ADVANCED REVIEW

Trending Machine learning Models in Cyber-Physical Building Environment - A survey

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Electricity usage of buildings (including offices, malls, and residential apartments) represents a significant portion of a nation's energy expenditure and carbon footprint. In the US, the buildings' appliances consume 72% of the total produced electricity approximately. In this regard, cyber-physical system (CPS) researchers have put forth associated research questions to reduce cyber-physical building environment energy consumption by minimizing the energy dissipation while securing occupants' comfort. Some of the questions in CPS building include finding the optimal HVAC control, monitoring appliances' energy usage, detecting insulation problems, estimating the occupants' number and activities, managing thermal comfort, intelligently interacting with the smart grid. Various Machine Learning (ML) applications have been studied in recent CPS researches to improve building energy efficiency by addressing these questions. In this paper, we comprehensively review and report the contemporary applications of ML algorithms such as deep learning, transfer learning, active learning, reinforcement learning, and other emerging techniques that propose and envision to address the above challenges in the CPS building environment. Finally, we conclude this article by discussing diverse existing open questions and prospective future di-

Abbreviations: CPS, Cyber-Physical Systems. NSF, National Science Foundation

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rections in the CPS building environment research.

KEYWORDS
Deep Learning, Transfer Learning, Active Learning, Reinforcement Learning and Control, Cyber-physical building environment.

1 | INTRODUCTION

According to the United States Environmental Protection Agency (EPA), households and commercial buildings consume 70% of the total electricity. The EPA further sorts the Heating, Ventilation, and Air Conditioning (HVAC) system, lighting, and other appliances as the major contributors to household energy usage. HVAC system alone accounts for more than 40% of the total household energy Energy (2010). The HVAC and some electrical appliances are not optimized for the occupants. Moreover, the existing thermal leakage in the building envelope forces the HVAC appliances to consume more energy to keep up the comfort level and cover the unwanted thermal losses. Still, this tremendous energy consumption causes thermal discomfort for occupants because of poor management, scheduling, and retrofitting. This gap has created a research opportunity both in energy-saving and appropriate comfort level management. To enable building as an intelligent system, the processing, modeling, learning, and inference of a large amount of the information on the building energy profile, thermal quality, occupancy, and comfort level are warranted. Numerous studies show that the intelligent usage of building electric appliances is a potential solution. The goal is to simultaneously improve the comfort of the occupants while minimizing the energy usage of household appliances such as the HVAC and other appliances. To solve these myriad sets of cyber-physical building environment challenges, various machine learning and data-driven solutions have been postulated.

Various machine learning methodologies from the literature have already been designed to practical models in order to solve the building decision-making problems such as effective usage of energy, occupancy detection, and comfort level navigation. Nevertheless, the ML algorithms' performance greatly depends on the data quality and quantity to develop them. However, some of the ML approaches can operate and sustain during data scarcity and sparsity, missing data, and limited ground truth information.

In this article, we review and study the most recent applications of ML algorithms to cyber-physical building environment energy efficiency-related problems. We posit the work related to solving the cyber-physical building environment decision problems such as occupancy detection, HVAC control, the activities of daily lives (ADL), energy disaggregation, and thermal leakage detection. We primarily focus on the trending ML methodologies used by researchers in the cyber-physical building environment in recent years. We put forth the challenges and solutions related to modeling, learning, and inferring the contextual information about the building leveraging novel technological innovations in Internet-of-Things devices such as smart plugs, smart thermostats, low-power IR cameras, Drones, etc. We articulate different experiments along with empirical and evaluation methods applied to building-related data for validating the ML models and approaches.

This review article is organized as follows. We look into the previous survey papers on the cyber-physical building environment and discuss the research gap we plan to bridge in this review article in section 2. We outline the relevant contents, scopes, and the focuses the review paper covers in section 3. We discuss the deep learning methodologies in section 4. Section 5 depicts the transfer learning, section 6 covers the active learning and section. Section 7 describes ensemble and classical machine learning algorithms with application to the cyber-physical building environment. We discuss machine learning control problems and summarizes their application, particularly reinforcement learning in the context of decision-making problems for cyber-physical building environment in section 8. Section

9 discusses a comparative analysis of the different methodologies, and section 10 positions the prospective future research directions in the field of ML application in the cyber-physical building environment. We conclude the review paper in section 11.

