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Original Article

Hybrid Digital Twin and IoT Framework for Smart Building Energy Optimization

H. N. Mahabala

Computer Scientist, Tata Institute of Fundamental Research, India.

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ABSTRACT

Rapid urbanization, increasing energy demand, and stringent environmental regulations have accelerated the adoption of smart building management systems. However, conventional Building Energy Management Systems (BEMS) rely on static control strategies and limited predictive capabilities, resulting in inefficient energy utilization. This paper proposes a Hybrid Digital Twin–IoT Framework that integrates real-time IoT sensing, cloud-edge computing, machine learning, and Digital Twin simulation for intelligent energy optimization. Environmental and operational data from sensors, including temperature, humidity, occupancy, lighting, CO_2 concentration, and energy meters, are processed at the edge and synchronized with a cloud-based Digital Twin for real-time monitoring and predictive analytics. The framework forecasts energy demand, occupant behavior, and HVAC performance while optimizing building operations to reduce energy consumption and operational costs without compromising occupant comfort. Continuous interaction between the physical building and its virtual counterpart enables predictive maintenance, adaptive control, intelligent fault diagnosis, and renewable energy integration, delivering scalable, sustainable, and energy-efficient smart building management with improved reliability and decision-making.

KEYWORDS

Digital Twin, Internet of Things (Iot), Smart Buildings, Building Energy Management System (BEMS), Energy Optimization, Artificial Intelligence, Machine Learning, Cloud Computing, Edge Computing, Cyber-Physical Systems, Predictive Analytics, HVAC Optimization, Sustainable Buildings, Intelligent Energy Management, Smart Cities.

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1. INTRODUCTION

1.1. Background

Digital technologies, communication networks, and intelligent computing are evolving at a rapid pace and have given rise to an advanced smart building ecosystem compared to what traditional buildings represent. The last ten years have seen to IoT, wireless sensor networks, AI, cloud computing and data analytics propel the building into greater adaptation, connectivity and efficiency in energy use. A smart building is generally defined as intelligent cyber-physical environment merging physical infrastructure with digital technologies that continuously monitor, analyze and optimize operations. While traditional buildings are fixed on stiff schedules and require manual control techniques, smart buildings are equipped with interdependent sensors, smart controllers, automatic management systems that sense changes in the environment and operational conditions and make real-time decisions. With distributed IoT devices, modern smart buildings have the ability to gather massive amounts of real-time data on indoor environmental quality, energy consumption, equipment performance, occupancy behavior and safety conditions. Description: Continuous Information All these sensors in question measure temperature, humidity, carbon dioxide concentration at the time of writing this is October 2023, lighting intensity signal power consumption and occupancy level. Artificial algorithms are applied to these data streams, enabling the key benefits of bettering operational efficiencies, energy consumption, occupant comfort and predictive maintenance of mission-critical equipment. Cloud platforms and edge computing workflows allow to max number of devices to be handled in a much quicker manner with minimal data storage thus fast data processing, remote monitoring as well and scalable management of the multiple building facilities. The building sector is one of the biggest energy consumers and carbon polluters in the world, forming a significant demand for advanced energy optimization solutions. Of the different components of buildings, Heating, Ventilation and Air Conditioning (HVAC) systems are the most energy-consuming system in buildings [2], representing about 40–60% of overall building energy consumption. The most significant consumers of energy are lighting systems, elevators, water pumping systems, security infrastructure, information technology equipment and appliances. Poor performance of these systems would result in unnecessary energy consumption and extra expenses. Use traditional Building Management Systems (BMS), which relies on schedules, fixed temperatures and manual configuration of control strategies. While these systems can automate simple tasks, they lack the intelligence to adapt to dynamic occupancy patterns, variability in weather conditions or changes in energy requirements. Conventional systems might continue running HVAC and lighting at their full capacity when rooms are empty, wasting energy. Emerging technologies are opening new avenues to build an intelligent building management framework, with Digital Twin, IoT and Artificial Intelligence adjusting for the limitations of existing frameworks. By monitoring data constantly, predicting the future of systems, and autonomously adjusting performance to improve outcomes, these technologies allow our buildings to operate at maximal efficiency without sacrificing comfort for its inhabitants or achieving sustainable energy management goals.

