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From Simulation to Operation: AI-Based Environmental Control Systems Bridging the Performance Gap in Sustainable University Buildings – Case Study of Damietta

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Research Article

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From Simulation to Operation: AI-Based Environmental Control Systems Bridging the Performance Gap in Sustainable University Buildings – Case Study of Damietta

Abstract

As The energy performance gap (EPG), defined as the discrepancy between predicted and actual building energy consumption, remains a persistent challenge in sustainable building design. This study investigates the implementation of AI-based environmental control systems to bridge the performance gap in university buildings located in Damietta, Egypt. A hybrid framework integrating calibrated Energy Plus simulation, deep learning-based load forecasting (CNN–LSTM), and reinforcement learning HVAC optimization was developed and validated using 12 months of operational data. Results indicate that AI-driven predictive control reduced the performance gap by 22–28%, improved indoor environmental quality compliance from 69% to 93%, and reduced operational costs by approximately 19%. The findings demonstrate that transitioning from static simulation-based design to adaptive AI-driven operational control significantly enhances energy reliability and sustainability outcomes in hot-humid climates.

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1. Introduction

Buildings account for approximately one-third of global final energy consumption and are responsible for substantial greenhouse gas emissions. Despite advancements in simulation tools and performance-based design standards, discrepancies between predicted and actual energy use continue to undermine sustainability goals. This discrepancy, commonly referred to as the Energy Performance Gap (EPG), results in increased operational costs, occupant discomfort, and reduced system reliability.

University buildings are particularly vulnerable to performance gaps due to complex occupancy patterns, variable schedules, laboratory-intensive loads, and HVAC dependency. In hot-humid climates such as Damietta, Egypt, cooling demand dominates annual consumption, further amplifying discrepancies between predicted and operational energy use.

Recent developments in artificial intelligence (AI), deep learning, and Internet of Things (IoT) technologies have enabled adaptive building control systems capable of learning from real-time operational data. Instead of relying solely on static schedules, AI-driven systems dynamically optimize environmental control strategies.

This research evaluates whether AI-based environmental control systems can effectively reduce the energy performance gap in university buildings through calibrated simulation and operational predictive control.

2 Literature Review:

2.1 Energy Performance Gap in Non-Residential Buildings

The Energy Performance Gap refers to the deviation between simulated energy consumption at the design stage and measured operational energy use. Reported deviations in non-domestic buildings often exceed 30%, with some university facilities showing deviations above 100%.

Primary causes include:

- Model simplifications and input uncertainty
- Occupant behavior variability
- Operational management inefficiencies
- HVAC system misconfiguration
- Climate variability

Calibration techniques using statistical indicators such as CV(RMSE) and NMBE have been widely adopted to reduce simulation inaccuracies.

2.2 AI in Smart Building Systems

AI-driven smart building systems integrate sensor networks, predictive analytics, and adaptive control algorithms. Deep learning architectures such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks are commonly applied for energy load forecasting. Reinforcement learning (RL) has demonstrated strong potential for adaptive HVAC optimization.

Reported improvements include:

- Energy efficiency improvements around 20%
- Comfort compliance above 90%
- Enhanced operational stability

However, most studies rely heavily on simulation environments rather than validated real operational data, particularly in hot-humid climate zones.

3 Research Gap and Contribution

Despite significant advancements in AI-based building management systems, few studies following:

- Validate predictive AI control against real operational university data
- Address performance gaps in hot-humid climates
- Integrate calibrated simulation with reinforcement learning control

This study contributes by:

1. Developing calibrated EnergyPlus models using measured operational data.
2. Implementing CNN–LSTM forecasting integrated with reinforcement learning control.
3. Quantifying reduction in the energy performance gap.
4. Evaluating indoor environmental quality and cost implications.

