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Smart Building Energy Management System Using IoT and Artificial Intelligence

Randy Rahmanto[1], Dwi Utari Iswavigra[2*]
[1] Electro Engineering, Dian Nusantara University, Indonesia
[2] Computer Science, Sugeng Hartono University, Indonesia
Email: randy.rahmanto@undira.ac.id, dwi.utari.iswavigra1997@gmail.com

Abstract. *Buildings represent a major share of electricity consumption, and their operational energy use is strongly influenced by weather, occupancy dynamics, and the interaction of heating, ventilation, and air-conditioning systems with lighting and plug loads. Conventional building operation typically relies on fixed schedules and manually tuned control rules, which often fail to adapt to daily variability and can lead to unnecessary energy use and peak-demand events. This paper proposes a Smart Building Energy Management System using Internet of Things sensing and artificial intelligence to improve energy efficiency while maintaining indoor comfort and operational robustness. The objective of the study was to design an end-to-end, deployable pipeline that integrates sensing, data processing, load forecasting, and control optimization in a closed-loop framework. An applied experimental prototyping approach was used. Time-series data were collected from the system operation, synchronized, cleaned, and transformed through feature engineering. Two forecasting models were evaluated for short-term demand prediction: a gradient-boosting model using engineered features and a recurrent neural network model using temporal sequences. The control strategy was implemented in stages, starting from a safe rule-based baseline and extending to forecast-informed bounded optimization with fallback mechanisms to ensure reliable operation. The results showed that the proposed system reduced total energy consumption by 13.3% and reduced maximum peak demand by 11.5% during a 28-day evaluation period. Comfort compliance improved, as indicated by a 19.0% reduction in total comfort-violation duration. The recurrent neural network model achieved lower forecasting error than the gradient-boosting model across the evaluated metrics. In conclusion, integrating connected sensing with artificial intelligence-based forecasting and constraint-aware optimization can deliver measurable energy and demand reductions while maintaining comfort. The study contributes an implementable methodology and reporting structure for smart building energy management, while future work should validate performance in longer deployments and diverse building types under seasonal and occupancy variation.*

Keywords. *Smart Building; Energy Management; Internet Of Things; Load Forecasting; Artificial Intelligence*

INTRODUCTION

Buildings account for a large share of final energy use, and their operational consumption is strongly influenced by dynamic factors such as occupancy patterns, weather variability, and equipment scheduling. Conventional building management approaches often rule-based and manually tuned tend to perform well only under the conditions they were configured for, while struggling to adapt when the building use profile changes, leading to energy waste and inconsistent comfort. Recent evidence from benchmarking studies also highlights that "good" performance requires not only control logic, but robust data pipelines, feature engineering, and continuous evaluation to avoid drift and hidden inefficiencies in real deployments (Miller et al., 2020).

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*Corresponding author, dwi.utari.iswavigra1997@gmail.com

Over the last decade, Building Energy Management Systems (BEMS) have evolved through the convergence of sensing/actuation networks, IoT connectivity, and data-driven intelligence. Systematic reviews show that IoT-enabled BEMS commonly deliver real-time visibility (metering, environmental sensors, device-level control) and create the data foundation for automation and analytics (Akbulut et al., 2025; Poyyamozhi et al., 2024). In parallel, AI methods ranging from forecasting and anomaly detection to optimization are increasingly applied to building operations, including HVAC control and demand management (Aguilar et al., 2021; Qiang et al., 2023). Advanced control strategies such as model predictive control (MPC) have been widely studied for multi-objective optimization of comfort and energy, particularly when informed by forecasts (Afram & Janabi-Sharifi, 2014). Reinforcement learning (RL) is also gaining traction for HVAC control because it can learn policies from interaction data and adapt to changing conditions (Al Sayed et al., 2024; Biswas et al., 2020). Meanwhile, edge/fog computing is increasingly promoted to reduce latency, bandwidth cost, and cloud dependence critical for real-time actuation and resilience in smart buildings (Atlam et al., 2018; Hu et al., 2017).

