A Review on Machine Learning for Thermal Comfort and Energy Efficiency in Smart Buildings

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Abstract

The integration of machine learning (ML) techniques in the field of smart buildings has gained significant attention in recent years. In this paper, we explore recent applications of machine learning in the context of smart buildings for thermal comfort and energy efficiency optimization. Through the examination of some papers, we will discuss common data collection techniques, ML models, and their applications (e.g., building management systems, energy management systems, occupancy-based heating, ventilation, and air conditioning control, indoor air quality monitoring, and many more). Finally, the paper wants to emphasize the challenges associated with integrating ML into building systems and highlight further research perspectives.

Keywords: Smart Buildings, Machine Learning, Reinforcement Learning, Thermal Comfort, Energy Efficiency.

1 Introduction

For decades, smart buildings (SBs) have been a luxury. Nowadays, people spend 80 to 90 percent of their time inside buildings, using a significant quantity of energy in various ways, for example, to heat/cool down their environments. In this context, energy efficiency is crucial because it will protect the environment from CO_2 emissions as well as save money. Machine Learning (ML) can play a vital role in optimizing energy consumption while still keeping high the thermal comfort level [2] in SBs.

Thermal comfort is the circumstance of an indoor environment where residents don't experience temperatures that are either too cold or too hot. Thermal comfort is a crucial component of creating a harmonious and relaxing indoor environment [1]. In SBs, thermal comfort is pivotal because it directly affects occupants' health, productivity, and satisfaction [2][22]. Thermal comfort (TC) and energy efficiency (EE) are both significant factors in SBs, but they have different objectives. Energy efficiency focuses on reducing energy use and expenses, whereas thermal comfort prioritizes occupant satisfaction and well-being. SBs can maximize Heating, ventilation, and air conditioning (HVAC) system efficiency, minimizing energy waste and operating expenses by maintaining ideal temperature conditions. In accordance with occupant comfort needs, proper insulation, effective control systems, and modern technology can aid in achieving a balance between thermal comfort and energy savings.

Internet of Things (IoT) technologies, including sensors, actuators, and smart objects, [5] are now at the basis of SBs and smart cities, enabling situational and spatial intelligence for the tangible control of dynamic occurrences. Such technologies in the field of TC and EE in SBs can collaborate in the calculation of specific thermal comfort measures, e.g., the predicted mean vote (PMV) [10]. Anyway, in the past years, these measures are often inferred through ML algorithms using IoT data [3]. Many ML algorithms have been used so far to optimize TC and EE in SBs, and the most common ones are highlighted in Figure 1. These algorithms are usually categorized using three basic ML models, such as Supervised Learning, Unsupervised Learning, and Self-supervised learning (i.e., Reinforcement Learning - RL). These models usually have, as input, some features coming from the environments or the humans.

In the defined context, in order to create ML models, several steps have to be followed [15]. In particular, the process of identification, in which the research questions and objectives are determined, and the experimental stage, in which data collection is performed and, on such data, is realized cleaning and handling of missing values. The collected and cleaned data is usually divided into three parts: training, validation, and test set. The training set is so used to train the chosen model, the validation set helps in validating the model created, and the test set is fundamental for the evaluation of the created model. Such evaluations are finally executed by using specific performance metrics, including, for example, Accuracy, Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R2 (R-Squared), Area Under the Curve (AUC) [8].

This paper aims to investigate the application of ML algorithms to EE with TC in SBs by taking into account papers published in the last few years.

In particular, we want to highlight the most used techniques in the recent literature and the performance parameters taken into account to evaluate them, compare the works analyzed, and discuss future research directions in this field.

The rest of the paper is organized as follows. Section 2 explores ML applications in intelligent buildings. Section 3 discusses the difficulties and potential directions for future research. Finally, Section 4 concludes the paper.

2 ML for Thermal Comfort and Energy Efficiency

In this section, we will delve into the application of various machine learning algorithms in the context of SBs, examining their objectives, performance, and other relevant factors. In particular, the next subsection will explore supervised and unsupervised learning algorithms for TC and EE. Nextly, we will go in-depth about some works using RL. It is worth noting that all the analyzed work has been summarized in Table 1.

