforcing the observation of continuous energy demand.

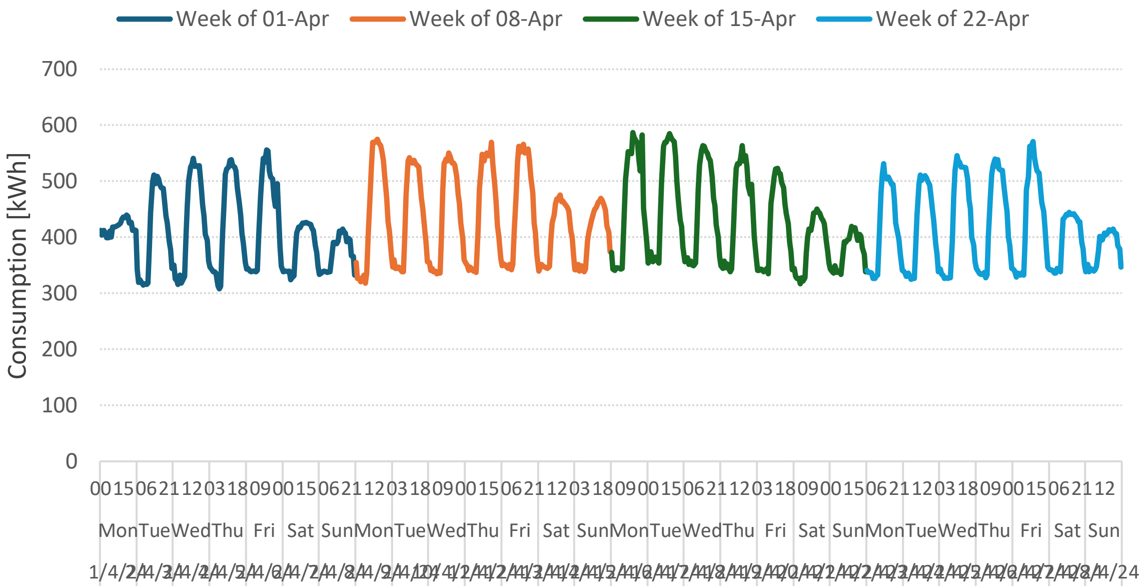

Figure 13. Hourly electricity consumption across four spring weeks, monthly view (April 2024). Monthly view.

Figure 14 summarizes the total monthly energy consumption for 2023 and 2024. In both years, usage increases progressively from March to July, reaching a peak in July of nearly 400,000 kWh. This represents a ~35% rise from the February level of approximately 300,000 kWh. Across most months, 2024 shows slightly lower values compared to 2023, with a consistent monthly difference ranging from 3% to 8%. Figure 15 shows the same data as Figure 14 but with a smoothed line format for clearer visual comparison. The seasonal trend is evident, with a pronounced increase from Q2 to Q3, followed by a sharp drop in October. The largest absolute difference between years is observed in August: approximately 380,000 kWh in 2023 versus 365,000 kWh in 2024, indicating a 5,6% year-over-year decrease.

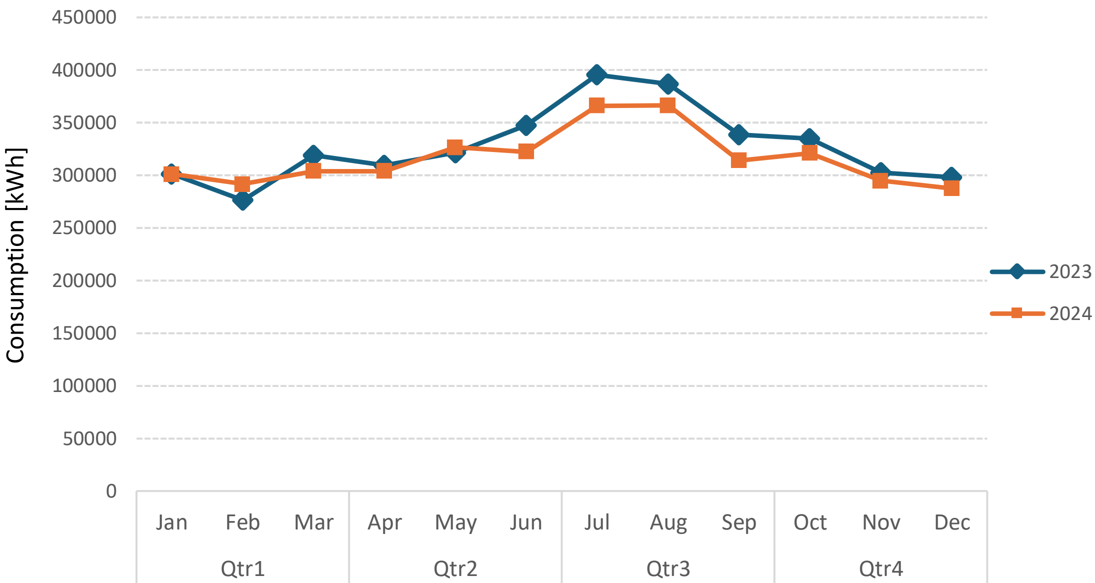

Figure 14. Monthly electricity consumption totals for 2023 and 2024. Yearly view.

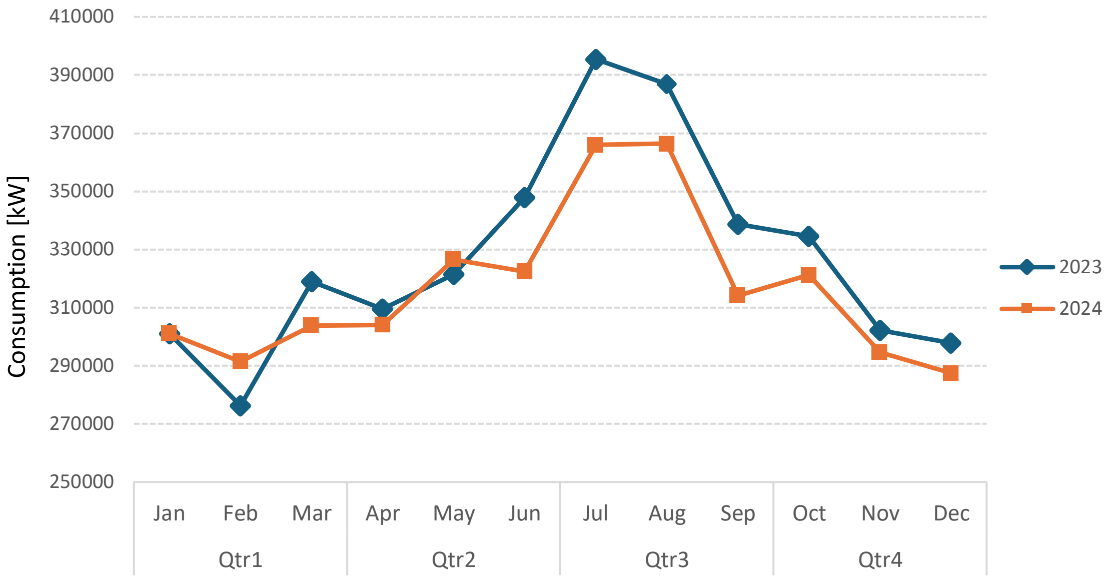

Figure 15. Monthly electricity consumption totals for 2023 and 2024, detailed fluctuation. Yearly view.

Finally, to further examine the seasonal variation observed between summer and winter. Figure 16 presents the average daily electricity consumption profile by quarter. Q3 (summer) exhibits the highest daytime demand, with midday hours (12:00–15:00) averaging approximately 596 kWh, compared to 490 kWh in Q1 (winter). This corresponds to a 21.6% increase in midday consumption between seasons, reflecting the seasonal impact of cooling-related energy loads.

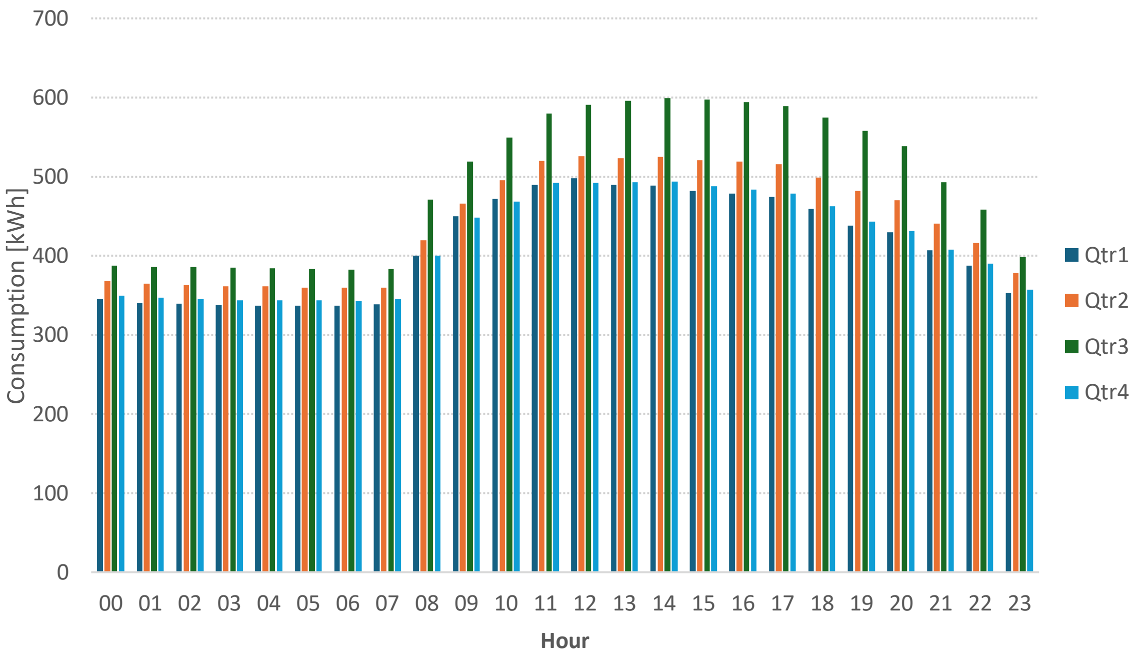

Figure 16. Average hourly electricity consumption by quarter (Q1–Q4) in 2024. Daily view.

