Issues in Information Systems
Volume 25, Issue 4, pp. 181-193, 2024

DOI: https://doi.org/10.48009/4_iis_2024_115

A survey of machine learning applications in commercial building management

Michael A. Bumpus, *bumpusma@gmail.com*

Abstract

Commercial building managers are faced with challenges in operating their facilities in an efficient and cost-effective manner. Energy and maintenance costs are large consumers of operational budgets and offer opportunity for improvement through machine learning and data analysis. From prediction and forecasting to outcome optimization, several machine learning techniques are uniquely suited for applications in building management. In addition to maintenance and operational improvements, machine learning, combined with sensors and intelligent environmental systems can help improve occupant satisfaction and worker productivity through improvements in air quality and lighting conditions. As enhancements in machine learning and artificial intelligence continue, the application for improvement in building operations will expand as well.

Keywords: machine learning, sustainability, neural networks, productivity, building management, energy

Introduction

Managers of commercial buildings, whether owner-occupied or as a contracted, third-party property management firm, face a variety of challenges that directly impact financial and operational activities. From managing utility consumption and equipment maintenance, to optimizing occupant experience and satisfaction, the challenges each rely on sound and data-driven decision-making. The rapid advancement of machine learning has helped to transform the dynamics of these decisions and drive automated and improved outcomes for both managers and users of commercial spaces.

Methodology and literature review

To better understand the prevailing concerns among building managers, a review of facility management literature was conducted. From this review the following themes emerged: reducing energy costs, maintenance planning and management, and occupant satisfaction. Energy costs stood out as the primary area of concern as well as chief operating expense, contributed both through the direct costs of energy consumption and through penalties and fines associated with sustainability compliance. Maintenance planning and operations are another significant area of concern for building managers, with goals of reducing downtime and system failures. Additionally, occupant satisfaction and experience round out the issues addressed in the research, with focus on comfort, productivity, and feedback mechanisms.

Understanding these themes and concerns in building management led to a review of current literature, published in the last five years, to explore how researchers have addressed each issue through machine learning models and algorithms. A selection of the machine learning literature reviewed is included in Table

1. To expand on the review, the primary areas of concern and their underlying drivers will be explored, and connections drawn between these building management issues and the relevant machine learning applications and concepts.

Table 1. Summary of selected machine learning literature

Reference	Topic	Summary
Alhammadi, 2023	Explores implementation of chatbots to optimize service delivery in facility management.	Showcases the benefits of machine learning chatbots to improve communications and reduce response times, while providing a human-like interaction.
Bouabdallaoui, Y. et al., 2021	Proposes a framework for predictive maintenance and includes a case study of an existing facility as well as potential barriers to implementation.	Outlines a five-step framework for implementing predictive maintenance models, applying these learnings to a case study for facility maintenance. Authors identified opportunities and limitations to successful model implementation.
Deng, X. et al., 2022	Reviews the role HVAC plays in energy consumption as well as how modern control systems can help offset these expenditures.	Proposes a control model based on a deep Q network and presented case study results indicating a 13% reduction in HVAC-driven energy consumption with limited impacts to occupant comfort.
Deng, Z., & Chen, Q., 2021	Details research on how occupant behavior impacts building performance using a simulation experiment built on reinforcement learning and Markov decision process to emulate occupants in the built environment.	Built and validated an occupant model using reinforcement learning and apply it to other buildings with success in accurately predicting the impact of occupant behavior on energy consumption in the surveyed buildings.
Koukaras, P. et al., 2022	Reviews concepts of prescriptive maintenance and related machine learning application for prescriptive analytics across system maintenance requirements.	Determined that prescriptive maintenance was more proactive than predictive maintenance in preventing system failures. The authors identified the limitations of current frameworks and available data, as well as the ability of machine learning algorithms to help bridge these gaps.
Kumar et al., 2020	Studies the use of air sensor data to predict next-day air quality through linear regression and machine learning.	Showed success in using time-series prediction methods in analysis and forecasting of air quality index levels based on IoT sensor data and proposes a model for future prediction considerations.
Mason, K., & Grijalva, S., 2019	Centers on the application of reinforcement learning in building automation and autonomous systems, with a focus on energy savings.	Determined reinforcement learning algorithms can improve energy savings, but most studies have been limited to simulations. Authors also noted that much of the literature does not account for environmental variances.
Saini et al, 2020	Explores the use of real-time indoor air quality sensing systems to reduce risks from indoor air pollution.	Recommends real-time IoT monitoring based on machine learning predictive systems for measuring and forecasting indoor air quality.
Zhou, S.et al., 2023	In-depth review of current literature on machine learning application in HVAC optimization, energy savings, and occupant comfort.	Determined that current machine learning research in HVAC optimization focuses heavily on supervised and reinforcement learning models, with a subset utilizing a mixed approach of machine learning techniques.

