Integrating Building Information Modeling (BIM) and the Internet of Things (IoT) for Smart Building Facility Quality Management

[1,2]Hassan Ahmed Hassan Youssef, [3]Miltiadis Kourmpetis, [4]Yasser Buomy Abdou, [5]Anwar Islem Basunbul

[6,7] Mohammed M. Gomaa,[8,9]Mohamed salah Ezz,[10] Fernando Sarce Thomann,

[11]Hamad Ahmed ALGHIRASH, [12.13]Neama Hassan Elsayed Omar

[1]Department of Architecture Engineering, Alasala Colleges, Dammam 32324, Saudi Arabia.
[2]Department of Architecture Engineering - Al-Safwa high institute of Engineering, Cairo, Egypt.
[3]Department of Mechanical Engineering, Alasala Colleges, Dammam 32324, Saudi Arabia.

[4]Associate professor in Science Methodology and quality assurance consultant Alasala Colleges, Dammam 32324, Saudi Arabia
[5] Department of Architecture Engineering, university of Business and Technology

[6]Department of Architecture, School of Engineering, Computing& Design, Dar Al-Hekma University,

Jeddah 22246, Saudi Arabia.

[7]Department of Architectural Engineering, Faculty of Engineering, Aswan University, Aswan 81542,

Egypt
[8]Architectural Department, College of Engineering and Information Technology, Onaizah Colleges, Qassim, Saudi Arabia.,
[9] Department of Architecture, The Higher Institute for Engineering and Technology, Obour City - K21 Cairo/Bilbies, Egypt,
[10] Al Yamamah University, Saudi Arabia,
[11]Department of Architecture Engineering, Alasala Colleges, Dammam 32324, Saudi Arabia
[12] Interior Design Department, College of Architecture and design- Alasala Colleges, Dammam 31483, Saudi Arabia
[13]Architecture Department, Bilbeis Higher Institute for engineering, Egypt.

Abstract
This study provides a comprehensive analytical review of the integration of Building Information Modeling (BIM), the Internet of Things (IoT), and Digital Twin (DT) technologies across the building lifecycle, with a specific focus on predictive maintenance, energy optimization, and facility management (FM). Modern BIM has evolved into a data-centric platform that supports real-time monitoring by incorporating IoT sensor networks, enabling continuous acquisition of environmental, operational, and behavioral data **(Volk et al., 2014; Lu et al., 2020)**. Recent research demonstrates that BIM–IoT integration enhances decision-making efficiency by up to 30% and reduces maintenance costs by 25–40% **(Riaz et al., 2021; Dave et al., 2021)**, while real-time analytics allow dynamic visualization of asset conditions and system performance. The emergence of Digital Twins further elevates this capability by providing high-fidelity, bidirectionally synchronized virtual models that leverage AI-driven analytics—including model predictive control and physics-informed neural networks—to forecast energy demand, identify faults, and predict the remaining useful life (RUL) of building systems **(Tao et al., 2019; Grieves & Vickers, 2017)**.
Within sustainable building design (SBD), BIM enables quantitative environmental assessment through energy simulation, life cycle costing (LCC), and life cycle assessment (LCA), supporting iterative design optimization during early RIBA stages **(Azhar, 2011; Bueno et al., 2018)**. The study highlights IoT's multi-layered architecture—perception, network, and control layers—

demonstrating its essential role as the sensory infrastructure for Digital Twins **(Gubbi et al., 2013)**. Case studies confirm the need for high-granularity data (over 300 measurement points in district-scale networks) to quantify performance gaps in auxiliary energy loads, user behavior, and automated system consumption (2–5 kWh/m² annually) **(Rasheed et al., 2020)**. Additional applications include decentralized HVAC control, behavioral load forecasting, advanced lighting and shading management, district-scale energy flexibility, and enhanced emergency response **(Zhang et al., 2021)**. Despite these advancements, significant challenges persist, including interoperability limitations, cybersecurity risks, inconsistent data standards, and the absence of early-stage IoT integration in building design **(Succar & Kassem, 2015; Alreshidi et al., 2017**

Keywords:
(BIM) Internet of Things (IoT) – Smart Buildings – Digital Twin – Energy Efficiency – Facility quality Management.

Predictive Maintenance Comprehensive Literature Review on Building Information Modeling (BIM)- Facility Management (BIM–FM)

Evolution and Core Concept of BIM- Integration with IoT and Real-Time Data

BIM has evolved from a 3D design tool into a data-centric digital ecosystem that integrates design, construction, and facility management. modern BIM systems serve as centralized digital repositories connecting geometric data with real-time operational data (sensors, IoT). Recent studies (e.g., Automation in Construction, 2023; Journal of Building Engineering, 2024) highlight BIM's role as the foundation for Digital Twin models.

Integration between BIM and IoT is now a dominant research trend.

IoT sensors continuously collect data (temperature, humidity, energy use, occupancy) and feed BIM platforms for dynamic building monitoring.

Key platforms used: Revit-Dynamo, Autodesk Forge, and IFC-based APIs for interoperability.

Studies in IEEE IoT Journal (2022–2024) demonstrate how this integration enables predictive maintenance, reducing maintenance costs by 25–40%. The shift from design to operation and maintenance phase is now central in BIM applications.

BIM–FM models enable visualization of maintenance schedules, asset tracking, and system performance in real time. Several papers (e.g., Building and Environment, 2023) report enhanced decision-making efficiency by 30% when BIM is used as a facility management platform. BIM supports sustainability assessment through energy simulation (via Green Building Studio, IES-VE, or EnergyPlus) and carbon footprint modeling Integration with Life Cycle Assessment (LCA) and Life Cycle Costing (LCC) tools is becoming standard practice. In Gulf-region case studies, BIM-assisted modeling helped achieve 15–25% reductions in total building energy demand. The Industry Foundation Classes (IFC) standard remains the main interoperability format.