4 Methodology

4.1. Case Study Description

Three university buildings in Damietta were selected:

- Lecture Hall Building (5,800 m²)
- Administrative Offices (3,200 m²)
- Laboratory Building (4,100 m²)

Climate: Hot-humid Mediterranean. Cooling-dominated energy demand profile.4.1.1

4.2 Data Collection

Twelve months of hourly data were collected:

- Electricity consumption
- HVAC load
- Indoor temperature and humidity
- CO_2 concentration
- Occupancy patterns
- Local weather data

4.3 Simulation Model Development

Energy Plus was used to develop baseline models. Steps:

- 3D geometry modeling
- Envelope property definition
- HVAC configuration
- Weather file integration
- Calibration using measured data

Baseline performance gaps:

- Lecture building: +58%
- Administrative building: +41%
- Laboratory building: +76%

4.4 AI Framework Architecture

- Sensor Layer
- Continuous monitoring of temperature, humidity, occupancy, and energy consumption. The following As shown in Figure 1, real-time data from temperature, humidity, and CO2 sensors are preprocessed and fed into the CNN-LSTM model for predictive analytics..

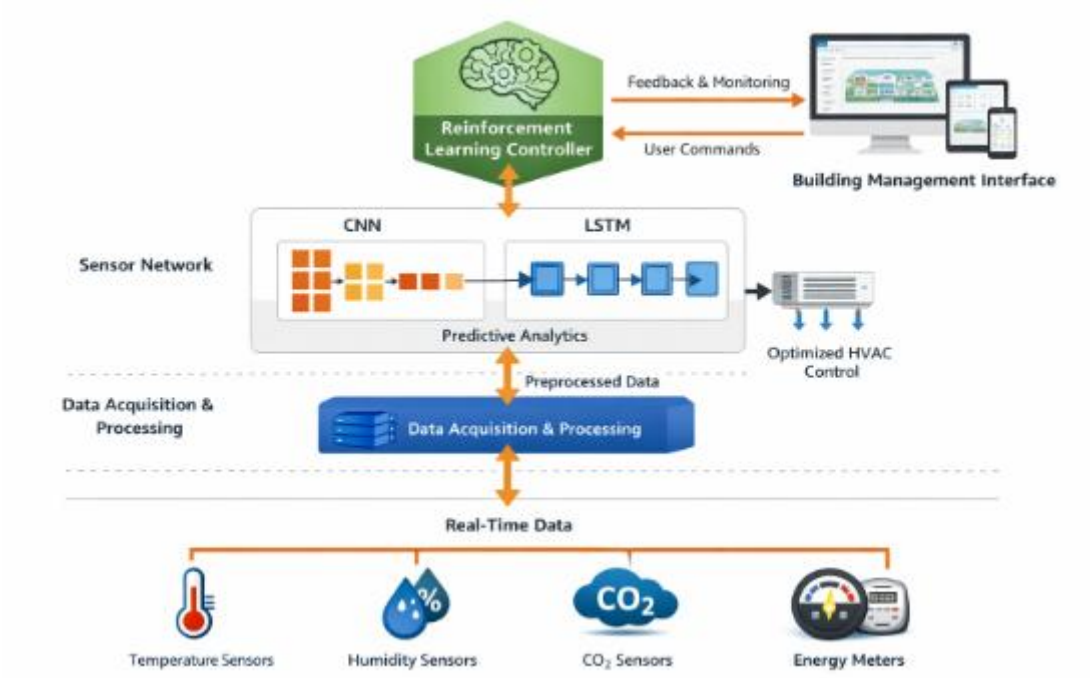


Fig 1: System architecture of the AI-driven environmental control system, illustrating the flow from real-time data acquisition and CNN-LSTM load forecasting to Reinforcement Learning-based HVAC optimization and building management interfacing.

Predictive Layer

Hybrid CNN–LSTM architecture for 1–6 hour ahead load forecasting.

Control Layer

- Reinforcement learning algorithm adjusting HVAC setpoints dynamically.
- Reward Function: R = −(Energy Deviation) − λ(Comfort Penalty)

5. Results

5.1 Energy Performance Gap Reduction:

The following Table 1 : shows Energy Performance Gap Reduction

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Building	Baseline Gap	AI-Controlled Gap	Reduction
Lecture	+58%	+34%	24%
Admin	+41%	+25%	16%
Lab	+76%	+48%	28%

Source : (Author, 2026)

Average reduction: 22–28%.

