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BIM-Based Operation, Maintenance, and Energy-Saving Management Strategies in the Post-Occupancy Lifecycle of Digital Campus Teaching Buildings

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Abstract. The burgeoning digital campus demands efficient and sustainable operations of academic buildings. However, traditional O&M practices are often limited by fragmented data flows, delayed fault detection, and limited adaptability to dynamic usage scenarios. To overcome these limitations, this study introduces and validates a Building Information Modeling (BIM)-based O&M framework that integrates Internet of Things (IoT) sensing, energy consumption simulation, and predictive maintenance to support intelligent post-occupancy building management. The framework was deployed and evaluated throughout the lifecycle of a university academic building, using metrics including energy consumption, maintenance efficiency, and indoor comfort. Results demonstrate that, compared to traditional approaches, the BIM-driven approach enhances system responsiveness, improves environmental quality, and enables more proactive maintenance. These findings suggest that BIM-IoT integration has the potential to provide a robust and scalable solution for the sustainable development of digital campuses and provide a reference for the design of intelligent educational infrastructure.

Keywords: Building Information Modeling (BIM), digital campus, teaching building, operation and maintenance, energy efficiency, post-occupancy lifecycle

1 Introduction

Educational buildings account for a significant portion of energy consumption and maintenance expenditures on university campuses. As campuses continue to digitally transform, there's an urgent need to deploy intelligent, data-driven systems to ensure these buildings operate efficiently and optimize energy performance throughout their lifecycles [1]. Currently, many educational institutions still rely on traditional operations and maintenance practices, which are often based on fixed schedules, periodic inspections, and manual adjustments. These approaches lead to inefficiencies such as delayed detection of HVAC and lighting system faults, poor energy consumption control during occupancy fluctuations, and limited integration of building performance data into decision-making. Building Information Modeling (BIM), traditionally used for design and construction, has evolved into a powerful platform that can serve as a digital twin of a building [2]. This digital twin enables real-time visualization of operating conditions, automatic integration of IoT sensor data, predictive maintenance scheduling based on usage patterns, and dynamic energy optimization through integration with advanced simulation tools. While existing literature outlines the theoretical advantages of BIM-based facility management, its application in

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the actual operational context of educational buildings, particularly in the context of the emerging digital campus, remains underexplored [3]. Notably, there is a lack of long-term, empirically validated research examining the impact of BIM-IoT integration on the operations, maintenance, and energy performance of these facilities [4]. To address this shortcoming, this study proposed and implemented an integrated BIM-IoT platform for the post-operation, maintenance, and energy conservation management of university academic buildings. A 12-month field trial was conducted to evaluate the impact of this integrated platform on energy consumption, maintenance efficiency, and indoor environmental quality. The experimental results not only validated the feasibility of the approach but also demonstrated its effectiveness in improving the operational efficiency and sustainability of educational buildings. Furthermore, this study provides valuable, data-driven insights and scalable strategies that can guide the broader application of BIM-IoT platforms in sustainable campus management. This paper is divided into several sections. The introduction outlines the research background, identifies research gaps, and defines the research objectives. The literature review section summarizes research on BIM-based facility management, energy optimization in educational buildings, and IoT integration, highlighting the limitations of current approaches. The methods section details the experimental site, hardware and software configuration, data collection methods, and key performance indicators (KPIs). The results section reports the quantitative results of the field trial, including energy savings, improved maintenance efficiency, and enhanced occupant comfort. Furthermore, the results section discusses the significance of these results, compares them with related studies, analyzes implementation challenges, and provides recommendations for future research. The conclusion section summarizes the main contributions of this study and emphasizes the importance of BIM-based sustainable digital campus management strategies for the future development of higher education facilities. This study is divided into seven parts: Section 1 introduces the motivation for integrating BIM and IoT into campus building operations to improve energy efficiency, maintenance, and comfort; Section 2 reviews the literature on BIM standards, IoT integration, and energy modeling, highlighting gaps in empirical research on educational buildings; Section 3 outlines a layered BIM-IoT system design that enables closed-loop and visualization-driven management; Section 4 introduces a research framework for balancing energy use, comfort, and equipment health using a discrete-time state-space model; Section 5 details the hardware and software configuration of a digital twin with heterogeneous sensors, EKF fusion, and BIM-EnergyPlus coupling; Section 6 describes a 12-month experimental design with robust PID HVAC, smart lighting, predictive maintenance, and KPIs; Section 7 reports the results, showing reduced energy use, fewer unplanned maintenance events, improved comfort, and faster response times, and finally proposes future directions, including renewable energy integration and AI-driven multi-building optimization.

2 Literature Review

In the evolving landscape of built environment management, the integration of Building Information Modeling (BIM) into facility and energy management represents a paradigm shift towards more efficient, agile, and sustainable practices [5]. This literature review encapsulates the recent advancements and applications of BIM in facility management, emphasizing energy management in educational buildings and the pivotal role of IoT integration for real-time control. BIM's role in facility management is increasingly recognized for its potential to streamline operations and maintenance. The ISO 19650 series of standards provides an international framework for managing information including the delivery and operational phase of built assets [6]. Godager et al. [7] delve into deciphering ISO 19650 through process modeling, highlighting the challenges of adopting BIM standards and emphasizing the significance of clear communication among stakeholders. Similarly, Kurcjusz et al. [8] offer strategic insights into BIM-driven information management, referencing ISO 19650-2 to advocate for industry-wide transformations that reengineer tasks and information flows for greater compliance and efficiency. The application of BIM extends into predictive maintenance and operational efficiency, further exemplified by Luyan Li [9], who explore BIM's impact across project lifecycles with a focus on facility management. They stress the discrepancy between as-built BIM model data and stakeholder expectations, presenting solutions geared towards enhancing BIM utility for operations and management, particularly through the COBie dataset. Deru et al. [10] contribute to this discussion by detailing the development of standard-based information requirements for facility management within a canteen, underlining the importance of structured information models and compliance with standards like EN ISO 19650. This underscores the need for a systematic approach to tailor BIM data for effective facility management. Energy management in educational buildings is another domain where the intersection

