

AI-Driven Predictive Composite Infrastructure for Energy-Efficient Smart Buildings

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ABSTRACT

Highly sustainable, lightweight, and energy-efficient building infrastructures that can dynamically interact with smart city grids are required due to the acceleration of urban intelligence. High strength-to-weight ratios and thermal resistance are features of advanced composite materials, but clever computational frameworks are needed to optimize their structural and energy performance in real time. The integration of modern composite materials with artificial intelligence in smart building ecosystems is reviewed systematically in this research. We conduct a comparative analysis of data-driven prediction models, such as Support Vector Machines (SVM), Random Forests (RF), and Artificial Neural Networks (ANN), used for thermal optimization, energy consumption forecasting, and structural health monitoring. Through the perspective of cyber-physical urban systems, the relationship between dynamic thermal loading and composite material qualities is assessed. The results show that predictive analytics based on machine learning greatly improves the management and design of smart building fabrics. In the end, combining cutting-edge materials with cognitive AI infrastructure offers a scalable route to sustainable, self-optimizing, and resilient smart cities.

1. Introduction

Buildings are among the largest consumers of global energy, making energy efficiency a critical objective for reducing operational costs and supporting sustainable development. Artificial intelligence (AI) and machine learning (ML) have become increasingly important in building energy management, enabling applications such as energy forecasting, anomaly detection, automated control, and demand optimization [1–3]. Previous studies have demonstrated that these techniques can improve the operational performance of smart buildings while contributing to significant energy savings [1,3]. Beyond operational strategies, the thermal performance of buildings is strongly influenced by the properties of construction materials. Parameters such as thermal conductivity, density, porosity, and structural configuration directly affect the energy efficiency of building components. Recent research has shown that ML models can accurately predict the thermal and mechanical properties of construction materials, reducing the need for costly and time-consuming

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experimental investigations [4]. In particular, advanced learning algorithms, including support vector regression (SVR), Gaussian process regression (GPR), and convolutional neural networks (CNNs), have achieved high accuracy in predicting the effective thermal conductivity of composite materials, providing an efficient framework for selecting energy-efficient materials in smart building applications [5]. Artificial intelligence (AI) has emerged as an effective approach for improving the energy performance of buildings through accurate prediction and optimization of thermal behavior. While previous studies have primarily focused on individual applications, such as energy demand forecasting or thermal analysis of construction materials, integrated AI-based frameworks remain relatively limited [5]. The increasing availability of comprehensive building datasets, including both simulated and real-world information, has enabled the development of more reliable predictive models across different building types and climate conditions [6]. Furthermore, the integration of AI-assisted generative design with predictive performance evaluation offers new opportunities for optimizing composite façade systems and enhancing building energy efficiency. Recent studies also indicate that AI is evolving from a supporting analytical tool into an intelligent decision-support system for building envelope design and façade optimization [7]. Nature has long served as a valuable source of inspiration for developing innovative architectural materials and structural systems. Biomimetic design, which adapts natural forms and processes to engineering applications, has become an important strategy for improving building sustainability [8]. For example, naturally ventilated termite mounds have inspired passive ventilation concepts that enhance indoor airflow and help maintain stable thermal conditions with reduced energy demand [8]. Likewise, the self-cleaning and water-repellent characteristics of lotus leaves have led to the development of hydrophobic façade coatings that minimize maintenance requirements while improving surface durability and solar reflectance [9].

2. Methodology

This study was conducted as a comprehensive literature review to evaluate recent advances in the application of machine learning (ML) for predicting the performance of energy-efficient composite components in smart buildings. The primary objective was to synthesize current knowledge, identify common research trends, and highlight existing gaps that may guide future investigations. Accordingly, published studies addressing smart building energy optimization, ML-based prediction of material properties, and the thermal performance of composite building materials were systematically examined [1–6].

The literature search was performed using keywords including *smart buildings*, *energy efficiency*, *machine learning*, *composite materials*, *building materials*, *thermal conductivity*, *thermal insulation*, and *thermal performance*. The selected publications were categorized into three groups: (i) review studies on ML applications in smart building energy systems, (ii) research focusing on ML-based prediction of material properties in construction and composite materials, and (iii) studies investigating thermal characteristics that directly influence building energy performance [1–6]. The collected findings were then analyzed thematically and organized according to three major research themes: building energy management, material property prediction, and sustainable building design [1,4]. To ensure a consistent comparison among studies, particular attention was given to the type of datasets used, the machine learning algorithms employed, the predicted output variables, and the reported performance metrics. This analytical framework enabled the identification of the most frequently adopted ML techniques and provided a comparative overview of the material

characteristics considered critical for improving the energy efficiency of composite building components [3,5,6].