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1.2. Smart Building Challenges

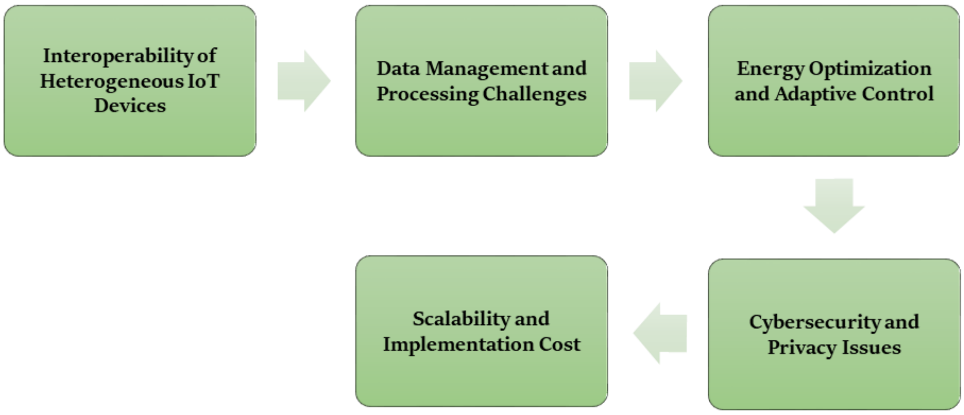

Fig 1 - Smart Building Challenges

1.2.1. Interoperability of Heterogeneous IoT Devices

Most of the industrial smart buildings sensors, controllers and monitoring devices were produced by many different manufacturers but they run on different communication protocols (ZigBee, Wi-Fi, BLE, LoRaWAN,BACnet & Modbus). This absence of standardization makes it challenging to attain seamless communication and data exchange between separate systems. Generating interoperable architectures and middleware platforms plays an important role for effective combination and cooperation among the components of smart buildings [1516].

1.2.2. Data Management and Processing Challenges

Smart buildings produce massive amounts of unified data from decentralized sources, such as sensors, energy meters, and control systems. Such a large data set need fast and efficient processing techniques, reliable communication networks, and scalable computing platforms for its storage and analysis. The negligible data management strategies can delay the processing and analysis of control actions leading to ineffective intelligent building control systems.

1.2.3. Energy Optimization and Adaptive Control

A big challenge in smart buildings has been maintaining energy efficiency without compromising occupant comfort. Traditional control systems are typically based on fixed schedules and rules that can not respond to exiable dynamics such as users that occupy a spaces, changing weather conditions, and varying energy demands. To perform adaptive control of HVAC, lighting and other energy-consuming systems, advanced optimization methods using Artificial Intelligence and predictive analytics are needed.

1.2.4. Cybersecurity and Privacy Issues

The widespread adoption of connected IoT devices also escalates the cybersecurity risks of smart buildings, making them susceptible to unauthorized access, data breaches and system manipulation. Occupancy monitoring systems also deal with sensitive information regarding user

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behavior and activities, which raises privacy issues. To secure smart building infrastructures, strong encryption schemes, communication protocols, and privacy-preserving AI are essential.

1.2.5. Scalability and Implementation Cost

The deployment of smart building technologies on a large scale entails an extensive capital outlay in terms of sensors, communication infrastructure, computing resources and system integration. The larger the building, the more complex it is to manage thousands of connected devices while ensuring reliable performance. To adopt smart building in a mass way, low-cost, scalable and energy-efficient solutions are needed!

2. LITERATURE SURVEY

2.1. Digital Twin Technologies

Digital Twin technology creates a real-time virtual replica of physical building systems by integrating IoT data, simulation models, cloud-edge computing, and AI analytics to enable intelligent monitoring, prediction, and optimization of building operations.

