Smart Digital Twin for Energy Efficiency in Buildings Using BIM, IoT and AI: Case Study of Villa in Morocco

Fatima Zahra Saaidi[1,*], *Abderrahim* Boulanouar[2], *Yves* Géraud[3], and *Abdelaali* Rahmouni[1]

[1]Laboratory of Solid State Physics, Department of Physics, Faculty of Science Dhar El Mahraz, Sidi Mohamed Ben Abdellah University, Fez, Morocco
[2]National School of Applied Sciences, Abdelmalek Essaadi University, Al Hoceima, Morocco
[3]ENSG, UMR 7359-GeoRessources, University of Lorraine, Nancy, France

Abstract. This work outlines the creation of an intelligent digital twin for residential Villa that integrates Building Information Modeling (BIM), the Internet of Things (IoT), and Artificial Intelligence (AI) to improve building energy efficiency. A comprehensive 3D model was developed using Revit 2024.3, allowing for solar and energy simulations through Insight and DesignBuilder. Real-time environmental data,such as temperature, humidity, lighting, and occupancy, were gathered via IoT sensors and analyzed using machine learning algorithms to forecast energy consumption patterns and identify anomalies.
Based on these insights, automated control strategies for HVAC and lighting systems were implemented to enhance comfort and reduce energy waste. The proposed framework offers a dynamic, scalable, and regulation-compliant solution for smart energy management in Moroccan buildings. Overall, the developed digital twin showcases the practical potential of integrating BIM, IoT, and AI to achieve sustainable and autonomous building operations.

Keywords: BIM, IoT, Artificial Intelligence, Energy Efficiency, Digital Twin, Revit Insight, Smart Buildings..

1 Introduction

The building sector is among the most energy-intensive worldwide, contributing significantly to global greenhouse gas emissions. According to Aguiar-Castro et al. [1, 2], residential and commercial buildings account for nearly 40% of total energy consumption. This alarming figure has increased the need for innovative approaches to energy management.

Building Information Modeling (BIM) is widely recognized as an effective tool for improving building performance throughout its lifecycle [3, 4]. When combined with the Internet of Things (IoT) and Artificial Intelligence (AI), BIM enables the creation of digital twins capable of simulating, monitoring, and optimizing energy use in real time[5] .

In Morocco, the implementation of the Réglementation Thermique de Construction au Maroc (RTCM) reflects the country's commitment to improving energy efficiency in the building sector. However, most existing buildings still lack integrated smart systems capable of dynamic energy optimization.

This research proposes a novel framework that combines BIM, IoT, and AI to develop a smart digital twin for Villa . The system enables real-time monitoring, predictive energy

*Corresponding author : fatimazahrae.saaidi1@gmail.com

modeling, and automated optimization, offering a scalable solution adapted to Moroccan climatic and regulatory contexts.

2 Methodology

2.1 Case Study and Digital Building Modeling

The proposed framework was implemented in a residential villa located in Meknès, Morocco (climate zone 3 according to RTCM [7]), characterized by hot, dry summers and relatively cold winters. The villa has a total area of 321 m² distributed over two levels, with the main façade oriented south to maximize passive solar gains, while the west façade faces potential overheating during summer.

A 3D BIM model was developed using Autodesk Revit 2024.3, defining the main architectural and thermal elements (walls, openings, roof, and floors). A multilayer wall approach [8] was adopted to represent the thermal behavior of the envelope, and thermal zones were defined according to functional spaces. This model formed the basis for solar and energy simulations carried out with Autodesk Insight and DesignBuilder. The generated 3D model is shown in Figure 1.