Challenges remain regarding data exchange consistency, especially when integrating IoT and BIM across platforms. Emerging standards: ISO 19650, COBie (Construction Operations Building Information Exchange), and BIM Level 3 for unified collaboration.

Digital Twins and BIM

The concept of Digital Twins has matured into real-time BIM models connected to sensor data and cloud analytics. Digital Twins enable continuous monitoring of building health, performance, and occupancy comfort. Research (e.g., Automation in Construction, 2024) shows how Digital Twins built on BIM improve operational efficiency and resilience in smart buildings.

AI-driven analytics (machine learning + BIM) are being applied to detect faults, optimize energy, and automate object recognition in 3D scans.
Integration of AI and BIM through Python APIs and cloud computing platforms like AWS IoT Core is becoming more widespread.
Major barriers: interoperability, cybersecurity of IoT-connected BIM systems, data privacy, and lack of unified digital policies.
Future direction focuses on blockchain-secured BIM, cloud-based collaboration, and context-aware digital twins.

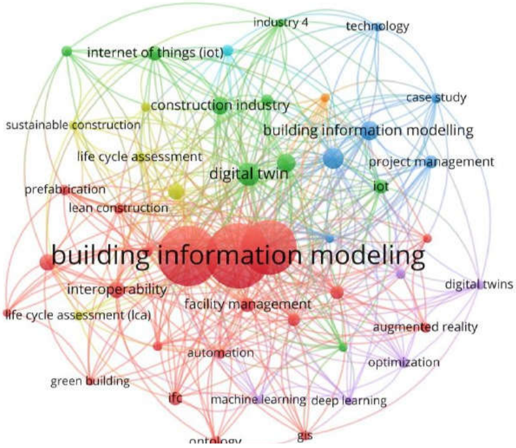

Fig1: Network of keywords co-occurrence

BIM and SBD

The graphics and digital information of components in BIM enable a function of analysis and control which can be linked to SBD. The functional support of BIM for SBD reflects in the ability of BIM tools for energy modelling and sustainable material selection to reduce environmental impact. Linking BIM to sustainable design analysis (SDA) tools facilitates comprehensive environmental trade-off evaluations during early design stages. By this, BIM, when paired with dynamic performance analysis software tools, can provide quantifiable measures such as operational energy consumption, carbon emissions, and waste management, which are fed back into the decision-making process. This approach deals with the calculation aspect of SDA. Zanni et al. has examined the scope of considerations for SBD and has aligned these to the RIBA Plan of Work 2013 stages 0, 1, and 2. Sustainability considerations need to be expressed qualitatively at stage 0, then quantified (through metrics and benchmarks) at stage 1, and finally tested and defined explicitly at stage 2. Feasibility of the sustainability criteria is the basis for optimising the design, by performing iterations at Concept Design (stage 2). The standardised process developed has aligned the RIBA Plan of Work with defined Level of Development (LOD) and non-graphical information to regulate the information exchanges between the project team participants. The LOD, i.e. modelling detail and information requirements, are treated as critical to the analyses for optimising the solution. Therefore, modelling detail and assumptions of design materials, specifications, and performance used for energy simulations are constraints for the SBD optimisation. Ideally, the modelling detail at Stage 1 must provide an outline which includes site location, layout, and massing. This helps optimise the design solution against criteria such as solar radiation studies and estimated energy consumption. At Stage 2, the focus shifts to performance. Here, the model must have sufficient and valid geometric detail and initial services specifications along with material specifications, U-values, capital cost, etc. This enables optimisation of the design against criteria including embodied carbon, toxicity, CO_2 emissions, etc.

The Internet of Things (IoT): An Exhaustive Analysis in the Built Environment

Architectural Depth and Data Fidelity

This analysis provides the highest level of technical and conceptual detail regarding the Internet of Things (IoT), its intricate architectural framework, its quantitative impact on building performance, and its indispensable role as the primary enabler for the Digital Twin (DT) within the Smart Building ecosystem.

The functioning of the IoT in a built environment is governed by a multi-layered architecture designed to achieve high data granularity, reliability, and bidirectional control.

The Perception Layer: Quantitative Data Granularity

The efficacy of a smart system is directly proportional to the fidelity of its sensory input. IoT provides this fidelity through pervasive, dense sensor networks.

Metric-Driven Monitoring: For complex energy systems, such as low-temperature heating and cooling networks, reliable performance verification and optimization demand an extraordinary level of detail. Monitoring studies confirm the necessity of utilizing more than 300 measuring points across the network to provide the monthly analytical depth required to detect subtle operational flaws and quantify the "performance gap" in auxiliary equipment consumption [Vetterli et al., 2017].

Behavioral Measurement: The IoT framework incorporates specialized sensing methodologies, such as utilizing distributed, portable sensor devices carried by occupants (e.g., students in a national science experiment), to infer user behavior. This allows researchers to accurately determine residential air-conditioning usage patterns and the subsequent energy load, which is essential for tackling the "performance gap" that arises primarily from the disparity between design assumptions and actual occupant behavior [Happle et al., 2017; Lehmann et al., 2017].