2 | RELATED WORKS

Various research groups, focused on different aspects of the problem, conduct multiple types of research on cyber-physical building environments. Several review papers cover various branches of current literature in conjunction with the cyber-physical building environment and signal processing section. Guo et al. (2019) provided an overview focusing on the recent products and technologies for the cyber-physical building environment. Qolomany et al. (2019) reviewed the application of ML and big data in different systems for comfort, security, and energy efficiency. Huang (2018) included the advancements in occupancy detection and energy-saving adopting Wi-Fi data usage in cyber-physical building environment. Chen et al. (2018) focused on reviewing occupancy estimation from the fusion of sensor data. Kim et al. (2018) provided the overall paradigm for the thermal comfort models. Vázquez-Canteli and Nagy (2019) comprehensively discussed works and advancements on multi-agent learning to control diverse energy systems for demand response using reinforcement learning algorithms. Miller et al. (2018) reviewed the applications of only unsupervised statistical learning algorithms, smart meter operation, optimization, and control. Saberi and Menes (2020) reported the prospect of application of artificial intelligence to improve building design and construction. Nguyen and Aiello (2013) surveyed the researches relevant to energy-saving and user activity recognition in the building domain. Their report analyzed the importance and impacts of activity recognition on energy savings for HVAC systems, lights, and plug loads.

To our knowledge to date, we found no review paper covering the spectrum of ML applications in cyber-physical building environments. A comprehensive review including the diverse domain focusing on data-driven ML methodologies would provide a helpful overview of this particular research area. This review would allow data domain researchers to perceive the state-of-the-art and trending ML solutions to these decision problems in cyber-physical buildings. This review would also provide a baseline and represent the state of the arts for new researchers in this field with potential research directions.

3 | SCOPE OF THIS REVIEW PAPER

In this paper, we have comprehensively studied the recent trending machine learning methodologies in the context of the cyber-physical building environment. We have focused on minimizing energy usage in building environments without any major retrofitting. We have covered scientific advancements in machine learning applications in cyber-physical building environments from 2015 - June 2020. We have incorporated the application specific to the field of occupancy detection, thermal leakage detection, non-intrusive load monitoring (NILM), ADL in a cyber-physical building environment for energy-saving, HVAC control, non-intrusive load monitoring, occupant's thermal comfort. Besides accumulating recent applications, we have explored and discussed the potential challenges, prospective directions in this field of the cyber-physical building environment for ML researchers to contribute and enhance as depicted in figure 1. We have searched for the potential papers by exhaustively looking at the top conferences, workshops featuring cyber-physical building envelopes. We have also navigated the researches of the leading researchers, research groups contributing to the cyber-physical building environment and machine learning applications. We have also used the dblp, google scholar, researchgate to explore the recent and follow-up publications in our selected timeline.

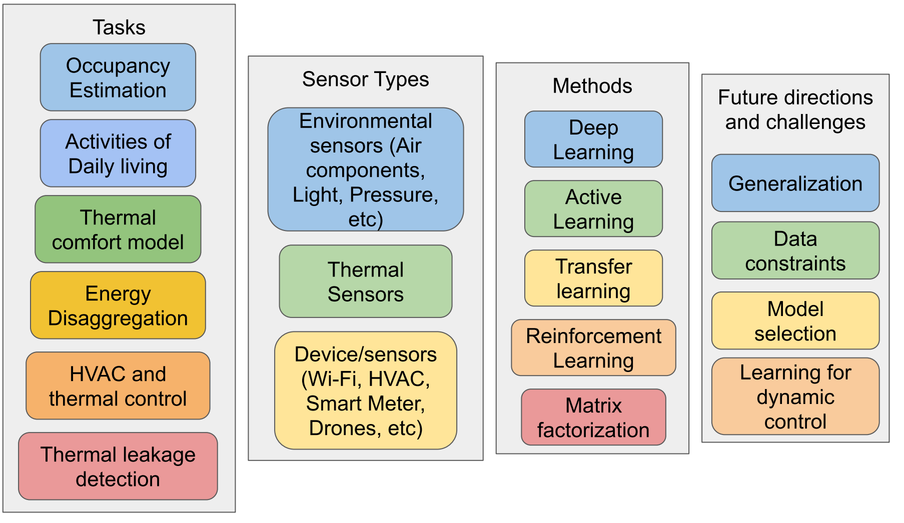

FIGURE 1 Contents and scope of this review paper.

