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The application of Artificial intelligence to control the energy consumption of Air Conditioner

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اهداء

بسم الله الرحمان الرحيم

عظمة المراد تهون طريق الوصول

الحمد لله الذي وفقني لنيل شهادة عملت عليها طوال مسيرتي الجامعية

اهدي تخرجي بداية لنفسي المثابرة و لعائلتي الداعمة

و للأساتذة الذين وقفوا على هذا البحث .

ها أنا في نهاية الطريق اكتب هذا الاهداء و دموع الفخر في عيني

اشكر ابي الذي أنار دربي و امي من سهرت معي الليالي

و بالتأكيد لن انسى اخي الذي دعمني في قراراتي و اختي التي اتمنى لها ان تعيش هذه اللحظة

دون أن انسى معلمتي الصينية على إيمانها بقدراتي و دعمها القوي

و الدائم لي .

Acronyms and Abbreviations

HVAC	Heating, Ventilation, and Air Conditioning.
BMS	Building Management System.
AI	Artificial Intelligence.
ML	Machine Learning.
SCADA	Supervisory Control and Data Acquisition .
SEER	Seasonal Energy Efficiency Ratio.
DL	Deep Learning.
CNNs	Convolutional neural networks .
Neural network	Type of machine learning model inspired by the way the human brain works.
Fuzzy logic	A type of logic that allows for degrees of truth instead of just true or false.
hybrid system	A system that combines two or more different technologies improve performance.
DRP	Demand response programs.
BILP	A Binary (0,1) Integer Linear Programm
ISO	International Organization for Standardization
EN	European Norm
RE	Environmental Regulation

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Abstract

Sustainable and energy-efficient buildings have become increasingly essential in light of growing environmental concerns and rising energy costs, with the building sector recognized as one of the largest energy consumers globally. Heating, Ventilation, and Air Conditioning (HVAC) systems alone can account for up to 50% of a building's total energy consumption, making the optimization of their performance a critical strategy for reducing both environmental impact and operational expenses. This study investigates the influence of varying levels of thermal insulation and HVAC system efficiencies on cooling energy consumption using a simulation-based analysis platform developed in a laboratory at the University of Abou Bekr Belkaid in Tlemcen. The analysis was structured around two scenarios: S1 (Midea MSAGB-12HRN1-Q) and S2 (LG S09EQ.NSJ). In the first scenario, the calculated change in energy consumption between the two cases was -1.4%, indicating no actual energy savings in the second case. Similarly, in the second scenario, the difference was -1.2%, again demonstrating the absence of meaningful savings. Overall, the total energy consumption in the first scenario was higher than in the second, primarily due to the superior performance of the LG unit, which is an inverter-type air conditioner with higher efficiency. These findings highlight the combined importance of high-quality thermal insulation and advanced HVAC system technologies in achieving significant reductions in cooling energy demand.

Keywords: Sustainable buildings,Energy efficiency , HVAC systems

Thermal insulation , Simulation analysis , Energy consumption.

Résumé

Les bâtiments durables et écoénergétiques sont devenus de plus en plus essentiels face aux préoccupations environnementales croissantes et à l'augmentation des coûts de l'énergie, le secteur du bâtiment étant reconnu comme l'un des plus grands consommateurs d'énergie à l'échelle mondiale. Les systèmes de chauffage, ventilation et climatisation (CVC) peuvent à eux seuls représenter jusqu'à 50 % de la consommation énergétique totale d'un bâtiment, ce qui fait de l'optimisation de leurs performances une stratégie cruciale pour réduire à la fois l'impact environnemental et les coûts d'exploitation. Cette étude examine l'influence de différents niveaux d'isolation thermique et d'efficacité des systèmes CVC sur la consommation d'énergie liée au refroidissement, en s'appuyant sur une plateforme d'analyse par simulation développée dans un laboratoire de l'Université Abou Bekr Belkaid de Tlemcen. L'analyse a été structurée autour de deux scénarios : S1 (Midea MSAGB-12HRN1-Q) et S2 (LG S09EQ.NSJ). Dans le premier scénario, la variation calculée de la consommation énergétique entre les deux cas était de -1,4 %, indiquant l'absence d'économies réelles dans le second cas. De même, dans le second scénario, la différence était de -1,2 %, démontrant également l'absence d'économie significative. Globalement, la consommation énergétique totale dans le premier scénario était plus élevée que dans le second, principalement en raison des performances supérieures de l'unité LG, qui est un climatiseur de type inverter offrant une meilleure efficacité. Ces résultats soulignent l'importance combinée d'une isolation thermique de qualité et de technologies CVC avancées pour réduire de manière significative la demande énergétique en refroidissement.

Mots-clés : Bâtiments durables, Efficacité énergétique, Systèmes CVC, Isolation thermique, Analyse par simulation, Consommation d'énergie.

الملخص

أصبحت المباني المستدامة وذات الكفاءة الطاقية أكثر أهمية من أي وقت مضى في ظل تزايد المخاوف البيئية وارتفاع تكاليف الطاقة، ويُعَدّ قطاع البناء من بين أكبر مستهلكي الطاقة على مستوى العالم. يمكن أن تمثل أنظمة التدفئة والتهوية وتكييف الهواء (HVAC) ما يصل إلى 50% من إجمالي استهلاك الطاقة في المبنى، مما يجعل تحسين أدائها استراتيجية بالغة الأهمية لتقليل الأثر البيئي وخفض التكاليف التشغيلية. تهدف هذه الدراسة إلى دراسة تأثير مستويات مختلفة من العزل الحراري وكفاءة أنظمة التكييف على استهلاك الطاقة الخاص بالتبريد، بالاعتماد على منصة تحليلية قائمة على المحاكاة تم تطويرها في مختبر بجامعة أبي بكر بلقايد بتلمسان. وقد تم بناء التحليل حول سيناريوهين السيناريو الأول، كانت نسبة التغير المحسوبة في استهلاك الطاقة بين الحالتين -1.4%، مما يشير إلى عدم تحقيق أي توفير فعلي في الحالة الثانية. وبالمثل، في السيناريو الثاني كانت النسبة -1.2%، ما يؤكد أيضًا غياب وفورات طاقية ذات دلالة. بوجه عام، كانت معدلات الاستهلاك الطاقي في السيناريو الأول أعلى مقارنة بالسيناريو الثاني، ويُعزى ذلك أساسًا إلى الأداء المتفوق لجهاز LG الذي يُعد مكيفًا من نوع "إنفرتر" وأكثر كفاءة. وتبرز هذه النتائج الأهمية المشتركة للجودة العالية للعزل الحراري وتقنيات التكييف المتقدمة في تحقيق خفض كبير في الطلب على الطاقة الخاصة بالتبريد.

<u>الكلمات المفتاحية:</u> المباني المستدامة، كفاءة الطاقة، أنظمة التدفئة والتهوية وتكييف الهواء، العزل الحراري، التحليل بالمحاكاة، استهلاك الطاقة

General Introduction

In recent years, sustainable and energy-efficient buildings have become a necessity due to growing environmental concerns and rising energy costs. The building sector is one of the largest energy consumers worldwide, largely because of Heating, Ventilation, and Air Conditioning (HVAC) systems. Numerous studies have shown that HVAC systems can account for up to 50% of a building's total energy consumption.

The objective of this study is to explore strategies for reducing the energy consumption of air conditioning systems indirectly, using a simulation platform that we have developed. This platform is a numerical tool designed to estimate the energy consumption of AC systems and to compare the results of two different scenarios. It also identifies the more efficient scenario through automated analysis powered by Artificial Intelligence (AI).

This study is organized into three chapters. The first chapter presents a comprehensive literature review. The second chapter discusses the development of the simulation platform, including the presentation of key Python code components. The final chapter provides a case study in which the platform is used to simulate and evaluate energy performance.

Chapter 1

Bibliography

1.1.Introduction

This chapter is aimed to provide a bibliographic review of some important studies concerning energy consumption in buildings that focuses specifically on the efficiency of HVAC systems, and AI-driven . The types of articles reviewed identified how new technologies such as artificial intelligence (AI) and smart automation can save energy demand while assuring thermal comfort for occupant .

1.2.State of the art

- **Aung Myat (2022)** highlighted that in the last decade, fast-paced urbanization has caused a big increase in energy demand which has in turn, caused GHG emissions growth at an alarming rate. A considerable amount of this energy consumption is from buildings, and the energy consumption of HVAC systems is almost half of the total consumption. As much as it is crucial to reduce energy consumption associated with HVAC systems, prevalent problems such as non-uniform thermal distribution (in the form of hot and cold spots) in office buildings also must be resolved. As a response to such difficulties, Aung Myat suggested the implementation of proactive control with the use of AI in HVAC systems. This research included the use of a demonstration testbed in the Singapore Institute of Technology where experiments were carried out pitting a normal operation mode against an intelligent mode governed by AI. The research split two big office areas into 43 micro-zones with intelligent dampers fitted at air diffusers for accurate and targeted temperature control. In his research he indicated that the AI-based proactive control system achieved 29% savings in cooling energy demand and reduced AHU electricity consumption by 50% while maintaining optimal levels of thermal comfort (23–25°C and 50–63% relative humidity). This approach improved the energy efficiency and also effectively removed hot and cold spots, and hence it has high potential to provide sustainable and occupant-friendly building management.[1]

- **the “Bilan Energétique Algérien 2023”**, Algeria's power generation in 2023 amounted to 95,627 GWh, 99.2% of which was primarily produced by combined cycles (53.2%) and gas turbines (35.5%), while only 0.7% was generated from renewable sources such as solar energy. The consumption of electricity represented 31% of the nation's energy consumption, totaling 22.086 m, with final consumption being 16.829 m

(31% of final energy consumption). The residential sector was the largest user (22.3% of final consumption), followed by industry and 7.281 m type industry (13.4%).

Electric losses represented 6.4% of the overall consumption of energy, and distribution losses (1.4 million cases) represented 65% of the losses.

it indicates that the heightened demand for domestic and industrial products led to a 3.2% rise in the consumption of electricity in 2023, pointing out Algeria's persistent over-reliance on gas-fueled production and the necessity for greater inclusion of renewable energies.[2]

- **C. H. Wong, M. H. Abdul Samad, and N. Taib (2021)** explored the use of artificial intelligence (AI) in building services to address the time-consuming nature of conventional human comfort analysis techniques. The research points out how AI incorporation in software simulations and building management systems (BMS) facilitates real-time comfort analysis, optimizing energy efficiency, occupant satisfaction, risk reduction, cost savings, and operational productivity. With a PRISMA review methodology, the authors explain the advantages and drawbacks of artificial intelligence in building services, highlighting issues such as lack of good quality large-scale data, lack of consistency in data input parameters, high upfront expenses, and requirements for expert proficiency. This study further highlights the contribution of AI to predictive maintenance where the premature identification of equipment breakdowns minimizes downtime and maintenance costs. Although AI-powered BMS systems can call for greater initial investment, the resulting long-term cost savings and operational effectiveness are in sync with sustainable, future-proofed building infrastructure. This transition from fixed, rule-based controls to dynamic, intelligent systems mirrors the worldwide move toward energy-efficient smart building solutions.[3]

- **Ghezlane Halhoul Merabet et al. (2021)** the study conducted a systemic interrogation of AI-based methods to manage energy efficiency and thermal comfort in building operations, of which HVAC systems form a major part. The study pointed out that not just AI, but also neural networks, fuzzy logic, and hybrid systems have grown the best tools to handle the conflicted goals of energy usage decreasing (possible savings from low to high values: 21.81% to 44.36%) while maintaining or improving occupant comfort (a range of occupancy comfort improvements: 21.67% to 85.77%).
  The authors signal opposite developments in the real world and the slippery path for AI to be the driver there.

