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The use of artificial intelligence (AI) methods in the prediction of thermal comfort in buildings: energy implications of AI-based thermal comfort controls

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ABSTRACT

Buildings consume about 40 % of globally-produced energy. A notable amount of this energy is used to provide sufficient comfort levels to the building occupants. Moreover, given recent increases in global temperatures as a result of climate change and the associated decrease in comfort levels, providing adequate comfort levels in indoor spaces has become increasingly important. However, striking a balance between reducing building energy use and providing adequate comfort levels is a significant challenge. Conventional control methods for indoor spaces, such as on/off, proportional-integral (PI), and proportional-integral-derivative (PID) controllers, display significant instabilities and frequently overshoot thermostats, resulting in unnecessary energy use. Additionally, conventional building control methods rarely include comfort regulatory schemes. Consequently, recent research efforts have focused on the use of advanced artificial intelligence (AI) methods to optimize building energy usage while maintaining occupant thermal comfort. We present a review of the current AI-based methodologies being used to enhance thermal comfort in indoor spaces. we focus on thermal comfort predictive models using diverse machine learning (ML) algorithms and their deployment in building control systems for energy saving purposes. We then discuss gaps in the existing literature and highlight potential future research directions.

1. Introduction

The use of fossil fuels as a primary source of energy, and the resulting environmental concerns (e.g., climate change), are arguably the most challenging issues of the 21st century. Consequently, there is an urgent need across many sectors to devise solutions that address global energy concerns [1]. The building sector is a key consumer of globally-produced energy. Buildings consume about 40 % of the total energy produced worldwide [2], which translates to about 30 % of the total global CO_2 emissions. As such, reducing the amount of energy consumed by the building sector would greatly assist the much-needed reductions in global energy consumption and the associated environmental concerns. However, the issue of energy consumption in buildings is rather challenging because buildings require energy to serve their many purposes. Although there is increasing debate surrounding the possibility of zero-energy buildings [3], such ideas are still in their infancy and have only been implemented in certain parts of the developed world [4]; it may be quite some time before they are seen in practice globally. Therefore, the best current alternative is to exercise energy consciousness, wherein buildings are designed to strictly utilize only the amount of energy required for their intended purposes, i.e., avoiding energy wastage. One area where this can be applied is in the thermal comfort design of indoor spaces. It is estimated that the average modern man spends 80–90 % of his time in indoor spaces [5]. Moreover, the rise in global air temperatures, primarily due to climate change, has exacerbated the issue of increased levels of discomfort and heat stress, which can result in heat-related mortality, especially in demographics at the extreme ends of the population curve (i.e., the elderly and the very young) [6]. Comfortable indoor spaces are also substantially linked to improved productivity [7] and the overall well-being of building occupants [8]. As such, the concept of thermal comfort is increasingly being considered in building service practices [9]. Moreover, because achieving sufficient comfort levels in living environments most often requires the use of energy-consuming mechanical equipment, the concept of thermal comfort in buildings has broad implications in relation to energy usage and the subsequent direct and indirect effects of energy usage on the

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environment [10]. Consequently, a key goal in the building service industry is achieving sufficient thermal comfort levels while minimizing energy consumption.

Traditionally, thermal comfort in buildings has been assessed and analyzed using the predicted mean vote (PMV) index [11]. The PMV model is based on the thermodynamic balance between occupants and their immediate thermal environments. It assumes that for the human body to be comfortable, there must be a thermal equilibrium between the body and its surrounding environment. The primary goal of the PMV index is to determine the mean thermal sensation vote for a group of occupants; it is computed based on four physical parameters (air temperature, air velocity, humidity, and mean radiant temperature) and two personal parameters (clothing and activity). Despite the wide adoption of the PMV model in several building standards, such as EN ISO 7730 [12], ASHRAE standard 55 [13], and CEN CR 1752 [14], it has also been criticized, primarily because it was developed under steady-state chamber conditions, which are not an accurate representation of everyday, dynamic conditions in the real world [15]. Also, the PMV model was developed based on data collected from healthy adult individuals in a defined age group; therefore, it may require certain corrections to be successfully applied in environments containing children, the elderly, or the unhealthy.

To address the shortcomings associated with the traditional PMV model, different variants of the PMV model have been developed and proposed, e.g., the adaptive PMV (aPMV) index [16], which considers outdoor air temperature as the only parameter (instead of the six conventional parameters) to estimate thermal comfort levels and the extended PMV (ePMV) index [17], which considers typical local climates as well as the six initial parameters used in the PMV index. In addition, besides these thermal comfort models, which are mere derivatives of the original PMV model and are based on the heat exchange theorem between the occupant and their immediate environment, there is an adaptive approach to understanding occupant thermal comfort. The adaptive approach considers factors beyond the physical parameters of the environment to include the influence of different psychological, physiological, and historical factors in the assessment of occupant thermal comfort. The adaptive approach was first proposed by De dear and Bragger [18] and has since been adopted in several building design standards [19,20]as the main tool for determining acceptable thermal conditions in naturally ventilated buildings.

The two approaches for estimating and modeling thermal comfort (as discussed above), use conventional statistical methods to relate occupant thermal comfort state to various factors likely to influence thermal comfort (e.g., the four physical parameters and two personal parameters used in the original PMV). However, the use of traditional statistical methods to analyze highly variable and complex scenarios such as the interaction between building occupants and their immediate environments is limited. This is perhaps the primary reason for consistent reports on the shortcomings of the traditional comfort models to accurately predict occupant thermal comfort levels [21]. Furthermore, to provide comfortable indoor environments, comfort models ought to be integrated into building control schemes; however, as extensively discussed by Park and Nagy, this has only recently been undertaken by the building industry [22]. Moreover, traditional control methods for indoor environments, e.g., on/off, proportional-integral (PI), and proportional-integral-derivative (PID) controllers, tend to display significant instabilities and frequently overshoot thermostats, resulting in unnecessary energy use [23,24]. As such, conventional control practices tend to be non-optimal in regards to both energy consumption and the provision of thermal comfort. However, recent developments in artificial intelligence (AI) analytical and data collection methodologies have been extensively applied in the building service industry, e.g., in the estimation of thermal comfort and the predictive control of thermal comfort levels [25]. These AI-based methods offer advanced analytical techniques capable of modeling the complex and non-linear nature of the interaction between occupants and their thermal environments. They also offer great promise in terms of readily bridging the gap between thermal comfort provision and building control, which inherently has significant implications for building energy use. The aim of the current paper is to (i) critically review recent publications that employ AI methodologies in the assessment and control of occupant thermal comfort levels (ii) analyze the building energy implications that result from the use of AI methodologies in the predictive control of occupant thermal comfort (iii) highlight potential future research directions.

