A Comprehensive Review of Machine Learning & Deep Learning Techniques for Improving Building Energy Efficiency

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Abstract. This review synthesizes recent advancements in Artificial Intelligence (AI), specifically Machine Learning (ML) and Deep Learning (DL), applied to Building Energy Management Systems (BEMS). The survey encompasses a wide array of data acquisition methods—ranging from non-intrusive WiFi sensing to computer vision—and their integration into occupancy modeling, thermal comfort prediction, and optimal control strategies.
The literature reveals a paradigm shift where traditional static models, such as Fanger's Predicted Mean Vote (PMV), and reactive controls are increasingly being replaced by data-driven approaches that adapt to real-time conditions. Deep learning architectures, including Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, demonstrate superior capability in capturing the stochastic nature of human behavior. Furthermore, Deep Reinforcement Learning (DRL) algorithms enable continuous control in high-dimensional state spaces without simplified mathematical models.
The integration of these AI techniques has demonstrated energy savings ranging from 7% to 58% across various building types, while maintaining or improving indoor environmental quality.

Keywords: Machine Learning · Deep Learning · Building Energy Management · Thermal Comfort · Reinforcement Learning

1 Introduction

The optimization of energy consumption within the built environment constitutes a pivotal challenge in the global pursuit of sustainability and carbon footprint reduction. While advancements in building envelope materials and high-efficiency HVAC systems have improved the theoretical baseline of building performance, a significant discrepancy persists between predicted energy models and actual operational consumption. This phenomenon, widely recognized as the "energy performance gap," suggests that technological hardware alone is insufficient to meet aggressive efficiency targets. The complexity of the problem lies not merely in the physical infrastructure but in the stochastic and dynamic nature of the occupants residing within it.

The critical role of occupant behavior in energy dynamics is rigorously examined by D'Oca et al. [7], who argue that "human dimensions" are as influential as technological specifications yet remain frequently oversimplified in practice. Their review highlights that variations in household energy use can differ by a factor of 3 to 10 due solely to human factors, independent of building characteristics. Furthermore, proactive occupant behavior in commercial settings has been shown to reduce energy consumption by up to 50%, while the integration of Human-in-the-loop (HIL) technologies can yield operational cost savings between 4% and 22% [7]. Despite this potential, traditional building performance simulations (BPS) often rely on synthetic schedules and static assumptions that suppress the diversity of real-world behavior. As noted in [7], traditional stochastic models frequently fail to represent complex cognitive processes, creating a reliability barrier that hinders the deployment of human-centered energy strategies.

To bridge this performance gap, the domain of energy efficiency is undergoing a paradigm shift from rigid, rule-based simulations toward flexible, data-driven approaches. Machine Learning (ML) has emerged as the preeminent vehicle for parsing the non-linear interactions between building systems, environmental constraints, and occupant behavior. Unlike traditional modeling, ML algorithms possess the capacity to learn from historical data, adapt to drifting operational patterns, and optimize control strategies in real-time without explicit programming of every contingency.

This survey synthesizes state-of-the-art methodologies in machine learning applied to building energy efficiency, distilling key insights from the recent literature to map the trajectory of the field. We provide a critical examination of the technological evolution from foundational statistical approaches to advanced, autonomous agents. Specifically, this paper contributes:

1. **A Holistic Synthesis of ML Evolution:** We trace the progression from traditional supervised learning techniques used for load forecasting to sophisticated Deep Learning (DL) and Reinforcement Learning (RL) architectures designed for autonomous control.
2. **Bridging the Human-Building Gap:** We analyze how modern data-driven approaches address the limitations of traditional stochastic models identified by [7], specifically regarding the integration of complex human behaviors into energy management systems.
3. **Critical Analysis of Implementation Trends:** Rather than simply cataloging algorithms, this work evaluates the practical applicability, scalability, and computational challenges associated with deploying these advanced models in real-world building management systems (BMS).

By delineating the strengths and limitations of current ML paradigms, this survey aims to provide researchers and practitioners with a comprehensive framework for understanding how intelligent systems can be leveraged to close the energy performance gap.

2 Taxonomy of Machine Learning Algorithms

The literature surveyed in this review employs a diverse array of computational intelligence techniques to address the complexities of building energy management, occupant behavior, and thermal comfort. The selected studies have been categorized into four primary taxonomic groups: Traditional Machine Learning, Deep Learning, Hybrid/Ensemble approaches, and Reinforcement Learning. **Figure ??** illustrates the distribution of these research papers by category, year of publication, and their respective application domains, highlighting a trend toward increasingly complex, data-driven architectures in recent years.

