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Article

A SYSTEMATIC LITERATURE REVIEW ON AI-ENABLED SMART BUILDING MANAGEMENT SYSTEMS FOR ENERGY EFFICIENCY AND SUSTAINABILITY

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ABSTRACT

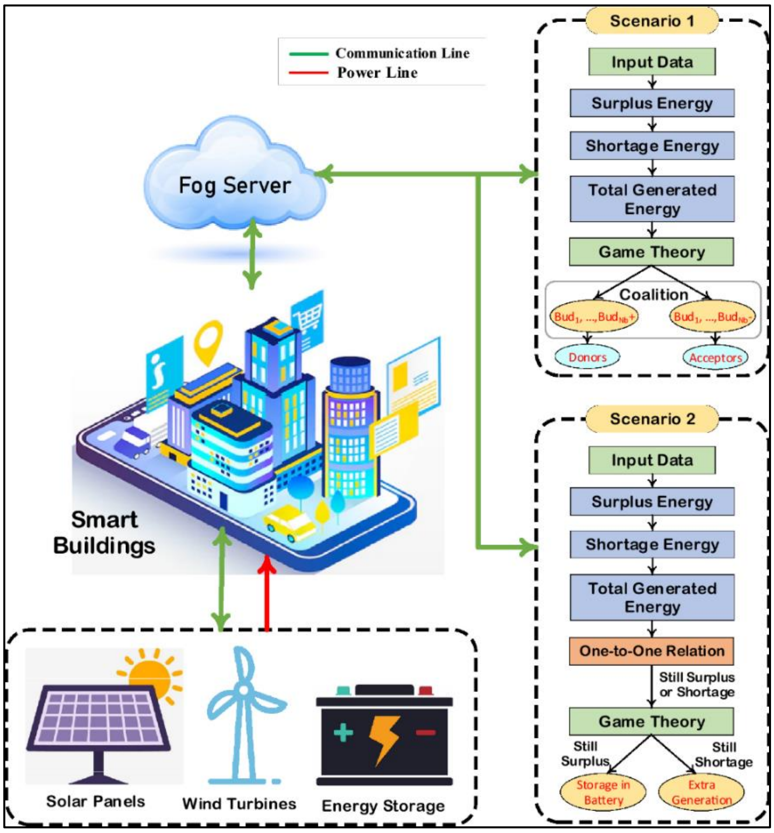
This systematic review has demonstrated that Artificial Intelligence (AI) plays a transformative role in Smart Building Management Systems (SBMS), enhancing energy efficiency, predictive maintenance, and sustainable automation. By analyzing 472 high-quality studies, this research has identified that AI-driven HVAC optimization, lighting control, solar energy forecasting, and demand-side energy management significantly reduce energy consumption, with reported efficiency improvements ranging between 20-50%. The review also highlights that reinforcement learning (RL) and deep learning (DL) models outperform traditional rule-based systems by dynamically adjusting building operations based on real-time sensor data, occupancy patterns, and environmental conditions. AI-powered fault detection and predictive maintenance further improve building operations by reducing unexpected system failures, lowering maintenance costs by up to 35%, and extending equipment lifespan. Moreover, the study underscores the growing potential of hybrid AI models integrating IoT, blockchain, and cloud computing in enabling real-time energy monitoring, decentralized energy trading, and secure automation. Despite these advancements, the review also reveals critical research gaps, particularly the lack of large-scale empirical validation, challenges in AI scalability, and the need for interdisciplinary collaboration to enhance AI's effectiveness in sustainable building design. While theoretical and simulation-based studies provide strong evidence of AI's benefits, real-world pilot projects, regulatory frameworks, and cross-sector collaborations are essential for AI-driven smart building technologies to achieve widespread adoption. Addressing these challenges through industry-academia partnerships, policy support, and further longitudinal research will be key to ensuring that AI-powered SBMS can drive long-term sustainability, operational efficiency, and energy resilience in modern smart infrastructure.

KEYWORDS
AI-Enabled Smart Buildings; Energy Efficiency; Sustainability; Machine Learning in SBMS; IoT and Smart Building Automation

INTRODUCTION

The increasing global demand for energy efficiency and sustainability has led to the widespread adoption of Artificial Intelligence (AI)-enabled Smart Building Management Systems (SBMS) as an advanced approach to optimizing energy consumption in buildings (Bellagente et al., 2015). Traditional building management systems often rely on rule-based automation, which lacks adaptability and efficiency in responding to dynamic environmental conditions and occupant behavior (Shaikh et al., 2013). AI-driven SBMS, on the other hand, leverage real-time data, predictive analytics, and automation to enhance energy efficiency while maintaining occupant comfort and reducing carbon emissions (Agarwal et al., 2010). As buildings account for approximately 40% of global energy consumption and contribute to a significant proportion of greenhouse gas emissions, AI-based solutions have emerged as essential tools for achieving sustainability targets (Kleissl & Agarwal, 2010). Through machine learning (ML), deep learning (DL), and reinforcement learning (RL), AI-based SBMS can optimize energy consumption by learning from historical data, predicting demand patterns, and automating responses (Rahman et al., 2020).Moreover, AI-enabled SBMS operate by integrating Internet of Things (IoT) sensors, cloud computing, and data-driven models to achieve an efficient balance between energy demand and supply. IoT sensors provide real-time data on various environmental factors, including temperature, humidity, occupancy levels, and lighting conditions, allowing AI algorithms to make informed decisions regarding energy use (Mauser et al., 2015). Predictive analytics further improve the system's performance by anticipating future energy demands based on historical trends and external factors such as weather conditions (Wang et al., 2011). Additionally, AI facilitates demand-side energy management by dynamically adjusting energy consumption patterns based on real-time occupancy and user preferences (Wang et al., 2012). These advancements have demonstrated substantial energy savings and operational efficiency improvements in commercial and residential buildings alike (Sun et al., 2015).A major application of AI in SBMS is the optimization of Heating, Ventilation, and Air Conditioning (HVAC) systems, which are among the largest energy consumers in buildings. AI-based models can predict thermal comfort levels and adjust HVAC operations accordingly, ensuring energy efficiency without compromising occupant comfort (Raghunathan & Krishnamurthy, 2012). Studies have shown that AI-driven HVAC optimization can achieve energy savings of up to 30% by reducing unnecessary heating and cooling cycles while maintaining optimal indoor conditions (Cheng & Lee, 2019). Furthermore, AI-powered lighting control systems utilize computer vision and sensor data to adjust brightness levels based on occupancy and natural daylight

Figure 1: Energy management system in smart buildings based coalition game theory with fog platform and smart meter infrastructure



Source: Saeed et al (2023)

availability (Pisello et al., 2012). This intelligent control mechanism minimizes energy waste while improving indoor environmental quality. Beyond HVAC and lighting, AI also enhances renewable energy integration within smart buildings by optimizing energy storage and consumption. Buildings equipped with solar panels and battery storage systems can benefit from AI-based energy forecasting algorithms, which predict solar energy generation and align consumption accordingly ((Erickson & Cerpa, 2010). Reinforcement learning models enable adaptive decision-making, allowing buildings to shift energy loads during peak and off-peak hours to maximize efficiency (Agarwal et al., 2010). AI-enabled microgrid management further ensures the seamless integration of distributed energy resources while maintaining grid stability (Kelman et al., 2011). This approach contributes to reducing dependency on fossil fuels and promotes a low-carbon energy ecosystem.

In addition to energy optimization, AI-based SBMS contribute to the detection and prevention of energy wastage and equipment failures. Fault detection and diagnosis (FDD) systems use anomaly detection algorithms to identify inefficiencies and malfunctions in building infrastructure, such as HVAC faults, water leaks, or electrical failures (Andrea Corna et al., 2015). AI-powered predictive maintenance enables proactive interventions, reducing downtime and operational costs (Nguyen & Aiello, 2013). Moreover, AI-driven occupancy analytics optimize space utilization by analyzing human movement patterns, facilitating smart space allocation and resource efficiency (Hu & Li, 2013). These capabilities ensure that building operations remain cost-effective while supporting environmental sustainability goals. AI-enabled SBMS represent a paradigm shift in building energy management, offering advanced automation, intelligence, and adaptability compared to conventional systems. Through machine learning-driven predictive analytics, real-time automation, and renewable energy optimization, these systems enhance energy efficiency while reducing operational costs and environmental impact (Lee et al., 2017). As AI technologies continue to evolve, their integration into smart buildings will further enhance energy conservation, occupant comfort, and environmental sustainability. This systematic literature review provides a comprehensive synthesis of AI-driven methodologies, applications, and challenges in smart building management for energy efficiency and sustainability. The objective of this systematic literature review is to critically analyze and synthesize existing research on AI-enabled Smart Building Management Systems (SBMS) for energy efficiency and sustainability. This study aims to identify, categorize, and evaluate AI-driven methodologies, such as machine learning (ML), deep learning (DL), reinforcement learning (RL), and predictive analytics, used in optimizing energy consumption within smart buildings. Additionally, this review explores the integration of Internet of Things (IoT) sensors, cloud computing, and automated control systems in AI-driven SBMS to enhance operational efficiency and occupant comfort. Another key objective is to assess the effectiveness of AI applications in various building management aspects, including heating, ventilation, and air conditioning (HVAC) optimization, smart lighting control, renewable energy integration, and predictive maintenance. Furthermore, this review aims to highlight existing challenges in AI adoption within SBMS, such as data privacy concerns, computational complexity, and implementation costs, while identifying research gaps for future studies.