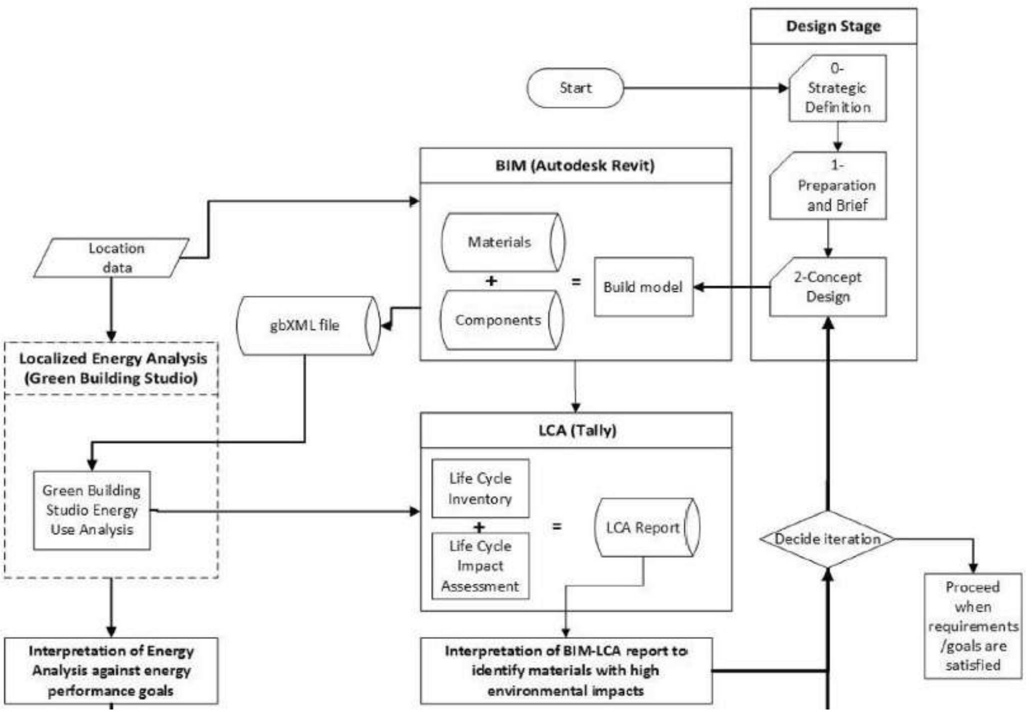

Fig2: process of Bim –LCA+ energy simulations

The Network Layer: Protocols and Bidirectional Flow

This layer is the backbone of connectivity, linking the physical world (sensors/actuators) to the cognitive layer (Digital Twin). It embodies the Network Technologies essential for DT [Wang et al., 2024].

Protocol Hierarchy: Communication relies on a hierarchy of protocols: MQTT (Message Queuing Telemetry Transport) is preferred for resource-constrained edge devices due to its low overhead and publish-subscribe model; HTTP/HTTPS handles larger data streams and centralized communications; while industrial automation relies on standards like Modbus and OPC UA for interoperability with Building Management Systems (BMS) [Chen et al., 2024].

Closed-Loop Control: The IoT network is fundamentally bidirectional. This is non-negotiable for smart operation, as it facilitates the execution mechanism for the DT. Data flows in for analysis and synchronization, and optimized control commands flow out to actuators (e.g., smart chillers or blinds), thereby closing the real-time feedback loop [Sakhardande et al., 2024].

IoT-Enabled Advanced Control and Energy Optimization Paradigms

IoT data acquisition is the catalyst for modern control strategies that aim for system-wide, dynamic efficiency.

Dynamic Decentralized Control Systems

IoT hardware enables computational intelligence to be distributed throughout the building systems, moving beyond the inherent limitations of rigid, centralized control.

Smart Chiller Plants: Instead of a single central controller dictating operation, IoT allows each chiller in a parallel-connected setup to function as a "smart chiller" with an embedded decentralized controller. These units communicate and collaborate to meet the thermal load while optimizing collective energy efficiency, demonstrating superior flexibility and efficiency compared to traditional supervisory control [Dai et al., 2017].

Critical Analysis of Automation's Own Energy Load

High-resolution IoT monitoring has led to the re-evaluation of assumptions in energy modeling.

BAS Consumption Quantification: Detailed studies of highly automated buildings using continuous monitoring revealed that the electricity consumption of the Building Automation System (BAS) itself—the collective power draw of controllers, sensors, actuators, and communication devices—is not negligible. Annual consumption for room automation can range from 2 to 5 kWh/m^{2}, a finding that mandates a focus on energy-efficient design for automation components [Kräuchi et al., 2017].

Harnessing Neighborhood Energy Flexibility

At the district level, IoT data informs urban-scale optimization and energy resiliency.

Inter-Building Energy Exchange: By analyzing load profiles (hourly thermal and electrical demand) across diverse building types within a district, IoT facilitates the identification of complementary, simultaneous heating and cooling loads. This provides the technical basis for implementing energy exchange possibilities and collective energy management, ultimately contributing to local energy self-sufficiency and grid stability [Walker et al., 2017].

IoT as the Indispensable Enabler of the Digital Twin (DT)

The IoT is one of the six core technological enablers for the Digital Twin, acting as the bridge between the physical and virtual realms [Wang et al., 2024].

Conceptual Role	IoT Function	DT Outcome and Value Proposition
Synchronization	Provides the constant, high-volume, real-time data stream required to update the DT's virtual model.	Maintains the DT as a high-fidelity, synchronized mirror of the physical building, validating its status and preventing model drift [Sakhardande et al., 2024; Zhao et al., 2022].
Cognitive Input	Supplies the granular operational data necessary for predictive algorithms and machine learning models running on the DT platform.	Enables advanced capabilities like predictive maintenance and effective building energy management by allowing the DT to reason and forecast system behavior [Wang et al., 2024].
Information Efficiency	Guarantees the accessibility and timeliness of dynamic building data to all stakeholders (users, managers, systems).	Achieves "information efficiency"—a major DT opportunity—by integrating disparate data sources and enabling robust user-system interaction [Jian et al., 2023].

In summary, the IoT framework is the essential sensory infrastructure; it provides the data granularity, protocol agility, and closed-loop control capacity that are prerequisites for transforming a building into a truly intelligent, predictive, and energy-optimized system governed by the Digital Twin, [Youssef 2025].

The Ultra-Detailed DT Architecture: Heterogeneous Data Fusion

The DT for a Smart Building is not merely a 3D model; it is a complex middleware architecture designed for the semantic integration of heterogeneous data sources, maintaining the high-fidelity synchronized mirror status [Sakhardande et al., 2024].