2.1 Supervised and Unsupervised ML

The research in [17] presents a novel personal thermal sensation method based on the C-Support Vector Classification (C-SVC) algorithm for personalized conditioning system (PCS) control. Throughout the modeling process, the method "learns" an occupant's thermal preferences from feedback, environmental parameters, and physiological and behavioral factors. The method is verified by comparing actual thermal sensation votes (TSV) with the modeled one, and the accuracy of each model is compared to the PMV model. Finally, the authors suggested that this method is an effective tool for modeling personal thermal sensations and could be integrated into PCS for optimized system operation and control. The TSV prediction achieves an average accuracy of over 89%. The paper at [32] focuses on the issue of keeping high indoor air quality in educational facilities and how it can affect the productivity of users. The authors discuss the limitations of existing rating systems in disclosing specific problems related to people density, usage intensity, and ventilation conditions in existing buildings. Then, they aim to create a forecasting tool for CO_2 concentration in educational facilities using an RNN model to provide better predictions of time-dependent variables.

The paper in [11] proposes a one-layer Gated Recurrent Unit (GRU) neural network for occupancy prediction to improve energy efficiency in SBs. The dataset used in the study was collected from hundreds of passive infrared (PIR) occupancy IoT sensors in a large academic building in California. The experimental findings reveal that GRU outperforms the Long Short-Term Memory (LSTM) network by obtaining a lower error of 1.21% and requiring fewer parameters (about 13.57% less) for training. As a result, GRU can be trained 10% faster and thus is better suited for large-scale occupancy prediction tasks in emerging SBs.

A few authors worked on the temperature of the skin on the face to understand individual thermal comfort. To this purpose, ML algorithms (i.e., GB, LR, SVM, ANN, and RF) were used in the studies [16] and [33]. The paper in [16] explores the potential use of human facial skin temperature as primary physiological data to develop data-driven thermal comfort and uses a series of environmental chambers to collect data. The study used a gradient boosting algorithm (GBM) and an ANN algorithm for data analysis. In [33], the work proposes prediction models for thermal comfort using infrared images and machine learning algorithms such as SVM, LR, and RF. The accuracy and area under the curve (AUC) of each model on the test set were calculated and used as the main evaluation indexes. The results show that the prediction accuracy of ML models based on local skin temperature is close to that of the PMV model and indicates significant feasibility for practical application. Among the models, the AUC and accuracy of the LR model reflect a relative advantage compared with other ML models. Another study [20] proposes an advanced TC prediction model by using RF, GBM, and ANN that, as a novelty, considers blood glucose and salivary cortisol as bio-signal features. The study proposed an advanced prediction model through supervised learning (RF, GBM, ANN). The predictive performances of the models were evaluated based on accuracy, AUROC, and AUPRC. The proposed model showed better predictive performance than conventional models, with an accuracy of 73.4%, which is 10% better than the conventional model's accuracy of 63.4%. The paper [4] proposes a DNN to predict the indoor thermal comfort of differently-abled people in real-time to facilitate remote monitoring. It uses A.P.E.I. building to record thermal comfort data. These data were then transferred to the remote cloud through gateways and routers for further processing. The deep learning-based model achieved an accuracy of 94% and a precision and recall of 98% and 97%, respectively.

In the works reported in [18] and [19], the authors discuss thermal comfort and privacy concern. In particular, the paper in [19] discusses the accuracy of the proposed algorithm, namely Fed-NN, for thermal comfort prediction in an industrial IoT environment. The experimental studies on a real dataset reveal the robustness, accuracy, and stability of the algorithm in comparison to other ML algorithms while taking privacy into consideration. A DNN and an LSTM network are used for modeling and forecasting TC. In [18], the introduced TC model is used to control the smart building environment, resulting in less energy consumption within a comfort zone.