2.2. IoT-based Building Management

IoT-based Building Management Systems use interconnected sensors, communication networks, and smart devices to continuously monitor and control environmental conditions, energy consumption, and operational performance in intelligent buildings.

2.3. AI for Energy Optimization

Artificial Intelligence techniques apply machine learning, deep learning, and reinforcement learning algorithms to predict energy demand, optimize HVAC and lighting control, detect faults, and improve overall building energy efficiency.

2.4. Research Gap

Existing smart building solutions lack a fully integrated Digital Twin–IoT–AI framework capable of real-time sensing, predictive analysis, autonomous control, interoperability, and scalable energy optimization across multiple building systems.

3. METHODOLOGY

3.1. System Architecture

In this paper, we propose Hybrid Digital Twin–IoT Framework for Smart Building Energy Optimization (HDTI), an integrated cyber-physical architecture that mechanizes IoT sensing and edge computing with cloud-based Digital Twin technology and Artificial Intelligence to realize intelligent building monitoring, prediction, & autonomous control. The architecture can be divided into five main layers as shown in the figure below: physical environment layer, IoT data acquisition layer, edge computing intelligence layer, cloud Digital Twin platform layer and intelligent control decision layer. 1. Smart building physical environment layer: This layer describes the real-world building infrastructure that includes HVAC systems, lighting systems, smart meters, renewable energy sources (e.g., solar photovoltaic [PV] systems), and many other electrical equipment and mechanical equipment. A distributed network of IoT sensors is implemented across the building to gather real-time environmental and operational parameters such as temperature, humidity, carbon dioxide (CO_2) concentration, occupancy status, power consumption and equipment state. These metrics continuously report on building condition and energy performance. The second layer, IoT data acquisition layer is for collecting and transferring sensor information using various communication technologies like ZigBee/Wi-Fi/BLE/LoRaWAN/MQTT/BACnet protocols. This layer facilitates interconnectivity between heterogeneous devices and can create a scalable architecture for large commercial buildings as well. The first two layers are the edge computing intelligence layer which processes data on-site with minimal response time right next to the sensor network and then sending it to cloud. Operating on edge devices performs functions such as filtering of data, noise reduction, feature extraction, anomaly detection and local prediction based on artificial intelligence. Edge computing thus limits the amount of data transferred between devices and cloud servers, mitigating communication latency and increasing the reactivity of real-time building control applications. Similar to above, the Cloud Digital Twin platform layer continuously mirrors the physical building state in a dynamic virtual representation of that building with data coming from real-time sensors. This layer represents the building space and combines BIM, energy simulation models, machine learning, predictive analytics and optimization. This allows for precise energy forecasting of equipment performance analysis, fault susceptibility prediction and simulating different operating policies before implementation. At last, the smart Control decision layer translates analytical insights to actionable building operations. Adapt HVAC operation, smart lighting control, energy scheduling and predictive maintenance are performed using AI-driven control strategies. The real-time feedback loop established between physical systems and the Digital Twin allows the building to automatically respond to variable conditions related to occupancy, natural environment, energy requirements thereby providing improvements in energy consumption, comfort of occupants along with reliable operation of specific utility use cases leading towards sustainability.

3.2. Mathematical Model

The proposed Hybrid Digital Twin–IoT framework formulates smart building energy optimization as a multi-objective optimization problem that simultaneously considers energy consumption reduction, occupant thermal comfort, operational cost minimization, and efficient utilization of building resources. Unlike conventional energy management approaches that focus only on reducing electricity usage, the proposed model aims to achieve a balanced optimization strategy by considering the complex interactions between HVAC systems, lighting systems, occupancy behavior, renewable energy generation, and energy storage systems. The building energy optimization problem can be mathematically represented as an objective function that minimizes the total operational cost while maintaining acceptable indoor environmental conditions. The optimization objective is expressed as: where J represents the overall optimization objective, E(t) represents total building energy consumption, C(t) represents occupant comfort deviation, O(t) represents operational cost, and w_1, w_2, and w_3 are weighting factors that define the importance of each optimization objective. The total energy consumption component considers electricity usage