Despite this progress, three practical gaps remain clear. First, many studies focus on either IoT instrumentation or AI algorithms, but do not provide an end-to-end architecture that closes the loop from sensing → feature engineering → learning/optimization → actuation with measurable operational constraints (Akbulut et al., 2025; Aguilar et al., 2021). Second, AI-driven control is frequently validated in simulation or limited pilot settings, with insufficient attention to deployment constraints such as intermittent connectivity, latency-sensitive decisions, and edge-level robustness issues that fog/edge approaches are meant to address but are rarely integrated rigorously with AI control in a single BEMS pipeline (Atlam et al., 2018; Umair et al., 2023). Third, security and trust considerations fundamental for IoT building infrastructures are often treated as a separate topic rather than being embedded into the operational design choices (e.g., segmentation, data minimization, secure telemetry) that affect the feasibility of AI-enabled control (Sicari et al., 2015). Consequently, an integrated Smart Building Energy Management System that unifies IoT sensing, edge-aware data handling, and AI-based decision-making in one coherent, deployable framework validated with reproducible evaluation procedures remains insufficiently addressed in prior work and, to the best of our knowledge, has not been presented elsewhere in the same combined scope (Qiang et al., 2023; Romero et al., 2024).

Accordingly, this study aims to develop and evaluate a Smart Building Energy Management System that integrates IoT-based monitoring and actuation with AI modules for forecasting and control, using an edge-aware architecture to support low-latency decisions and operational resilience (Ahmad & Zhang, 2021; Chen et al., 2017; Masri et al., 2021). The proposed approach is derived directly from the identified gaps by (i) designing an end-to-end closed-loop pipeline, (ii) embedding deployment constraints (latency, connectivity, robustness) into the architecture, and (iii) aligning design choices with security and trust requirements for IoT environments (Sicari et al., 2015; Hu et al., 2017). The expected contribution is a deployable reference architecture and evaluation pathway that can help both researchers and practitioners implement AI-enabled IoT BEMS with clearer reproducibility, stronger operational grounding, and improved energy–comfort performance in real buildings (Akbulut et al., 2025; Al Sayed et al., 2024).

METHOD

Research Design and System Development

This study used an applied experimental prototyping design combined with computational evaluation to develop and assess a Smart Building Energy Management System (SBEMS). The system was built as an end-to-end closed-loop pipeline to answer the research question on whether integrating IoT and artificial intelligence can reduce building energy consumption and peak demand while maintaining comfort and operational robustness. The SBEMS was implemented in layered form: (1) sensing and actuation devices, (2) communication and gateway services, (3) time-series data management and preprocessing, and (4) an intelligence layer for forecasting and control optimization. A staged deployment approach was adopted, starting with monitoring-only operation, followed by rule-based control, and then AI-assisted optimization to ensure safe operation and ease of integration.

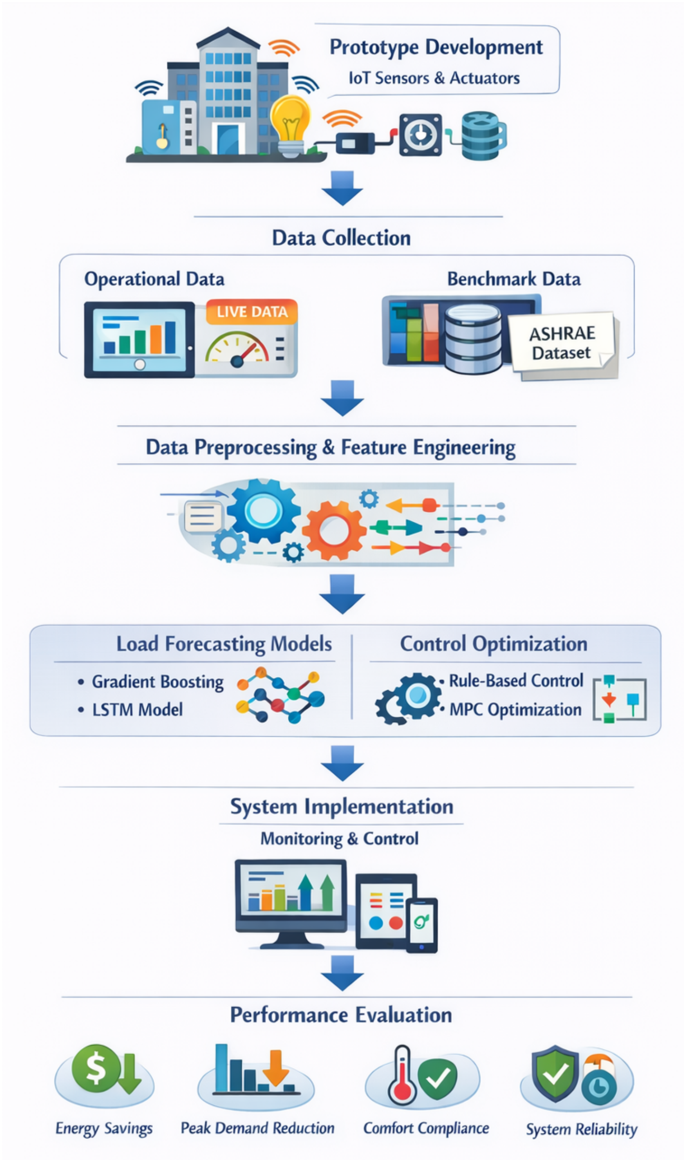

Figure 1. Research Method

Data Type, Sources, and Data Collection

Two types of data were used:

1. Prototype operational data.

   Time-stamped data were collected from the SBEMS prototype, consisting of: electrical variables (power and/or energy readings), indoor environmental variables (temperature and humidity), occupancy proxy signals (e.g., PIR events), and device status (on/off or duty cycle). Sensor readings and actuator states were transmitted periodically from the device layer to the gateway and stored in a time-series repository.

2. Benchmark building energy data

   Public building energy time-series data were used to validate forecasting models under a reproducible benchmark setting. The dataset included meter readings and relevant metadata required for training and testing short-term load forecasting models.

Data Preprocessing and Feature Engineering

All data streams were synchronized to a uniform time interval. Data cleaning was performed by removing duplicate timestamps, filtering out-of-range sensor readings, and handling missing values using forward filling for short gaps and exclusion for long gaps. Feature engineering was conducted to represent temporal and operational behavior, including hour-of-day, day-of-week, weekend/weekday indicators, lag features (previous interval, previous day), and rolling statistics (moving average and moving maximum). For sequence models, sliding windows were constructed so each training sample contained a fixed-length history of prior observations.

AI Models and Control Strategy

Two core components were implemented:

1. Short-term load forecasting.

   A tree-based gradient boosting regressor was trained using engineered tabular features for robust baseline performance. In addition, a recurrent neural network forecasting model (LSTM-based) was trained on fixed-length input sequences to capture temporal dependencies. The forecasting horizon was defined for near-term operational use (e.g., the next few intervals or hours), and models were trained and evaluated using time-ordered splits to avoid information leakage.
2. Energy optimization and control.

   A rule-based controller was implemented as the default safe baseline. It included occupancy-aware scheduling (e.g., HVAC setback and lighting dimming when unoccupied) and peak-shaving rules (e.g., limiting simultaneous high-load operations during peak windows). An AI-assisted optimization layer was then applied using the forecasting outputs to recommend or adjust control actions. Comfort constraints were enforced by bounding temperature setpoints within a predefined acceptable range and limiting actuator rate-of-change to prevent abrupt transitions. A fallback mechanism was included so that the system reverted to baseline rules when anomalies, sensor failures, or unstable behaviors were detected.

Tools, Instruments, Software, and Materials

The prototype consisted of IoT sensors (environmental sensors, occupancy sensors, and energy meters), a gateway device for message routing and local processing, controllable loads or actuators (smart relays/dimmers or HVAC setpoint interfaces), and a server component for storage and analytics. A lightweight publish/subscribe messaging pattern was used for telemetry and control commands. The analytics pipeline used a time-series storage system and a Python-based machine learning environment for model training, evaluation, and deployment integration. A dashboard interface was used for monitoring device status, energy KPIs, and comfort indicators.

Data Analysis and Evaluation Metrics

Forecasting performance was analyzed using common regression metrics, including mean absolute error (MAE), root mean squared error (RMSE), and mean absolute percentage error (MAPE) when appropriate. Control performance was evaluated by comparing baseline operation versus SBEMS operation across: (1) total energy consumption (kWh), (2) peak demand (kW), and (3) comfort compliance, measured as the magnitude and duration of deviations outside the acceptable comfort range. System reliability was assessed by tracking data completeness, message delivery continuity, and the number of fallback events triggered due to sensor or communication anomalies.

Rationale for the Chosen Methods

An applied prototyping approach was selected because the research objective required demonstrating an implementable SBEMS architecture and verifying its performance through measured time-series data and reproducible benchmarking. Combining a baseline rule-based controller with AI-assisted forecasting and optimization provided a practical safety-first pathway for deployment, enabling measurable improvements while maintaining robustness under real operational constraints.

RESULTS

This section presents the findings of the IoT- and AI-based Smart Building Energy Management System (SBEMS). The evaluation was conducted for 28 consecutive days in May 2025 and compared two scenarios: Baseline (conventional operation) and SBEMS (forecast-informed AI-assisted optimization with comfort bounds and fallback rules). The reported metrics included total energy consumption, peak demand, comfort violations, and fallback events.