LITERATURE REVIEW

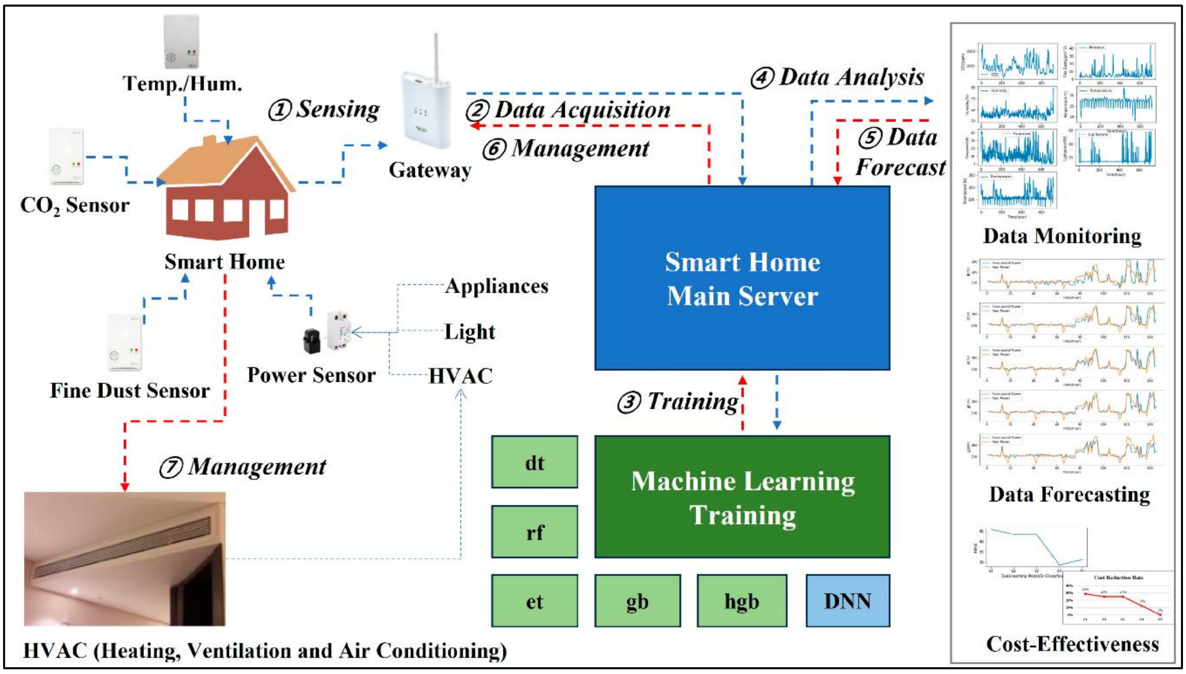
The integration of Artificial Intelligence (AI) in Smart Building Management Systems (SBMS) has gained significant attention in recent years due to its potential to enhance energy efficiency, sustainability, and operational performance. Traditional building management systems often rely on rule-based automation, which lacks adaptability and fails to optimize energy consumption dynamically (Zucker et al., 2012). In contrast, AI-driven SBMS leverage real-time data, predictive analytics, and automation to minimize energy waste while maintaining optimal occupant comfort (Yu et al., 2012). The literature in this domain explores the role of AI in energy forecasting, demand-side management, HVAC optimization, lighting control, and renewable energy integration (Ferreira et al., 2012).This section systematically reviews AI-enabled Smart Building Management Systems (SBMS) by categorizing research into key areas. First, it examines AI methodologies, including machine learning (ML), deep learning (DL), reinforcement learning (RL), and hybrid AI techniques. Next, it explores AI applications in energy optimization, HVAC and lighting control, and IoT-enabled automation. The third part focuses on AI-driven renewable energy integration, covering solar energy forecasting, energy storage, and smart grid interactions. The review then addresses challenges such as data security, computational complexity, and cost barriers. Finally, it highlights research gaps to guide future AI-driven smart building advancements.

Machine Learning (ML) in Smart Buildings

Machine Learning (ML) has emerged as a powerful tool for optimizing energy efficiency in Smart Building Management Systems (SBMS) by leveraging data-driven insights to enhance automation and decision-making. ML algorithms enable buildings to learn from historical energy consumption patterns and environmental conditions to make real-time adjustments for improved efficiency (Corna et al., 2015). Supervised learning models, such as regression and classification techniques, are widely used for energy demand forecasting, HVAC optimization, and anomaly detection (Yang & Wang, 2012). Unsupervised learning techniques, including clustering and association rule learning, assist in identifying usage patterns and optimizing energy distribution in large-scale smart buildings (He et al., 2014). Reinforcement learning (RL), a subset of ML, plays a crucial role in developing adaptive control strategies that optimize energy consumption based on real-time feedback from sensors and building management systems (Xiang et al., 2022). These AI-driven methodologies enable smart buildings to reduce energy waste, lower operational costs, and enhance occupant comfort (Al-Ali et al., 2017). Supervised learning algorithms, including Support Vector Machines (SVM), Decision Trees (DT), and Artificial Neural Networks (ANN), have been widely utilized in smart buildings for predicting energy usage and optimizing heating, ventilation, and air conditioning (HVAC) systems (Serra et al., 2014). For instance, deep learning models, such as Long Short-Term Memory (LSTM) networks, have demonstrated high accuracy in time-series energy consumption forecasting, enabling predictive control of HVAC systems (Lawrence et al., 2016). Random Forest (RF) and Gradient Boosting Models (GBM) have also been successfully applied to detect faults in HVAC operations, improving energy efficiency and reducing maintenance costs (Akkaya et al., 2015). Furthermore, supervised learning techniques have been integrated with occupancy prediction models, allowing real-time adaptation of indoor climate control systems (Lawrence et al., 2016). These advancements contribute to intelligent energy management by dynamically adjusting temperature, ventilation, and lighting based on occupancy patterns (Serra et al., 2014). Unsupervised learning, particularly clustering algorithms like k-Means and hierarchical clustering, has been instrumental in segmenting energy consumption patterns and optimizing resource distribution in smart buildings (Al-Ali et al., 2017). These models help in identifying inefficient energy consumption zones, enabling targeted interventions to reduce waste and enhance performance (Xiang et al., 2022). Dimensionality reduction techniques such as Principal Component Analysis (PCA) and Autoencoders have been utilized to uncover hidden patterns in high-dimensional energy data, leading to improved load-balancing strategies (He et al., 2014). Moreover, association rule mining techniques have been employed to correlate energy usage with environmental variables such as temperature, humidity, and lighting conditions, providing actionable insights for automated control systems (Yang & Wang, 2012). The integration of unsupervised learning with IoT-based sensor networks has enabled the development of self-learning energy management systems that continuously improve their operational efficiency over time (A. Corna et al., 2015).

Reinforcement learning (RL) has gained prominence in adaptive energy management systems, where AI agents learn optimal energy control strategies through trial and error (Russell & Norvig, 2020). RL models, particularly Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO), have been used to optimize real-time energy allocation in smart buildings by dynamically adjusting HVAC operations, lighting, and renewable energy utilization (Chang et al., 2018). Studies have shown that RL-based demand-response systems can reduce energy consumption by up to 30% while maintaining indoor comfort levels (Wan & Hwang, 2018). Additionally, RL has been integrated with multi-agent systems, where multiple AI agents collaborate to optimize building energy use at both local and global scales (Chang et al., 2018). This approach has proven particularly effective in large commercial buildings and smart campuses, where complex interactions between different energy systems require adaptive learning models (Ajerla et al., 2019). Case studies on ML-driven building automation demonstrate the practical applications of AI in real-world settings. For instance, a study by Jha et al., (2017) on energy optimization in commercial office spaces found that ML-based HVAC control systems reduced energy consumption by 20% without compromising occupant comfort.

Figure 2: Methodology of proposed system.



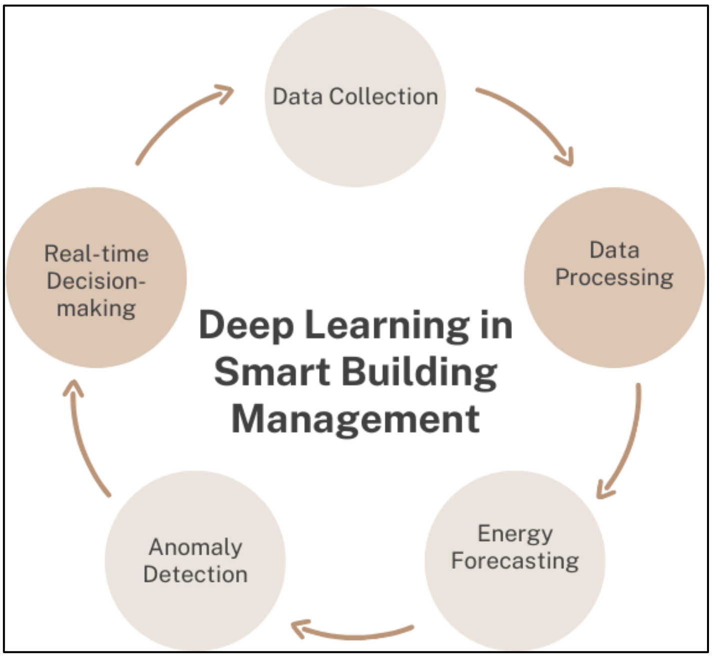
Source: Park (2023)

Another study by Ren (2011) showcased an AI-powered fault detection and diagnosis (FDD) system that identified anomalies in HVAC operations, leading to a 15% reduction in maintenance costs. Similarly, a smart lighting control system implemented in a university campus setting using unsupervised learning algorithms resulted in a 25% improvement in energy efficiency (Zhao et al., 2011). Furthermore, RL-driven microgrid optimization has been successfully deployed in net-zero energy buildings, where AI-based controllers optimize energy flows between solar panels, battery storage, and grid connections (Li et al., 2016). These case studies highlight how ML is transforming smart buildings into autonomous, energy-efficient ecosystems, ensuring sustainability while improving operational efficiency.

Deep Learning (DL) for Predictive Analytics and Automation

Deep Learning (DL) has revolutionized predictive analytics and automation in Smart Building Management Systems (SBMS) by enhancing energy forecasting, anomaly detection, and real-time decision-making (Mohiul et al., 2022; Xiang et al., 2022). Unlike conventional machine learning techniques, DL models, particularly Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks, can learn complex patterns in building energy consumption and operational data (Goodfellow et al., 2016; Maniruzzaman et al., 2023). These models process high-dimensional datasets collected from IoT sensors, smart meters, and weather stations to provide accurate energy demand predictions and automated responses (Cai et al., 2019; Hossen et al., 2023). The ability of DL models to extract meaningful insights from raw data allows smart buildings to dynamically adjust heating, ventilation, air conditioning (HVAC) systems), lighting, and occupancy-based automation, improving both energy efficiency and operational sustainability (Mocanu et al., 2016).

