AI-Based Energy Optimization in Smart Buildings with Renewable Energy Integration: A Construction Project Management Perspective

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Abstract

Smart buildings are increasingly being promoted as a solution to rising global energy demand, yet many of them still suffer from inefficiencies in energy usage due to poor forecasting, suboptimal control strategies, and limited coordination between energy generation and consumption systems. At the same time, the integration of renewable energy sources such as solar, wind, and hybrid storage systems has introduced additional complexity because of their intermittent and unpredictable nature. In this context, artificial intelligence offers promising capabilities for improving energy optimization through demand prediction, adaptive control, and intelligent scheduling of energy resources. However, most existing studies focus either on AI-based energy management or renewable integration in isolation, with limited attention given to how these systems can be effectively incorporated into construction project management processes. This gap is particularly important during the design and planning phases, where early decisions significantly influence long-term building performance. This paper proposes a conceptual framework that integrates AI-driven energy optimization with renewable energy systems from a construction lifecycle perspective. The framework emphasizes data-driven decision support, lifecycle energy planning, and sustainability-aware project management. The key contribution lies in connecting energy modeling, AI techniques, and construction project decision-making into a unified approach aimed at improving both operational efficiency and environmental performance of smart buildings.

Keywords: AI, Smart Buildings, Energy Optimization, Renewable Energy, Construction Project Management, IoT, Machine Learning, Sustainability, Energy Management Systems

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I. Introduction

Global energy demand has continued to rise over the years, and buildings remain one of the largest contributors to overall energy consumption worldwide. Residential, commercial, and institutional buildings consume a significant share of global electricity due to daily operations such as heating, cooling, lighting, and appliance usage. In addition to high energy consumption, buildings also contribute heavily to carbon emissions because many facilities still depend on conventional energy sources and inefficient energy management practices. Recent studies indicate that buildings are responsible for nearly 40% of global final energy consumption and approximately 36% of energy- related CO_2 emissions, highlighting the major role of the built environment in global sustainability challenges. Furthermore, the International Energy Agency (IEA) projected in 2019 that energy demand from the building sector could increase by almost 50% by 2050 as a result of rapid urbanization, population growth, and improving living standards, particularly in developing countries. These trends emphasize the urgent need for energy-efficient building solutions and sustainable infrastructure strategies to reduce environmental impact and support global climate goals.

In response to these challenges, smart buildings have emerged as a promising solution. Equipped with sensors, automation systems, and data-driven control mechanisms, smart buildings aim to optimize energy consumption while maintaining occupant comfort. By integrating monitoring and control technologies, these systems enable more efficient use of lighting, heating, cooling, and other energy-intensive operations. However, despite these advancements, many smart buildings still operate below optimal efficiency levels. Studies show that actual energy performance often differs from predicted performance by nearly 20–40%, a phenomenon commonly referred to as the "performance gap" [2]. Several factors contribute to this issue. First, many Building Energy Management Systems (BEMS) still rely on reactive and threshold-based control methods that respond to changes only after they occur rather than anticipating them in advance. Second, renewable energy sources such as solar and wind are inherently intermittent and difficult to manage using static scheduling approaches. Solar energy generation changes with weather conditions and seasonal variations, while wind energy in urban environments is often unpredictable due to turbulence and inconsistent airflow patterns. Another important challenge is that energy optimization is

mostly treated as an operational concern after building construction has been completed. Limited attention is given to how design-stage and construction-stage decisions influence long-term energy performance. Factors such as building orientation, material selection, HVAC system configuration, and renewable energy planning can significantly affect future energy efficiency outcomes, yet they are rarely integrated into early construction planning and decision-making processes.