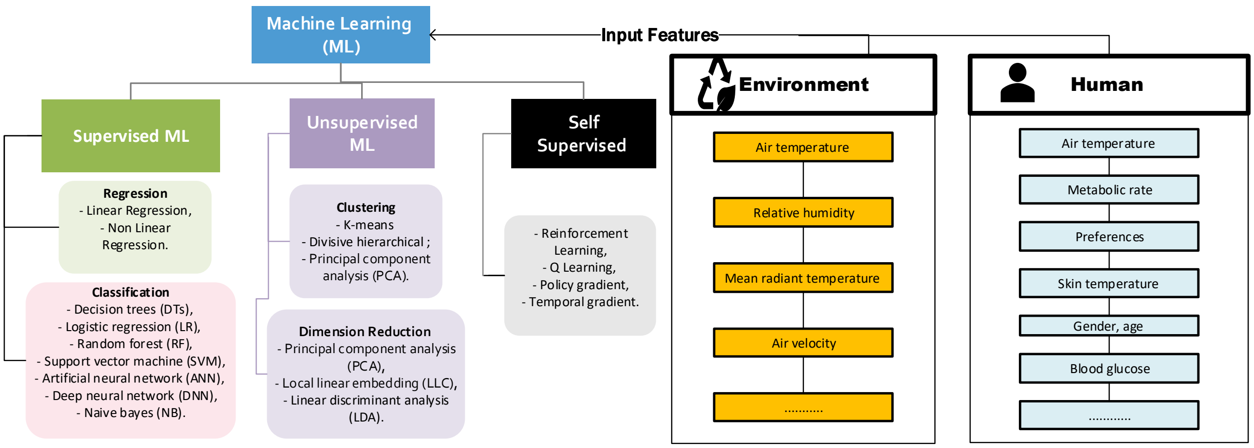

Figure 1. An overview of the main machine learning algorithms used in SBs to optimize energy consumption and thermal comfort.

Table 1. Comparison of the analyzed work.

Paper	Objectives	Algorithms	Environment	Performance metric	Limits
[11]	Occupancy prediction and EE	LSTM	Academic Building	MAE, Precision, recall	Real implementation missing
[17]	Personal TC	C-SVM	Not mentioned	Accuracy	No real-world scenarios considered
[32]	EE and comfort improvement	RNN	Educational Institute	R2	Limited ML model considered
[18]	Privacy concern and TC prediction	LSTM	CU-BEMS Home, Thailand	MAE	Low accuracy
[19]	Privacy concern and TC management	NN	Not mentioned	MAE, MSE	Low accuracy
[13]	Occupancy Prediction for TC and EE	LSTM	Laboratory dataset	R2, MAE, RMSE, SD	Limited generalizability of the model
[31]	Forecasting Indoor air quality for TC	ANN	Not mentioned	R2	Limited training data used
[16]	Forecast Skin Temperature with individual TC	GBM, ANN	Environment Chamber		Small application scenario considered
[33]	Prediction of TC and EE	KNN, ANN, SVM, RF	-	AUC	Data source is not described
[20]	TC estimation blood glucose and salivary cortisol	RF, GBM, ANN	-	Accuracy	Data source is not described
[4]	Indoor TC and EE	DNN	Building	Accuracy, Recall, Precision	Does not discuss real implementation
[25]	EE and TC	ANN	Not mentioned	MAE	The use case considered is too specific
[21]	EE and TC for HVAC	2 Layer NN	Two rooms	R2	The use case considered is too specific
[26]	EE and TC (Inertia weight)	Bat Algorithm	Educational (University)	Not mentioned	Misses comparison with the state of the art
[28]	EE and TC	Non-dominated Sorting Genetic Algorithm	Office	Not mentioned	Performance metrics are not discussed
[12]	Heating controller optimization for EE and TC	DQN DNN	Building	Not mentioned	Some limits in the simulations
[24]	Control Home Appliances for EE and TC	TRPO DNN	Home	Not mentioned	Performance metrics are not discussed
[30]	TC and EE for HVAC	DRL	Office	Effective	The use case considered is too specific

The authors of [13] propose an IoT framework with data analysis using an LSTM network for occupancy prediction in a building considering factors such as TC and EE. The LSTM model's accuracy is 96% on the tested multivariate captured data, which is nearly 16% better than other algorithms compared in the paper (i.e., SVM and NB).

The authors of [31] propose a data-driven approach for predicting indoor air quality in educational facilities using an IoT network. The paper proposes the use of predictive models in Building Energy Management System (BEMS) and Building Automation System (BAS)s. The paper used ML techniques, such as neural networks, to define hourly load profiles and energy consumption in university buildings. Distributed Sensing has been adopted to confirm the models. The Smart Campus of the University of Brescia has been used for the experiments.