2.1. Composite Materials

Composite materials are engineered by combining two or more distinct constituents to obtain superior mechanical, thermal, and functional properties that cannot be achieved by individual materials alone [7]. Due to their high strength-to-weight ratio, corrosion resistance, durability, and customizable thermal characteristics, composite materials have become increasingly important in energy-efficient buildings and sustainable construction applications [8]. They are widely employed in façade systems, wall panels, roofing elements, insulation layers, and sandwich structures to improve both structural performance and thermal efficiency. The thermal behavior of composite materials is governed by several interacting factors, including constituent composition, fiber orientation, matrix properties, porosity, and layer configuration. Proper optimization of these parameters can significantly reduce heat transfer, enhance indoor thermal comfort, and decrease the energy demand associated with heating and cooling systems [9]. Recent advances have also promoted the development of multifunctional composites incorporating bio-based fibers, recycled materials, phase-change materials (PCMs), aerogels, and nanomaterials, which simultaneously improve energy efficiency and environmental sustainability [10]. Owing to the complexity of their thermal behavior, conventional experimental characterization is often expensive and time-consuming. Consequently, machine learning techniques are increasingly being adopted to predict the thermal performance of composite materials, accelerate material design, and support the development of next-generation energy-efficient building components [11]. Figure 1. depicts the application areas of transfer learning in smart buildings [12]

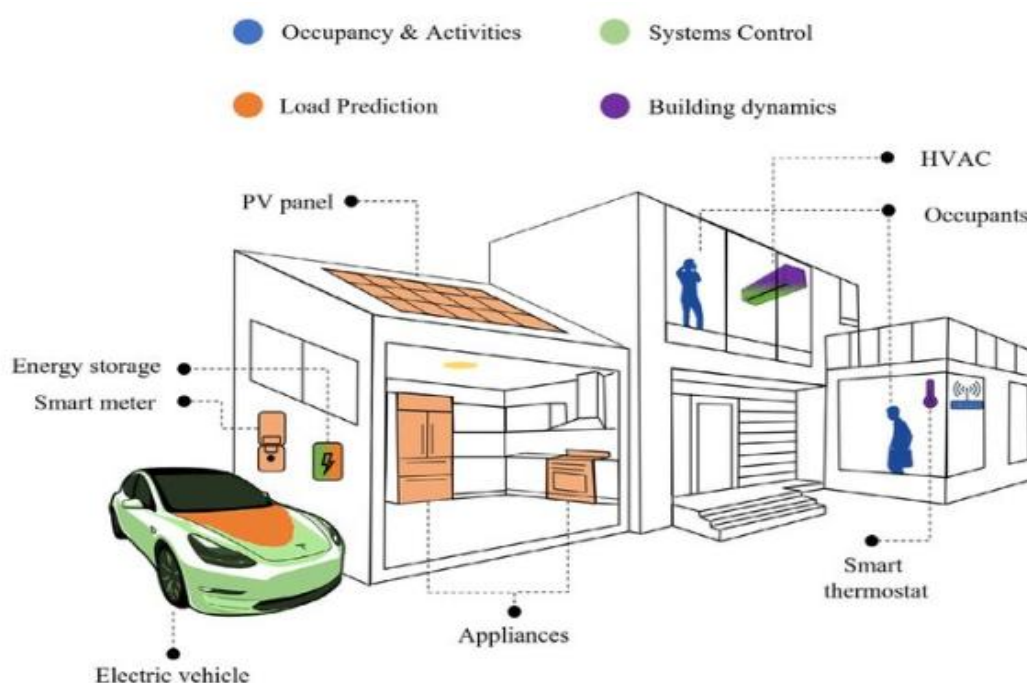


Fig. 1. Application Areas of Transfer Learning in Smart Buildings [12]