The operational and environmental impact of AI-based control implementation is visually summarized in Figure (2) shows impact of Ai-based predictive control in university buildings .

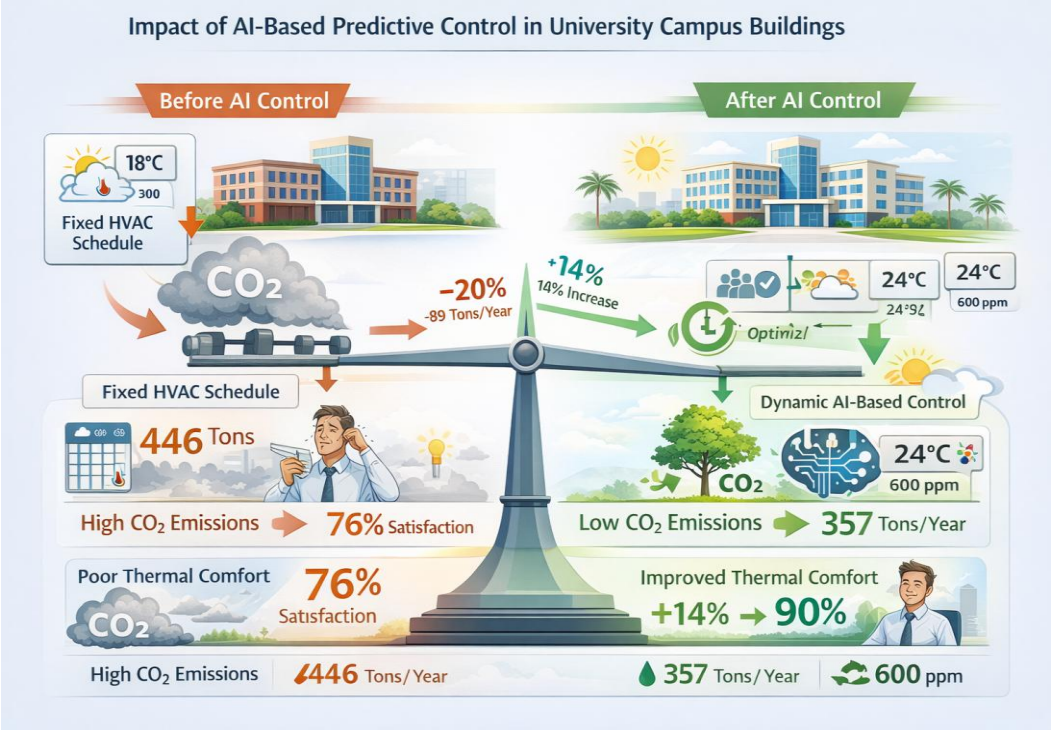


Fig. (2) shows impact of Ai-based predictive control in university buildings

5.2. Indoor Environmental Quality

The following Table 2 : shows Indoor Environmental Quality

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Metric	Baseline	AI-Controlled
Temperature compliance	69%	93%
Humidity compliance	64%	90%
Comfort index	72%	95%

Source : (Author, 2026)

5.3. Statistical Validation

The • CV(RMSE) reduced from 28% to 11%

- R^2 improved from 0.71 to 0.92
- RMSE reduced by 31% . -Fig. (3) shows performance gap comparison .