The search always stays on the priority list of AI-based control systems is indeed a potential but evolving field. The research points to the potential of personalized comfort models and intelligent system design in combining energy efficiency with comfort, as well as the identification of key future research directions to improve practical implementation.[4]

- **Hooman Farzaneh, Ladan Malehmirchegini, Adrian Bejan, Taofeek Afolabi, Alphonce Mulumba, and Precious P. Daka (2021)** provided a comprehensive overview of artificial intelligence (AI) applications in smart buildings with a particular focus on building management systems (BMS) and demand response programs (DRPs). Their research demonstrates the extent to which AI-centered smart buildings rely on sensors and data analytics to improve energy efficiency through enhanced control, automation, and dependability. The authors propose an assessment model for AI-based building energy consumption prediction featuring topics in the renewable energy field like energy optimization, comfort management, design, and maintenance. The investigators articulate the process through which conventional BMS turned into smart systems incorporating the Internet of Things and AI, and thus leading to data-driven real-time functionalities. These next-generation BMS use a network of sensors to keep watch over occupancy, temperature, and energy consumption in real-time while the AI algorithms extract information for the optimization of HVAC operations and the guarantee of comfortable conditions. Being able to foresee occupancy behavior and adjust to weather or other external conditions, AI based BMS are empowered to cut down the energy consumption usage. The researchers end their discussion by predicting the challenges and presenting the possible future research prospects of the AI applications in smart buildings, emphasizing how the latter will influence the urban power supply significantly.[5]

- **Kashif Hesham Khan, Caspar Ryan, and Ermyas Abebe (2017)** explore the rising energy usage in industrial buildings, where HVAC (heating, ventilation, and air conditioning) systems account for more than half of total energy use. They stress that weather, seasonal variations, time of day, and round-the-clock in-building activities with different needs all affect HVAC energy consumption.
  The authors address this by suggesting a Binary (0,1) Integer Linear Programming (BILP) model that reduces HVAC energy use by up to 30% by arranging activities in accordance with weather forecasts.

They also emphasize how real-time environmental condition modifications are made possible by specialized industrial HVAC systems that are coupled with automation technologies like SCADA, which further improves energy efficiency.[6]

- An article about mixed-mode buildings and their design problems was published in **2017 by Nancy M. Badawy, Ahmed R. Abdin, and Abbas M. El-Zafarany.** The article's content emphasizes how passive buildings save energy by lowering the demand on HVAC systems, yet they frequently fall short of air-conditioned buildings in terms of thermal comfort. Natural ventilation and active cooling are combined in mixed-mode buildings, which alternate between mechanical and passive modes to maximize comfort and energy efficiency. Their hybrid character, however, necessitates special design approaches, making implementation difficult. In order to reduce energy consumption, the project focuses on creating an envelope design approach for mixed-mode buildings in Greater Cairo.The study suggests that buildings should prioritize natural ventilation with a somewhat heavier south envelope (0.8 $W/m^2 \cdot K$, 20% WWR) and a lightweight north façade (2 $W/m^2 \cdot K$, 50% WWR). Furthermore, the article states that mixed-use buildings, which combine residential, commercial, and industrial spaces, require adaptable HVAC systems that can adjust to changing occupancy and usage patterns. Mixed-mode HVAC systems, which combine natural and mechanical ventilation, are marketed as viable solutions for balancing energy economy and indoor comfort in these complicated complexes.[7]

- **Ideen Sadrehaghighi's technical study "Artificial Intelligence (AI) & Machine Learning (ML/DL/NNs)" (2024)** presents the interrelated relationship between these topics in a methodical manner. Artificial intelligence (AI) is the overall discipline that focuses on developing systems capable of human-like reasoning, which includes anything from rule-based programs to advanced learning algorithms. Within AI, Machine Learning (ML) emerges as a critical subset, defined by its ability to extract patterns from data without explicit programming, using approaches such as supervised learning (e.g., decision trees, regression), unsupervised learning (e.g., clustering), and reinforcement learning (e.g., game-playing agents).Deep Learning (DL), a transformative subset of machine learning, distinguishes itself through multi-layered Artificial Neural Networks (ANNs) computational models inspired by biological neurons which enable breakthroughs in complex tasks such as computer vision (via Convolutional NNs/CNNs), sequential data processing (via Recurrent NNs/RNNs) and even physics-informed modeling (via Physics-Informed NNs/PINNs). The paper emphasizes that, while standard

ML focuses on feature engineering, DL automates it through hierarchical layers, with NNs serving as the foundation for DL's performance. This progression from AI's broad goals to ML's data-driven approaches, and eventually to DL's layered architectures powered by NNs demonstrates how advances in neural network design (e.g., attention mechanisms, transformer models) continue to push the bounds of what AI systems can accomplish.[8]

- **Yayla et al. (2022)** created an AI-powered, occupant-centric HVAC control system to solve the inefficiencies of standard HVAC systems, which consume roughly 40% of total building energy. Using a two-year dataset from an Istanbul shopping mall and artificial neural networks (ANN) for occupancy prediction, their sensor-free control technique incorporated real-time weather data and building attributes. Simulation results using IDA Indoor Climate and Energy (ICE) software revealed significant energy savings: at least a 10% reduction compared to traditional systems, with further optimizations reaching 22% savings (Azuatalam et al., 2020) via reinforcement learning and up to 52% (Peng et al., 2018) via machine learning-based occupancy prediction. Furthermore, their proposed system with precooling (Scenario S4) saved 35% compared to full-powered HVAC systems (S1) and 20% during high-temperature months. Beyond energy efficiency, the AI-powered technology boosted thermal comfort by dynamically responding to occupancy patterns and weather fluctuations, beating sensor-based methods. These findings demonstrate AI's ability to turn HVAC systems into long-term, high-performance solutions for commercial buildings.[9]

- **V. Shenbagalakshmi and T. Jaya, Assistant Professor (2020)** released a study evaluating modern air conditioning regulation utilizing machine learning approaches. To maximize AC performance, the study investigates Support Vector Machine (SVM), Artificial Neural Networks (ANN), and a stream-based machine learning strategy combining an effective decision tree and a Stochastic AdaBoost-based logic model. These technologies solve the issue of uneven temperature distribution caused by human behavior by allowing for automatic cooling adjustments depending on occupancy reducing energy consumption when fewer people are present and increasing cooling when occupancy increases. The researchers analyzed the three strategies using performance indicators such as accuracy, sensitivity, and specificity, as well as simulations in MATLAB R2018A.The article also discusses the history of air conditioning, starting with Willis Carrier's 1902 innovation, which was primarily focused on humidity management rather than temperature.
Early systems used ammonia and then R22 refrigerant, which was phased out owing to environmental concerns and replaced by the environmentally friendly R410A. The advancement of air conditioning technology has prioritized

energy efficiency, as assessed by SEER ratings, with higher ratings indicating reduced energy use (e.g., SEER 16 vs. SEER 13). From massive industrial systems to tiny home units (first in 1914) to the first window-mounted AC (1931), air conditioning has evolved from a luxury to a requirement, balancing comfort with sustainability.[10]

1. Conclusion

In conclusion the studies mentioned in this chapter collectively highlight the important role of energy use in buildings focusing on improving HVAC system efficiency through artificial intelligence (AI). AI-based solutions show strong potential for optimizing energy consumption by reduction often between 20% and 50% while maintaining or even enhancing occupant comfort, showing great potential and sustainable approaches to building management. However, several contradictions and gaps persist. Although the concept shows promise ,real-world implementation of these systems remains limited due to high initial costs, system complexity, and the need for specialized expertise barriers that are especially relevant in developing contexts such as Algeria. Additionally, many studies underline the shortage of high-quality, standardized datasets, which limits the accuracy and applicability of AI-based simulations. These challenges highlight the need for practical, adaptable tools capable of assessing AI-driven energy strategies in context-specific environments. The next chapter presents a simulation platform specifically developed for air conditioning (AC) systems, designed to evaluate and validate energy consumption scenarios through AI integration.

Chapter 2

Development of the Intelligent Platform

2.1 Introduction

This chapter introduces a user-friendly simulation platform developed with Streamlit to evaluate summer comfort and building energy performance no installation required. Compliant with standards like ISO 13790, EN 52016-1, and RE 2020, it combines a simplified 1R1C thermal model with AI-powered analysis to enhance results.

The platform is organized into four main modules weather, envelope, thermal model, and AI analysis and allows users to upload EPW files and compare scenarios side by side. This chapter outlines the tool's structure, modeling approach, and AI integration, offering a compact but powerful solution for energy assessment.

2.2 Tool Architecture

2.2.1 Code Structure

(GitHub repository: streamlit_app.py + package acsim/)

The simulation platform developed for this study is structured around two main components: a Streamlit-based user interface, and a custom Python package named acsim, which contains all thermal modeling and calculation modules.

streamlit_app.py

This file represents the graphical user interface (GUI). It allows users to:

- Import weather files in EPW format
- Configure two simulation scenarios (insulation level, glazing, ventilation, AC type, etc.)
- Launch hourly energy consumption simulations
- Visualize results as interactive charts
- Compare the two simulated scenarios
- Export results in CSV format
- Generate an automatic AI-generated analysis using the DeepSeek/OpenAI API, providing a technical explanation of the performance gap between scenarios

Python Package acsim/

The core simulation engine is organized into specialized modules, each responsible for modeling a specific physical or functional component of the building and air conditioning system. The main modules are as

Module	Main Function
weather.py	Reads and processes weather files (temperature, solar radiation)
envelope.py	Calculates thermal losses through walls and solar gains through glazing
ventilation.py	Models losses due to air renewal (ventilation and infiltration)
internal_loads.py	Adds internal heat gains (occupants, lighting, appliances)
ac_model.py	Defines air conditioner performance (COP curves based on outdoor temperature)
thermal_model.py	Computes the hourly thermal balance and total electricity consumption
scenario.py	Creates scenario objects that contain all simulation parameters (building + system)
ai_analysis.py	Generates automatic commentary using an AI language model

TABLE 02 (1): Module and functions

2.2.2 Functional Description of the Modules

The `acsim/` package is organized into modular components. Each module represents a physical process or simulation function and contributes to calculating the energy performance of air conditioning systems. Below is a functional description of each main module, accompanied by a representative code excerpt.

weather.py – Weather Data Import

This module imports and processes EPW-format weather data, extracting outdoor temperature and solar radiation.

Code Example:

```
    df = pd.read_csv(epw_file, skiprows=8, header=None, names=col_names, usecols=use_columns)
    # Génération d'une colonne datetime pour chaque heure
    start_year = int(df.loc[0, "Year"])
    # La première heure du fichier EPW correspond à 01:00 le 1er janvier de l'année de départ
    start_timestamp = f"{start_year}-01-01 01:00"
    df['datetime'] = pd.date_range(start=start_timestamp, periods=len(df), freq='H')
```

envelope.py – Building Envelope & Solar Gains

This module calculates heat loss through the building envelope and heat gain from solar radiation, based on user-selected insulation and glazing quality.

Code Example:

```
def calcul_H_enveloppe(niveau_isolation, niveau_vitrage):
    """Calcule le coefficient global de pertes thermiques par l'enveloppe (W/K) en fonction de l'isolation et du vitrage."""
    H_wall = UA_wall[niveau_isolation]
    H_win = UA_window[niveau_vitrage]
    return H_wall + H_win
```

ventilation.py – Ventilation & Infiltration Losses

Calculates ventilation-related heat loss depending on air change rate (ACH) and internal building volume.

Code Example:

```
def calcul_H_ventilation(niveau_ventilation):
    """Calcule le coefficient de pertes par ventilation/infiltration (W/K) pour le niveau donné."""
    ACH = ACH_values[niveau_ventilation]
    # Formule : H_vent = 0.34 * ACH * Volume, où 0.34 convertit (m3/h) * (J/(m3.K)) en W/K (air ~ 0.34 Wh/m3.K)
    return 0.34 * ACH * VOLUME_M3
```

ac_model.py – Air Conditioner Performance Modeling

Provides the COP (efficiency) of the air conditioner using linear interpolation based on outdoor temperature and AC quality.

Code Example:

```
def cop_temperature(type_ac: str, T_ext: float) -> float:
    """
    Interpole linéairement le COP en fonction de la température extérieure
    pour le type de climatiseur choisi.
    """
```

thermal_model.py – Thermal Load Simulation

Computes hourly cooling load and the required electric power using all other modules' outputs.

Code Example:

```
            Q_sol  = envelope.gain_solaire(ghi, sc.vitrage)
            Q_tot  = Q_env + Q_vent + Q_sol + Q_int          # W
```

scenario.py – Scenario Configuration

Defines all simulation inputs for a single building and AC system setup.

Code Example:

```
    def __init__(self,
                 isolation: str,
                 vitrage: str,
                 ventilation: str,
                 interne: str,
                 T_int: float,
                 type_ac: str,
                 cap_nom_kW: float,
                 mod_min_pct: int):
```

ai_analysis.py – AI-Generated Commentary

Uses the DeepSeek/OpenAI API to generate an automatic summary comparing two simulation scenarios.