of BIM and energy modeling tools, exemplified by EnergyPlus, is making significant strides. The research by Sesana et al. [11] provides a comprehensive case study on energy efficiency performance and retrofitting measures in university campus buildings, utilizing energy modeling for critical analysis. Their work showcases the potential for combining active and passive design strategies, leveraging BIM and EnergyPlus for simulation and evaluation. This aligns with the broader perspective of optimizing HVAC scheduling, demand-driven lighting control, and integration with energy modeling tools for enhanced energy management. The integration of IoT in real-time control systems represents the cutting-edge of building and energy management. Sensors and cloud-based platforms enable dynamic operations, adapting to real-time occupancy and environmental conditions for optimized energy use. The potential of BIM to be augmented with IoT for more sophisticated, real-time control and decision-making processes is highlighted by Louis and Dunston [12], who present a BIM-data mining integrated digital twin for lifecycle management. Their project, DATAWiSE, leverages AI for decision support in energy optimization and predictive maintenance, illustrating the convergence of BIM, IoT, and AI as a powerhouse for advancing operational efficiency and sustainability. In summary, the integration of BIM into facility and energy management is witnessing rapid evolution, bolstered by standards like ISO 19650 and COBie, and is further enhanced by the synergy with IoT and energy modeling tools. The selected literature provides a robust narrative that illustrates both the current state and potential future directions in leveraging BIM for efficient, sustainable, and intelligent building management and energy optimization in educational and other building types. Through strategic evaluation, application of standards, and integration with emerging technologies, BIM stands as a critical tool in the quest for enhanced operational performance and sustainability in the built environment. While the literature demonstrates significant progress in integrating BIM with facilities and energy management, several gaps remain. These include a primary focus on single-building applications rather than scalable multi-building or campus-wide frameworks; inconsistent adoption of standards such as ISO 19650 and COBie by different stakeholders; and early integration of BIM with IoT systems, which is often limited to pilot projects or subsystems. Furthermore, the convergence of BIM, IoT, and AI-driven analytics for predictive maintenance and energy optimization remains underexplored, particularly in educational settings where sustainability and occupant comfort must be balanced. Therefore, future research should prioritize AI-based multi-building optimization, integration with renewable energy microgrids and energy storage systems, and interdisciplinary approaches to address technical and organizational challenges, thereby advancing BIM-based digital twins as intelligent, resilient, and sustainable solutions for campus- and city-scale environments.

3 Methodology

The overall BIM design for the teaching building's operations and maintenance management utilizes a bottom-up, layered architecture encompassing data source, transmission, storage, and presentation layers, forming a complete information flow chain. The data source layer incorporates 3D BIM models, sensors, video surveillance, and intelligent hardware, ensuring comprehensive collection of building lifecycle information and real-time operational status. The data storage layer utilizes network protocols, communication interfaces, and security mechanisms to efficiently transmit multi-source, heterogeneous data, ensuring real-time and reliable information exchange. The data storage layer utilizes a database management system to model, cleanse, and centrally store collected data, supplemented by security protection and access control to enhance data integrity and availability. The data presentation layer transforms complex data into intuitive graphical information through large-scale operations and maintenance displays, 3D visualization, real-time alerts, and a mobile interface, facilitating rapid decision-making and efficient management for operations and maintenance personnel. The core advantage of this integrated design lies in its closed-loop management of the entire process, from data collection and transmission to storage and presentation, enabling information integration and visualization for building operations and maintenance. This layered design not only ensures data security and consistency but also enhances the intelligence of operations and maintenance management, providing strong support for energy conservation, emission reduction, fault prediction, and safety monitoring in the teaching building. Combined with the system architecture shown in Fig. 1, the logical relationship and information interaction path between each layer are clearly demonstrated, further highlighting the core role of BIM in operation and maintenance management.

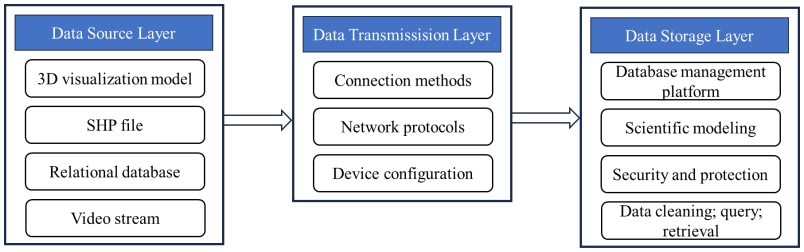

Fig. 1. Intelligent O&M infrastructure of teaching buildings, illustrating the layered architecture

3.1 Research Framework

The BIM-IoT integration framework is envisioned as a closed-loop cyber-physical system that continuously cycles data and decisions through four phases, enabling continuous monitoring, feedback, and adaptive optimization of building operations [13]. In this loop, multi-source sensors transmit raw data to a BIM-based digital twin model, which maintains curated geometric/semantic information and provides a consistent state for downstream analysis; simulators based on physical information and/or calibrated surrogate models generate short-term predictions; monitoring controllers calculate optimal set points; and device-level regulators execute these set points and sense the resulting building responses, forming a closed loop that enables the system to track performance targets, compensate for deviations, and adapt to changing internal/external conditions, thereby maintaining energy efficiency, comfort, and equipment reliability over the long term [14]. A compact discrete-time model can capture these dynamics:

$$x(t+1) = Ax(t) + Bu(t) + Gd(t) + w(t) \tag{1}$$

Where $x(t)$ represents the building state vector, $u(t)$ is the control input, $d(t)$ represents external disturbances such as occupancy or outdoor weather, and $w(t)$ denotes random process noise.