Energy consumption and sustainability

According to a report from the US Department of Energy's National Renewable Energy Laboratory (NREL), buildings make up 40% of all energy consumption in the United States and contribute 35% of US carbon emissions (Shoemaker, 2023). The United States government-backed ENERGY STAR program, which focuses on energy efficiency and environmental protection, reports that "energy use is the single largest operating expense in commercial office buildings" (ENERGY STAR, n.d.).

Beyond merely the direct costs associated with energy consumption, high energy usage can have significant impacts on a building's carbon footprint and sustainability score. With nearly 80% of energy in the United States being generated from fossil fuels, this accounts for a sizable opportunity to directly impact carbon emissions through sustainability and energy efficiency improvements (Center for Sustainable Systems, University of Michigan, 2023). In many municipalities and regions, both across the United States and globally, legislation has been enacted to help curb the impact of carbon emissions through taxation and penalties levied for non-compliance (Brightly, 2023).

Sustainability and greenhouse gas regulation

Over the last several decades, many individual governments and organizations have implemented programs focused on limiting greenhouse gas (GHG) emissions. In 2015, large scale, international focus intensified with the realization of the Paris Agreement. This agreement, ratified by 125 parties by 2017, paved the way for additional legislative actions at all levels of government. While each legislative act is unique, many share commonalities such as reducing GHG and reporting carbon emissions, with penalties and fines assessed for noncompliance. Table 2 lists a selection of some of the local, regional, and multi-national regulatory legislation that developed following the Paris Agreement (Lu & Lai, 2020; *Key Aspects of the Paris Agreement*, n.d.).

Table 2: Examples of Sustainability Legislation

Locale	Program	Scope
Washington (State)	Clean Building Performance Standards	Tier 1: All buildings over 50,000 sqft except multifamily residential Tier 2: Buildings 20,000-50,000 sqft and multifamily residential over 50,000 sqft[1]
Washington, D.C.	Building Energy Performance Standard	All ENERGY STAR buildings greater than 10,000 sqft must be scored at or above the District median score[1]
New York City	Local Law 97	All commercial and multifamily buildings greater than 25,000 sqft must file annual greenhouse gas reporting[1]
Colorado	House Bill 21-1286	All buildings larger than 50,000 sqft other than single family homes, duplexes, triplexes or spaces used for manufacturing or storage, must set and maintain benchmarks (Brightly, 2023)
Boston, Massachusetts	310 CMR 7.71: Massachusetts Greenhouse Gas Emissions Reporting	All non-residential buildings larger than 20,000 sqft must report emissions of CO_2, CH_4, N_2O, SF_6, HFCs, and PFCs
European Union	European Union Emissions Trading System	Cap and Trade program with annually decreasing limits driving to climate neutrality in 2050(;toCarbonZero, 2023; What Is the EU ETS?, n.d.)

Contributing factors to energy consumption in buildings

According to research from Zhou et al. (2023), heating, ventilation, and air conditioning (HVAC) systems contribute anywhere from 35 to 65 % of energy consumption within buildings, with variances according to building type. Additionally, the rise in extreme weather events has led to increased demands on HVAC systems to maintain occupant thermal comfort. Studies have shown the occupants' presence has a significant impact on energy consumption (Abuimara et al., 2021). Research from Roetzel et al. (2014), compared the energy consumption of two scenarios, one ideal and the other an extreme worst case, to best represent the full range of possible conditions. Roetzel et al. concluded that there would be a 250% increase in energy consumption in the worst-case scenario compared to the ideal scenario. The interaction between occupant activities, comfort preferences, building systems, and the physical environment can vary widely across schedules and spaces, making whole-building normalization difficult and in many cases, ineffective. Subsequently, the rise of hybrid work environments with variations in occupancy and space utilization has made the ability to forecast, prioritize, and manage the HVAC response to a variety of demand signals an even more crucial component of managing energy consumption (Kim & Srebric, 2017; Pérez-Lombard et al., 2008).

