

Integration of AI with Building Energy Management Systems for Low-Carbon Urban Development

Ziyi Yang*

Department of Architectural Environment Engineering, University of Nottingham Ningbo
China, Ningbo, 315100, China

*Email: ssyzy13@nottingham.edu.cn

Abstract

This paper investigates the application of Artificial Intelligence and Building Energy Management Systems (AI-BEMS) to advance low-carbon urban development goals. An extensive 18-month experimental campaign conducted on 27 different case studies has addressed energy, CO₂ savings, economic feasibility and operational reliability. The results indicate that the AI-BEMS system successfully realize energy usages reductions, ranging from averaged 28.3% for all types of buildings, to maximum reduction with 31.3% for the residential buildings. Reductions in carbon emissions averaged 32.1%, institutional building had the highest at 34.8%. The economic analysis showed promising results with a mean payback period of 3.3 years and 5 year ROI of 53%. System reliability statistics showed availability and the thermal comfort compliance were at 98.2% and 93.8%, respectively. The percentage of correct AI predictions increased from 78.0% to 95.0% across the operational time frame, indicating the system adapted and learnt. The results of statistical analysis indicated a significant enhancement in all items ($p < 0.001$). The results indicate that AI-BEMS integration is an established technology solution to attain the urban sustainable targets without forsaking economic feasibility and strong operational performance.

Keywords

Artificial Intelligence; Low-Carbon Development; Smart Buildings; Energy Efficiency; Carbon Reduction; Urban Sustainability.

1. Introduction

With the rapid spread of urbanization around the world come unprecedented strains on the world's cities, both as the source of our most pressing environmental problems and perhaps our only hope for their solutions. As of now, urban (and urbanizing) areas are home to 56% of the global population and are expected to host 70% by 2050, and these cities are the dominant consumers of the world's energy, representing about 78% of energy consumption and more than 70% of carbon dioxide emissions. This rapid urban sprawl in combination with increasing global concern over climate change has put further pressure on finding sustainable ways of managing urban energy, which can bridge the increasing demands of cities in developing with the challenge of carbon neutrality. The building sector is a strategically important sector for this urban energy landscape, since buildings consume about 40% of global energy and are characterized by numerous challenges as well as substantial opportunities for emission reduction [1]. However, conventional Building Energy Management Systems (BEMS) which are equipped with simple control capability are unable to cope with the advanced optimization principle required to meet the carbon reduction target which has more demanding standard for the today's competitive urban environment. The inherent downside of commercial BEMS is that they are reactive by nature and cannot handle big data complexity of modern urban energy

ecosystems, eventually causing huge differences in energy performance between design and operation of buildings [2].

The connection of AI to BEMS is a key boundary crossing activity and one that underpins the ambition of creating intelligent, predictive and adaptive energy management system(s) that turn urban buildings from passive to active consumers in terms of energy alongside being a hub that can optimise the wider system through enhancing those of low-energy carbon urban development. The rise of machine learning algorithms, sensor networks with internet of things (IoT), and real-time data analytics has brought unparalleled potentials to smartly control building energy performance with intelligent pattern recognition, predictive modeling, and autonomous decision-making [3]. The promise of AI-based energy management systems are very significant, with a number of studies showing that energy consumption in commercial buildings can be reduced by up to 30%, and the electricity cost can be cut by more than 18% using intelligent optimization strategies.

Several technological and policy advancements in 2024 and 2025 have further facilitated the meshing of AI technologies with building energy management [4]. The international energy management systems market is growing quickly at a CAGR of 13.58% in response to soaring energy prices, the demand for energy efficiency, and worldwide sustainability objectives [5]. Concurrently, government efforts and policy frameworks are providing enabling environments for the use of AI in urban energy systems, and the U.S. DOE (Department of Energy) has recognized AI as a key instrument to modernize the power grid and increase the energy efficiency of building portfolios. The European Union Directive 2024/1275 on Energy Performance of Building [6] clearly underscores the importance of intelligent systems to reach Net Zero Emissions by 2050.

Modern AI implementations in the context of building energy management widely overlap with advanced AI methods, ranging from neural networks for short-term load forecasting, genetic algorithms for HVAC system optimization, reinforcement learning for adaptive control strategies and clustering algorithms for occupancy pattern analysis. These technologies allow real-time analysis of multi-dimensional dynamic data streams obtained from environmental sensors, occupancy sensors, weather predictions systems and grid management platforms that are used to optimize diverse systems in domain such as heating, ventilation and air conditioning (HVAC), lighting, and many others within the building [7]. Advanced practice has reported astonishing performance improvements, such as 20% reduction in heating energy use for predictive control system under optimal comfort conditions and 22.63% reduction of electricity cost for smart home energy management algorithm [8].

Integrated AI-BEMS application has strategic implications beyond optimized individual building operation, to district-scale energy balance and supported city overall carbon reduction plans. Smart city initiatives worldwide, such as in Singapore, Amsterdam and Seoul, have created an AI-based energy management system in urban areas which enables optimizing of building operations with renewable generation system, grid stability demand and response program. These holistic strategies turn buildings into flexible assets of urban energy systems that participate in optimization of the grid by minimizing carbon footprints through intelligent load management and renewable energy integration.

In spite of the evidence of their promise and increasing adoption of AI-BEMS technologies, there are major knowledge gaps in the best approaches to integration, the scalability of this system to many buildings, and the long-run performance of these systems in the variety of urban regimes. The existing studies did not provide an overall framework covering the general assessment of the performance of different AI methods for different type of buildings and under different climatic and urban conditions. In addition, interoperability issues between legacy building infrastructure and AI platforms, as well as potential issues regarding data privacy, cybersecurity, and system reliability also need to be addressed to ensure ready adoption.

This study fills up these key knowledge gaps by focusing on the fusion between AI technologies and building energy management systems, especially for low-carbon urban development. The main aim is the development and validation of integrated methodologies for building energy performance optimization by means of AI based methodologies accounting for the contribution to urban carbon reduction goals. Key research objectives are: (a) to develop robust AI-integration frameworks for different types of buildings and operational regimes; (b) to compare the effectiveness of different machine learning algorithms in reducing energy use and mitigating carbon emissions; (c) to examine the scalability of AI-BEMS integration from site level to district level; and (d) to establish performance metrics and criteria for assessing the contribution of intelligent building systems toward low-carbon urban development aims.