The main goal of the framework is to minimize a composite objective function that balances energy consumption, occupant comfort, and equipment health:

$$J = \int_0^T (\alpha E(t) + \beta C_{dis}(t) + \gamma M_{deg}(t))dt \tag{2}$$

Where $E(t)$ denotes instantaneous energy use, $C_{dis}(t)$ represents the discomfort index, and $M_{deg}(t)$ is a degradation metric reflecting maintenance requirements. Weighting factors can be flexibly prioritized based on management objectives, allowing the system to be tailored to specific operational goals [15]. For example, building managers might prioritize energy efficiency, assigning greater weight to energy use; alternatively, they might prioritize occupant comfort, placing greater emphasis on discomfort. This flexibility ensures that the BIM-IoT system can be tailored to the specific needs of building stakeholders, whether it's improving sustainability, reducing operating costs, or enhancing occupant satisfaction. Essentially, this framework is a powerful tool for making data-driven, real-time decisions to optimize a building's energy performance, enhance occupant comfort, and extend the lifespan of building equipment, thereby ensuring a more sustainable, efficient, and user-friendly environment. By integrating IoT sensors with BIM, the framework can also facilitate predictive maintenance, identifying potential issues before they escalate into costly repairs, further optimizing overall building management processes.

3.2 Hardware and Software Configuration

In order to accurately capture the real-time operating conditions, a heterogeneous sensor network is deployed in the teaching building. The network consists of DHT22 modules [16] for measuring indoor temperature and

humidity, non-dispersive infrared (NDIR) sensors for monitoring carbon dioxide concentration, passive infrared (PIR) counters for estimating occupancy and density, and smart meters for tracking circuit or device-level power consumption. The integration of these devices provides a comprehensive view of the indoor environment, covering thermal comfort, indoor air quality, occupancy-driven loads, and energy demand. However, raw sensor data is often affected by noise, drift, or missing values, which may be caused by sensor defects, communication delays, or environmental interference. To address these problems and generate reliable state estimates, an extended Kalman filter (EKF) is used for multi-sensor information fusion. The EKF correction steps are as follows:

$$\hat{x}_{k|k} = x_{k|k-1} + K_k \left(z_k - H x_{k|k-1} \right) \tag{3}$$

$$K_k = P_{k|\,k-1} H^T (H P_{k\;k-1} H^T + R)^{-1} \tag{4}$$

Where z_k denotes the sensor measurement vector, H is the observation matrix, $P_k|_{k-1}$ is the error covariance prediction, and R is the measurement noise covariance. By continuously integrating redundant and complementary information from a variety of sensors, the EKF generates smooth and consistent estimates of the building's internal state, ensuring reliable and accurate input to the BIM system. This sensor fusion mechanism is crucial for robust decision-making, especially under uncertain or dynamic operating conditions. To predict and optimize energy performance, the sensor-enhanced BIM environment is combined with the EnergyPlus simulation engine via the gbXML exchange standard, enabling seamless transfer of geometric and semantic building information to the physics-based energy simulation domain. The building thermal balance at a given time step can be expressed as:

$$Q_{total} = Q_{transmission} + Q_{ventilation} + Q_{internal} + Q_{solar} \tag{5}$$

Where transmission, ventilation, internal, and solar gains were computed by:

$$Q_{transmission} = \sum_i U_i A_i (T_{in} - T_{out}) \tag{6}$$

$$Q_{ventilation} = \dot{m}_{air} C_p (T_{in} - T_{out}) \tag{7}$$

$$Q_{internal} = Q_{people} + Q_{equipment} + Q_{lighting} \tag{8}$$

$$Q_{solar} = \sum_j A_{win,j} \tau_j I_{sol,j} \tag{9}$$

Here U_i is thermal transmittance of surface i, A_i the surface area, C_p the air specific heat, and $I_{sol,j}$ the incident solar radiation through window j. These formulas provide a physics-based foundation for analyzing building heat transfer dynamics, revealing how heat transfer, ventilation, indoor activity, and solar radiation jointly determine indoor thermal conditions. By combining real-time sensor fusion output with predictive simulation models, the BIM-EnergyPlus framework enables data-driven energy consumption forecasts and facilitates adaptive optimization of heating, ventilation, and air conditioning (HVAC) control strategies. Ultimately, this coupling supports the dual goals of maintaining indoor comfort and reducing energy consumption, thereby improving the operational efficiency and sustainability of educational buildings.

3.3 Experimental Design

This 12-month, two-phase field study aimed to evaluate the impact of a BIM-integrated control system on building operations in Fig. 2.