We consider articles published in the last 10 years from three main databases: Scopus, Google Scholar, and Thomas Reuters' Web of Science. In addition, we searched for relevant publications in specific journals and conference proceedings associated with building science. The journals considered in our search were Sustainable Energy Reviews, Energy and Buildings, Building and Environment, and Indoor and Built environment. We also searched IEEE conference proceedings. During our search, we utilized the following keywords: thermal comfort, ML, AI, adaptive PMV, thermal comfort control, indoor environment, indoor thermal comfort, comfort index, indoor air temperature control, and control strategy. We used these keywords as single items and also as a combination of two or more keywords. For example, we would try the keyword "*thermal comfort*" individually and then try a combination of two keywords such as "*thermal comfort and ML*"

The remaining components of this paper are organized as follows. Section 2 gives an overview of AI methodologies employed in thermal comfort studies. It then critically discusses recent studies using AI algorithms to model the thermal comfort state of occupants. Section 3 presents studies illustrating the use of AI-based predictive models in thermal comfort control and discusses the energy implications of using such controls. Section 4 discusses gaps in our knowledge and indicates potential future research directions in this field. Section 5 gives conclusive remarks regarding the use of AI methodologies for thermal comfort control in buildings.

2. AI-based thermal comfort predictive models

AI can subtly be defined as the ability of computers to develop intelligent qualities, similar to those of humans, and consequently perform tasks that could previously only be performed by humans alone. AI is a broad field with several diverse applications. For example, AI has seen extensive application in the medical industry [26], gaming industry [27], general computing industry [28], etc. A large section of AI is devoted to data analytics and predictive modeling. This involves using past experiences or historical data to teach machines how to reason with human-like capabilities. After proper learning, the machine can be used in the prediction or forecasting of certain events or future occurrences. Most AI methods used in data analytics and predictive modeling can be placed under the ML category of AI.

This section briefly discusses common ML methods and algorithms that have been extensively used in modeling occupant thermal comfort. It then provides a discussion on studies that have used ML techniques to model thermal comfort and the benefits and drawbacks associated with the use of such methods.

2.1. ML methods and algorithms for thermal comfort modeling

2.1.1. Learning methods

ML is a sub-category or AI that employs advanced algorithms to learn patterns in historical data and attempts to deduce future occurrences or occurrences under certain defined conditions.

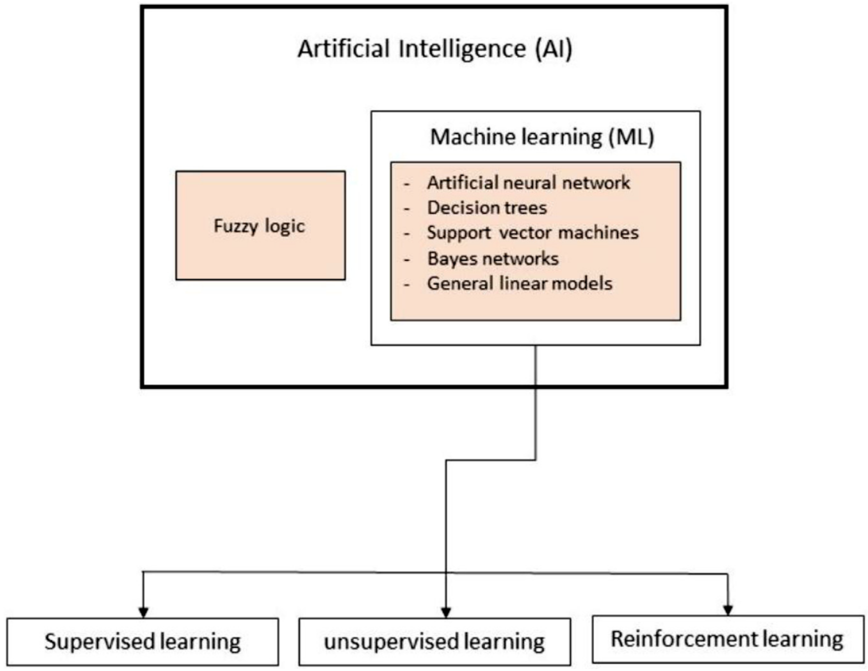

Fig. 1. Artificial intelligence (AI)-based fuzzy logic and machine learning (ML) algorithms.