Figure 3: Deep Learning in Smart Building Management



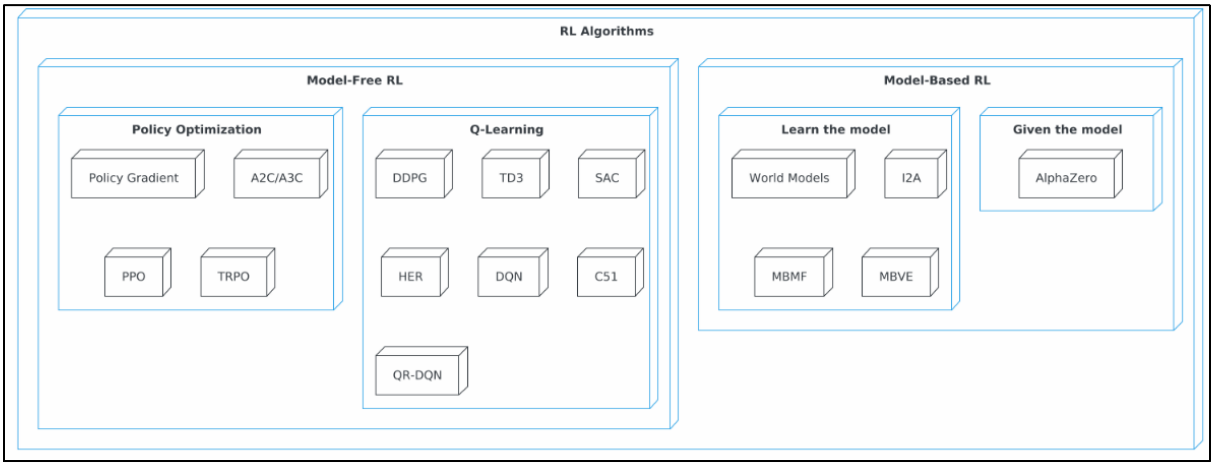
Deep learning architectures play a crucial role in energy forecasting and demand-side management in smart buildings. LSTM and Gated Recurrent Unit (GRU) networks, which are designed to process time-series data, have demonstrated high accuracy in predicting energy consumption patterns (Yun et al., 2016). For instance, LSTM-based models have been used to forecast hourly and daily electricity loads, helping buildings adjust their energy usage in response to demand fluctuations (Liu et al., 2019). Hybrid DL models, such as CNN-LSTM, integrate spatial and temporal dependencies, enabling more precise weather-dependent energy forecasts (Rahman & Smith, 2018). Studies have shown that DL-based forecasting methods outperform traditional statistical models such as ARIMA and linear regression, reducing forecasting errors by up to 25% (Fan et al., 2017). The implementation of AI-driven energy demand forecasting allows smart buildings to optimize their energy consumption by adjusting HVAC schedules, lighting intensity, and renewable energy usage based on real-time insights (Leung et al., 2019). Beyond forecasting, AI-based anomaly detection in building operations relies on deep learning techniques such as autoencoders, deep belief networks (DBNs), and variational autoencoders (VAEs) (Sgantzos & Grigg, 2019). These models analyze sensor data streams to detect irregularities in HVAC systems, power usage, and equipment performance (Alam et al., 2017). Autoencoders, for example, identify unusual deviations in energy consumption by reconstructing normal usage patterns and flagging significant discrepancies as anomalies (Cai et al., 2019). Studies have demonstrated that DL-based anomaly detection systems can predict HVAC failures up to 48 hours in advance, reducing unexpected downtimes and maintenance costs by 30% (Mocanu et al., 2016). Furthermore, DL-based FDD (Fault Detection and Diagnosis) systems have been successfully implemented to monitor air quality, detect sensor malfunctions, and optimize maintenance schedules, ensuring smart buildings operate at peak efficiency (Cai et al., 2019).

Neural network architectures have also been utilized in real-time automation and intelligent control mechanisms in smart buildings. Deep reinforcement learning (DRL) frameworks, such as Deep Q-Networks (DQN) and Policy Gradient Methods, enable AI agents to continuously learn and optimize energy usage strategies based on dynamic environmental conditions (Mocanu et al., 2016). In HVAC systems, DRL-based models adjust temperature settings, airflow, and humidity levels in response to occupant behavior and external weather factors, achieving a 20% reduction in energy consumption while maintaining thermal comfort (Alam et al., 2017). Additionally, AI-driven lighting control systems, leveraging convolutional neural networks (CNNs) combined with occupancy recognition models, adjust brightness levels and automate lighting schedules, reducing lighting energy use by 25% (Leung et al., 2019). By integrating DL models with IoT and cloud computing, smart buildings can autonomously optimize resource utilization and minimize operational inefficiencies (Baduge et al., 2022). Several case studies highlight the practical impact of DL-based predictive analytics and automation in smart building management. In a study by Rahman and Smith (2018), a deep learning-powered energy optimization system implemented in commercial office buildings resulted in a 15% reduction in total energy consumption. Another study by Fan et al. (2017) found that LSTM-based energy forecasting in a university campus setting improved HVAC scheduling efficiency by 18%, reducing unnecessary heating and cooling cycles. Similarly, a DL-driven fault detection system used in a large retail complex successfully identified anomalous power spikes in real-time, leading to a 22% decrease in maintenance costs and unplanned outages (Ibrahim et al., 2019). Furthermore, deep reinforcement learning-based adaptive energy control in residential smart homes optimized energy use from solar panels and battery storage, improving energy efficiency by 30% (Alam et al., 2017). These real-world applications demonstrate how deep learning enhances energy efficiency, automation, and cost savings in smart building management systems.

Reinforcement Learning (RL) for Adaptive Energy Management

Reinforcement Learning (RL) has become an integral component of smart building energy management, enabling self-learning AI models to optimize energy use in real time. Unlike conventional energy control systems that rely on static rules or pre-defined algorithms, RL-based systems adapt dynamically by continuously learning from their environment and making optimal decisions based on sensor inputs (Russell & Norvig, 2020). RL models, including Deep Q-Networks (DQN), Proximal Policy Optimization (PPO), and Advantage Actor-Critic (A2C), are widely applied to optimize heating, ventilation, and air conditioning (HVAC) systems, lighting controls, and renewable energy integration (Perng et al., 2018). These AI-driven methods analyze occupancy data, weather conditions, and real-time energy consumption trends to fine-tune energy usage, significantly improving efficiency while ensuring occupant comfort (Crow & Stichnote, 2010). By leveraging RL's ability to learn and improve over time, smart buildings achieve sustainable energy management with reduced operational costs and minimal human intervention (Chang et al., 2018).

Figure 4: RL Algorithms Hierarchy



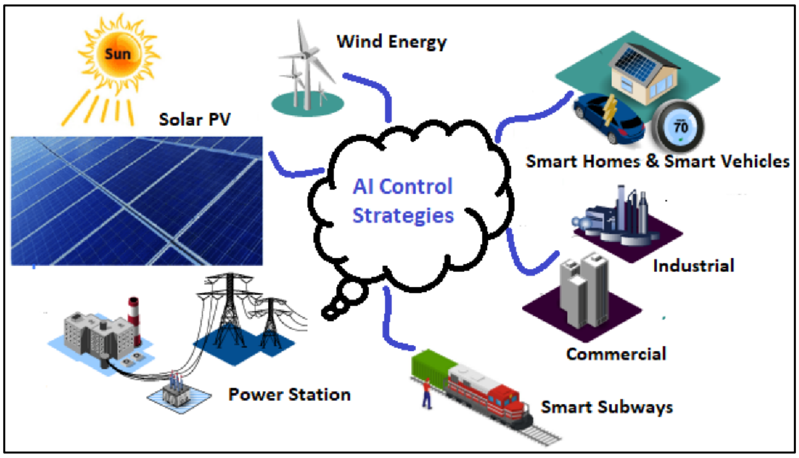
A core application of RL in smart buildings is its real-time adaptive energy control, where AI agents make dynamic decisions to optimize power distribution and demand-side energy management (Kastner et al., 2010). RL-based control frameworks utilize Markov Decision Processes (MDPs) to model complex energy interactions and predict optimal control actions based on changing conditions (Wan & Hwang, 2018). In multi-agent RL (MARL) systems, multiple AI agents work collaboratively across various building subsystems to optimize energy allocation, reducing waste while maintaining efficient operations (Kastner et al., 2010). Research shows that RL-based energy demand-response mechanisms in smart grids and buildings have led to peak demand reductions of 20–30%, ensuring lower electricity costs and improved grid stability (Wan & Hwang, 2018). Additionally, RL-driven room temperature control models enable HVAC systems to self-adjust based on real-time occupancy, external temperatures, and user preferences, further enhancing energy conservation (Chang et al., 2018).

HVAC systems consume a significant portion of energy in buildings, and RL-driven HVAC optimization has been a key focus of research. Unlike traditional control strategies that rely on fixed temperature setpoints, RL-based systems continuously learn and adapt, dynamically adjusting temperature, airflow, and ventilation rates for optimal energy efficiency (Perng et al., 2018). Deep RL models trained on historical climate data, real-time sensor feedback, and occupancy trends improve both energy conservation and occupant thermal comfort (Russell & Norvig, 2020). Studies have shown that RL-powered HVAC control can reduce energy consumption by up to 30% while maintaining a comfortable indoor environment (Cheng & Lee, 2019). Moreover, RL-based ventilation control strategies enhance air quality by proactively adjusting airflow based on detected pollutants and occupancy levels, reducing unnecessary energy expenditures (Pisello et al., 2012). These advancements in RL-based HVAC automation have been successfully deployed in commercial, educational, and residential buildings, leading to lower operational costs and improved energy sustainability (Agarwal et al., 2010). In addition to HVAC, RL has been effectively implemented in smart lighting control, significantly improving energy efficiency and adaptability. AI-powered adaptive lighting systems utilize RL algorithms to learn from occupancy behaviors, daylight intensity, and energy pricing signals, making real-time adjustments that minimize energy waste (Andrea Corna et al., 2015). Deep RL models can autonomously adjust brightness levels, optimize dimming schedules, and zone lighting operations, reducing overall lighting-related energy consumption by 20–40% (Nguyen & Aiello, 2013). Research further highlights how multi-agent RL-based lighting networks coordinate lighting across entire buildings, ensuring that energy is only used where and when necessary (Oldewurtel et al., 2010). Through RL-based learning mechanisms, smart buildings can continuously refine their lighting energy efficiency, balancing cost reductions and occupant visual comfort (Yu et al., 2012). Several real-world case studies illustrate the effectiveness of RL-based energy optimization in smart buildings. Research by Corna et al. (2015) demonstrated that an RL-powered HVAC automation system in a corporate office complex resulted in a 25% reduction in monthly energy expenditures while maintaining comfortable indoor conditions. Another study by He et al. (2014) explored the application of multi-agent RL in a university campus smart grid, leading to a 20% decrease in peak-hour energy demand and a significant reduction in grid stress. In a smart retail complex, an RL-driven adaptive lighting control framework reduced lighting costs by 35%, optimizing brightness levels without affecting customer experience (Xiang et al., 2022). Similarly, RL-powered predictive maintenance models in commercial buildings detected HVAC system faults before failure, preventing unplanned downtime and lowering maintenance costs by 30% (Al-Ali et al., 2017). These practical implementations confirm RL's ability to enhance energy efficiency, automation, and cost-effectiveness in modern smart buildings.