2.1 Traditional Machine Learning

Traditional machine learning (ML) algorithms constitute a significant portion of the reviewed literature (12 papers). These methods generally rely on statistical learning theory to map input features—such as environmental sensor data or survey responses—to target variables. In the context of building energy, these algorithms are favored for their interpretability, lower computational requirements, and effectiveness on smaller, structured datasets.

The core working principle of these methods involves defining a decision boundary or a regression function that minimizes error on training data. For instance, Support Vector Machines (SVM) and shallow Artificial Neural Networks (ANN) are extensively used for thermal comfort prediction. As demonstrated by [3] and [4], these models significantly outperform traditional Fanger's PMV models by capturing non-linear relationships between environmental parameters (temperature, humidity) and subjective human sensation. Similarly, [5] applies curve-fitting techniques based on economic utility theory to optimize air-conditioning loads, proving that established mathematical regression remains highly effective for system optimization.

Furthermore, stochastic and probabilistic models are critical for simulating occupant presence. Markov chains are employed to model the probability of state transitions (e.g., entering or leaving a room) [6], while Extreme Learning Machines (ELM)—single-hidden layer feedforward networks—are utilized for rapid occupancy estimation using WiFi signals [20] or CO_2 concentrations [11]. These traditional methods establish robust baselines for detection and forecasting tasks, though they may struggle with high-dimensional unstructured data.

2.2 Deep Learning

Deep Learning (DL) represents a subset of machine learning utilizing neural networks with multiple hidden layers, enabling the automatic extraction of high-level features from raw, complex data. This capability is particularly advantageous for building applications involving computer vision or complex time-series forecasting, where manual feature engineering is impractical.

The reviewed studies (5 papers) leverage specific DL architectures tailored to the data modality. Convolutional Neural Networks (CNNs) are prominent in vision-based tasks because they preserve spatial hierarchies in data. For example, [16] utilizes CNNs to detect occupant activities (e.g., sitting, walking) from camera feeds to estimate heat emissions, while [15] applies CNNs to Doppler spectrograms from passive WiFi radar for crowd counting.

For temporal dynamics, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are essential. These architectures possess "memory" mechanisms that capture long-term dependencies in time-series data. This is exemplified by [21], which combines CNNs for feature extraction with LSTMs to recognize human activities via WiFi Channel State Information (CSI). Additionally, [19] employs Nonlinear Autoregressive Exogenous (NARX) models to predict building thermal dynamics for Model Predictive Control (MPC), demonstrating DL's capacity to model the non-linear thermal inertia of buildings more accurately than linear state-space models.

2.3 Hybrid and Ensemble Methods

Hybrid and ensemble methods (7 papers) combine multiple algorithms to enhance predictive performance, improve generalization, or overcome the limitations of individual models. The underlying principle is that a collection of weak learners can form a strong learner (boosting/bagging), or that fusing different modalities (e.g., vision and time) provides a more holistic view of the building environment.

Ensemble learning techniques such as Random Forest and Gradient Boosting are frequently applied to occupancy prediction. [18] demonstrates that ensemble classifiers like AdaBoost can effectively interpret noisy WiFi probe data to predict categorical occupancy profiles. Similarly, [2] introduces a "late fusion" approach, processing egocentric images with CNNs and contextual metadata with Random Decision Forests, achieving higher accuracy than either model could in isolation.

Hybrid approaches also bridge unsupervised and supervised learning. [13] proposes a framework where unsupervised k-means clustering first identifies occupancy patterns, which then train a supervised k-Nearest Neighbor (k-NN) classifier for real-time prediction. This multi-stage approach allows the system to adapt to the specific usage patterns of an office before making control decisions. Such methods are particularly valuable in scenarios where data is noisy or multimodal, such as parking occupancy detection using transfer learning [1] or multi-modal action recognition using RGB-D data [10].

2.4 Reinforcement Learning

Reinforcement Learning (RL) differs fundamentally from the supervised approaches described above. Instead of learning from a static dataset of labeled examples, an RL agent learns by interacting with an environment (the building) to maximize a cumulative reward signal. This paradigm is specifically suited for control and optimization problems where the goal is to develop a sequential decision-making policy.

[INSERT FIGURE: Diagram of a Hybrid Occupancy Detection System (e.g., Sensor Fusion)]

Fig. 1. Diagram of a Hybrid Occupancy Detection System

In the reviewed papers (3 studies), RL is applied to the dynamic control of HVAC systems. The core mechanism involves an agent observing the state (e.g., indoor temperature, occupancy) and taking an action (e.g., changing a set-point), receiving a reward based on energy savings and thermal comfort. [12] utilizes tabular Q-learning to learn optimal temperature set-points based on a statistical thermal comfort model.