In the study at [25], authors developed a multi-objective optimization model for controlling air-conditioning and ventilation systems to balance TC and energy conservation or sustainability. An ANN is constructed as a prediction model of TC and energy consumption. A semi-empirical model is used to build the component power consumption pattern of the ACMV system (fan, pump, and compressor). Also, in the study in [21], the authors used a side-by-side experimental approach to quantify the performance of occupancy-based control in commercial buildings. Three state-of-the-art occupancy sensing technologies were integrated into real-time HVAC system control, analyzing their accuracy and effectiveness in energy-saving and thermal comfort. The study found that occupancy-based control maintains good thermal comfort and perceived indoor air quality, with a satisfaction ratio greater than 80%. The research paper used a two-layer neural network model to predict energy-saving. The model was trained using ten days' outdoor temperature as input and energy savings as the target. The results showed a good overall performance of the model with an R2 value of 0.96795.

In [26], the authors introduce a solution using the Bat algorithm (BA), which is a swarm intelligence algorithm inspired by the communication of bats via echolocation, with exponential inertia weight to optimize comfort and energy consumption in SBs. The algorithm tries to find the best set of values for three main parameters that influence the occupant's comfort, namely, temperature, illumination, and indoor air quality. An exponential increase of the inertia weight is introduced to BA for performance improvement. The performance of the introduced BA with exponential inertia weight is proven as significantly better than the original BA and other variants of inertia weight. Moreover, the comfort level achieved by BA with exponential inertia weight is found to be better than previously reported works using the firefly algorithm, genetic algorithm, ant colony optimization, and artificial bee colony algorithm [35]. The superior performance is achieved due to better convergence behavior. Authors of [28] presented a multi-objective genetic algorithm to reduce energy use in an office building, resulting in a 50% improvement in TC and a 2% reduction in energy use compared to scheduled control.

2.2 Reinforcement Learning

RL is one of the ML models which acts according to a trial and error process, where an agent can learn from the environment through different policies or rules. Deep Reinforcement Learning (DRL), Deep Q-Network (DQN), Deep Deterministic Policy Gradient (DDPG), and Trust Region Policy Optimization (TRPO) are some of the most famous RL algorithms. We will discuss in the following some works made for SBs to reach EE with TC by using RL algorithms.

For single buildings, the paper at [12] aims to design an energy-efficient heating controller for smart buildings using DRL. The DRL-based heating controller is designed using a neural network that learns the optimal control policy for the heating system. The paper presents simulation experiments using real-world outside temperature data to evaluate the performance of the DRL-based smart controller. The results show that the DRL-based smart controller outperforms a traditional thermostat controller by improving TC between 15% and 30% and reducing energy costs between 5% and 12% in the simulated environment.

In [24], the authors propose an approach for scheduling household appliances to minimize electricity costs while ensuring user comfort. They propose a DRL approach that is based on trust region policy optimization (TRPO) and uses a neural network to learn the optimal scheduling policy. The paper used real-world data on electricity prices and outdoor temperature during the same period in 2017 for training. Some different sets of simulation data of the appliance's working time and hot water flow rate are generated for testing. The average rewards of the proposed approach increase quickly at the beginning and converge after 1500 iterations. The paper uses real-world data for training and simulation data for testing.

The paper in [30] proposes the use of DRL for the automatic control of heating, ventilation, and air conditioning systems in an office to manage TC. The learning process is driven by a reward that includes multiple components related to energy consumption, indoor temperature, and user perceptions, which are inferred by human interactions with the system. The authors made several experiments in the paper but the approach that they used may not be applicable to all building types and may require customization for different environments.

The authors of [7] developed an RL model starting from the interactions of SB residents with their thermostats. They also used the transfer learning technique to transfer the knowledge of the RL-trained model to other buildings with different HVAC control systems. The model predicts the behavior of modifying the thermostat set point with R2 from 0.75 to 0.8, and the (MAE) is less than 1.1 °C in an office building.

The authors of [9] used a (DDPG) algorithm to implement a DRL-based system to reduce energy consumption while maintaining the occupant in their preferred environment. The system implemented in the paper achieved an economic control strategy for both cooling and heating scenarios. In the paper, the DRL system is compared with a rule-based benchmark case and a single-task deep deterministic policy gradient algorithm to verify its effectiveness in optimizing HVAC operation. The model was tested in a two-zone residential HVAC building.