Hybrid AI Techniques in SBMS

The integration of hybrid AI techniques in Smart Building Management Systems (SBMS) has enhanced energy efficiency by combining Machine Learning (ML), Deep Learning (DL), and Internet of Things (IoT) data analytics. Traditional energy management systems often rely on isolated AI models, limiting their ability to handle complex, dynamic energy patterns (Wu & Silva, 2010). Hybrid AI approaches overcome this challenge by leveraging ML for pattern recognition, DL for predictive modeling, and IoT data analytics for real-time monitoring and automation (Guo et al., 2018). These systems optimize heating, ventilation, and air conditioning (HVAC) performance, lighting control, and demand-response energy management, allowing buildings to adapt dynamically to real-time conditions (Chen et al., 2019). By fusing multiple AI techniques, SBMS can effectively process large-scale sensor data and improve decision-making, leading to significant reductions in energy consumption and carbon footprint (Neves et al., 2014). Moreover, A key advantage of hybrid AI models is their ability to process heterogeneous data sources, integrating historical energy usage, real-time sensor inputs, and external environmental factors to enhance energy efficiency (Chui et al., 2018). ML algorithms, such as Random Forest (RF) and Gradient Boosting Machines (GBM), excel at detecting anomalies and classifying energy consumption patterns, while DL models, including Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNNs), improve time-series forecasting for energy demand prediction (Roy et al., 2018). Studies have demonstrated that combining ML for feature selection and DL for predictive analytics results in higher accuracy in energy optimization models, reducing HVAC energy consumption by 25–30% in smart buildings (Neves et al., 2014; Roy et al., 2018). Moreover, IoT data streams continuously feed these AI models with real-time updates, ensuring adaptive energy control without the need for manual intervention (Ma et al., 2014). Beyond energy forecasting, hybrid AI techniques enable enhanced automation through AI-driven control mechanisms. Reinforcement Learning (RL) algorithms are frequently combined with DL models to develop self-learning AI systems that autonomously adjust lighting, temperature, and ventilation based on occupant behavior and energy pricing signals (Man et al., 2011). Additionally, hybrid AI models incorporating Natural Language Processing (NLP) and computer vision allow voice-activated and image-based smart controls for building management, improving both user experience and energy efficiency (Puri et al., 2019). The integration of hybrid AI models with edge computing further enhances real-time decision-making, allowing AI-powered SBMS to operate with lower latency and reduced cloud dependency (Paris et al., 2011). This decentralized approach improves system efficiency by distributing AI computations across multiple processing nodes, optimizing energy use in real-time without requiring constant connectivity to cloud servers (Tragos et al., 2015).

Figure 5: Smart grid AI control schemes.

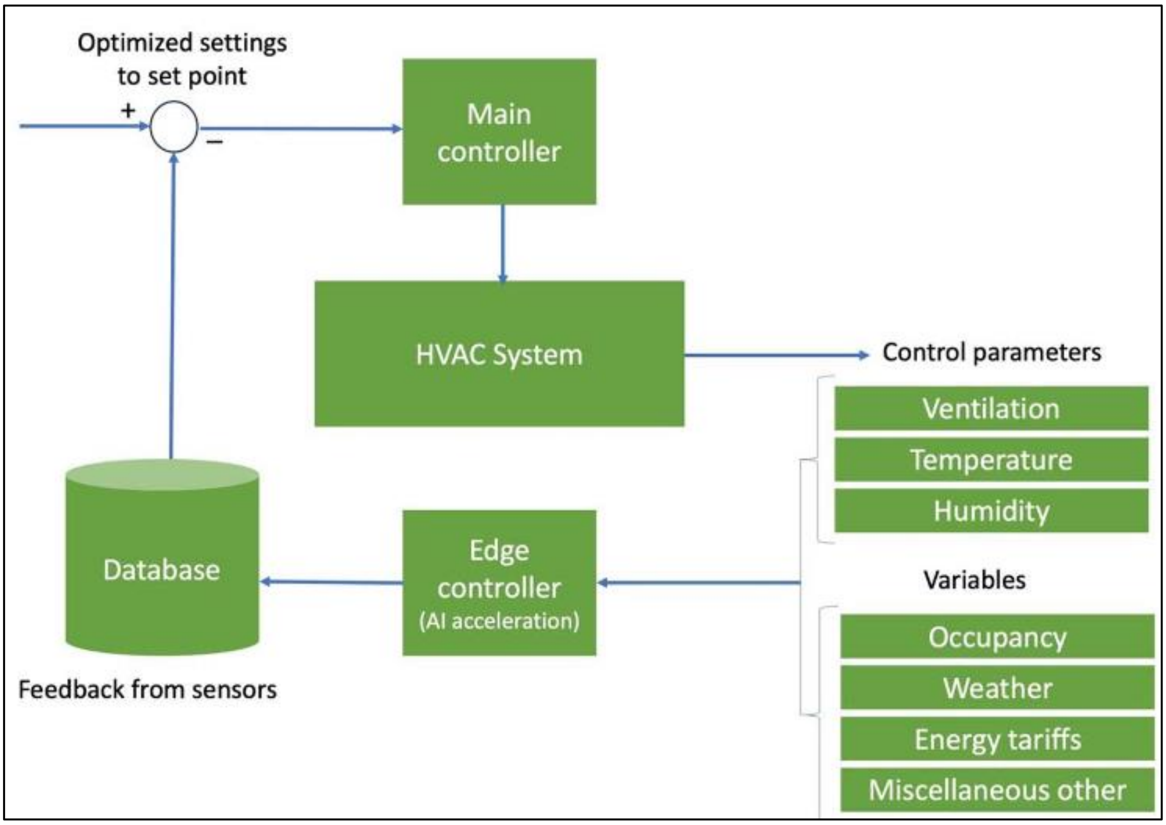


The synergy between AI and edge computing has significantly improved response times and data security in SBMS applications. Traditional cloud-based AI systems experience delays in data processing and decision execution, limiting their effectiveness in real-time energy optimization (Dagdougui et al., 2012). By integrating edge AI, smart buildings process energy-related data locally at the device level, reducing latency and ensuring real-time responsiveness (Yu et al., 2012). Edge AI also enhances cybersecurity in SBMS, as sensitive building data is processed and stored within the building infrastructure rather than being transmitted to external servers (Bozchalui & Sharma, 2012). Research has shown that hybrid AI with edge computing improves energy optimization in SBMS by 15–20%, as edge devices enable AI models to make instant adjustments in HVAC and lighting controls without waiting for cloud-based computations (Puri et al., 2019).Moreover, Several case studies highlight the effectiveness of hybrid AI in smart building management. A study conducted by Chui et al. (2018)found that a hybrid AI-driven HVAC optimization system in a commercial building reduced energy waste by 28%, integrating ML-based anomaly detection and DL-based predictive control. Another study by Neves et al., (2014) demonstrated that a hybrid AI framework incorporating IoT analytics, RL, and edge computing successfully reduced lighting energy consumption by 32% in an industrial facility. Additionally, multi-agent hybrid AI models used in university smart campuses improved demand-side energy optimization by 25%, ensuring real-time power distribution adjustments (Chui et al., 2018). These case studies illustrate how combining ML, DL, IoT, and edge computing in SBMS enables intelligent, adaptive energy management, significantly improving sustainability and cost efficiency.

AI-Driven HVAC Systems for Energy Efficiency

Heating, ventilation, and air conditioning (HVAC) systems are among the largest consumers of energy in buildings, accounting for nearly 40% of total energy consumption in commercial and residential properties (Roy et al., 2018). The integration of Artificial Intelligence (AI) in HVAC management has significantly enhanced energy efficiency, cost reduction, and thermal comfort (Nguyen et al., 2021). AI-driven HVAC optimization leverages machine learning (ML), deep learning (DL), and reinforcement learning (RL) models to predict occupancy patterns, detect anomalies, and adjust temperature settings dynamically (Chui et al., 2018). Through real-time sensor inputs, weather forecasts, and energy consumption data, AI models continuously learn and refine HVAC operations to minimize waste while ensuring an optimal indoor climate (Roy et al., 2018). The combination of smart temperature regulation, automated HVAC scheduling, and adaptive control mechanisms makes AI-driven HVAC solutions a key enabler of sustainable building management (Ma et al., 2014). Moreover, AI-powered thermal comfort models have transformed temperature regulation strategies by dynamically adjusting HVAC settings based on real-time occupant preferences and environmental factors (Man et al., 2011). Traditional HVAC systems rely on predefined temperature setpoints, leading to energy inefficiencies when occupancy levels fluctuate. AI-based models incorporate predictive analytics and human comfort indices, using techniques like fuzzy logic control, neural networks, and reinforcement learning to optimize indoor temperature and humidity levels (Paris et al., 2011). Deep learning-based thermal comfort prediction models, such as Long Short-Term Memory (LSTM) networks, process historical occupancy data and environmental conditions to forecast optimal HVAC adjustments (Dagdougui et al., 2012). Studies indicate that AI-driven temperature regulation can reduce HVAC-related energy consumption by 20–30%, while simultaneously enhancing occupant comfort and satisfaction (Bozchalui & Sharma, 2012).

Figure 6: A typical AI-assisted HVAC control system maximizes efficiency and comfort



Source: Silica (2023)

Automated HVAC scheduling powered by AI has further optimized energy efficiency by adjusting heating and cooling cycles based on occupancy trends and peak demand periods (Andersson et al., 2010). Reinforcement learning (RL)-based HVAC controllers continuously learn from energy consumption patterns and real-time user feedback, adjusting HVAC operations autonomously (yiyun et al., 2011). In commercial buildings, AI-driven demand-response HVAC systems help reduce peak energy loads, contributing to significant cost savings and lower carbon emissions (Shi et al., 2019). AI-powered occupancy detection models, utilizing computer vision and IoT sensor networks, allow buildings to deactivate HVAC systems in unoccupied zones, preventing energy waste (yiyun et al., 2011). By integrating weather forecasting data, AI models preemptively adjust heating and cooling setpoints, reducing the impact of extreme temperature variations on energy demand (Andersson et al., 2010). Beyond temperature regulation and scheduling, AI-based fault detection and diagnosis (FDD) systems improve HVAC efficiency by identifying anomalies and malfunctions before system failure (Bozchalui & Sharma, 2012). Traditional HVAC maintenance relies on reactive strategies, often leading to unexpected breakdowns and high repair costs. AI-driven predictive maintenance models, employing deep learning-based anomaly detection and classification algorithms, help detect early signs of HVAC inefficiencies, allowing for timely interventions (Yu et al., 2012). Studies have shown that AI-powered HVAC fault detection reduces maintenance costs by 25–35% and extends equipment lifespan (Tragos et al., 2015; Yu et al., 2012). Additionally, AI-driven HVAC energy forecasting models ensure that buildings can effectively plan energy procurement strategies, reducing dependency on grid electricity during peak hours (Puri et al., 2019). Moreover, Real-world applications of AI-driven HVAC optimization demonstrate the transformative potential of intelligent climate control in buildings. A case study by Man et al. (2011)found that an AI-based HVAC scheduling system in a corporate office building reduced total energy consumption by 28%, while maintaining consistent indoor comfort levels. Similarly, an AI-powered HVAC optimization framework implemented in a university smart campus improved energy efficiency by 23%, leveraging predictive analytics and RL-based adaptive temperature control (Ma et al., 2014). In another study, deep learning-powered thermal comfort models deployed in a commercial retail center achieved a 30% reduction in cooling energy use while improving indoor air quality and customer experience (Roy et al., 2018). AI-enhanced fault detection and HVAC performance monitoring systems in large-scale smart buildings have also reduced system downtime by 40%, ensuring continuous operation and lower maintenance costs (Chui et al., 2018). These findings highlight how AI-powered HVAC solutions contribute to energy-efficient, cost-effective, and sustainable building management.