5.5. Statistical Assessment of Energy Consumption Drivers

Building on the temporal trends identified in the previous section, this part of the analysis investigates the underlying factors influencing electricity demand at the CEK building. Specifically, it explores the relationship between energy consumption, outdoor temperature, and building occupancy.

A two-stage methodology is applied. First, in Section 5.5.1, a visual inspection is conducted using time-aligned plots to explore qualitative patterns of co-variation between electricity consumption and the explanatory variables. This step helps identify potential relationships and temporal structures. Next, in Section 5.5.2, these relationships are formally tested using Ordinary Least Squares (OLS) regression model. This statistical modeling quantifies the magnitude and significance of each driver, enabling a more rigorous interpretation of their influence.

Both analyses were based on daily and hourly datasets from the year 2024, comprising energy readings from Datadis, meteorological data from Meteostat API, and access control logs for estimating occupancy. The complete Python workflow used to process, merge, and analyze these datasets can be found at Annex 12.5 (Folder 4: 4_GlobalLoad_StatisticalModeling/ CEK_Energy_Analysis_Code).

5.5.1. Visual Inspection of Energy Drivers

A preliminary visual inspection assessed whether temperature and occupancy qualitatively co-varied with electricity use, offering intuitive support for their inclusion in regression models

Temperature and Energy Consumption

Daily temperature data was extracted using the meteostat Python library (v1.6.8), which aggregates open-access meteorological information from authoritative sources such as national weather services, SYNOP stations, and METAR reports [38]. The selected data reflects average daily temperatures in Barcelona (41.388703° N, 2.151188° E), the location of the CEK building.

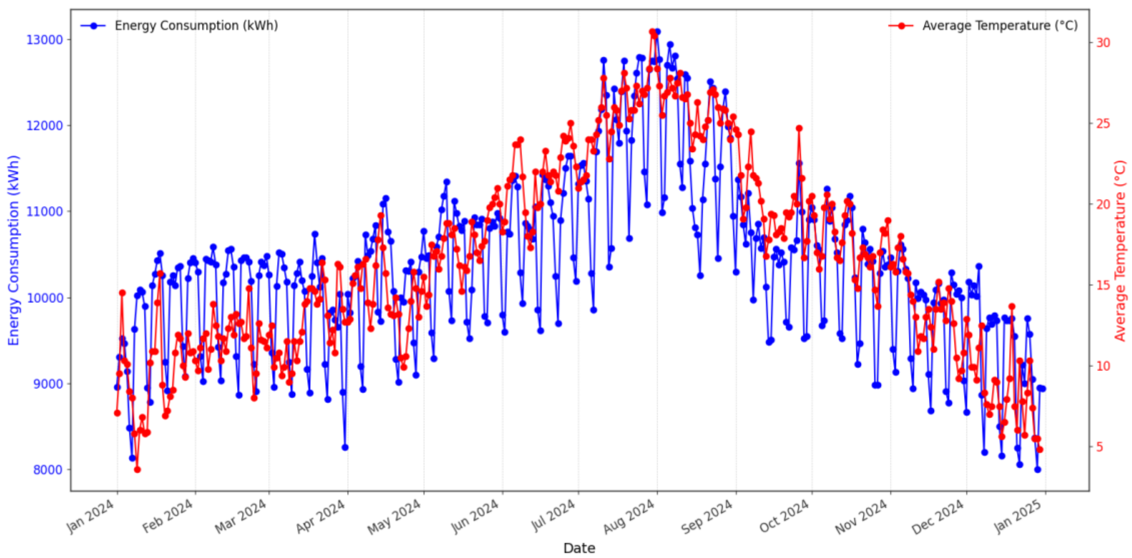

Figure 17. Correlation between daily energy consumption and outdoor temperature (2024).

Figure 17 illustrates the temporal trend between temperature and energy consumption. The plot suggests a strong seasonal and positive relationship between average outdoor temperature and daily energy consumption at the CEK building in 2024. The alignment of peaks and troughs supports the hypothesis that ambient temperature is a primary driver of energy demand, particularly during warmer periods.

Occupancy and Energy Consumption

Building occupancy was estimated through validated access records at CEK entrances (Torn 1, 2, and 3). These data represents the daily activity levels with in the facility.

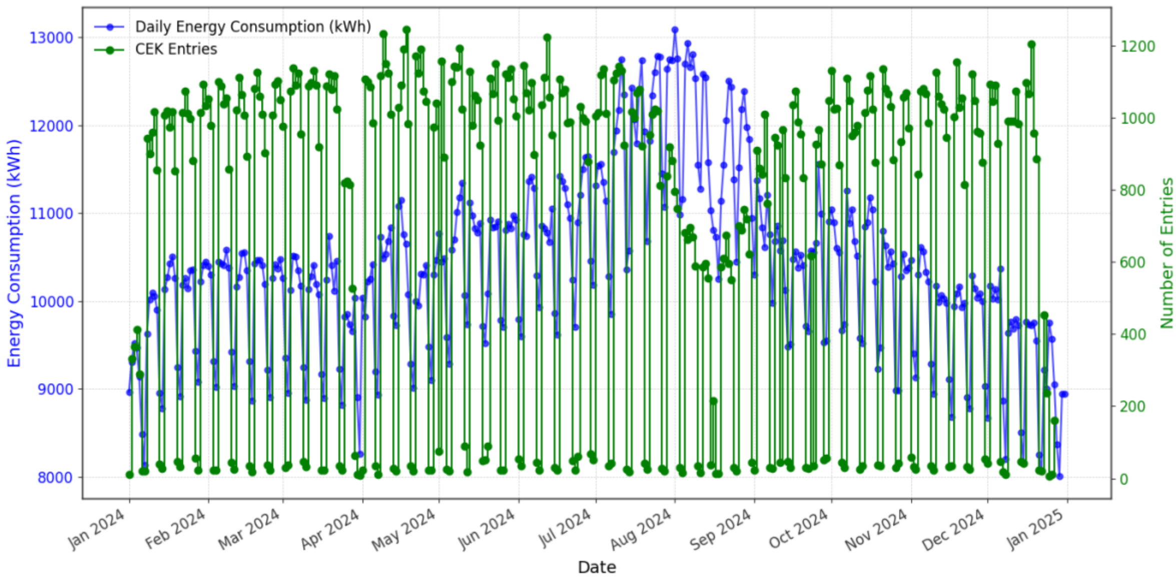

Figure 18. Daily energy consumption and Occupancy entries at the CEK building (2024).

Figure 18 compares daily energy use and entry counts. This chart reveals that CEK entries and energy consumption show partially alignment, particularly through weekly activity cycles and institutional breaks. Entry counts drop sharply and consistently during weekends (roughly four times per month) which corresponds with dips in daily energy consumption. It is important to note, however, that the energy drops appear more pronounced than they truly are, due to the non-zero y-axis scale, which visually exaggerates fluctuations.

Interestingly, during extended periods of reduced activity such as the summer holidays (August), where entries decrease by nearly 50%, energy consumption does not decline proportionally. This suggests that while occupancy influences daily energy demand, it is not the sole driver. The irregular magnitude of the energy response indicates that other factors likely contribute to maintaining a relatively stable level of consumption even when occupancy is low.

5.5.2. Statistical Modeling of Energy Consumption Drivers

Following the exploratory analysis, this subsection formalizes the investigation by applying an Ordinary Least Squares (OLS) regression model to quantify the relationship between electricity consumption and two explanatory variables: outdoor temperature and building occupancy.

As represented in Equation 3, the OLS formulation expresses electricity consumption (*energy_kWh*) as a linear function of average temperature (*temperature_C*) and number of building entries (*entries*). This method allows for the isolation and estimation of each variable's contribution while controlling for the influence of the other [39], yielding interpretable coefficients in physical units (kWh per °C and kWh per entry).

Equation 3. Multiple linear regression model of daily energy consumption as a function of temperature and occupancy.

$$energy_kWh_t = \beta_0 + \beta_1 \cdot temperature_C + \beta_2 \cdot entries + \varepsilon_t$$

Where β_0 is the intercept (baseline energy level), β_1 and β_2 represent the estimated effect of a one-unit increase in temperature and entries respectively and ε_t is the error term accounting for residual variation not explained by the model.

Model performance is assessed using standard indicators such as R-squared, F-statistic, and p-values, while residual diagnostics including the Durbin-Watson statistic are used to evaluate temporal autocorrelation. Full model summary is presented in Table 8.

Daily OLS Model Results

A total of 366 daily observations in 2024 were used. The regression yielded a strong fit, with an **R-squared of 0.834**, indicating that 83.4% of the variation in daily energy consumption is jointly explained by temperature and occupancy.

Table 8. OLS regression summary (daily data, 2024).

Variable	Coefficient	Std. Error	t-Statistic	P-value
Intercept	7,556.5	70.4	107.32	< 0.001
Temperature (°C)	126.9	3.53	35.90	< 0.001
Entries	1.09	0.05	23.77	< 0.001

These results indicate that each additional degree Celsius is associated with an increase of approximately 127 kWh in daily energy consumption, likely reflecting intensified HVAC demand. Additionally, each building entry contributes roughly 1.09 kWh, consistent with the effect of internal activity on system loads. As expected, positive autocorrelation was observed (Durbin-Watson = 0.851), indicating that daily energy usage is partly dependent on its previous values, a common characteristic of building load time series.