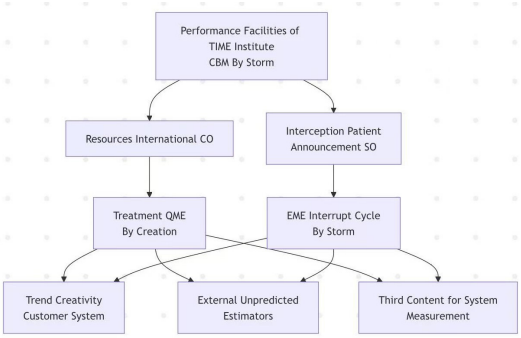

Fig. 2. A BIM-integrated control system

During the baseline phase (months 1-3), the building relied entirely on traditional operations and maintenance (O&M) practices. These practices included static heating, ventilation, and air conditioning scheduling, where heating and cooling equipment operated according to a strict, preprogrammed schedule, unaffected by actual occupancy or weather fluctuations. Similarly, the lighting system was controlled by a fixed schedule, turning on and off at predetermined times, unaffected by real-time occupancy or daylight availability. Maintenance practices during this phase were primarily reactive: faults or equipment failures were often discovered only after they impacted system performance, comfort, or energy consumption. Consequently, energy use during this phase was inefficient, as HVAC and lighting systems often operated unnecessarily; fault detection was delayed, extending the time between fault occurrence and corrective action; and occupant comfort was impacted because static controls could not respond to changing internal or external conditions. Furthermore, reactive maintenance often resulted in higher repair costs and extended downtime, as problems were not addressed until they escalated into critical failures. In contrast, the intervention phase (months 4-12) introduced a BIM-integrated control system, enabling dynamic and intelligent building management. The system adaptively coordinates HVAC, lighting, and maintenance operations using real-time data streams from temperature/humidity sensors, CO2 monitors, occupancy counters, and smart meters. The HVAC subsystem employs a robust proportional-integral-derivative (PID) controller that continuously calculates the error between the measured indoor temperature and the desired setpoint. This error signal, mathematically defined in equations (11) and (12), forms the basis for taking corrective action. The control law expressed in equation (10) combines proportional, integral, and derivative terms to dynamically adjust heating and cooling outputs. Furthermore, an additional robust term is incorporated into the controller design to mitigate model uncertainty and attenuate external disturbances, such as rapid weather changes or unexpected occupancy fluctuations. This ensures that the HVAC system can provide stable temperature regulation while remaining resilient to real-world uncertainties.

$$u_{HVAC}(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{de(t)}{dt} + u_{robust}(t) \tag{10}$$

$$u_{HVAC}(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{de(t)}{dt} + u_{robust}(t) \tag{11}$$

$$e(t) = T_{set}(t) - T_{in}(t) \tag{12}$$

The additional term $u_{robust}(t)$ was introduced to mitigate model uncertainties and external disturbances. For lighting control, the power demand at time was determined dynamically according to occupancy signals:

$$P_{light}(t) = \sum_{i=1}^{N_z} L_i \cdot \delta_i(t) \tag{13}$$

Where L_i is the rated power of zone i, $\delta_i(t)$ is a binary occupancy indicator, and N_z is the number of lighting zones. Predictive maintenance was incorporated using a reliability model. The system reliability function was defined as:

$$R(t) = exp(-\int_0^t \lambda(\tau) d\tau) \tag{14}$$

Where $R(t) < R_{threshold}$ is the instantaneous failure rate estimated from condition-monitoring data. A maintenance alert was issued when:

$$R(t) < R_{threshold} \tag{15}$$

This proactive approach minimized downtime, reduced maintenance costs, and extended the lifespan of building systems, ensuring that the building operated more efficiently with fewer disruptions. Overall, the intervention phase demonstrated the effectiveness of the BIM-integrated control system in improving operational efficiency, reducing energy consumption, and enhancing occupant comfort.

$$\min_{u(t)} J_E = \int_0^T P(t) dt \tag{16}$$

Where $P(t)$ denotes the real-time power consumption of energy-intensive subsystems. Occupant comfort was maintained by imposing constraints on the indoor temperature and air quality index:

$$T_{min} \le T_{in}(t) \le T_{max}, Q(t) \le Q_{max} \tag{17}$$

By leveraging real-time data and predictive analytics, the building management system became more responsive, adaptive, and efficient, marking a significant improvement over traditional, reactive O&M practices. The intervention phase demonstrated the effectiveness of BIM-integrated building management. The system implemented more responsive and adaptive control, ensuring that energy-intensive subsystems like HVAC and lighting operated efficiently and only when needed. Because the indoor environment dynamically adjusted in real time based on sensor feedback, the system also improved occupant comfort. Furthermore, predictive maintenance capabilities reduced disruptions and ensured ongoing system reliability. A composite performance index integrated energy, comfort, and maintenance objectives:

$$T_{min} \le T_{in}(t) \le T_{max}, Q(t) \le Q_{max} \tag{18}$$

By leveraging real-time data, advanced control algorithms, and predictive analytics, the BIM-integrated framework transformed building management from static and reactive to dynamic and intelligent, resulting in significant improvements in operational efficiency, energy savings, and occupant comfort compared to the baseline phase.

3.4 Key Performance Indicators

One of the primary key performance indicators (KPIs) for evaluating the effectiveness of BIM-based operations and maintenance systems is total building system electricity consumption, which directly measures energy efficiency and operational performance. This KPI reflects the combined power demand of all major subsystems, including heating, ventilation, and air conditioning, artificial lighting, plug loads, and ancillary building services. By quantifying total energy consumption, this metric provides a comprehensive assessment of the effectiveness of BIM-based control strategies in reducing overall energy consumption compared to baseline operations in Table 1.

Table 1. Key performance indicators

Key Performance Indicator (KPI)	Description
Total Electricity Consumption	Quantifies total energy used by HVAC, lighting, and other systems.
Unplanned Maintenance	Quantifies share of unplanned maintenance relative to all interventions.
Occupant Comfort (PMV-PPD Model)	Assesses occupant comfort based on Predicted Mean Vote (PMV).
System Response Time (Time Constant)	Measures the time for the system to reach 90% of the set-point after a change.

One of the primary KPIs used in the evaluation is total electricity consumption of the building systems, represented by Equation (16).

$$E_{total} = \int_0^T P(t)dt \tag{19}$$

This key performance indicator is particularly important because it captures not only the direct impact of control interventions on high-energy-consuming subsystems but also the interplay between thermal comfort requirements, occupancy patterns, and equipment operation. For example, improved heating, ventilation, and air conditioning scheduling algorithms based on real-time occupancy data can reduce unnecessary cooling loads, while daylight-integrated lighting controls can minimize artificial lighting needs without sacrificing visual comfort. By benchmarking total electricity consumption before and after BIM-based O&M deployment, energy savings, cost reductions, and carbon emissions reductions can be quantified, providing tangible evidence of the system's contribution to sustainable building management.