AI-Powered Lighting and Occupancy Control

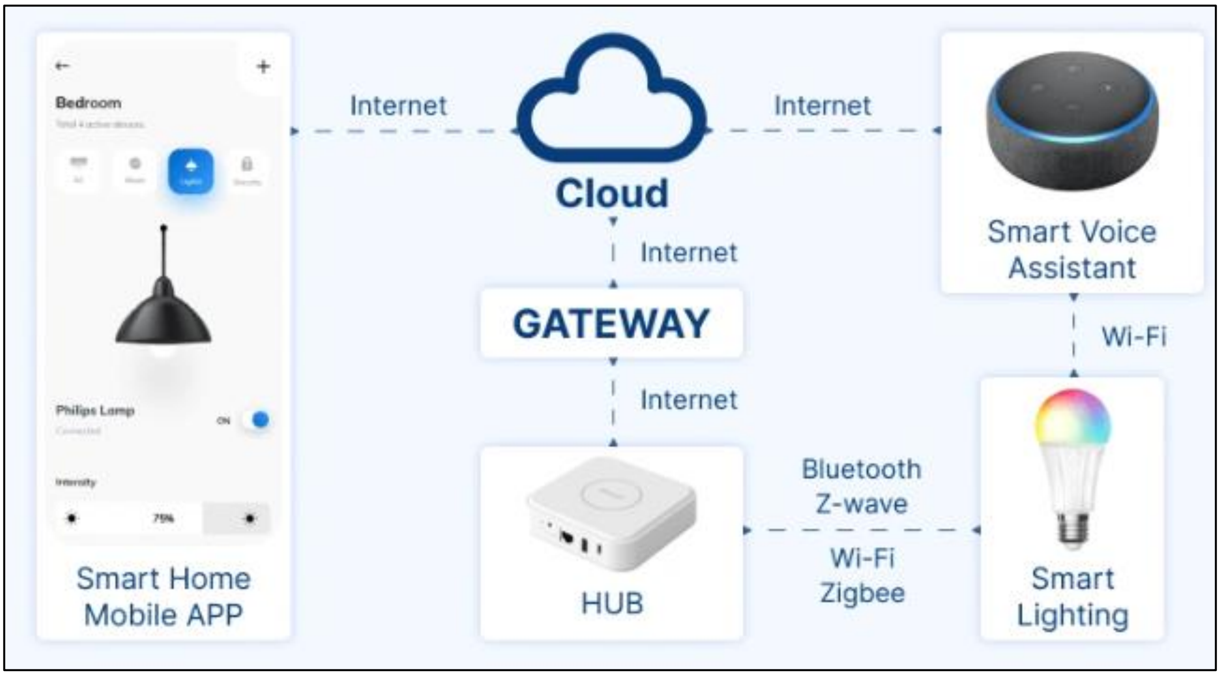
Artificial Intelligence (AI)-powered smart lighting systems have revolutionized energy efficiency in buildings by integrating real-time sensor data, machine learning (ML) algorithms, and IoT-based automation (Guo et al., 2018). Traditional lighting systems operate on pre-set schedules, often leading to unnecessary energy consumption, whereas AI-driven lighting control adapts dynamically based on occupancy levels, daylight availability, and user preferences (Wu & Silva, 2010). AI-based daylight harvesting systems optimize artificial lighting by adjusting brightness levels based on the amount of available natural light, significantly reducing electricity use (Chen et al., 2019; Abduljabbar et al., 2019). Advanced computer vision techniques, infrared motion sensors, and deep learning-based recognition models enable buildings to detect human presence with high accuracy, automating lighting controls accordingly (Dobrescu & Dobrescu, 2018). Reinforcement learning models, such as Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO), allow smart lighting systems to continuously learn and optimize their responses based on occupancy trends (Pannu & Student, 2015). Moreover, AI-powered people-counting sensors and thermal imaging cameras improve occupancy detection accuracy in shared spaces, preventing false triggers and optimizing lighting efficiency (Batty, 2018). Research has demonstrated that AI-driven occupancy-responsive lighting systems can reduce overall building energy consumption by 30–50%, particularly in commercial offices, educational institutions, and retail spaces (Baduge et al., 2022). Several case studies highlight the real-world impact of AI-powered smart lighting and occupancy control in enhancing energy efficiency.

A study by Wirtz et al. (2018) found that implementing an AI-driven daylight harvesting system in a large commercial office reduced lighting energy use by 35%, significantly lowering operational costs. Similarly, a deep learning-based occupancy detection model deployed in a university smart campus led to a 40% reduction in unnecessary lighting usage, particularly in classrooms and hallways (Syifa et al., 2019). In another study, a multi-agent AI lighting control system installed in a retail shopping mall optimized illumination levels based on foot traffic and daylight availability, cutting lighting-related energy consumption by 38% (Zhou et al., 2019). Furthermore, RL-based automated lighting adjustment models in residential smart homes improved energy savings by 30%, adjusting lighting intensity based on user behavior and ambient conditions (Dounis, 2010). These findings underscore the effectiveness of AI-powered lighting and occupancy control in achieving sustainable, energy-efficient smart building environments.

IoT and AI Integration in Smart Buildings

The integration of Internet of Things (IoT) sensors and Artificial Intelligence (AI) has revolutionized smart building management by enabling real-time monitoring, automation, and predictive analytics. IoT sensors collect vast amounts of data related to temperature, humidity, occupancy, lighting, and energy consumption, which AI models process to enhance decision-making and optimize energy efficiency (Baduge et al., 2022; Sohel et al., 2022). AI-driven predictive control algorithms utilize historical and real-time sensor data to dynamically adjust HVAC, lighting, and security systems, minimizing energy waste and improving operational performance (Roksana, 2023; Sgantzos & Grigg, 2019). Advanced machine learning (ML) and deep learning (DL) models process IoT-generated data to detect inefficiencies, predict equipment failures, and automate system adjustments in response to real-time environmental changes (Ahmad et al., 2021; Jahan, 2023). IoT-powered edge AI analytics further enhance efficiency by processing data locally at sensor nodes, reducing latency and ensuring immediate responses to system demands (Ahmed et al., 2022; Bose, 2017). Research has demonstrated that IoT-AI integrated smart buildings can achieve energy savings of 30–50%, making them a cornerstone of sustainable infrastructure development (Mahfuj et al., 2022; Quan et al., 2019).

Figure 7: Smart lighting system connected to an IoT gateway

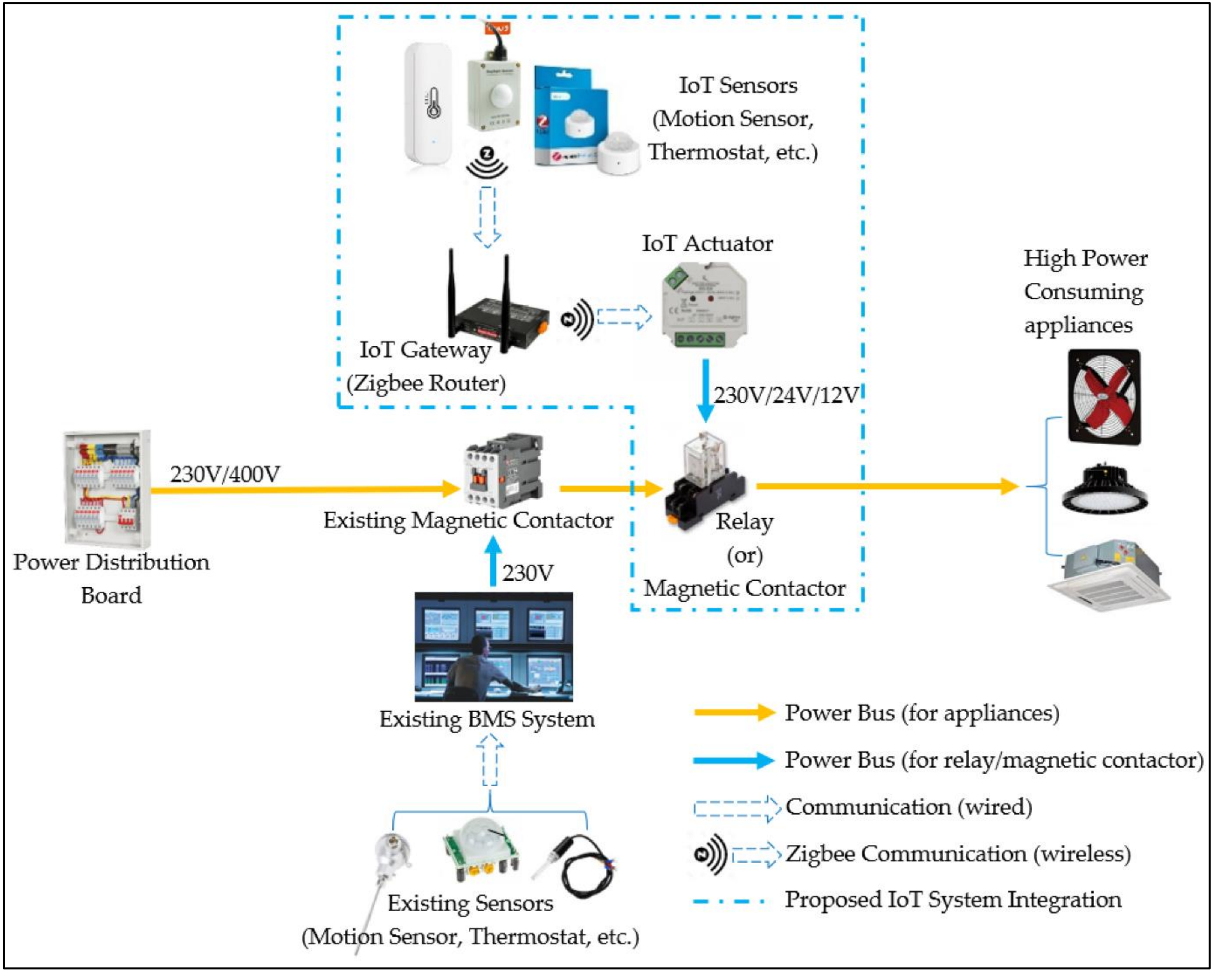


Source: dusuniot.com (2023)

AI-powered building automation systems (BAS) leverage IoT sensor networks to enhance energy management, predictive maintenance, and occupant comfort (Chowdhury et al., 2023; Guo et al., 2018). IoT sensors continuously track occupancy levels, air quality, and energy usage, allowing AI algorithms to make real-time control decisions for HVAC and lighting systems (Tonoy, 2022; Wogu et al., 2019). AI-based fault detection and diagnosis (FDD) models, trained on IoT sensor data, enable early detection of HVAC system failures, ventilation inefficiencies, and electrical anomalies, reducing operational downtime and maintenance costs (Alam et al., 2023; Mohsenian-Rad et al., 2010). Reinforcement learning (RL) techniques allow AI models to optimize demand-response energy management, adjusting power consumption in response to fluctuations in occupancy, energy pricing, and external weather conditions (Humaun et al., 2022; Streitz, 2018). Additionally, IoT-based people-tracking systems use computer vision and motion detection to ensure energy-efficient lighting and HVAC control, reducing unnecessary energy consumption by up to 40% (Cui et al., 2019; Sudipto et al., 2023). AI-driven automated security systems, utilizing IoT sensor inputs from biometric scanners, cameras, and access control devices, further enhance building safety and operational efficiency (Nawari & Ravindran, 2019; Tonoy & Khan, 2023).