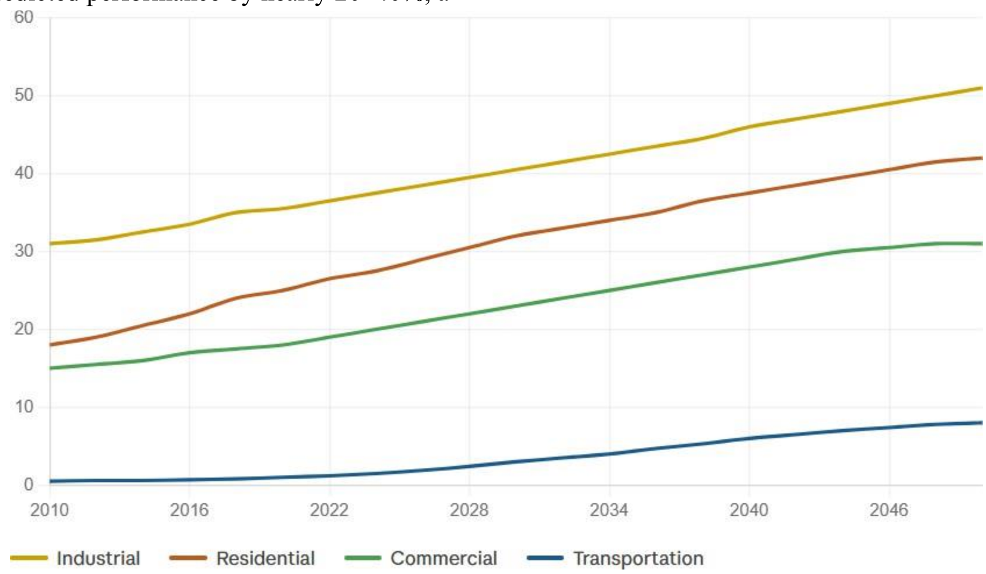

Fig. 1. Projections of Global Electricity Use by Sector [1]

The increasing complexity of modern building energy systems has created a growing need for smarter and more predictive optimization approaches. Managing energy consumption has become more challenging due to changing occupancy patterns, varying environmental conditions, and the integration of renewable energy sources. In this context, artificial intelligence offers valuable capabilities for predicting energy demand, improving resource utilization, and enabling more adaptive control of building operations. These features are especially useful not only during real-time building operations but also during the planning and design stages, where early decisions can greatly influence long-term energy performance. For construction project managers, incorporating AI-based energy insights into project planning and execution can support more effective and informed decision-making throughout the building lifecycle.

In past decade, the application of AI to building energy management has expanded rapidly. Machine learning models now achieve sub-5% mean absolute error in 24-hour load forecasting; reinforcement learning agents have demonstrated energy savings of 15-30% in HVAC control; and optimization algorithms can schedule battery storage dispatch to minimize electricity costs under dynamic tariff regimes [3]. However, virtually all of this work treats the building as an operational artifact, ignoring the project management lifecycle through which it was designed and built. Construction project managers make decisions during design, procurement, and construction phases that lock in decades of energy performance: building orientation, envelope specifications, HVAC system selection, PV array sizing, and smart metering infrastructure. Integrating AI-driven energy intelligence into these early-stage decisions represents a high-leverage, under-explored opportunity that this paper seeks to address.

Hence, existing research in this area tends to focus on isolated aspects of the problem. Many studies investigate energy systems, artificial intelligence models, or smart grid technologies independently, without establishing strong linkages between them. While valuable, this fragmented approach limits the development of holistic solutions for smart building energy management. More importantly, there is a clear lack of integration between AI-based energy optimization and construction lifecycle decision-making. Early-stage planning, which plays a crucial role in determining a building's long-term energy performance, is often overlooked in existing models.

This paper addresses the identified gaps by proposing a conceptual framework that integrates AI-based energy optimization with renewable energy systems within a construction project management context. The framework

emphasizes the role of intelligent decision-making across the entire building lifecycle, from design and construction to operation and maintenance. Additionally, it incorporates renewable energy integration as a core component of building energy systems, focusing on how solar, wind, and hybrid configurations can be optimized using AI techniques. A dedicated construction project management decision layer is also introduced to bridge the gap between technical energy models and practical project execution. Finally, this study consolidates and synthesizes state-of- the-art research in AI-driven energy management, renewable integration, and smart building technologies, providing a structured foundation for future research in this interdisciplinary domain.

II. Background and State-of-the-Art

A. Smart Buildings and Energy Systems

A smart building is broadly defined as a structure that uses automated processes to control the building's operations, including heating, ventilation, air conditioning (HVAC), lighting, security, and energy systems representing an evolution of traditional infrastructure where physical systems are integrated with digital intelligence to improve operational efficiency, comfort, and sustainability. Unlike conventional buildings that rely on static control mechanisms, smart buildings utilize real-time data and automated decision-making systems to regulate energy consumption dynamically. Over the past two decades, this evolution has been driven by advancements in sensing technologies, connectivity, and computational intelligence. The evolution from conventional facilities management to smart buildings has proceeded through three generations: rule-based Building Automation Systems (BAS) in the 1980s, networked BEMS with centralized monitoring in the 2000s, and IoT-enabled, data-driven systems in the 2010s onwards [4]. Contemporary BEMS integrate thousands of sensor data points such as temperature, CO_2, occupancy, power consumption transmitted over Ethernet, Zigbee, or wireless protocols to cloud analytics platforms. These systems are designed to monitor, control, and optimize energy usage across various subsystems such as heating, ventilation, air conditioning (HVAC), lighting, and electrical appliances. BEMS typically rely on rule-based or model-based control strategies, but more recent developments are increasingly incorporating data- driven and AI-based methods to improve adaptability and accuracy. The rise of Internet of Things (IoT) technologies has further strengthened smart building capabilities. IoT-enabled sensors allow continuous monitoring of environmental conditions such as temperature, humidity, occupancy, and energy consumption. These sensors generate large volumes of real-time data, which can be analyzed to identify inefficiencies, predict demand patterns, and optimize energy usage [16]. As a result, IoT has become a foundational layer in modern energy-efficient building systems. The frontier of smart building research now focuses on predictive control: using forecasts rather than measurements to pre-empt energy demand.

