MACHINE LEARNING PRACTICES DURING THE OPERATIONAL PHASE OF BUILDINGS: A CRITICAL REVIEW

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Abstract:
Machine Learning (ML) is gaining attention in civil engineering especially within operational phase of building life cycle. This phase is crucial for managing every energy aspect while ensuring occupant comfort. Previous ML experiments have explored occupant behavior, occupancy estimation, load prediction, defect detection, and Heating, Ventilation, and Air Conditioning (HVAC) system diagnostics. However, challenges such as ML transferability and limited literature on ML components for the operational phase hinder broader industry adoption. This critical review aims to assess the potential of ML in building operations, focusing on energy consumption, big data control, reinforcement learning, and thermal comfort modeling. By identifying knowledge gaps, the study recommends further research to leverage ML for sustainable energy consumption and occupant comfort. It highlights ML's promising role in striking a balance between energy efficiency and occupant wellbeing.

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1. INTRODUCTION

Current world population, according to the World meter, is about 8.1 billion [1]. At the dawn of agriculture, about 8000 B.C. the world's population was about 5 million, swelling to around 200 million by 1 A.D. [1]. The Industrial Revolution sparked rapid growth: the first billion by 1800, then each subsequent billion in shorter intervals. In the 20th century alone, population grown from 1.65 billion to 6 billion [2]. By 1970, the world had half its current population. By 2050, it is highly anticipated that the global population will reach almost ten billion [3, 4]. The requirement for buildings is increasing due to the increase of inhabitants in both rural and urban ecosystems. According to Census studies [5], only half of the global population was settled in urban environments while contributing to 2/3 of energy consumption.

The consequent developments in building constructions have caused more energy consumption specified to non-renewable earth resources such as minerals and fossil fuels [6]. While analyzing the building life-cycle stages, it is evident that the operational phase of buildings consumes more energy compared to all the other building life phases [7, 8]. The main cause of this enormous energy expenditure is the intense amount of water and electricity usage during the operational life stages [9, 10]. It is critical to assure user comfort whilst still regulating the rise of energy consumption in buildings.

Studies indicate that during building operational phase, which includes activities like heating,

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cooling, lighting, and appliance usage, buildings account for a substantial portion of global energy consumption, often around two-thirds or more [11, 12]. This emphasis on energy usage underscores the critical need for implementing energy-efficient practices and technologies during the operational lifespan of buildings to mitigate environmental impact and promote sustainability. The studies based on urban energy consumption modelling have suggested that simulation studies are more effective than data analytical works and trial-oriented experiments to investigate the impact of urban morphological factors on energy consumption [13, 14]. It is also noteworthy to mention here that the distinguished feature of simulation study over traditional field and data analyses is its capability to administrate the input parameters and the output energy consumption.

ML offers the advantage of observing and detecting abnormalities in building operations that may go unnoticed by humans. It can effectively analyze building energy consumption during the operational phase in urban ecosystems. While previous research focused on limited applications, this comprehensive review examines ML's use throughout the building life cycle's operational phase, including maintenance. It helps researchers identify trends, issues, and ML applications in building operations. The study conducted a critical review of scientific literature published in the last 30 years, focusing on articles with significant impact, novelty, and quality. This review article contributes to the establishment of sustainable development infrastructure beyond civil engineering, ML, data science, and environmental engineering, and provides valuable insights into the operational stage of buildings.

2. MACHINE LEARNING AT THE OPERATIONAL STAGES OF THE BUILDINGS

2.1 Energy Consumption of Buildings

Buildings significantly impact the global energy usage and greenhouse effect by accounting for about 30% of global energy consumption [15]. The operational phase of buildings, responsible for maintaining the internal conditions contributes for the most of energy emissions, emphasizing the need of energy efficiency improvements. One study focused on HVAC system on building planning process, identifying three types of optimization difficulties: model estimation, decision making and uncertainty analysis [16]. A comprehensive HVAC automation and optimization design framework were successfully designed in this study by using the Building Information Modelling (BIM), to counterfeit these challenges by improving the design quality and efficiency through interconnecting multiple design phases.