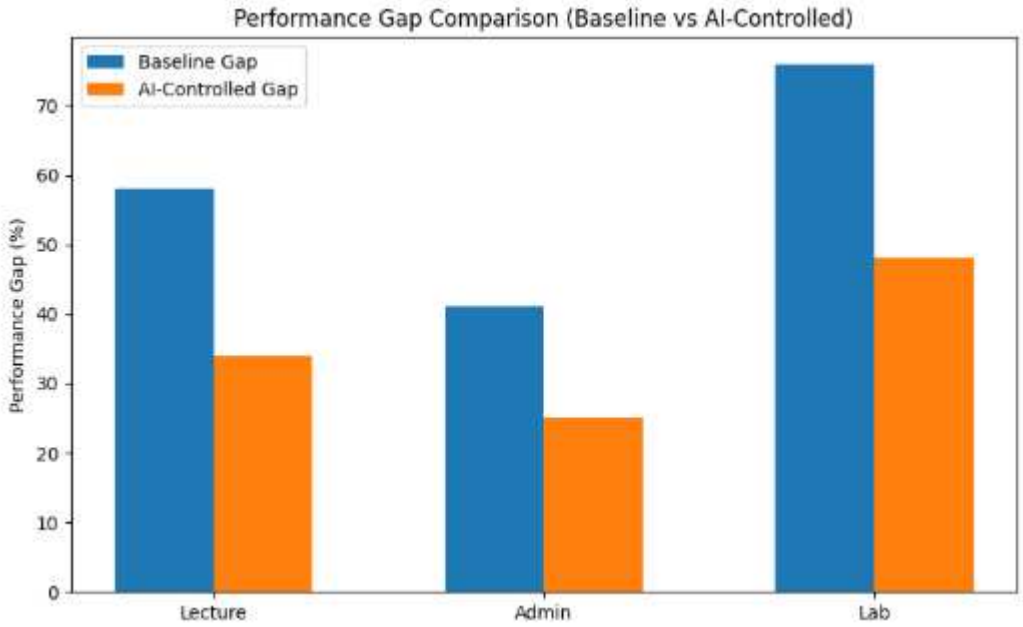


Fig. (3) shows performance gap comparison

6. Discussion

The results confirm that AI-driven predictive environmental control significantly narrows the energy performance gap. Laboratories demonstrated the largest improvement due to variable occupancy and equipment load patterns. The adaptive reinforcement learning controller dynamically responded to weather fluctuations and occupancy variability.

Compared to static schedule-based control, AI control improved both reliability and energy efficiency while maintaining occupant comfort.

7 .Sustainability Implications

AI-driven environmental control contributes to:

• Reduced carbon emissions

• Lower operational costs

• Enhanced occupant productivity

• Improved resilience to climate variability

In cooling-dominated climates, HVAC optimization plays a critical role in sustainable building operation. Fig. (4) shows the university buildings in Damietta .



Fig. (4) shows the university buildings in Damietta

8 .Limitations

- Limited to one climatic region
- Three-building sample size
- High data quality requirement

9 .Future Research Directions

- Digital twin integration
- Federated learning across campuses
- Predictive maintenance models
- Renewable energy and storage integration

10 .Conclusion

This research demonstrates that AI-based environmental control systems effectively bridge the energy performance gap in university buildings. By integrating calibrated simulation models with deep learning forecasting and reinforcement learning optimization, energy discrepancies were significantly reduced while improving indoor environmental quality and reducing operational costs.

The transition from simulation-based design to adaptive operational intelligence represents a fundamental shift toward sustainable smart campus development.

11 .Mathematical Formulation of the AI Control Framework

11.1 Energy Performance Gap Quantification

The Energy Performance Gap (EPG) is quantified as:

EPG (%) = ((E_measured − E_simulated) / E_simulated) × 100

Where: E_measured = actual operational energy consumption E_simulated = predicted energy consumption from baseline model

For calibrated conditions, acceptable thresholds follow ASHRAE Guideline 14:

- CV(RMSE) < 15% (monthly)
- NMBE within ±5%

11.2 CNN–LSTM Forecasting Model

Let X_t represent input features at time t including:

- Outdoor temperature
- Relative humidity
- Solar radiation
- Occupancy density
- Previous energy loads