Code Example:

```
        response = client.chat.completions.create(
            model       = "deepseek-chat",      # ou un autre modèle DeepSeek
            messages    = [{"role": "user", "content": prompt}],
            temperature = 0.7,
            max_tokens  = 300
```

3.3 Thermal Modeling

Thermal modeling is a fundamental component in assessing of the energy performance of buildings and the efficiency of air conditioning systems. In this context, such a simplified yet representative approach has been adopted, and this approach allows dynamic thermal exchanges to be simulated on an hourly basis. This section fully details the modeling assumptions as well as the hourly energy balance. It also details the operation of the control logic and part-load functions.

3.3.1 Assumptions and Simplifications: 1R1C Model and Thermal Mass Representation

The modeling approach is based on the electrical analogy of the thermal transfers, on a 1R1C model (one of resistance, one of capacitance). In this model, the building is treated as being a single thermal zone. A constant indoor temperature is assumed. Heat losses through the envelope are represented via thermal resistance R, while the building's thermal inertia is reflected through thermal capacity C.

The evolution of indoor temperature $Tint$ is governed by the differential equation:

$$C \cdot \frac{dT_{int}}{dt} = \frac{T_{ext} - T_{int}}{R} + \Phi_{int} + \Phi_{sol} - \Phi_{HVAC}$$

where: $Text$ is the outdoor temperature

Φint are internal gains

Φsol are solar gain

ΦHVAC is the heating or cooling power provided by the HVAC system.

The following simplifying assumptions are adopted:

- The building is treated as a single zone with uniform temperature.
- Heat transfers through the envelope are assumed steady-state at each timestep.
- Thermal bridges are either neglected or incorporated into corrected U-values.
- Humidity and latent heat effects are ignored.
- Weather conditions are assumed constant during each hourly step

The building's global thermal mass is modeled using a single thermal capacity value, calculated from the thermal properties of heavy internal materials. This allows the simulation to reflect the damping and thermal lag effects in a simplified manner, compared to more detailed multi-node models.

3.3.2 Hourly Energy Balance: Envelope Losses, Ventilation, Internal and Solar Gains

The hourly energy balance is established to quantify all thermal gains and losses at each timestep. It includes four major components: transmission losses through the envelope, ventilation losses, internal gains, and solar gains.

Transmission losses through the envelope
Transmission heat losses are calculated using:

$$\Phi_{trans} = \sum_i U_i \cdot A_i \cdot (T_{int} - T_{ext})$$

where: Ui is the thermal transmittance,

Ai is the surface area of the element,

Tint, Text are the indoor and outdoor temperatures.

Ventilation losses
Ventilation heat losses are given by:

$$\Phi_{vent} = \dot{V} \cdot \rho \cdot c_p \cdot (T_{int} - T_{ext})$$

where : $\dot{V}$ is the airflow rate,

ρ the air density,

cp the specific heat capacity of air.

If a heat recovery system is present, its effectiveness can be included as a correction factor.

Internal gains
Internal gains come from occupants, equipment, and lighting, and are usually modeled with standardized hourly profiles (e.g., from ISO 13790 or ASHRAE guidelines), typically expressed in W/m² based on usage type and occupancy patterns.

Solar gains
Solar gains through glazing are calculated with:

$$\Phi_{sol} = \sum_j g_j \cdot A_{win,j} \cdot I_{sol,j}$$

where : gj is the solar heat gain coefficient (SHGC),

Awin,j the window area,

Isol,j the incident solar radiation corrected for shading.

Solar gains often constitute a major component of cooling loads during the summer.

This hourly energy balance determines the net heating or cooling demand required from the HVAC system to maintain indoor comfort.

3.3.3 Control and Part-Load Operation: COP Curve, Minimum Modulation, Thermostat Logic

Accurate simulation of HVAC energy performance requires modeling of the system's actual behavior, particularly its operation under part-load conditions and its control strategy.

Part-load operation and COP modeling
The system's coefficient of performance (COP) varies depending on the load. This relationship is typically modeled using a polynomial expression:

$$COP_{eff}(P) = a \cdot \left(\frac{P}{P_{nom}}\right)^2 + b \cdot \left(\frac{P}{P_{nom}}\right) + c$$

where: a, b, and c are coefficients derived from manufacturer data.

This reflects the reduction in efficiency during underloaded or unfavorable outdoor conditions.

Minimum modulation and cycling losses
Below a certain threshold, the HVAC system cannot modulate continuously and must cycle on and off. This introduces efficiency losses, modeled with a degradation factor:

$$COP_{cycled} = COP_{eff} \cdot (1 - f_{cycl})$$

where : fcycl depends on the frequency of cycling and the building's thermal inertia.

Thermostat control algorithm
The control logic is implemented through a simple on/off thermostat with hysteresis. The system activates when:

$$T_{int} > T_{set} + \Delta T \quad \text{or} \quad T_{int} < T_{set} - \Delta T$$

This basic control logic allows realistic estimation of HVAC runtime. More advanced predictive or AI-based controls could be explored in future work for smart building applications.

Integrated hourly model behavior
At each timestep, the model calculates:

- the net heating or cooling demand,
- the system's actual delivered thermal power,
- the real-time COP,
- and the resulting electrical energy consumption.

This level of modeling allows for a seasonally relevant estimation of HVAC performance under realistic operating conditions.

2.4 Automatic Analysis Using Artificial Intelligence (AI)

The integration of artificial intelligence (AI) into energy simulation workflows enables not only the automation of certain analytical tasks but also the enrichment of interpretation through intelligent, contextualized insights. In this project, an automatic analysis module was developed using a large language model (LLM) to generate qualitative commentary based on dynamic thermal simulation results. This section outlines the technical implementation, provides an example of the AI-generated analysis, and offers a critical assessment of the system's strengths and limitations.

2.4.1 Integration of DeepSeek: API, Prompt Engineering, and Secrets Management

The AI engine used in this project is based on **DeepSeek**, a state-of-the-art large language model (LLM) capable of interpreting technical input and generating coherent analytical discourse. Its integration into the simulation pipeline follows a modular architecture, connected via a secure RESTful API.

The automated analysis process includes the following key steps:

- **API Call**: Simulation output data (temperatures, loads, energy use, etc.) is structured in JSON format and sent to the DeepSeek API via a `POST` request.

- **Prompt Engineering**: A context-aware prompt is dynamically constructed to instruct the AI model to analyze simulation results in the manner of a building energy performance expert. The prompt specifies the key points to address (e.g., overheating, HVAC modulation, power peaks), the academic tone to adopt, and the technical detail required.

- **Secrets Management**: API keys are stored securely in a `.env` file and are not exposed in the source code repository, following software security best practices. The Python **`python-dotenv`** library is used to load these secrets securely at runtime.

This infrastructure enables the AI module to access simulation results in real time and generate customized textual analyses based on the specific thermal behavior observed during each scenario.

2.4.2 Example of an AI-Generated Smart Analysis

The following is a typical excerpt from the AI-generated analysis module, based on a summer scenario in a poorly insulated building with a low-inertia HVAC system:

> *"The simulation reveals significant overheating between 2 PM and 6 PM, with indoor temperatures regularly exceeding 28 °C despite active cooling. This suggests either undersizing of the HVAC system or insufficient responsiveness to high solar gains. The daily electrical consumption of the HVAC system peaks at 4.1 kWh, indicating poor energy performance during peak demand. The absence of thermal mass or solar shading intensifies this effect. Optimizing envelope parameters (solar factor, thermal capacity) and refining the control strategy could substantially reduce thermal loads."*

This excerpt demonstrates the AI's capacity to synthesize raw simulation outputs into structured diagnostic commentary. It identifies abnormal trends, formulates hypotheses, and proposes actionable improvements — all without manual intervention.

2.4.3 Critical Assessment and Complementarity of AI Analysis

The incorporation of a generative AI module into thermal simulation offers several notable advantages:

- **Automation of Interpretation**: Reduces the time and effort required for manual result analysis by generating relevant summaries rapidly.

- **Standardization of Technical Language**: Ensures consistency in terminology and structure across multiple simulations.

- **Accessibility**: Helps non-expert users better understand complex thermal dynamics through narrative explanations.

Nonetheless, important limitations must be considered:

- **Prompt Dependency**: The quality and relevance of the output heavily depend on how the prompt is constructed, requiring careful calibration for each use case.

- **Lack of Explicit Physical Reasoning**: The model does not apply thermodynamic laws explicitly and may sometimes produce imprecise or overly general interpretations.

- **Black-Box Nature**: The internal reasoning process of the model is not transparent, which can hinder traceability and confidence in high-stakes decision-making contexts.

Therefore, it is advisable to use the AI-generated analysis in conjunction with objective performance metrics (e.g., thermal balance, overheating hours, load factors) and retain expert oversight when interpreting simulations for critical applications.

2.5 Conclusion

In this chapter, we presented the method used to develop the simulation platform. This online platform is designed to evaluate air conditioning (AC) design scenarios.

By choosing a web-based and accessible tool, we were able to avoid technical issues such as Python library conflicts, making the platform easier to access and use. The simulation platform was developed in accordance with ISO standards.

In the next chapter, we will study two scenarios using this platform and compare their results.

Chapter 3
case study

3.1 Introduction

In this chapter, we present the case study starting by describing the project location, building characteristics, and the parameters required for the analysis. The study focuses on two different scenarios: in the first, we used an air conditioning unit from **Midea**, while in the second, we used a unit from **LG**. Additionally, each scenario incorporates a different type of insulation. This comparison allows us to evaluate the impact of both insulation quality and air conditioner performance on overall energy consumption.

3.2 Hypotheses

T = 23°C………….ISO

UA=300W/K…………. Hypotheses for simulation

UA=120W/K………….Hypotheses for simulation

equipement power

Grinding machine	500 W
Compression testing machine	1000 W
Mortar mixer	500 W
Laboratory mixer	500 W
Computer	350 W
Laboratory drying oven	1000W

TABLE 03(1) : Equipement power

Occupancy factor ………………..full occupancy of space

equipment usage factor..………..Maximum equipment usage

Usage profile ……………………..light are on at full power

3.3 The description of the project

3.3.1 Location and Climate (Tlemcen, EPW Source)

The study area is located in Tlemcen in northwestern Algeria.The site is sited at a latitude of 34.82000 and a longitude of -1.77000, with an elevation of 426 meters above sea level. The climate data used for this analysis is based on the NCEI ISD/ERA5 reanalysis dataset, covering the period from 2009 to 2023. The weather file includes hourly data for the year 2023 and partial data from 2021, providing key variables such as dry bulb temperature, dew point, humidity, atmospheric pressure, wind conditions, solar radiation, and cloud cover.

Typical and extreme weeks are identified for each season summer, winter, autumn and spring based on maximum, minimum, or average temperatures. Ground temperatures are also available for depths of 0.5 m, 2 m, and 4 m, representing undisturbed earth conditions derived from long-term climate data. The location observes neither holidays nor daylight saving time.

3.3.2 Building Characteristics (surface area, current insulation, glazing)

The laboratory has a surface area of 37.54 m², with Wall A insulated with 60 cm polystyrene and Walls B, C, and D insulated with 17.5 cm polystyrene, while the windows feature single glazing and The ceiling height measures 3.62 meters .