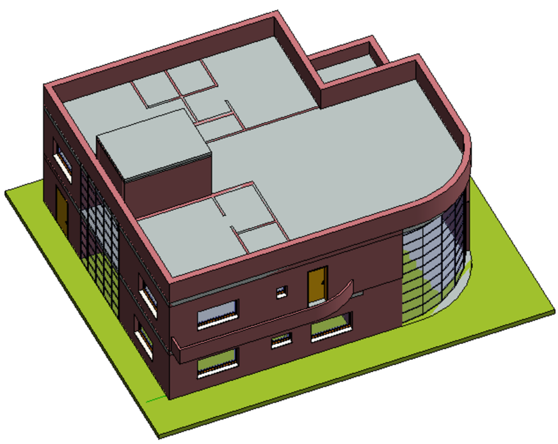

Figure 1. 3D BIM model of Villa generated in Revit

2.2 Energy and Solar Simulations

The BIM model of Villa was exported from Revit 2024.3 to Autodesk Insight 360 and DesignBuilder to assess solar and energy performance through a BIM-to-BEM workflow [8]. The model was converted to gbXML format to maintain geometric and thermal consistency during data exchange.

Two analyses were conducted:

- **Solar analysis:** for the summer (June 21) and winter (December 21) solstices to evaluate orientation and seasonal effects on solar gains.
- **Energy simulations:** to estimate heating, cooling, and lighting demands, total energy use, and CO_2 emissions.

A Dynamic Thermal Simulation (DTS) using DesignBuilder and the EnergyPlus engine evaluated thermal behavior under local climate conditions of Meknès. This workflow ensured accurate interoperability and reliable performance assessment, establishing a baseline scenario later compared with IoT- and AI-based optimizations within the digital twin framework.

Both Insight 360 and DesignBuilder were used to assess the villa's energy performance. Insight 360 provided a quick preliminary evaluation, while DesignBuilder offered detailed dynamic simulations with EnergyPlus for accurate assessment of energy efficiency strategies. This dual-tool approach was adopted to ensure result validation and to benefit from both the conceptual speed of Insight and the detailed dynamic accuracy of DesignBuilder. This combination enabled cross-validation of results and established a reliable baseline for further optimizations.

2.3 Integration of IoT and AI for Intelligent Energy Management

The proposed IoT-based system adopts a four-layer architecture ensuring interoperability and scalability within the digital twin framework .

- **Perception layer:**gathers real-time data (temperature, humidity, occupancy, CO_2 , lighting) through sensors and actuators connected to HVAC and lighting systems.
- **Network layer:** supports wireless communication (Wi-Fi, ZigBee),
- **Processing layer:** manages cloud-based data and applies machine learning (ML) algorithms.
- **Application layer:** enables real-time monitoring, prediction, and automated control [9].

IoT data were preprocessed and used to train Linear Regression, Random Forest, and XGBoost models [10] to predict energy consumption and detect anomalies. The ensemble models, especially Random Forest and XGBoost, efficiently identified abnormal patterns (e.g., HVAC operation without occupancy), enabling predictive maintenance and optimization [11].

The trained AI models were integrated into the BIM environment (Revit Insight) to create a functional digital twin of Villa , supporting real-time visualization and adaptive control. The combined IoT–AI–BIM framework provides a dynamic and intelligent approach to smart energy management and improved building performance [12].

3 Results and discussion

3.1 Solar Simulation as Baseline Analysis

A solar simulation was conducted for the case study villa to assess the effect of orientation and seasonal variations on solar exposure. Two representative dates were selected: June 21 (summer solstice) and December 21 (winter solstice), with hourly analysis from 08:00 to 18:00. The objective was to visualize how the solar radiation varies throughout the year and to identify the most and least exposed areas of the building envelope. Figures 2 and 3 illustrate the solar exposure distribution for these two key dates.

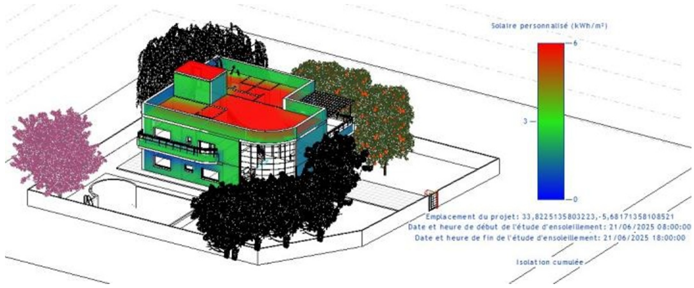

Figure 2. Solar exposure map on June 21 (summer solstice) The colors visible on the 3D model illustrate the impact of solar radiation : red = High solar exposure ; Green = Moderate exposure ; Blue = Very low or no exposure

The scale on the right of the figure shows insolation values ranging from 0 to 6 kWh/m² . During summer (Figure 2), the analysis indicates that the flat roof and the south-west façades receive the highest levels of solar radiation, as shown by the red areas. These unshaded zones are particularly exposed to direct sunlight throughout the day, heightening the risk of overheating and increasing cooling loads. The green to blue areas represent shaded regions, including façades beneath roof overhangs or those partially obstructed by nearby vegetation.