2.2. Thermal Loads

Thermal loads refer to the amount of heating or cooling energy required to maintain indoor thermal comfort under varying environmental and operational conditions. In smart buildings, thermal loads are influenced by outdoor climate conditions, solar radiation, building envelope characteristics, occupancy, lighting, electrical equipment, ventilation, and HVAC operation. Since these variables change continuously over time, thermal load prediction is considered a complex nonlinear problem requiring advanced modeling techniques [13,14]. Accurate prediction of thermal loads is essential for reducing building energy consumption, optimizing HVAC system operation, and maintaining indoor thermal comfort. Recent advances in machine learning and deep learning have demonstrated that algorithms such as Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), Random Forest (RF), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost) can effectively capture the complex nonlinear relationships among weather conditions, occupancy patterns, building characteristics, and operational parameters. Furthermore, recent studies have emphasized that incorporating weather forecast uncertainty into thermal load prediction models improves forecasting reliability and enhances the performance of predictive HVAC control strategies. These data-driven approaches enable intelligent energy management, real-time operational optimization, and more sustainable building performance [15–17]. Figure 2 depicts the factors that contribute to the cooling load in a house [18].

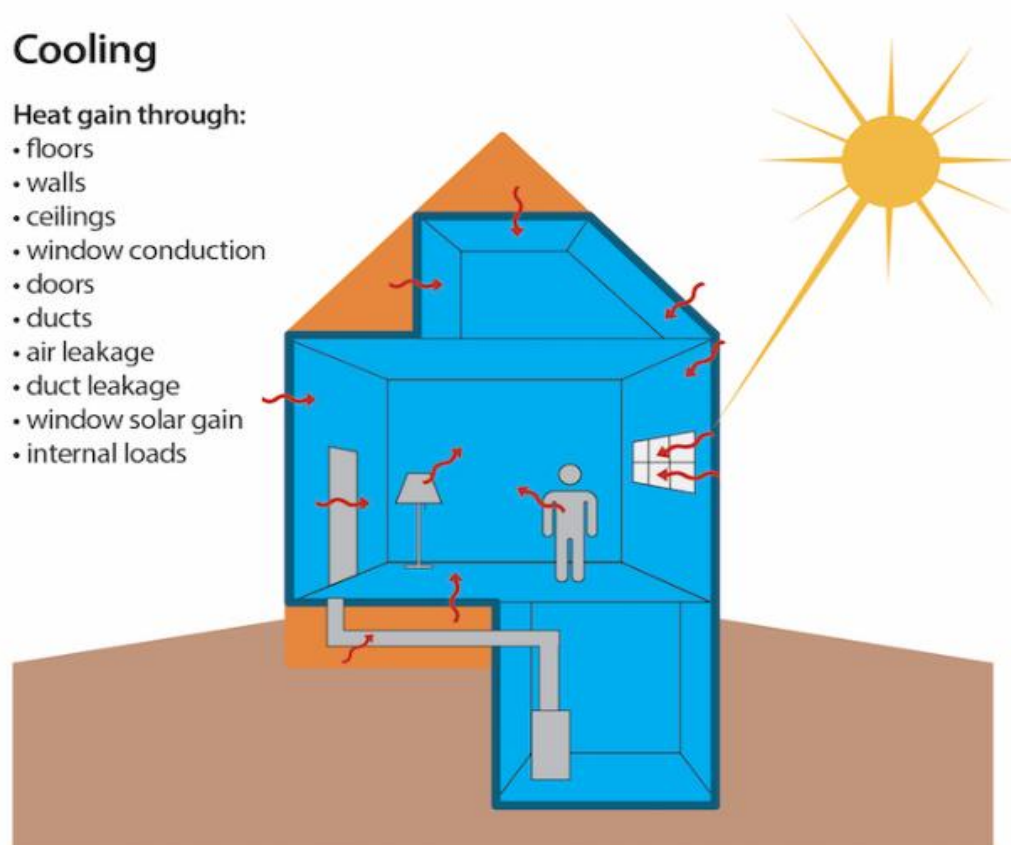


Fig. 2. The factors that contribute to the cooling load in a house [18].

2.3. Energy Efficiency

Energy efficiency refers to achieving the same or a higher level of building performance while consuming less energy through the optimal use of resources and advanced technologies. In smart buildings, energy efficiency is achieved by integrating high-performance building envelopes, efficient HVAC systems, renewable energy technologies, Internet of Things (IoT) devices, and intelligent control algorithms. These integrated systems continuously monitor environmental conditions and operational parameters to optimize energy consumption while maintaining occupant comfort and indoor environmental quality [19,20]. Recent advances in artificial intelligence have significantly transformed energy management strategies in smart buildings. Machine learning and deep learning algorithms enable accurate prediction of building energy demand, intelligent optimization of HVAC systems, equipment fault detection, predictive maintenance, and real-time energy management. Furthermore, the integration of Artificial Intelligence (AI) with Building Energy Management Systems (BEMS), Internet of Things (IoT) technologies, and digital twins enables adaptive, data-driven control strategies that improve operational efficiency, reduce energy consumption and greenhouse gas emissions, and support the development of sustainable smart buildings [21–23]. Figure 3 depicts the structural and functional elements of energy-efficient buildings [24].