Equipment optimization

Improving the efficiency of building equipment can lead to a longer life and reduced energy expenditure, both reducing operational costs. Deng et al. (2022) discuss optimizing equipment through a combination of active change detection and reinforcement learning in the building environment, specifically focusing on the non-stationary nature of HVAC systems due to weather conditions, occupancy, run schedules, and equipment life. Reinforcement learning is a machine learning technique that utilizes an interactive environment for an agent to learn through trial and error. Each iteration in reinforcement learning provides feedback for subsequent iterations, with the goal being to refine the solution to maximize the reward signal, rather than focus on the hidden data patterns. A subset of reinforcement learning, Deep Q-Networks, was proposed by Deng et al. to accommodate the non-stationary environment with the goal of reducing energy consumption while maintaining acceptable occupant comfort levels. Deep Q-Networks utilize a neural network to estimate expected future rewards for a given action to optimize for complex environments. This process relies on learning from a variety of raw data which is ideal for complex decision making (Deng et al., 2022; Mason & Grijalva, 2019; Neelarghya, 2022). The case study covered by Deng et al. showed a 13% reduction in HVAC-driven energy consumption, while another review of existing studies by Zhou et al. (2023) indicated that machine learning optimization could improve HVAC energy consumption by as much as 30% while maintaining occupant comfort.

Forecasting and predicting demand for HVAC systems

Anticipating heating and cooling needs can enable energy cost reductions in HVAC systems through pre-cooling or pre-heating building spaces in response to weather forecasts, occupancy trends, or as a means of offsetting demand charges. This anticipation can be driven by machine learning applications either as stand-alone systems or embedded in other building and energy management systems. We can apply a combination of simulations, rule-based controls, and a deep-learning comparison of the preconditioning time vs historical weather data to forecast occupancy and preemptively condition spaces to improve thermal comfort. To fully optimize for energy savings, this must also be weighed against factors such as peak demand charges and occupant thresholds for comfort (Zhou et al., 2023; Deng & Chen, 2021; Parmar, 2023).

Zhou et al. (2023) explains that the first applications of machine learning to HVAC systems began as early as the 1990s and have expanded since then with a substantial amount of research geared towards balancing the needs for energy consumption and thermal comfort. This contribution from Zhou et al. delineates the application of machine learning, utilizing data from both indoor and outdoor sources, to anticipate the number and behavior of indoor occupants and modify the operation of air-conditioning or heating systems to ensure a more comfortable indoor environment. These machine learning applications utilize data such as historical occupancy trends, humidity and CO_2 levels, and indoor and outdoor temperatures to facilitate prediction and forecasting. Zhou et al. proposes the application of a combination of machine learning processes to address occupancy and comfort requirements, citing the work of Deng and Chen (2021). In Deng and Chen's research, the Markov Decision Process was used to mimic occupant behaviors. The Markov Decision Process is a mathematical framework that models decision-making problems with partially random and partially controllable outcomes and in this case, can address randomness through the probability that a particular state is or will occur. Deng and Chen also used Q-learning, an off-policy reinforcement learning algorithm, to account for occupant comfort. In this context, the meaning of off-policy is two-fold, indicating updates are made from the data of another policy rather than the one being evaluated, and also that it is model-free, learning through trial and error as opposed to requiring a pre-built model. (Deng & Chen, 2021; Jagtap, 2022; Mason & Grijalva, 2019; Papakyriakou & Barbounakis, 2022; Zhou et al., 2023).

Maintenance planning and operational improvements

Beyond reducing energy consumption, facility and equipment maintenance make up another large expense item for property owners and building managers. Machine learning can play a key role in both system optimization and predictive maintenance, reducing the frequency of service and repair visits, while increasing the usable lifespan of expensive assets. Traditional system maintenance required routine visits by technicians and inspectors to change filters, assess equipment condition, and make preemptive repairs. Each of these visits, while key to ensuring continued and effective operations, carries a cost. These traditional maintenance approaches are best described as either preventative or corrective. Preventative maintenance relies heavily on periodic inspections triggered by time or "usage-based" events (p.2). While this methodology has proven effective by reducing the occurrence of failures, it requires unnecessary and potentially disruptive inspections, and is still prone to unforeseen malfunctions. Corrective maintenance adopts a more hands-off approach, allowing equipment to operate until it fails. This failure can be costly both in repair and replacement, as well as in downtime. Predictive maintenance, however, monitors equipment operation to "predict the future machine health state" and "aims to predict when, where, and which components may have potential failures" (Bouabdallaoui et al., 2021).