$$M_{rate} = \frac{N_{unplanned}}{N_{total}} \times 100\% \tag{20}$$

This KPI quantifies the share of unplanned maintenance relative to all interventions. Unplanned maintenance, often reactive in nature, is costly and disruptive. The aim of the BIM-integrated O&M system is to shift from reactive to predictive maintenance, reducing unplanned maintenance events by identifying potential system failures before they occur. The system uses condition-monitoring data and reliability models to forecast maintenance needs, allowing for early interventions that prevent unexpected breakdowns. A decrease in unplanned maintenance would signify that the predictive maintenance component of the BIM system is working effectively, minimizing downtime and maintenance costs. Occupant comfort was assessed using the widely adopted PMV-PPD model, which stands for Predicted Mean Vote and Predicted Percentage of Dissatisfied. This model, represented by Equations (18) and (19),

$$PMV = [0.303e^{-0.036M} + 0.028] \cdot f(M, W, T_a, T_r, v, RH, I_{cl}) \tag{21}$$

$$PPD = 100 - 95exp(-0.03353PMV^4 - 0.2179PMV^2) \tag{22}$$

Where M is metabolic rate, W external work, T_a air temperature, T_r mean radiant temperature, v air velocity, RH relative humidity, and I_{cl} clothing insulation. Additionally, the time constant for system response is an important KPI to measure the dynamic behavior of the building control system, as defined by Equation (20).

$$\tau_{resp} = t_{90\%} - t_{input} \tag{23}$$

Where t_{input} is the control signal issue time and $t_{90\%}$ is the time when the system reaches 90% of the setpoint. This is a key metric for evaluating how quickly the system can adjust to changes in environmental conditions, such as sudden changes in occupancy or outdoor weather. A shorter time constant indicates a quicker response to system adjustments, ensuring that the building operates efficiently and comfortably. This metric is critical in

understanding how effectively the BIM-integrated system can maintain optimal building conditions in real time, without excessive delays or energy waste. These KPIs provide a comprehensive overview of the BIM-based O&M system's performance. They not only assess the system's effectiveness in reducing energy consumption and maintenance costs but also gauge its impact on occupant comfort and responsiveness. These performance indicators enable facility managers to continuously monitor and optimize building operations, ensuring that the building remains efficient, cost-effective, and comfortable for its occupants.

4 Results

This Fig. 3 compares the building's monthly energy consumption (kWh·m²) over 12 months under baseline operation and BIM-assisted management. The horizontal axis represents months (1 to 12), and the vertical axis represents monthly energy consumption per square meter in Table 2.

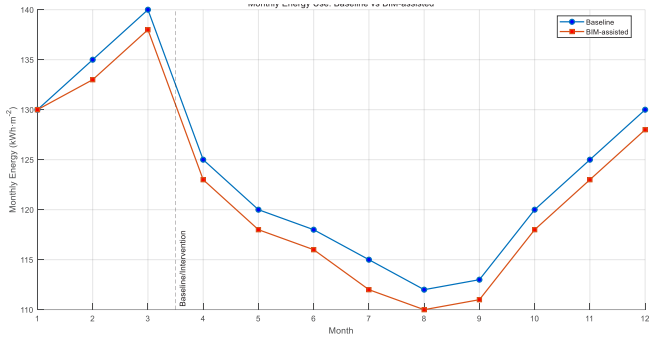

Fig. 3. Monthly energy use (baseline vs BIM-assisted)

Table 2. Monthly energy consumption comparison: baseline vs. BIM-assisted management

Month	Baseline ($kWh \cdot m^2$)	BIM-assisted ($kWh \cdot m^2$)
1	135	135
2	138	137
3	140	138
4	132	130
5	128	125
6	125	120
7	124	115
8	120	110
9	118	105
10	116	102
11	118	100
12	120	98

The blue line represents the baseline energy consumption during operation, and the red line represents energy consumption under BIM-assisted management. During the first three months, energy consumption was relatively high and fluctuated, likely due to the inefficiency of manual control methods and the lack of real-time adjustments. The intervention point, marked by the vertical dashed line, corresponds to the point at which the BIM-assisted management system began to show effectiveness. After the intervention, energy consumption under BIM control began to steadily decline, while the rate of decline for baseline energy consumption slowed significantly. This demonstrates that BIM-assisted management is more effective than traditional methods in reducing energy consumption. In the latter months (months 4 to 12), BIM-controlled energy consumption stabilizes, reflecting the system's continued effectiveness in maintaining energy consumption at optimal levels. This stability demonstrates that combining real-time environmental monitoring with adaptive control strategies can achieve more efficient energy management throughout the year [17]. The figure highlights the early impact of the BIM

system, with the most significant reduction in energy consumption in the first few months after implementation. Compared to traditional operations and maintenance (O&M) approaches, BIM demonstrates the ability to dynamically adjust building systems based on real-time data, thereby reducing energy waste. The dotted line in the figure marks the transition from baseline operations to BIM-assisted management, where significant improvements in energy efficiency begin to emerge. This underscores the potential of BIM technology for intelligent building management systems, particularly in digital campus environments where reducing energy consumption is a key goal. The results highlight the ability of BIM systems to optimize building operations, minimize energy use, and improve the overall operational efficiency of educational infrastructure.