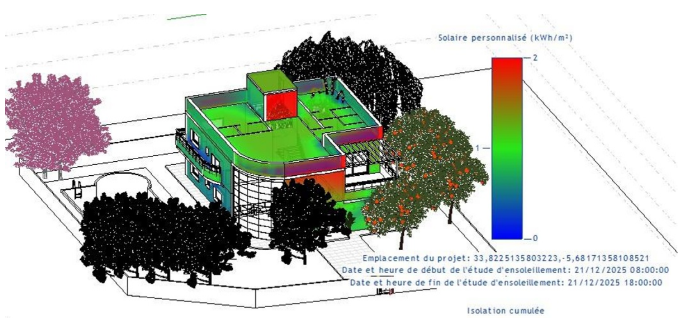

Figure 3. Solar exposure map on December 21 (winter solstice) The colors visible on the 3D model illustrate the impact of solar radiation : red = High solar exposure ; Green= Moderate exposure ; Blue= Very low or no exposure

The scale on the right of the figure indicates insolation values ranging from 0 to 2 kWh/m².
In winter (Figure 3), solar exposure is significantly reduced, particularly on the northern façades which stay shaded for most of the day. However, the southern façade benefits from passive solar gains, helping to reduce heating needs during the colder season. The variation in sunlight distribution demonstrates the seasonal shift in solar performance.

These results underscore the dual impact of solar exposure on building performance: it aids heating in winter while increasing cooling demand in summer. This variation significantly influences indoor comfort, emphasizing the need for intelligent IoT- and AI-based control strategies to optimize solar gains throughout the year.

3.2 Energy Simulation with Revit Insight

The initial energy analysis of Villa was conducted using Autodesk Revit Insight 2024.3 to assess the building's energy performance and carbon footprint over a 20-year operational period. The simulation offered a detailed overview of energy consumption, end-use distribution, and carbon emissions.The results revealed an annual Energy Use Intensity (EUI) of 200.99 kWh/m²/year, which is relatively high for a residential building. This finding confirms the significant impact of cooling demand, driven by the hot climatic conditions of the Meknès region (Zone Z3). Figure 4 summarizes the energy and carbon indicators derived from Insight, while Table 1 outlines the distribution of consumption by end use. Cooling accounts for the largest share, while heating demand is minimal, aligning with the regional climate profile.

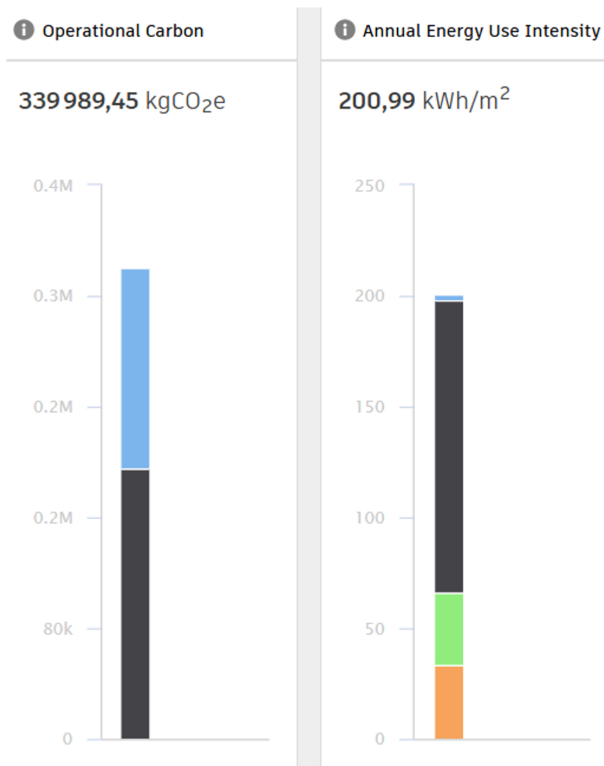

Figure 4. Carbon footprint and energy consumption results from Revit Insight.