A standardized version of the model (where all variables were z-scored) was also tested to assess the relative influence. While the p-values and goodness-of-fit statistics remained unchanged, β values confirmed that temperature is the dominant driver of consumption variation. The raw (unscaled) model was retained as the primary reference for its interpretability in real units (kWh).

Model selection Justification

Although time-series models such as SARIMAX were also tested, showing improved fit through lower AIC values and autoregressive terms, but their role in this study is secondary. This analysis prioritizes interpretability and the quantification of direct dependence on explanatory variables, not forecasting behavior over time [40]. OLS regression was therefore selected as the primary analytical tool, as it allows effect magnitudes to be expressed in physical units (kWh per °C or per entry), which are directly applicable to energy management and operational decision-making.

SARIMAX models served only as a validation tools, confirming that temperature and entries remain significant even when accounting for autocorrelation. The slightly reduced coefficients in SARIMAX simply reflect that some of the explained variance is captured by the autoregressive structure. These results support the robustness and reliability of the OLS findings, reinforcing that temperature and occupancy are independent, consistent, and statistically significant drivers of energy consumption in the CEK building.

5.6. Results and Discussion

This section consolidates the main findings from Chapter 5 to assess the CEK building's energy performance. It first compares estimated subsystem-level consumption with total measured data, then analyzes intra-day load profiles using simulated versus actual values. Finally, it interprets statistical modeling results to identify key energy drivers. Figures, calculations and aggregations are included in Annex 12.5 (Folder 4: 4_GlobalLoad_StatisticalModeling/ Global_Load_Patterns).

5.6.1. Overview of Subsystem Energy Contributions Relative to Measured Consumption.

The calibrated bottom-up model predicts a total electricity demand of **71,878 kWh/week**, while the weekly average derived from the 2023–2024 utility data is **74,073 kWh/week.** The **2,195 kWh/week** difference represents a **3 % residual** and yields an excellent fit **(R^2 = 0.97; MAPE = 6.8 %)** confirming that the three modelled subsystems reproduce almost the entire measured load.

Figure 19 shows each subsystem's share of that measured baseline:

- **HVAC Systems – 52%.** Represents the most significant weekly energy load consistent with expectations given the building's high ventilation rates and year-round climate control needs (38,319.15 kWh/week).
- **Laboratory Equipment – 36%.** Includes both continuous-load infrastructure and variable-use devices, giving a stable yet diverse load profile (26,761.04 kWh/week).
- **CPD – 9%.** The Data Processing Center exhibits steady consumption due to consistent operation, with little seasonal or diurnal fluctuation (6,798.30 kWh/week).
- **Unexplained (Residual) – 3%.** This portion reflects the gap between the model's aggregated subsystem estimates and the measured total. It corresponds to approximately 2,194.80 kWh/week and may include unaccounted auxiliary systems or classification uncertainties.

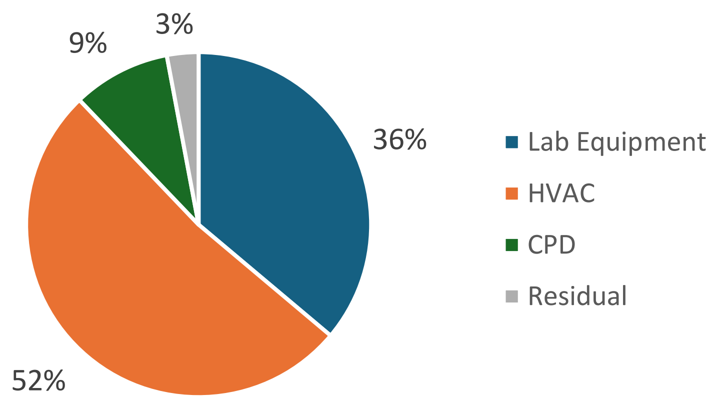

Figure 19. Model-predicted shares of the CEK building's average weekly electricity consumption (2023–2024 baseline). See Table 9 for absolute values; residual slice bridges the 3 % gap between model and meter.

As demonstrated in Sections 5.2, 5.4, and 5.6, consumption exhibits pronounced seasonal variation. Quarterly disaggregation (Annex 12.7) shows that model accuracy ranges from **88 % in winter** to **97 % in summer**, sustaining the **6.8 %** mean absolute percentage error (MAPE) across all seasons.

Table 9 compiles the weekly, daily, and hourly energy estimates for each subsystem, aggregating the results derived in Sections 5.1 to 5.3. For laboratory equipment, daily and hourly figures were obtained by proportionally dividing the weekly total, while for HVAC, estimates were derived from seasonal simulations, with the weekly average calculated across all four quarters to align with the measured weekly baseline. CPD values reflect the average across the two measurement campaigns conducted in 2024 and 2025. Notably, these daily and hourly estimates serve only as rough approximations, given the variability in actual use profiles.

Table 9. Subsystem consumption breakdown (weekly, daily, hourly).

		Weekly Consumption kWh/week	Daily Consumption kWh/day	Hourly Consumption kWh
Lab Equipment	24/7 Equipment	20,690.92	2,955.85	123.16
	9-5 Equipment	6,070.12	1,214.02	134.89
	Total	26,761.04	4,169.87	258.05
HVAC	Winter Q1	24,541.44	3,505.92	146.08
	Spring Q2	39,906.69	5,700.96	237.54
	Summer Q3	45,879.79	6,554.26	273.09
	Autumn Q4	29,170.98	4,167.28	173.64
	Average	38,319.15	5,474.16	228.09
CPD	2024	7,218.83	1,031.26	42.99
	2025	6,373.86	910.55	37.94
	Average	6,798.30	971.19	40.47

5.6.2. Temporal Patterns and Graph-Based Discussion

To analyze intra-day dynamics, Figure 20 compares simulated hourly loads for HVAC, 24/7 and 9–5 laboratory equipment, and CPD systems against the actual building demand recorded on 3 February 2024 (Datadis; see Section 5.4).

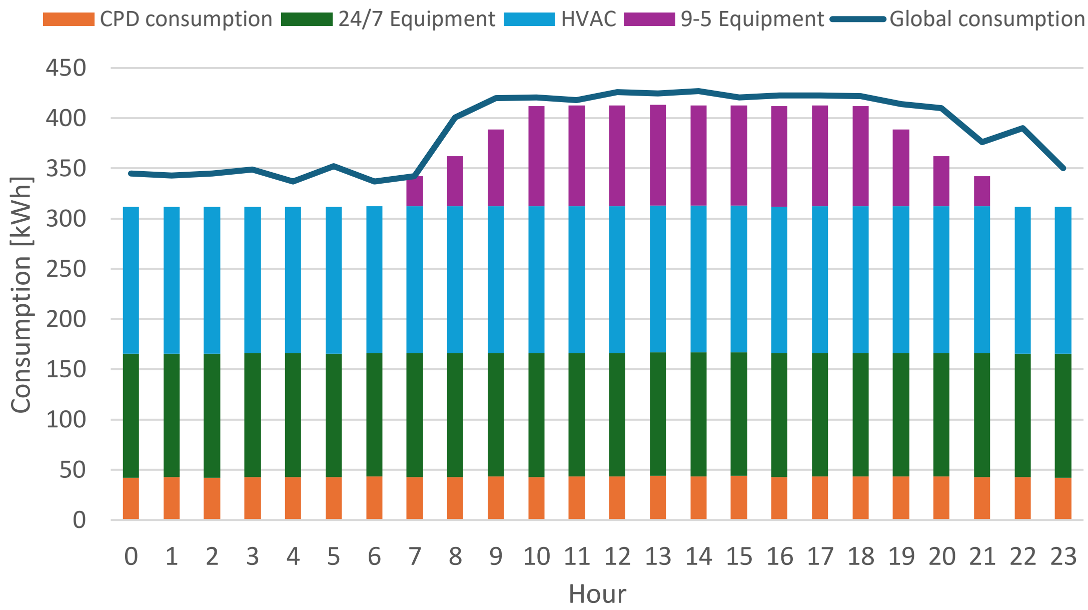

Figure 20. Simulated hourly subsystem consumption in comparison with the actual global load [kWh]. Simulation based on 3 February 2024.

To verify how well the simulated subsystem sum reproduces the measured load of 3 February 2024, four standard error metrics were calculated on an hourly basis: mean absolute error (MAE), mean absolute percentage error (MAPE), root-mean-square error (RMSE) and mean bias error (MBE). Table 10 summarises the results; the formulas are given in Annex 12.4.

Table 10. Hourly and daily error metrics for Figure 20 simulation [41].

Metric	Value	Interpretation
MAE	25.4 kWh h^{-1}	Typical hourly deviation
MAPE	6.7 %	Average relative error; well below the 10 % audit threshold
RMSE	30.6 kWh h^{-1}	Emphasises peak mismatches
MBE	+25.4 kWh h^{-1}	Positive → model slightly under-predicts load
Day-total error	−610 kWh (−6.6 %)	Simulation 8.71 MWh vs. real 9.32 MWh

Nocturnal Load (00:00–07:00): Stable, Time-Invariant Demand

During nighttime hours, total consumption remains nearly constant, fluctuating narrowly around 345 kWh/hour. This load is entirely attributed to:

- CPD systems (~43 kWh/h)
- 24/7 laboratory equipment (~123 kWh/h)
- Baseline HVAC operation (~146 kWh/h)

This observed stability confirms the structural nature of the base load, driven by essential systems that operate independently of occupancy or schedule. The close match between real and simulated values during this phase validates the modeling assumptions for continuous infrastructure. The mean absolute hourly deviation between the simulated and empirical values during this interval remains within 4 %, which is within typical audit tolerance.

Morning Ramp-Up and Daytime Plateau (07:00–17:00): Operational Activation

Demand increases due to the activation of user-dependent equipment. A Gaussian profile was used to simulate 9–5 lab loads, calibrated to match the estimated 1,214 kWh daily total from Table 10. Although this assumes peak use at midday, the approach reflects a conservative upper bound given the absence of sub-hourly metering.