4 | DEEP LEARNING

Deep learning (DL) methods cover a family of artificial neural network-based machine learning methods. DL enables representation learning from the input to the output by parametric function approximation. The recent advancement in algorithms, innovation of high power computing resources and storage, and availability of large amounts of data have contributed significantly to develop DL methods and their widespread applications in numerous fields. With enough data examples and varieties, appropriate supervised deep learning architecture can learn approximate functions to achieve desired output from input data with generalization. Besides, unsupervised and semi-supervised DL methods can benefit from the unlabeled data by understanding hidden structure and distribution properties. Learning the generalized information about data, DL models can perform with high accuracy and reliability in test cases. Another benefit of DL methods that they can work directly on sensor data as they are capable of extracting features by learning better data representation, whereas traditional ML methods require different selected features (mean, median, max, Fourier of the sensor data) to work with. Various state-of-the-art DL techniques have been deployed to cyber-physical building environment building settings. These models leverage the raw or minimum prepossessed input data to infer the target information. In this section, we will cover Generative Adversarial Network (GAN), convolutional neural network (CNN), recurrent neural network (RNN), deep neural network (DNN), long short-term memory (LSTM) method based applications in cyber-physical system (CPS) building environment research.

Chen and Jiang (2018) applied a generative adversarial network (GAN) to learn the occupancy distribution in the office environment via a generator network. Their result demonstrates the effectiveness of GAN to predict occupancy characteristics in a certain setting. Convolutional network architectures perform excellently in computer vision-related problems. Royuela-del Val et al. (2019) applied CNN architecture on thermal images to estimate the leakage and air infiltration rate through the building environment. Their report shows the CNN model outperforms the fully connected neural network. Chaudhuri et al. (2019) proposed a personal thermal comfort model using CNN. They also design a neural network to find optimal operating conditions for HVAC to meet thermal comfort while saving energy. Jia et al. (2019b) applied tree-based CNN (TreeCNN) architecture to iterative energy disaggregation. They claim applying TreeCNN does better to separate the energy of different appliances of different load scales. They extract the heavy load first and carry on for further energy disaggregation. Adeogun et al. (2019) analyzed Lora-based Internet of things (IoT) sensor data by applying a fully connected neural network to estimate occupancy in office settings. Abedi and Jazizadeh (2019) applied a deep neural network to detect occupancy presence using Doppler radar sensors. Bienvenido-Huertas et al. (2019) applied two layers of a neural network to estimate building envelope U-value within certain confidence bound using multi-modality data. Gayathri et al. (2017) applied a multi-layer neural network on fusion of motion, temperature sensors data for monitoring ADL. Park et al. (2019a) presented a poster describing the modeling of occupancy using CNN-based autoencoder. They represented the American time use survey data in their low dimensional latent space to infer important insight into the occupancy profiles. For quick diagnostic of building wall defects, Perez et al. (2019) proposed CNN-based classifiers to classify three types of building weaknesses; Moulds, deterioration, strain. The further localized building defects area from building envelope images via class activation map (CAM) techniques using their trained CNN architectures. The author argued about the potential of their methods to scale up and automation using mobile devices and drones.

RNN architectures are designed to work with time-series data. Wang et al. (2018b) proposed a Markov-based feedback RNN occupancy estimation system. The authors used a sequential Wi-Fi signal strength index (RSSI), MAC address to estimate occupancy in an office environment with high accuracy. Zhao et al. (2018) used Elman RNN architecture on temperature and light features of the office environment to accurately estimate occupancy. LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Units) overcomes the vanishing or exploding gradient problems of RNN architecture for time series by gating mechanism. Kelly and Knottenbelt (2015) demonstrated that LSTM outperformed other methodologies in their nonintrusive load monitoring problem on their collected data. Pathak et al. (2018) proposed architecture consists of one CNN and two LSTM layers to disaggregate energy on the Dataport dataset psd (2020). The authors further proposed an autoencoder-based network to the same problem and considered different time sampling to energy disaggregation problems. Singh et al. (2017) applied a network of convolutional and LSTM layers to detect activities of daily lives on data from Van Kasteren et al. (2008). Their architecture outperforms the probabilistic baseline models in the test case. Recently, Wi-Fi routers' signals have gained attention for building occupancy monitoring due to their ubiquitous presence in both household and commercial buildings. Wang et al. (2019) applied the LSTM network to estimate a large number of the occupant in a commercial building environment by monitoring Wi-Fi access points data simultaneously considering the privacy issues.