Table 1. Energy consumption breakdown from Revit Insight.

End-use	Consumption (kWh/m²/year)
Cooling	132.07
Lighting	33.05
Equipment	33.05
Heating	2.83

The estimated operational carbon footprint over 20 years is approximately 339,989 $kgCO_2e$, which constitutes nearly 90% of the total carbon impact. These findings highlight the building's reliance on fossil fuel-based energy sources and emphasize the necessity of integrating energy efficiency strategies, renewable energy systems, and intelligent control mechanisms to mitigate cooling demand and lower operational emissions.

3.3 Energy Simulation with DesignBuilder

To enhance the baseline results from Revit Insight, a dynamic thermal simulation was performed using DesignBuilder, powered by the EnergyPlus engine. Unlike the conceptual assumptions of Insight, this simulation incorporated detailed weather, envelope, and occupancy data specific to Meknès (Zone Z3).

The findings revealed an annual on-site energy consumption of 18,461.29 kWh (75.84 kWh/m²·year), while the source energy reached 204.90 kWh/m²·year, accounting for production and distribution losses. Table 2 summarizes these results, illustrates the distribution of heating and cooling loads. The heating demand was estimated at 6,466.98 kWh (22.1 kWh/m².year), whereas the cooling load was 6,070.79 kWh (20.7 kWh/m².year). Cooling loads were the predominant factor due to the region's hot climatic conditions, confirming the impact of seasonal variations on energy demand.

Overall, the dynamic simulation validated that DesignBuilder offers more realistic and detailed results compared to Insight, particularly for cooling analysis in warm climates.

Table 2. Annual energy consumption results from DesignBuilder.

Indicator	Value
On-site consumption	18,461.29 kWh (75.84 kWh/m².year)
Source consumption	49,878.12 kWh (204.90 kWh/m².year)
Heating load	6,466.98 kWh (22.1 kWh/m².year)
Cooling load	6,070.79 kWh (20.7 kWh/m².year)

3.4 Comparison between Revit Insight and DesignBuilder

A comparison was conducted between the conceptual analysis from Revit Insight and the dynamic simulation from DesignBuilder to assess differences in predicted energy performance. Table 3 summarizes the key indicators. The results indicate that Revit Insight tends to overestimate energy consumption and cooling demand due to its simplified assumptions, whereas DesignBuilder, utilizing detailed local inputs and dynamic calculations, offers more accurate results reflective of Meknès' climatic conditions.

Table 3. Comparison between Insight and DesignBuilder results.

Indicator	Revit Insight	DesignBuilder
EUI (kWh/m²/year)	200.99	75.84
Cooling demand	132.07	20.7
Heating demand	2.83	22.1
Type of simulation	Conceptual (default inputs)	Dynamic (real data)

3.5 Smart Energy Management Scenarios

Energy simulations indicated that cooling and lighting are the most energy-intensive uses in Villa , with heating demand being minimal. In response to these findings, two AI-assisted optimization scenarios were implemented within the BIM–IoT framework.

Scenario 1: Smart HVAC Optimization : AI algorithms utilized real-time data on temperature, humidity, and occupancy to dynamically adjust HVAC setpoints. This strategy reduced unnecessary cooling during unoccupied periods, enhancing thermal comfort while conserving energy.

Scenario 2: Smart Lighting Control: Light and occupancy sensors facilitated adaptive regulation of blinds and lighting intensity based on daylight availability. This approach minimized lighting energy consumption without sacrificing visual comfort.

Together, these scenarios illustrate how integrating BIM, IoT, and AI transforms static energy models into a dynamic, responsive management system, leading to predictive and user-centered building control.

3.6 Digital Twin Framework

IoT sensors in Villa (temperature, humidity, occupancy, air quality) send real-time data via MQTT to a cloud platform, where it is processed and synchronized with the BIM model. Machine learning algorithms update the digital twin with predictions of energy use and thermal comfort, enabling proactive control of HVAC and lighting.