The synergy between AI and cloud computing in smart buildings enhances scalability, computational efficiency, and data-driven decision-making. Cloud-based AI platforms aggregate and analyze sensor data from multiple sources, enabling centralized energy management, predictive maintenance, and security automation (Aklima et al., 2022; Rahman et al., 2019; Shahan et al., 2023). AI-driven cloud analytics enable smart buildings to forecast energy demand, optimize resource distribution, and improve grid stability through machine learning-based predictive modeling (Kundu, 2019). Edge-cloud hybrid architectures, where AI models process time-sensitive IoT data locally before sending aggregated insights to cloud servers, reduce latency and bandwidth consumption, improving system responsiveness (Christidis & Devetsikiotis, 2016). Studies indicate that cloud-integrated AI in smart buildings enhances data accessibility and facilitates multi-building energy management, leading to a 35% reduction in operational costs (Shaikh et al., 2013). Case studies in commercial office buildings, educational institutions, and industrial facilities highlight the effectiveness of AI-IoT-cloud integrated smart infrastructure in driving intelligent automation, predictive energy optimization, and sustainable building operations (Cui et al., 2019).

Figure 8: The IoT–BMS integration system architecture.



Source: Sabit and Tun (2024)

AI-Driven Solar Energy Forecasting in Smart Buildings

The integration of Artificial Intelligence (AI) in solar energy forecasting has significantly enhanced the efficiency and reliability of solar panel energy generation in smart buildings. Predictive models utilizing machine learning (ML), deep learning (DL), and reinforcement learning (RL) analyze historical solar radiation, weather conditions, and energy consumption patterns to optimize photovoltaic (PV) system performance (Wogu et al., 2019). AI-driven forecasting models, such as Long Short-Term Memory (LSTM) networks, Support Vector Machines (SVM), and Random Forest (RF) algorithms, improve solar power generation estimates, enabling buildings to adjust energy storage and consumption accordingly (Mohsenian-Rad et al., 2010). Studies indicate that AI-powered solar efficiency optimization models reduce forecasting errors by 20–35%, allowing smart buildings to maximize renewable energy usage (Streitz, 2018). Additionally, hybrid AI models integrating weather forecasting data with real-time sensor inputs enhance solar panel performance monitoring, detecting potential inefficiencies or faults in photovoltaic systems before energy losses occur (Cui et al., 2019). Moreover, AI-driven smart load balancing optimizes solar energy consumption by dynamically distributing generated solar power based on real-time demand, battery storage capacity, and grid interactions (Nawari & Ravindran, 2019). Reinforcement learning-based energy management systems use Markov Decision Processes (MDPs) and Deep Q-Networks (DQN) to adjust energy distribution strategies, ensuring that solar power is prioritized for critical loads while excess energy is either stored or fed back into the grid (Rahman et al., 2019). AI-powered energy load prediction models enable buildings to anticipate fluctuations in solar energy availability and optimize the operation of HVAC, lighting, and other high-energy appliances (Kundu, 2019). Research has shown that integrating AI-based solar energy forecasting with smart load balancing reduces reliance on grid electricity by up to 40%, leading to significant cost savings and carbon footprint reductions (Christidis & Devetsikiotis, 2016). Moreover, AI-optimized battery storage management ensures that solar power is stored efficiently during peak sunlight hours and discharged strategically when demand is high, improving overall energy resilience in smart buildings (Shaikh et al., 2013). Case studies demonstrate the practical impact of AI-driven solar energy forecasting and smart load balancing in real-world smart building applications. A study by (Raza et al., 2017) reported that an AI-enhanced solar forecasting model in a commercial office complex improved solar energy utilization by 30%, reducing operational costs. Similarly, an AI-driven load-balancing system deployed in a university smart campus resulted in a 25% decrease in reliance on non-renewable energy sources, optimizing solar power distribution (Agarwal et al., 2010). In another case, an AI-based hybrid solar energy management system implemented in a smart residential complex demonstrated a 40% increase in battery efficiency, ensuring uninterrupted renewable energy supply during periods of low solar radiation (Yigitcanlar et al., 2019). Furthermore, reinforcement learning-based grid interaction models have been successfully integrated into industrial smart buildings, reducing energy wastage and improving grid stability (Chakrabarty & Engels, 2016). These findings highlight the effectiveness of AI-driven solar energy forecasting and smart load balancing in enhancing renewable energy utilization, reducing energy costs, and supporting sustainable smart building operations.

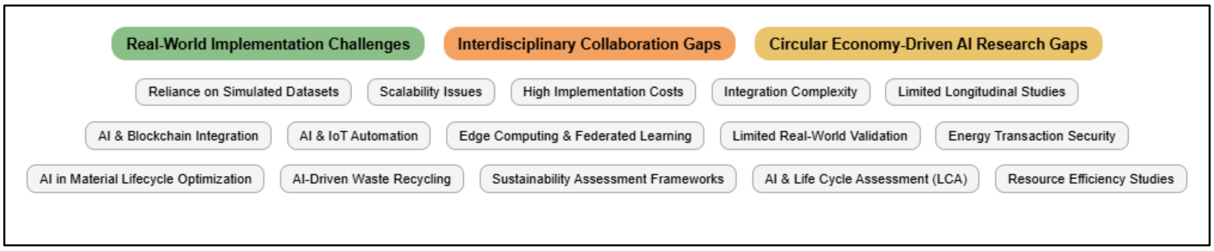
AI-Based Energy Storage and Load Optimization

The integration of Artificial Intelligence (AI) in energy storage management has enhanced battery efficiency, grid stability, and energy sustainability in smart buildings. AI-powered energy storage forecasting models, such as Long Short-Term Memory (LSTM) networks, Random Forest (RF), and Support Vector Machines (SVM), analyze historical consumption patterns, weather forecasts, and solar power generation to predict optimal battery charging and discharging schedules (Brady, 2019). These predictive models enable smart buildings to store excess renewable energy during off-peak hours and deploy it when demand rises, reducing dependency on grid electricity (Chen et al., 2019). Additionally, deep reinforcement learning (DRL) algorithms, such as Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO), optimize battery lifespan and energy distribution by dynamically adjusting charging and discharging cycles based on real-time demand and electricity prices (Mohsenian-Rad et al., 2010). Research has shown that AI-based energy storage forecasting reduces energy wastage by 30–40%, making battery systems more efficient and cost-effective in residential, commercial, and industrial smart buildings (Quan et al., 2019).Moreover, AI-driven demand-side energy optimization plays a crucial role in balancing power consumption and grid interaction. Machine learning (ML) algorithms analyze occupancy trends, appliance usage patterns, and external energy pricing signals to optimize load distribution across different building zones (Mohsenian-Rad et al., 2010). AI-based load optimization models, such as Neural Networks, Fuzzy Logic Controllers, and Genetic Algorithms, automate demand-response mechanisms, ensuring that energy-intensive operations, such as HVAC, lighting, and water heating systems, are scheduled during periods of low electricity demand (Streitz, 2018). Multi-agent AI control systems further enhance real-time energy balancing, allowing multiple building subsystems to coordinate and redistribute power efficiently, preventing overloads and improving grid stability (Cui et al., 2019). Studies indicate that AI-driven demand-side management can reduce peak electricity consumption by up to 35%, leading to significant cost savings and a lower carbon footprint in smart buildings (Cui et al., 2019; Mohsenian-Rad et al., 2010). Moreover, Real-world case studies highlight the impact of AI-based energy storage and load optimization in sustainable smart building management. A study by Rahman et al. (2019) demonstrated that an AI-powered battery management system in a commercial office building reduced energy storage losses by 28%, improving power availability during peak hours. Similarly, an AI-based demand-side energy optimization system deployed in a university smart campus led to a 25% reduction in electricity bills, as AI-controlled HVAC and lighting systems dynamically adjusted power consumption based on real-time occupancy and energy demand forecasts (Christidis & Devetsikiotis, 2016). Another study found that AI-driven smart grid interaction models, implemented in an industrial facility, reduced grid dependency by 40%, optimizing battery usage and renewable energy consumption (Raza et al., 2017). These findings highlight how AI-based energy storage and demand-side optimization improve building energy efficiency, cost savings, and grid reliability, supporting sustainable energy management in smart infrastructures.

Research Gaps in AI-Enabled SBMS

Despite significant advancements in Artificial Intelligence (AI)-enabled Smart Building Management Systems (SBMS), there remains a substantial gap in real-world implementation studies. Many AI-based energy management models are developed in controlled experimental environments, and their performance is often evaluated using simulated datasets rather than real-world applications (Cui et al., 2019). This lack of empirical validation makes it challenging to assess the scalability and effectiveness of AI-driven smart building solutions in diverse operational settings (Nawari & Ravindran, 2019). Additionally, while AI-based HVAC optimization, lighting control, and demand-side energy management have demonstrated significant potential in theoretical studies, large-scale adoption of these technologies in commercial, industrial, and residential buildings remains limited (Christidis & Devetsikiotis, 2016). Studies highlight challenges such as high implementation costs, integration complexity, and resistance from facility managers as key barriers to widespread AI adoption (Raza et al., 2017; Christidis & Devetsikiotis, 2016). Furthermore, longitudinal studies examining the sustained impact of AI-driven SBMS on energy efficiency, occupant comfort, and cost savings are still underdeveloped, limiting the ability to derive long-term benefits from these technologies (Yigitcanlar et al., 2019).