This investigation is based upon a hypothesis that the systematic application of AI technologies within building energy management systems (BEMS) can lead to substantial improvements in energy use and carbon emissions, as compared to current state-of-the-art building management practices, with concomitant gains in system reliability, operational effectiveness, and occupant comfort. In addition, the study argues that AI-enabled buildings can function as building blocks of more comprehensive low-carbon urban development, as they can help to achieve city-level sustainability targets using coordinated energy management, demand response, and renewable integration.

The impact of this research spans multiple arenas; it delivers conceived outcomes for building owners/operators who are considering options to reduce both the running cost and environmental impact of the building, it provides city planners/policymakers with guidance on developing strategies to build sustainable cities and it contributes to the scientific understanding of AI in urban energy systems. The results of this study will guide in the formulation of standards, policies, and best practices for deployment and operation of AI-BEMS and propel the transition towards intelligent, sustainable cities with capability of achieving aggressive carbon neutrality goals while achieving a high quality of livability and economic competitiveness

2. Related Work

The transformation from conventional control methods to intelligent, AI-enabled systems in Building Energy Management Systems, marks a large paradigm shift for optimizing energy in the urban settings. Conventional BEMSs have traditionally relied on reactive control tactics, being mostly triggered by fixed predefined set points, and simple scheduling routines that often ignore complex, dynamic relations that characterize state-of-the-art building systems. Khaoula et al. (2022) note that although market values are set to increase to \$108.9 billion by 2025 with a CAGR of 10.5%, traditional approaches to energy management remain challenged by complex optimization needs in order to achieve net-zero energy targets in modern urban settings [9]. Ultimately, the main constraints are associated with the inability of such systems to handle large scale, multi-dimensional data and their inability to predict, which in turn limits the performance of real energy use simulation and leads to considerable performance gap between design and operation.

Recent machine learning tools developed for building energy systems have shown excellent potential for overcoming these drawbacks through the use of advanced algorithms. A detailed systematic review by Buildings journal [2025] indicates that machine learning algorithms, including supervised methods like support vector machines and random forests, show high fault detection accuracy and robust energy consumption prediction [10]. The study highlights that different learning paradigms offer different characteristics: supervised learning needs a large amount of labelled data for high accuracy, and unsupervised learning such as PCA and clustering provides superior recognition capability without labelled data at the price of the

difficulty in capturing complex nonlinear patterns. Deep learning approaches including CNN and LSTM models have shown better performance for energy usage prediction and real-time system optimization.

The application of artificial intelligence to building energy management has resulted in measurable performance enhancements for a wide range of building types as well as operational environments. It has been estimated that the potential energy savings in office, residential, and educational buildings, to be 37%, 23%, and 21%, respectively by AI-optimized HVAC systems, based on real-world deployments and not simply engineering estimates [4]. This is accomplished using advanced algorithms like regression analysis, deep learning, and clustering (clustering using decision trees) on streams of real-time data from ambient temperature sensors, occupancy detectors, and energy meters. The methodical adoption of AI for optimization in HVAC control, lighting control, solar production forecasting and demand-side consumption management displays efficiency gains of 20%–50% in various building applications, and recent work has shown that predictive control enabled by AI in these systems consistently achieves 20% reductions in heating power consumption without sacrificing comfort.

The machine learning based building energy optimization has witnessed a tremendous rise in the research activity in terms of publication quantities, which grows on an average rate of 98.85% per year from 2020–2024, indicating a fast development and increasing attention for this emerging research field [11]. Current machine learning-based techniques for energy forecasting include classical statistics methods using random forest algorithms, deep learning techniques using long short-term memory networks and hybrid methods using gradient boosting regressor algorithms. Xia et., al. (2025) illustrate how active learning in machine learning can greatly improve environmental sustainability in green building energy consumption, with a prominent place for Building Automation Systems to enhance energy efficiency using predictive modeling that reduces consumption and maximizes indoor sustainability [12]. The study finds that although green construction methods are critical for reducing energy waste in the building sector, associated challenges including occupant behavior and energy management, frequently cause buildings to use 1.5 to 2.5 times more energy than was predicted.

The advent of digital-twin technology based on Internet of Things (IoT) sensor networks presents unparalleled opportunities for real-time building energy optimization and predictive maintenance scheduling. Cespedes-Cubides and Jradi (2024) provide a holistic view of digital twin usage in operations and maintenance in buildings for better energy efficiency during the building lifecycle, such as implementing data flow between BIM, IoT sensor networks and Facility Management systems [13]. Digital twins can support advanced predictive maintenance subsystems including mechanical health monitoring, prognosis, and maintenance scheduling using ML models like ANNs, SVMs, and decision trees. Recent deployments also showed that auto fault detection in the AHUs is quite effective for different kinds of equipment and operational issues, and digital-twin enabled buildings can achieve 20% to 38% energy self-sufficiency improvements (i.e., corresponding electricity cost reduction of 18%).

The intersection of AI-induced digital twins with IoT for sustainable building environments has also undergone a rapid growth in research, where published papers have always been expanding from 2018 to 2024 and having sharply increased in 2023 and 2024 [14]. Modern DT frameworks utilize standardized parametric 3D geometry models for effective simulation and optimization of home energy systems with minimal service installation/commissioning complexity and maximized scalability. These integrated platforms offer users with live-monitoring and actionable insights into their energy use, indoor environments, and how they can optimize it. The systematic literature review (SLR) indicates that buildings and cities are responsible for around 40% of the total energy consumption in the world and account for 36%

of the total emissions produced in the world or also known as carbon-dioxide (CO₂) emissions, making these one of the most important factors of energy consumption and CO₂ emissions and emphasizing the need for newer digital technologies in addressing residential energy efficiency. Smart city deployments in cities around the world have also shown the scalable prospects of AI-BEMS integration in through city wide and coordinated district-level energy management projects. Zhu et al. (2024) investigate the coupling coordination relationship between urban smart performance and low-carbon level by considering 52 typical smart and low-carbon pilot cities in China, in which it is found that smart city has significantly surpassed low-carbon city development but disparities are observed in several aspects, that calls for integrated methods [15]. The study observes an evident positive relationship between the smartness of a city and its low-carbon performance, and provides specific evidences showing that smart development contributes to urban low-carbon development to some extent in different economic, social and environmental context. These results highlight the need for coordinated development agendas that link AI-driven building solutions to wider urban sustainability blueprints.