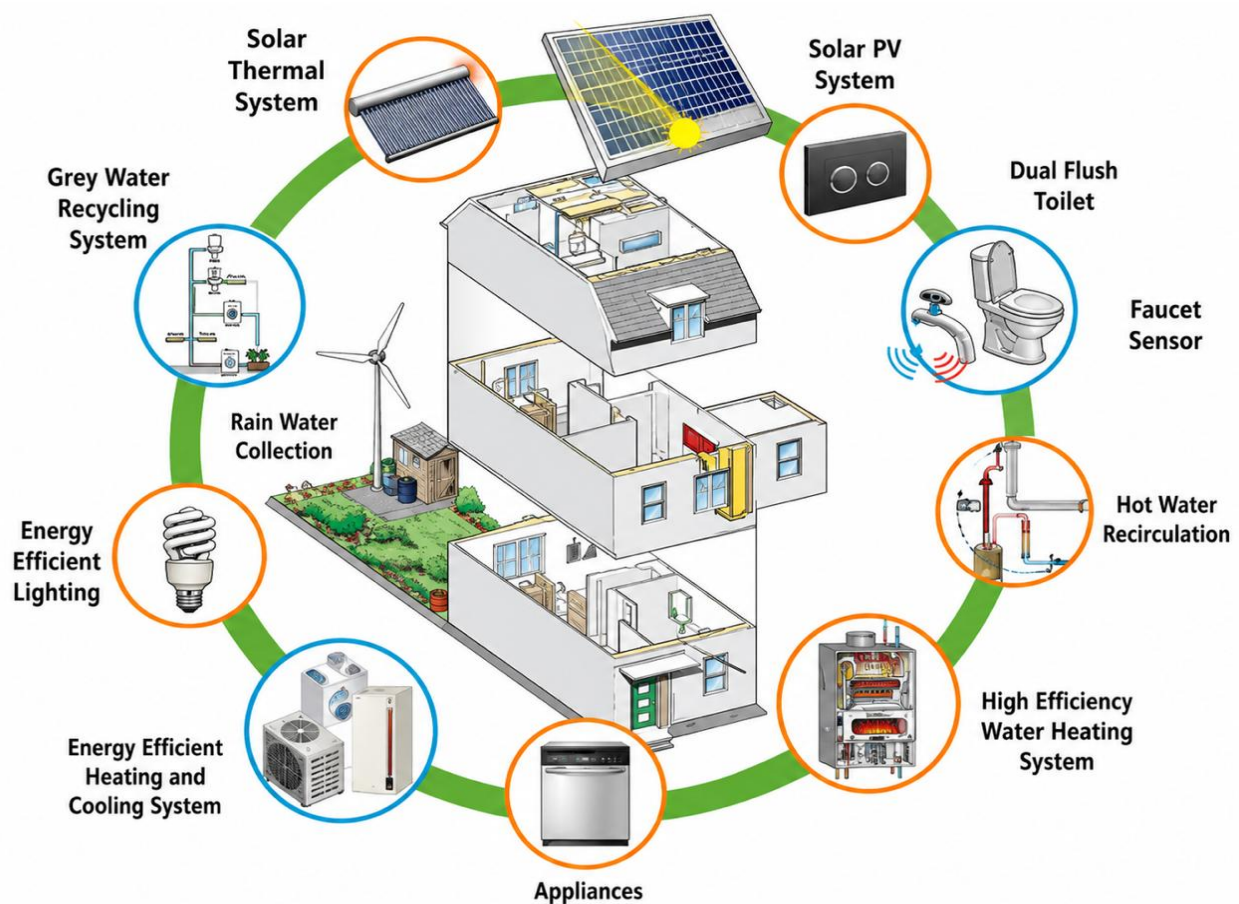


Fig 3. Structural and Functional Elements of Energy-Efficient Buildings [24].