Fig. 2. Buildings Evolution From Physical Infrastructure to Data Driven Predictive Control

B. Renewable Energy Integration in Buildings

The integration of renewable energy sources into buildings has gained significant attention as part of global decarbonization efforts. On-site solar PV is now the dominant form of building-integrated renewable energy, with global installed capacity in the building sector exceeding 400 GW in 2023 [5] due to their scalability, declining installation costs, and ease of integration into rooftops and façades. Solar energy can directly offset grid electricity consumption, particularly during peak daylight hours. Urban wind integration remains limited due to the turbulent and low-velocity wind conditions in built environments, though building-integrated wind turbines are emerging in purpose-designed high-performance buildings. Battery energy storage systems (BESS), particularly lithium-ion chemistries, have fallen 90% in cost since 2010 and are increasingly paired with PV to play a critical role in balancing supply and demand by storing excess energy during peak production periods and releasing it during low- generation intervals [6]. Hybrid renewable systems combining PV, BESS, and grid connection represent the current state of practice in high-performance smart buildings, though their optimal scheduling remains a technically challenging problem due to the simultaneous need to maximize self-consumption, minimize cost, and preserve battery longevity.

Despite these advantages, renewable integration introduces challenges such as intermittency, storage limitations, and load balancing complexities, which require advanced control and optimization strategies.

C. AI Techniques in Energy Optimization (State-of-the-Art)

Artificial intelligence has become a key enabler in addressing the complexity of modern energy systems. Machine learning techniques are widely used for predicting energy consumption and identifying usage patterns. Regression- based models are commonly applied for short-term load forecasting due to their simplicity and interpretability. In contrast, neural networks provide improved accuracy by capturing nonlinear relationships between environmental and operational variables. Deep learning approaches, particularly Long Short-Term Memory (LSTM) networks, have shown strong performance in time-series energy prediction tasks. LSTM models are capable of learning temporal dependencies in historical energy consumption data, making them suitable for forecasting dynamic demand in smart buildings.

Reinforcement learning has also emerged as a powerful technique for real-time control applications. In the context of energy management, reinforcement learning algorithms are used to optimize HVAC system operations by continuously learning optimal control policies based on environmental feedback and energy costs. This allows systems to adapt to changing conditions without explicit programming. In addition to learning-based methods, classical optimization algorithms such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) are widely used for energy scheduling and resource allocation problems. These algorithms are particularly effective in solving multi-objective optimization problems involving trade-offs between cost, comfort, and energy efficiency.

Table I summarizes the principal AI techniques applied to building energy optimization, their primary applications, and their key strengths and limitations.

TABLE I. AI TECHNIQUES IN BUILDING ENERGY OPTIMIZATION

AI Technique	Application	Advantage	Limitation
Regression (RF/XGBoost)	Short-term load forecasting	Fast, interpretable	Non-sequential
LSTM Neural Network	Time-series energy prediction	Captures temporal patterns	Data-hungry
Reinforcement Learning	HVAC real-time control	Adaptive, no explicit model	Slow convergence
MILP / Genetic Algorithm	Energy scheduling & dispatch	Guaranteed optimality	›mputationally heavy
Model Predictive Control	Rolling horizon optimization	Handles constraints well	ıuires accurate model

Among supervised learning approaches, gradient-boosted regression trees (XGBoost, LightGBM) deliver strong performance for short-term load forecasting with limited training data. Long Short-Term Memory (LSTM) networks excel at multi-step time-series prediction, capturing the diurnal and weekly cycles inherent in building energy consumption patterns [7]. Deep Reinforcement Learning (DRL) has shown particular promise for HVAC control optimization, where the agent learns a policy that minimizes energy cost while maintaining thermal comfort through interaction with a simulated or real building environment [8]. Model Predictive Control (MPC), while not strictly an AI technique, is frequently combined with ML forecasting models to create hybrid AI-MPC systems that solve a rolling-horizon constrained optimization problem at each control interval.