Lighting and office electronics, although they switch on during the morning ramp-up, were omitted because their share is minor in this laboratory-centred facility, and widespread LED adoption further reduces their impact.

HVAC was represented as a constant daytime load to keep the analysis at a macro level. In practice, HVAC output rises through the day as occupancy, equipment heat gains, and outdoor temperature increase, a pattern visible in Figures 12 and 13 and discussed in Section 5.6.4. Those intra-day swings were not modelled here, not because they are unimportant, but because the study's scope is to map broad demand patterns rather than minute-by-minute control behaviour. A more granular HVAC profile could be incorporated in future work.

Evening Decline (17:00–23:00): Load Recession and Thermal Inertia

After 17:00, the 9–5 equipment contribution gradually decreases, returning to zero by approximately 22:00. This decline mirrors the reduction in laboratory activity. However, the total building demand does not decline as sharply, suggesting the influence of thermal inertia in HVAC systems, which remain active to maintain temperature stability and residual equipment loads, including devices left operating after working hours.

These findings underscore the non-linear relationship between occupancy and energy demand, especially in buildings with critical technical infrastructure.

Modeling Considerations

The simulation enables subsystem-level disaggregation in the absence of high-resolution metering and provides operational insight into intra-day patterns. Its validity is reinforced by close alignment with measured data, offering a reliable foundation for energy-use characterization.

5.6.3. Statistical Model Insights

OLS regression results (Section 5.4) identified outdoor temperature as the primary driver of energy consumption, with occupancy exerting a secondary influence. This finding aligns with the subsystem analysis: HVAC, the most temperature-responsive system, dominates total consumption.

The model achieved strong fit metrics ($R^2 = 0.834$), confirming the building's climate-sensitive load structure. The relatively low impact of occupancy supports the observation that energy use is largely governed by continuously operating systems rather than user-driven variability. These statistical findings corroborate the bottom-up estimates and reinforce the interpretive consistency of the study.

5.6.4. Synthesis and Limitations

The convergence of subsystem decomposition, temporal simulation, and regression analysis consistently indicates that HVAC is the principal energy driver in the CEK building, followed by laboratory equipment and the CPD. This hierarchy reflects the prominence of systems with continuous or climate-dependent operation

However, several modeling simplifications must be acknowledged:

- Lab equipment schedules were based on interview data and booking logs, potentially misrepresenting real usage.
- HVAC loads were assumed constant across the day within each season, neglecting intra-day modulation.
- Occupancy was proxied using entry data, which does not reflect internal movement or equipment interaction.
- Lighting, IT loads, and miscellaneous plug loads were excluded due to lack of disaggregated data, though their contribution is minor relative to the primary systems.

Despite these limitations, the integrated modeling framework provides a robust approximation of the building's energy profile and supports strategic targeting of high-impact systems in future energy management efforts.

6. Execution Schedule

This chapter focuses on the development of the diagrams necessary for the proper planning of the project's execution timeline. It includes the definition of the main phases of the project, the breakdown into work packages and their corresponding tasks, and the scheduling of these tasks over time to ensure a coherent and structured workflow.

6.1. Phases and Milestones

The first step in the project's execution, following the definition of objectives (see Section 1.2), was to establish a set of key milestones. These milestones provided structure and direction, forming the basis for developing the Work Breakdown Structure (WBS), the Gantt chart, and the PERT diagram in a logical and organized manner.

The selected milestones were intended to reflect both the technical needs of the project and the academic framework of the final degree thesis, ensuring a well-paced and trackable progression of tasks. While the following schedule was originally created as an initial estimation at the start of the project, it served as a valuable guide to maintain coherence and monitor progress throughout the different phases of development. Table 11 summarizes the main project phases and their corresponding milestones.

Table 11. Phases and milestones of the project.

Phase	Milestone	Milestone description	Date
Planning	Objectives and scope of the project	Define and document the specific objectives of the project, outlining what is and isn't included in the analysis.	20/04/2024
	Feasibility analysis	Conduct an economic feasibility study, taking into account ethical and legal considerations. Perform a SWOT analysis.	19/05/2024
	Preparation of the Project Plan	Develop the WBS diagram and the EDT dictionary. Prepare the Gantt chart and PERT chart to guide project execution.	25/05/2024
Conception	Literature review and context analysis	Review existing literature to build a solid theoretical framework and understand strategies applied in similar projects.	15/05/2024
	Site visit and IDIBAPS context	Be able to visit and see the facilities by context in the energy study building.	27/05/2024
	Energy supply understanding	Investigate and confirm how energy is supplied to the center, including detailed technical specifications.	30/6/2024
Execution	Data collection	Collect raw data and an inventory of equipment for further analysis.	23/03/2025
	Creation of a functional code	Create functional code capable of processing and analyzing the collected data.	13/04/2025
	Obtaining clear graphics	Generate clear and informative graphics to represent the analyzed data.	21/04/2025
	Making an accurate interpretation	Interpret the results accurately, taking into account the project's temporal and contextual dimensions.	04/05/2025
	Propose possible solutions	Develop optimization strategies based on the interpreted data, aiming to provide impactful and feasible recommendations.	16/05/2025
Ending	Completion of the writing of the entire work	Compile the final report, ensuring all content is unified, well-formatted, and ready for submission.	31/05/2025

6.2. Work Breakdown structure (WBS)

The project has been structured in a simple and logical manner, divided into four main phases following a chronological approach, see also Figure 21.

1. Project Conception: This initial phase takes place prior to the practical execution of the project. It includes the precise definition of objectives, early-stage planning, and the review of theoretical and technical knowledge required for the project's successful development.

2. Energy Consumption Analysis: focusing on the systematic collection, processing, and evaluation of energy-related data. The objective is to quantify energy consumption and extract the percentages across different systems and areas within the CEK building in order to identify consumption patterns and potential inefficiencies.

3. Interpretation and Proposal of Solutions: Based on the analytical results, this phase aims to identify energy usage patterns, determine underlying causes, and formulate feasible proposals for improvement. It includes drafting a preliminary report with optimization strategies.

4. Final Reporting and Communication: This closing phase includes the preparation of the final written report (thesis document), the defense presentation, and a summary of the findings, which may be adapted for internal use by IDIBAPS or as a basis for a potential scientific publication.

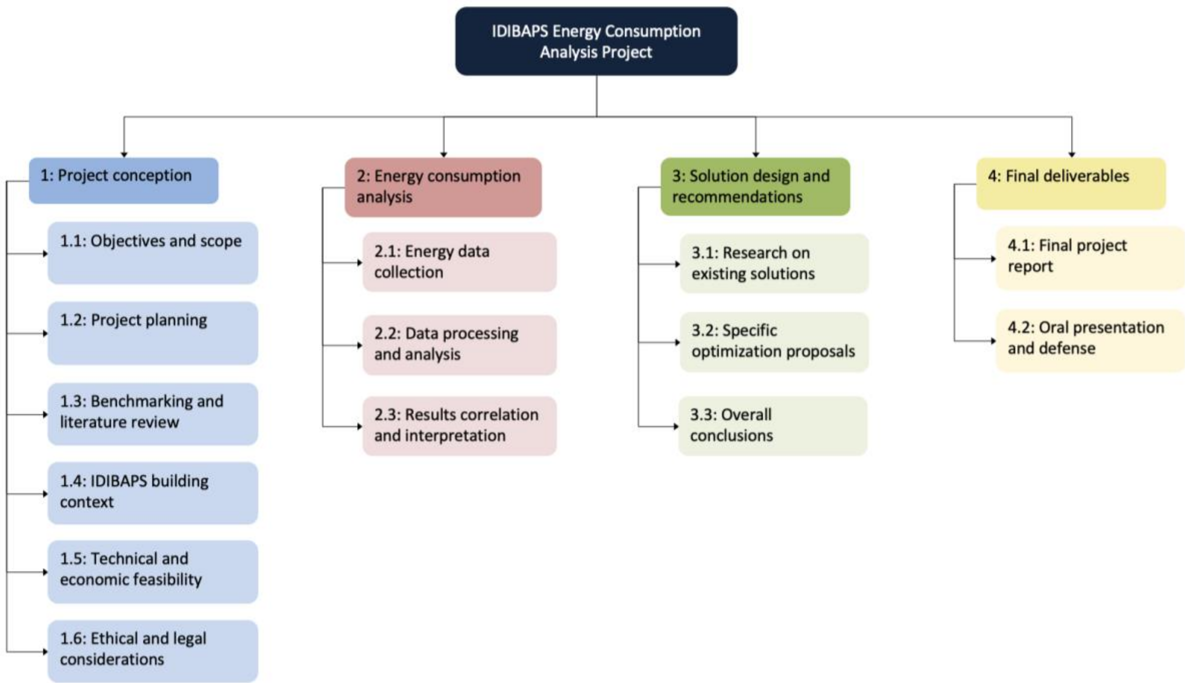

Figure 21. WBS Diagram of the Final Degree Project showing the main tasks and its division. Diagram produced by the author.

6.3. PERT-CPM

Once all the tasks involved in the project have been clearly defined, a scheduling analysis can be carried out using the Program Evaluation and Review Technique (PERT), often complemented by the Critical Path Method (CPM). This analytical approach is used to estimate the overall project duration and to identify the sequence of critical tasks that determine the minimum time required to complete the project.

To construct the PERT diagram, the logical relationships and dependencies between the different tasks were first established, as shown in Table 12. Based on these dependencies, the network diagram illustrated in Figure 22 was developed. In this representation, arrows correspond to specific activities, while nodes represent the points in time when these activities begin and end. Each node includes information on the earliest and latest times at which it can be reached.