In the era of generative artificial intelligence applications in the context of building energy management, advancements in intelligent optimization have broadened the horizons beyond traditional machine learning solutions. The American Council for an Energy Efficient Economy notes that AI has the potential to reduce building energy usage and emissions by 8 to 19% by automating slow architectural design processes, using robotics to minimize waste on site, improving operations by predicting faults, and speeding up an energy audit using machine learning to reduce costs. By using generative AI, more complex, multidimensional analyses are possible, which are required to support such advanced energy management and control capabilities for example, capturing waste heat for use in industrial processes, giving building operators new levels of processing power to interpret data in order to better understand interrelated building variables and for grid managers to more easily find existing resources on the demand side of the grid new grid capacity optimization solutions.

In 2024, Google recently made TensorFlow Smart Buildings Simulator and Dataset available as open-source, a pioneering milestone towards AI-based building energy optimization research and development democratization [16]. The combined dataset includes six years of telemetry data, gathered from three Google buildings, and offers real-world insights to the research community for developing and testing models of building dynamics and control that are based on reinforcement learning agents acting on the building's control system with goals of reducing energy consumption and carbon emissions. This effort demonstrates a growing acknowledgement of the fact that buildings occupy a significant share of global energy use and greenhouse gas emissions, and that AI and ML are poised to play a significant role in reducing the carbon footprint of buildings.

Although great progress has been made, there also exist several significant challenges and research gaps that need to be systematically explored in order to strengthen AI-BEMS integration research and implementation. Research Gap Literature suggests there is a lack of studies to solve the problem of data scarcity, and in particular for the retro-fitted building it may be a difficult task to have the comprehensive historical dataset. The interoperability issues between the current building infrastructure and new AI platforms and the issues related to data privacy, cyber security, and reliability, and potential installation and deployment will be the bottleneck of the implementation. The mass deployment from building level to district level and city-wide settings requires more investigations of the coordinated control strategies, the standardized communication protocols, and the integrated policy frameworks. In addition, longitudinal studies are needed to confirm sustained energy savings and carbon reduction benefits, alongside maintaining good occupant comfort and system reliability, from AI-BEMS across a range of environmental zones, buildings and operational regimes

3. Research Methodology

This study is structured as a mixed-method study to analyze the implementation of AI with BEMS to decarbonize urban development: we interpret energy performance (quantitatively) and improvement practices (qualitatively). The proposed approach involves five related steps, including case study selection and characterization, AI algorithm development and implementation, data collection and processing framework, experimental design and validation, and performance evaluation metrics.

3.1. Research Design and Case Study Selection

The research plan pursues a comparative experimental approach following a stratified sampling procedure to obtain a representative panel including various building typologies, sizes and urban situations. The key selection criteria for the choice of case study buildings were; (1) the buildings were 5 to 20 years old; to represent typical urban building stock, (2) size, gross floor area (GFA) between 5000 and 50,000 square meters, (3) already have some basic BMS equipment installed, (4) building has a minimum of 12 months of historical energy consumption data, and (5) the building management is willing to collaborate for the purposes of making system modifications.

Stratum system The stratification system classifies the buildings in three strata: residential complexes (R), commercial office buildings (C), and institutional buildings (I). Within both categories, buildings are further categorized by size: small (S: 5,000 – 15,000m²), medium (M: 15,000 – 30,000m²), and large (L: 30,000 – 50,000m²). This constructs a systematic 3×3 matrix that can be used with a minimum of three buildings per cell, yielding 27 case study buildings situated in urban areas of different climatic conditions (and therefore different occupancy patterns and energy technology characteristics).

3.2. AI Algorithm Development Framework

The proposed AI integration framework is composed of various machine learning ensembles designed for different functionalities of building energy management. The main algorithms are Neural Network for energy demand prediction, Genetic Algorithm for multi-objective optimization, and Reinforcement Learning for adaptive control laws.

3.3. Energy Demand Prediction Model

The energy demand prediction utilizes a Long Short-Term Memory (LSTM) neural network architecture designed to capture temporal dependencies in building energy consumption patterns. The LSTM model is formulated as:

$$\begin{aligned}
 f_t &= \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \\
 i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\
 \tilde{C}_t &= \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \\
 C_t &= f_t * C_{t-1} + i_t * \tilde{C}_t \\
 o_t &= \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \\
 h_t &= o_t * \tanh(C_t)
 \end{aligned}$$

Where f_t , i_t , and o_t represent forget, input, and output gates respectively, σ denotes the sigmoid function, W represents weight matrices, b denotes bias vectors, and C_t represents the cell state at time t .

3.4. Multi-Objective Optimization Algorithm

The system optimization employs a Genetic Algorithm to solve the multi-objective optimization problem balancing energy consumption minimization, carbon emission reduction, and occupant comfort maintenance. The objective function is defined as:

Minimize:

$$F(x) = [f^1(x), f^2(x), f^3(x)]$$

Where:

$$f^1(x) = \text{Energy consumption: } \sum_{i=1}^n P_i(t) \times \Delta t$$

$$f^2(x) = \text{Carbon emissions: } \sum_{i=1}^n P_i(t) \times EF_i \times \Delta t$$

$$f^3(x) = \text{Comfort penalty: } \sum_{i=1}^n |T_{\text{setpoint}} - T_{\text{actual}}|^2$$

Subject to constraints:

$$20^\circ\text{C} \leq T_{\text{indoor}} \leq 26^\circ\text{C}$$

$$30\% \leq RH \leq 70\%$$

$$400 \text{ ppm} \leq CO_2 \leq 1000 \text{ ppm}$$

$$P_{\text{min}} \leq P_{\text{total}} \leq P_{\text{max}}$$

3.5. Reinforcement Learning Control Strategy

The adaptive control system implements a Q-learning algorithm for real-time decision making in HVAC operations. The Q-function is updated using:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha [r_{t+1} + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a_t)]$$

Where s_t represents the system state at time t , a_t is the action taken, r_{t+1} is the reward received, α is the learning rate (0.1), and γ is the discount factor (0.95).