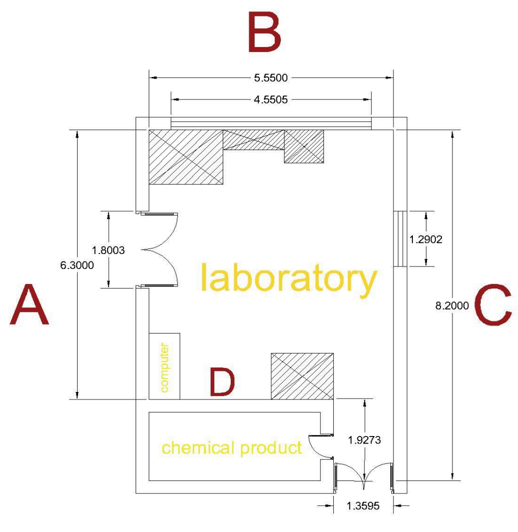
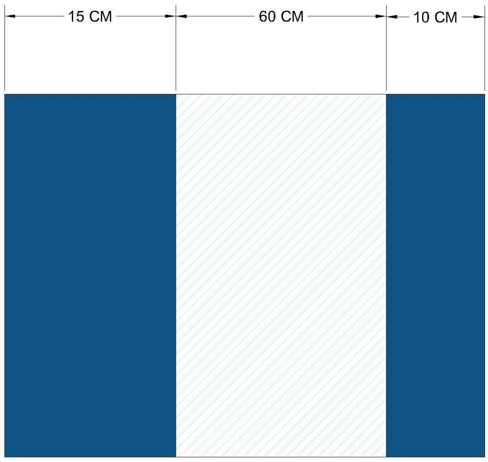
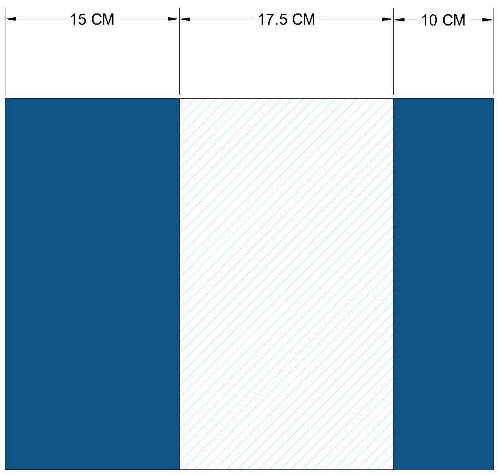


Figure 3.(1): Floor plan view

wall layers



wall A
Current insulation: polystyrene



wall B,C,D
Current insulation: polystyrene

Figure 3.(2): The laboratory

	L(m)	H(m)	S(m²)
door 1	1.36	2.2	2.99
door 2	0.87	2.2	1.91
door 3	1.8	2.9	5.22
window 1	1.29	2.2	2.83
window 2	4.55	1.5	6.82
Wall A	6.3	3.62	22.8 _ 17.58
Wall B	5.55	3.62	20.09 _ 13.27
Wall C	8.2	3.62	29.68 _ 26.85
Wall D	6.09	3.62	22.04 _ 20.13

TABLE 03(2) : Building Characteristics

3.3.3 Existing Air Conditioning System (Capacity, COP)

The current air conditioning system is a Midea MSAGB-12HRN1-Q unit.

cooling capacity	3.22 kW
COP	1.74

3.4.4 Definition of the Two Scenarios

A)- Scenario 1

In this scenario, the space is conditioned using a Midea MSAGB-12HRN1-Q air conditioning unit. In the first case, the building envelope includes polystyrene insulation and single-pane glazed windows. In the second case, the insulation is upgraded to fiberglass, and the windows feature double-pane glazing.

A.1- <u>CASE 01 : polystyrene insulation</u>

<u>wall A</u>

Materials	Thermal Conductivity W/(m·C)	Thickness m	Thermal resistance C·m²/W
Cement plaster	0.87	0.02	0.022
Hollow brick	0.48	0.15	0.312
Polystyrene	0.036	0.6	16.66
Hollow brick	0.48	0.10	0.208
Gypsum plaster	0.35	0.02	0.057

TABLE 03 (3): Thermal resistance wall A

The thermal resistance of this wall is high due to the high thermal resistance of the insulation material and the significant thickness of the insulation used.

$R = e/\lambda$

$R_T = R + 1/he + 1/hi$

$1/he + 1/hi$ = 0.14 c·m²/w…………..(DTR)

$$R_T = 17.4\ c{\cdot}m^2/w$$

$K = 1/R_T = 0.057\ w/c{\cdot}m^2$

$UA = K * S = 1\ w/c$ …………………(ISO

<u>wall B</u>

Materials	Thermal Conductivity W/(m·C)	Thickness m	Thermal resistance C·m²/W
Cement plaster	0.87	0.02	0.022
Hollow brick	0.48	0.15	0.312
Polystyrene	0.036	0.175	4.86
Hollow brick	0.48	0.10	0.208
Gypsum plaster	0.35	0.02	0.057

TABLE 03 (4) : Thermal resistance wall B

The thermal resistance of this wall is lower compared to Wall A, even though the same insulation material was used. This is because the insulation in this wall is thinner, resulting in reduced thermal resistance.

$1/he + 1/hi$ = 0.14 c·m²/w…………..(DTR)

$$R_T = 5.59\ c{\cdot}m^2/w$$

$K = 1/R_T = 0.178\ w/c{\cdot}m^2$

$UA = K * S = 2.36\ w/c$……………(ISO)

wall C

Materials	Thermal Conductivity W/(m·C)	Thickness m	Thermal resistance C·m²/W
Cement plaster	0.87	0.02	0.022
Hollow brick	0.48	0.15	0.312
Polystyrene	0.036	0.175	4.86
Hollow brick	0.48	0.10	0.208
Gypsum plaster	0.35	0.02	0.057

TABLE 03 (5) : Thermal resistance wall C

The thermal resistance of this wall is slightly lower than that of Wall B, even though both use the same insulation material and thickness. This difference is due to the wall's location being an interior wall, the thermal resistance from convection and conduction differs slightly compared to an exterior wall. However, the overall difference in thermal resistance is minor.

$1/he + 1/hi$ = 0. 21 c·m²/w…………..(DTR)

$$R_T = 5.66 c \cdot m^2/w$$

$K = 1/R_T = 0.176\, w/c \cdot m^2$

$UA = K * S = 4.72\, w/c$…………..(ISO)

wall D

Materials	Thermal Conductivity W/(m·C)	Thickness m	Thermal resistance C · m²/W
Cement plaster	0.87	0.02	0.022
Hollow brick	0.48	0.15	0.312
Polystyrene	0.036	0.175	4.86
Hollow brick	0.48	0.10	0.208
Gypsum plaster	0.35	0.02	0.057

TABLE 03 (6): Thermal resistance wall D

The thermal resistance of this wall is the same as that of Wall C, since both walls have identical characteristics

$1/he + 1/hi$ = 0.21 c · m²/w…………..(DTR)

$$R_T = 5.66 c{\cdot}m^2/w$$

$K = 1/R_T = 0.176\, w/c{\cdot}m^2$

$UA = K * S = 3.54\, w/c$…………(ISO)

- **The value of the coefficient *k* is taken from the DTR (Design Technical Regulation) for the window and door specifications**

	K(w/c.m²)	UA(w/c)
door 1	4.5	13.45
door 2	4.5	8.59
door 3	5.8	30.27
window 1	5.8	16.41
window 2	5.8	39.55
Wall A	0.O57	1
Wall B	0.178	2.36
Wall C	0.176	4.72
Wall D	0.176	3.54

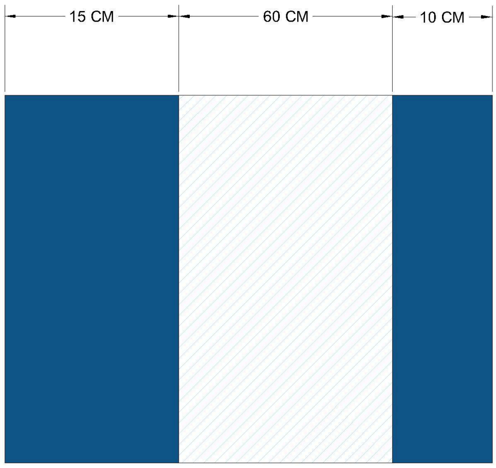
TABLE 03(7) :heat transfer coefficient (case1)

UA TOTAL = 119.89 w/c (moderate insulation)

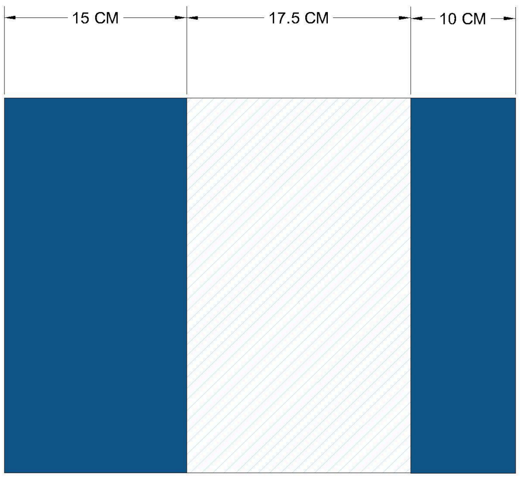
The heat transfer through Wall C is slightly higher compared to the other walls because its insulation layer is thinner than that of Wall A, and its surface area is larger than that of Walls B and D. The total heat transfer in the laboratory, according to simulation data, indicates that the overall insulation level is moderate.

A.2- CASE 02 : fiberglass insulation

wall layers



wall A
Current insulation:Fiberglass



wall B, C, D
Current insulation:Fiberglass

wall A

Materials	Thermal Conductivity W/(m·C)	Thickness m	Thermal resistance C·m²/W
Cement plaster	0.87	0.02	0.022
Hollow brick	0.48	0.15	0.312
Fiberglass	0.034	0.6	17.64
Hollow brick	0.48	0.10	0.208
Gypsum plaster	0.35	0.02	0.057

TABLE 03(8):Thermal resistance wall A

This wall has the highest thermal resistance, even higher than the thermal resistance of the same wall in the previous case, due to the use of a more effective insulation material.

$R = e/\lambda$

$R_T = R + 1/he + 1/hi$

$1/he + 1/hi$ = 0.14 c·m²/w…………..(DTR)

$$R_T = 18.37\ c{\cdot}m^2/w$$

$K = 1/R_T = 0.054\ w/c{\cdot}m^2$

$UA = K * S = 0.956 w/c$…………(ISO)

<u>wall B</u>

materials	Thermal Conductivity W/(m·C)	Thickness m	Thermal resistance C · m²/W
Cement plaster	0.87	0.02	0.022
Hollow brick	0.48	0.15	0.312
Fiberglass	0.034	0.175	5.14
Hollow brick	0.48	0.10	0.208
Gypsum plaster	0.35	0.02	0.057

TABLE 03(9) : Thermal resistance wall B

$$R_T = 5.88\ c{\cdot}m^2/w$$

$K = 1/R_T = 0.17\ w/c{\cdot}m^2$

$UA = K * S = 2.25\ w/c$…………..(ISO)

wall C

Materials	Thermal Conductivity W/(m·C)	Thickness m	Thermal resistance C · m²/W
Cement plaster	0.87	0.02	0.022
Hollow brick	0.48	0.15	0.312
Fiberglass	0.034	0.175	5.14
Hollow brick	0.48	0.10	0.208
Gypsum plaster	0.35	0.02	0.057

TABLE 03(10): Thermal resistance wall C

$1/he + 1/hi$ = 0.21 c · m²/w…………..(DTR)

$$R_T = 5.95 c{\cdot}m^2/w$$

$K = 1/R_T = 0.17\ w/c{\cdot}m^2$

$UA = K * S = 4.56\ w/c$………………(ISO)

wall D

Materials	Thermal Conductivity W/(m·C)	Thickness m	Thermal resistance C·m²/W
Cement plaster	0.87	0.02	0.022
Hollow brick	0.48	0.15	0.312
Fiberglass	0.034	0.175	5.14
Hollow brick	0.48	0.10	0.208
Gypsum plaster	0.35	0.02	0.057

TABLE 3(11) : Thermal resistance wall D

$1/he + 1/hi$ = 0. 21 c·m²/w…………..(DTR)

$R_T = 5.95\ c{\cdot}m^2/w$

$K = 1/R_T = 0.17\ w/c{\cdot}m^2$

$UA = K * S = 3.42 w/c$……………..(ISO)

- **The value of the coefficient *k* is taken from the DTR (Design Technical Regulation) for the window and door specifications**

The thermal resistance of walls B, C, and D is also higher than in the first case, primarily due to the use of more effective insulation materials.

	K(w/$c \cdot m^2$)	UA(w/c)
door 1	4.5	13.45
door 2	4.5	8.59
door 3	5.8	30.27
window 1	4	11.2
window 2	4	27.28
Wall A	0.O57	0.956
Wall B	0.178	2.25
Wall C	0.176	4.56
Wall D	0.176	3.42

TABLE 3(12) : heat transfer coefficient (case2)

UA TOTAL = 101.97 w/c (High insulation)

The total heat transfer coefficient in this case is lower than in the first case, which indicates that the insulation used here is more effective.