The diagram also highlights the critical path, marked in dark orange, which includes all activities that directly affect the project's duration. Any delay in these critical tasks would result in a delay of the entire project. On the other hand, non-critical tasks represented in grey possess some degree of scheduling flexibility, meaning they can be postponed without impacting the overall timeline.

This method provides valuable insights for project management, as it helps prioritize activities that require strict monitoring to ensure timely delivery. In the context of this project, the critical activities identified include A, D, E, G, H, I, K, L, M, N and the total estimated duration for completion is 155 working days, which corresponds to approximately 620 working hours under a part-time schedule.

Table 12. Project's tasks and relationship between them.

ID	Task Name	Duration	Dependence
A	Objective and scope	7	-
B	Planning	7	A
C	Market analysis	15	-
D	IDIBAPS building context	16	A
E	Technical and economic feasibility	10	C, D
F	Ethics and legal aspects	7	A
G	Energy data collection	45	B, E, F
H	Data processing and analysis	27	G
I	Results correlation and interpretation	15	H
J	Research on existing solutions	20	C
K	Specific optimization proposals	14	I, J
L	Overall conclusions	5	I,K
M	Final project report	9	L
N	Oral presentation and defense	7	M
	End	-	N

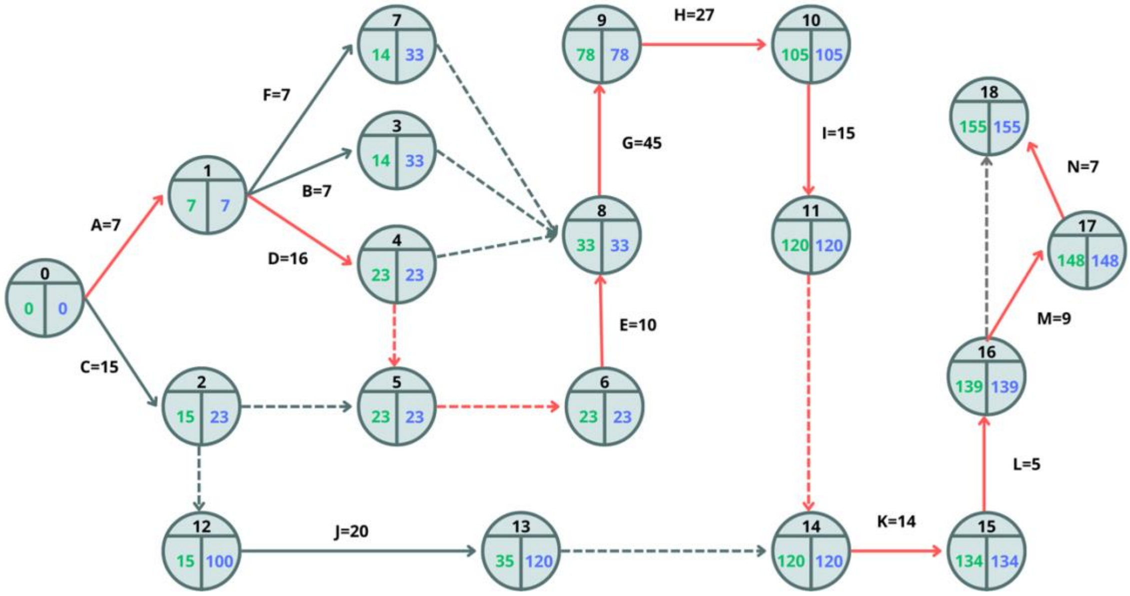

Figure 22. PERT-CPM diagram corresponding to the tasks established in the WBS structure. Critical activities forming the Critical Path are highlighted in red, while non-critical activities are shown in grey. Dashed arrows indicate fictious activities used to represent task dependencies. Each node displays its respective earliest and latest time values. Diagram produced by the author.

6.4. GANTT Chart

After determining the sequence and duration of all tasks through the PERT-CPM method, the next step involves creating a Gantt chart to visualize the temporal distribution of the project. This chart serves as a practical tool for monitoring the execution of the work plan, clearly showing the planned start and end dates for each activity along a linear timeline.

The scheduling data used to build the GANTT chart was obtained directly from the analysis performed in the PERT diagram. Specifically, the earliest and latest possible start and finish times were calculated for each task, allowing for the identification of both critical activities and flexible activities. The corresponding data is summarized in Table 13, which includes each task's total float — the amount of time a task may be delayed without affecting the overall project duration.

Based on this information, the GANTT chart shown in Figure 23 has been developed. The diagram highlights the critical activities in red, representing tasks with zero margin that directly impact the project's total duration. Flexible tasks are shown in green, along with their respective time margins represented with a light grey bar, indicating the scheduling flexibility available without delaying the overall project.

Following the critical path, the total duration of the project has been estimated at 155 working days, distributed over the period from May 2024 to May 2025. The initial work, mainly focused on project conception, was carried out between May and June 2024, toward the end of the second semester of the third academic year. Following this, there was a pause in project development during the 2024–2025 academic year to prioritize academic commitments. The project was then resumed in February 2025 with no setbacks, allowing for consistent progress through the remaining phases. This timeline reflects a realistic distribution of work time, balancing academic responsibilities with the demands of the project. While task execution may not follow a perfectly linear pattern, the

GANTT chart provides a reliable baseline for managing and adjusting the project schedule throughout its life cycle.

Table 13. Summarizing task identifiers, durations, dependencies, and time margins. This data serves as the basis for critical path identification and Gantt chart construction. Table produced by the author.

PERT ID	WBS ID	Duration	Dependence	Early beginning	Early end	Late beginning	Late end	Margin
A	1.1.	7	-	0	7	0	7	0
B	1.2.	7	A	7	14	26	33	19
C	1.3.	15	-	0	15	8	23	8
D	1.4.	16	A	7	23	7	23	0
E	1.5.	10	C, D	23	33	23	33	0
F	1.6.	7	A	7	14	26	33	19
G	2.1.	45	B, E, F	33	78	33	78	0
H	2.2.	27	G	78	105	78	105	0
I	2.3.	15	H	105	120	105	120	0
J	3.1.	20	C	15	35	100	120	85
K	3.2.	14	I, J	120	134	120	134	0
L	3.3.	5	I,K	134	139	134	139	0
M	4.1.	9	L	139	148	139	148	0
N	4.2.	7	M	148	155	148	155	0
End		-	N	155	155	155	*155*	0

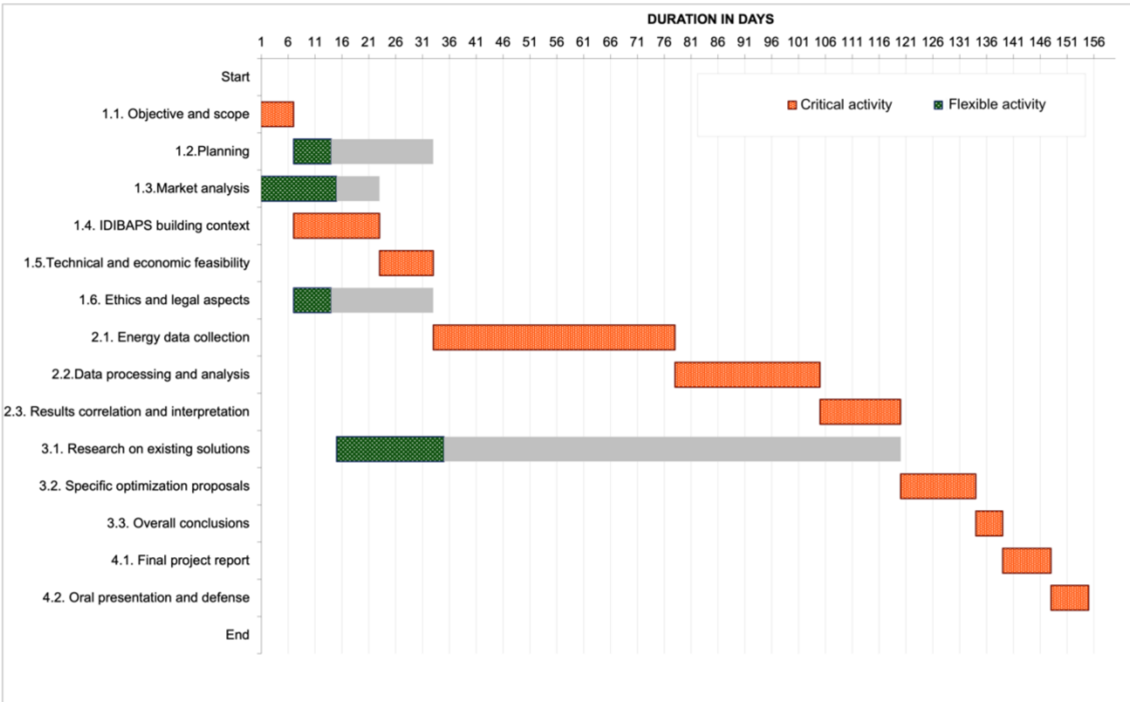

Figure 23. GANTT chart showing the 155-day timeline. Critical tasks (zero margin) in red; flexible tasks in green. Diagram produced by the author.

7. Technical Viability: SWOT Analysis

To assess the technical feasibility of the project, a SWOT (Strengths, Weaknesses, Opportunities, and Threats) analysis was conducted presented in Table 14. This framework systematically evaluates internal capabilities and external conditions that may influence the project's development and implementation. Key elements considered include access to infrastructure data, institutional engagement, technical resources, and limitations related to methodology and instrumentation.

Table 14. SWOT matrix of the project.