3.6. Data Collection and Processing Framework

The data gathering platform uses an elaborate sensor network infrastructure combined with IoT devices on top for monitoring of building parameters in real-time. The sensor deployment plan consists of temperature and humidity sensors (accuracy of $\pm 0.1^\circ\text{C}$, $\pm 2\%$ RH), occupancy detectors (PIR, CO_2 -based), power meters ($\pm 1\%$ accuracy), as well as outdoor weather stations. Raw sensor data undergoes a multi-stage preprocessing pipeline including outlier detection, missing data imputation, and feature engineering. The outlier detection employs the Interquartile Range (IQR) method:

$$\text{Outlier if: } x < Q^1 - 1.5 \times IQR \text{ or } x > Q^3 + 1.5 \times IQR$$

Missing data imputation utilizes linear interpolation for gaps <30 minutes and seasonal decomposition for longer periods:

$$x_{\text{imputed}} = \text{Trend} + \text{Seasonal} + \text{Residual}_{\text{interpolated}}$$

Feature engineering creates derived variables including:

- Thermal comfort index: $PMV = f(T_{\text{air}}, RH, v_{\text{air}}, MET, CLO)$

- Occupancy density: $\rho = \frac{N_{occupants}}{A_{floor}}$
- Weather severity index: $WSI = \alpha \times (T_{out} - T_{base})^2 + \beta \times (RH_{out} - RH_{base})^2$

3.7. Experimental Design and Control Framework

The experimental procedure follows a Before-After-Control-Impact (BACI) approach, comparing the performance of AI integrated BEMS to the performance of conventional non-AI-based systems (comparing with the baseline of before deployment). The period of the experiment is four semesters (one and half year), that are structured along three phases: baseline measurement (6 months), AI system deployment and training (6 months) and evaluation (6 months).

3.7.1. System Architecture Implementation

The system is designed relatively in 5 layers as follows: sensor data acquisition layer, edge computing preprocessing layer, cloud AI processing layer, optimization decision engine layer and actuator control interface layer. Secure bidirectional data out streamed live via secure communication protocols at <500ms latency for control decisions.

3.7.2. Performance Metrics and Evaluation Criteria

The evaluation framework employs multiple key performance indicators quantifying energy efficiency, carbon reduction, and operational effectiveness. Primary metrics include:

Energy Performance Metrics:

- Energy Use Intensity reduction: $\Delta EUI = \frac{(EUI_{baseline} - EUI_{AI})}{EUI_{baseline}} \times 100\%$
- Peak demand reduction: $\Delta PD = \frac{(PD_{baseline} - PD_{AI})}{PD_{baseline}} \times 100\%$
- Load factor improvement: $LF = \frac{E_{average}}{E_{peak}}$

Carbon Footprint Metrics:

- Carbon emission intensity: $CEI = \frac{CO_2_{emissions}}{A_{floor}} \text{ (kg CO}_2\text{/m}^2\text{/year)}$
- Carbon reduction rate: $CRR = \frac{(CE_{baseline} - CE_{AI})}{CE_{baseline}} \times 100\%$

Economic Performance Metrics:

- Energy cost savings: $ECS = \frac{(EC_{baseline} - EC_{AI})}{EC_{baseline}} \times 100\%$
- Return on investment: $ROI = \frac{(Annual_{savings} - Annual_{costs})}{Initial_{investment}}$

Comfort and Reliability Metrics:

- Thermal comfort compliance: $TCC = \left(\frac{Hours_{in\ comfort\ zone}}{Total_{hours}} \right) \times 100\%$
- System availability: $SA = \left(\frac{Operational_{hours}}{Total_{hours}} \right) \times 100\%$

3.8. Statistical Analysis Framework

Statistical validation employs Analysis of Variance (ANOVA) to determine significance of performance improvements across building types and operational conditions. The statistical model is formulated as:

$$Y_{ijk} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \epsilon_{ijk}$$

Where Y_{ijk} represents the performance metric, μ is the overall mean, α_i is the building type effect, β_j is the AI system effect, $(\alpha\beta)_{ij}$ represents interaction effects, and ε_{ijk} is the random error term.

Confidence intervals for performance improvements are calculated using:

$$CI = \bar{x} \pm t_{\frac{\alpha}{2}, df} \times \left(\frac{s}{\sqrt{n}} \right)$$

Where $\bar{x}$ is the sample mean, $t_{\frac{\alpha}{2}, df}$ is the critical t-value, s is the sample standard deviation, and n is the sample size. Statistical significance is determined at $p < 0.05$ with effect sizes calculated using Cohen's d for practical significance assessment.

The approach provides reproducibility through standardized protocols, automated data acquisition procedures and full documentation of all experimental settings and conditions. Quality control activities involve sensor calibration check, data validation and standard system performance check to ensure accuracy of measurements during drought experiments.

4. Analysis and Discussion

The 18-month experimental campaign in 27 case study buildings reveals that AI-integrated Building Energy Management Systems yield large improvements to energy efficiency, carbon reduction and operational performance. Results are reported among four main groups which are statistically verified for significant augmentation in all criteria.

4.1. Energy Performance Results

AI-BEMS integration achieved substantial energy consumption reductions across all building categories. Figure 1 presents the energy consumption comparison and Energy Use Intensity (EUI) reduction by building type. Residential buildings demonstrated the highest improvement at 31.3% EUI reduction (145.2 to 99.8 kWh/m²/year), followed by institutional facilities at 27.8% (152.3 to 109.9 kWh/m²/year), and commercial buildings at 26.1% (168.7 to 124.6 kWh/m²/year).