Predictive maintenance offers facility managers the ability to plan maintenance activities for better alignment with building operations, budgets, and resources. As reported by Bouabdallaoui et al. (2021), studies have been conducted on applying data mining techniques along with time series forecasting with the goal of improving maintenance scheduling. In this context, time series forecasting analyzes patterns and data structure to develop a prediction model used to forecast future values based on previous data (Khan et al., 2023). The data behind these algorithms can come from the building systems' maintenance history, system logs, and operational metrics. Additional studies have centered around fault detection and diagnostics (FDD) simulations as well as vibration analysis "using Fourier transformation and fuzzy logic" to better assess equipment health and predict failures (p. 3). Fourier Transformation, named after French physicist and mathematician Jean-Baptiste Joseph Fourier, enables frequency analysis by transforming complex signals into frequency models, where distinct patterns begin to emerge. Further analysis of these patterns against volumes of time series data unlocks new insights into system operations and performance as well as detecting deviations or anomalies from the pattern. While, initially developed for signal processing, Fourier transformation now plays a crucial role in machine learning, especially in mechanical systems (Gomede, 2024). In addition to Fourier transformation, FDD simulations rely on fuzzy logic to uncover connections between variables. To do this, fuzzy logic utilizes the concept of degrees of truth as a spectrum of more true or more false values, often expressed linguistically rather than numerically. These variable connections have wide applications in predictive analytics and forecasting with large datasets and allow for the development of conditional rulesets driven by multiple variable states in concert to determine the most likely outcome (Jane & Ganesh, 2019; Uzoukwu, 2022; Cheng et al., 2023).

Bouabdallaoui et al. (2021) describes issues faced in model development for the built environment, specifically the time required to develop accurate models, the unique nature of each installation due to differences in building types, occupancy patterns, and design, as well as the broad categories and limited availability of building systems data (pp.11-12). However, since Bouabdallaoui et al.'s 2021 publication, data modeling, cloud computing, and edge analytics have undergone vast improvements. These fields' growth continues to accelerate and expand the capabilities and availability of complex machine learning applications. These advances are rapidly democratizing machine learning and opening new opportunities to understand and utilize diverse data to a greater degree (24x7 Offshoring, n.d.). Additionally, systems designers, installers, and maintainers have developed sensors and analytics to aggregate, store, and process the volumes of data generated by building equipment operations. Bulut and Özcan explain that as increases in system complexity and operating dynamics evolve, so must maintenance strategies. This has led researchers to develop solutions using "genetic algorithms, particle swarm optimization [and]… system-specific metaheuristics…designed for maintenance scheduling" (Bulut & Özcan, 2024, pp. 1-2). These techniques expand upon the previously discussed maintenance methodologies and leverage foresight to enable what is known as prescriptive maintenance.

Prescriptive maintenance combines predictive and descriptive analytics to enable the detection of system issues in an effort to prevent failures rather than just predicting them. Through the analysis of raw data coupled with time series and sensor-driven learning, prescriptive maintenance identifies potential failures and provides actionable recommendations for maintenance and repair. Various machine learning algorithms are employed in prescriptive maintenance, including time series forecasting and multi-objective reinforcement learning, to allow facility operators to make data-driven maintenance plans to optimize for cost, equipment performance, and operational cadences (Koukaras et al., 2022).

Occupant Satisfaction

Energy consumption, building maintenance, and equipment lifecycle management are all significant operational cost drivers, but an additional application for improvements through machine learning is in occupant satisfaction. As a key concern of building managers, occupant satisfaction can entail transparent and timely feedback loops using chatbots for ticketing and customer service inquiries, as well as operational and facility improvements that improve employee productivity.

Chatbots and customer service

An important aspect of occupant satisfaction is responsiveness to issues and requests. Alhammadi (2022) suggests that the use of facility management chatbots to manage service delivery through improved communication, improved responsiveness, and automated workflows. Another study focused on the use of a pre-trained Large Language Model (LLM) to summarize and categorize trouble tickets to improve routing and ticket management (Arici et al., 2023). LLMs are a subset of machine learning with the ability to understand and generate human-friendly text responses to prompts. They are trained on vast amounts of text data, consisting of billions of input parameters. Examples of common LLMs include BERT, or

Bidirectional Encoder Representations from Transformers, as well as GPT, or Generative Pre-trained Transformer. The Arici et al. study focuses on a BERT LLM, while GPT has become almost synonymous with LLM through the popularization of OpenAI's ChatGPT, now in its fourth iteration with GPT-4. ChatGPT has enabled more human-like chatbot experiences, with an ability to nuance context and generate responses that bridge domains across immense streams of information (Alhammadi, 2022; Arici et al., 2023; Dam et al., 2024).

Employee productivity

While there are many factors that contribute to productivity, a 2021 review by Van Der Voordt and Jensen, concluded that healthy workspaces had a positive impact on employee absences related to illness. Additional studies, referenced by the International WELL Building Institute, attributed the achievement of a WELL certification to a 10-percentage-point increase in median employee productivity. WELL v2 Certification is focused on ten concepts, but air quality and lighting stand out as important targets for improvement through building systems and machine learning (International WELL Building Institute pbc, 2022; Ildiri et al., 2022).