The two-way communication between the physical villa and its virtual counterpart provides actionable insights, ensuring both comfort and energy savings. Beyond operations, the framework also supports proactive maintenance and contributes to future energy-efficient building design (Figure 5).

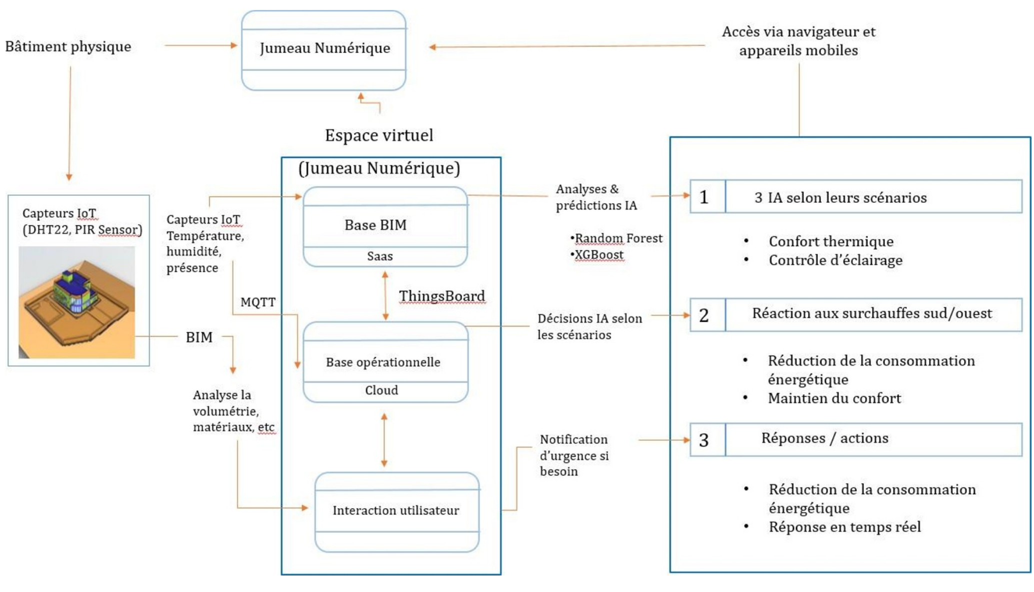

Figure 5. Development of an IoT–AI–BIM-Based Digital Twin for Smart Energy Management of Villa.

4 Limitations of the Models Used

While the models and tools used in this study effectively assessed and optimized the building's energy performance, several limitations should be noted. The Revit Insight model is based on simplified assumptions and default input parameters, which can lead to an overestimation of energy consumption and do not fully represent the building's dynamic thermal behavior.

Similarly, although DesignBuilder provides more detailed and realistic simulations, it relies on static input data like occupancy schedules, user behavior, and standard weather scenarios, which may not accurately reflect actual operating conditions. Additionally, the Artificial Intelligence (AI) models employed for prediction and optimization require larger and longer-term datasets to improve their robustness, generalization capacity, and predictive accuracy.

5 Conclusion

This study detailed the development of an intelligent digital twin for a residential villa by integrating Building Information Modeling (BIM), the Internet of Things (IoT), and Artificial Intelligence (AI). The combined BIM–IoT–AI framework facilitated real-time monitoring, predictive analytics, and automated control, resulting in enhanced energy efficiency and user comfort.

Simulation results from Revit Insight and DesignBuilder indicated that cooling and lighting are the primary energy consumers in the villa, while heating demand is minimal. To tackle these issues, two smart control strategies were implemented:

An AI-driven HVAC optimization system utilizing temperature and occupancy data. An adaptive lighting control mechanism responsive to real-time illuminance levels. Overall, the proposed digital twin framework offers a practical pathway for achieving intelligent, energy-efficient, and sustainable building management within Morocco's climatic context. Future work will focus on scaling this approach to larger building stocks, integrating renewable energy sources, and employing advanced AI algorithms for predictive and adaptive energy optimization.

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