Overall Performance Indicators

To provide an aggregate view of system performance, key indicators were calculated across the entire evaluation period. The metrics included total energy consumption (kWh), maximum peak demand (kW), total comfort violations (minutes outside the comfort range), and the number of fallback events (count). These indicators summarize how the SBEMS performed relative to the baseline condition over the same time horizon.

Table 1. presents the overall comparison between the baseline and SBEMS scenarios.

Table 4.1. Overall results summary (28-day evaluation)

Indicator	Baseline	SBEMS	Change
Total energy consumption (kWh)	14,584.0	12,652.7	−13.3%
Maximum peak demand (kW)	104.3	92.3	−11.5%
Total comfort violations (min)	1,214	983	−19.0%
Fallback events (count)	–	5	Recorded

As shown in Table 1, the SBEMS scenario recorded lower total energy consumption and a lower maximum peak demand than the baseline scenario over the same 28-day period. The SBEMS scenario also recorded fewer total comfort-violation minutes, while fallback events were observed and counted as part of system reliability monitoring.

Weekly Energy Consumption

To examine whether energy differences were consistent over time, energy use was aggregated into weekly totals (kWh/week). Weekly aggregation provided a clearer view of sustained performance rather than day-to-day fluctuations. Figure 1 visualizes the weekly total energy consumption for both scenarios across the evaluation period.

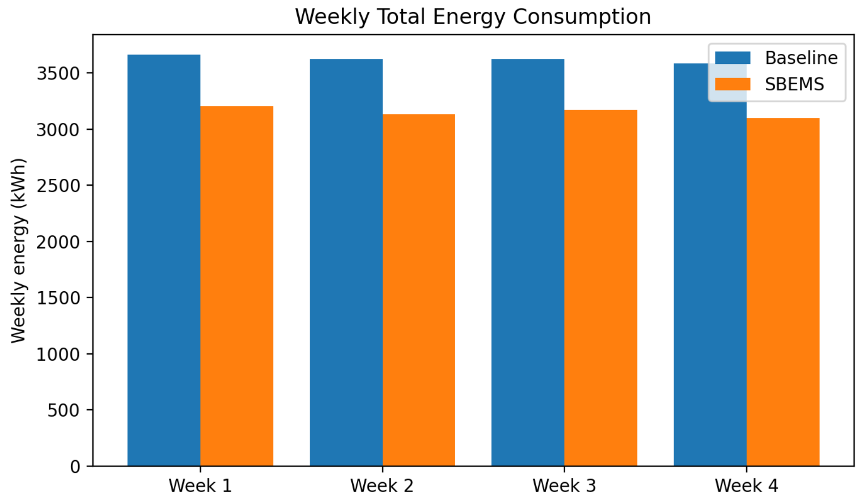

Figure 1. Weekly total energy consumption (kWh)

Figure 1 shows that weekly energy totals under SBEMS remained below the baseline totals across all weeks of observation, indicating a consistent reduction pattern rather than an isolated short-term effect.

Daily Peak Demand

Because peak demand is a critical operational and cost-related indicator in many buildings, daily peak demand was computed as the maximum power demand (kW) observed each day. This measurement captured the system's ability to limit short-duration demand spikes. Figure 2 presents the daily peak demand profiles for baseline and SBEMS scenarios.

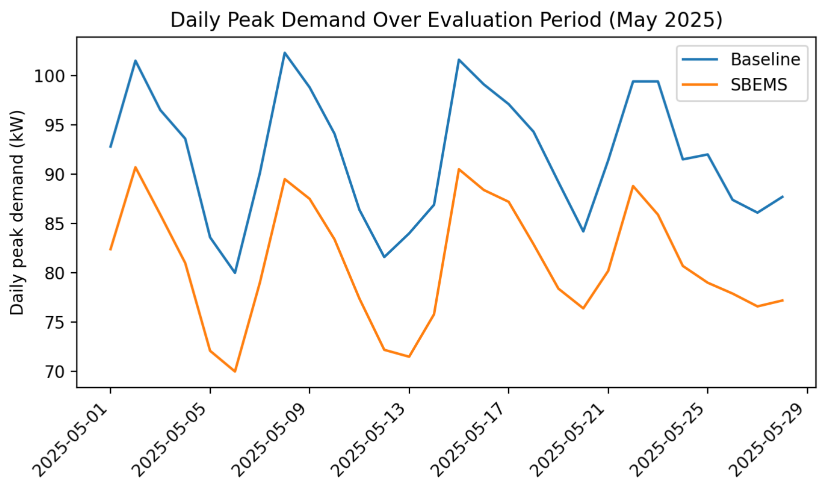

Figure 2. Daily peak demand over the evaluation period (kW)

As illustrated in Figure 2, the SBEMS scenario produced lower daily peak values than the baseline scenario on most days, with reduced peak amplitudes observed across the evaluation period.