Deep Data Integration Challenges (Semantic Interoperability)

The core technical challenge is integrating the unstructured, dynamic data from the Internet of Things (IoT) with the static, structured data from the Building Information Model (BIM):

BIM as the Semantic Ontology: The BIM model provides the semantic backbone (location, asset type, geometry) that organizes the chaotic, high-frequency data streams from the IoT sensors. Without the BIM, the IoT data is just a time series; with it, data is contextualized (e.g., mapping a temperature reading to a specific room, occupant, and HVAC unit) [Zhao et al., 2022].

Data Heterogeneity: The DT must handle protocols ranging from low-bandwidth sensor data (MQTT) and industrial standards (Modbus, OPC UA) to high-bandwidth feeds (CCTV, LiDAR). The DT platform acts as an aggregator and translator to ensure all inputs are uniformly readable for the AI/ML layers [Chen et al., 2024].

The Cognitive Layer: AI/ML and Simulation

The DT's intelligence is defined by its ability to process this integrated data:

Model Predictive Control (MPC): The DT utilizes MPC algorithms, running on the synchronized model, to forecast future building states (e.g., indoor temperature, energy demand) hours or days in advance. It then calculates and executes the globally optimal control sequence for the building's actuators (HVAC, lighting, shading) to minimize cost, energy, and comfort deviation simultaneously [Wang et al., 2024].

Physics-Informed Neural Networks (PINNs): Advanced DTs move beyond simple black-box AI by incorporating physical laws (thermodynamics, fluid dynamics) directly into the simulation model, creating more robust and explainable predictions for complex phenomena like air flow or heat transfer.

Quantitative Proof and System Performance Metrics

IoT, functioning within the DT framework, provides the quantitative evidence to measure and close the gap between design and reality.

Precision in Performance Gap Analysis

Operational Discrepancy: The DT quantitatively verifies the Performance Gap observed in residential buildings where actual heat demand often exceeds thermal regulation limits (e.g., a case study showing actual heat demand of 8MJ/m^{2} for heating, exceeding the MINERGIE label limits). The DT uses this gap to recalibrate its operational models [Lehmann et al., 2017].

Granular System Verification: For critical infrastructure projects, the DT's reliance on over 300 measurement points (as demonstrated in low-temperature district networks) is the minimum granularity required to verify design goals and accurately identify minute consumption deviations, such as the performance gap in electricity use by auxiliary pumps and equipment [Vetterli et al., 2017].

Quantified Energy Load of Automation

The BAS Load Challenge: Detailed IoT monitoring has quantified a previously "negligible" load: the consumption of the Building Automation System (BAS) itself. High-automation systems were found to consume a significant 2 to 5 kWh/m^{2} annually in electricity, a figure the DT must now account for and optimize in its BEM strategies [Kräuchi et al., 2017].

Distributed and Flexible Control Metrics

Decentralization Efficiency: The DT leverages the IoT's communication layer to implement Decentralized Control for assets like chillers. This method has been quantitatively validated to be "much more flexible and more efficient" than traditional centralized control, achieving better system-wide efficiency by treating each unit as a collaborative, intelligent agent [Dai et al., 2017].

NZEB Multi-Factor Balancing: The DT's models must address the quantitative complexity of achieving Net Zero Energy Building (NZEB) goals, specifically the impact of asymmetric primary energy weighting factors and time-step balancing methods (e.g., hourly vs. annual) on the required size and output of onsite renewable energy systems [Hall & Geissler, 2017].

DT's Advanced Value Proposition in Facility Quality Management

The DT transforms the Smart Building lifecycle by delivering capabilities far beyond simple automation.

Modern Facility Management is defined by its reliance on high-granularity data acquisition (IoT) and predictive, quantitative analysis (DT) to transition from reactive maintenance to strategic, energy-optimized operation.

DT Opportunity	Advanced Functionality	Risk Mitigation & Business Value
Predictive Maintenance (PdM)	Forecasting Remaining Useful Life (RUL): Uses vibration and thermal IoT data, combined with historical maintenance records (from the BIM/CMMS), to forecast the exact probability of failure and the RUL of critical assets (e.g., pumps, fans) [Wang et al., 2024].	Reduces unplanned downtime by transitioning from scheduled or reactive maintenance to highly precise, condition-based interventions.
Occupant-Centric Optimization	Inferred Behavioral Modeling: Incorporates occupant-dependent operation patterns (e.g., AC usage inferred from portable sensors) into the DT's energy models to provide hyper-personalized comfort optimization and accurate energy forecasting [Happle et al., 2017].	Increases occupant well-being and productivity while simultaneously minimizing wasted energy from behavioral factors.
Information Efficiency	Single Source of Semantic Truth: Integrates all operational (IoT), static (BIM), and organizational data into a platform that supports semantic querying and standardized data visualization [Jian et al., 2023; Zhao et al., 2022].	Reduces operational friction and information loss across management handovers, ensuring data integrity for the entire building lifecycle.

Quantitative Performance Assurance and Auditing (The FM Data Core)

FM is primarily responsible for bridging the gap between a building's designed energy performance and its actual consumption, a task requiring rigorous, numerical validation.

FM Challenge	Case Study Location & Details	Key Quantitative Finding for FM	Illustrative Diagram
High-Fidelity Monitoring of Complex Networks	Suurstoffi District, Central Switzerland: A CO_2-neutral low-temperature heating and cooling district network. Monitoring spanned five years.	FM operations required monthly analysis of over 300 measuring points to verify project goals. The most relevant observation for FM was the quantified performance gap in the electricity consumption of auxiliary equipment (e.g., pumps), demonstrating that even with innovative design, auxiliary loads require intense monitoring [Vetterli et al., 2017].	
VHEP Building Compliance Failure	A Very High Energy Performance (VHEP) Student Residency, Geneva: Benchmarked against the MINERGIE label and thermal regulations.	The FM audit revealed non-compliance: Actual heat demand (8MJ/m^{2}) and hot water consumption (116MJ/m^{2}) exceeded the limit values. This quantitative failure forces FM to address the root causes of the performance gap in high-performance residential sectors [Lehmann et al., 2017].	
Quantifying the Hidden BAS Energy Load	Six Constructed Buildings (Five Office Buildings and One School, Switzerland): Highly automated facilities where the electricity consumption of the Building Automation System (BAS) was isolated and quantified.	FM must now budget and optimize this load: annual electricity consumption for room automation (controllers, sensors, actuators) was measured between 2 to 5 kWh/m^{2}. This finding challenges the old FM assumption that this load is negligible [Kräuchi et al., 2017].	