Strengths	**Weaknesses**
• Strong institutional motivation from the IDIBAPS Sustainability Committee, which has shown clear commitment to advancing energy efficiency within the center. • Potential technical collaboration with the infrastructure department of Hospital Clínic de Barcelona, providing access to operational data and technical expertise. • Unrestricted physical access to the CEK building, enabling detailed on-site equipment verification and contextual assessment. • Use of advanced measurement tools (e.g., Fluke Power Analyzer) to capture granular energy consumption data.	• Limited prior expertise in electrical and energy systems may constrain the technical depth of specific analyses. • Availability of only one year of historical energy data hinders long-term trend identification • Absence of domain-specific software for energy modeling requires reliance on general-purpose tools and custom code. • Budget constraints limit the acquisition of simulation tools or precision-grade sensors. • Lack of high-resolution equipment-level monitoring reduces granularity of consumption attribution..
Opportunities	**Threats**
• Potential to significantly improve the energy efficiency and economic performance of the CEK building by identifying specific areas of inefficiency. • Possibility to establish IDIBAPS as a reference center in sustainable biomedical research, aligning its operational model with current global sustainability goals. • Opportunity to design a replicable analysis framework that could be applied to other biomedical research centers or institutional buildings with similar characteristics. • Professional growth in emerging fields such as energy analytics, environmental engineering, and sustainable design, enhancing the student's interdisciplinary competencies. • Future collaboration opportunities with other institutions.	• Risk of coding errors or analytical misinterpretations during the data processing phase, potentially impacting the validity of the results. • Challenges in accurately identifying the primary sources of energy consumption due to limited equipment-level granularity or incomplete records. • Financial constraints may delay or prevent the implementation of proposed energy optimization strategies. • Possible resistance to change from end users or research staff, particularly in adopting new operational practices or behavioral adjustments.

The project is technically feasible within the scope of a final degree thesis. Institutional support, expert input, and access to global consumption data provide a solid analytical foundation. Limitations such as short data history and lack of specialized software were addressed through custom tools and expert guidance and consultation.

Risks are manageable and do not affect overall viability. On balance, the study offers a technically robust and institutionally relevant contribution to the field of applied energy analytics and sustainable infrastructure management in biomedical research facilities.

8. Economic Viability

The cost estimation of the project considers only the resources directly involved in the development of the energy modeling and analysis tasks described in this thesis. As no specific hardware, software licenses, or external services were acquired exclusively for this work, the cost structure is centered primarily on human resources.

The author's contribution was estimated at 15 €/hour for a total of 300 hours, reflecting standard undergraduate research assistant rates. Occasional consultation with several domain experts—specifically in laboratory equipment, HVAC systems, and CPD infrastructure—was assumed at a rate of 30 €/hour for up to 10 hours. No cost was attributed to the Fluke Power Quality Analyzer used during the CPD measurement campaign, as it was provided by IDIBAPS. Similarly, all data processing was performed using open-source tools (Python, Pandas, Statsmodels), and no commercial licenses were required. The personal laptop used throughout the project is considered pre-existing equipment and was not included in the financial assessment.

The total estimated cost of the project amounts to 4,800 €, as summarized in Table 15.

Table 15. Total estimated cost of the project.

Item	Description	Cost per Unit	Total Cost (€)
Human Resources			
Engineering Student	300 hours (research, data modeling, thesis writing)	15 €/hour	4,500
Lab/HVAC/CPD Experts Support	10 hours (consultation + technical validation)	30 €/hour	300
Software and Tools			
Python, Pandas, Statsmodels	Open-source tools used for data analysis	Free	0
Microsoft Excel	License via university	Free	0
Fluke Analyzer	Power quality analyzer used for CPD monitoring	Owned by IDIBAPS	0
Hardware			
Personal Laptop	Used for all modeling and processing, research and writing.	Provided	0
Total Estimated Cost			**4,800 €**

9. Legislation and Regulations

This project has been conducted in strict adherence to applicable data protection laws and information security standards, ensuring compliance with the General Data Protection Regulation (GDPR) (Regulation (EU) 2016/679) [42] and Spain's Organic Law 3/2018 on the Protection of Personal Data and Guarantee of Digital Rights (LOPDGDD) [43]

To analyze the correlation between occupancy and energy consumption, anonymized biometric data—specifically, fingerprint records from the building's access control system—were utilized. These data underwent irreversible anonymization processes, eliminating any potential for direct or indirect identification of individuals. According to Article 4(1) of the GDPR, such anonymized data fall outside the scope of personal data and, consequently, the regulation's applicability [42].

The architectural layouts and HVAC (Heating, Ventilation, and Air Conditioning) schematics employed in this study are classified as confidential organizational assets. Access to these documents was restricted to authorized personnel, and their use was confined to analytical purposes within the project's scope. This approach aligns with the principles outlined in the ISO/IEC 27000 series, which advocate for the protection of sensitive information through robust Information Security Management Systems (ISMS) [44].

All data handling and information management activities within this project were designed and executed to ensure compliance with the aforementioned legal frameworks and standards. This included implementing appropriate technical and organizational measures to safeguard data integrity and confidentiality, thereby upholding the rights of individuals and the security of organizational information.

10. Conclusions and Future Steps

This study demonstrates that a simplified, bottom-up audit methodology can accurately model the CEK building's electricity use. The model explains **97%** of the measured weekly consumption, with a relative error of just **3%**, and also captures seasonal variations with a Mean Absolute Percentage Error (MAPE) of **6.8%** as detailed in Annex 12.7. Based on this strong validation, the analysis reveals a concentrated energy profile: **HVAC accounts for ~52%**, **laboratory cold-storage and process equipment for ~36%,** and the **data center for ~9%,** with only **3%** remaining unexplained. These results meet the project's goals: to break down energy use by subsystem, validate the estimates with real data, and create a repeatable audit method. They also make clear that HVAC systems are the dominant energy driver and the most promising target for future efficiency gains.

While conventional thermostat-based strategies are constrained in biomedical environments, two complementary approaches offer high-impact opportunities for HVAC optimization. First, the installation of system-level submetering would improve visibility into energy use across circuits such as chillers, AHUs, and fan-coil units. Literature shows that this level of granularity can yield up to 13% additional energy savings by uncovering inefficiencies and operational faults [46]. Second, submetering would enable advanced control strategies, including reinforcement learning, which has shown 9–13% HVAC energy savings in real-world deployments [47, 48]. As an initial step, CEK should **prioritize submetering of major HVAC loops**. Applying reported savings rates from [46] to CEK's estimated HVAC consumption, this could unlock **estimated weekly savings** of **4,980 kWh**—equivalent to **6.8%** of the CEK building's total energy use—while laying the groundwork for intelligent control.

Further significant savings can be achieved through targeted action on laboratory ultra-low temperature (ULT) freezers. Although they account for fewer than 25% of lab devices, they consume over 60% of total lab equipment electricity. Replacing ageing units with high-efficiency models can cut energy use by up to 60%, as demonstrated by large-scale upgrades at the Mayo Clinic and Washington University [49, 50]. A complementary, low-cost intervention involves raising ULT **freezer setpoints** from **-80 °C to -70 °C**. Experimental results from the University of Copenhagen indicate energy reductions of 20–22% per unit, with no compromise to sample integrity [51]. At CEK, where 116 ULT freezers are assumed to operate at –80 °C by default, applying the reported 20–22% energy reduction to this load yields estimated savings of **3,000 kWh per week,** equivalent to **4.0%** of the building's consumption [51].

In the CEK data center, a near-flat hourly load of 38–39 kWh/h suggests a conservative cooling setpoint. ASHRAE guidelines allow IT equipment inlet temperatures of up to 27 °C without compromising hardware reliability [52]. Real-world case studies, such as the UPC Omega Data Centre, have shown that modest setpoint increases (e.g., from 24 °C to 26 °C) can yield measurable improvements in Power Usage Effectiveness (PUE) without operational risk [25]. If CEK adopts a similar strategy, it could save approximately **91.8 kWh per week**—about 1.35% of CPD consumption, or **0.12% of the CEK building's total energy use**. This estimate is based on a typical Power Usage Effectiveness (PUE) of 1.6, which aligns with industry benchmarks for non-optimized, small-to-medium data centers [52].

Beyond technical measures, **institutional benchmarking and behavioral engagement** represent key no-cost levers. As a member of the Sustainable Research Catalonia (SuRe-Cat) network, IDIBAPS is in a strong position to lead cross-organization transparency efforts by sharing building-level energy consumption data across research centers. This would allow for benchmarking, detection of anomalies, and mutual learning—practices that are currently limited but vital for systemic progress [53].

Finally, climate data underscore the urgency of proactive planning. According to the Copernicus ERA5 dataset, 2024 was expected to be the hottest year on record, exceeding **+1.5 °C above pre-industrial levels**—a key threshold in global climate policy (see Figure 24) [54]. This global trend is also evident locally, as Barcelona has shown a consistent warming pattern in recent years [55]. Regression results in this thesis attribute 127 kWh/°C·day of additional electricity demand to rising ambient temperatures. This implies that each degree of warming may add approximately 46 MWh/year to CEK's energy burden. While CEK cannot reverse climate change, it must anticipate its effects by investing in high-efficiency cooling, predictive controls, and continuous metering to manage rising demand [54].

In summary, this thesis provides a clear picture of where and how energy is used in the CEK building and offers a realistic roadmap for reducing consumption. By combining targeted HVAC upgrades, lab equipment strategies, CPD adjustments, data transparency, and climate adaptation planning, the CEK building can trim its electricity use by **≈ 0.43 GWh year^{-1} (≈ 8.1 MWh week^{-1}), an 11 % cut in the current 3.87 GWh baseline**, setting a benchmark for sustainable research facilities.