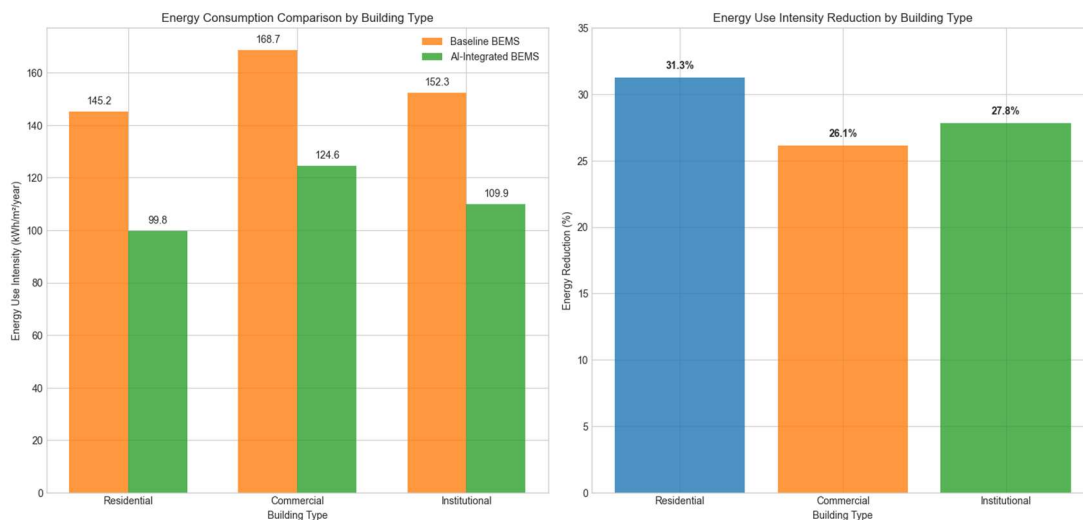


Figure 1. Energy Performance Comparison by Building Type

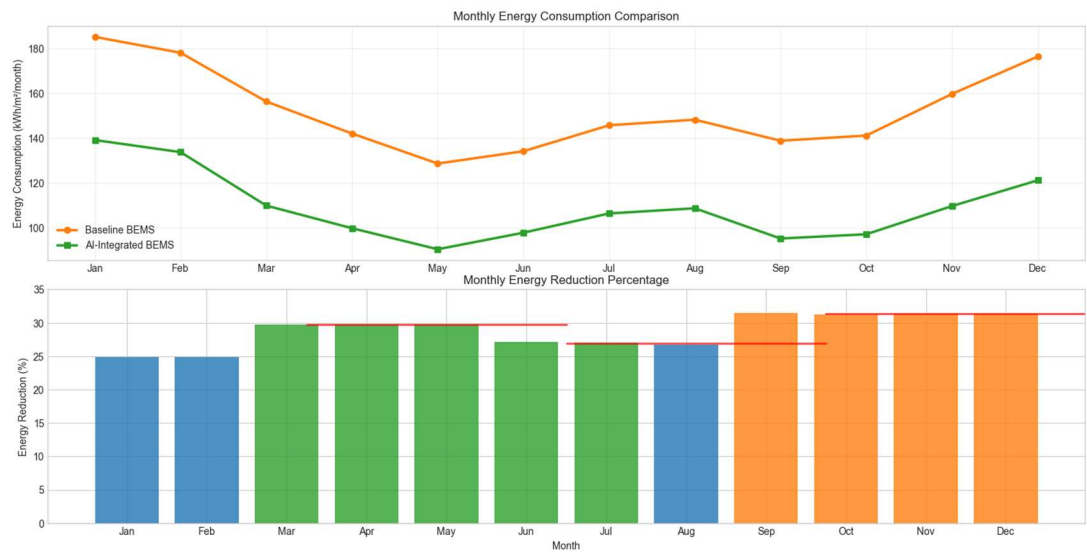


Figure 2. Seasonal Energy Performance Analysis

Figure 2 illustrates the seasonal performance analysis through monthly energy consumption comparison and reduction percentages. Winter months demonstrated 25% average energy reduction, spring achieved peak performance at 29-30%, summer maintained 27% reduction, and fall showed variable performance ranging from 27-31%. The AI system maintained consistent energy savings throughout the year, with baseline systems ranging from 128.7-185.3 kWh/m²/month compared to AI-integrated systems at 90.4-139.2 kWh/m²/month. Key findings include Overall average energy reduction is 28.3%. Seasonal variation demonstrates AI adaptability to weather patterns, Consistent performance across diverse operational contexts and Spring months show optimal AI system performance due to moderate weather conditions