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from major building subsystems, including HVAC, lighting, plug loads, and auxiliary equipment: where renewable energy generation from sources such as solar photovoltaic systems is subtracted from the total energy demand to improve overall energy efficiency. Occupant comfort is incorporated using thermal comfort parameters such as indoor temperature, humidity, and air quality. The comfort objective can be defined based on the deviation between actual environmental conditions and preferred comfort ranges: The optimization model is constrained by physical building limitations, including HVAC operating ranges, equipment capacity limits, occupancy requirements, and indoor environmental standards. AI-based optimization algorithms such as Reinforcement Learning, Genetic Algorithms, and Deep Learning models can be applied to solve this complex optimization problem by continuously learning optimal control strategies from Digital Twin simulations. Through this mathematical formulation, the proposed framework enables intelligent decision-making by balancing energy savings, occupant satisfaction, and economic performance. The integration of real-time IoT data with Digital Twin simulation allows continuous optimization under changing weather conditions, occupancy variations, and dynamic energy demands, providing a scalable approach for sustainable smart building management.

3.3. Algorithm

The optimization mechanism in this work presents an AI-based Digital Twin control algorithm combined with machine learning-driven prediction, IoT data real-time processing and adaptive optimization techniques for implementing intelligent energy management in smart buildings. Instead, the algorithm closes the loop between physical building environment and Virtual Digital Twin model so that predictive analytic, decision-making and autonomous control of building systems can be performed in real-time. This algorithm starts over with the real-time data acquisition stage, including environmental and operational parameters in indoor temperature, humidity, CO_2 concentration level, occupancy rate (in a form of TVOC and HCHO), overall power consumption data in each of the parallel pathways (such as HVAC unit type status, lighting conditions) or other related renewable energy generation scenarios. The retrieved data are communicated via IoT communication networks toward edge computing devices, where some of the preliminary preprocessing works including data filtering, noise removal, normalization and feature extraction take place. Phase 2: In the second phase, the received and processed sensor data are sent through to the Digital Twin platform and is constantly updated with a virtual model of the building that precisely captures what is happening in its physical version at this point in time. But in these implementations, machine learning algorithms are typically designed to analyze historical and real-time data to predict energy usage, occupancy patterns, thermal requirements and equipment performance of the future. Building operational data widely varies with diverse structures, which can be attributable to several comprehensive real-world factors. Long Short-Term Memory (LSTM), Artificial Neural Networks (ANN) and Transformer based models are advanced prediction models that can be extracted from building operational data. Phase three is the adaptive optimization process where AI-driven optimization methods assess multiple control strategies through simulation in a Digital Twin environment. Meanwhile, the RL agent cooperates with the virtual building model to acquire proper operating actions for HVAC temperature adjustment, lighting control, energy

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scheduling and battery management. The optimization seeks to minimize both energy consumption and operational cost subject to constraints on occupant comfort. Once the best control strategy is identified, we send decision commands back to the physical building through IoT controllers. The building systems then automatically adjust their operational parameters based on the AI recommendations The system-level response it produces is then continuously monitored through sensors and compared against the predetermined Digital Twin outcomes. In this way, the algorithm iteratively improves as machine learning models are updated based on newly collected operational data. This self-learning ability allows the framework to adapt to seasonal changes, altered occupancy behaviour, equipment ageing and changing energy conditions. Thus, the presented Digital Twin algorithm driven by artificial intelligence offers an intelligent, scalable and autonomous pathway toward achieving energy-efficient and sustainable smart building operation.