Heat gains

- General Internal Heat Gains Equation

Qint =Qpeople+Qequipment +Qlighting

1. Heat Gains from People

Qpeople=Npeople*qperson*focc

Where:

- Npeople: Number of occupants (3 People)
- qperson: Heat gain per person (sensible + latent) 100 W/person
- focc(t): Occupancy factor 1

Qpeople(t)= 300 w

2. Heat Gains from Equipment

Qequipment =Pequip*fequip *η

Where:

- Pequip: Installed equipment power (depends on each equipment)
- fequip: Time-dependent usage profile(1)
- ηgain: Fraction of energy converted to useful heat (1 for computer 0.95)

Qequipment = 3832.5 w

3. Heat Gains from Lighting

Qlighting=Plighting*flight*ηgain

Where:

- PlightingP: Installed lighting power (18W)
- flight: Usage profile (1)
- ηgain: Heat gain factor (0.8 for LED)

Qlighting= 86.4 W

Qint =Qpeople+Qequipment +Qlighting

Qint = 4218.9 W= 4.22 KW (High internal load)

The total heat gains from equipment, lighting, and occupants are high, mainly due to the significant heat output of the equipment, which runs frequently and releases nearly all of its energy as heat

Figure 3.(3): computer

Figure 3.(4): Laboratory mixer

Figure 3.(5): Mortar mixer

Figure 3.(6): laboratory drying oven

Figure 3.(7): grinding machine

Figure 3.(8):compressive testing machine

B)- Scenario 2

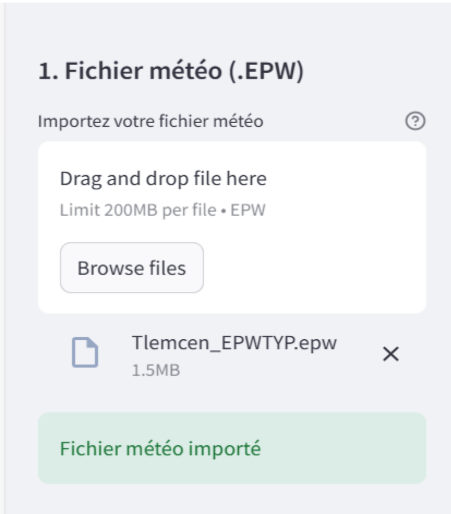
In this scenario, the space is conditioned using an LG S09EQ.NSJ air conditioning unit. Similar to Scenario 1, two cases were analyzed however, in this scenario, the only change is the type of air conditioner used.

LG S09EQ.NSJ air conditioning unit:

cooling capacity	3.52 kW
COP	4.13

3.4 Configuration in the Platform

3.4.1 Importing the EPW File (Tlemcen_EPWTYP.epw)



The file is already saved on my device,I uploaded it.

3.4.2 Input of the Scenario 1

A)- Case 01

Filled with the results of the calculation from the previous section.

<u>**The graphs shown on the platform for this case**</u>

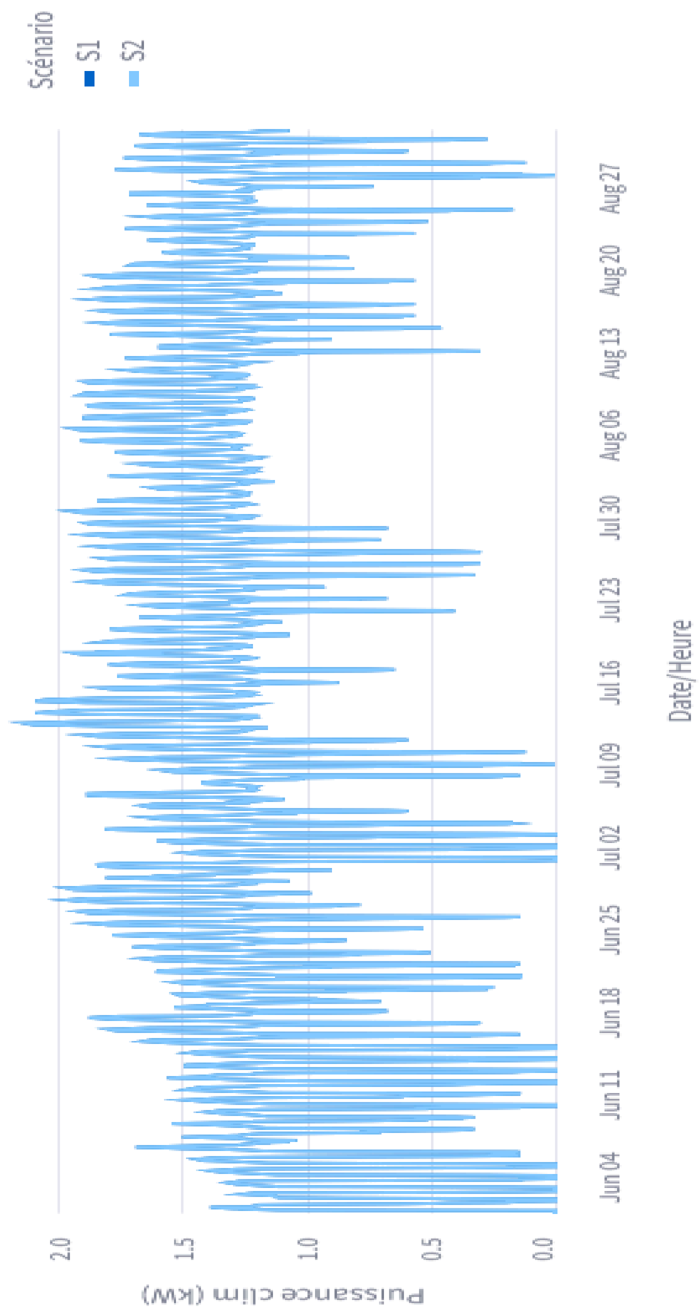


Chart 01

This graph represents the cooling power (KW) from June to August of the first case of the first scenario , where the cooling power demand increased significantly during summer .

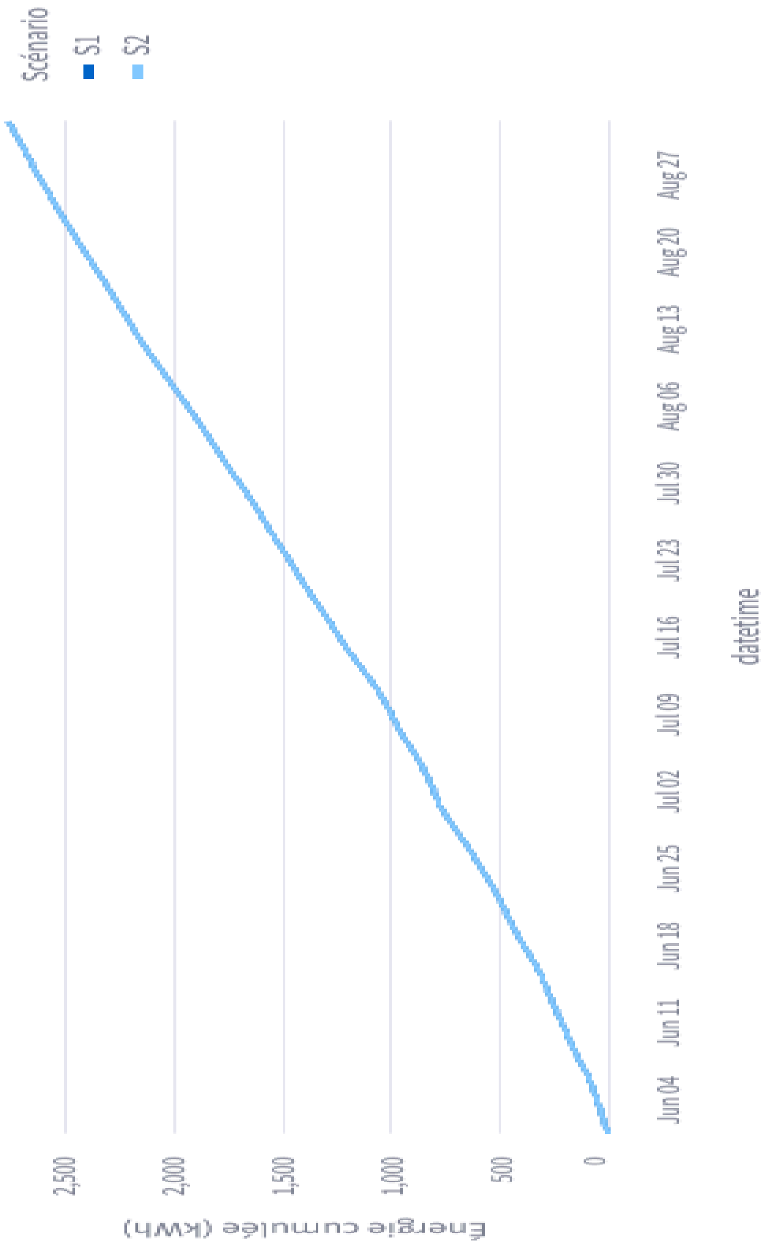


Chart 02

This graph represents the cumulative cooling energy consumption (Kwh) ; it indicate a continuous accumulation of energy from June to August .

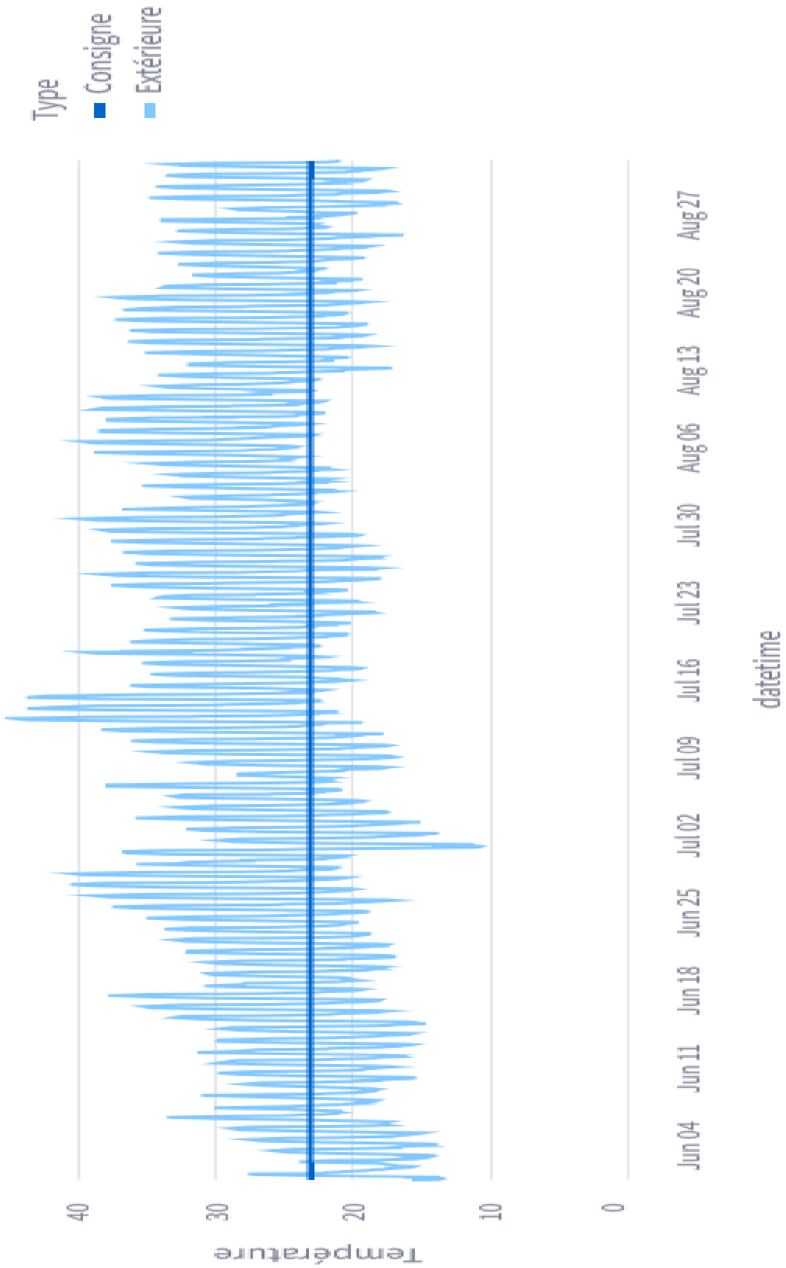


Chart 03

This graph illustrates the variation in outdoor temperature from June to August , compared to a fixed indoor temperature set at 23°C.

A)- Case 02

Filled with the results of the calculation from the previous section.