Air Quality

A large component of any health-focused productivity program, air quality is a measure of the concentration of contaminants suspended in the air and is often referred to as indoor air quality or IAQ. IAQ sensors commonly measure particulate matter 2.5 micrometers and smaller (PM2.5), carbon dioxide (CO_2), volatile organic compounds (VOCs), temperature, and relative humidity. Some at-risk populations with underlying respiratory issues have shown that these contaminants pose potential health risks, even at low concentrations. Studies have shown that sensor data combined with machine learning can be effective in predicting IAQ issues, allowing building operators and automated systems to react preemptively and reduce the risk of degraded air quality (Saini et al., 2020). Traditional statistical methods have been employed in the past to predict air quality impacts, but advances in machine learning offer additional solutions to aid in this effort. Techniques such as artificial neural networks and recurrent neural networks allow for the consideration of larger volumes and varieties of data in the prediction strategy (Kumar et al., 2020). These artificial neural networks are machine learning models inspired by the structure of the human brain and composed of a series of interconnected nodes. These nodes, or neurons, analyze complex data to make predictions and improvements in system efficiency. Recurrent Neural Networks are a type of artificial neural network that processes sequential time-series data to capture dependencies between data points over long periods of time by using a state value that carries information about prior occurrences of the data sequence (Bouabdallaoui et al., 2020).

Lighting

As covered in the previous sections, reducing energy consumption is a key issue among facility managers, however there must be a balance between energy conservation measures and building usability. Lighting, while contributing as much as 40% of energy expenditure, is also a significant factor in worker productivity (Putrada et al., 2022). Following their study on the impacts of light intensity and temperature (color), Lu et al. (2020) indicated that increasing lighting brightness and tuning lighting temperature to 4000k (Kelvin) directly improved working efficiency. Their study considered the subjective, task, and physiological impacts of lighting variations to accommodate variances in perception vs observed efficiency improvements. This study also revealed a potential relationship between light intensity and color within a "comfort zone" that could inform model design and training (p.11).

Issues in Information Systems
Volume 25, Issue 4, pp. 181-193, 2024

As most building work areas employ a mix of natural and artificial light sources, systems are needed to balance the added artificial lighting with current space illumination to optimize conditions. Smart and adaptive lighting systems can actively adjust lighting levels in response to natural light to maintain lighting intensity within a space. Furthermore, these adaptive systems can adjust lighting temperature to better mimic natural light at different times throughout the day, becoming warmer or more amber near sunrise and sunset and transitioning to cooler or more blue near midday. Figure 1 shows the relationship of the Kelvin lighting temperature scale's relationship to common lighting types.

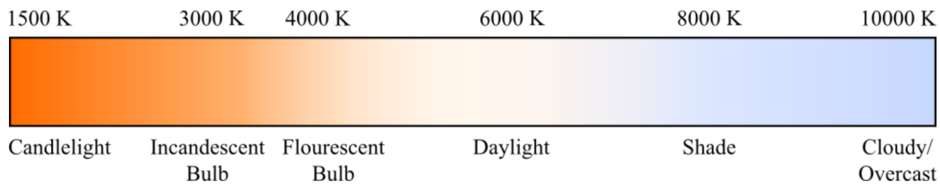

Figure 1: Comparison of Kelvin Temperature Scale to Common Lighting Types

The system feature that allows for scheduled control of lighting temperature is commonly known as circadian lighting as it follows the natural pattern of sunlight throughout the day. Circadian lighting has been shown to reduce fatigue, positively impacting productivity. Modern smart lighting systems use model predictive control to forecast future scenarios based on learned data models. These predictions are then used to control lighting intensity and temperature to maintain a desired level within the space. In addition to predictive control, intelligent control uses sensors to detect light levels, motion, and occupancy to drive lighting settings through fuzzy logic algorithms. More advanced systems can take advantage of existing digital CCTV cameras and computer vision to adjust lighting conditions to optimize for particular activities. In activity recognition, machine learning can draw upon training models to extract and understand the activities observed in the camera image and categorize the activity into "learned" activity types, allowing for relevant lighting scenes and setpoints to be activated accordingly (Putrada et al., 2022).

Commercialized solutions and patents in-force

As discussed throughout this survey, machine learning has a multitude of applications tailored to building and equipment management, with theoretical applications appearing as early as the 1990s. Technological enablement over the last decade has moved this field from theory to commercialization, with tools such as vibration analysis and fault detection being embedded within building automation systems. Advances in cloud computing and industrial IoT continue to make more complex machine learning available to the commercial sector and have given rise to the concept of smart buildings. According to *Intelligent Power Today* (n.d.), the integration of machine learning applications into building automation systems is already changing the way buildings operate through prioritizing maintenance activities, automatically adjusting HVAC and lighting settings to optimize energy consumption during peak demand, and tailoring system setpoints to balance individual comfort needs. A *Conexus Community* blog post by Gable (2022), imagines a near future, where machine learning can use data from wearable technology to automatically drive room setpoint changes and adjust to occupancy fluctuations throughout a building in real time. Machine learning is already beginning to find its way into these building systems and will continue to shape building outcomes as the technology advances. Table 3, while not exhaustive, shows a sampling of currently in-force patents relevant to commercially available machine learning implementations.