Recent advances in ML models aid in various activities related to energy systems and HVAC structures. Energy estimation methods are divided into physics-oriented models (i.e., forward models) and data-driven or "inverse" models [17]. Forward models require numerous inputs and find primary use in the building design. Inverse models are effective in predicting the performance of buildings and rely on existing data access through Building Energy Management Systems (BEMS). Statistical methods such as TRNSYS or ML techniques like EnergyPlus are applied to energy forecasts [18]. Statistical methods and ML techniques are applied to energy forecasts. Inverse models are effective during the operational stages since the studies, such as those presented by Turhan et al. [19] have in-depth analysis of theoretical implications of inverse models but the practical feasibility of these applications in real-time building operation simulations needs further validations.

Optimizing energy efficiency in buildings is essential for sustainability. Computer intelligence provides solutions through frameworks and algorithms for enhancing the energy system design. In terms of usage, both physical-based and data-driven models possess advantages, with data-driven models requiring past data and ML applications. The development and application of energy estimation models offer valuable insights for energy management and decision making in building lifecycle.

2.2 Machine Learning in the Sustainability of Smart Building

Interest in smart buildings has grown due to increased awareness regarding passive designs, energy use, and circular economic methods. Leveraging ML, sensor technologies, the Internet of Things (IoT), and big data analytics, regular buildings can be transformed into cost-effective smart buildings with minimal infrastructure adjustments. Smart buildings can be designed to adapt with advanced technologies and algorithms such as forecasting, robotics, wireless sensors, sensing applications and cloud computing [6]. ML and big data analytics are essential for delivering these intelligent services.

Occupancy-based solutions have evolved throughout time from basic binary inferences to advanced estimation techniques using sensor information and ML. A mathematical study [20] created a customized platform that incorporated acoustic sensors, light sensors, and humidity sensors through a mesh network. Data from these sensors and correlating building networks were fused using sensor fusion methods to extract relevant information. The study introduced three levels of occupancy estimation granularity: binary occupancy, category occupation, and precise number. Each level was analyzed and used to enhance the occupancy estimation in the subsequent stages. The mathematical analysis introduced a recurrent formula to determine the features at each level based on the previous phases and occupant classifications. These outcomes are used as new feature sets in the following stage.

Activity-based recognition in buildings involves identifying the current activities of occupants. A study [21] proposed dynamic K- means clustering and active learning for activity recognition in residential structures. Dynamic K-means clustering is used to collect unlabeled data and combines resulting clusters with previously undiscovered activities. Outliers pose a challenge in the clustering process [21] since they are extremely sensitive to clusters. Modeling studies have investigated typical activity patterns in residential buildings for predicting occupancy using the Markov Modulated Poisson Process (MMPP) [22, 23].

Transfer learning was studied to transfer the knowledge of occupant activity recognition among different settings. The focus of Chiang et al.'s [24] study was on variations created by sensors and the target domains in buildings. Single-resident situations with identical processes were examined, and a corresponding information distribution system based on a Support Vector Machine (SVM) was developed to transmit categorization results from a reference building to a target building. Two scenarios were examined: when identified datasets were available from both input and output sites and when only data sensor data from the source location was available. The first scenario aimed to boost activity learning in targeted location models using the information from the source location, while the second scenario used sensor readings to learn the activity models during the building's operational stage. The outcomes of the study of Chiang et al. [24] suggested that both scenarios can outperform the non-transfer learning models in terms of precision by 8%, and the success of the framework enables the testing of different models to enhance human-centric information systems regarding activity identification.