More advanced Deep Reinforcement Learning (DRL) methods integrate neural networks to approximate the Q-value function, allowing agents to handle continuous state spaces. [17] employs Double Q-learning to balance energy consumption, thermal comfort (PMV), and indoor air quality (CO_2), while [8] uses the Deep Deterministic Policy Gradient (DDPG) algorithm for continuous control of temperature and humidity. These studies highlight RL's potential to autonomously navigate the trade-off between energy efficiency and occupant satisfaction without relying on rigid, rule-based control logic.

3 Quantitative Comparison and Discussion

Table 1 summarizes the performance metrics of the most significant studies reviewed. The selection prioritizes research demonstrating quantifiable improvements in energy efficiency, prediction accuracy, or detection rates over traditional baselines.

3.1 Critical Discussion

The quantitative results highlight a distinct dichotomy between simulation-based optimization and real-world implementation. Studies utilizing Model Predictive Control (MPC) and Deep Reinforcement Learning (DRL) in controlled testbeds or simulations, such as [19], report exceptional energy savings reaching nearly 60%. However, when algorithms are applied to complex, operational environments with multi-objective constraints (balancing energy, CO_2, and comfort simultaneously), the gains are more conservative yet highly significant. For instance, the DRL approach in [17] achieved a modest 4–5% energy reduction but succeeded in drastically improving indoor air quality and thermal comfort stability. This suggests that while theoretical models indicate massive potential for energy reduction, the practical application of these algorithms must often trade raw energy savings for holistic environmental quality and system robustness.

Table 1. Comparative Analysis of Selected Algorithms and Key Results

Ref.	Year	Algorithm	Application	Metrics & Best Result
[5]	2014	EMUT (Curve Fitting)	Chiller Load Allocation	**Energy Reduction:** 4.74% avg. (72–100 kW savings) vs. average loading method.
[4]	2017	ANN	Thermal Comfort Prediction (Tropics)	**Accuracy:** 85.3% (HVAC), significantly outperforming Fanger's PMV (65.5%).
[13]	2018	Hybrid (K-means + KNN)	Occupancy-based Cooling Control	**Energy Savings:** 21% average (Range: 7%–52%) compared to static scheduling.
[14]	2018	Statistical Thresholding	Action Detection (Windows/Heating)	**Detection Accuracy:** >99.7% for occupant actions using environmental sensors.
[9]	2018	ITCNN (Deep Learning)	Personal Thermal Comfort	**MAE Improvement:** 13.1% reduction in error compared to the PMV baseline.
[17]	2019	Deep RL (Double Q-Learning)	Multi-objective HVAC Control	**Multi-metric:** 4–5% energy savings; CO_2 reduced to 689 ppm (vs 1039); PMV improved to -0.125.
[3]	2020	ANN	Thermal Sensation Prediction	**MSE:** 0.8179 (Lowest error); R^2**:** 0.4872, outperforming SVM and PMV (R^2=0.4073).
[19]	2020	NARX-ANN + MPC	HVAC Optimization	**Energy Reduction:** 58.5% (thermal) and 36.7% (electrical) in testbed environments.
[16]	2020	CNN (Vision-based)	Heat Emission Estimation	**Detection Accuracy:** 80.62%; Identified ∼30% variance in heat gains vs. static profiles.

Furthermore, a comparison of algorithmic performance reveals the superior capability of Deep Learning (DL) over traditional modeling in capturing non-linear building dynamics. Across multiple studies [3], [9], [4], Artificial Neural Networks (ANN) consistently outperformed Fanger's traditional PMV model, reducing prediction errors by margins of 13% to 20%. This indicates that static, physics-based models are increasingly insufficient for modern, dynamic building environments. However, complexity is not always a prerequisite for high performance. As evidenced by [13] and [14], simpler statistical or hybrid machine learning approaches (such as KNN or statistical thresholding) can achieve detection accuracies exceeding 99% or energy savings of up to 52% when applied to specific, well-defined tasks like occupancy detection or window monitoring. Therefore, the optimal algorithmic choice appears to be context-dependent: deep learning for complex, non-linear comfort modeling, and lighter, interpretable models for discrete event detection and immediate control responses.

4 Challenges & Future Directions

While the application of machine learning (ML) and reinforcement learning (RL) in HVAC control has demonstrated superior performance compared to traditional rule-based and thermal balance models, several critical impediments remain. The transition from theoretical simulation to robust, real-world deployment is hindered by challenges regarding data integrity, deployment scalability, and model interpretability.