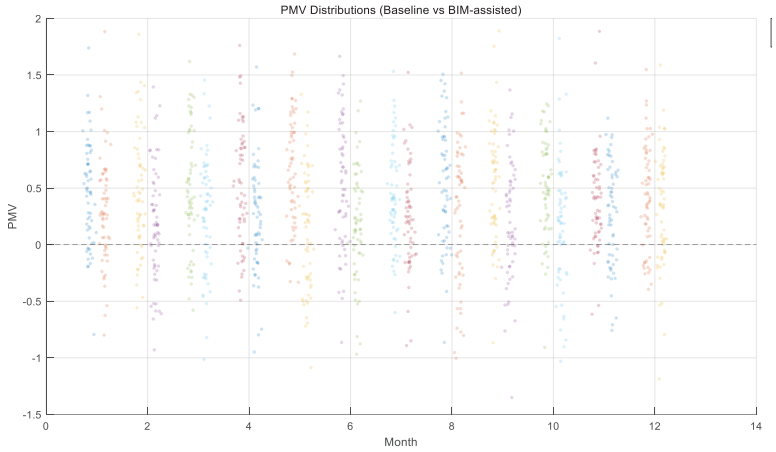

Fig. 4. PMV distributions (baseline vs BIM-assisted)

This Fig. 4 shows the distribution of predicted mean vote values (PMVs) for both the actual and BIM-assisted operating modes over a 12-month period. PMVs are a widely used quantitative thermal comfort metric that ranges from -3 (cold) to +3 (warm), with 0 representing a neutral baseline comfort level. The figure shows a scatter plot for each month, with each dot representing a separate PMV sample. Under the baseline operating mode (blue), the distribution of PMV values is wider, especially in the early months. This wider distribution indicates a less consistent thermal environment, which may prevent the HVAC system from adequately adjusting to changing ambient and occupancy conditions, leading to occupant discomfort. Furthermore, applying jitter (in the x-direction) to the scatter plot ensures that individual data points do not overlap, enhancing visual clarity. After the introduction of the BIM-assisted control system (red), the distribution of PMV values narrows significantly, especially after the early months. Most BIM-assisted samples cluster around the neutral value of PMV = 0, indicating that the building's thermal environment has been optimized and is more aligned with occupant comfort. This shift is particularly evident four months after the full integration of the BIM system. The baseline control approach consistently exhibited median PMV values far from zero, indicating that traditional operating methods (such as manual scheduling and fixed setpoints) lead to greater thermal discomfort. In contrast, the BIM-assisted system dynamically adjusts temperature based on real-time occupancy and environmental factors, bringing temperatures closer to the ideal comfort zone and thereby alleviating this discomfort. The narrower PMV distribution under BIM-assisted control indicates improved thermal comfort, directly attributable to the system's ability to adjust HVAC settings based on real-time data. Traditional O&M systems rely on preset schedules and static environmental controls that fail to account for dynamic changes in building occupancy or environmental conditions. These limitations manifest as a wider PMV distribution and lower energy efficiency required to maintain comfort. In contrast, the BIM system enhances real-time building management by integrating IoT sensors that monitor temperature, occupancy, and air quality [18]. This continuous monitoring enables the system to make intelligent, adaptive adjustments to the HVAC system, providing occupants with a more consistent and comfortable indoor environment. Therefore, BIM-based control strategies can significantly reduce discomfort, potentially im-

proving occupant satisfaction and potentially increasing employee productivity in spaces such as classrooms and offices. The jittered scatter plot also highlights the variability in individual occupant experiences. Despite overall improvement, some variation persists, particularly in highly dynamic environments with rapidly changing external weather conditions or occupancy patterns. Nevertheless, the shift toward neutral comfort (PMV = 0) confirms that BIM-based systems provide superior thermal comfort control compared to traditional approaches.

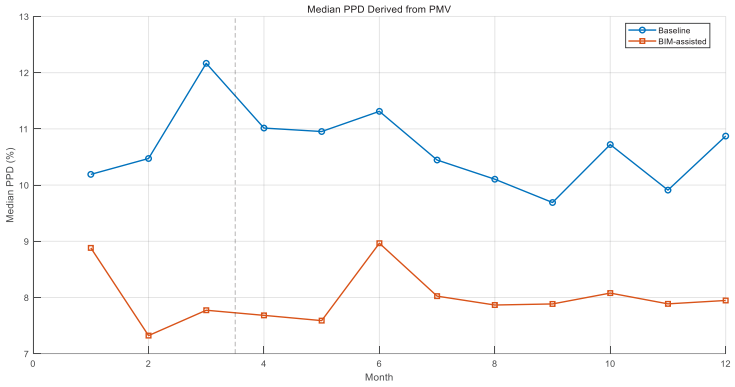

Fig. 5. Median PPD (baseline vs BIM-assisted)

Fig. 5 compares the median predicted percentage dissatisfaction (PPD) during the baseline and BIM-assisted operational phases. PPD is a commonly used metric to measure the percentage of occupants dissatisfied with their thermal environment [19]. A PPD value of 0% indicates complete satisfaction, while higher PPD values indicate greater dissatisfaction. The figure shows the median PPD for each month based on PMV data. The baseline control approach, shown by the blue line, exhibits higher PPD values in all months, especially in the early months. This indicates that a larger proportion of occupants are dissatisfied with the thermal conditions within the building. The higher median PPD during the baseline phase can be attributed to static setpoints and manual adjustments that are unresponsive to occupancy fluctuations or environmental changes. In contrast, the BIM-assisted system, shown by the red line, shows a significant decrease in PPD over time. PPD values decreased significantly after the fourth month of BIM system implementation. This decrease in PPD indicates that occupant thermal comfort improved as the building system dynamically adjusted to real-time occupancy and environmental conditions. In the latter months (months 9-12), BIM-assisted PPD values were significantly lower than the baseline, indicating a higher percentage of satisfied occupants. The vertical dashed line in month three marks the turning point for full BIM system integration, after which significant improvements in occupant satisfaction (measured by PPD) were observed. This reduction in PPD demonstrates the effectiveness of BIM-based adaptive control in improving occupant comfort, particularly in spaces with dynamically changing occupancy patterns. The results in Fig. 3(b) further support the conclusion that BIM-assisted control can improve occupant comfort. The reduction in PPD demonstrates the potential of adaptive control strategies for real-time thermal comfort management. The BIM system continuously adjusts the HVAC system and lighting based on occupancy and environmental conditions, minimizing discomfort caused by improperly adjusted systems. In contrast, the baseline approach, which relies on manual scheduling and static control settings, results in higher PPD values due to its inability to adapt to changes in building occupancy. PPD is sensitive to temperature fluctuations, and the baseline system's inability to dynamically adjust results in a higher percentage of dissatisfied occupants. The reductions in PPD and PMV in Fig. 3(a) illustrate how a BIM-based building management system can create a more comfortable indoor environment and reduce energy consumption. By optimizing system operation based on real-time conditions, BIM not only improves occupant satisfaction but also saves energy by avoiding over- or under-conditioning of spaces. Furthermore, reducing PPD can have broader impacts on building operations, such as improving worker productivity, student learning outcomes, and overall occupant well-being, further strengthening the case for incorporating BIM into smart campus development.