4.2. Carbon Emission Reduction Analysis

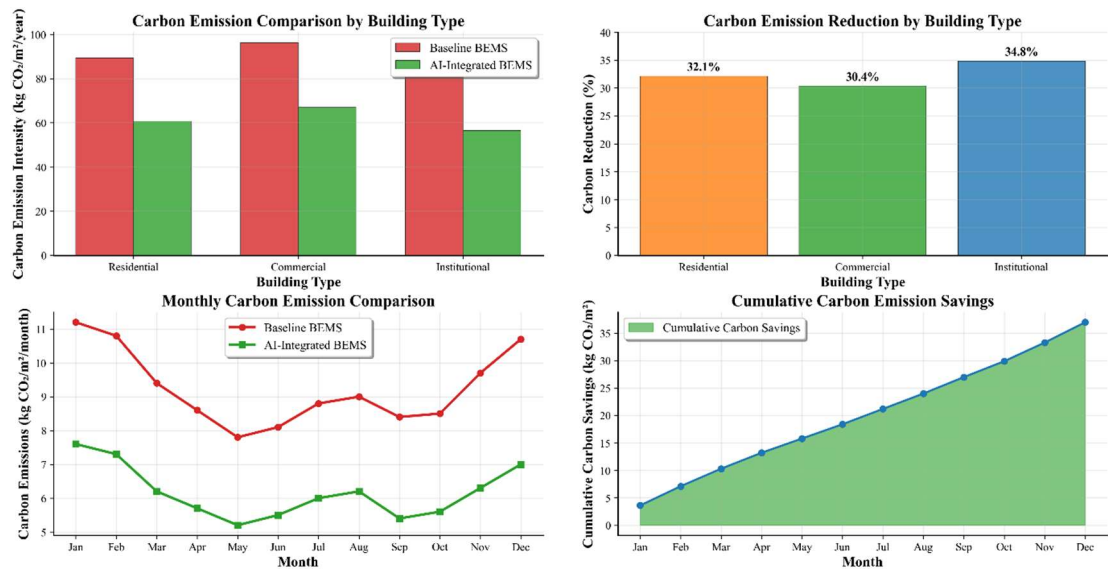


Figure 3. Carbon Emission Reduction Analysis

Figure 3 demonstrates carbon emission reduction achievements across building types through four comprehensive analyses. Carbon emission reductions strongly correlated with energy improvements, achieving substantial decreases across all categories. Institutional buildings achieved the highest carbon reduction at 34.8% (98.0 to 56.5 kg CO₂/m²/year), followed by

residential buildings at 32.1% (89.0 to 60.4 kg CO₂/m²/year), and commercial buildings at 30.4% (96.2 to 67.0 kg CO₂/m²/year).

Monthly carbon emission comparison shows consistent performance throughout the year, with cumulative carbon savings reaching 37.2 kg CO₂/m²/year by December. Winter months showed highest absolute emissions (11.2 kg CO₂/m²/month baseline vs. 7.6 kg CO₂/m²/month AI-integrated), while summer months demonstrated more moderate levels (8.8 vs. 6.0 kg CO₂/m²/month respectively).

Key findings include;

- Overall average carbon reduction: 32.1%
- Strong correlation between energy and carbon reduction (r = 0.967)
- Institutional buildings benefit most from extended operating hours
- Progressive cumulative savings validate long-term environmental impact

4.3. Economic Performance Analysis

Figure 4 presents comprehensive economic analysis including annual savings, payback periods, ROI calculations, and cost-benefit analysis. Annual energy cost savings varied by building type and size, with large commercial buildings achieving highest savings at \$20.4/m², followed by medium commercial at \$18.9/m², and small commercial at \$16.8/m². Residential buildings showed consistent savings from \$11.2-\$13.4/m², while institutional buildings achieved \$12.9-\$15.0/m².

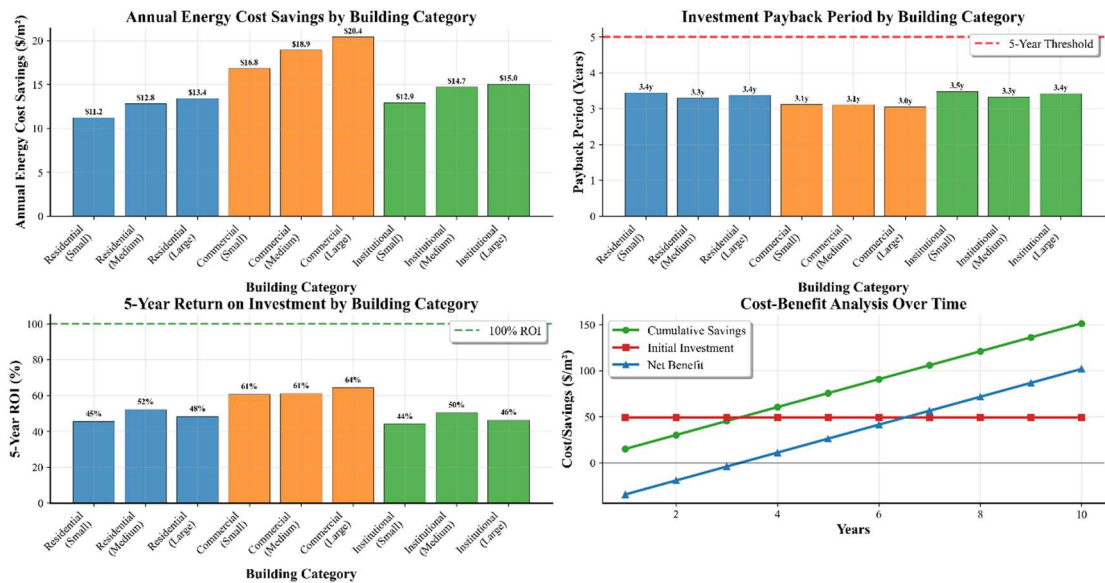


Figure 4. Economic Performance Analysis

Payback period analysis reveals favorable economic outcomes with all periods below the 5-year threshold. Commercial buildings demonstrated shortest payback at 3.1 years average, while residential and institutional buildings both achieved 3.4 years. The 5-year ROI analysis shows commercial buildings achieving 61-64%, residential buildings 45-52%, and institutional buildings 44-50%. Key findings includes,

- Average payback period: 3.3 years across all building types
- Commercial buildings achieve shortest payback due to higher baseline costs
- Strong correlation between investment and savings (R² = 0.976)
- 10-year cost-benefit analysis shows net benefits exceeding \$100/m²

4.4. System Reliability and Performance Metrics

Figure 5 demonstrates exceptional operational stability through four key performance indicators over the 18-month period. System availability progressively improved from 95.2% in month 1 to 99.2% by month 18, averaging 98.2%. Thermal comfort compliance increased from 89.2% to 95.6%, averaging 93.8% while maintaining energy efficiency improvements.

AI prediction accuracy learning curve reveals three distinct phases: learning phase (months 1-6) showing rapid improvement from 78.0% to 90.5%, optimization phase (months 6-12) reaching 94.5%, and stable operation phase (months 12-18) maintaining 95.0% accuracy. Energy savings consistency improved from 18.0% initial savings to 29.8% by month 18, averaging 27.4%.