Table 3: Sample of Relevant Patents

Patent Number	Year Granted	Inventor(s)	Description
US10852023B2	2020	Viswanath Ramamurti, Young M. Lee, Youngchoon Park, Sugumar Murugesan	Building management autonomous HVAC control using reinforcement learning with occupant feedback
EP3627261B1	2021	Babak Mohajer Ashjaei	Diagnosis system and method using parallel analysis paths
US11126171B2	2021	Charles Howard Cella, Gerald William Duffy, JR., Jeffrey P. McGuckin, Mehul Desai	Methods and systems of diagnosing machine components using neural networks and having bandwidth allocation
US11774922B2	2023	Robert Locke, Sudhi R. Sinha	Building management system with artificial intelligence for unified agent based control of building subsystems
US11604441B2	2023	Sugumar Murugesan, Young M. Lee, ZhongYi Jin, Jaume Amores	Automatic threshold selection of machine learning/deep learning model for anomaly detection of connected chillers
US11732967B2	2023	Yohann Lilian Rousselet, Ellie M. Litwack	Heat exchanger system with machine-learning based optimization

Conclusions and recommendations for future research

This survey has explored several prevailing methodologies in machine learning and their application in solving common issues faced in building management. The vastness and variety of building data coupled with complex and competing outcomes make machine learning uniquely positioned to help derive solutions across domains. While each distinct use case has specific uniqueness that aligns well to a particular machine learning methodology, much of the role machine learning plays in areas of energy management, maintenance planning, even productivity connect back to predicting future states based on simulations and historic data sets. By tailoring these requirements to the appropriate methodology, building management processes and systems can be enhanced to reduce costs, downtime, and increase occupant satisfaction. In addition to predictive and forecasting models, the recent rise of ChatGPT and the use of LLMs offer new opportunities to apply machine learning to text and conversational data in the building environment, with implications ranging from chatbot assistants to trouble ticket prioritization and routing. The volumes of data generated in commercial buildings will continue to offer new opportunities for the expansion of machine learning in the space.

While many of these concepts are still based on theory and simulation data, future research should focus on implementation and operations case studies, highlighting real-world observations in comparison to theoretical scenarios. As the footprint of machine learning techniques and commercialization in this space continue to grow, additional analysis and systematic review of outcomes and improvements could add considerably to the body of thought in commercial building management. Advancements in this research will also continue to create efficiencies applicable to cost savings in energy management, maintenance planning, and occupant satisfaction.

References

24x7 Offshoring. (n.d.). *Machine Learning in 2024: Best Navigating the frontier of innovation*. https://24x7offshoring.com/machine-learning-in-2024-navigating-the/?feed_id=44026 &_unique_id=65f55e82e2b25

Abuimara, T., Hobson, B. W., Gunay, B., O'Brien, W., & Kane, M. (2021). Current state and future challenges in building management: Practitioner interviews and a literature review. *Journal of Building Engineering*, *41*, 102803. https://doi.org/10.1016/j.jobe.2021.102803

Alhammadi, M. (2023). Optimising Customer Service Delivery and Response Time through AI-Enhanced Chatbots in Facilities Management-A Mixed-Methods Research. *American Journal of Smart Technology and Solutions*, *2*(2), 43–54. https://doi.org/10.54536/ajsts.v2i2.2206

Arici, N., Putelli, L., Gerevini, A. E., Sigalini, L., Serina, I., Department of Information Engineering, University of Brescia, & Mega Italia Media. (2023). LLM-based Approaches for Automatic ticket Assignment: a real-world Italian application. *NL4AI 2023: Seventh Workshop on Natural Language for Artificial Intelligence*, 1. https://ceur-ws.org/Vol-3551/paper4.pdf

Bouabdallaoui, Y., Lafhaj, Z., Yim, P., Ducoulombier, L., & Bennadji, B. (2020). Natural Language processing model for managing maintenance requests in buildings. *Buildings*, *10*(9), 160. https://doi.org/10.3390/buildings10090160

Bouabdallaoui, Y., Lafhaj, Z., Yim, P., Ducoulombier, L., & Bennadji, B. (2021). Predictive Maintenance in Building Facilities: A Machine Learning-Based approach. *Sensors*, *21*(4), 1044. https://doi.org/10.3390/s21041044