Advanced Control and System Optimization (The FM Strategy)
Modern FM utilizes decentralized control and sophisticated data modeling to optimize system efficiency far beyond conventional scheduling.

FM Application	**Case Study Location & Details**	**Key Technical Insight & Outcome for FM**	**Illustrative Diagram**
Decentralized HVAC Control	A Factory in South China: Validation of a decentralized optimal control algorithm for parallel-connected chillers via hardware application.	The FM system using this technique is "much more flexible and more efficient" than traditional centralized control. Each chiller acts as a "smart chiller," enabling collaborative operation to minimize total operational energy cost [Dai et al., 2017].	
Behavioral Load Forecasting	Residential Buildings in Singapore: Data collected from 43,000 students carrying distributed, portable sensor devices (part of the National Science Experiment).	This behavioral data is crucial for FM to accurately determine and model residential split-system AC usage patterns. This directly improves the accuracy of load forecasting and allows FM to target behavioral factors contributing to the energy gap [Happle et al., 2017].	
Dynamic Lighting and Shading Control	Implementation of the new Swiss Standard SIA 387/4: A new hourly calculation model for lighting and solar protection was developed.	FM must manage and monitor six control options for daylight-dependent lighting and three control options for solar protection (e.g., automated blind slat angles). This necessitates a dynamic, hourly-based FM strategy, moving away from simple annual estimates [Zweifel, 2017].	

District-Scale Management and Design Influence (The FM Scope)

The FM role is expanding from managing a single asset to optimizing resources across multiple buildings and influencing early design decisions for future operational benefit.

FM Application	Case Study Location & Details	FM Implication for System Integration & Planning	Illustrative Diagram
Neighborhood Energy Flexibility	Two different neighborhoods in the Netherlands: Analysis of the electrical and thermal load profiles of diverse buildings (office, residential) in the same microgrid.	FM identifies useful simultaneous loads (e.g., one building needs cooling, another needs heating) to facilitate energy exchange between buildings, leading to collective energy savings and optimized district operation [Walker et al., 2017].	
NZEB Compliance Decisions	General NZEB Modeling (SIA Standard Analysis): Analysis of balancing methods for Net Zero Energy Buildings.	FM planning must understand that the choice of asymmetric primary energy factors (versus symmetric) and time steps (e.g., hourly vs. annual balancing) directly impacts the required size and output of the onsite PV system necessary to achieve NZEB status [Hall & Geissler, 2017].	
Design Phase Influence (FMESG)	Research funded by the German Federal Ministry for Economic Affairs and Energy (FMESG project): Focus on new 3D-ETFE spatial transformed foils for membrane structures.	FM's input is critical in evaluating new architectural solutions (like this advanced façade material) via dynamic thermal simulations to quantify the potential for cooling energy saving and improvement of thermal comfort, which directly simplifies future operational costs [Cremers & Marx, 2017].	

Energy Efficiency

- IoT sensors and actuation: Use of temperature, humidity, occupancy, CO_2, light sensors plus smart meters enable continuous monitoring and real-time control of building services (HVAC, lighting, ventilation). For example, A Review of Using IoT for Energy Efficient Buildings and Cities: A Built Environment Perspective found up to ~32.9 % electricity savings in a hospital case through IoT monitoring of solar water heating, flow meters and other devices.[*Hassan Ahmed Hassan Youssef], (2020)*
- Integration with BIM and Digital Twin: When IoT data is fed into BIM models or digital twin platforms, operators obtain richer decision-support: trending, simulation, predictive maintenance. The systematic review by Application of Building Information Modeling for Energy Efficiency: A Systematic Review highlights that BIM–IoT integration enables continuous monitoring and optimization of operations.
- Occupant behaviour & control logic: The impact of occupant behaviour is non-negligible: some studies estimate ~30 % savings possible when building users adopt energy-aware behaviour patterns.
- Advanced analytics (AI / anomaly detection): AI and anomaly detection frameworks help identify inefficient consumption patterns. For example, Artificial Intelligence based Anomaly Detection of Energy Consumption in Buildings: A Review, Current Trends and New Perspectives reviews how ML/AI supports this in smart buildings.

Illustrative table – Technology vs Energy Efficiency Impact

Technology/Approach	Typical Application	Reported Energy Savings
IoT occupancy + lighting/AC control	Occupancy sensors + smart scheduling	3%–60% for lighting; up to ~20% HVAC GeoSphere™+1
IoT + solar/renewables integration	Solar water heaters + IoT monitoring	~32.9% electricity saving in case study MDPI
BIM–IoT integrated operational monitoring	Data feed into BIM model + dashboard	Not always quantified explicitly MDPI
Digital Twin for operational stage (retrofit)	Virtual replica + real-time sensor data	Emerging – qualitative evidence only SpringerOpen

Savings depend upon building type, baseline, climate, and the maturity of implementation. These diagrams illustrate layered architecture: IoT sensors → gateway/edge/fog → cloud platform → dashboards/analytics → building controls, figure 2.

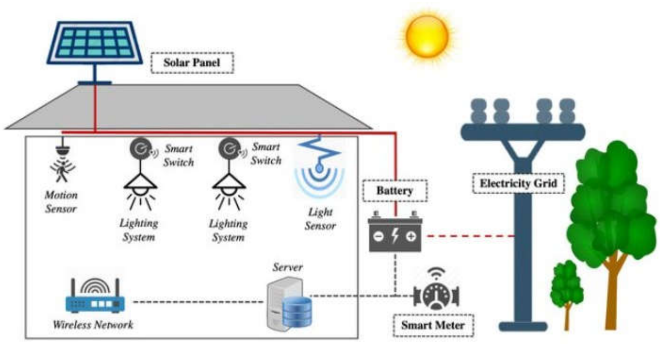

Fig2: the concept of IoT- enable building energy, management system

The architecture of the smart building energy system illustrated into fig (3) herein, the left part is associated graphical user interface used mainly to control.