<u>The graphs shown on the platform for this case</u>

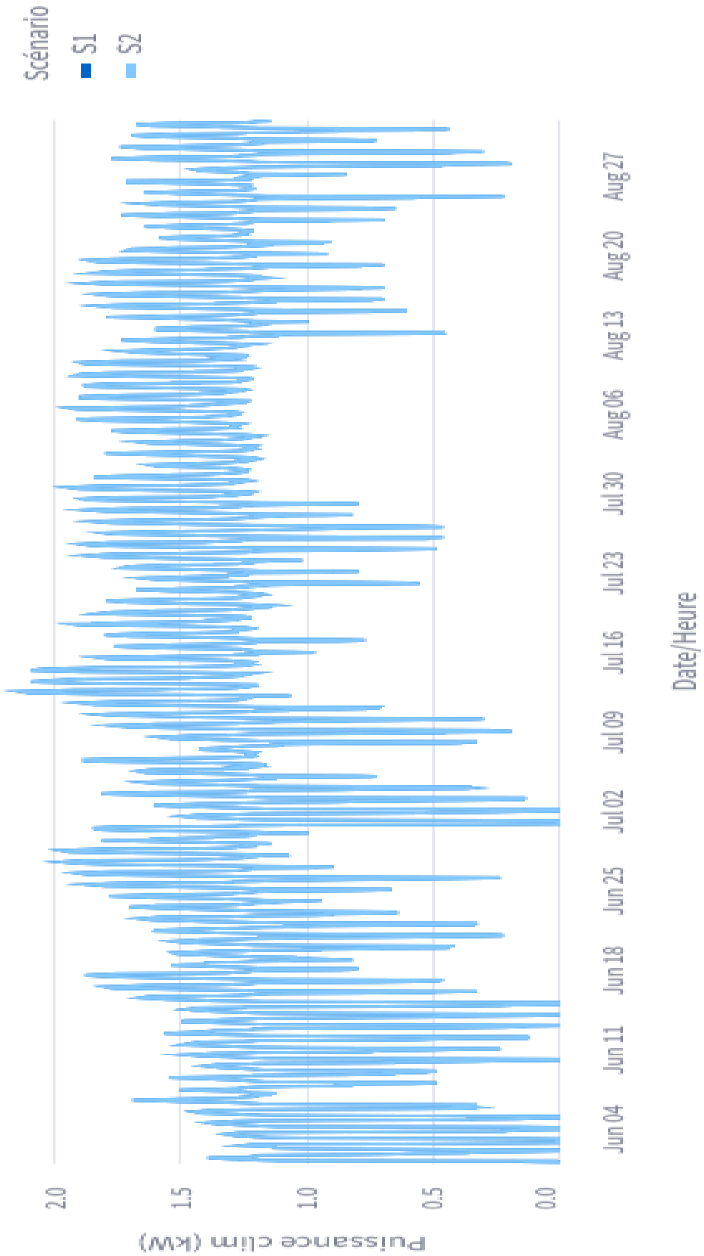


Chart 04

This graph shows the cooling power (KW) from June to August of the second case of the first scenario , where electrical power output is generally higher during summer.

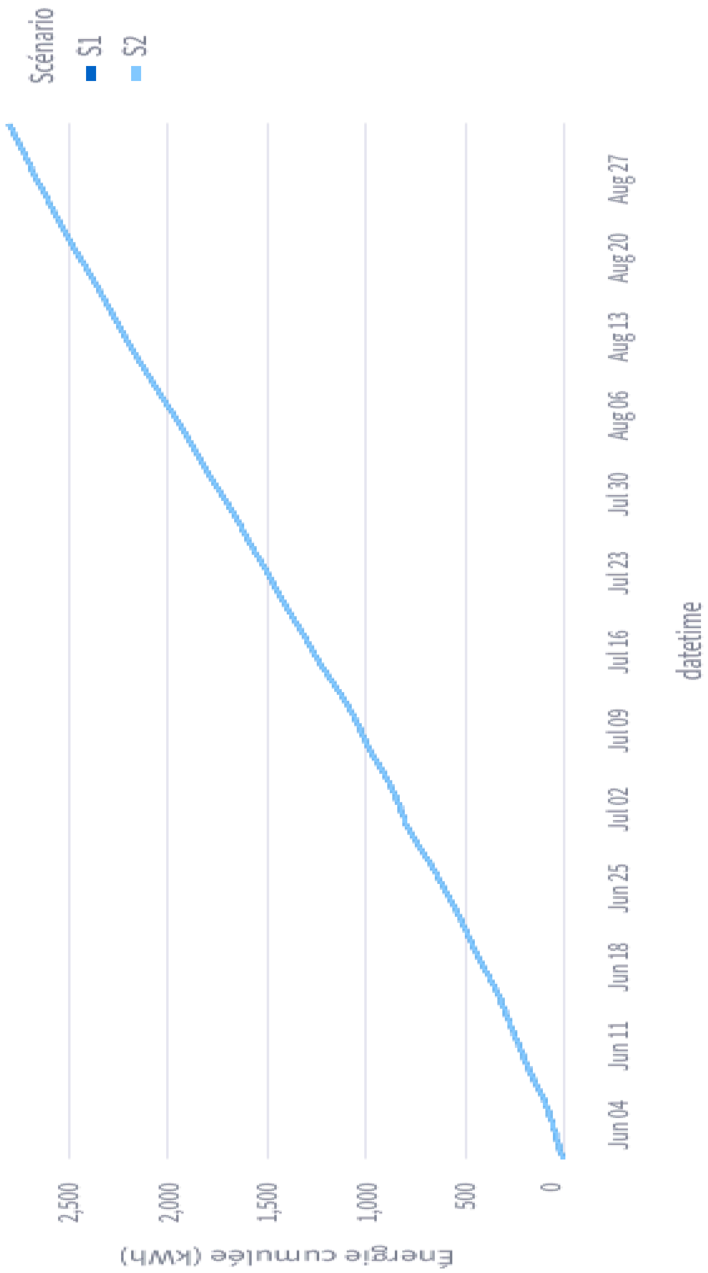


Chart 05

This graph represents the cumulative cooling energy consumption (Kwh) ; it indicate higher consumption during summer,

3.4.3 Input of the Scenario 2

A)- Case 01

Filled with the results of the calculation from the previous section.

The graphs shown on the platform for this case

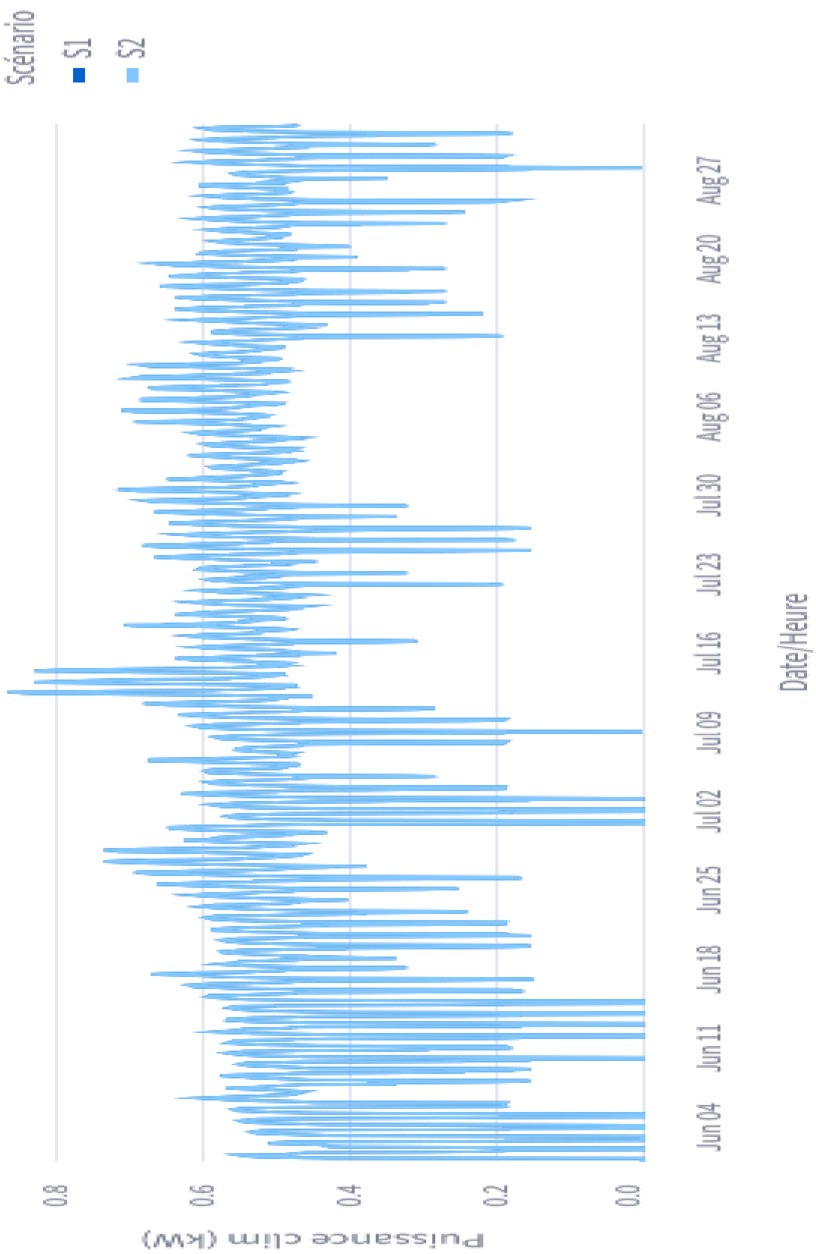


Chart 06

This graph represents the cooling power (KW) from June to August of the first case in the second scenario , where the cooling power demand increased significantly during summer, especially in July and August due to the higher outdoor temperature
.

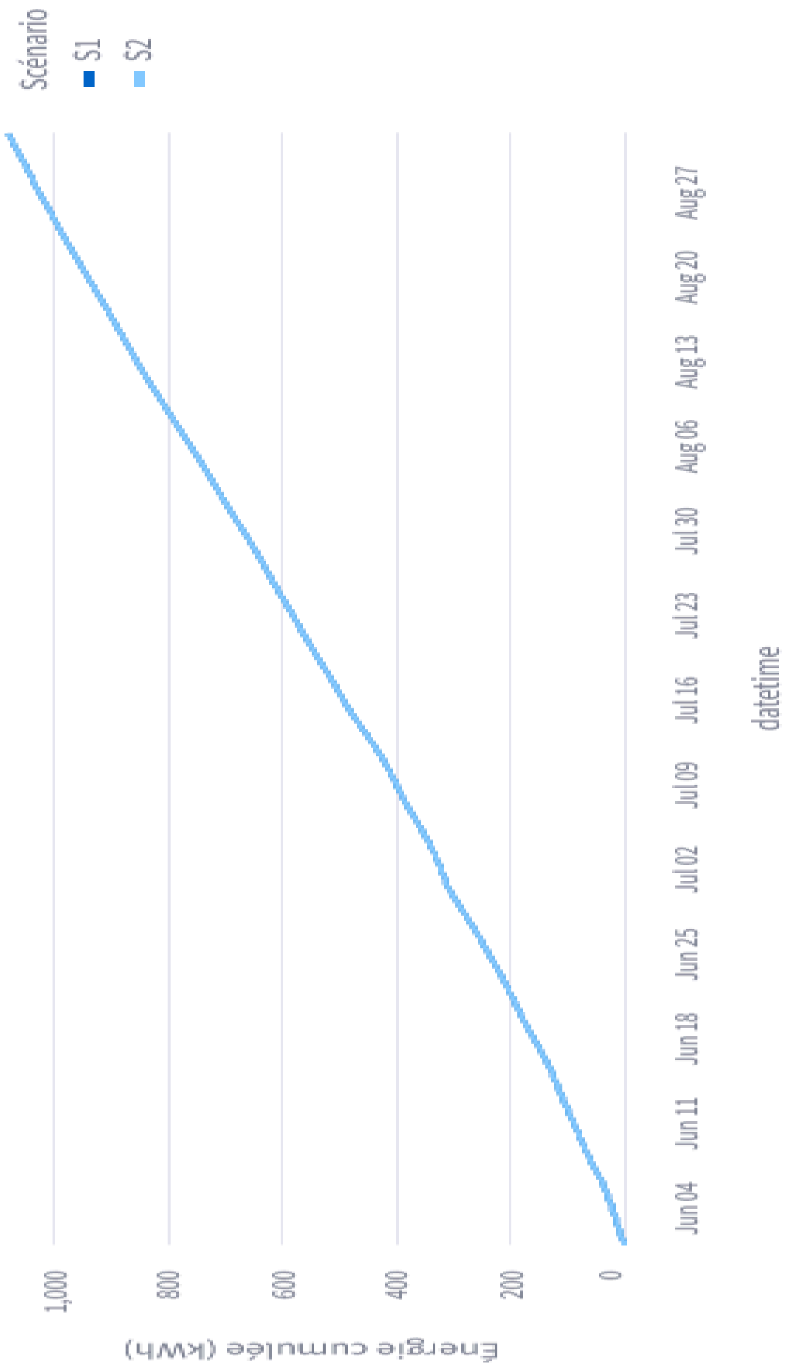


Chart 07

This graph represents the cumulative cooling energy consumption (Kwh) ; it indicate higher consumption during summer,

B)- Case 02

Filled with the results of the calculation from the previous section.