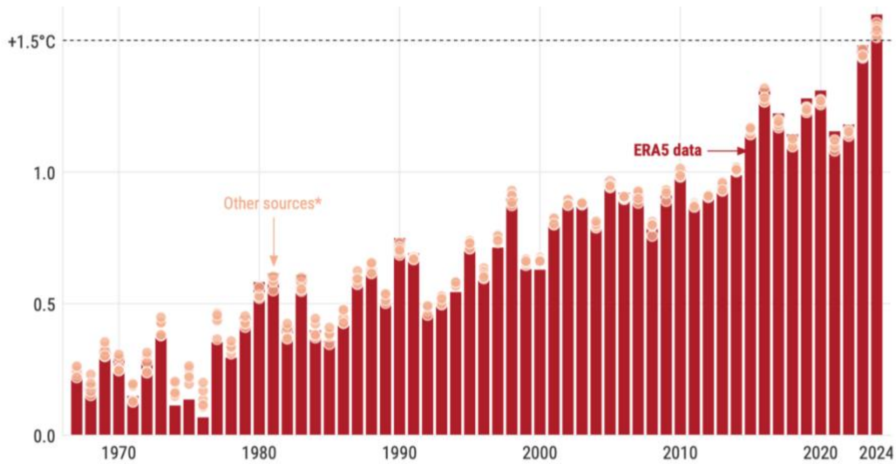

Figure 24. Global surface air temperature (ºC) increase relative to the 1850–1900 designated pre-industrial reference period, shown as annual averages from 1967 to present. Credit: C3S/ECMWF [54].

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12. Annexes

12.1. Laboratory Floor Plan

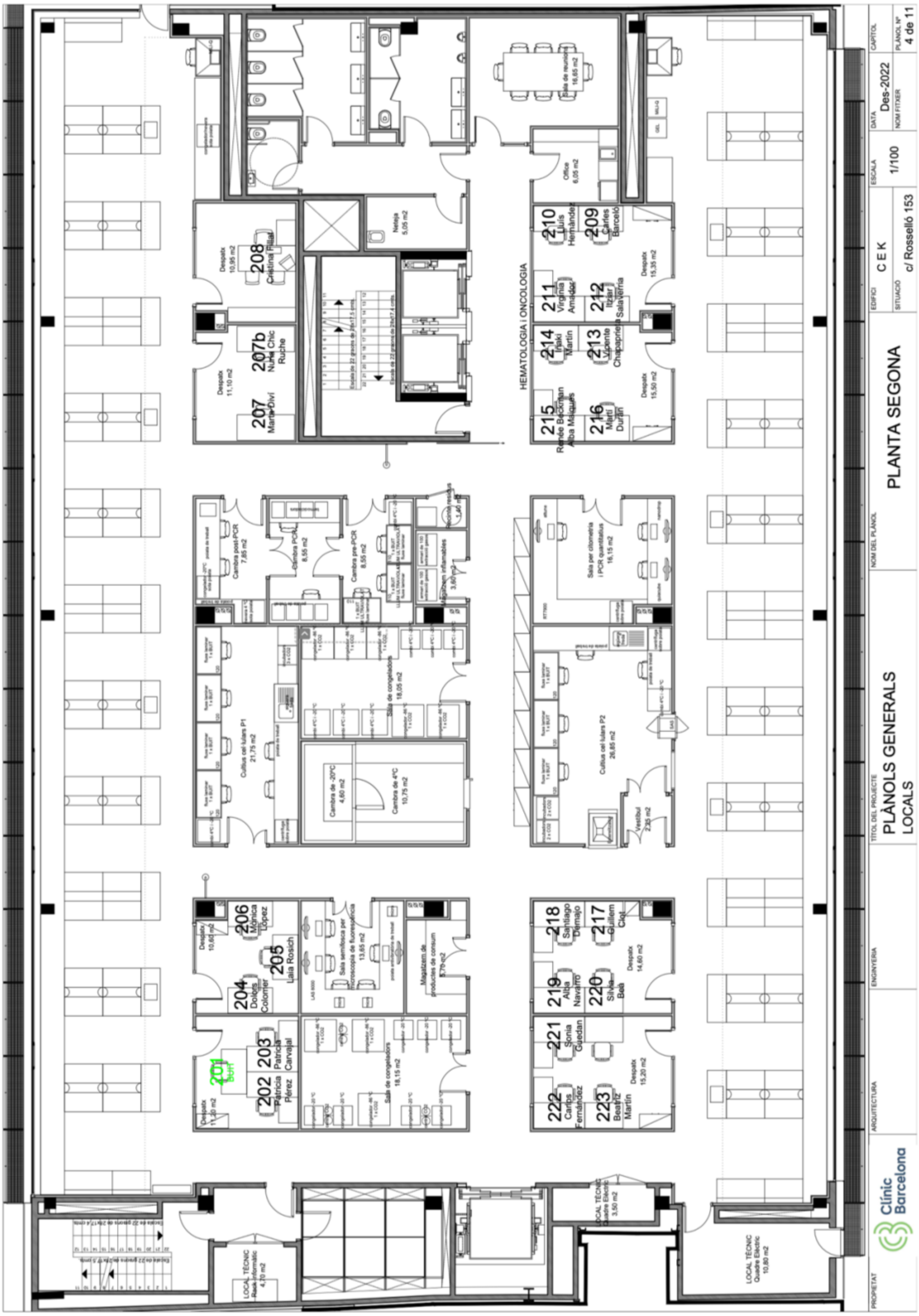

Figure 25. Floor plan of the second floor (Planta Segona) of the CEK building.

12.2. Equipment Inventory

Table 16 contains the hierarchical classification and energy consumption estimates for laboratory equipment used in Section 5.1. It includes device count, weekly consumption (kWh), and category breakdowns. Main categories are in dark blue, subcategories in light blue, and specific equipment types in plain rows. The full dataset is available in Annex 12.5 (Folder A: 1_Equipment_Inventory).

Table 16. Hierarchical classification of laboratory equipment and corresponding energy consumption.

Row Labels	Count	Consumption kWh
Cell Culture Equipment	**141**	**4451,42**
BANY AIGUA	6	480,00
BANY AIGUA AGITACIO	5	72,00
BANY FLOTACIO	2	48,00
CABINA BIOSEGURETAT	38	912,00
CABINA FLUXE LAMINAR HORITZONTAL	2	20,00
CENTRIFUGA POLIVALENT REFRIGERADA	19	1064,00
INCUBADOR AGITADOR	2	23,52
INCUBADOR CO2	43	1444,80
INCUBADOR CO2 CAMISA AIGUA	4	117,60
INCUBADOR CO2-N2 (HIPOXIA)	1	168,00
INCUBADOR N2	2	49,70
MICROSCOPI FLUORESCENCIA	3	4,20
MICROSCOPI INVERTIT	11	44,00
MICROSCOPI OPTIC VERTICAL	3	3,60
Cooling and Refrigeration Equipment	**231**	**4927,40**
Combis	**12**	**403,20**
COMBI	12	403,20
Freezers	**156**	**4051,06**
CONGELADOR -20	42	384,83
CONGELADOR -20 SOTA POIATA	50	197,06
CONGELADOR -80	63	3395,66
CONGELADOR -80 GRAN	1	73,50
Refrigerators	**63**	**473,13**
NEVERA	13	119,66
NEVERA SOTA POIATA	50	353,47
Heat and Pressure Equipment	**77**	**366,14**
Gas Incubators	**13**	**282,69**
INCUBADOR AGITADOR	8	2,49
INCUBADOR AMB AGITACIO REFRIGERAT	2	45,00
INCUBADOR CO2	2	67,20
INCUBADOR CO2 / O2	1	168,00
Pumps	**8**	**32,40**
BOMBA DE BUIT	8	32,40
Thermal Blocks	**56**	**51,05**
BLOC TERMIC	41	2,05
BLOC TERMIC AGITACIO	15	49,00
Safety and Air Flow Equipment	**28**	**239,81**
Cabinets	**23**	**185,73**
CABINA BIOSEGURETAT	12	128,90

CABINA EXTRACCIO GASOS	11	56,83
EQUIP AIGUA ULTRAPURA	5	54,08
Sample Analysis and Processing Equipment	**457**	**3006,25**
Agitation Equipment	**84**	**154,74**
AGITADOR BALANCEIG	50	48,50
AGITADOR CALEFACTOR	1	9,00
AGITADOR MAGNETIC CALEFACTOR	23	30,00
AGITADOR ORBITAL CALEFACTOR	5	64,00
ANALITZADOR IMATGES	3	1,32
ANALIZADOR FLEXIBLE CITOMETRE FLUXE	2	1,92
Analysis Equipment	**7**	**15,43**
EQUIP FOTODOCUMENTACIO	7	15,43
Baths Equipment	**47**	**107,58**
BANY AIGUA	23	9,66
BANY AIGUA AGITACIO	8	20,00
BANY CONGELACIO	2	3,20
BANY FLOTACIO	10	72,12
BANY SEC	4	2,60
Centrifugues	**99**	**900,41**
CENTRIFUGA ALTA VELOCITAT REFRIGERADA	3	31,50
CENTRIFUGA MICRO	26	55,25
CENTRIFUGA MICRO REFRIGERADA	24	252,00
CENTRIFUGA POLIVALENT	9	23,49
CENTRIFUGA POLIVALENT REFRIGERADA	26	436,80
CENTRIFUGA REFRIGERADA	6	35,87
CENTRIFUGA ULTRA	5	65,50
Cutting Equipment	**5**	**20,43**
MICROTOM	5	20,43
Cutting Equipment	**2**	**510,72**
CRIOSTAT	2	510,72
Electrophoresis Equipment	**77**	**99,86**
EQUIP ELECTROFORESI HORITZONTAL	44	54,41
EQUIP ELECTROFORESI VERTICAL	30	9,45
EQUIP EXTRACCIO I PURIFICACIO AUTOMATITZAT ACIDS NUCLEICS	3	36,00
Microscopes	**27**	**36,91**
MICROSCOPI CONFOCAL	2	21,21
MICROSCOPI FLUORESCENCIA	10	12,54
MICROSCOPI INVERTIT	2	0,64
MICROSCOPI OPTIC VERTICAL	13	2,52
PCR and Thermocyclers	**80**	**1158,29**
PCR A TEMPS REAL	16	192,04
PCR DIGITAL EN GOTES (ddPCR)	1	21,25
TERMOCICLADOR	63	945,00
Spectrophotometers	**29**	**1,87**
ESPECTROFOTOMETRE CUBETA	11	1,38
ESPECTROFOTOMETRE NANOMOSTRES	11	0,15
ESPECTROFOTOMETRE PLAQUES	7	0,35
Grand Total	**934**	**12991,02**

12.3. Correlation Analysis by Floor and Category

Table 17 shows the correlation between equipment count and energy share per floor and category. It supports the cross-floor analysis in Section 5.1.3 and 5.6.1, highlighting disparities between device count and energy intensity.