User Preference Estimation (UPE) methods in smart buildings focus on thermal comfort and aesthetic comfort. However, existing approaches for UPE, like Predicted Mean Value (PMV), lack personalized comfort criteria that vary among individual buildings [25]. Sarkar et al. [26] explored long-term user preferences to develop a sustainable dynamic controller to cater to the comfort levels of all co-occupants. They introduced a smartphone application to gather data on visual and thermal preferences. Gaussian and Beta functions were used to model thermal and light comfort preferences, respectively. These functions were determined using comfort indicators and least-squares linear regression.

Research using wireless sensor networks [27] utilized a wireless sensor network to monitor household devices based on user behavior. They employed data analysis clustering techniques to create user profiles based on temperature and light preferences. A modified Bayesian network was used by Shoji et al. [28] to learn residential preferences in home energy management networks. This allowed for appropriate device control in response to electricity price fluctuations while considering tenant comfort, particularly for devices like air conditioners and heat pump water heaters. These studies contribute to enhancing occupant comfort and energy management in smart buildings.

Research by Lange and Bergés [29] explored the electricity usage patterns of appliances in building operational phases. Waveform patterns were observed in this study using high-frequency current cycles to identify correlations among appliance components and using Artificial Neural Networks (ANN) to construct aggregate waveforms, applying recurrent selection to minimize training errors. The unsupervised waveform classification problem was studied using a Deep Neural Network (DNN) with binary activations.

An analytical study was implemented focusing on precooling techniques to reduce energy costs in commercial buildings [30] by adapting a grey box approach to evaluate thermodynamics in building materials and employing linear regression models and the Building Management System (BMS) to address regression problems. The results of the study exhibited substantial cost savings in energy bills of up to 34% and in energy consumption of 28%.

Statistical studies by [31] compared hybrid ML algorithms for heating and cooling load estimation using building architectural information. They evaluated the algorithms using standard deviation and absolute error analysis, finding that the hybrid solutions outperformed traditional neural network approaches. K-means clustering was used by Iyengar et al. [32] to analyze utility company datasets to classify the consumption profiles. The identified energy efficiencies in this study at residential buildings suggest the impact of solar penetration levels on utility operations as well as overhead energy consumption. These extensive research studies have paved the way for alternative but accurate ML techniques with high scopes for implementation in building energy calculation studies with enhanced accuracy and a comprehensive outlook.

A study by Ferdoash et al. [33] developed a framework to detect excessive airflow and determine the optimal starting time for precooling building HVAC systems. The authors used temperature sensors in two buildings and integrated the data with meteorological conditions to create basic models for HVAC energy reduction using linear regression and SVM. The study assessed how these models improved the predictive implementation of green HVAC policies. The researchers analyzed the extra flow above the lowest setting in variable air volume (VAV) systems and computed the observed change ratio at the Air Handling Unit (AHU) level to identify energy-efficient options.

In civil engineering's operational phase, Machine Learning (ML) is pivotal for managing energy aspects and occupant comfort. ML explores occupant behavior, load prediction, and HVAC diagnostics. Despite advancements, industry adoption hurdles persist, including ML transferability challenges. The approach to a sustainable building concept is presented in Fig. 1.

This review evaluates ML's potential in building operations, focusing on energy consumption and thermal comfort. It advocates for further research to enhance sustainability and occupant comfort. Integrating building information modeling and IoT technology shows promise, aiding energy monitoring and community comfort assessment. Adopting digital modeling for comfort indices and energy efficiency in smart buildings is crucial for sustainability goals.