4.1 Data Availability and Quality

The efficacy of data-driven models is intrinsically linked to the quantity and quality of the training datasets. A recurrent limitation in current literature is the scarcity of comprehensive, balanced datasets. For instance, data collection is often seasonally skewed; studies such as [3] note that datasets dominated by summer measurements introduce bias, potentially compromising model performance during transitional or winter seasons. Furthermore, datasets derived from field surveys frequently exhibit class imbalance. As observed in [12], the ASHRAE RP-884 database contains a preponderance of "neutral" thermal sensation votes, causing classifiers to bias predictions toward the majority class and reducing recall for "cool" or "warm" sensations.

Data granularity and sensor reliability also present significant hurdles. While pervasive sensing offers granular data, the accuracy of consumer-grade wearable devices can be inconsistent, with errors up to 4.8% reported in physiological measurements [9]. Additionally, missing parameters in legacy databases often necessitate the exclusion of valuable data points, as seen in [4] where the absence of demographic data limited the scope of analysis.

4.2 Real-World Deployment and Generalizability

A substantial "simulation-to-reality gap" exists in the current body of research. Many advanced control strategies, particularly those utilizing Deep Reinforcement Learning (DRL), are validated primarily within simulation environments like TRNSYS or EnergyPlus [8]. When applied to physical testbeds, these models often struggle with the stochastic nature of real-world dynamics. For example, DRL agents have shown difficulty managing season transitions (e.g., when AC systems are typically dormant) and handling unpredictable manual overrides by occupants, which can corrupt the reward signal [17].

Furthermore, the generalizability of these models is limited by the "cold start" problem. Adaptive models, such as the NARX neural networks utilized in [19], require historical operational data specific to the building in question to train effective controllers. This requirement renders such systems unsuitable for newly constructed buildings or those lacking historical instrumentation. Similarly, vision-based occupancy detection models are sensitive to environmental variations, such as lighting changes, and may struggle to distinguish between similar static postures, limiting their robustness in diverse office settings [16].

4.3 Model Interpretability

The "black box" nature of complex algorithms remains a barrier to widespread industry adoption. While Artificial Neural Networks (ANNs) consistently outperform traditional PMV models in prediction accuracy, they lack transparency regarding how specific input parameters influence outputs [3]. Facility managers are often reluctant to deploy control logic they cannot audit or explain. This opacity is compounded in DRL approaches, where hyperparameter tuning is described as a time-consuming, trial-and-error process without standardized guidelines [17].

4.4 Future Directions

To bridge the gap between academic research and industrial application, future work must address the following trajectories:

- **Transfer Learning and Meta-Learning:** To overcome the cold-start problem described in [19], research should focus on transfer learning techniques that allow models trained on data-rich buildings to be adapted for new or data-poor environments with minimal fine-tuning.
- **Hybrid Modeling:** Combining physics-based principles (like EMUT [5]) with data-driven ML approaches could offer a compromise between accuracy and interpretability, fostering greater trust among building operators.
- **Multi-Objective Optimization:** Future frameworks should move beyond binary energy/comfort trade-offs to simultaneously optimize for indoor air quality, visual comfort, and acoustic constraints, as initially explored in [17].

5 Conclusion

This review has synthesized recent advancements in optimizing HVAC performance through data-driven methodologies, highlighting the paradigm shift from static, reactive control to dynamic, predictive management. The distilled insights from the surveyed literature demonstrate that integrating machine learning and economic theories into building management systems yields quantifiable benefits that traditional mechanisms cannot achieve.

The evidence is compelling: data-driven approaches consistently outperform conventional baselines. Optimization strategies based on Equal Marginal Utility Theory (EMUT) have shown energy reductions of approximately 4.74% without hardware changes [5], while demand-driven controls responding to real-time occupancy can achieve savings between 7% and 52% [13]. Furthermore, advanced Model Predictive Control (MPC) and Deep Reinforcement Learning (DRL) frameworks have demonstrated the capacity to reduce cooling energy consumption by up to 58.5% [19] while simultaneously improving indoor environmental quality [17].

In terms of thermal comfort, the literature confirms that machine learning classifiers (SVM, ANN) provide significantly higher prediction accuracy than Fanger's PMV model, particularly in naturally ventilated and equatorial climates [3], [4]. By incorporating diverse inputs—ranging from wearable sensor data [9] to computer vision-based activity recognition [16]—these models capture the complex, non-linear relationship between human thermal sensation and environmental variables.

However, the transition to intelligent building control is not without obstacles. The reliance on large, high-quality datasets, the "black box" nature of deep learning models, and the challenges of generalizing controls across different building typologies remain significant hurdles. Future research must prioritize the development of interpretable, transferrable models that can operate robustly in the face of real-world stochasticity. Ultimately, the successful deployment of these technologies depends on balancing the granular accuracy of complex algorithms with the reliability and transparency required for facility management operations.

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