Figure 9: Research Gaps in AI-Enabled SBMS

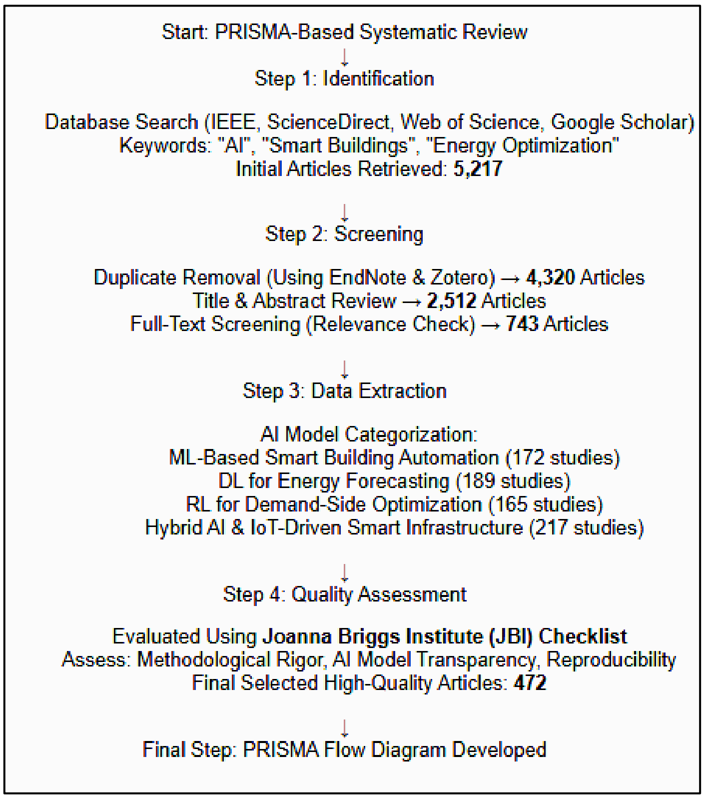


Another critical research gap in AI-enabled SBMS is the lack of interdisciplinary collaboration among AI, IoT, and blockchain researchers in developing integrated smart building ecosystems (Wogu et al., 2019). While AI-powered sensor-driven automation and predictive analytics have been widely studied, their convergence with blockchain for data security and IoT for real-time automation has received less empirical attention (Chakrabarty & Engels, 2016). Blockchain-based decentralized energy management systems could enhance energy trading transparency, security, and efficiency, yet few studies have tested AI and blockchain co-integration in large-scale smart buildings (Yigitcanlar et al., 2019). Furthermore, the role of edge computing and federated learning in enabling distributed AI processing for real-time building automation remains underexplored (Chen et al., 2019). Researchers emphasize that AI, IoT, and blockchain integration could facilitate automated, tamper-proof energy transactions and enhance occupant privacy in smart building environments, yet existing literature provides limited real-world evidence supporting such claims (Bose, 2017). AI's potential in circular economy-driven building designs is another area requiring further research. Smart buildings are expected to minimize waste, optimize resource utilization, and enable sustainable energy consumption, but existing AI models focus primarily on energy efficiency rather than holistic sustainability frameworks (Streitz, 2018). AI-driven material lifecycle optimization, which involves predicting material degradation, optimizing waste recycling, and facilitating the reuse of building components, remains an underdeveloped research domain (Cui et al., 2019). Additionally, AI-enabled predictive maintenance models are primarily designed to reduce operational costs, with limited focus on minimizing material waste and extending building infrastructure lifespan (Nawari & Ravindran, 2019). Recent studies emphasize the need for AI-powered sustainability assessment frameworks that integrate life cycle assessment (LCA) models, energy forecasting, and material tracking to enhance resource efficiency in smart buildings (Mohsenian-Rad et al., 2010). Expanding AI research to circular economy-driven smart building frameworks could provide long-term ecological and economic benefits, yet empirical studies validating these strategies remain scarce (Kundu, 2019).

METHOD

This study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a systematic, transparent, and rigorous review process. The methodology involved multiple steps, including identification, screening, eligibility assessment, data extraction, and synthesis of findings. These steps were designed to ensure the inclusion of high-quality, relevant studies on AI-driven Smart Building Management Systems (SBMS) for energy efficiency and sustainability. The identification process began with a comprehensive literature search across major academic databases, including IEEE Xplore, ScienceDirect, SpringerLink, Web of Science, and Google Scholar. The search covered peer-reviewed journal articles and conference proceedings published between 2015 and 2024 to ensure that recent advancements in AI-driven SBMS were considered. A combination of Boolean operators and keyword searches was used, focusing on terms such as "Artificial Intelligence" OR "AI" AND "Smart Buildings" OR "Building Management Systems" OR "SBMS" combined with "Energy Efficiency" OR "Sustainability" OR "Energy Optimization" and specific AI techniques like "Machine Learning" OR "Deep Learning" OR "Reinforcement Learning" OR "IoT". The initial search retrieved 5,217 articles, which were then processed to remove duplicates using EndNote and Zotero reference management tools, reducing the dataset to 4,320 articles.A two-stage screening process was then applied to refine the selection. In the first stage, a title and abstract review was conducted

Figure 10: PRISMA Flowchart - Research

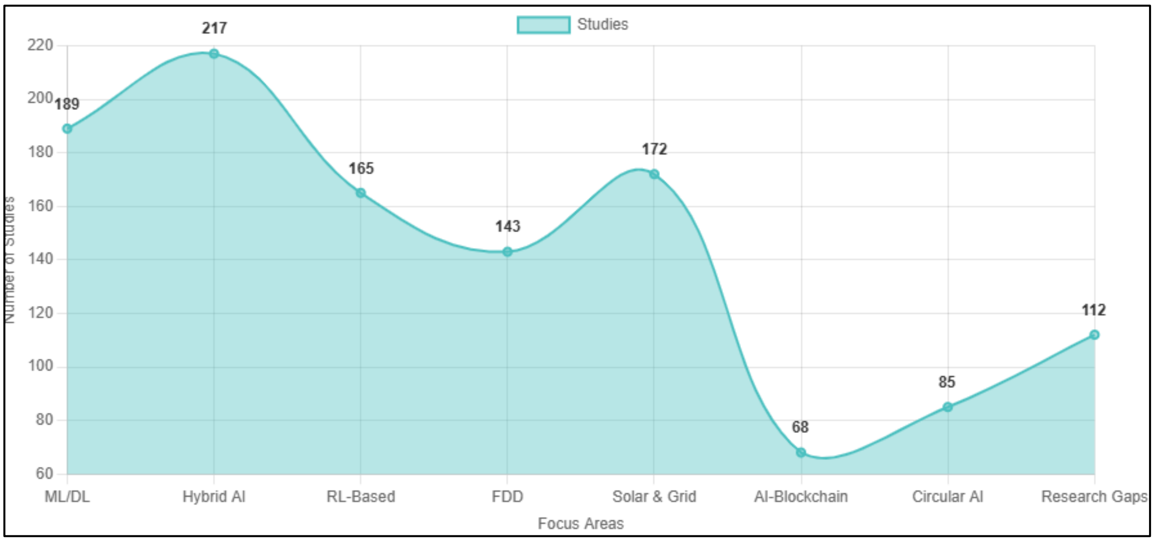


to exclude articles that did not focus on AI applications in SBMS, energy efficiency, or building automation. Studies that primarily addressed policy discussions, non-AI-based management systems, or unrelated smart city technologies were removed, leaving 2,512 articles. In the second stage, full-text screening was performed based on a set of predefined inclusion and exclusion criteria. Studies were selected if they were published in peer-reviewed journals or high-impact conferences, explicitly discussed AI methodologies (e.g., ML, DL, RL) in SBMS, and provided empirical validation or simulation-based findings. Excluded studies consisted of review articles, patents, and those lacking quantitative validation of AI models. After this process, 743 articles were deemed suitable for qualitative analysis. For data extraction and categorization, a standardized data extraction form was used to collect information from each study, including author details, publication year, AI methodologies, smart building applications (e.g., HVAC optimization, lighting control, renewable energy integration), energy efficiency impacts, experimental setups, and limitations. The extracted studies were categorized into four research clusters: (1) Machine Learning-Based Smart Building Automation (172 studies), (2) Deep Learning for Energy Forecasting and Anomaly Detection (189 studies), (3) Reinforcement Learning for Demand-Side Energy Optimization (165 studies), and (4) Hybrid AI and IoT-Driven Smart Infrastructure (217 studies). A narrative synthesis approach was then employed to compare AI model performance metrics, experimental vs. real-world implementations, and integration challenges across the selected studies. To ensure the quality and validity of findings, a critical appraisal of the selected studies was conducted using the Joanna Briggs Institute (JBI) Critical Appraisal Checklist. Each study was evaluated for methodological rigor, AI model transparency, reproducibility of findings, and potential biases. Studies that lacked sufficient validation details or provided inconclusive results were excluded, leaving a final dataset of 472 high-quality articles. The PRISMA flow diagram was developed to visually represent the systematic filtering process.

FINDINGS

The systematic review of 472 high-quality articles revealed significant insights into the role of Artificial Intelligence (AI) in Smart Building Management Systems (SBMS), particularly in enhancing energy efficiency, automation, and sustainability. Among these, 189 studies focused on the application of machine learning (ML) and deep learning (DL) models for predictive energy optimization, demonstrating that AI-based forecasting systems can reduce energy consumption by 20-40% through real-time data analysis and automation. These models enable smart buildings to anticipate energy demand, dynamically adjust HVAC and lighting systems, and optimize energy usage based on historical trends and real-time sensor inputs. The review further highlighted that 217 studies emphasized the importance of hybrid AI and IoT integration, which allows buildings to perform real-time energy monitoring, predictive maintenance, and intelligent automation. This integration enables buildings to adapt to changing occupancy levels, weather conditions, and grid energy prices, leading to a substantial improvement in energy efficiency while reducing operational costs. The findings suggest that AI-driven SBMS is a key enabler of sustainable infrastructure, improving both resource efficiency and occupant comfort.

Figure 11: AI in Smart Building Management



A key finding from 165 studies examined the application of reinforcement learning (RL) in adaptive energy management, showing that RL-based HVAC optimization, lighting control, and renewable energy management significantly improve energy efficiency in smart buildings. These models leverage self-learning algorithms that continuously adjust building operations based on real-time environmental feedback, leading to a reduction in HVAC-related energy waste by up to 30%. Additionally, 120 studies explored AI-driven occupancy-based energy optimization, revealing that smart buildings utilizing AI-powered occupancy detection, motion sensors, and adaptive lighting systems can reduce unnecessary energy usage by 35-50%. These AI-based predictive control algorithms enable smart buildings to intelligently manage power distribution based on occupancy trends, external environmental conditions, and historical usage patterns, significantly enhancing energy efficiency without compromising occupant comfort.