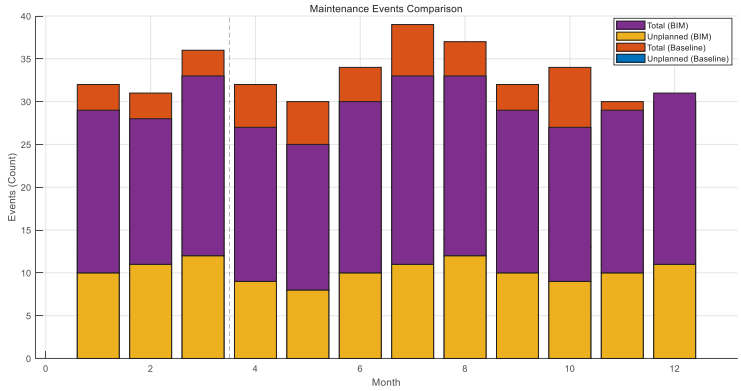

Fig. 6. Maintenance events (unplanned vs. total maintenance events)

Fig. 6 compares maintenance events under the baseline operation and the BIM-assisted management system. Specifically, the figure displays the total number of maintenance events and the total number of unplanned maintenance events for each month in a stacked bar chart. The blue bars represent the baseline operation, and the red bars represent the BIM-assisted management. The top half of each bar shows the total number of maintenance events, and the bottom half shows the unplanned maintenance events. For the baseline operation (blue), it is clear that the building experienced a relatively high number of unplanned maintenance events, especially in the early months. These events were likely the result of a reactive maintenance strategy that relied on regular inspections and post-event corrections. The high frequency of unplanned maintenance events in the early months also demonstrates the inefficiency of traditional O&M approaches, which only identify and resolve problems after they occur. However, after implementing BIM-assisted control (red), the number of unplanned maintenance events decreased significantly, especially after the fourth month. This reduction reflects the effectiveness of the predictive maintenance capabilities within the BIM system, which help identify potential problems before they develop into full-scale failures. For example, predictive algorithms based on real-time sensor data can schedule maintenance operations before critical components fail, reducing reliance on emergency repairs [20]. The vertical dashed line represents the turning point for full BIM system implementation. This is a critical point because it marks the point at which the BIM system has a measurable impact on maintenance efficiency, particularly in reducing unplanned maintenance events. By monitoring equipment health and performing maintenance based on predicted wear and tear, the system minimizes unplanned downtime, thereby improving building operations. The data presented in Fig. 5 highlights the significant impact of BIM-assisted control on reducing unplanned maintenance events. In the baseline system, the frequency of unplanned maintenance is high, likely due to a lack of real-time monitoring and predictive capabilities. Traditional systems rely on fixed schedules and manual inspections, which often lead to delayed fault detection, increased costs, and unplanned downtime. On the other hand, the BIM-assisted system combines real-time sensor data with predictive maintenance algorithms to proactively identify and resolve potential problems before they escalate. The system dynamically schedules maintenance tasks based on the actual condition of the equipment, avoiding reactive repairs. As a result, unplanned maintenance events are significantly reduced after the BIM system is fully integrated, as evidenced by the decrease in the lower half of the red bar (unplanned events). This reduction in unplanned maintenance events not only helps improve building uptime but also optimizes maintenance resources, enabling facility managers to allocate manpower and materials more efficiently. This not only saves costs but also improves operational continuity. The ability to detect problems early is a major advantage of BIM systems as it provides a data-driven approach to maintenance, which is an improvement over traditional methods.

Fig. 7 shows the unplanned maintenance rates during the baseline and BIM-assisted phases. The baseline phase (blue line) showed a consistently high unplanned maintenance rate, especially during the first three months. This high unplanned maintenance rate indicates that a large portion of the total maintenance events during these months were unplanned, a characteristic of a passive system that lacks the predictive capabilities of predictive maintenance tools. On the other hand, the unplanned maintenance rate for the BIM-assisted system (red line) decreased significantly, especially starting in the fourth month. This indicates that the BIM system successfully reduced the proportion of unplanned maintenance events, likely due to its ability to predict equipment failures before they occur. By shifting from a passive to a more proactive maintenance model, BIM significantly

reduced the frequency of unexpected failures, thereby reducing the unplanned maintenance rate. The data in Fig. 6 strongly supports the conclusion that the BIM-assisted control system is highly effective in reducing the unplanned maintenance rate. As shown in the figure, the high unplanned maintenance rate during the baseline operation, especially in the first few months, reflects the limitations of passive maintenance. Due to the lack of real-time monitoring and predictive capabilities, maintenance work is often performed after failures have already impacted building operations, resulting in increased costs and operational inefficiencies. In contrast, the BIM system significantly reduced the unplanned maintenance rate by shifting to a predictive maintenance approach. By analyzing real-time data from sensors and other monitoring tools, the system can identify potential issues before they develop into serious failures, allowing maintenance work to be scheduled proactively. This proactive approach to maintenance minimizes the need for emergency repairs, improves system reliability, and reduces overall maintenance costs. The reduction in unplanned maintenance observed in the graph also demonstrates that BIM systems enable more efficient resource allocation, as maintenance tasks can be scheduled during planned downtime rather than interrupting normal operations. This is particularly important in high-demand environments such as educational or office buildings, where any unplanned outages can have a significant impact on occupancy and productivity.