2.4. Artificial Intelligence and Its Types

Artificial Intelligence (AI) is a branch of computer science that focuses on developing computational systems capable of performing tasks that traditionally require human intelligence, including learning, reasoning, decision-making, pattern recognition, and problem-solving. In recent years, AI has become a fundamental technology driving the digital transformation of smart buildings. The widespread deployment of sensors, Internet of Things (IoT) devices, cloud computing, and Building Management Systems (BMS) has enabled AI algorithms to analyze large volumes of real-time data and support intelligent building operation. Consequently, AI-based approaches are increasingly employed for building energy demand prediction, occupancy estimation, HVAC optimization, fault diagnosis, predictive maintenance, renewable energy integration, and intelligent energy management. These applications improve energy efficiency, enhance indoor thermal comfort, increase operational reliability, and contribute to the reduction of greenhouse gas emissions and sustainable building operation [25–28,29]. Figure 4 presents the classification of artificial intelligence (AI) technologies. [30].

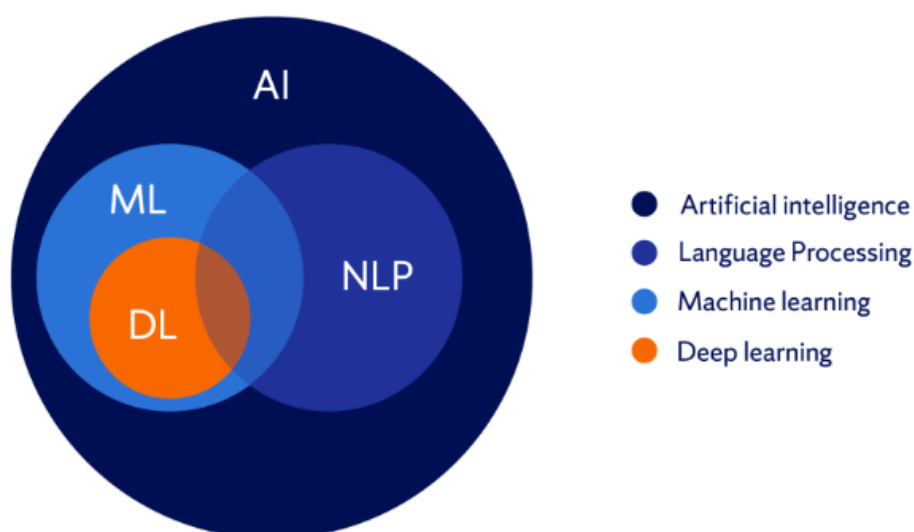


Fig 4. Classification of Artificial Intelligence technologies [30].

2.4.1. Deep Learning

Deep learning (DL) is an advanced branch of machine learning that employs multilayer artificial neural networks to learn hierarchical representations directly from raw data. Compared with traditional ML algorithms, DL models automatically extract relevant features without extensive manual preprocessing. This capability is particularly advantageous when dealing with large-scale sensor data generated in smart buildings. Deep learning architectures such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Transformer-based models have achieved excellent performance in energy demand forecasting, occupancy recognition, thermal load estimation, and anomaly detection. Their ability to model nonlinear temporal relationships makes them particularly suitable for dynamic building environments [26–29].

Figure 5 illustrates the deep learning framework for BIM-based building energy efficiency optimization [31].