There are three common ways that machines can learn said patterns: supervised learning [29], unsupervised learning [30], and reinforcement learning [31]. The choice of which learning methods a machine adopts is often dependent upon the type of data available. Supervised learning is often used when the inputs and associated outputs are both available such that we have a dataset encoded as pairs, (m,n). The general goal is to produce a function, F: $m \rightarrow n$,that accurately mimics the patterns between m and n. Thus, given a new set of inputs (m_x), the function can accurately deduce the corresponding outputs (n_x). In most cases, the goal with supervised learning is to adjust the parameters in the input variable to correctly fit or match the output variable by assigning weights. In unsupervised learning, the inputs are available but the corresponding outputs are not available (i.e., m is available without the corresponding output n). In such cases, the general goal is to learn the patterns hidden within the datasets. For example, a possible outcome of unsupervised learning is a model that learns the patterns underlying a given dataset. Then, based on the learned patterns, the model learns how to cluster the data into different groups. Consequently, the general goal is such that when the model is fed with new data, it successfully identifies the group to which the data belongs. Similarly, with reinforcement learning, there are no encoded data that directly pair the input to the output; rather, given the inputs, we only have an estimate of how good or bad is the output. The estimate of an output is referred to as a reward and can be either a positive or negative value. The general goal of the developed model is to learn patterns within a dataset that maximize the chances of acquiring a desired output or reward.Another AI technique that is employed in computer systems to mimic human-like reasoning is fuzzy logic. Fuzzy logic modeling is an improvement on the classical Boolean set of rules [32]. Whereas the possible outputs for a classical Boolean system are constrained to 0 or 1 or true or false, a fuzzy logic system considers intermediate values that represent partial truth. Fuzzy logic systems are largely dependent upon expert rules to make decisions. For example, given a set of input parameters, a fuzzy logic system will make decisions based on certain rules to yield a desired output. Fig. 1 illustrates the placement of ML techniques and fuzzy logic systems within the larger concept of AI and which have been extensively applied in thermal comfort studies.

2.1.2. Learning algorithms

There are several ML algorithms that are commonly used to develop predictive models of different ranges and capabilities [33]. Recent studies have mostly employed neural network-based and decision tree-based methodologies to directly estimate thermal comfort levels or improve upon the already existing indices of thermal comfort (e.g., PMV). Other instant-based learning algorithms such as support vector machine (SVM) and K-nearest neighbor have also been extensively used to estimate thermal comfort levels.

2.2. Air temperature and relative humidity models

Most studies that have employed ML methods in the prediction of thermal comfort have done so in many different ways. For example, some studies have predicted indoor air temperature using diverse factors (e.g., physical weather elements) and diverse deep learning techniques. In such studies, the general goal of the developed models is to predict indoor air temperature at a given future outdoor temperature and thus be able to preemptively control the indoor environment. In addition to the large variety of deep learning architectures and properties, most of these studies used different features to predict indoor air temperature and sometimes indoor relative humidity, which can also impact occupant thermal comfort significantly. For example, Moon et al.. [34] used outdoor temperature, solar radiation, and window operating conditions to train and develop an artificial neural network (ANN) model for a building with a double façade. In a different study by the same author [35], indoor temperature and outdoor temperature were used to train and develop an ANN model that predicted the indoor set temperature. Several other studies [36–42] used different variables to train and develop deep learning models that predict indoor air temperature. Table 1 compares different studies using ML techniques to predict different variants of indoor air temperature and humidity.

Table 1
Summary of studies on ML-based temperature/relative humidity models.

Reference	Model	Features	Number of hiddenlayers	Number of hidden neurons	Output
[34]	ANN	- outdoor temperature - cavity temperature - solar radiation - window opening conditions	5	20	- indoor temperature
[35]	ANN	-indoor temperature - outdoor temperature - temperature difference from the setback temperature	4	9	- set temperature
[36]	ANN	- outdoor temperature - change in outdoor temperature - outdoor humidity - change in outdoor humidity - indoor temperature - indoor humidity - change in indoor temperature - change in indoor humidity	1	17	- indoor temperature
[37]	ANN,ML	- sol-air temperature - wind speed - outdoor relative humidity - time of the day	3	10	- indoor dry-bulb temperature
[38]	ANN	- outdoor temperature - relative humidity - solar intensity - wind speed	1	10	- indoor temperature
[39]	ANN,MLP	- day of the year - outdoor temperature - outdoor relative humidity - wind speed	10	-	- indoor temperature - indoor relative humidity
[40]	ANN,MLP	- outdoor temperature - past indoor temperature values - past relative humidity vales	1	10	- indoor temperature - indoor relative humidity
[41]	NNARX	- outdoor temperature - outdoor relative humidity - supply air temperature - supply relative humidity	1	12	- dry-bulb temperature
[42]	NNARX	- outdoor temperature - outdoor relative humidity	1	6	- indoor temperature - indoor relative humidity

One of the major shortcomings of this set of studies is the inconsistency in the types of variables used to determine temperature levels likely to provide sufficient thermal comfort. This makes it difficult to successfully employ the developed models in other building scenarios as they would require identical input variables to those used in model training in order to make sensible predictions. Moreover, when the variables used in model training are difficult to obtain, the developed models become less generalizable. Furthermore, such models are likely to suffer from inaccuracies as a result of not considering several important elements, especially those pertaining to individual behavior and state (e.g., clothing and activity). However, at the same time, the simplicity of temperature/humidity models means that they may be easier to develop and deploy in building systems than complex models, which require the consideration of complex factors during model training.

Another major observation arising from these studies is that their general outcome is mostly concerned with the predictive accuracy of the developed models. While the accuracy of predictive models is important, a further important step for such studies would be to elaborate on how the developed predictive models can be integrated into building systems for indoor environment control. A few studies [34,36] have proposed control algorithms using the developed ANN models and have demonstrated the usefulness of their predictive models based on computer simulation programs. However, the precise benefits of the predictive models developed in most studies using deep learning to predict indoor air temperature for thermal comfort purposes are not quantified (e.g., in terms of building energy reductions).

2.3. Thermal sensation (PMV index) models

In the previous section, we discussed one of the major shortcomings of simple temperature/humidity predictive models in the assessment of thermal comfort, i.e., their inability to consider important elements known to affect thermal comfort [15]. To some extent, studies that develop predictive models to estimate the PMV index attempt to address the issue of limited explanatory factors by using advanced ML techniques to explain thermal sensation as a resultant function of the four physical factors (i.e., air temperature, relative humidity, air velocity, and mean radiant temperature) and two personal factors (i.e., clothing and activity) first described by Fanger [11]. In our review, we found that the majority of studies that use ML methods to predict thermal comfort belong to this group of studies. As such, this section reviews a number of previous studies that employed diverse ML algorithms to predict occupant thermal sensations based on the six factors mentioned above.