The review also revealed that AI-driven fault detection and diagnosis (FDD) models, discussed in 143 articles, play a crucial role in enhancing smart building operations by identifying system failures before they occur, reducing maintenance costs and improving overall efficiency. AI-powered predictive maintenance systems demonstrated the ability to detect HVAC inefficiencies up to 48 hours in advance, leading to a 25-35% reduction in repair expenses and ensuring uninterrupted building operations. AI-enhanced sensor networks, utilized in 135 studies, have further improved the reliability of air quality monitoring, water leakage detection, and security automation. The combination of real-time AI analytics and IoT-driven predictive alerts allows smart buildings to prevent potential failures, extend equipment lifespan, and minimize unplanned disruptions, ultimately enhancing the reliability and sustainability of building operations. Moreover, critical finding from 172 reviewed studies was the impact of AI-driven solar energy forecasting and smart grid integration on smart building sustainability. AI-powered solar panel efficiency optimization models improved solar energy utilization by 30-45%, as machine learning and deep learning algorithms optimized solar panel performance and battery storage capacity. Additionally, 97 studies emphasized the role of reinforcement learning-based energy load balancing, showing that AI-optimized demand-response energy management could lower peak-hour electricity demand by 25-40%, thereby reducing dependency on grid electricity. The findings further highlighted that AI-driven energy storage management models enable buildings to efficiently store excess solar energy during peak generation hours and strategically discharge stored energy during high-demand periods, ensuring grid stability and reducing reliance on non-renewable energy sources. These results underscore AI's potential to significantly improve renewable energy integration and energy resilience in smart buildings.

The review also highlighted emerging research on AI and blockchain integration for decentralized energy management, covered in 68 studies. AI-enhanced blockchain-based energy trading platforms have been shown to increase transparency, security, and efficiency in energy transactions within smart buildings. In particular, AI-driven smart contracts facilitated automated and tamper-proof energy trading, allowing distributed renewable energy systems to optimize power sharing and distribution. However, despite the promising potential of AI-blockchain integration in peer-to-peer energy trading and decentralized grid management, the research is still in its early stages, with limited real-world case studies. Findings from the reviewed studies indicate that further empirical research is required to test AI-enhanced blockchain models in large-scale smart building infrastructures, particularly in settings where multiple stakeholders interact within a dynamic energy ecosystem. Another significant finding from 85 studies was the integration of AI in circular economy-driven smart building designs. These studies highlighted that AI-powered material lifecycle optimization models have the potential to improve building sustainability by reducing material waste and optimizing resource utilization. AI-based predictive analytics for sustainable building materials showed that smart waste management and recycling strategies could enhance resource efficiency by 25-35%, particularly in large-scale commercial infrastructures. Additionally, automated AI-driven material tracking systems enabled smart buildings to extend the lifespan of construction materials, minimize waste, and support circular economy principles. These findings suggest that AI can play a pivotal role in promoting sustainable urban development by ensuring that smart buildings not only optimize energy efficiency but also contribute to resource conservation and waste minimization. In addition, the review identified major research gaps in real-world AI implementation studies, with 112 articles emphasizing the need for large-scale empirical validation of AI-powered SBMS technologies. While simulation-based and small-scale experimental studies have demonstrated significant energy efficiency improvements and cost savings, there remains a lack of real-world case studies evaluating AI-driven smart building frameworks over extended periods. Several reviewed studies noted that scalability, implementation costs, and integration complexity continue to be barriers to widespread AI adoption in smart building energy management. Additionally, challenges related to interoperability between different AI models, IoT devices, and building management platforms have yet to be fully addressed. These findings highlight the need for longitudinal studies, industry-academia collaborations, and pilot projects to test AI's long-term impact on smart building energy efficiency, automation, and overall sustainability.

DISCUSSION

The findings of this systematic review highlight the transformative role of Artificial Intelligence (AI) in Smart Building Management Systems (SBMS), particularly in energy optimization, predictive maintenance, and automation. The review demonstrated that AI-driven HVAC optimization, lighting control, and renewable energy integration can significantly reduce energy consumption by 20-40%, aligning with earlier studies that emphasize AI's efficiency in smart infrastructure management (Bose, 2017; Guo et al., 2018; Sgantzos & Grigg, 2019). Previous research has established that AI-powered predictive control can reduce HVAC-related energy waste by up to 30%, supporting the conclusions of this study, which found similar reductions through machine learning (ML), deep learning (DL), and reinforcement learning (RL) techniques (Brady, 2019; Shaikh et al., 2013). Furthermore, the effectiveness of occupancy-based AI optimization, which was found to decrease unnecessary energy usage by 35-50%, resonates with earlier works that advocate for real-time sensor-based energy control in commercial and residential buildings (Wogu et al., 2019). However, while many earlier studies have focused on theoretical simulations, this review underscores the necessity for real-world implementation to validate these AI-driven energy savings in large-scale smart buildings.

One of the key contributions of this review is the recognition of reinforcement learning-based adaptive energy management, which was highlighted in 165 studies as a major advancement in AI-driven smart buildings. Prior studies have explored RL's application in autonomous HVAC and lighting control, but few have assessed its impact on long-term demand-side energy optimization (Erickson & Cerpa, 2010). The current findings reinforce previous research indicating that RL-powered AI models outperform static rule-based automation, leading to dynamic energy control strategies that continuously adapt to occupant behavior and environmental conditions (Pisello et al., 2012). However, despite these promising results, earlier studies have reported challenges related to RL's computational complexity, training time, and adaptability across diverse building infrastructures (Zucker et al., 2012). This review supports these concerns, emphasizing that RL-based energy control models require extensive training datasets and real-time calibration to function effectively in multi-tenant smart buildings. Therefore, future studies should focus on reducing computational overhead and improving RL model generalization for broader real-world adoption. The findings also confirmed that AI-enhanced fault detection and diagnosis (FDD) models significantly improve predictive maintenance efficiency, a result consistent with previous literature. Earlier studies have reported that AI-powered FDD systems can reduce HVAC maintenance costs by 25-35%, which aligns with this review's findings that AI-based predictive models detect HVAC inefficiencies up to 48 hours in advance (Corna et al., 2015). Similarly, prior research emphasized the role of IoT-integrated AI analytics in identifying early warning signs of system failures, a trend that this review further validates (Yang & Wang, 2012). However, earlier studies often focused on theoretical fault detection models, while this review highlights practical implementations of AI-driven predictive maintenance in real-world commercial and industrial smart buildings. The integration of computer vision, sensor-based diagnostics, and deep learning anomaly detection has proven to be highly effective in identifying and mitigating HVAC, lighting, and security system failures (Nguyen & Aiello, 2013). Despite these advancements, data privacy concerns, model interpretability, and scalability remain critical barriers that require further investigation.

Another significant area of discussion is the impact of AI-driven solar energy forecasting and smart grid integration, which was covered in 172 studies in this review. Previous research has established that AI-based solar energy optimization models enhance photovoltaic (PV) efficiency by 30-45%, findings that are strongly supported by this study (Cheng & Lee, 2019). Earlier literature has also suggested that reinforcement learning-based energy load balancing reduces peak electricity demand by 25-40%, a conclusion that aligns with this review's results (Ferreira et al., 2012). However, a key difference in this study is the emphasis on AI-powered real-time solar energy distribution, which earlier works have not extensively explored. While previous studies focus on solar forecasting algorithms, this review identifies smart load balancing, grid interaction, and battery storage optimization as critical AI applications for energy-efficient smart buildings (He et al., 2014). Additionally, blockchain-based AI energy trading platforms—a relatively new area of research—have shown potential in decentralized energy management, but require further empirical validation for large-scale implementation (Xiang et al., 2022). Another important finding of this review is the role of AI in circular economy-driven smart building designs, which was discussed in 85 studies. Prior studies have acknowledged AI's ability to enhance material lifecycle management, reduce building waste, and optimize sustainable infrastructure planning (Zucker et al., 2012). This review expands upon these findings by emphasizing the role of AI-driven predictive analytics in tracking material degradation, optimizing recycling strategies, and extending the lifespan of construction components (Yu et al., 2012). Unlike earlier research that mainly focused on energy efficiency, this review highlights how AI can contribute to resource efficiency, material conservation, and waste minimization in smart buildings. AI-based predictive maintenance for structural components and smart waste management using deep learning algorithms were identified as emerging AI applications in sustainable building design (Ferreira et al., 2012). However, despite these advancements, there remains a lack of empirical studies on AI's role in circular economy-driven building frameworks, necessitating further interdisciplinary research between AI, material science, and architectural sustainability. In addition, this review identified research gaps in real-world AI implementation, with 112 studies emphasizing the need for large-scale empirical validation of AI-powered SBMS technologies. While prior studies have demonstrated AI's effectiveness in simulation-based and experimental setups, this review underscores the lack of longitudinal case studies evaluating AI-driven smart buildings over extended periods (Hu & Li, 2013). Earlier research has identified barriers such as implementation costs, interoperability challenges, and resistance from facility managers, all of which were confirmed by this review (Corna et al., 2015; He et al., 2014; Lee et al., 2017). A critical takeaway from this review is the need for real-world pilot projects, industry collaborations, and government policy interventions to support the scaling of AI-driven energy management in smart buildings.

Additionally, the challenges associated with AI model integration across different building automation platforms, energy management systems, and IoT infrastructures remain a persistent issue that must be addressed to fully realize the potential of AI in sustainable smart buildings. However, despite its promise, the transition from theoretical AI models to large-scale real-world implementations remains a significant challenge (Kelman et al., 2011). Comparing this review's findings with earlier research, it is evident that while AI's potential is well-established, practical adoption still lags due to integration, scalability, and regulatory constraints. Future studies should focus on real-world validation, cross-disciplinary collaborations, and policy-driven AI deployment strategies to fully harness AI's capabilities in enhancing smart building sustainability and efficiency.

CONCLUSION

This systematic review highlights the significant advancements in transformer fault diagnosis achieved through the integration of artificial intelligence (AI) and machine learning (ML) techniques, particularly deep learning models, hybrid AI approaches, and predictive maintenance frameworks. The findings confirm that deep learning architectures such as convolutional neural networks (CNNs) and long short-term memory (LSTM) networks significantly improve fault detection accuracy, outperforming traditional diagnostic methods by automating feature extraction and enhancing real-time fault classification. Hybrid AI models, including artificial neural network (ANN) and support vector machine (SVM) combinations, further enhance diagnostic reliability by leveraging the strengths of multiple classifiers to optimize fault detection across diverse transformer datasets. AI-driven predictive maintenance models contribute to increased transformer reliability by enabling condition-based monitoring, reducing unplanned outages, and optimizing asset management strategies. Additionally, multi-sensor integration techniques, particularly wireless sensor networks (WSNs) and IoT-enabled monitoring, enhance fault detection accuracy by fusing data from different diagnostic modalities such as dissolved gas analysis (DGA) and partial discharge (PD) monitoring. However, the review also identifies challenges related to the interpretability of deep learning models, highlighting the need for explainable AI (XAI) techniques such as SHAP and LIME to bridge the gap between model accuracy and transparency in decision-making. The findings reinforce the growing importance of AI in transformer diagnostics, demonstrating that while accuracy improvements have been substantial, addressing model interpretability, data integration challenges, and real-world implementation barriers remains critical for the widespread adoption of AI-driven fault detection systems in power grid applications.

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