D. Digital Technologies in Smart Construction

Digital transformation in the construction industry has introduced several technologies that support energy-efficient building design and management. Building Information Modeling (BIM) that provides a three-dimensional, data- rich digital representation of a building is one of the most widely adopted tools, enabling digital representation of building geometry, systems, and performance characteristics. Tools such as EnergyPlus and DesignBuilder integrate with BIM platforms to predict annual energy performance under different design scenarios and also facilitates better coordination among stakeholders allowing early-stage simulation of energy performance [9]. Digital twins represent an advanced extension of BIM, where a virtual replica of a physical building is continuously updated using real- time data. This enables dynamic energy simulation, predictive maintenance, and performance optimization

throughout the building lifecycle. Digital twins are increasingly being integrated with AI systems to enhance decision-making capabilities. IoT and sensor networks further complement these technologies by providing real- time data during both construction and operational phases. During construction, sensors can monitor material usage, environmental conditions, and equipment efficiency, contributing to improved resource management and reduced waste but poor sensor placement or coverage during construction creates permanent blind spots in the operational energy management system.

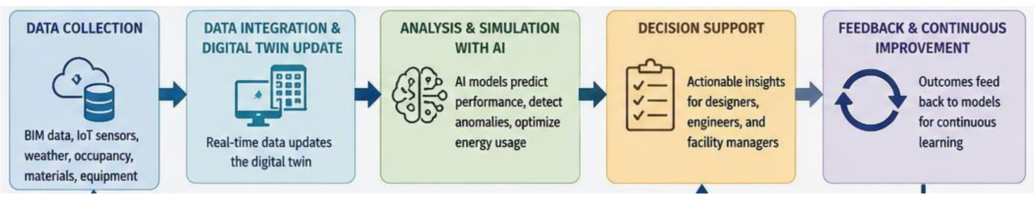

Fig. 3. Integrated Workflow across Building Lifecycle

E. Construction Project Management Perspective

Construction project management (CPM) has historically focused on the triple constraint of time, cost, and quality. Sustainability has been added as a fourth dimension through green building rating systems (LEED, BREEAM, Green Star) and increasingly through regulatory energy performance requirements. From a construction project management perspective, energy efficiency must be considered across all phases of the building lifecycle. During the design phase, critical decisions such as building orientation, material selection, and system configuration significantly influence long-term energy performance. Early integration of energy modeling tools can help project managers evaluate different design alternatives based on energy efficiency outcomes. During the construction phase, energy efficiency focuses on minimizing resource wastage, optimizing equipment usage, and ensuring adherence to sustainable construction practices [10]. Efficient project scheduling and resource allocation can indirectly contribute to reduced energy consumption on-site. In the operation and maintenance phase, energy management becomes more data-driven, relying on real-time monitoring and optimization systems. Sustainability Key Performance Indicators (KPIs) are increasingly being used in project management to evaluate environmental performance. These include metrics such as energy consumption per square meter, carbon emissions, and renewable energy utilization ratio. Integrating these KPIs into project decision-making enables more sustainable outcomes.

Energy Use Intensity (EUI), expressed as kWh/m²/year eq. 1, has become the primary operational sustainability metric in commercial construction.

$$\mathrm{EUI} = \frac{\text{kWh (or MJ) consumed in a year}}{\text{Total building area in m}^2} \quad (1)$$

However, the connection between CPM decisions during the design and construction phases and the eventual operational EUI remains weakly understood and poorly managed in practice. Lifecycle cost analysis (LCCA) provides the theoretical framework for evaluating the long-run financial implications of early-stage energy decisions [11], but its adoption in practice is limited by data availability and the complexity of probabilistic energy forecasting.

F. Research Gap Synthesis

Despite significant advancements in smart building technologies, AI methods, and renewable energy integration, the existing literature remains fragmented. Most studies focus on individual components such as AI-based prediction models, renewable energy systems, or smart grid optimization, without establishing a unified framework that connects these domains. Furthermore, there is limited research that directly links predictive energy systems with construction scheduling, budgeting, and lifecycle decision-making processes [12]. This disconnect prevents the effective translation of energy optimization insights into practical project management actions. Another major gap is the minimal integration of energy forecasting and optimization techniques into early-stage construction decision- making. As a result, many opportunities for improving long-term energy efficiency are lost during the design and planning phases.

Table II maps the coverage of major research streams against the three dimensions addressed by this paper: AI optimization, renewable energy integration, and construction project management (CPM) integration. The analysis reveals a clear gap: no existing framework simultaneously addresses all three dimensions.