In our search, we found that most studies that employed ML-based techniques to predict occupant thermal sensations relied mostly on neural networks of diverse architectures. For example, Liang and Du [43] developed an ANN model to predict the PMV index based on Fanger's six variables and subsequently demonstrated how such a model can be integrated into the control system of the variable air volume unit of a residential building. Atthajaryakul and Leephakpreeda [44] computed the PMV index in real-time using a feed-forward ANN and reported good agreement between the occupant thermal comfort levels calculated using the developed ANN model and those calculated using the conventional PMV model. Similarly, Yao and Xu [45], developed a back-propagation ANN model to approximate the PMV index using Fanger's six variables and reported a 5 % error in accuracy. Li et al.. [46] also developed a back-propagation ANN model that output the PMV index based on Fanger's six variables of thermal comfort. They also theoretically demonstrated its potential usage in HVAC control systems. Castilla et al.. [47] highlighted the expenses involved in calculating the classical PMV index in terms of the computational load and the extensive network of sensors required to collect the input data. To reduce such costs, they proposed and developed the use of ANN models to approximate the PMV index. They noted that the advantages of using such deep learning models to compute the PMV index over traditional methods were a reduction in the number of sensors required and the ability to control HVAC systems in real-time based on occupant thermal comfort. Garnier et al. [48] developed multiple low-order ANN models that forecast the PMV index at a future time and demonstrated the energy benefits of their model for the control of the multi-zone HVAC system of a residential building. In general, one of the main advantages of deep learning algorithms and ML is their ability to provide accurate estimations of the desired elements using limited explanatory variables (i.e., input variables) [26]. This attribute of deep learning algorithms is beneficial in thermal comfort modeling in terms of reduced cost and time. This was evidenced by Buratti et al. [49] who developed a feed-forward ANN model to predict the PMV index using two (i.e., air temperature and relative humidity) of the six variables introduced by Fanger[11]. The remaining studies are listed in Table 2.

Decision trees, especially random forests (RFs), have also been extensively employed in the development of predictive models for thermal sensations. For example, Chaudhuri et al developed a RF to estimate the thermal sensation, thermal preference, and thermal comfort votes of building occupants using physical environment elements and physiological measurements as explanatory variables. The physical environmental elements included air temperature, global temperature, relative humidity, and air velocity. Physiological measurements obtained from wearable devices included skin temperature, pulse rate, blood oxygen saturation, and blood pressure. The developed RF model is reported to predict thermal sensation votes with an accuracy of 92.86 % and 94.29 % for female and male subjects, respectively [50]. Wang et al. [51] developed two RF models to predict the thermal sensation of older people in indoor spaces. The first of the models was trained on data collected from field studies, whereas the second model was developed using data collected from a chamber study. Comparing the two developed models, the authors reported a prediction accuracy of 56.6 % by the model developed with field study data and 76.6 % by the model developed using the chamber studies data. Both models were reported to predict thermal sensations with a higher accuracy than the traditional PMV model. Lu et al. [52] used the publicly available ASHRAE database to develop five different types of classifiers that categorize occupant thermal sensation votes based on mean radiant temperature, air velocity, air temperature, air humidity, clothing insulation, and metabolic rate. The authors reported a 48.70 % recall success rate with RF algorithms, which was higher than that of PMV (43 %). Similarly, Lu et al. [53] developed a RF model using indoor air temperature, skin temperature, and clothing surface temperature collected using infra-red cameras to predict thermal sensation votes. They report a 92.5 % recall rate for the RF model, which was significantly higher than that of the traditional PMV model at 48.6 % for male subjects. A similar comparison for models developed using data from female subjects showed a 91.4 % and 33.3 % for the RF model and PMV model, respectively.

Other studies employed further ML algorithms that are neither deep learning nor decision tree techniques to model occupant thermal comfort. For instance, Farhan et al. [54] developed a comfort model based on a support vector machine (SVM) algorithm as well as physiological, environmental elements, and behavioral elements. The accuracy of the developed SVM model in predicting thermal sensation votes was reported as 76.7 %, which was around double that of the conventional PMV model (35.4 %). Bin and Ke [55] used least-square SVM algorithms to develop a model that predicts the PMV index using the six variables first described by Fanger (i.e., air temperature, air velocity, relative humidity, mean radiant temperature, clothing insulation, and metabolic rate) and reported good prediction performance using the developed model. Using the same six variables discussed above, Megri and Naqa [56] developed a SVM that predicted thermal comfort levels of building occupants. They compared the performance of the developed model with that of several other thermal comfort indices including the PMV and effective temperature. They reported strong correlations between the developed SVM model and common thermal comfort indices. In addition, Chaudhuri et al. [57] compared the performance of six ML classifiers, including the SVM, in estimating thermal comfort levels and compared their performance with that of the traditional PMV model. The authors report better predictive performance with the SVM model (79.90 %) than with the PMV model (65.50 %). Li et al. [58] also proposed a RF-based HVAC control system. The developed RF classifier is trained on occupant physiological and behavioral data to continuously predict personal thermal preference in real time. The developed model is reportedly able to correctly predict 80 % occupant thermal preference.

From reviewing the above studies, we found that nearly all the ML models developed to predict occupant thermal sensation were reported to provide better estimates of occupant thermal sensations than the original PMV/PPD model. In addition to the improved predictive accuracy of occupant thermal sensations, properly trained ML algorithms are likely to provide reduced computation loads in estimating thermal sensation votes, as compared with simplified models [59], relevant tables [11,60], and computer models [61], which are commonly used in computing thermal sensation votes. An added advantage of ML models that predict occupant thermal sensations based on the Fanger PMV model relates to the consistency in the input variables used, i.e., the input variables are well known, making these models more likely to be generalizable and easily deployable in new buildings. While the use of ML algorithms has clear advantages in the assessment of occupant thermal sensations, the current literature indicates that there are still major concerns that need to be addressed. For instance, we found that most of the existing studies tend to be concerned with the predictive accuracy of the developed ML-based models, especially in comparison with the conventional PMV/PPD model; they rarely discuss the deployment of such models in building control systems. Moreover, most of these studies tended to use clothing and activity level values derived from simplified sources such as ASHRAE tables, which can affect the predictive accuracy of the developed models.