5 | TRANSFER LEARNING

Transfer learning uses the gained knowledge and information of one problem domain to different but somewhat related domains. Cyber-physical building domain researchers have massive opportunities to apply transfer learning due to commonalities among source domains and target tasks as in figure 2. The trained ML models expect to perform accurately and consistently on different data environments it was originally trained upon by learning better generalization and scale-ability. But various proposed cyber-physical building environment system performs only on the training environment. The change in input data distribution impacts the

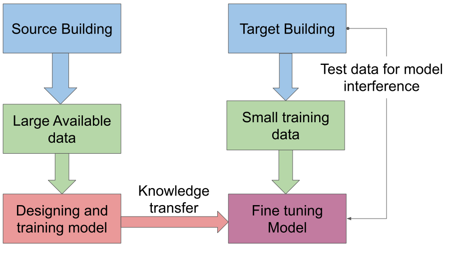

FIGURE 2 Transfer learning scheme for home.

decision accuracy. Transfer learning strategies would make the ML models robust under diverse scenarios by learning better representation. It also reduces the necessity of enormous data and training time for the fine-tuning models for the target domain as the models have already converged and contained domain knowledge. In the case of dissimilarity between source and target domain heterogeneous transfer learning (HTL) methods performs well. Domain adaptation (DA) can be formulated as HTL problems in the case of source domain variability.

Transfer learning algorithms and strategies have their wide application as a prospective solution in the cyber-physical building environment domain. Hu et al. (2019) proposed a multi-layer neural network-based HTL architecture to decide on personal thermal comfort intelligently. The authors include heterogeneous features in two staged learning architectures. Their architecture can successfully integrate different features in the target domain with the learned parameters from the source domain. In Arief-Ang et al. (2017) the authors incremented their earlier developed model in different settings using DA methods to estimate occupancy with higher precision. The author reported reducing the training data while maintaining a similar model performance. Zheng et al. (2018) applied clustered multitasking ML model to predict and measure the performance of the chiller-based HVAC system combining different temporal and mechanical features of the HVAC. Zimmermann et al. (2017) experimented and discussed the performance variability across various environments for the residential house occupancy detection model using environmental sensors. The authors of Jiang and Lee (2019) proposed deep neural network-based domain adaption for developing temperature evolution and energy consumption model disregarding the explicit knowledge about the state of building's physics. The authors' experiment showed improved predictive performance in estimating building thermal evolution using pre-training weights and fine-tuning LSTM models on a publicly available dataset. The authors of Zhang et al. (2019b) implemented and open-sourced python based machine learning toolkits using different supervised learning models for occupancy detection named ODToolkit. The authors extended their methods by enabling scaling and DA by incorporating three semi-supervised domain-adaptive occupancy detection algorithms to develop a better accurate occupancy detection model.

6 | ACTIVE LEARNING

Data with limited labeling options offer a great opportunity in cyber-physical building environment research areas. It's not always convenient to collect and accurately label a large amount of data in a home-based setting due to privacy, convenience, and memory constraint device issues. There are existing techniques to overcome data limitations like data augmentation, self-supervised learning, active learning (AL). AL prioritizes the data whose labels would have the highest impact to train a supervised learning model. AL actively selects the most informative data in a smart structured way to be labeled iterative to train the supervised models. AL algorithms use the annotator in the loop to get the most informative data annotated after querying the unlabeled data as shown in figure 3. These algorithms select the minimum training data to build a robust model. These reveal the most informative data to label from the data pool in the building environment domain to develop learning architectures. The model can perform with similar accuracy to models that have been trained upon massive labeled data.

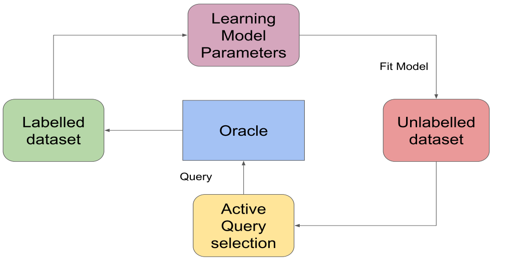

FIGURE 3 Active learning setup for building data.