TABLE II. COVERAGE ACROSS STUDY FOCUS AREAS

Study Focus	AI Optimization	Renewable Integration	CPM Integration
Smart building energy systems	Yes	Partial	No
AI forecasting & HVAC control	Yes	No	No
Renewable + storage systems	Partial	Yes	No
BIM & digital twin energy models	No	Partial	Partial
Construction project sustainability	No	No	Yes

III. Conceptual Framework

A. System Overview

The proposed framework conceptualizes the smart building as a four-layer energy ecosystem. The energy generation layer comprises on-site renewable sources (primarily PV arrays) supplying variable, weather-dependent power. The consumption layer encompasses controllable electrical loads HVAC (typically 40-60% of total demand), intelligent lighting, and smart appliances each offering scheduling flexibility. The storage layer uses battery energy storage as a temporal buffer, absorbing surplus renewable generation and discharging during demand peaks or high-tariff periods. The AI decision layer is the cognitive core: it continuously ingests data from the physical layers, generates forecasts, solves optimization problems, and issues control commands. These four layers are not independent; they exchange energy flows, data signals, and control commands in continuous real time, creating a cyber-physical system that is more than the sum of its parts.

B. AI-Based Energy Optimization Layer

The AI optimization layer transforms the building from a passively monitored facility into a self-optimizing system. It operates on four principal data streams:

- **Weather data:** Real-time and forecast meteorological feeds (irradiance, temperature, humidity, wind speed) drive solar generation forecasting and inform HVAC load prediction.
- **Occupancy patterns:** PIR sensors, CO_2 monitors, and Wi-Fi probe tracking generate real-time and predictive occupancy profiles that determine conditioning and lighting demand.
- **Energy pricing signals:** Dynamic tariff and time-of-use (TOU) price feeds from utility APIs govern the economic logic of load-shifting and battery dispatch decisions.
- **Historical consumption data:** Longitudinal time-series records provide the training corpus for machine learning models and the baseline for measuring optimization gains.

From these inputs the AI layer performs three core functions. Load forecasting employs gradient-boosting or LSTM neural network models to produce 15-minute to 48-hour demand predictions. Demand-response optimization formulates load-curtailment and load-shifting as a constrained problem minimizing cost subject to comfort bounds solved via mixed-integer linear programming (MILP) or reinforcement learning. Energy distribution scheduling applies a rolling Model Predictive Control (MPC) approach to dispatch generation, storage, and grid import optimally at each time step, updating every 15 minutes as new data arrive.

C. Renewable Energy Integration Model

Solar forecasting spans three horizons: intra-hour models use sky imagery and autoregressive statistics to track rapid cloud-driven irradiance changes; day-ahead models combine Numerical Weather Prediction (NWP) outputs with site-calibrated PV conversion models; and seasonal projections use climatological data to support investment planning. All outputs are probabilistic distributions rather than point estimates, supplying uncertainty bounds to the optimizer for robust scheduling.

Battery charge-discharge optimization is governed by a multi-objective function balancing electricity cost minimization, technical constraints (state-of-charge limits, maximum charge/discharge rates), and cycle-life degradation cost explicitly monetized as a penalty to avoid economically marginal cycling that accelerates battery ageing. The grid interaction strategy supports three dynamic operating modes: self-consumption maximization, demand-response participation, and virtual power plant (VPP) aggregation, with the AI layer selecting the active mode based on prevailing tariffs and grid conditions.

D. Construction Project Management Integration

The framework extends lifecycle thinking into the construction phase by embedding energy as a fourth project constraint alongside time, cost, and quality. Energy-aware project planning links energy modelling outputs directly to the construction schedule via BIM platforms, ensuring smart metering, BESS installation, and AI commissioning milestones are correctly sequenced relative to civil and electrical works.

The cost-time-energy tradeoff model evaluates competing design options across three vectors capital cost, schedule impact, and predicted operational energy performance generating a Pareto frontier of non-dominated solutions assessed through Lifecycle Cost Analysis (LCCA) over a 20–25 year horizon. Projectlevel sustainability KPIs Energy Use Intensity (EUI, kWh/m²/year) eq.1, Renewable Energy Fraction (REF) eq.2 which if 0 indicates no renewable energy was used and if 1 indicates 100% renewable energy was consumed, Carbon Intensity Index (kg CO_2e/m^2/year) eq.3, and green building certification alignment are tracked at key milestones to ensure construction- phase decisions remain aligned with the sustainability brief.

$$\mathrm{REF} = \frac{E_{\text{renewable}}}{E_{\text{total}}} \quad (2)$$

Where,

Erenewable is the energy produced or consumed from renewable sources (solar, wind, hydro, etc.) and *Etotal* is the total energy consumption (renewable + non-renewable)

$$\text{Carbon Intensity Index (CII)} = \frac{E_{\mathrm{CO_2e}}}{A} \quad (3)$$

Where,

E_{CO_2e} is the total annual greenhouse gas emissions (*kg* CO_2 equivalent per year) and A is total floor area (m^2).

Energy uncertainty risk is managed through a probabilistic risk register covering generation variability, equipment supply disruptions, demand deviation from design assumptions, and regulatory changes to tariff structures. Monte Carlo simulation propagates these uncertainties through the energy performance model to generate confidence intervals around projected savings and payback periods, informing contingency budgeting and contractual performance guarantees.