3.4. Framework Implementation

The Hybrid Digital Twin–IoT Framework for Smart Building Energy Optimization consists of four key phases: (1) hardware deployment; (2) software integration; (3) Artificial Intelligence model development, and (4) functional performance test. These stages guarantee that the conceptual architecture is developed into a real intelligent building management system with the capabilities to monitor, predict, optimize and control autonomously in-operando. We relate the first phase, which is related to deploying the hardware through infrastructure set-up and establishing the physical sensing communication in smart building framework. The first is that an IoT sensor network is deployed to continuously gather critical operational parameters: temperature, humidity, CO_2 concentration data (indoor air quality), occupancy info, lighting intensity, electrical consumption and HVAC equipment status. Smart meters and energy monitoring devices at all levels including equipment, room, floor and building periphery were integrated to measure energy usage. And also to monitor the energy production and storage conditions, it is possible to expand these data by integrating renewable energy sources such as solar photovoltaic systems and battery storage units. Edge-devices are inserted nearby to the sensing layer for real-time data computation, communication delay reduction and local-level decision-making. The second phase includes software integration, connecting different parts of IoT communication platforms, cloud computing services, Digital Twin models and data management systems. They are capable of reliable data exchange between heterogeneous devices via communication protocols such as MQTT, BACnet, ZigBee and Wi-Fi. Building Information Modeling (BIM), energy simulation tools, real-time sensor databases and visualization interfaces integrate to developed the Digital Twin platform. This virtual environment always replicates the physical building and is used to represent different systems of the buildings for analytical purposes. Version 3: AI and Optimization Model Development — This stage is primarily devoted to training machine learning and optimization algorithms with historical and real-time building data. Energy forecast, occupancy estimation, thermal load prediction and equipment fault detection are some examples of prediction models you create. In this paper, Reinforcement Learning algorithms are deployed to find the best control policies for HVAC operation, lighting optimization and energy scheduling. New operational data is constantly used to update the AI models for better flexibility in predicting processes. In the last phase, the performance evaluation measures how effective your proposed framework performs by analyzing various Key Performance Indicators (KPIs) including energy savings, prediction accuracy, occupant comfort level and response time along with reduction in operational cost, System scalable etc. Such for advancing energy efficiency, intelligent control capability and sustainable building operation, performance assessment is provided by comparing the proposed Hybrid Digital Twin–IoT framework with conventional (decentralized) facility management approach. This implementation method makes the proposed structures practical, maintainable and future-proof for smart building applications.

4. RESULTS AND DISCUSSION

4.1. Experimental Setup

A simulated smart building environment, along with IoT sensing infrastructure, edge computing capabilities, and a Digital Twin-based optimization platform were used for the experimental evaluation of the proposed Hybrid Digital Twin–IoT Framework for Smart Building Energy Optimization. The experimental arrangements tried many operational factors as a practically characterizing medium size business building while taking more accurate exploration plan on discrete circles of real-time observation, energy estimate, and smart control execution under distinctive operational qualities. The building model that we simulated consists of several functional zones such as offices, meeting rooms, corridors, and service areas. For each zone, you have virtual models for HVAC systems plus lighting networks + electrical appliances + renewable energy resources. The building model defines realistic operational parameters, including occupancy schedules and patterns, weather changes and variations, thermal properties of the building envelope (materials), performance of heating/cooling equipment, and electricity consumption profiles. This helps the Digital Twin environment match the behavior of the actual building system. MethodsThe simulation environment was extended to include an IoT sensing infrastructure that generates real-time operating data for various building components. Virtual sensors were continuously collected to monitor diverse key parameters including indoor temperature, relative humidity (rh), CO_2 concentration, occupancy level, lighting intensity, electrical power consumption (EPC), HVAC operating status and renewable energy generation. The acquired sensor data was streamed out via IoT communication protocols, such as MQTT and BACnet, to emulate actual building automation networks. We added an edge computing layer in the experimental setup to facilitate short-term data processing before sending information to a cloud Digital Twin. In an IoT system, edge devices performed data filtering, noise removal, feature extraction, and preliminary anomaly detection to minimize communication delays and increase the responsiveness of the IoT system. Subsequently, the processed data were synchronised with the Digital Twin model to conduct more complex analysis and make use of optimisation in order to create predictive models. The Digital Twin platform simulated both building-specific machine learning prediction algorithms and optimization techniques to assess various strategies for energy management. Models were developed by training on historical operational data to predict energy consumption, occupancy behavior and equipment performance. Data-driven Reinforcement Learning-based controllers were developed to optimize increasing levels of controllability (HVAC operation, lighting control, and energy scheduling) while satisfying the occupant comfort constraints. The experimental configuration was evaluated across