Jia et al. (2019a) applied the active learning-based algorithm to perform energy disaggregation on household energy consumption with requiring labels for a small amount of data after query. The authors validated their approach from the Dataport dataset psd (2020) by systematically selecting necessary information to feed the learning agent. In this work, the authors proposed an active sensors' placement strategy to maximize the model output using a fixed number of sensors. The authors also considered the cost of sensor placement and searched for the optimal position and number of the sensors. Lin et al. (2019) applied and validated sequential active learning-based algorithms to map metadata for building sensor labeling. Further, to reduce human efforts, their algorithm utilizes the partial labeling of the data.

7 | OTHER ML ALGORITHMS

CPS researchers are applying different machine learning algorithms like instance-based, tree-based, ensemble algorithms, matrix factorization, cluster-based algorithms suitable for multiple settings in the cyber-physical building environment context numerous times. We have covered the most recent implementation of these classical and ensemble-based machine learning algorithms with various trending data modalities in our review. We have considered the latest technologies used to collect data and infer them using different ML methods.

Zou et al. (2017) considered channel state information (CSI) and signal tendency index (STI) of Wi-Fi information to detect active occupants in the loving home environment. The authors applied random forest (RF) on greedily selected sub-carrier features to decide on occupants. Petrovic et al. (2018) proposed two models based on the random forest from Wi-Fi power consumption by connecting the smart plug to monitor power usage. The authors validated their proposed RF-based model for both single and multiple Wi-Fi routers. Wang et al. (2018a) proposed a neural network architecture to estimate occupancy in a large office environment. The authors used the fusion of Wi-Fi sensor data and environmental sensor data to validate the precision of occupancy detection via the neural network.

Javed et al. (2015) used a random neural network architecture to control HVAC by detecting occupancy. The authors chose the environment and current HVAC setting features for their target. Javed et al. (2016) later extended their works on multiple room occupancy estimation and HVAC control by using cloud computing from the base station. Kraipeerapun and Amornsamankul (2017) applied two variants of the neural network; stacking method and complementary neural network, to detect presence from environmental sensor data. Feng et al. (2019) estimated occupancy in a teaching room from Wi-Fi indicators and RSSI from Wi-Fi sniffer by applying neural networks. Georgievski et al. (2017) adopted the hierarchical task network planning of Erol et al. (1994) to solve building energy coordination problem by incorporating building occupants' behavior detection. Their experiments in offices and restaurant settings showed a significant reduction in energy usage.

Pathak et al. (2019) focused on learning the distribution of building envelope parameters such as thermal resistance per unit (R-value), heat transfer coefficient (U-value). The authors proposed a computational efficient and precise automatic differentiation variational interface (VI) based algorithm to find the distribution of building parameters. The authors extensively validated their proposed generative process method on two datasets. Rahimpour et al. (2017) proposed a non-negative matrix factorization method to monitor the load consumption of electrical appliances non-intrusively.

The building researchers have explored control optimization-based approaches to obviate the manual fine-tuning in Building Optimization Control (BOC). Particularly, Parametrized Cognitive Adaptive Optimization (PCAO) have been proposed for Building Optimization Control because of its' flexibility in terms of model-based and model-free design Baldi et al. (2013), Baldi et al. (2014). In the BOC research, Baldi et al. (2015) used PCAO to design BOC systems while reducing human input in both model-based and model-free settings. Their experiments on simulated data and 10-

office building data demonstrated improved energy efficiency while maintaining higher thermal comfort. Michailidis et al. (2018) focused the PCAO application on the decentralized model-free BOC system. Their experiments with practical building controllable-HVAC system depicted the state-of-the-art results with fewer data. It showed the PCAO's adaptiveness under complex building dynamics, building occupancy, and thermal characteristics. Baldi et al. (2018) proposed rule-based PCAO to solve load management with smart zoning problem described in Turner (2008). The authors experimented in a realistic office building and dynamically provided dedicated thermal setpoints for each room to optimize the building's thermal and comfort performance.