The framework's most distinctive contribution is the explicit embedding of energy decision-making into the construction project lifecycle. Table III maps AI and sustainability tools to each project phase from design through operations.

TABLE III. ENERGY-AWARE ACTIONS AND TOOLS ACROSS THE CONSTRUCTION PROJECT LIFECYCLE

Project Phase	Energy-Aware Actions	AI/Sustainability Tool
Design	rgy modelling, PV/BESS sizing, orientation optimization	gy simulation, solar irradiance modelling
Procurement	st-based equipment selection, green specs	radeoff model, supplier carbon scoring
Construction	itoring on site, commissioning sequencing	smart metering, BIM milestone tracking
Commissioning	AI system integration, baseline performance testing	AI prediction engine calibration, EUI baseline
Operations	uous AI optimization, demand- response, reporting	op (Stages 1-5), KPI dashboard, VPP

E. Conceptual Workflow

The system operates as a closed-loop, five-stage process connecting physical sensing to strategic management:

1) Stage 1 (Data Collection): IoT sensors, smart meters, weather APIs, and occupancy detectors continuously feed validated, timestamped readings into a central time-series database.

2) Stage 2 (AI Prediction): Trained machine learning models generate probabilistic forecasts for energy demand, solar generation, and occupancy over the look-ahead horizon, updated as new data arrive.

3) Stage 3 (Optimization): The MPC/MILP engine ingests forecasts and current system state (battery state-of- charge, active loads, grid price) to compute an optimal, constraint-satisfying dispatch schedule for all controllable assets.

4) Stage 4 (Decision Support): Strategic recommendations, KPI summaries, and alerts are surfaced to facility managers and project management teams through a dashboard; actions requiring human authorization are flagged for review, preserving a human-in-the-loop governance layer that prevents fully autonomous control of safety-critical systems.

5) Stage 5 (Feedback Loop): Actual outcomes are compared against forecasts; systematic deviations trigger model retraining and are reported as evidence of sustainability target achievement or as early warning of performance deterioration.

Together, these five stages create a self-improving system in which operational intelligence from each cycle informs and refines subsequent decisions, progressively narrowing the gap between predicted and actual energy performance. Figure 4 illustrates the five-stage closed-loop workflow governing the AI-driven energy management system.

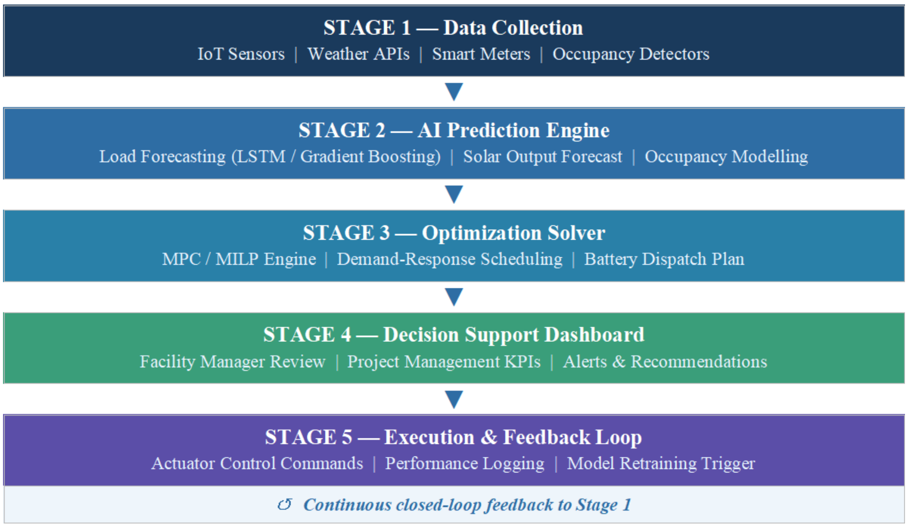

Fig. 4. Integrated Workflow across Building Lifecycle Five-Stage Operational Workflow of the AI-Driven Smart Building Energy Management System

IV. Discussion

A. Key Insights

The proposed framework highlights the growing importance of artificial intelligence in improving energy efficiency within smart buildings. One of the major insights derived from this study is that AI enables adaptive and predictive energy control rather than relying on conventional static management approaches. Traditional systems typically operate using predefined rules that may not respond effectively to dynamic environmental conditions or occupant behavior. In contrast, AI-driven systems can continuously analyze real-time and historical data to predict future energy demand, optimize energy usage, and adjust operational strategies automatically. This predictive capability allows buildings to operate more efficiently while maintaining occupant comfort and reducing unnecessary energy consumption.