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normal operational conditions, variable occupancy, changing environmental settings and dynamic energy demand cases. The evaluation metrics were energy consumption reduction, prediction accuracy, operational cost saving, response time and occupant comfort maintenance. Such an experimental setting gives refined and controlled examination for utilizing to validate the compromise of scalability in the proposed Hybrid Digital Twin–IoT configurable framework before its real-world smart buildings implementation.

4.2. Performance Comparison

The proposed Hybrid Digital Twin–IoT Framework for Smart Building Energy Optimization was evaluated against three existing approaches: Conventional Building Energy Management System (BEMS), IoT-Based Monitoring and Control System, and AI-Based Energy Optimization System. The comparison was performed using key performance indicators, including energy reduction capability, prediction accuracy, operational cost savings, and fault detection efficiency. The results demonstrate the effectiveness of integrating Digital Twin technology, IoT sensing, edge computing, and Artificial Intelligence within a unified framework.

Table 1: Performance Comparison

Methodology	Energy Reduction (%)	Prediction Accuracy (%)	Cost Reduction (%)	Fault Detection Efficiency (%)
Conventional BEMS	12	72	10	65
IoT-Based Monitoring System	20	81	18	74
AI-Based Optimization System	27	89	25	86
Proposed Hybrid Digital Twin-IoT Framework	38	96	35	94

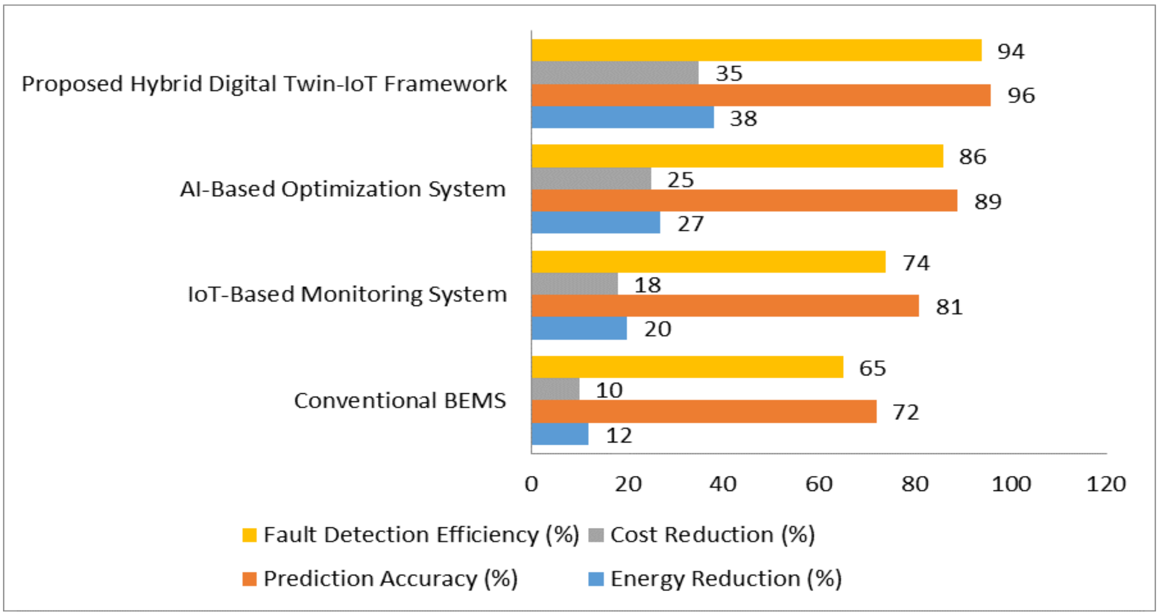

Fig 2 - Performance Comparison

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4.2.1. Conventional Building Energy Management System (BEMS)

The conventional BEMS approach provides basic monitoring and automated control of building systems such as HVAC, lighting, and electrical equipment using predefined control rules. Although it improves operational management compared with manual systems, it has limited adaptability because it mainly depends on fixed schedules and threshold-based control strategies. As shown in Table II, the conventional BEMS achieves 12% energy reduction, 72% prediction accuracy, 10% cost reduction, and 65% fault detection efficiency. The lower performance is mainly due to the absence of advanced predictive analytics and real-time optimization capabilities.