2.4. Clothing and activity models

Occupant clothing insulation and activity level make major contributions to occupant thermal comfort. Clothing provides insulation to the body and is therefore an important determinant of heat exchange between the body and the environment and consequently thermal comfort [65]. On the other hand, activity is correlated with human metabolic rate and is an inherent

Table 2
Summary of studies on ML-based thermal sensation (PMV) predictive models.

Reference	Model	Features	Number of hidden layers/ number of trees	Number of neurons (hidden layer)	Output/class
[36]	ANN	- outdoor temperature - outdoor humidity - Indoor temperature - indoor humidity - change in indoor temperature, outdoor temperature and humidity	1	17	- change in temperature - change in humidity - change in PMV
[44]	BPNN	- indoor air temperature - wet-bulb temperature - globe temperature - air velocity - clothing insulation - activity	2	[8] [4]	- PMV
[46]	FFANN	- mean radiant temperature - indoor air temperature - indoor air humidity - indoor air flow rate - activity - clothing	3	6,2,1	- PMV
[47]	FFNN	- mean radiant temperature - indoor air temperature - indoor air humidity - indoor air flow rate - activity - clothing	2	8,4	- PMV
[49]	FFNN	- air temperature - relative humidity	2	41,41	- PMV
[62]	BPNN	- outdoor temperature - indoor temperature -outdoor humidity - indoor humidity	1	17	- PMV
[63]	RBFN	-wet-bulb temperature -globe temperature -clothing insulation -indoor air temperature -indoor relative humidity	1	30	-PMV
[64]	FFNN	- relative humidity - metabolic rate - clothing insulation levels - air speed -air temperature -mean radiant temperature -outdoor temperature -outdoor vapor pressure -outdoor wet-bulb temperature -horizontal total solar radiation -age -gender	3	-	-TSV
[50]	RF	- air temperature - black globe temperature -relative humidity -air velocity -skin conductance -skin temperature -pulse rate -blood oxygen saturation -blood pressure	500	-	-PMV
[51]	RF	-air temperature -air velocity - CO_2 emissions -illuminance -health status - acclimatization	-	-	-TSV
[52]	RF	- average three height temperature -indoor relative humidity -outdoor average min/max air temperature -outdoor average min/max relative humidity -average metabolic rate Clothing + chair insulation levels -average three heights of Mean Radiant Temperature			-PMV

determinant of the amount of heat loss by the body [11]. Although these two factors (i.e. clothing insulation and activity level) are core elements of human thermal comfort, their contribution to occupant comfort is not well represented in many thermal comfort indices. This is primarily because it is difficult to obtain data relating to these two factors. Luo et al. [66] provide an extensive review on the challenges associated with estimating metabolic rates in built environments. Similarly, Haldi and Robinson [67] discuss the challenges associated with the estimation of occupant clothing insulation levels. Owing to the difficulty in obtaining accurate clothing and activity data in thermal comfort studies, efforts have been made to develop data-driven predictive models that estimate these parameters more accurately using ML methods. For example, Ngarambe et al. [68] used climatic data and mode of transport to train a 5-layered deep neural network model that forecast daily mean clothing insulation levels of university students. The developed model predicted 90 % of the variations in mean clothing levels. Similarly, Na et al. [69] developed a deep learning model based on a convolutional neural network with eight layers that predicted the metabolic rates of individual occupants. They used IoT-based kinetic cameras to collect physiological data (e.g. heart rate) that were then used in the training of the developed model.

One major observation from these sets of studies is that given the advantages offered by AI, there have been minimal efforts by researchers in this field to employ AI-based techniques to improve the estimation/prediction of occupant clothing insulation and activity levels (i.e., in relation of the recent availability of IoT-based wireless devices which are capable of collecting large datasets related to the clothing status and activity of occupants and the advanced ML-based analytical methods capable of finding meaningful patterns within such complex datasets compared with conventional statistical methods). For instance, in our review, we found only two studies that employ AI-based methods to predict clothing levels [68] and activity [69]. Consequently, the usefulness of AI methods, especially ML-based predictive techniques, in the estimation of occupant clothing levels and activity, together with the subsequent implications of accurate estimations of these parameters on the overall state of occupant thermal comfort, still require further exploration.

Nevertheless, the shortcomings of ML-based predictive models for clothing and activity may be anticipated. One of the major issues with, for instance, ML-based predictive models for clothing is likely to be a lack of generalization. This is because the clothing factor in building occupants is influenced by myriad factors, e.g., culture, dress code, and gender. Consequently, it would be nearly impossible to obtain a universal clothing model that can be employed in buildings of all types without the need to consistently develop individual models to fit each building of interest. The issue of a lack of generalizable models is also applicable to models developed to predict occupant activity (although on a much smaller scale than that in ML-based predictive models for occupant clothing state). This is one of the main elements likely to discourage the development of ML-based predictive models for clothing and activity—the financial costs and time associated with developing clothing and activity models to suit each individual building are likely to outweigh the profits yielded by such models in terms of building energy consumption and the provision of thermal comfort.