Another important insight is that renewable energy integration cannot achieve maximum efficiency without intelligent scheduling and optimization mechanisms [13]. Renewable sources such as solar and wind energy are highly dependent on environmental conditions, making their output variable and uncertain [14]. As a result, balancing energy generation, storage, and consumption becomes a complex task. The proposed framework demonstrates how AI techniques can support demand-response management, energy scheduling, and storage optimization to improve the reliability and efficiency of renewable-integrated smart buildings.

The study also emphasizes that construction-phase decisions play a critical role in determining long-term building energy performance. Many energy-related challenges originate during the early design and planning stages, where decisions regarding building orientation, insulation materials, HVAC configurations, and renewable system integration are made. Incorporating AI-supported energy analysis during these phases can help project teams evaluate different alternatives and select designs that optimize long-term sustainability outcomes. This highlights the need to treat energy optimization not only as an operational concern but also as a strategic component of construction project management.

B. Practical Implications

The proposed framework offers several practical implications for different stakeholders involved in smart building development and management.

For construction project managers, the framework provides a structured approach for integrating energy considerations into project planning and execution processes. AI-driven decision support can assist managers in selecting energy-efficient building designs, evaluating renewable energy options, and optimizing resource allocation. Additionally, predictive analysis can improve budgeting and scheduling decisions by identifying long- term operational savings associated with sustainable construction strategies [15]. This can ultimately contribute to reduced lifecycle costs and improved project sustainability.

For engineers and system designers, the framework supports more informed technical decision-making. AI-based forecasting and optimization tools can help engineers design more efficient HVAC systems, storage solutions, and renewable integration strategies. The use of predictive models also enables better estimation of future energy demand patterns, allowing systems to be designed with improved scalability and reliability [17]. From a policy perspective, the framework can support the development of sustainable construction regulations and standards. Policymakers can use AI-driven energy optimization models to establish performance benchmarks, encourage renewable energy adoption, and promote smart infrastructure development. Integrating sustainability indicators into construction practices can also support national and international carbon reduction goals. Furthermore, the framework aligns with broader smart city initiatives that aim to improve environmental performance through intelligent infrastructure systems.

V. FUTURE DIRECTIONS

The rapid advancement of intelligent technologies is expected to further transform energy management practices in smart buildings and sustainable construction. One of the most promising future directions is the integration of Artificial Intelligence with Digital Twin and Building Information Modeling (BIM) platforms. Digital twins can provide real-time virtual representations of building systems, enabling continuous monitoring, simulation, and optimization of energy performance throughout the building lifecycle. When combined with BIM, AI-driven analysis can support more accurate decision-making during both the design and operational phases of construction projects.

Another important direction involves the development of real-time adaptive AI control systems. Current energy management approaches often rely on periodic analysis and predefined optimization rules. Future systems are expected to become more autonomous and responsive, continuously adapting to changing occupancy patterns, weather conditions, and renewable energy availability. Such adaptive control mechanisms could significantly improve energy efficiency while maintaining occupant comfort and operational reliability.

Majorly five priority directions for future research are identified:

- Digital twin integration: Connecting the AI optimization framework to a continuously updated digital twin would enable real-time simulation of “what-if” scenarios during both construction and operations, improving both design-phase decision support and operational adaptability. BIM-to-digital-twin workflows are maturing rapidly and represent a natural extension of the proposed framework.

- Blockchain-enabled energy trading: Peer-to-peer energy trading between buildings participating in VPP arrangements requires transparent, tamper-proof transaction records. Blockchain technology offers a decentralized settlement layer for energy trades, enabling buildings to sell surplus renewable generation directly to neighbours without utility intermediation.

- Edge AI for decentralized control: Cloud-dependent AI systems introduce latency and connectivity risks. Deploying lightweight AI models on edge computing hardware (within the building’s network perimeter) enables millisecond-level control responses and maintains optimization capability during internet outages critical for safety-related HVAC functions.

- Carbon-aware construction scheduling: Extending the cost-time-energy tradeoff model to incorporate embodied carbon the emissions from material production and construction processes would create a genuinely whole-lifecycle sustainability decision model. Integrating real-time grid carbon intensity signals into construction scheduling (timing energy-intensive operations for periods of high renewable grid penetration) is a near-term practical application.

- Federated learning across building portfolios: AI models trained on data from a single building are limited by that building's occupancy patterns and operational history. Federated learning allows models to be trained collaboratively across a portfolio of buildings without sharing raw data, improving generalization and enabling faster model adaptation in new deployments.

VI. Conclusion

The increasing demand for sustainable infrastructure has accelerated the need for intelligent energy management solutions in modern buildings. This paper explored the integration of artificial intelligence, renewable energy systems, and construction project management within the context of smart buildings. The study highlighted how AI-driven techniques can improve energy efficiency through predictive analysis, adaptive control, and optimized resource allocation, while renewable energy integration contributes to reducing dependence on conventional power sources and lowering carbon emissions.