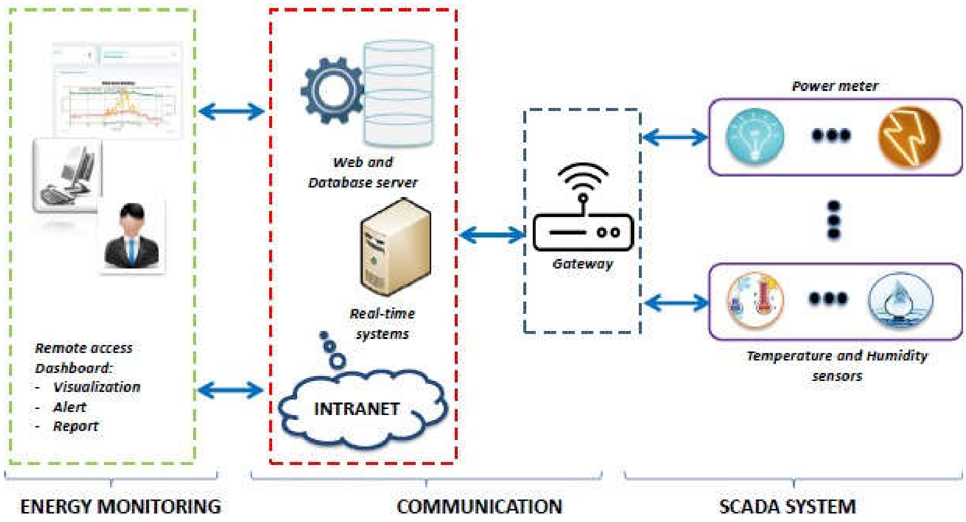

Fig (3) smart building energy management system architecture

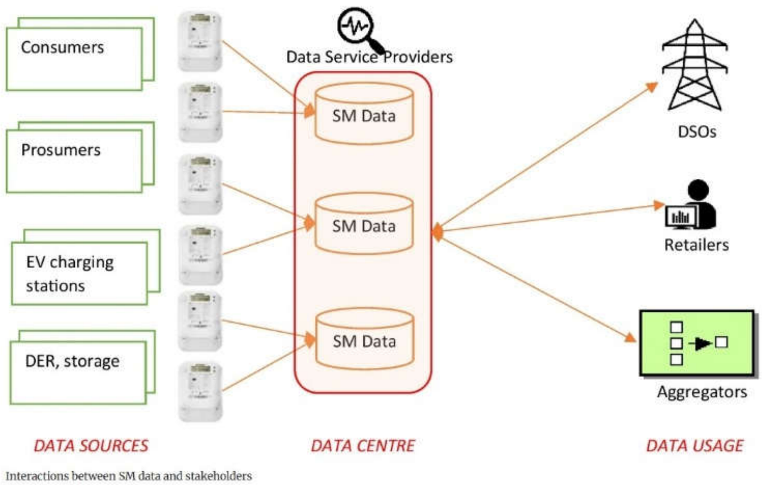

Fig (4): An edge-fog-cloud computing architecture for IOT and smart metering data

Major challenges

- Lack of early-stage integration of IoT in building design phases (pre-design to operations) remains a barrier.
- Interoperability issues between devices, protocols, systems.
- Data management, security/privacy, scalability of analytics.
- Limited large-scale empirical studies in operational buildings (many are pilot or lab studies).

Integration Approaches and Technical Architectures

Among studies that examined BIM-IoT integration, several distinct architectural approaches emerged. The most comprehensive framework utilized Wireless Sensor Networks and RFID systems to enhance monitoring and resource allocation efficiency, with BIM serving as a visualization platform for IoT device data . This approach enabled real-time data exchange and decision-making support, though implementation remained in early conceptual stages .

Facility Management Applications Supported by BIM-IoT Integration

BIM-IoT integration enabled multiple facility management functions across the reviewed implementations. Energy management and optimization emerged as the dominant application, supported by 35 studies .

Environmental monitoring of HVAC, lighting, and air quality constituted the second most common application . Systems collected real-time data on temperature, occupancy, humidity, CO_2 levels, and air quality through WiFi and ZigBee communication networks . Artificial neural networks processed this data to estimate and predict thermal behavior across instrumented and non-instrumented zones .

Asset tracking and lifecycle management capabilities were implemented through IoT sensors providing real-time asset data to BIM models . Preventive and predictive maintenance frameworks utilized this data for fault prediction and reduced overtime costs .

Emergency response and safety functions integrated IoT monitoring with BIM visualization . Security and access control systems enhanced building monitoring through IoT sensors and BIM models . Space utilization and allocation improved through spatial information tracking .

One implementation specifically addressed user engagement by providing advice through a graphical interface rather than direct HVAC automation, inviting occupants to optimize energy consumption behaviors . This human-centered approach complemented technical automation strategies.

Technology Specifications and Implementation Components

BIM software platforms included Autodesk Revit , Graphisoft Archicad , SketchUp with Trnsys3d plugin , and Rhino 3D . Energy analysis utilized Green Building Studio , while lifecycle assessment employed Tally software . Simulation platforms included EnergyPlus , IDA ICE , TRNSYS .

IoT hardware specifications revealed diverse sensor deployments. Temperature, occupancy, humidity, CO2, and air quality sensors connected via WiFi and ZigBee protocols. BLE beacons and sensor-enhanced personal protective equipment enabled localization tracking. Advanced implementations incorporated 218 sensors for comprehensive data collection, 3D sonic anemometers (Gill WindMaster), meteorological stations (Gill GMX 300), and surface temperature sensors (Optris OPTCSLT15K) .