2.5. Personal comfort models

Currently, the debate surrounding occupant thermal comfort is focused on individual thermal comfort. This is because in the past, thermal comfort was quantified collectively for a group of occupants (e.g., the PMV–PID model). However, thermal comfort in real-life scenarios is a matter of personal preference—how one individual feels under certain thermal conditions is likely to be different from another individual. The differences in thermal preference between individuals are primarily due to differences in physical factors such as gender and health conditions, or psychological factors such as perception and state of mind. Wang et al. [70] provide an extensive review on the individual differences associated with thermal comfort within a space; these differences warrant the shift from a group-centered understanding of thermal comfort to an individual-centric stance on thermal comfort. Moreover, recent developments in IoT-based devices (e.g., wearable sensors) have made it easy to collect data that can be used in developing and calibrating personal thermal comfort models without being overly intrusive. In addition, as highlighted throughout the current paper, advancements in ML technologies have made it easy to study highly complex datasets and extract meaningful insights that can be condensed into a function and integrated into a system that is able to continuously learn and update itself. Therefore, in this section, we summarize the current research that utilizes diverse ML techniques to develop personal thermal comfort models and discuss current gaps.

Liu et al. [71] developed a back-propagation ANN model using air temperature, air humidity, air velocity, and mean radiant temperature as input variables, with field survey responses of thermal sensation as data labels. In their study, thermal comfort level, which was also the output parameter of their model, was assessed based on three categories (i.e., 0, 0.5, and 1), where 0 stood for cool, 0.5 stood for comfort, and 1 stood for warm. The chosen scale to assess thermal comfort levels is different from the original 7-point scale proposed by Fanger [11]. This is because as explained Liu, the 7-point thermal comfort scale was designed for a large group of people and is therefore inaccurate for individuals; for example, an individual does not have to distinguish between cool and slightly cool. Kim et al. [72] used six ML algorithms to explore the relationships between occupant heating behavior, cooling behavior, and individual thermal preference, with thermal preference gauged on a 3-category scale (warmer, no change, cooler). The ML algorithms considered included RF, GBM, SVM, logistic regression, Gaussian classifiers, and conventional classification trees. The data used for model training were collected from field measurements taken from 38 participants in an office building setting. These researchers reported that better estimations were given by individual thermal comfort models than by conventional PMV models. Auffenberg et al. [73] proposed a model that estimates the comfort temperature of an individual based on Bayesian networks. The model was trained on the ASHRAE RP-884 dataset. They reported 17.5–23.5 % higher accuracy with the developed models compared with the conventional PMV index. Similarly, Ghahramani et al. [74] used field data collected from 33 subjects to develop a Bayesian network model that estimates personal thermal preference using only air temperature as an input variable. They reported better accuracy in the estimation of thermal comfort with the developed Bayesian model (70 %) than with the original PMV model (56 %). Li et al. [58] developed a RF model that predicts thermal preference on a 3-point scale (warm/no change/ cooler). The model was trained on data related to physical elements (i.e., indoor air temperature, relative humidity, carbon dioxide, window opening status, and outdoor humidity) collected using sensors and occupant-related data (heart rate, clothing level, skin temperature, and activity) collected using wristbands. They reported 80 % accuracy when using the developed model to estimate actual individual thermal preferences levels. Lee et al. [75] also developed a Bayesian inference clustering model that learned individual thermal preference on a 3-point scale (warm/no change/cooler). The model was trained using Fanger's six variables as model parameters acquired from the RP-884 ASHRAE database. Similarly, Jiang and Yao [76] developed a personalized thermal sensation model. The model was trained using the six variables introduced by Fanger and also discussed above. The thermal sensation votes were predicted on the 7-point scale dictated by ASHRAE. Comparing the performance of the developed model for predicting thermal sensation votes with that of the conventional PMV model, the authors reported a better performance with the SVM model (89.82 %) than with the PMV model (49.71 %). Peng and Hsie[77] discussed the shortcomings of traditional comfort models in modeling individual comfort and as a solution, proposing a hybrid SVM classifier that efficiently classifies individual thermal sensation votes. Shetty et al. [78] developed three separate tree-based algorithms (i.e., decision trees, random forest, and boosted trees) to predict fan usage preferences. The fan usage preferences were determined using two factors (i.e., fan state and fan speed). The fan state was treated as a binary classification problem with two possible outcomes, ON or OFF, and the fan speed was treated as a regression problem with 0 and 100 as the lowest and highest values, respectively. The variables used to predict fan usage preferences (i.e., fan state and fan speed) included presence state (e.g., if the occupant is within the vicinity of his/her desk), hour (as a proxy for time), the moving average of indoor air temperature, and the moving average of the presence state. Among the three tree-based algorithms used, the RF model was reported to achieve the highest accuracy (97.73 %) in the prediction of fan state and lowest errors when used to predict fan speed.

As shown from the discussion of relevant studies above, the region of thermal comfort that could potentially reap substantial benefits from AI-based methodologies is that involved with the provision of individual thermal comfort. Moreover, there are building energy benefits that could potentially be gained from the employment of individual comfort models. However, there remain significant elements of personal comfort models that are not well explained in the literature and which need further exploration in order to convince many in the building industry of the usefulness of such models. One of these elements, and perhaps the most concerning, related to the application of such models in every day buildings. While it is understandable how personal comfort models can be beneficial in circumstances that involve individualized heating/cooling systems (i.e., desk fans), it is still not clear how these models are beneficial for large buildings, e.g., open-plan offices that rely on centralized HVAC systems to provide comfort. As the application of personalized comfort models may require some sort of personalized comfort equipment for each occupant, it is worth noting that there remains a lack of experimental studies that quantify the costs associated with the use and provision of such equipment as compared with conventional centralized HVAC or decentralized HVAC systems. Furthermore, during operation, predictive models require a consistent in-feed of data (i.e., input data) about the environment to be controlled in order to make predictions. For general predictive models, the input data can be obtained from sensors installed within thermal zones that then send the information to the control/predictive system via analog or wireless channels. However, for personal comfort models, this process is not clearly described in the literature. While the usefulness of wearable devices in collecting the occupant personal data necessary in the early stages of model development and training is well established in the literature, it is not clear if the occupants would be required to wear these devices constantly so as to provide input data during the operation of the models. If this is the case, there remains a need for extensive experimental studies that quantify the energy benefits of deploying comfort models in comparison with the financial costs of providing occupants with wearable devices. Moreover, the potential discomfort likely to be experienced by occupants as a result of constantly wearing monitoring devices requires further research considerations.