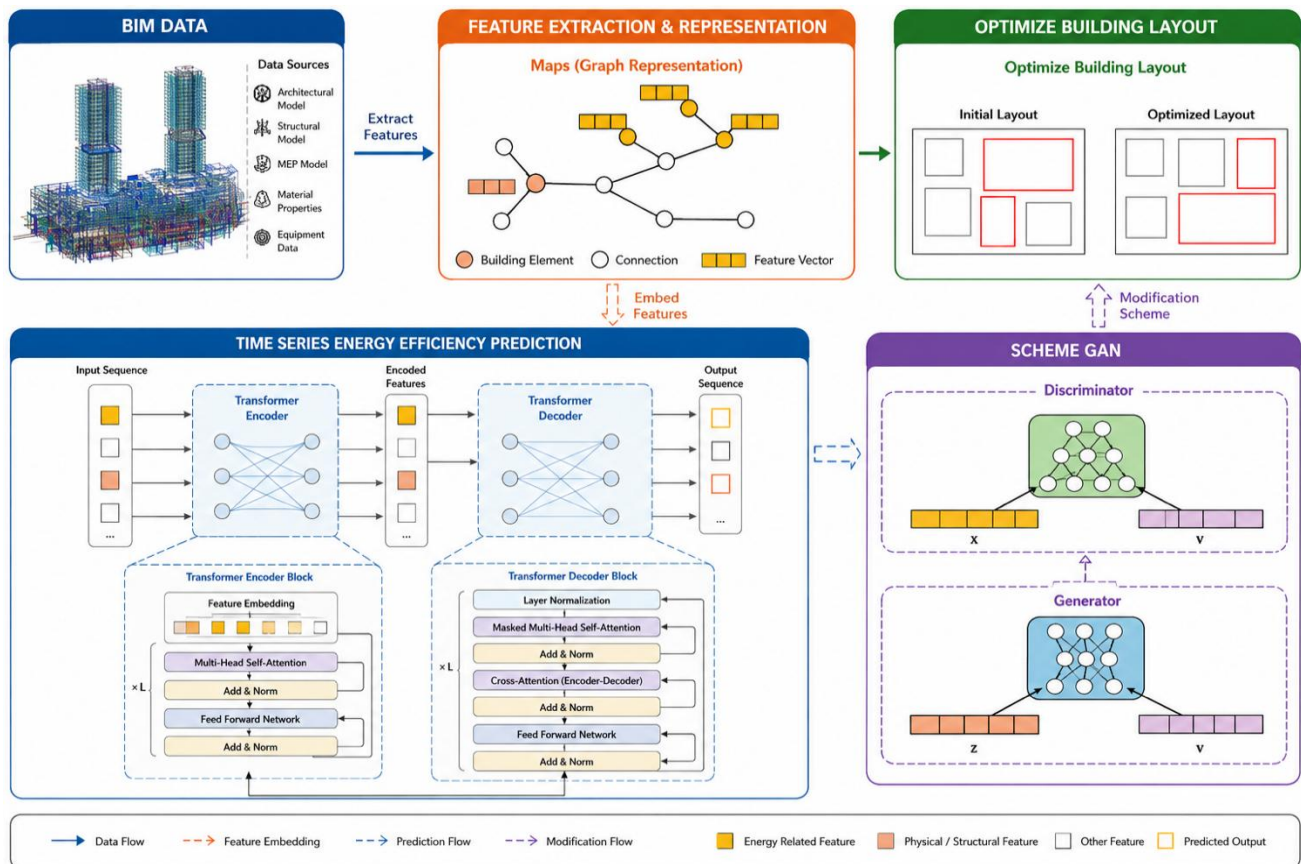


Fig 5. Deep Learning Framework for BIM-Based Building Energy Efficiency Optimization [31].

2.4.2. Artificial Neural Networks

Artificial Neural Networks (ANNs) are computational models inspired by the structure and functioning of biological neural systems. An ANN consists of interconnected neurons organized into input, hidden, and output layers that learn complex nonlinear relationships through iterative training processes. Because building energy performance depends on numerous environmental and operational variables, ANNs have become one of the most frequently used techniques for predicting energy consumption, indoor temperature, thermal loads, and HVAC performance. Recent studies have reported that ANN-based models generally outperform conventional regression techniques in terms of prediction accuracy, especially when sufficient historical operational data are available [26–29].

2.4.3. Transfer Learning

Transfer learning (TL) is a machine learning paradigm in which knowledge acquired from one learning task is transferred to another related task. Instead of training predictive models entirely from scratch, transfer learning utilizes previously learned representations to improve model performance under limited data conditions. This characteristic is particularly valuable in smart

buildings because newly constructed buildings or facilities with insufficient historical operational data often suffer from poor model accuracy. Transfer learning reduces training time, decreases data requirements, and improves model generalization by adapting knowledge obtained from existing buildings to new environments. Consequently, TL has become an increasingly important technique for energy forecasting, fault diagnosis, occupancy prediction, and intelligent building control, particularly when combined with deep learning architectures [27–29].

2.4.5. Machine Learning

Machine learning (ML) is a subset of artificial intelligence that enables computer systems to identify patterns from historical data and improve prediction accuracy without being explicitly programmed. Unlike conventional rule-based approaches, ML algorithms continuously adapt to new information, making them suitable for complex engineering systems where numerous interacting variables exist. In smart buildings, ML is widely applied to predict heating and cooling loads, estimate electricity consumption, optimize HVAC operation, detect equipment faults, and forecast renewable energy production. Common supervised learning algorithms include Random Forest (RF), Support Vector Machine (SVM), Decision Tree (DT), Gradient Boosting (XGBoost), LightGBM, and CatBoost. These algorithms have demonstrated high prediction accuracy and computational efficiency for building energy applications [25–27]. This review aims to provide a comprehensive synthesis of previous studies on the machine learning-based prediction of energy-efficient composite components for smart buildings. The reported findings are comparatively analyzed and integrated to establish the current state of knowledge, identify research gaps, and present future research perspectives in the conclusion section.