Communication technologies included Bluetooth Low Energy, with planned LoRaWAN standard adoption . Build- ing automation protocols encompassed BACnet, LonWorks, KNX, OPC, SDN, and SaaS . Data exchange utilized EddyStone Protocol and RSSI measurements , IFC technology , and spatial ETL workflows .

Cloud platforms supported data management through PTC Thingworx and Microsoft Azure IoT platform. Edge computing approaches employed decentralized processing using Colored Petri Nets. Data analytics tools included artificial neural networks using multilayer perceptron models with Levenberg-Marquardt algorithms, YALMIP and CPLEX for optimization , and Python-based Load Shape models .

System integration costs and cybersecurity measures were notably absent from reporting across all studies.

Performance Outcomes and Measured Improvements

Energy consumption reductions represented the most frequently quantified outcome. One academic building demon- strated 10% reduction in energy costs with potential heating cost reductions of 10-20% . A solar thermal installation covered 50% of hot water demand while heat recovery ventilation reduced space heating demand by 40% . Thermal energy consumption achieved half that of comparable student residencies and multifamily buildings .

Advanced envelope systems showed dramatic improvements. Integrated airflow windows with optimized external louver shading demanded 80% less energy than double-glazed windows during cooling seasons in semi-arid climates
. Specific fenestration configurations achieved 87% improvement in cooling energy loads and 71% thermal comfort enhancement . A heliostat-based daylighting system reduced artificial lighting electricity by 9-20% while improving daylight uniformity by 39-55% .

HVAC system optimization demonstrated measurable efficiency gains. A modular low-lift chiller achieved 13.5% reduction in annual electricity consumption compared to central high-lift systems . Heat pump seasonal performance factors reached 3.2 without ancillary electricity and 3.0 with ancillaries, while integrated IceSol systems achieved SPFs of 3.8 and 3.5 respectively . Renewable energy covered 93% of heating demand through direct and indirect solar sources.

Occupancy-based heating control yielded savings of 20-24% in original buildings and 30-40% in refurbished apart- ments when applied to single units. Building-wide implementation produced 4-9% savings in original structures and 3-13% in refurbished ones. Model predictive control strategies achieved energy cost savings of 22-26% while maintaining comfort levels and increasing total energy use by only 2-4% .

Urban-scale interventions demonstrated substantial potential. One renovation strategy achieved global primary energy consumption reduction of approximately 49%, with 70% of buildings reaching 80-140 kWh/m²·year and 29% achieving 140-180 kWh/m²·year . A second strategy produced 25% global reduction with 70% of buildings in the 180-220 kWh/m²·year range .

Performance forecasting accuracy varied significantly with scenario complexity. Heat demand predictions main- tained error margins below 20% when considering only weather changes . However, introducing renovation scenar- ios increased error margins to 59.5% .

Computational efficiency improvements emerged through surrogate modeling. One optimization approach reduced computation time by a factor of 4 while maintaining 1.6% optimality loss . Reinforcement learning minimized energy consumption through adaptive control in residential setting

Smart City Standards in Saudi Arabia under Vision 2030

Saudi Arabia's Vision 2030 emphasizes transforming urban areas into smart, sustainable, and livable cities. The Kingdom has developed comprehensive standards and frameworks to guide smart city development, which include(Youssef,2025):

- **Sustainability and Environmental Responsibility**
- Optimize energy, water, and waste management systems.
- Adopt green building standards and low-carbon infrastructure.
- **Digital Infrastructure and Connectivity**
- Deploy high-speed broadband and IoT networks for real-time monitoring and data-driven urban management.
- Integrate digital platforms for public services and intelligent transportation systems.
- **Governance and Citizen Engagement**

- Enable e-governance and transparent data-sharing for efficient urban management.
- Encourage citizen participation in decision-making processes.
- **Innovation and Technology Adoption**

- Promote AI, digital twins, robotics, and predictive analytics to enhance urban operations.
- Implement smart mobility solutions including autonomous vehicles and intelligent traffic systems.
- **Quality of Life and Inclusivity**

- Enable e-governance and transparent data-sharing for efficient urban management.
- Encourage citizen participation in decision-making processes.
- **Economic and Investment Opportunities**

- Design smart cities to attract technology and innovation investments.
- Support start-ups and innovation hubs contributing to economic diversification.

Integration with Digital Twins and AI: Digital twin technology in NEOM operationalizes these standards by combining real- time monitoring, predictive AI, and IoT data. This integration ensures sustainability, optimizes resources, and enhances overall urban quality of life in alignment with Vision 2030 objectives.

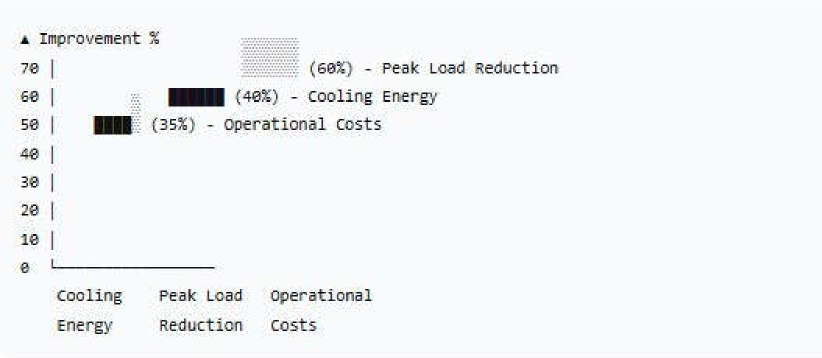

Fig 5. NEOM Project Performance Metrics

References

Chen, D. et al. (2024). Smart Buildings and Digital Twin to Monitoring the Efficiency and Wellness of Working Environments: A Case Study on IoT Integration and Data-Driven Management. Applied Sciences, 15(9), 4939.

Dai, Y., Jiang, Z., & Wang, S. (2017). Decentralized control of parallel-connected chillers. Energy Procedia, 122, 86–91.