The graphs shown on the platform for this case

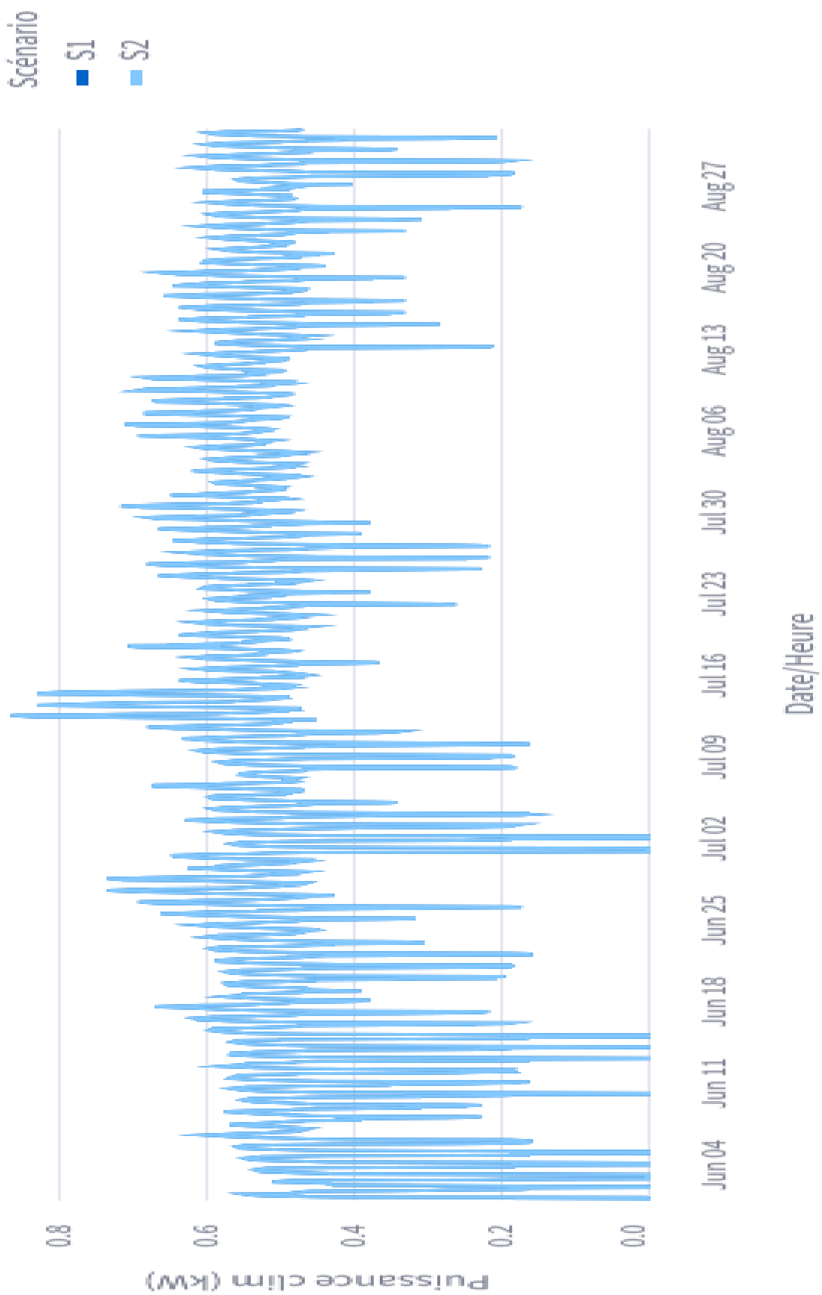


Chart 08

This graph represents the cooling power (KW) from June to August of the second case in the second scenario , where the cooling power demand increased significantly during summer, especially in July and August due to the higher outdoor temperature .

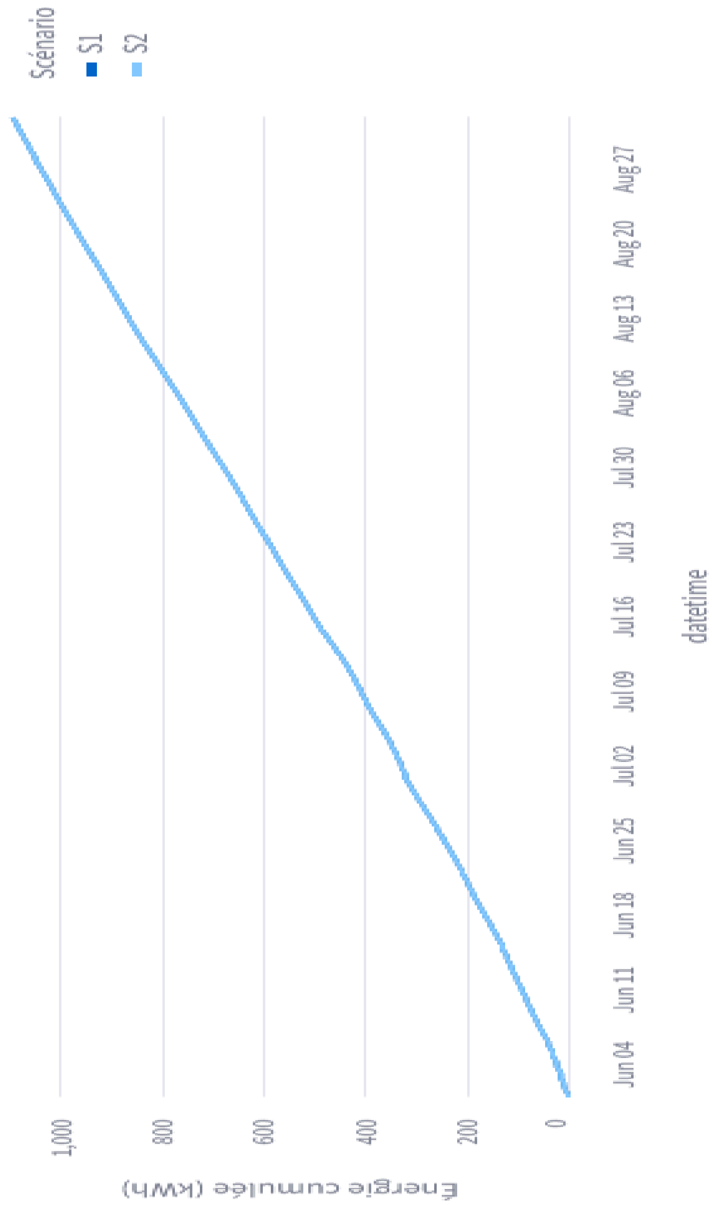


Chart 09

This graph represents the cumulative cooling energy consumption (Kwh) it indicate higher consumption during summer,

3.5 Results and Discussion

3.5.1 Comparative Charts (Power, Cumulative Energy)

A)- Scenario 1

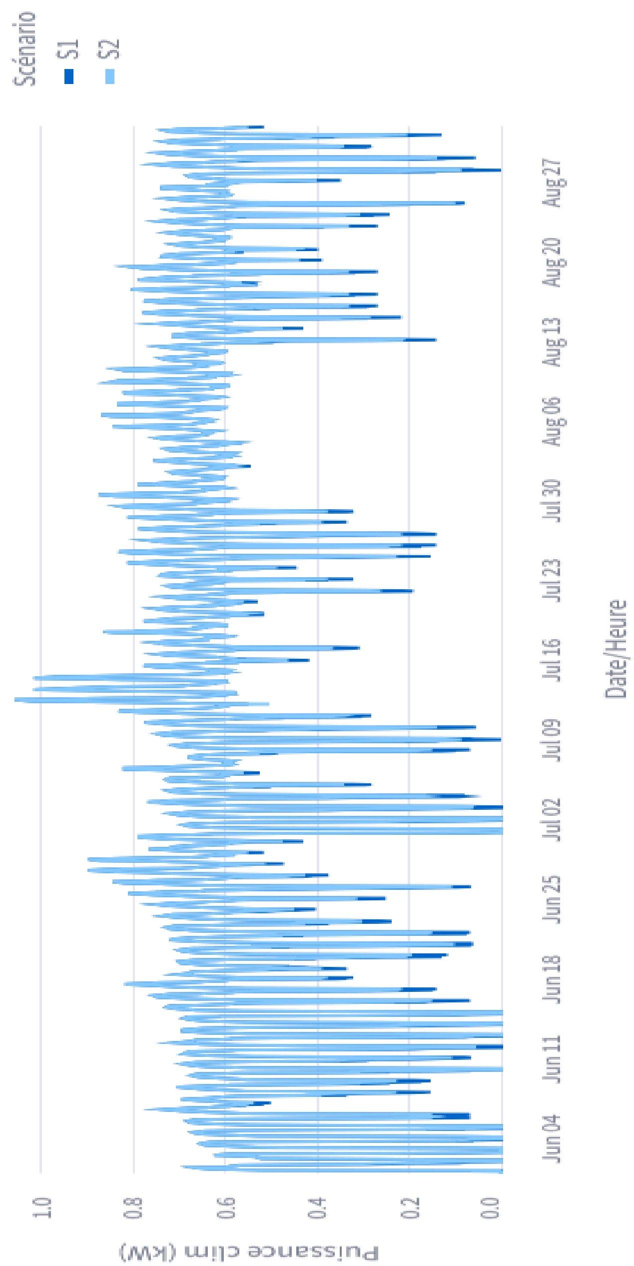


Chart 10

This graph represents the cooling power demand in the two cases of the first scenario. It is used to compare the cooling demand in both cases, where we used a Midea air conditioner with a cooling capacity of 3.22 kW.

Chart 11

This graph shows the cumulative cooling energy consumption of the two cases in the first scenario. In the first case, the energy consumption was approximately 2,755.5 kWh, while in the second case it increased to 2,795.3 kWh. This represents an increase of 39.8 kWh over the course of one year. According to the simulation platform, this corresponds to a change of -1.4%, indicating that instead of saving energy, the second case actually resulted in higher energy consumption despite the use of improved insulation.

B)- Scenario 2

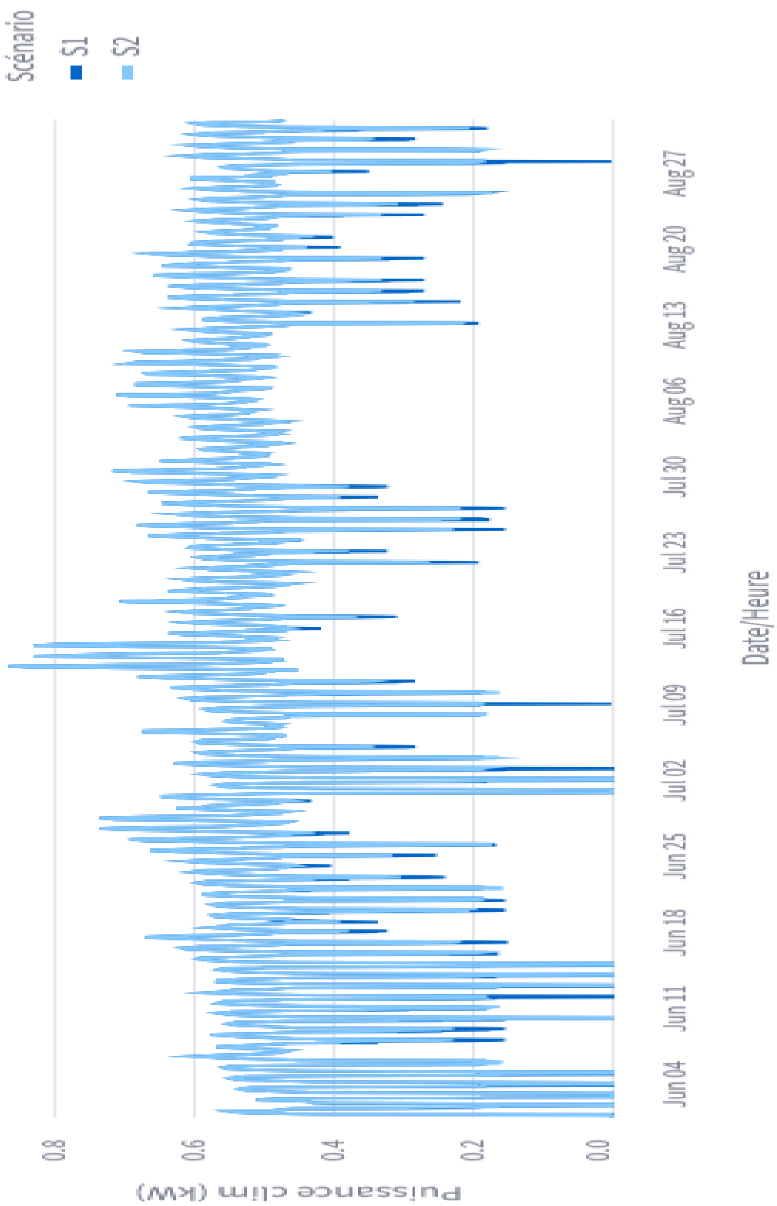


Chart 12

This graph represents the cooling power demand in the two cases of the second scenario. It is used to compare the cooling demand in both cases, where we used a LG air conditioner with a cooling capacity of 2.63 kW.