Machine learning methods have been widely applied to estimate building energy consumption and evaluate energy performance. Linear Regression has been used to investigate the relationship between building characteristics and energy efficiency [28]. K-Nearest Neighbors (KNN) has been successfully employed for residential energy consumption prediction, particularly in datasets with complex historical consumption patterns and for estimating energy savings after retrofit applications [30–32]. Accurate prediction of building energy consumption is one of the primary objectives of deep learning-based energy management systems. During model training, optimization is typically achieved by minimizing the discrepancy between predicted and observed energy consumption values using appropriate loss functions. Among these, the Mean Squared Error (MSE) remains the most widely adopted objective function due to its simplicity, computational efficiency, and effectiveness in regression tasks. Recent studies have extended conventional single-objective optimization by incorporating multi-task learning strategies that simultaneously predict total building energy consumption and individual sub-meter energy usage. This approach enables the model to capture energy distribution patterns among different building systems, such as heating, ventilation, air conditioning (HVAC), lighting, and plug loads. Ge et al. (2025) proposed a composite spatial loss function that combines the prediction error of total energy consumption with auxiliary prediction errors corresponding to individual sub-meter measurements, as expressed in Eq. (1).

$$\mathcal{L}_{\text{spatial}} = \text{MSE}(E_{\text{total}}, \hat{E}_{\text{total}}) + 0.3 \sum_{i=1}^{N_{\text{sub}}} \text{MSE}(E_{\text{sub},i}, \hat{E}_{\text{sub},i}) \quad (1)$$

$$\mathcal{L}_{\text{temporal}} = \frac{1}{N} \sum_{i=1}^N \left(E_{t+1}^{(i)} - \hat{E}_{t+1}^{(i)} \right)^2 \quad (2)$$

where E_{total} and $\hat{E}_{\text{total}}$ denote the actual and predicted total energy consumption, respectively; $E_{\text{sub},i}$ and $\hat{E}_{\text{sub},i}$ represent the actual and predicted energy consumption of the i th sub-meter; and N_{sub} is the number of monitored sub-meter categories. According to Ge et al. [31], this multi-task learning framework improves the model's ability to characterize spatial energy consumption patterns across different building systems. In addition to spatial modeling, temporal dependencies in energy consumption are commonly modeled using Transformer-based neural networks. In these architectures, optimization is generally performed by minimizing the Mean Squared Error between the predicted and measured energy consumption values at the next time step. Ge et al. (2025) formulated the temporal loss function as follows;

where E_{total} and $\hat{E}_{\text{total}}$ denote the actual and predicted total energy consumption, respectively; $E_{\text{sub},i}$ and $\hat{E}_{\text{sub},i}$ represent the actual and predicted energy consumption of the i th sub-meter; and N_{sub} is the number of monitored sub-meter categories. This multi-task learning framework improves the model's ability to characterize spatial energy consumption patterns across different building systems [31]. In addition to spatial modeling, temporal dependencies in energy consumption are commonly modeled using Transformer-based neural networks. In these architectures, optimization is generally performed by minimizing the Mean Squared Error (MSE) between the predicted and measured energy consumption values at the subsequent time step [31,32]. The temporal loss function can be expressed as follows:

Support Vector Regression (SVR) has been applied to model building energy performance by incorporating weather conditions, construction materials, and occupancy characteristics [33]. Machine learning techniques have been widely applied to identify the key factors influencing building energy consumption, improve prediction accuracy, and support intelligent energy management strategies for energy-efficient building operation [34]. Random Forest has demonstrated high prediction accuracy by capturing nonlinear relationships among building parameters, insulation properties, occupancy behavior, and historical energy consumption [35,36]. In addition, Gradient Boosting has achieved superior forecasting performance for commercial building energy demand by integrating design characteristics, occupancy profiles, and climatic variables [37].

Figure 6 illustrates the fundamental architecture of a smart building and the interaction between its main components. The system integrates sensors and actuators, networking and communication technologies, software platforms, HVAC systems, and smart control devices through Internet of Things (IoT) technologies. Data collected from sensors are transmitted via communication networks to software platforms, where machine learning and data analytics support intelligent decision-making for energy management, occupant comfort, and operational efficiency. This integrated architecture forms the technological foundation of modern energy-efficient smart buildings and enables real-time monitoring, automation, and predictive control strategies [3].