3. Energy implications of AI-based thermal comfort controls

The primary purpose of studying occupant thermal comfort in buildings, and of the subsequent theoretical models that arise from such studies, is to optimize building energy consumption while providing sufficient levels of thermal comfort. For this to happen, thermal comfort models ought to be integrated into building control systems. Although there are standards (such as the ASHRAE 55 [79] and ISO 7730[80](standard) that have been developed to solely address the issue of indoor thermal comfort, they are rarely consulted when designing building control systems. For example, it is reported that in North America, 97 % of those involved in the HVAC industry are not familiar with the ASHRAE standard [79]. The evidence regarding the significant disconnect between thermal comfort studies and building control studies is provided in the extensive review by Park and Nagy [22]. Their online review considering 5536 publications on both thermal comfort and building control showed very few cross-citations between the two fields. In the current study, we observed the same disconnect—only a few studies that developed AI-based comfort models go on to analyze the performance of the models by fully integrating them into building control systems. In this section, we discuss those few studies that use AI-based thermal comfort models in actual building control systems and the energy benefits that arise from using such models.

Garnier et al. [48] used simulation methods to demonstrate the energy saving and occupant comfort benefits of a neural predictive HVAC control method over two other non-predictive methods in a multi-zoned non-residential building. The neural predictive method adjusted the HVAC settings based on the predictions of a low ANN thermal comfort model, whereas one of the non-predictive methods kept the HVAC system in operation mode continually and the other scheduled system operation based on occupancy levels. The authors reported energy savings between 20 and 140.5 Wh/day.m^2 and between 6.4 and 82.3 Wh/day.m^2 when using the predictive controller during the heating season and cooling season, respectively. Similarly, Ferreira et al. [81,82] employed model based predictive control (MBPC) methods in the control of an HVAC system in a university building. The predictive models used in the MPBC system were implemented by the RBF NN. The authors report electric energy savings greater than 50 % while maintaining comfort levels within an acceptable range. A series of other articles [83–85] have also demonstrated the energy saving and occupant comfort benefits of MPBC over conventional control methods for HVAC systems.

Fuzzy logic controllers have also been extensively employed in HVAC optimization control in relation to thermal comfort. For example, Ciabattoni et al. [86] conducted a field experiment to compare the energy consumption of an HVAC system controlled via fuzzy logic schemes with that of one controlled by conventional PID methods. They reported better performance for the fuzzy control system than for the PID system. Similarly, Hussain et al. [87] used simulation studies to compare the energy saving potential and thermal comfort implications of an HVAC system utilizing a comfort-based fuzzy control system with those of a traditional ON/OFF control system. They reported decreases in energy consumption of 16.1 % and 18.1 % in the cooling and heating seasons, respectively, when using the fuzzy controller. Collotta et al. [88] proposed a neural-fuzzy network system that automatically regulated indoor air temperature. The actual energy savings of the systems were not quantified but the authors reported the better performance of the network system over the conventional methods when maintaining the thermal comfort levels within an acceptable range. Sung et al. [89], proposed an advanced smart system that consisted of IoT network sensors and a fuzzy logic controller developed using a multi-input multi-output mathematical model. The

Table 3
Summary of studies on thermal comfort control and energy savings.

Reference	Control method	Comfort element	Verification method	Energy savings/benefits
[91]	MPC	temperature range	experiment	20 % reductions cooling season 70 % reductions in heating season
[92]	MPC/linear stochastic functions	temperature range	simulation	13.7 % reductions in total energy usage
[93]	MPC/linear functions		simulation	16 % energy reductions compared to PI-based controls
[94]	MPC	temperature range	simulation	-0 % reductions in heating season -20 % reductions in cooling season
[95]	MPC	PPD	simulation	18 % compared to PI controllers
[96]	PI/genetic algorithm	temperature range	simulation	-
[97]	Fuzzy controller	Actual vote	simulation	39 % reduction in daily average airflow
[98]	Fuzzy controller	Actual vote	simulation	12.08 % reductions in daily average airflow
[99]	Fuzzy controller/gausian adaptive theorem	temperature range	experiment	-
[87]	Fuzzy controller/genetic algorithm	PMV-PPD	simulation	16.2 % reductions in cooling 18.1 % reductions in heating
[100]	Fuzzy controller	temperature	simulation	
[101]	MPC	PMV	experiment	4 % - 9.1 % reductions in total energy usage compared to PI controllers
[102]	MPC/particle swan optimization elements	temperature	experiment	-NA
[103]	MPC	temperature range	experiment	15 % reduction in electricity consumption
[104]	MPC	PMV-PPD	experiment	-
[105]	MPC/NARX	temperature	experiment	30.95 % savings in energy costs
[106]	MPC	PMV-PPD	experiment	NA
[107]	MPC	temperature range	simulation	17 % reductions in energy use

proposed smart system was developed with three comfort mode settings (1) PMV = 0, (2) PMV = 0.5 and, (3) PMV = 0.7, with the 3rd mode setting as the energy saving mode. They estimated the optimum energy savings of the 3rd mode, which strikes a balance between thermal comfort provision and energy savings. Several other studies discuss the potential energy savings associated with the use of fuzzy-logic systems in building control for thermal comfort and energy savings [Table 3].