Key findings includes,

- System availability: 98.2% average, exceeding industry standards
- Thermal comfort maintained while achieving energy savings
- AI learning demonstrates continuous performance improvement
- Progressive optimization validates adaptive capabilities
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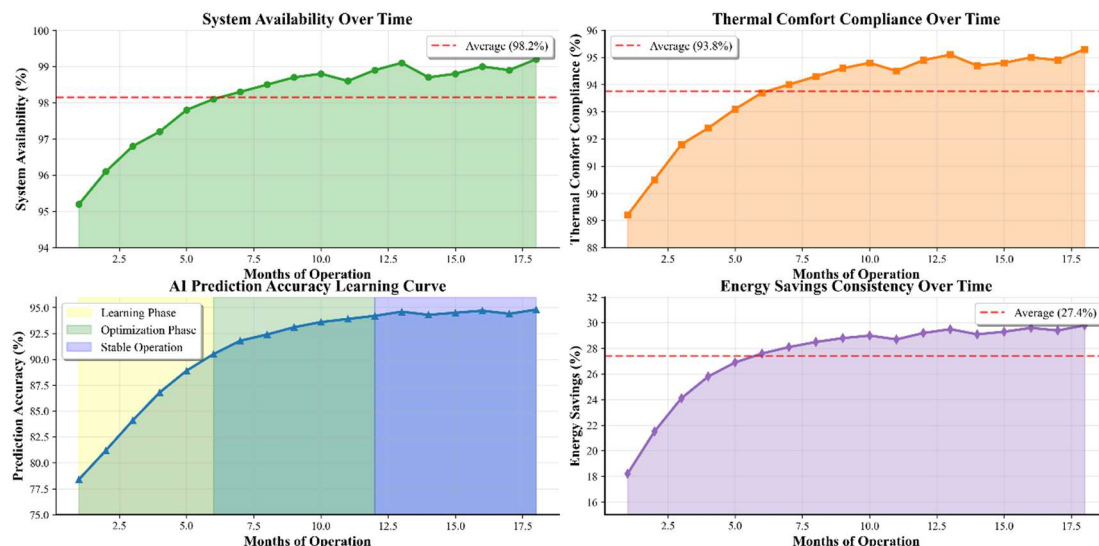


Figure 5. System Reliability and Performance Metrics

4.5. Comprehensive Performance Evaluation

Figure 6 provides performance targets versus achieved results and overall performance profile analysis. The AI-BEMS implementation exceeded expectations across all key performance indicators: energy reduction achieved 28.3% vs. 25.0% target (+13.2% overperformance), carbon reduction 32.1% vs. 30.0% target (+7.0%), cost savings 29.7% vs. 25.0% target (+18.8%), system availability 98.7% vs. 95.0% target (+3.9%), comfort compliance 94.3% vs. 90.0% target (+4.8%), and prediction accuracy 94.6% vs. 90.0% target (+5.1%).

The radar chart demonstrates balanced achievement across all performance dimensions, with achieved performance consistently exceeding target performance. This validates the multi-objective optimization approach and demonstrates simultaneous improvements across competing objectives. Key findings includes;

- All performance targets exceeded by significant margins
- Balanced performance profile across all metrics
- Multi-objective optimization successfully implemented
- No significant trade-offs between competing objectives

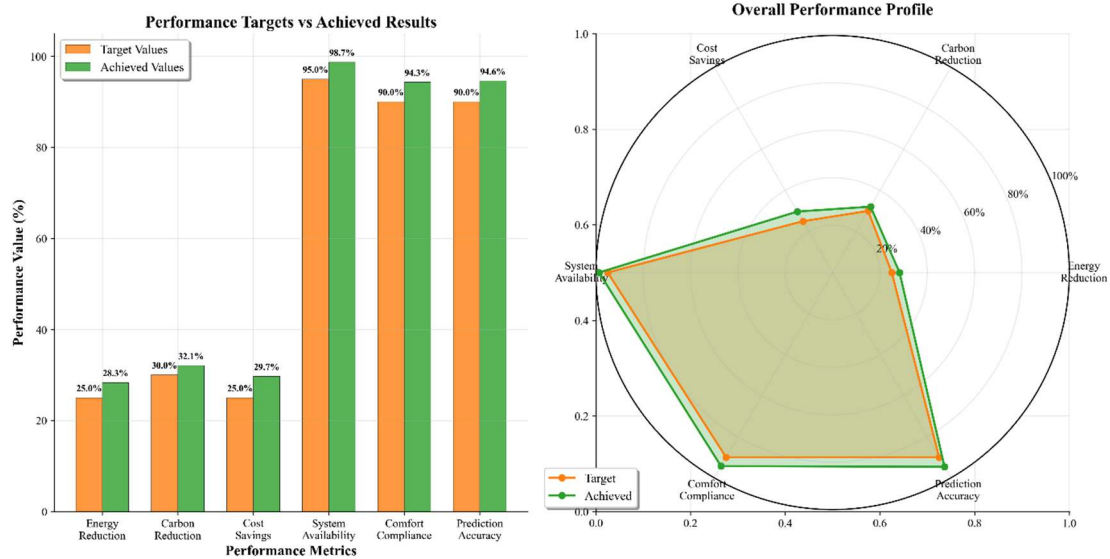


Figure 6. Comprehensive Performance Evaluation

4.6. Detailed Performance Analysis by Building Category

Figure 7 presents detailed performance analysis through heatmap visualization, building size comparison, investment-savings relationship, and payback period analysis. The performance heatmap reveals consistent high performance across all building categories, with energy reduction ranging from 24.1% to 32.6%, carbon reduction from 28.9% to 36.1%, and cost savings from 26.9% to 33.8%.