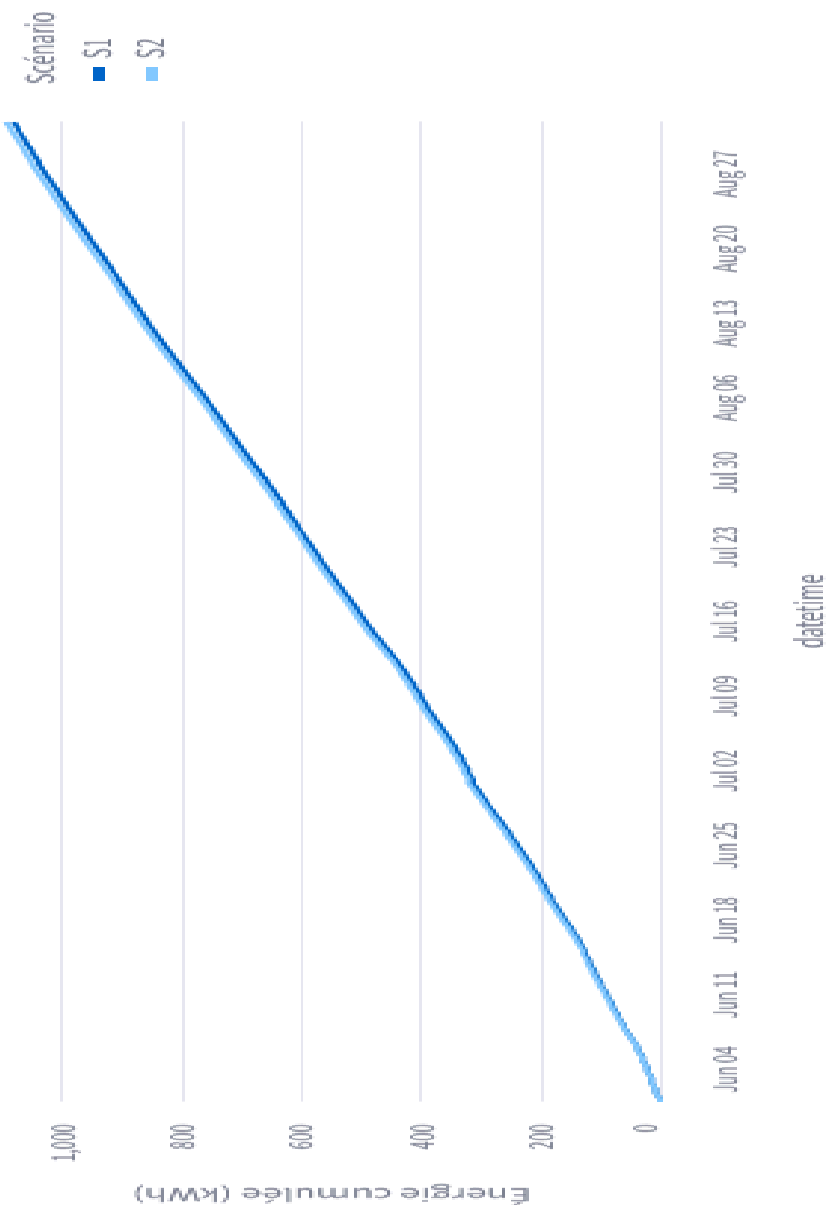


Chart 13

This graph shows the cumulative cooling energy consumption of the two cases in the second scenario. In the first case, the energy consumption was approximately 1,078.8 kWh, while in the second case it increased to 1,091.8 kWh. This represents an increase of 13 kWh over the course of one year. According to the simulation platform, this corresponds to a change of -1.2%, indicating that instead of achieving energy savings, the second case actually resulted in higher energy consumption despite the use of improved insulation and a more efficient air conditioner.

C)- Comparing the 2 scenarios

A comparison of the two scenarios reveals a consistent pattern in the cumulative cooling energy consumption results over the three-month simulation period. In the first scenario, the energy consumption in the first case was approximately 2,755.5 kWh, while in the second case it increased to 2,795.3 kWh, representing an increase of 39.8 kWh over three months. According to the simulation platform, this corresponds to a change of -1.4%, indicating that, contrary to expectations, the second case with improved insulation led to higher energy consumption. Similarly, in the second scenario, the first case consumed approximately 1,078.8 kWh, while the second case increased to 1,091.8 kWh, an increase of 13 kWh over three months. This result represents a change of -1.2%, again demonstrating that improved insulation and the use of a more efficient air conditioner did not yield the anticipated energy savings. These findings suggest that in both scenarios, other factors—such as high ventilation rates and internal heat gains may have offset the expected benefits of enhanced envelope performance and more efficient HVAC equipment. Such results underscore the complexity of achieving energy savings in practice and highlight the importance of holistic design strategies that consider the interactions among building envelope characteristics, HVAC system efficiency, and operational conditions.

3.5.2 Deviation Table (Δ kWh, Peak kW, % Savings)

A)- Scenario 1

Case 1	2755.5 (KWh)
Case 2	2795.3 (KWh)
Δ kWh	39.8 (KWh)
Peak	2.12 (KWh) July/12/2023 (case2)
% Savings	-1.4%

TABLE 3(13) : Deviation Table S1

B)- Scenario 2

Case 1	1078.8 (KWh)
Case 2	1091.8 (KWh)
Δ kWh	13(KWh)
Peak	0.861 (KWh) July/12/2023(case2)
% Savings	-1.2%

TABLE 3(14): Deviation Table S2

3.5.3 Impact on Comfort (Temperature/Interior)

The Impact on Comfort (Temperature/Interior) Indicates how changes in temperature and solar energy and how well that energy is controlled affects how comfortable the indoor environment feels for occupants. Based on the graphs presented before . a high energy and power levels can make indoor spaces uncomfortable and warm if there isn't good ventilation or cooling in place, especially in summer .

The solar energy is inconsistent and may cause indoor spaces to feel cold, especially without good insulation or heating, especially in winter .

3.5.4 AI DeepSeek Commentary and Critical Analysis

A)- Scenario 1

1. Comparison of consumption
   Case 1: Medium insulation, low-performance glazing, high ventilation rate, high internal loads → 2,755.5 kWh/year.
   Case 2: High insulation, high-performance glazing, high ventilation rate, high internal loads → 2,795.3 kWh/year.
   Result: Case 2 consumes 1.4% more than case 1, which is counterintuitive given its better insulation and glazing.

2. Technical reasons for the difference
   Several factors can explain this difference:

- High ventilation rate: In both cases, the ventilation rate is high, which increases thermal losses through air renewal, partially offsetting the benefits of improved insulation.

- High internal loads: Internal gains (equipment, occupants) are identical, but in cese 2, better insulation reduces heat losses, which can raise indoor temperatures and thus increase cooling demand.

B)- Scenario 2

1. Comparison of energy consumption
   Case 1 (medium insulation, low-performance glazing, high ventilation rate, high internal loads): 1,078.8 kWh/year
   Case 2 (high insulation, high-performance glazing, high ventilation rate, high internal loads): 1,091.8 kWh/year
   Difference: +13 kWh/year (+1.2%), which is counterintuitive since Scenario 2 has better insulation and glazing.

2. Technical reasons for the difference
   Several factors can explain this difference:

Effect of high ventilation rate:

- High ventilation increases thermal losses in summer (hot air entering) despite better insulation.

- If the ventilation system is not equipped with a heat recovery unit (dual-flow system), the benefits of improved insulation are offset by the infiltration of hot air.

3.6 Conclusion

In conclusion, the results of the simulations demonstrate that improving the building envelope through better insulation and glazing can contribute to reducing cooling energy demand. However, the efficiency of the air conditioning system remains a critical factor in overall energy performance. Even with good insulation, the use of an air conditioner with a low coefficient of performance (COP) leads to high energy consumption.

Our analysis clearly shows that switching to a more efficient inverter-type air conditioner significantly reduces energy use. In both cases studied, despite having the same insulation characteristics, the use of a high-efficiency air conditioner resulted in substantial energy savings. This highlights the importance of combining envelope improvements with the selection of energy-efficient HVAC systems to optimize building performance and reduce operational costs.

General Conclusion

This research investigated the effects of insulation quality, window glazing performance, and air conditioning system efficiency on cooling energy consumption in an indoor environment. The simulation results demonstrated that improving insulation and glazing can reduce overall energy demand. Moreover, employing a high-performance air conditioner particularly an inverter unit with a high Coefficient of Performance (COP) had an even more significant impact on energy savings. Notably, even when insulation levels were held constant, substantial reductions in energy consumption were achieved simply by upgrading to a more efficient air conditioning unit.

Additionally, the use of an AI-powered simulation platform proved highly valuable, as it not only automated the analysis of raw data but also provided meaningful interpretation of the results. This highlights the growing potential of artificial intelligence in building performance diagnostics, offering faster, more accurate, and scalable energy analyses. While this study relied on fixed assumptions, such as constant ventilation rates and internal loads, future work could incorporate variable occupancy patterns, dynamic ventilation strategies, seasonal shading effects, and renewable energy integration. Further advancing the use of AI-driven tools may also enable real-time optimization and predictive control, making them essential components of future sustainable building design.

Appendices

Air conditioner technical data sheet

Midea MSAGB-12HRN1-Q (S1) : (https://www.mbsm.pro/50561.html)

Mono-Split

UNITÉ				9K
UNITÉ INTÉRIEURE				S09EQ.NSJ
Puissance restituée	Froid	Min. / Nom. / Max.	W	890 / 2500 / 3700
	Chaud +7°C	Min. / Nom. / Max.	W	890 / 3300 / 5000
	Chaud -7°C	Nom.	W	2600
Puissance absorbée	Froid	Nom.	W	656
	Chaud -7°C	Nom.	W	800
EER			W/W	3,81
S.E.E.R.				7,0
P design F			kW	2,5
COP			W/W	4,13
S.C.O.P.				4,0
P design C			kW	2,5
Classe énergétique (de A+++ à D)	Froid			A++
	Chaud			A+
Consommation énergétique annuelle	Froid		kWh	125
	Chaud		kWh	875
Pression sonore (à 1m)	Froid	MN/PV/MV/GV*	dBA	19 / 27 / 35 / 41
	Chaud	PV/MV/GV*	dBA	27 / 35 / 41
Puissance sonore	Froid	GV*	dBA	59
Débit d'air	Froid	MN/PV/MV*	m^3/h	180 / 252 / 450 / 600
		Max.	m^3/h	750
	Chaud	MN/PV/MV*	m^3/h	336 / 432 / 600
Déshumidification			l/h	1,1
Intensité absorbée	Froid	Nom./ Max.	A	3,3 / 6,0
	Chaud	Nom./ Max.	A	4,0 / 7,0
Alimentation			Ø/V/Hz	1 / 220-240 / 50
Dimensions		L x H x P	mm	837 x 308 x 189
Poids net			kg	8,7

LG S09EQ.NSJ (S2): (LG website)

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