The authors of [23] proposed a framework that uses a Branching Dueling Q-network (BDQ) as a learning agent. They used a tabular-based personal comfort modeling method to emulate human-in-the-loop operations. So, the BDQ agent is pre-trained in a virtual environment, and it is then deployed online in a real office space. Real-time comfort votes are collected during the running of the system. The results showed a 14% reduction in cooling energy and an 11% improvement in total thermal acceptability.

The authors of [34] propose a real-time control algorithm based on attention-based multi-agent DRL to solve the coordination control problem of personal comfort systems (PCSs) and heating, ventilation, and air conditioning (HVAC) systems in a shared office space. Formulate an expected energy consumption minimization problem related to PCSs and an HVAC system. Reformulate the problem as a Markov game with heterogeneous agents. The proposed algorithm can reduce energy consumption by 0.7%-4.18% and reduce average thermal comfort deviation by 64.13%-72.08% simultaneously compared with baselines. The simulation results based on real-world traces show the convergence, flexibility, effectiveness, robustness, and versatility of the proposed algorithm.

The paper in [27] presents a DRL-based model for building energy management that addresses the challenges of non-stationary behaviors and inefficiency problems. The paper also introduces a relearning loop triggered by performance degradation detection. The proposed approach is tested on the standard ASHRAE 5-zone testbed and in a real building and is compared with state-of-the-art algorithms, such as Guideline-36, Proximal Policy Optimization, DDPG, and Model Predictive Path Integral control. The introduced approach performs significantly better than the other control strategies.

3 Discussion and Future Directions

This section will discuss some important points and will introduce some future directions of research in the considered domain.

Since ML offers a variety of different algorithms to use, it's important to select ones that are appropriate for the study's goals. Black-box machine learning models such as SVM and ANN learning methods are better suited for handling complex problems but are not easily interpretable and can be time-consuming, while white-box models such as NB, KNN, and DT are interpretable but may not capture the subjective nature of comfort levels [14].

What is also very important in designing and realizing ML models is the integration of a plethora of devices to monitor the environment effectively. Moreover, advanced techniques for controlling appliance usage could be integrated with this. IoT devices would be very important to this scope because they can help in the process of data gathering so as to have large and significant datasets to train ML models to reach TC and EE in building environments.

By reviewing the state of the art, it is clear the importance of RL algorithms for reaching in SBs both TC and EE. This is due to the fact that RL can take into account the users' preferences in any environment together with other IoT data. Anyway, RL techniques still need to be refined so to reach very good results with a limited amount of input data. Moreover, RL algorithms are sensitive to hyper-parameters, making it challenging to determine the best-performing hyper-parameters for SBs.

Since much data is actually required by RL algorithms to be trained, several researchers are already looking for methods to have RL models already available for new SBs, in which historical data may be very limited. To address this issue, a solution that is impacting the ML community is to introduce transfer learning, which means transferring knowledge from one task to another [36]. While some efforts have been made to use transfer learning in existing works, they have mainly focused on simple scenarios where there is a small similarity gap between the source and target SBs. When the similarity gap is large, such as when the dimensions of state spaces and action spaces in two SBs are much different, designing an efficient intertask mapping function and selecting the proper form of transferred knowledge becomes very challenging.

Since ML algorithms applied to TC and EE were, until now, just research efforts, researchers didn't take care so much about privacy concerns [18]. This is why some works in literature are trying to start the implementation of ML techniques to the edge [29] so as to decentralize model training and keep all the sensitive data close to where the data itself is produced. In this direction, several works based on Federated Learning (FL) [6] [19] are also appearing. FL is a technique on which researchers are focusing a lot in the last few years that allows to train models at the edge of the network and then merge such models in the cloud. This allows exchanging with the cloud model weights only (instead of the training data), but the model aggregation allows to increase in the performances with respect to the single models.

4 Conclusions

Nowadays, Machine Learning is considered the most effective instrument to optimize energy consumption in smart buildings, still keeping into account the comfort required by the buildings' inhabitants. Indeed, many works in the literature focus on applying several kinds of Machine Learning algorithms for this scope with very good results.

In this direction, this paper examined some works published in the last few years, with the aim of highlighting the most used techniques and the performance parameters taken into account to evaluate them. Moreover, a quick comparison of the works analyzed was made, and some future research directions in this field were discussed. It should be noted that this paper aims to present a work in progress and is unable to comprehensively address all aspects of the research papers under consideration.

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