8 | REINFORCEMENT LEARNING

Reinforcement learning (RL) stands as one of the three basic ML paradigms along with supervised and unsupervised learning. RL algorithms aim to train the agents to take action based on the observed state information to maximize the notion of cumulative rewards as in figure 4. Deep learning methods have enabled the function approximation for the RL agents using available knowledge from the state. Recently, researchers have applied RL methods in the domain of cyber-physical building environment appliances to enable data-driven smart control. Observing the current building environment from different sensors, the RL agent learns to intelligently control and schedule both the household and commercial building appliances to maximize both energy-saving and occupant's comfort simultaneously.

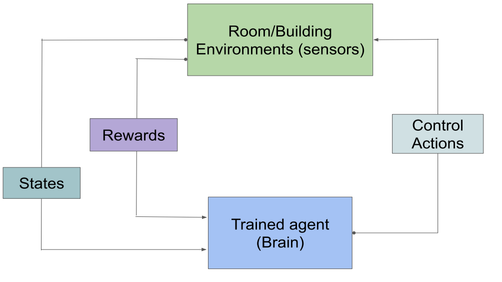

FIGURE 4 Reinforcement learning for HVAC and device control system for the building/home.

Yu et al. (2019) formulated the building energy usage as a Markov decision process (MDP). The author considered the load, generation, temperature, and electric price as state descriptors. Based on the descriptors' state the agent assigns a schedule for the energy storage system and HVAC to reduce cost and maximize comfort. The author applied a Deep Deterministic Policy Gradient (DDPG) algorithm to optimize the decision network. Park et al. (2019b) proposed a occupant centered controller system named *LightLearn*. The authors formulated an MDP problem and designed a workflow to learn to control light using the value iteration algorithm. The defined state by four parameters and trained the agent to perform three actions based on the rewards of saving and comfort. Gao et al. (2019) used the DDPG algorithm to optimize a neural network to control the HVAC system given the state described by temperature, humidity, and some other building environment sensor data. Zhang and Lam (2018) applied deep reinforcement learning algorithm Asynchronous Advantage Actor-Critic (A3C) algorithms to train the agent to control an HVAC heating in office setup. The learned agent performed to save more than 17% energy without compromising comfort. Zhang et al. (2019a) designed simulation on OpenAi gym environment. The authors proposed a model to learn system dynamics learning and energy saving using the proximal policy optimization (PPO) algorithm. Wei et al. (2017) trained an agent to control the HVAC system by learning Q-value using a neural network. The authors considered a simulation-based state and designed reward function as cost and temperature discomfort. The agent saved 20∼70% more energy. Mirra et al. (2018) used the notion of delayed reward to train an agent using a policy-based method to control light and appliances. In the work of Chen et al. (2019), the author proposed differentiable model predictive control (MPC) based policy to counter the sample inefficiency problem in the practice of controlling HVAC in the real scenario. The authors focused on learning better representation in RL by pre-training on historical data by imitation learning. They have been shown to save more than 6% energy in both simulation and real-world test-bed by adopting their proposed Gnu-RL approach. The authors of Nagarathinam et al. (2020) proposed a multi-agent-based reinforcement learning system to control the HVAC systems. The authors proposed multiple learning agents for multiple set points by considering both the air-handling units and the water-side chiller control. They validated and scaled their approach in both simulation and real-world environments.

9 | COMPARATIVE ANALYSIS

Recently, different ML methodologies and a family of algorithms have been proposed and validated in various environments and settings to solve diverse cyber-physical building decision and fault detection problems. These methodologies have their advantages and disadvantages. DL methods generalize and perform better than other handcrafted feature-dependent models in case of the availability of enough quality data examples to train models by optimizing appropriate loss function. Moreover, DL models can learn approximate task-performing functions directly from raw sensor data. DL models learn the better representation from the data towards the target output. This enables scaling and transferring knowledge to the new target domain. On the other hand, DL algorithms require a considerable amount of data and memory to train properly and fast. Sometimes it's not feasible to integrate with memory constraint low-cost devices. Besides, DL models work like a black box and hard to interpret decision reasoning. It takes exhaustive efforts to devise the optimized network architecture, hyper-parameters, loss functions, optimization techniques for the specific task. To avoid data limitation, transfer learning is intervening to get better performance all around. Transfer learning techniques are utilizing different trained networks and domain knowledge in building environments. On the downside, transfer learning may transfer irrelevant knowledge, class imbalance, and sometimes complementary knowledge, to cause performance degrading instead of boosting. The source domain data quality impacts learning. Another line of researches focuses on using available building data efficiently via active learning methodologies. Active learning algorithms greatly rely on the available high-quality data and error-free labeling in the crucial data points. In other cases, rule-based algorithms are still in practice among researchers. This is mainly due to the fast learning, convenient to apply, design, and interpret the outcomes more explicitly. But the classical rule-based ML methodologies suffer from generalization issues and bias towards model and algorithm selection and are often under-performed compared to the DL models. For control and learning dynamics, RL methodologies are ubiquitously applied in the building domain. RL performs well in the control problems and learning activities based on environment states. The RL agents need proper environment information and a well-formulated reward function to train the agent. Sometimes it not straightforward to set up RL problems with appropriate designs like reward function, optimization algorithms for agents. It is not always desirable to train RL agents in a real-life environment because of sample inefficiency and safety reasons. But, appropriate RL algorithms with the proper setup and sensor information would enable RL agents to efficiently control the appliance for a better reward under dynamic circumstances. Table 1 summarizes the application of different methodologies to cyber-physical building environment setting so far.