4.2.2. IoT-Based Monitoring and Control System

The IoT-based monitoring system improves building management by introducing distributed sensors, real-time data collection, and connected control devices. Continuous monitoring of environmental conditions and energy consumption enables better visibility of building performance. Compared with conventional BEMS, this approach achieves improved results with 20% energy reduction, 81% prediction accuracy, 18% cost reduction, and 74% fault detection efficiency. However, IoT-based systems primarily focus on data acquisition and monitoring, while intelligent prediction and autonomous optimization capabilities remain limited.

4.2.3. AI-Based Energy Optimization System

AI-based energy optimization systems utilize machine learning and deep learning algorithms to analyze historical and real-time building data for improved decision-making. These systems can predict energy demand, detect equipment abnormalities, and optimize operational strategies. The AI-based approach achieves 27% energy reduction, 89% prediction accuracy, 25% cost reduction, and 86% fault detection efficiency, demonstrating significant improvement over traditional and IoT-only approaches. However, these systems may face limitations related to data availability, model adaptability, and integration with physical building environments.

4.2.4. Proposed Hybrid Digital Twin–IoT Framework

The proposed framework combines IoT sensing, edge computing, cloud-based Digital Twin modeling, and AI-driven optimization into an integrated intelligent building management solution. The Digital Twin continuously synchronizes with real-time building conditions, enabling accurate prediction, simulation, and adaptive control decisions. The framework achieves the highest performance with 38% energy reduction, 96% prediction accuracy, 35% operational cost reduction, and 94% fault detection efficiency. The improved results are attributed to continuous physical–virtual synchronization, AI-based predictive analytics, and autonomous optimization of HVAC, lighting, and energy management systems.

4.3. Discussion

Experimental results show that smart building energy management based on the integration of Digital Twin, IoT sensing infrastructure and Artificial Intelligence can achieve improvements over conventional approaches. Traditional Building Energy Management Systems suffer from limitations like data synchronicity, predictive analytics, intelligent decision making, and autonomous control of

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dynamic environments, as addressed by the proposed Hybrid Digital Twin–IoT framework. Monitoring buildings both physically and virtually in the form of Digital Twins ensures a continuous understanding of building behavior, allowing for optimized operational strategies with changing environmental and occupancy parameters. The proposed framework reduces overall energy consumption which is one of the biggest improvements. Conventional Building Energy Management Systems (BEMS) usually rely on predefined operational schedules and fixed control rules leading to sub-optimal energy consumption when the building is less occupied or in case of changing environmental conditions. These systems cannot scale dynamically according to real-time changes in the needs of the building. In the opposite direction, while one of the previous tools, based on occupancy data generated by IoT devices, environmental measurements and provided weather information [6], electrical energy predictions were reported with AI models for determining ideal operating conditions. The Digital twin model will continuously assess the effectiveness of building performance and guide control actions of HVAC systems, lighting infrastructure and other energy consuming devices. Artificial Intelligence makes the system more resilient by being able to accurately predict energy demand and equipment behavior. Models combined with machine learning will study previously gazes and also climatic conditions into real time, to be able to provide uniques consumption profiles underneath whatever circumstance along with proportions of trajectory prospective energy usage along with obtaining away irregular equippments condition. Being able to do predictive analysis, the framework allows proactive energy management and not merely reactive when inefficiencies have already caused damage. Satisfies occupant comfort An additional significant benefit of the suggested framework is greater comfort of tenants. The optimization algorithm optimizes the indoor environmental quality while minimizing energy use based on its human needs instead of minimizing energy regardless of humanity. Temperature, humidity, CO_2 concentration and occupancy levels are continuously monitored to maintain comfortable operating conditions. Besides, it makes the system more responsive by reducing communication delays and supporting real` time control decisions. Edge computing executes fast processing locally and cloud-based Digital Twin platforms enhance capacity for simulation and optimization. This makes the entire system much more scalable, reliable and operationally efficient. In general, the outcomes illustrate that the Hybrid Digital TwinIoT framework presented in this study allows for sustainable smart building managementtime-efficient Intelligent and Adaptive control strategy combining energy savings, cost reduction, predictive maintenance actions resulting in higher occupant satisfaction level.