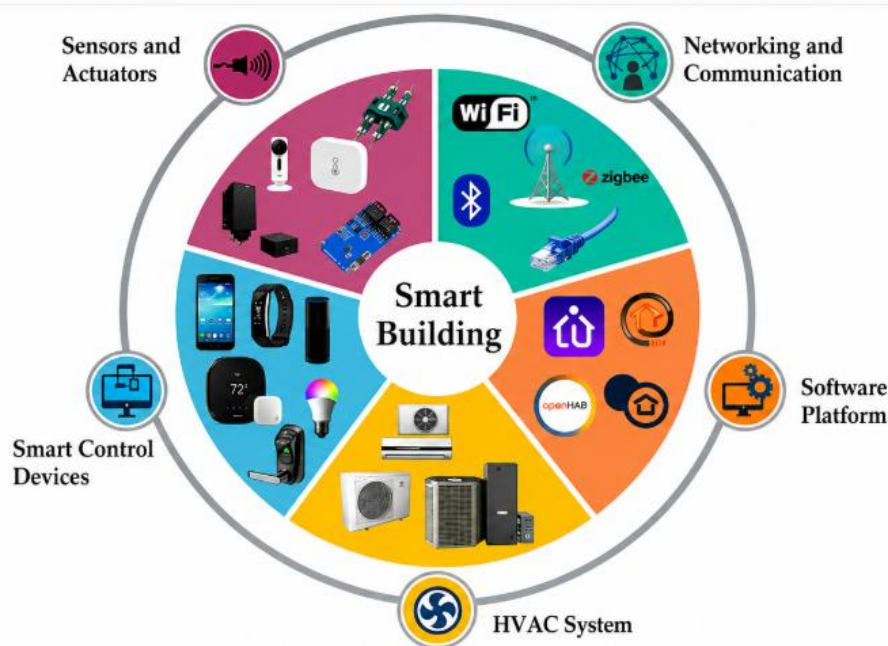


Fig.6. Smart building architecture and its main components [37].

4. Conclusions

This study has provided a comprehensive synthesis of the recent academic literature surrounding the integration of machine learning (ML) techniques and advanced composite materials to optimize energy efficiency in smart buildings. The reviewed body of work underscores that data-driven predictive frameworks—specifically Artificial Neural Networks (ANN), Deep Learning (DL), Transfer Learning (TL), and ensemble methods like Random Forest and Gradient Boosting—demonstrate substantial capabilities in mapping the complex, non-linear relationships governing building thermal loads and material performance. Rather than acting as isolated analytical methods, these intelligent tools are evolving into essential instruments for accelerating computational material selection and predicting the macro-scale energy behavior of multi-functional facades, bio-composites, and insulation elements under dynamic environmental conditions.

The findings derived from this literature review point toward several critical pathways for future research. While existing computational studies establish high baseline accuracies for specific component predictions or building types, there remains a prominent need to bridge the gap between material-level characterization and building-level energy dynamics through holistic, multi-scale modeling frameworks. Furthermore, practical constraints such as data scarcity in newly constructed facilities highlight the vital importance of expanding transfer learning applications. Ultimately, transitioning from purely descriptive and analytical toolsets toward robust, AI-assisted generative design models represents a key frontier. Encouraging future interdisciplinary research at the intersection of material science, data engineering, and architectural computing will be crucial to driving forward the practical development of highly resilient, autonomous, and sustainable smart building systems.

Author Contributions

“Conceptualization, Hüseyin Firat Kayıran; methodology, Hüseyin Firat Kayıran; software, Hüseyin Firat Kayıran; validation, Hüseyin Firat Kayıran; formal analysis, Hüseyin Firat Kayıran; investigation, Hüseyin Firat Kayıran; resources, Hüseyin Firat Kayıran; data curation, Hüseyin Firat Kayıran; writing—original draft preparation, Hüseyin Firat Kayıran; writing—review and editing, Hüseyin Firat Kayıran; visualization, Hüseyin Firat Kayıran; supervision, Hüseyin Firat Kayıran; project administration, Hüseyin Firat Kayıran. The author has read and agreed to the published version of the manuscript.”

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Data Availability Statement

The article does not use any data.

Conflicts of Interest

There are no known competing financial interests or personal relationships that could have influenced the work reported in this article.

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