Table 17. Correlation between equipment count and energy share by category and floor.

	Metrics	Cell Culture	Cooling and Refrigeration	Heat and Pressure	Safety and Air Flow	Sample Analysis & Processing	Grand Total
Floor -1	Nº devices		91	11	18	133	253
	% Nº devices floor	0,00%	35,97%	4,35%	7,11%	52,57%	100,00%
	% Nº devices	0,00%	6,90%	0,83%	1,36%	10,08%	19,18%
	% Consump kWh floor	0,00%	82,15%	5,48%	1,83%	10,54%	100,00%
	% Consumption kWh	0,00%	42,27%	2,82%	0,94%	5,42%	51,46%
Floors 1-5	Sum of Nº devices	141	231	122	66	506	1066
	% Nº devices floor	13,23%	21,67%	11,44%	6,19%	47,47%	100,00%
	% Nº devices	10,69%	17,51%	9,25%	5,00%	38,36%	80,82%
	% Consump kWh floor	34,27%	37,93%	2,82%	1,85%	23,14%	100,00%
	% Consump kWh	16,63%	18,41%	1,37%	0,90%	11,23%	48,54%
Total Sum of Nº devices		141	322	133	84	639	1319
Total % Nº devices		10,69%	24,41%	10,08%	6,37%	48,45%	100,00%
Total % Consumption kWh floor		16,63%	60,68%	4,19%	1,84%	16,66%	100,00%
Total % Consumption kWh		16,63%	60,68%	4,19%	1,84%	16,66%	100,00%

12.4. Hourly-model accuracy metrics

Formulas follow Garrett & New [41]; acceptable calibration limits are taken from ASHRAE Guideline 14-2014 [46]. A brief rationale for using MAE/MAPE is given by Willmott & Matsuura [56].

Table 18. Hourly model-accuracy metrics: formulas, units, and ASHRAE Guideline 14 acceptance limits.

Metric	Symbol	Formula	Units	Guideline-14 hourly limit **	Comment
Mean absolute error	MAE	$\frac{1}{N}\sum_{i=1}^{N}\lvert e_i\rvert$	kWh h⁻¹	–	kWh h⁻¹
Mean absolute % error	MAPE	$\frac{100}{N}\sum_{i=1}^{N}\left\lvert\frac{e_i}{P_{r,i}}\right\rvert$	%	–	%
Root-mean-square error	RMSE	$\sqrt{\frac{1}{N}\sum_{i=1}^{N}e_i^2}$	kWh h⁻¹	–	penalises peaks
Mean bias error	MBE	$\frac{1}{N}\sum_{i=1}^{N}e_i$	kWh h⁻¹	$\pm$10%*	signed error
Normalised MBE	NMBE	$100\,\frac{\sum e_i}{(N-1)\,\overline{P_r}}$	%	$\pm$10%*	used in Guideline 14
Coeff. of variation of RMSE	CV(RMSE)	$100\,\frac{\sqrt{\sum e_i^2\,/(N-1)}}{\overline{P_r}}$	%	30%*	Guideline 14 acceptance test

where $\mathrm{e_i} = \mathrm{P_{r,i}} - \mathrm{P_{s,i}}$; $P_{r,i}$ and $P_{s,i}$ are real and simulated loads for hour i, N=24 and $\overline{\mathrm{P_r}}$ is the mean real load.

** Hourly acceptance limits from ASHRAE Guideline 14-2014 [42].

* Guideline 14 specifies NMBE and CV(RMSE); the thesis adds MBE and RMSE in absolute units for intuitive interpretation.

12.5. Access to Digital Annex Folder

All supporting data, spreadsheets, and source files referenced in this thesis are available at:

Google Drive Folder: TFG_JuliaPassada_CEK_Annexes
(Read-only access; last updated: 10 June 2025)

Folders are organized by analytical component. All files are provided in original formats (.xlsx, .csv, .ipynb) to ensure transparency and reproducibility. Table 19 summarizes the structure of the digital annex, detailing the contents of each folder and their relevance to the analytical sections of the thesis.

Table 19. Structure and contents of Digital Annex Folders.

#	Folder and Contents	Importance
0	0_CEK_Building	
	· **CEK_Plans.pdf** : complete architectural & MEP drawings.	Floor areas, Chapters 2 & 5.
1	1_Equipment_Inventory	
	· **Equipment_Inventory_P1-5.xlsx**: consolidated inventory & floor totals. · **Equipment_Inventory_S-1.xlsx**: basement inventory	Inputs for the bottom-up load estimation (Section 5.3)
2	2_HVAC_Data	
	· **HVAC_Consumption.xlsx**: power & energy calcs by subsystem · **HVAC_Diagrams/:** single-line circuit schematics · **Technical_Sheets/** : manufacturer datasheets	Sources for HVAC energy model (Section 5.4)
3	3_CPD_Measurements	
	· **CPD_Data.xlsx**: raw & processed electrical logs (Feb 2024 & May 2024)	CPD load profile (Section 5.5)
4	4_GlobalLoad_StatisticalModeling	
	· **Global_Load_Patterns.xlsx**: load-profile graphs, simulation outputs, MAPE/error metrics, and calculations for future savings. · **CEK_Energy_Analysis.ipynb**: profile graphs, correlations, stats models · **CEK_Energy_Analysis/** CSV inputs	Consumption patterns, full statistical model & sensitivity tests (Section 5.5 and 5.6)

12.6. Benchmarking CPD Load Profiles: Comparison with UPC Vertex Facility

This section includes any figures or data excerpts referenced for validation but not included in the main body due to space

Figure 26 presents the data obtained from the SIRENA platform, shows a consistent baseline of approximately 72–74 kWh, with pronounced daily peaks corresponding to working hours.

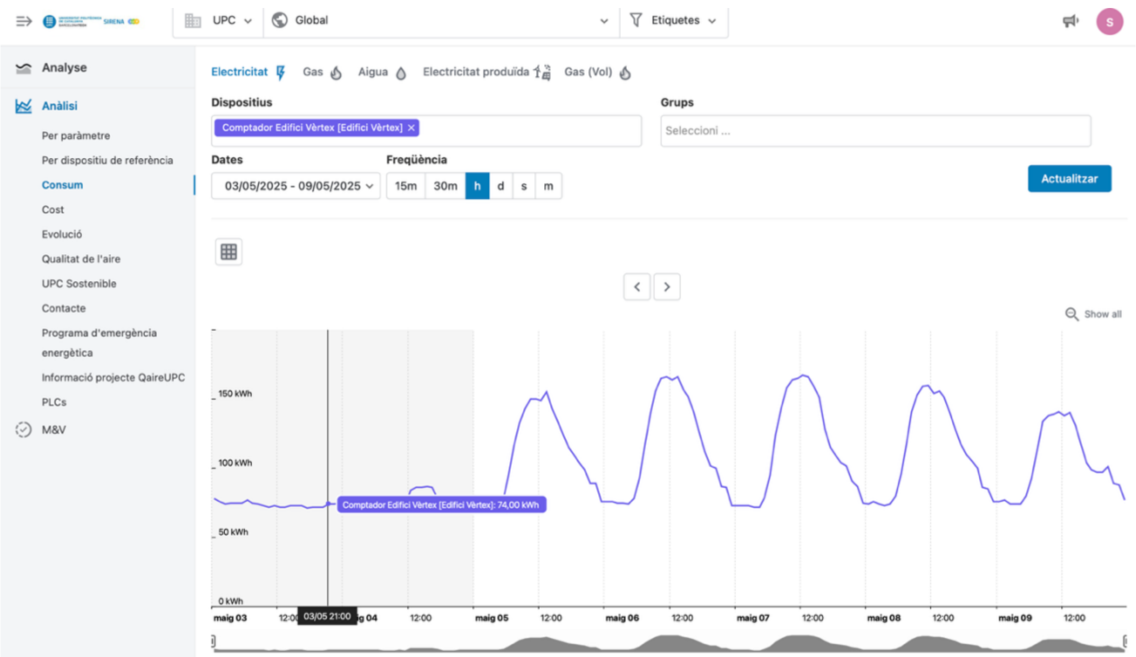

Figure 26. Hourly electricity consumption profile of the UPC Vertex CPD building (May 3–9, 2025).

12.7. Statistical Model Validation

This annex provides additional validation of the bottom-up model through the seasonal analysis introduced in Section 5.6. Table 20 compares empirical and estimated weekly consumption by quarter. While Section 5.6.1 reports an average relative error of 3%, this breakdown confirms that the model also captures seasonal variation, with accuracies ranging from 88% to 97% and a Mean Absolute Percentage Error (MAPE) of 6.8%.

Table 20. Empirical vs. Estimated weekly consumption by quarter.

Quarter	Empirical kWh/week	Estimate kWh/week	Signed Error kWh/week	%AbsError	Accuracy
Q1	66,397.00	58,100.78	-8,296.22	12.5%	87.5%
Q2	71,551.74	73,466.02	1,914.28	2.7%	97.3%
Q3	77,413.14	79,439.13	2,025.99	2.6%	97.4%
Q4	65,647.43	71,878.49	6,231.06	9.5%	90.5%

* MAPE is computed as the simple mean of the four quarterly absolute percentage errors.