The paper also emphasized that effective energy optimization should not be limited to the operational stage of buildings alone. Decisions made during the early planning and construction phases significantly influence long-term energy performance, operational costs, and environmental sustainability. Integrating energy-aware strategies into construction project management enables project stakeholders to consider sustainability objectives from the beginning of the building lifecycle. This approach supports better design selection, improved resource utilization, and more informed decision-making throughout project execution. Furthermore, the study discussed the growing role of digital technologies such as IoT, BIM, digital twins, and AI-based optimization systems in shaping the future of smart infrastructure. These technologies collectively provide the foundation for intelligent, adaptive, and data- driven building ecosystems capable of responding to dynamic environmental and operational conditions. Despite the advancements in smart building technologies and renewable energy integration, the existing research landscape remains fragmented across separate domains. The findings of this paper reinforce the need for unified frameworks that connect AI-driven energy optimization, renewable integration, and construction lifecycle management into a comprehensive system. Such integrated approaches are essential for achieving long-term sustainability goals, improving energy resilience, and supporting the development of future smart cities and environmentally responsible construction practices.

References

1. U.S. Energy Information Administration, "Global energy consumption driven by more electricity in residential, commercial buildings," *Today in Energy*, Oct. 21, 2019. [Online]. Available: EIA Today in Energy Article[Accessed: May 21, 2026].
2. Menezes, A. C., Cripps, A., Bouchlaghem, D., & Buswell, R. (2012). Predicted vs. actual energy performance of non-domestic buildings: Using post-occupancy evaluation data to reduce the performance gap. Applied energy, 97, 355-364.
3. Lazaridis, Charalampos Rafail, et al. "Evaluating reinforcement learning algorithms in residential energy saving and comfort management." Energies 17.3 (2024): 581.
4. Javed, A., Larijani, H., Ahmadinia, A., & Gibson, D. (2016). Smart random neural network controller for HVAC using cloud computing technology. *IEEE Transactions on Industrial Informatics*, *13*(1), 351-360.
5. Rena, I. (2023). Renewable power generation costs in 2022. International Renewable Energy Agency, Abu Dhabi.
6. Saldarini, A., Longo, M., Brenna, M., & Zaninelli, D. (2023). Battery electric storage systems: Advances, challenges, and market trends. Energies, 16(22), 7566.
7. Kim, T. Y., & Cho, S. B. (2019). Predicting residential energy consumption using CNN-LSTM neural networks. Energy, 182, 72-81.
8. Zhang, Z., Chong, A., Pan, Y., Zhang, C., & Lam, K. P. (2019). Whole building energy model for HVAC optimal control: A practical framework based on

deep reinforcement learning. Energy and Buildings, 199, 472-490.

9. Garg, V., Mathur, J., & Bhatia, A. (2020). Building energy simulation: A workbook using designbuilder™. CRC Press.
10. Nwaogbe, G., Urhoghide, O., Ekpenyong, E., & Emmanuel, A. (2025). Green construction practices: Aligning environmental sustainability with project efficiency. International Journal of Science and Research Archive, 14(1), 189-201.
11. Alaloul, W. S., Altaf, M., Musarat, M. A., Javed, M. F., & Mosavi, A. (2021). Life cycle assessment and life cycle cost analysis in infrastructure projects: a systematic review.
12. Amasyali, K., & El-Gohary, N. M. (2018). A review of data-driven building energy consumption prediction studies. Renewable and Sustainable Energy Reviews, 81, 1192-1205.
13. Javaid, N., Hafeez, G., Iqbal, S., Alrajeh, N., Alabed, M. S., & Guizani, M. (2018). Energy efficient integration of renewable energy sources in the smart grid for demand side management. IEEE access, 6, 77077-77096.
14. Bessa, R., Moreira, C., Silva, B., & Matos, M. (2019). Handling renewable energy variability and uncertainty in power system operation. Advances in Energy Systems: The Large-scale Renewable Energy Integration Challenge, 1-26.
15. Ajirotutu, R. O., Matthew, B., Garba, P., & Johnson, S. O. (2024). Advancing lean construction through Artificial Intelligence: Enhancing efficiency and sustainability in project management. World Journal of Advanced Engineering Technology and Sciences, 13(02), 496-509.
16. Cao, X., Dai, X., & Liu, J. (2016). Building energy-consumption status worldwide and the state-of-the-art technologies for zero-energy buildings during the past decade. Energy and buildings, 128, 198-213.
17. Drgoňa, J., Arroyo, J., Figueroa, I. C., Blum, D., Arendt, K., Kim, D., ... & Helsen, L. (2020). All you need to know about model predictive control for buildings. Annual reviews in control, 50, 190-232.