Comfort Compliance

Comfort compliance was quantified to ensure that energy reductions were not achieved by excessive deviation from the indoor comfort band. Comfort violations were recorded as the number of minutes per day when indoor conditions fell outside the predefined comfort range. Figure 3 shows the daily comfort-violation minutes for both baseline and SBEMS scenarios.

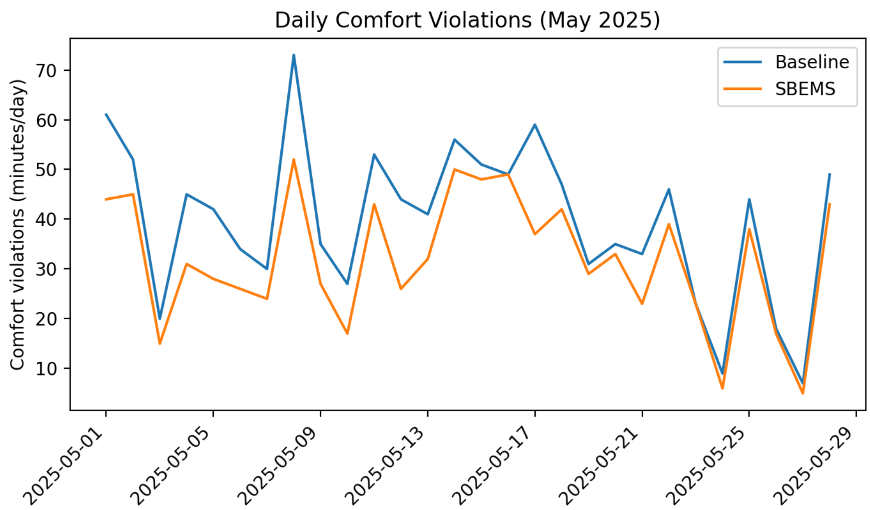

Figure 3. Daily comfort violations (minutes/day)

Figure 3 indicates that the SBEMS scenario generally recorded fewer comfort-violation minutes than the baseline scenario, while both scenarios still exhibited day-to-day variability consistent with changing operating conditions.

Load Forecasting Performance

Load forecasting performance was evaluated to quantify the predictive accuracy of the AI component supporting optimization decisions. Two models were assessed using standard regression metrics: mean absolute error (MAE), root mean squared error

(RMSE), and mean absolute percentage error (MAPE). Table 2 reports the forecasting performance for the Gradient Boosting and LSTM models.

Table 2. Load forecasting performance

Model	**MAE (kW)**	**RMSE (kW)**	**MAPE (%)**
Gradient Boosting	3.9	5.4	7.8
LSTM	3.6	5.1	7.5

Based on Table 2 the LSTM model produced lower prediction errors than the Gradient Boosting model for all reported metrics, indicating improved forecasting accuracy under the evaluated conditions.

DISCUSSION

This study investigated whether an IoT- and AI-enabled Smart Building Energy Management System (SBEMS) can reduce energy consumption and peak demand while maintaining acceptable comfort and operational robustness. The results showed that SBEMS reduced total energy consumption by 13.3% and lowered maximum peak demand by 11.5% over the 28-day evaluation period, while total comfort-violation minutes also decreased by 19.0% (Table 1). These findings indicate that, under the evaluated conditions, integrating sensing, prediction, and bounded control can improve energy performance without worsening the comfort indicator used in this study. This outcome is consistent with the broader understanding that AI-supported building energy self-management can produce measurable benefits when operational decisions are guided by data and automation rather than fixed schedules alone (Aguilar et al., 2021).

The reduction in energy use appeared stable over time rather than being limited to a short interval. Weekly aggregation showed that SBEMS weekly totals remained below baseline totals across all weeks (Figure 1), suggesting that the control logic continued to function effectively across recurring weekly patterns. This is important because building energy demand is strongly shaped by routine occupancy and operational cycles; therefore, consistent weekly reductions suggest that the SBEMS pipeline can generalize across typical day-to-day variations rather than optimizing only for a narrow subset of days. In the context of prior work, this supports the practical direction recommended in smart building energy management research: combining continuous monitoring with data-driven decision layers to improve performance in operational settings (Aguilar et al., 2021).