10 | FUTURE DIRECTION AND TRENDS

The first research direction may target the generalization performance of the models. Most ML models work in a controlled setting where test data distributions are the same as the training data. During our survey, we have found different methods that enabled decision-making in building settings that perform only to a particular scenario. These

TABLE 1 Summary of different ML Methodologies with Application to Cyber-Physical Building

Algorithms	Scope and application	Advantages	Disadvantages
Deep Learning	ADL, Occupancy estimation, NILM, Thermal leakage detection, RL function approximation, Thermal comfort design, Data generation	Better generalization and performance, Features extraction, Raw sensor data	Need large dataset, computationally heavy, Needs large memory
Active Learning	ADL, Occupancy estimation, NILM, Thermal leakage detection, Thermal comfort design	Consider the cost of data collection. Identifies the most informative data to learn from. Performs on smaller dataset	Requires high quality processed data.
Transfer Learning and Domain Adaptation	ADL, Occupancy estimation, NILM, Thermal leakage detection, Thermal comfort design	Utilizes already learned knowledge, requires less data for target domain	May transfer irrelevant or negative knowledge, target domain and source domain needs to be related.
Reinforcement Learning	Appliance Control and personal thermal comfort	Iterative learning based on reward feedback	Needs correct understanding of environment and proper reward design
Other Machine Learning methods	ADL, Occupancy estimation, NILM, Thermal leakage detection, Thermal comfort design	Smaller dataset, computational simplicity, context aware solutions	lack of generalization, may need hand crafted features

models were validated using a controlled dataset and from specific applications. This diversity in data collection, preprocessing, and developing models makes it hard to compare these models from the common ground since varying distribution in the train and test data from a different building. ML researchers may look into the robustness and scope of the model in multiple environments. The transferability of the models should be more thoroughly studied in diverse conditions. Research can focus on identifying and overcoming hindering factors for the re-usability of the ML models.

The second direction may target to overcome the issues with the large dataset collection and repository. The dataset comes from different settings each time. They vary in sampling rate, scene, time, and other observable variables like room size, shape, room position, window condition, etc. The training dataset influences the performance and safety of the target function to minimize the loss Gu and Easwaran (2019). Collecting reliable data from a home setting remains challenging because of the privacy and convenience consideration of the occupants. These independent variables change the data distribution and affect the model testing performance significantly. This scarcity of datasets hinders the application of many data-hungry powerful ML algorithms. There exist different learning strategies that may be further analyzed to leverage small datasets efficiently. Active learning, transfer learning, careful dataset augmentation may play a crucial role in overcoming the data barriers. GAN can learn the distribution of the collected dataset and learn to generate the synthetic dataset. Another major issue with the ML methods with the scale-ability of the model. The observed data distribution may vary across multiple buildings due to their construction variation. ML models need to adapt this change to effective decision-making across different platforms. ML model needs to adapt to different unseen situations in a new home environment. Zero-shot and few-shot learning settings address the unavailability of data issues. They may add robustness to the ML models in case of data scarcity. These may reduce the influence of independent variables involved in building data using semantic or other related information. We have not encountered any paper to explore this spectrum to improve cyber-physical building environment ML model performance. Further analysis requires to narrow down the scaling and scope of the method used to solve cyber-physical building environment problems.