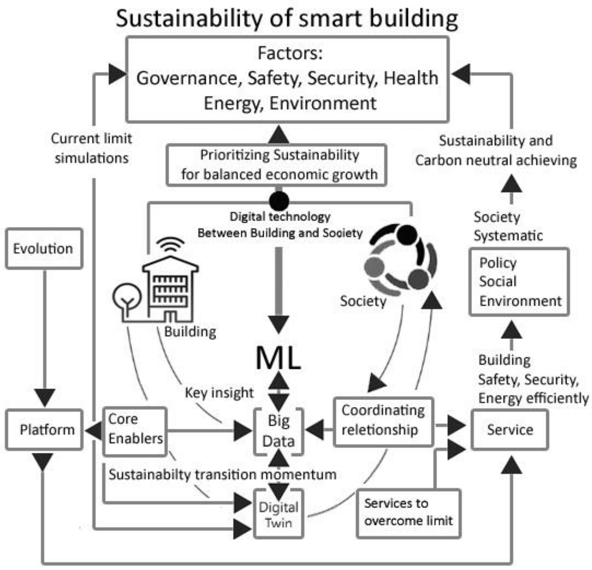

Fig. 1. Approach to a sustainable building concept

By analyzing this flowchart we advocates for adopting a model to foster sustainability in building environments, emphasizing economic and social perspectives. While building systems manage energy effectively, their efficacy falls short in broader sustainable contexts. Limitations include isolated building operations, hindering scalability, and data reliability issues due to lack of connectivity and lack of studies focusing on the integration of multiple computer-based simulation approaches. Addressing these challenges requires revising data protocols and tailoring operating policies to complex social environments. New technology, including ML platforms, big data analytics, and digital twin simulations, offers promise in achieving sustainable building operations aligned with economic, social, and environmental goals.

2.3 Reinforcement Learning Applications in the Building Control

Reinforcement Learning (RL) is an ML methodology that focuses on how intelligent entities should behave in a given environment. It incorporates user feedback into control logic, making it adaptable to human preferences. RL agents optimize cumulative rewards through actions in response to the environment's rewards [34]. Unlike supervised and unsupervised learning, RL does not rely on labeled data but instead considers the short and long-term consequences of inputs when deciding on the next strategy. Deep learning is often combined with RL in decision-making.

RL is particularly effective in complex contexts and can be programmed with specific scenarios to expedite learning. Simpler simulators have been developed to train RL controllers through simulation, showing promise for practical applications. Dimensionality compression is essential for reducing input patterns and training time, achieved through feature selection and extraction techniques like Principal Component Analysis [35]. Transfer learning is useful when datasets for a specific problem are unavailable, leveraging information from related issues.

While many studies focus on human comfort and fixed environments, there is a need to explore RL in managing multi-agent systems that respond to customer power prices and demand policies. RL research should also consider changing urban environments such as building renovation and expansion. Incorporating RL has demonstrated energy savings of over 20% in complex building energy management issues, Future research areas include deep RL algorithms, multitask RL for energy optimization, and the application of meta-learning to address RL challenges in building energy management [36]. Overall, RL offers a model-free approach to adaptively learn and optimize behaviors in dynamic environments. It shows potential for enhancing building sustainability and energy management.

2.4 Building a Thermal Comfort Model Based on Machine Learning

Thermal comfort is crucial for the wellbeing of occupants in building. Various comfort models like PMV, are used to assess occupant comfort but are complex and difficult to understand [37]. Enhancing interpretability in thermal comfort models is essential for modeling transparency, development, and operation [38]. It facilitates modeling accuracy, identifies design flaws, and optimizes building thermal control. Black box thermal ML models can be interpretable using the "input or output" (I/O) technique [39] to evaluate the effects of features on the model output. Studies by [40] introduced interpretable thermal comfort systems that surrogates using interpretable ML techniques and programmed thermal comfort solutions that are compatible with existing building management systems. Model surrogates were built based on interpretable machine-learning techniques to reveal the model processes for data processing that provided excellent realism for reproducing genuine model mechanisms [41], and surrogate-based interpretations are intuitive and instructive.

Improving interpretability in thermal comfort models is vital for transparency, accuracy, and optimization in building design and operation, enabling better identification of design flaws and enhancing occupant wellbeing.

3. DISCUSSIONS

This critical review focuses on the impact of ML studies in the operational stage of buildings. It highlights the significance of ML and identifies key areas for effective implementation. Binary occupancy, which determines if a location is inhabited, is a very fundamental consideration. Applications like light control, binary classification is sufficient. However, estimating the number of occupants using complex regression algorithms is valuable for scenarios like personalized room allocation, though implementation can be challenging.