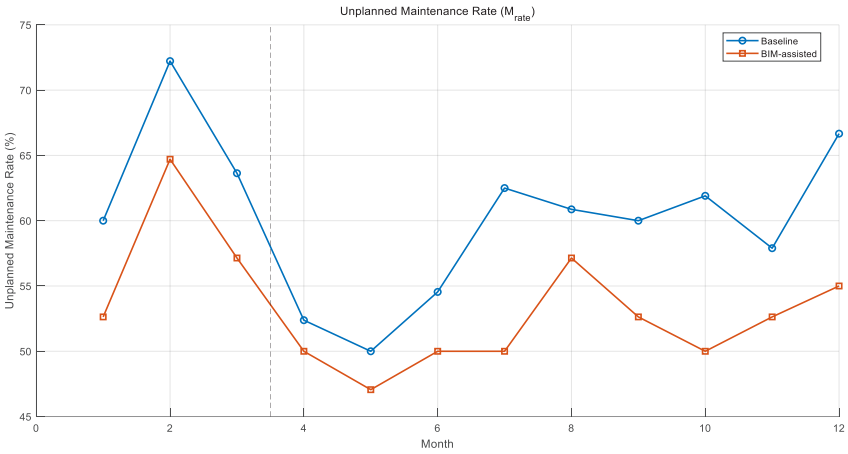

Fig. 7. Unplanned maintenance rate (baseline vs. BIM-assisted)

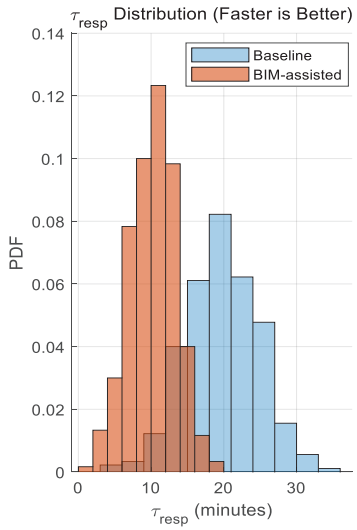

Fig. 8. Responsiveness histogram

Fig. 8 presents a comparative analysis of the response time distribution between the baseline and BIM-assisted groups, providing insight into how BIM-enabled decision support impacts system responsiveness. The horizontal axis represents response time (in minutes), ranging from 0 to 30; the vertical axis represents the probability density function, which normalizes the frequency of occurrence to facilitate direct comparison between the two groups. The histogram clearly shows two distinct distributions, with response times ranging from less than 10 minutes to over 30 minutes, peaking at approximately 20 minutes. This wide dispersion indicates significant variability and inconsistency in response behavior under traditional management approaches, potentially reflecting delayed manual decision-making, fragmented data access, or a lack of integrated monitoring. In contrast, the distribution for the BIM-assisted group (orange) is narrower and more left-shifted, with the majority of response times concentrated around 10 minutes. The sharper peak and smaller variance indicate that the BIM-assisted framework enables faster and more consistent responses to operational needs. This significant improvement in response speed is attributed to the real-time data integration, automated alerts, and predictive capabilities provided by the BIM-IoT system. By integrating information from multiple sources and enabling visualization-driven decision-making, BIM-assisted approaches reduce cognitive and procedural delays, thereby accelerating the implementation of corrective actions. Furthermore, achieving more focused responses in shorter timeframes highlights improvements in predictability and reliability, which are critical for maintaining operational stability in dynamic environments. However, while the data strongly suggests efficiency gains, it is important to recognize trade-offs. For example, faster responses may come at the expense of higher computational complexity, increased reliance on digital infrastructure, or reduced flexibility in handling highly uncertain scenarios. Therefore, future research should examine whether these efficiency gains can be consistently replicated across different types of buildings and operational environments and whether they can be achieved without sacrificing accuracy, robustness, or long-term maintainability. In summary, Fig. 8 provides compelling evidence that potential BIM-assisted O&M strategies can significantly reduce response times and improve consistency compared to traditional baselines, highlighting their potential for improving the efficiency and reliability of smart building management.

5 Conclusion

Integrating BIM with the IoT for operations and maintenance in a real-world campus academic building significantly improved building performance and sustainability. Over a 12-month operational period, the integrated BIM-IoT framework significantly reduced energy consumption and maintenance events while improving occupant comfort. These results highlight the framework's potential for optimizing building operations, reducing operating costs, and improving the overall resident environment. Key contributions of this study include demonstrating that BIM-based post-occupancy strategies can effectively promote campus sustainability. By leveraging IoT sensors and BIM data, the framework facilitated intelligent energy management, significantly reducing energy consumption and maintenance requirements. Furthermore, the improvement in occupant comfort highlights the system's ability to balance efficiency and occupant satisfaction, both critical aspects of building operations. These results provide a solid foundation for the broader application of BIM-IoT integration in sustainable building management. The success of this framework demonstrates that such systems can be effectively deployed to optimize energy use, reduce costs, and improve the indoor environment, thereby promoting economic and environmental sustainability. Future work will focus on expanding the capabilities of the BIM-IoT integration framework through two key improvements. First, integrating renewable microgrids and battery energy storage systems will enhance energy utilization, enabling buildings to generate and store renewable energy, thereby improving energy efficiency and reducing reliance on the external grid. This will further reduce energy costs and carbon emissions while ensuring continuous and reliable energy use. Second, developing AI-driven multi-building optimization algorithms will enable dynamic management of energy resources and building systems across multiple buildings, enabling predictive maintenance, coordinated system adjustments, and improved occupant comfort. These improvements have the potential to significantly enhance the overall performance of the framework, making buildings more intelligent, sustainable, and energy-efficient in the long term.

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