Brightly, A Siemens Company. (2023, February 22). 7 US-based emissions reporting mandates with potential penalties you should know about. *Brightly Software*. https://www.brightlysoftware.com /blog/7-us-based-emissions-reporting-mandates-potential-penalties-you-should-know-about#

Bulut, M., & Özcan, E. (2024). Planning of prescriptive maintenance types for generator with fuzzy logic-based genetic algorithm in a hydroelectric power plant. *Expert Systems With Applications*, *240*, 122480. https://doi.org/10.1016/j.eswa.2023.122480

Center for Sustainable Systems, University of Michigan. (2023). U.S. Renewable Energy Factsheet. In *https://css.umich.edu/publications/factsheets/energy/us-renewable-energy-factsheet* (No. CSS03-12). University of Michigan. https://css.umich.edu/sites/default/files/2023-10/Renewable% 20Energy_CSS03-12.pdf

Chen, Z., O'Neill, Z., Wen, J., Pradhan, O., Yang, T., Lu, X., Lin, G., Miyata, S., Lee, S., Shen, C., Chiosa, R., Piscitelli, M. S., Capozzoli, A., Hengel, F., Kührer, A., Pritoni, M., Liu, W., Clauß, J., Chen, Y., & Herr, T. (2023). A review of data-driven fault detection and diagnostics for building HVAC systems. *Applied Energy*, *339*, 121030. https://doi.org/10.1016/j.apenergy.2023.121030

Dam, S. K., Hong, C. S., Qiao, Y., & Zhang, C. (2024). A complete survey on LLM-based AI chatbots. *arXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2406.16937

Deng, X., Zhang, Y., Zhang, Y., & Qi, H. (2022). Towards optimal HVAC control in non-stationary building environments combining active change detection and deep reinforcement learning. *Building and Environment*, *211*, 108680. https://doi.org/10.1016/j.buildenv.2021.108680

Deng, Z., & Chen, Q. (2021). Reinforcement learning of occupant behavior model for cross-building transfer learning to various HVAC control systems. *Energy and Buildings*, *238*, 110860. https://doi.org/10.1016/j.enbuild.2021.110860

ENERGY STAR. (n.d.). *Commercial Real Estate: An overview of energy use and energy efficiency opportunities*. https://www.energystar.gov/sites/default/files/buildings/tools/Commercial RealEstate.pdf

Gable, K. (2022, April 19). Building automation systems can benefit from machine learning. *Conexus Community*. https://www.conexuscommunity.com/blog/building-automation-can-benefit-from-machine-learning/

Gomede, E., PhD. (2024, April 11). The Fourier Transform and its Application in Machine Learning. *Medium*. https://medium.com/p/edecfac4133c

Ildiri, N., Bazille, H., Lou, Y., Hinkelman, K., Gray, W. A., & Zuo, W. (2022). Impact of WELL certification on occupant satisfaction and perceived health, well-being, and productivity: A multi-office pre- versus post-occupancy evaluation. *Building and Environment*, *224*, 109539. https://doi.org/10.1016/j.buildenv.2022.109539

Intelligent Power Today. (n.d.). *Building Automation: Artificial intelligence and machine learning*. Intelligent Power Today Magazine. https://intelligent-power-today.com/building-automation/building-automation-artificial-intelligence-and-machine-learning

International WELL Building Institute pbc. (2022). The WELL factor: Understanding the impact of WELL certification. In *https://www.wellcertified.com/*. Retrieved May 20, 2024, from https://7039796.fs1.hubspotusercontent-na1.net/hubfs/7039796/WELLStudy.pdf

Jagtap, R. (2022, November 21). *Understanding the Markov Decision Process (MDP)*. Built In. https://builtin.com/machine-learning/markov-decision-process

Jane, J. B., & Ganesh, E. N. (2019). A review on big data with machine learning and fuzzy logic for better decision making. *International Journal of Scientific & Technology Research*, *8*(10), 1121–1125. *Key aspects of the Paris Agreement*. (n.d.). [Website]. UNFCC.Int. https://unfccc.int/most-requested/key-aspects-of-the-paris-agreement

Khan, S. U., Khan, N., Ullah, F. U. M., Kim, M. J., Lee, M. Y., & Baik, S. W. (2023). Towards intelligent building energy management: AI-based framework for power consumption and generation forecasting. *Energy and Buildings*, *279*, 112705. https://doi.org/10.1016/j.enbuild.2022.112705

Kim, Y., & Srebric, J. (2017). Impact of occupancy rates on the building electricity consumption in commercial buildings. *Energy and Buildings*, *138*, 591–600. https://doi.org/10.1016/j.enbuild. 2016.12.056