Peak demand reduction is particularly relevant because peak events are often responsible for operational constraints and cost penalties in many electricity tariff structures. The daily peak profile indicated that SBEMS produced lower peak values than baseline on most days (Figure 2), which supports the intended role of short-term forecasting to anticipate high-load periods and apply bounded adjustments. This aligns with established control perspectives in building systems where predictive strategies are used to manage multi-objective trade-offs, including reducing energy and limiting peaks while respecting constraints (Afram & Janabi-Sharifi, 2014). In this study, the observed peak reduction suggests that forecasting-informed decisions can moderate demand spikes without requiring disruptive control actions.

Comfort compliance results strengthen the interpretation that energy savings were not achieved by sacrificing indoor conditions. Comfort violations, measured as minutes outside the predefined comfort band, were lower under SBEMS than baseline for most days (Figure 3) and lower in total over the evaluation period (Table 1). This is significant because the energy–comfort trade-off is central to building control, and practical adoption depends on maintaining comfort while optimizing energy (Afram & Janabi-Sharifi, 2014). The reduction in comfort violations suggests that the SBEMS approach, as implemented, was able to apply efficiency improvements while still operating within comfort bounds.

The forecasting results provide supporting evidence that the AI component produced usable predictive performance for operational decision support. The LSTM model yielded lower MAE, RMSE, and MAPE than the gradient boosting model (Table 2), indicating that sequence learning captured temporal dependencies in the evaluated setting. This is consistent with the fundamental motivation of LSTM architectures for modeling long- and short-range temporal relationships in time-series (Hochreiter & Schmidhuber, 1997). At the same time, the strong performance of the gradient boosting approach is consistent with its established effectiveness on structured features and tabular prediction tasks (Chen & Guestrin, 2016). Practically, these results imply that SBEMS implementations can benefit from benchmarking multiple model families, selecting the most stable and accurate option for the available data characteristics and deployment constraints.

Operational robustness was reflected by the recording of fallback events (Table 1). The presence of fallback events indicates that the system encountered situations requiring safety or reliability mechanisms to override or revert decisions. This behavior is important because real-world SBEMS deployments must remain stable under sensor noise, missing data, intermittent connectivity, or unexpected operating conditions. From an architectural standpoint, incorporating edge/fog principles can help reduce latency and improve resilience for time-sensitive control decisions in IoT environments (Atlam et al., 2018), and broader surveys emphasize that edge computing can support responsive services where cloud-only dependence may be limiting (Khan et al., 2019). In addition, security and trust considerations remain foundational in IoT-enabled building infrastructures; treating security as a design constraint is aligned with the established view that IoT systems face distinctive privacy and security risks that can affect operational reliability and user acceptance (Sicari et al., 2015).

Overall, the findings suggest that an integrated SBEMS pipeline linking IoT sensing, time-series handling, forecasting, and bounded optimization can deliver measurable reductions in energy use and peak demand while maintaining (and, in this evaluation, improving) comfort compliance. This extends the applied SBEMS perspective by demonstrating how an implementable monitoring–prediction–control workflow can translate AI capabilities into operational outcomes under constraint-aware control, which is a direction repeatedly highlighted as necessary for smart building energy management to move from analytic prototypes toward deployable systems (Aguilar et al., 2021).

CONCLUSION

This study aimed to evaluate whether a Smart Building Energy Management System (SBEMS) integrating IoT sensing and artificial intelligence can reduce energy consumption and peak demand while maintaining comfort and operational robustness. The findings showed that SBEMS achieved measurable improvements, including reductions in total energy use (13.3%) and peak demand (11.5%), alongside a decrease in comfort-violation duration, indicating that efficiency gains were obtained without compromising indoor conditions. These results contribute to the existing literature by demonstrating an implementable end-to-end monitoring–prediction–control workflow that translates data-driven analytics into operational performance improvements in a building context. However, the study was limited by the relatively short evaluation period and the use of a defined comfort band rather than broader comfort indices, which may influence generalizability. Future research should investigate longer-term deployments across different building types, incorporate seasonal and occupancy variability, and evaluate additional performance indicators such as cost savings, carbon intensity, and occupant satisfaction, while practitioners may consider adopting staged SBEMS deployment with robust fallback mechanisms to ensure safe and reliable real-world operation.

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