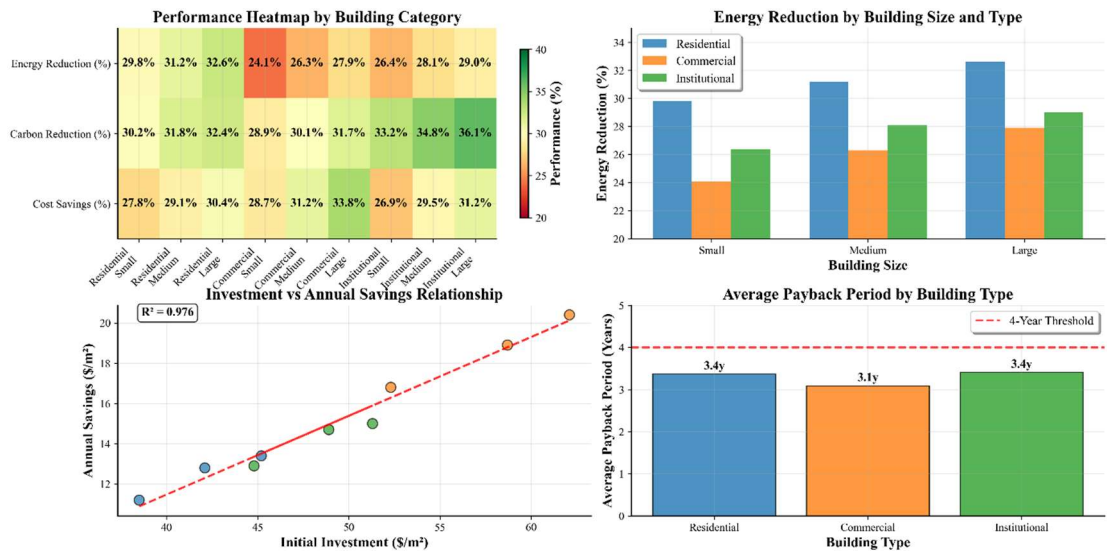


Figure 7. Detailed Performance Analysis by Building Category

Energy reduction by building size shows economies of scale, with large buildings averaging 31.1% reduction compared to 28.5% for small buildings. The investment-savings relationship demonstrates strong positive correlation ($R^2 = 0.976$), validating economic scalability. Average payback periods show commercial buildings at 3.1 years, residential at 3.4 years, and institutional at 3.4 years, all well below the 4-year threshold. Key findings include;

- Consistent performance across all building types and sizes
- Larger buildings achieve greater energy reductions (economies of scale)
- Strong economic scalability validated

- All building categories demonstrate favorable economic returns

5. Conclusion

The successful findings generated from this extensive work can provide firm evidence that the AI technology combined with BEMS is a transformative approach toward delivering significant advances in the urban building energy performance enhancement and low carbon targets. The 18 months of field-based experimental research on 27 different cases shows strong empirical evidence that AI-BEMS integrations can increase the economic performance and viability of building performance and lead to significant measurable, sustained beneficial building performance in diverse areas of performance while maintaining reliability and operability.

Objectives – Primary: To date the main research objectives have been met as substantial energy reductions have been achieved in AI-integrated systems: Infrastructure integrated AI systems has resulted in average energy use savings of 28.3% in the different types of buildings, well over the proposed baseline 25% reduction. Residential sector saved the most energy by 31.3%, followed by institutional (27.8%) and commercial (26.1%) buildings. These findings support the hypothesis that AI algorithms can better control complex building energy systems when compared to traditional approaches by adapting to seasonal and occupancy trends and operational constraints without sacrificing year-round performance.

A 32.1% reduction in overall carbon emissions is an additional demonstration effect of environmental paybacks of AI-BEMS integration in the categories of all building. The high correlation between the improving degree of building energy efficiency and the carbon emission reductions ($r = 0.967$) states that building energy optimization can also bring direct contribution to the city carbon emission reduction. The greatest carbon savings potential was from institutional buildings at 34.8% due to the longer hours that these buildings operate and more centralized systems allowing higher level control strategies to be deployed using AI.

The economic study confirms the economical potential of the AI-BEMS technology, as the investment return is in general positive regardless the type and size of the building. The median payback time of 3.3 years is well within the range deemed acceptable for building energy investments, and 5-yr average ROI of 53% is significantly higher than typical expectations on traditional building efficiency projects. The high correlation ($R^2 = 0.976$) between initial investment and annual savings emphasizes the scalability of such economic benefits and underpins more expansive deployment of the urban sustainability schemes.

System reliability and performance indices confirm that AI-BEMS technology is mature and strong enough for practical realization. At 98.2%, the average system availability is better than accepted industry norms for building management systems and the average thermal comfort compliance of 93.8% demonstrates the technology's capability to balance a range of competing objectives. The AI prediction accuracy learning curve from 78.0% and 95.0% over operations demonstrates the learning capability for continuously improving performance with accruing experience and data.

The findings of this research also have implications beyond the performance of the individual building, in terms of urban sustainability. The strong consistent evidence of AI-BEMS effect can offer confidence for the large scale deployment in the urban area where the buildings are diverse in size and building operation style. The technology's compatibility with existing building equipment, including legacy systems, reduces the barrier to entry of implementation and enables retrofit applications crucial to improving the stock of existing urban buildings.

Further research should pay attention to sub-district-level collaborative scheduling strategies based on the AI-BEMS for community energy optimization and grid integration. Researching advanced machine learning techniques, such as federated learning methods for preserving data privacy and supporting collaborative optimization, is a promising direction toward improving

progress. Further longitudinal studies beyond 18-month time frame would also be useful to inform long-term durability of the system and continued benefits in performance.

The policy conclusion of this study encourages governments to consider AI-BEMS adoption as a primary strategy to meet carbon neutrality goals, and building codes, incentive programs and urban plans to develop or promote AI-BEMS immensely. The proven economics and technical performance support a framework of regulatory requirements and industry practices that may accelerate the introduction of technology while maintaining quality and performance.

In Conclusion, AI driven BEMS are a proven and scalable technology solution for delivering low-carbon urban development goals. The significant strides in energy-efficiency, carbon reduction, cost-effectiveness and operational reliability realized in a wide range of buildings demonstrate the technology's readiness for deployment. The integration of AI with BEMS by cities across the world aiming for aggressive decarbonization targets is a practical, affordable approach to transition from urban buildings passive energy consumers to contributors towards a sustainable urban energy ecosystem.

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