Category estimation aims to generalize binary estimation by defining HVAC control categories. Some methods use noninvasive sensed data to identify inhabitants, benefiting security systems in buildings. SVM and Decision Trees are commonly used in this category. Transfer learning requires examining the temporal dependency of data instances. Models addressing short-term dependency, such as dynamic Bayesian Networks and Auto Regression Integrated Moving Average (ARIMA), are suitable [42, 43].

Survey-based procedures often involve engaging with residents, which can be intrusive. Some solutions employ regression ML methods such as curve fitting to fill in data gaps and minimize direct contact requirements for gathering information from occupants [44, 45]. Systems linking comfort levels to environmental factors like air temperature and natural lighting map occupants' satisfaction into groups to assess the extent of comfort promotion.

Energy profiling anticipates load by appliance and function using regression-based ML methods integrated with time series. Metrics such as p-value, correlation coefficient, and root mean square error (RMSE) are used for performance evaluation [35, 46]. ML studies in this category primarily focus on predicting peak hours and hold the potential for utilizing in-response systems of buildings.

Clustering and analytical tools assist in the characterization of large-scale data, exploring the impact of weather and time on energy consumption.

Some solutions like [47, 48] are applicable to isolated buildings, while others target buildings connected to smart grids and rely on advanced data acquisition. Convex piecewise linear classifiers and Bayesian Networks are commonly used for classification.

Association Rule Mining (ARM) aims to determine sensor location and anticipate sensor measurements. Classification efficiency in ARM is assessed using precision, confidence, support, and the magnitude of detected similarities [49]. Deep reinforcement learning enables the learning of complex rules and is essential for settings with larger action spaces and increasing sensor data. Multitask learning is effective for HVAC control strategies focusing on the number of occupants, and multi-objective optimization algorithms balance thermal comfort and energy expense.

There is a lack of research on meta-reinforcement learning in operational energy management, and methods like RL show promise for diverse control problems [50, 51]. Integrating multi-agent reinforcement learning for operating groups of houses can lead to cost-saving control plans. Applying multi-agent reinforcement learning in large-scale buildings can further enhance energy control and management in the operational stage of the building life cycle.

4. CONCLUSION

With abundant data and advanced algorithms, machine learning (ML) has garnered significant attention in the construction industry. While ML has matured in various fields, its application in building sustainability assessment is still in the early stages. Comprehensive solutions to enhance the operational phase energy management in buildings need advancements in required subtopics. Challenges include replicating experiments and comparing system effectiveness. Upcoming studies should possess multidisciplinary approach to address these challenges and focus on energy-saving building designs, programs and policies. Standardized control framework, methodology, and simulation tools are needed for consistency and comparison in building energy management systems implied in the operational stage.

The research delves into how ML models can optimize energy systems, particularly during the operational phase of buildings. It distinguishes between physics-oriented models and data-driven models, highlighting the effectiveness of the latter in predicting building performance and energy consumption. Exploring methods such as inverse modeling and statistical techniques like TRNSYS and EnergyPlus, it provides insights into energy forecasting and management.

The study showcases how ML, coupled with sensor technologies and IoT, can transform regular buildings into smart, energy-efficient structures. It discusses occupancy-based solutions, activity recognition, and user preference estimation methods, demonstrating how ML can enhance occupant comfort and energy management in smart buildings. The research explores the application of reinforcement learning (RL) in building control systems, emphasizing its adaptability to dynamic environments and potential for optimizing energy usage. It suggests future research directions in deep RL algorithms and multi-task RL for energy optimization, indicating the promising role of RL in enhancing building sustainability. The study addresses the importance of interpretable thermal comfort models for building occupants' well-being. By introducing interpretable ML techniques and surrogate-based interpretations, it offers transparent and realistic solutions for modeling thermal comfort, which can aid in optimizing building thermal control and design.

Conflicts of Interest

The authors declare no conflict of interest.

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