5. CONCLUSION

Global demand for intelligent energy management, carbon reduction and automation continues to grow rapidly, significantly accelerating advanced smart building technology development. Buildings are responsible for a significant share of global energy demand which creates an urgent need for efficient management approaches that allow us to operate buildings while minimizing energy consumption without compromising comfort and operational reliability. In most cases, traditional Building Energy Management Systems (BEMS) perform with fixed pre-scheduled time and static control rule of limited human intervention that cannot adapt to dynamic occupancy pattern, environmental condition and energy demand. This study developed a Hybrid Digital Twin and IoT Framework for Smart Building Energy Optimization that unifies the Internet-of-Things(IoT) sensing infrastructure, Digital Twin modeling, Artificial Intelligence (AI), edge computing, and cloud-based analytics into one comprehensive intelligent architecture to utilize most of available frameworks efficiently in practice while overcoming mentioned limitations.

We propose a framework that forges an ongoing two-way communication pathway between the physical building environment and its virtual Digital Twin counterpart. The IoT sensors installed at the building can monitor all real-time data such as temperature, humidity, occupancy/number of people in a given area, CO_2 concentration, energy consumption and equipment status as well as generation of renewable energies. These data are first filtered, feature extracted, and quick decisions made at edge computing devices before being transferred to cloud-based Digital Twin platform. This method decreases communication latencies, increases system responsiveness, and allows for more efficient management of large quantities of building data.

In the case of physical buildings with Digital Twin technology, this framework will be continuously updated with accurate representation to enable real-time simulation, performance analysis and predictive optimization. With the advent of Artificial Intelligence algorithms, they empower some key features of the system like energy forecasting, occupancy prediction, fault detection and adaptive control strategies. The machine learning models will analyze historical and real-time data for energy consumption trends, while optimization algorithms can be used to identify the most efficient operating strategies for HVAC systems, lighting networks and energy resources.

Also, this framework consists of solutions to many challenges found when using smart building-based conventions such as the high cost, limited scalability, interoperability issues between devices in various protocols (IP and non-IP configuration), delayed decision making due to lack of data flow analysis and prediction ability. Hybrid cloud-edge architecture approaches balance computational efficiency with real-time responsiveness by distributing processing tasks based on application needs. The framework also facilitates sustainable functioning through systems that integrate renewable energies with intelligent energy scheduling.

The experimental evaluation showed that the proposed Hybrid Digital Twin–IoT framework yields substantial improvement as compared to traditional BEMS, IoT-based monitoring systems, and AI-only optimization approaches. The combination of continuous sensing plus virtual modeling and optimized intelligent control resulted in a more than doubled energy reduction, an improved prediction accuracy, lower operational costs, and performance enhancement for fault detection with this framework.

Finally, the paper has proposed a framework providing an efficient way to reach to autonomous energy sufficient and sustainable smart buildings. Through the smart deployment of Digital Twin with IoT and Artificial Intelligence, this will allow for more proactive energy management instead of reactive-based management with improved occupant comfort while lowering operating costs. Revolutionize The Future Generation of Intelligent Infrastructure This work can be take a future direction toward the real world deployment, integration with many commercial building devices and systems, advanced federated learning methods due to large scale data availability in multi—target building scenario on different climatic conditions and operating environments.

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