The third direction may search for the appropriate model selection with theoretical justification and standardization. We have encountered experiment results by applying ML algorithms without justification and based on intuition. The data collection procedure varies significantly from one research to another. These pose a hindrance to standardize the experiments. ML researchers may investigate these disjointed efforts and call for standardization of data collection of different modality and model applications. These would enable validation and test the performance of various models based on a common platform. It would also facilitate various algorithms' application in cyber-physical building environment decision and control problems with a proper benchmark. Standardization would remove the model performance variance with commonalities between the train and test data. Suitable models with the optimum hyper-parameters with the relevant data should provide more reliable estimations across experiments. ML researchers should also be concerned with the model implementation on limited memory devices. Different compression techniques for large-scale ML models can provide matching performance on cheap portable memory-constrained devices. RL problems should be applied carefully by properly designing state, action, and rewards. Standardization of data and models certainly would enable controller agents to learn cross-domain for human benefits.

ML with control is an intriguing recent trend in modeling the behaviors of the dynamic system. These particular branches have application scope in real-life dynamic systems. It is expensive to model building behaviors over time due to the buildings' dynamic properties. Further, the process depends on specific physics-based building information. Moreover, complex modeling is construction-specific and needs a timely update. ML and data-driven approach can save the complexity of learning hand-crafted building physics-model for decision and control regarding home and buildings. Recently, Jain et al. (2020) applied an MPC-based neural network for efficient energy management in an academic building. Yang et al. (2020) proposed an ML-based building dynamics model to regularly update the building model parameters. The update process uses online building operation data via a nonlinear ANN. Their proposed MPC approach outperformed reactive control systems in energy efficiency and indoor thermal comfort by controlling the AC and mechanical ventilation in two separate single-zone test-beds. Wolisz et al. (2020) developed a self-learning MPC algorithm to measure structural thermal mass (STM) based residential load shifting (LS) without requiring extensive data or expert knowledge. Their approach dynamically optimized the necessary heating operations for LS and reduces energy demand while maintaining thermal comfort in a simulated environment. Drgoňa et al. (2018) explored simple MPC for ubiquitous temperature control using edge hardware to replace rule-based controller for energy efficiency. Their experiments with temperature control in six-zone building demonstrated the linear MPC's ability to approximate the performance of the complex MPC while reducing the complexity and cost during the real-scenario implementation. Besides energy management, a framework for learning building dynamics explicitly and efficiently would enable better monitoring of thermal energy leakage, envelope conditions, faults detection for timely repair.

We believe data-driven dynamic physics learning prospects for building and home would allow learning better approximation of complex building models across time, environments, and building types efficiently. Buisson-Fenet et al.

(2019) proposed and validated a data-efficient active learning approach to learn dynamic systems lately. Khojasteh et al. (2019) used Bayesian learning to autonomously identify the distribution of the high degree system dynamics to optimize with high probabilities the system behavior and safety. The control and dynamic system learning have applications in automatic building properties inspection, monitoring via autonomous unmanned sensors like drones, robots, and learning building system dynamics.

11 | CONCLUSION

The recent advent of machine learning algorithms and data availability offers a powerful data-driven solution to the cyber-physical building environment energy-saving and occupants' comfort. In this paper, we have studied and discussed the application of recent and emerging ML algorithms to solve cyber-physical building environment decision problems. Our report aims at grouping and assembling trending methodologies, innovative solutions to a different cyber-physical building environment-related problem probable in real-life cases together in single literature as a benchmark for building domain researchers. To achieve that, we have included and reviewed both decision-making and control problems extensively with their contributions and overview of approaches. In our study, we have found DL algorithms edge over other traditional algorithms in decision makings. It's because of their better generalization ability, increasing data availability, and the development of heavy computational power across devices. On the anther hand, we reviewed existing reinforcement learning methods performing appliance control to optimize comfort and energy usage in cyber-physical building environment settings. Still, there are challenging problems that require further research to achieve better performance and cover unexplored territories in the cyber-physical building environment domain. We have also pointed out some potential challenges and prospective future directions that may shape the ML applications in the building environment research domain. This review article comprehensively discusses the trending and emerging machine learning methodologies in energy-saving decision-making and control without occupant comfort compromise in cyber-physical building environment domains.

Conflict of Interest

The authors claim no conflict of interest in this study.

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