Koukaras, P., Dimara, A., Herrera, S., Zangrando, N., Krinidis, S., Ioannidis, D., Fraternali, P., Tjortjis, C., Anagnostopoulos, C., & Tzovaras, D. (2022). Proactive buildings: a prescriptive maintenance approach. In *IFIP advances in information and communication technology* (pp. 289–300). https://doi.org/10.1007/978-3-031-08341-9_24

Krödel, M., & Martin, G. (n.d.). Artificial intelligence in the field of building automation. *EnOcean Alliance*. https://www.enocean-alliance.org/wp-content/uploads/2020/10/201004_Artificial-Intelligence-in-the-field-of-Building-Automation_final.pdf

Kumar, R., Kumar, P., & Kumar, Y. (2020). Time Series Data Prediction using IoT and Machine Learning Technique. *Procedia Computer Science*, *167*, 373–381. https://doi.org/10.1016/j.procs.2020.03.240

Lu, M., Hu, S., Mao, Z., Liang, P., Xin, S., & Guan, H. (2020). Research on work efficiency and light comfort based on EEG evaluation method. *Building and Environment*, *183*, 107122. https://doi.org/10.1016/j.buildenv.2020.107122

Lu, M., & Lai, J. (2020). Review on carbon emissions of commercial buildings. *Renewable & Sustainable Energy Reviews*, *119*, 109545. https://doi.org/10.1016/j.rser.2019.109545

Mason, K., & Grijalva, S. (2019). A review of reinforcement learning for autonomous building energy management. *Computers & Electrical Engineering*, *78*, 300–312. https://doi.org/10.1016/j.compeleceng.2019.07.019

Neelarghya. (2022, January 6). Reinforcement Learning vs Genetic Algorithm — AI for Simulations. *Medium*. https://medium.com/xrpractices/reinforcement-learning-vs-genetic-algorithm-ai-for-simulations-f1f484969c56

Papakyriakou, D., & Barbounakis, I. S. (2022). Data Mining Methods: a review. *International Journal of Computer Applications*, *183*(48), 5–19. https://doi.org/10.5120/ijca2022921884

Parmar, D. (2023, October 8). The role of machine learning in building automation. *Medium*. https://medium.com/@devanshi.parmar14/the-role-of-machine-learning-in-building-automation-36731519e8a4

Pérez-Lombard, L., Ortiz, J., & Pout, C. (2008). A review on buildings energy consumption information. *Energy and Buildings*, *40*(3), 394–398. https://doi.org/10.1016/j.enbuild.2007.03.007

Putrada, A. G., Abdurohman, M., Perdana, D., & Nuha, H. H. (2022). Machine learning Methods in Smart Lighting Toward Achieving User Comfort: a survey. *IEEE Access*, *10*, 45137–45178. https://doi.org/10.1109/access.2022.3169765

Roetzel, A., Tsangrassoulis, A., & Dietrich, U. (2014). Impact of building design and occupancy on office comfort and energy performance in different climates. *Building and Environment*, *71*, 165–175. https://doi.org/10.1016/j.buildenv.2013.10.001

Saini, J., Dutta, M., & Marques, G. (2020). A comprehensive review on indoor air quality monitoring systems for enhanced public health. *Sustainable Environment Research*, *30*(1). https://doi.org/10.1186/s42834-020-0047-y

Shoemaker, S. (2023, September 14). *NREL researchers reveal how buildings across United States do—and Could—Use Energy*. News | NREL. https://www.nrel.gov/news/features/2023/nrel-researchers-reveal-how-buildings-across-the-united-states-do-and-could-use-energy.html

toCarbonZero. (2023, March 9). *The different carbon emission regulations around the world*. https://www.linkedin.com/pulse/different-carbon-emission-regulations-around-world-51tocarbonzero/

Uzoukwu, N. (2022, September 18). Machine Learning with Fuzzy Logic - Towards Data Science. *Medium*. https://towardsdatascience.com/machine-learning-with-fuzzy-logic-52c85b46bfe4

Van Der Voordt, T., & Jensen, P. A. (2021). The impact of healthy workplaces on employee satisfaction, productivity and costs. *Journal of Corporate Real Estate*, *25*(1), 29–49. https://doi.org/10.1108/jcre-03-2021-0012

What is the EU ETS? (n.d.). Climate Action. https://climate.ec.europa.eu/eu-action/eu-emissions-trading-system-eu-ets/what-eu-ets_en

Zhou, S., Shah, A., Leung, P., Zhu, X., & Liao, Q. (2023). A comprehensive review of the applications of machine learning for HVAC. *DeCarbon*, *2*, 100023. https://doi.org/10.1016/j.decarb.2023.100023