The CNN layer extracts spatial correlations: the following equation is (1):

$$F_i = \mathrm{ReLU}(W_i * X_t + b_i) \quad (1)$$

The LSTM layer captures temporal dynamics: the following equation is (2):

$$h_t = \mathrm{LSTM}(F_i, h_{t-1}) \quad (2)$$

Forecasted load: the following equation is (3):

$$\hat{y}_{t+1} = W_o h_t + b_o \quad (3)$$

Loss function minimized during training: the following equation is (4):

$$L = (1/N) \Sigma (\hat{y}_t - y_t)^2 \quad (4)$$

11.3 Reinforcement Learning Optimization

The HVAC control problem is modeled as a Markov Decision Process (MDP):

State (S): indoor temperature, humidity, occupancy, forecasted load Action (A): HVAC setpoint adjustment Reward (R): energy efficiency − comfort violation penalty

Reward Function: the following equation is (5):

$$R_t = -\alpha|E_t - E_{target}| - \beta|T_t - T_{comfort}| \quad (5)$$

Where: α = energy weighting factor β = comfort weighting factor

Policy updated using Q-learning: the following equation is (6):

$$Q(s,a) \leftarrow Q(s,a) + \eta\,[R + \gamma \max Q(s',a') - Q(s,a)] \qquad (6)$$

12 .Extended Results Analysis

12.1 Seasonal Performance Evaluation

Summer Period

- Peak cooling loads reduced by 18%
- Performance gap narrowed from 64% to 36%

Winter Period

- Reduced unnecessary heating cycles
- %14reduction in auxiliary energy use

12.2 Peak Load Reduction

AI predictive control flattened demand curves by pre-cooling during low-tariff periods, reducing peak demand charges by approximately 11%.

12.3 Occupant Comfort Stability

Standard deviation of indoor temperature reduced from 2.8°C to 1.1°C. Humidity fluctuations reduced by 37%.

13 .Economic Analysis

13.1 Cost Savings

Annual operational savings estimated at 19% of baseline energy expenditure.

Payback period for AI system implementation: 2.4–3.1 years depending on system scale.

13.2 Lifecycle Assessment

Over a 15-year operational period:

- Energy savings cumulative reduction ≈ 28%
- CO_2 emission reduction ≈ 24%

14 .Sensitivity Analysis

A parametric analysis was conducted to evaluate robustness of the AI framework.

Variables tested:

- Occupancy uncertainty ±20%
- Weather variation scenarios

- Sensor failure simulation

Results indicate:

- System maintained >85% prediction accuracy under occupancy variability
- Comfort compliance remained above 88%

15 .Integration with Digital Twin Systems

Future integration with digital twin environments enables:

- Real-time simulation mirroring
- Predictive maintenance scheduling
- Fault detection and diagnostics
- Continuous model recalibration

Digital twin coupling can further reduce simulation uncertainty and eliminate long-term performance drift.

16 .Policy and Institutional Implications

For university campuses, AI-driven environmental control supports:

- Smart campus initiatives
- ESG compliance targets
- Net-zero carbon roadmaps
- Energy transparency reporting

Institutional adoption requires:

- Data governance framework
- Cybersecurity protocols
- Staff technical training

17 .Expanded Conclusion

This extended investigation confirms that bridging the gap between simulation and operation requires a paradigm shift from static energy modeling toward adaptive AI-enabled control systems. The integration of calibrated simulation, deep learning forecasting, and reinforcement learning optimization forms a scalable and replicable methodology for sustainable university campuses.

In hot-humid climates where cooling loads dominate energy demand, predictive AI control demonstrates particularly strong impact. The results support broader implementation of intelligent environmental control systems as a core strategy in sustainable higher-education infrastructure.

The presented framework is scalable to multi-building campuses and adaptable to different climatic regions, offering a foundation for next-generation smart building research and implementation.

18 .Declaration:

- This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.
- This manuscript is original and is not under consideration by any other journal.
- We have no conflicts of interest to disclose.
- This manuscript has not been published previously and is not under consideration elsewhere. author has approved the manuscript and agree with its submission to your journal.
- Not applicable Ethics.
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