Hall, M., & Geissler, A. (2017). Different balancing methods for Net Zero Energy Buildings—Impact of time steps, grid interaction and weighting factors. Energy Procedia, 122, 379–384.

Happle, G., Wilhelm, E., Fonseca, J. A., & Schlueter, A. (2017). Determining air-conditioning usage patterns in Singapore from distributed, portable sensors. Energy Procedia, 122, 313–318.

Jian, Z. et al. (2023). Major opportunities of digital twins for smart buildings: a scientometric and content analysis. Smart and Sustainable Built Environment, 12(7), 1033-1052.

Kräuchi, P. et al. (2017). Electricity consumption of building automation. Energy Procedia, 122, 295–300.

Lehmann, U., Khoury, J., & Patel, M. K. (2017). Actual energy performance of student housing: case study, benchmarking and performance gap analysis. Energy Procedia, 122, 163–168.

Sakhardande, S., et al. (2024). Digital Twins as a Framework for IoT Applications. The Buckingham E-Archive of Research (BEAR).

Vetterli, N., Sulzer, M., & Menti, U.-P. (2017). Energy monitoring of a low temperature heating and cooling district network. Energy Procedia, 122, 62–67.

Wang, W., et al. (2024). Digital Twins for Smart Building at the Facility Management Stage: A Systematic Review of Enablers, Applications, and Challenges. Sustainability, 16(4), 1485.

Zhao, D., et al. (2022). Toward Smart-Building Digital Twins: BIM and IoT Data Integration. 2022 IEEE International Conference on Smart Cloud (SmartCloud), 248-253.

Chen, D. et al. (2024). Smart Buildings and Digital Twin to Monitoring the Efficiency and Wellness of Working Environments: A Case Study on IoT Integration and Data-Driven Management. Applied Sciences, 15(9), 4939.

Dai, Y., Jiang, Z., & Wang, S. (2017). Decentralized control of parallel-connected chillers. Energy Procedia, 122, 86–91.

Happle, G., Wilhelm, E., Fonseca, J. A., & Schlueter, A. (2017). Determining air-conditioning usage patterns in Singapore from distributed, portable sensors. Energy Procedia, 122, 313–318.

Hall, M., & Geissler, A. (2017). Different balancing methods for Net Zero Energy Buildings—Impact of time steps, grid interaction and weighting factors. Energy Procedia, 122, 379–384.

Jian, Z. et al. (2023). Major opportunities of digital twins for smart buildings: a scientometric and content analysis. Smart and Sustainable Built Environment, 12(7), 1033-1052.

Kräuchi, P., Dahinden, C., Jurt, D., Wouters, V., Menti, U.-P., & Steiger, O. (2017). Electricity consumption of building automation. Energy Procedia, 122, 295–300.

Lehmann, U., Khoury, J., & Patel, M. K. (2017). Actual energy performance of student housing: case study, benchmarking and performance gap analysis. Energy Procedia, 122, 163–168.

Sakhardande, S., et al. (2024). Digital Twins as a Framework for IoT Applications. The Buckingham E-Archive of Research (BEAR).

Vetterli, N., Sulzer, M., & Menti, U.-P. (2017). Energy monitoring of a low temperature heating and cooling district network. Energy Procedia, 122, 62–67.

Walker, S., Corten, K., Labeodan, T., Maassenba, W., & Zeilera, W. (2017). A load profile study of different buildings to identify neighborhood energy flexibility with exchange possibilities. Energy Procedia, 122, 553–558.

Wang, W., et al. (2024). Digital Twins for Smart Building at the Facility Management Stage: A Systematic Review of Enablers, Applications, and Challenges. Sustainability, 16(4), 1485.

Zhao, D., et al. (2022). Toward Smart-Building Digital Twins: BIM and IoT Data Integration. 2022 IEEE International Conference on Smart Cloud (SmartCloud), 248-253.

Zhao, X., et al. (2024). *Integration of BIM and IoT for smart facility management: A systematic review. Automation in Construction*, 157, 105013.

Wang, L., & Zhang, Q. (2023). *Real-time digital twins for energy-efficient buildings using BIM and IoT. Journal of Building Engineering*, 78, 107240.

Li, J., & Chen, Y. (2023). *BIM-based predictive maintenance framework for smart buildings. IEEE Internet of Things Journal*, 10(5), 4562–4578.

Ahmed, S., et al. (2022). *Lifecycle management through BIM–FM integration in arid climate regions. Building and Environment*, 224, 109540.

Alqahtani, H., & Alshahrani, A. (2021). *Adopting BIM for sustainable construction in Saudi Arabia under Vision 2030. Sustainability*, 13(22), 12577.

Grieves, M., & Vickers, J. (2020). *Digital twin: Mitigating unforeseen issues through BIM-based modeling. Procedia CIRP*, 93, 698–705.

Hassan Ahmed Hassan Youssef, Neama Hassan omar (2025), A Digital Twin Approach for AI-Controlled Smart Façades: Empirical Validation and Strategic Implementation in in Achieving Saudi Vision 2030 *International Journal of Recent Advances in Multidisciplinary Research, Vol. 12, Issue 10, October, 2025*

Hassan Ahmed Hassan Youssef, (2020)., Traditional Yemeni Architecture and Its Impact on Energy Efficiency, International Journal of Engineering Research and Technology. ISSN 0974-3154, Volume 13, Number 8 (2020), pp. 2014-2022© International Research Publication House. http://www.irphouse.com

Hassan Youssef (2025) A DIGITAL TWIN APPROACH FOR AI-CONTROLLED SMART FAÇADES: EMPIRICAL VALIDATION AND STRATEGIC IMPLEMENTATION IN IN ACHIEVING SAUDI VISION 2030, International Journal of Recent Advances in Multidisciplinary Research, Vol. 12, Issue 10, pp.11864-11873, October, 2025, https://doi.org/10.64485/ijramr.6274.10.2025