As demonstrated above, there is a near consensus that favors the use of "intelligent" control methods (e.g., MBPC and neuro-fuzzy logic systems) compared with conventional controllers (e.g., PI and PID controllers). This is primarily because conventional methods tend to perform poorly when dealing with dynamic, non-linear processes with large time delays [23,24,90]. However, the literature evidence regarding the benefits of intelligent controllers over conventional controllers for thermal comfort control and building energy optimization is barely sufficient to sway the building industry toward the replacement of conventional controllers with intelligent controllers. Much knowledge from experimental and actual field studies is still required to better quantify the benefits of intelligent controllers over conventional controllers in building control. Moreover, from a control engineer's point of view, conventional controllers may prove to be better tools than intelligent controllers given their simplicity and ease of deployment.

4. Future research directions

To effectively discuss gaps in the current use of AI methods for the provision of thermal comfort in buildings, we show the main steps taken (Fig. 2) in the development of thermal comfort predictive models and the implementation of such models in building control systems. We then discuss each step and its potential improvements.

Step 1—Lack of AI-based modeling in residential buildings and non-waking occupants

Existing studies on the use of AI methods in thermal comfort prediction and control mostly deal with non-residential buildings. In our review, we found only a few studies that deal with residential buildings. This is primarily because of the difficulty in collecting data and obtaining sufficient thermal comfort-related feedback from people in a home setting. AI-based methods such as ML predictive algorithms often work best on copious amounts of data, which can be difficult to gather in residential settings. In addition, factors such as clothing insulation levels and activity are likely to be similar in, e.g., an office building owing to dress codes or uniforms and similarities in the type of work being conducted. This makes it less tedious to compute thermal comfort levels in non-residential buildings than in residential buildings. Similarly, most AI comfort models have been developed for waking people, neglecting the necessity of thermal comfort for sleeping people. This is again possibly due to the difficulties associated with collecting comfort-related feedback from sleeping individuals. However, as we explained earlier, and as illustrated through some of the articles summarized in the present study, recent advancements in IoT devices and wireless technologies have made it possible to collect physiological data in a non-intrusive manner. By using such devices for data collection, it would be interesting to see how (i) the current use of advanced analytical methods for the modeling and control of thermal comfort extend to residential buildings, in particular to sleeping occupants, and (ii) the subsequent implications of using these methods in regards to occupant satisfaction and building energy use.

Step 2—Lack of sufficient amounts of data and biases in datasets

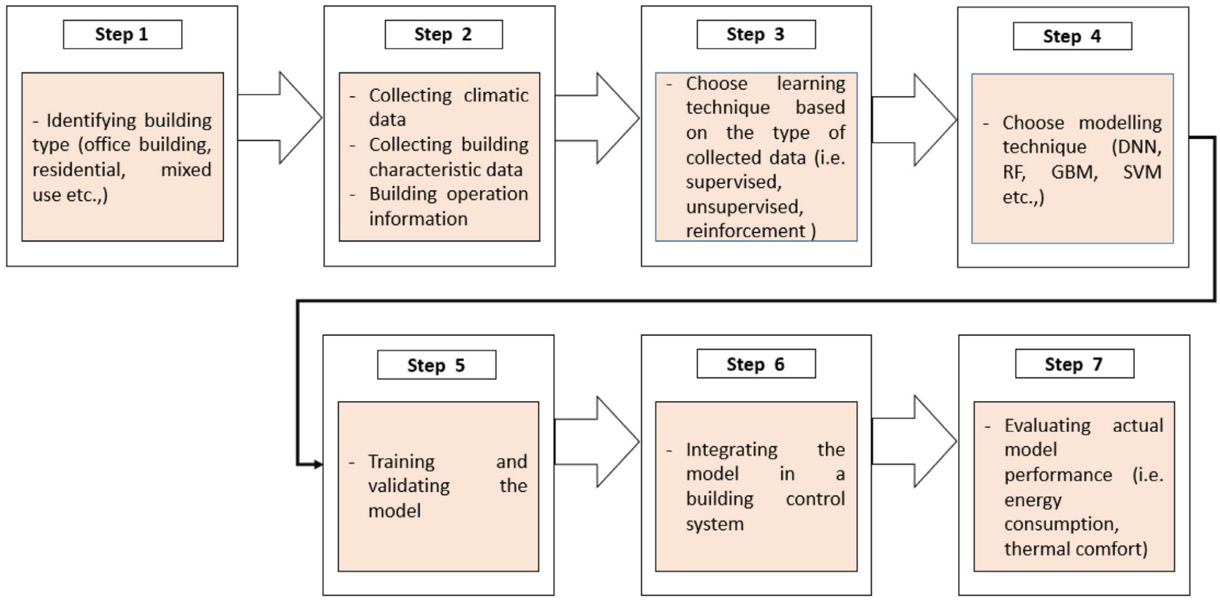

Fig. 2. Development and implementation of thermal comfort models.

Although AI-based modeling and control of thermal comfort has picked up pace in the building industry, it is still difficult to envisage such systems being widely employed. This is because training ML models require copious amounts of data for effective learning. While data collection methods in many fields have improved significantly over the last few years, data related to building usage, occupant-building interaction, etc., is still difficult to gather. Where such data is available, it is collected by government agencies and is usually large scale data; for example, a block of buildings within a district rather than individual buildings. A possible solution to this is the incorporation of new technologies such as in-stream supervision [108], where streaming data is inherently labeled and used for predictions, into buildings.

Moreover, biases are inevitable when dealing with large datasets. Such biases may result in inaccurate outcomes from the developed models. For instance, a model that seemingly demonstrates good performance may be picking up and ultimately considering noise in the data during model training. The problem with noisy data is further exacerbated by a lack of neutrality in the training dataset. To mitigate this problem, future research should endeavor to establish a means to collect building-usage data that are genuine and heterogeneous.

Step 3—High dependency on "supervised learning" methods

Most ML techniques used in this field have mainly relied on supervised learning methods. Supervised learning methods involve the use of labeled data (i.e., input variables and the corresponding output variables) for model training [29]. However, labeled databases for buildings are rarely available, making the process of data acquisition and labeling prior to modeling quite tedious. This lack of readily available labeled data for buildings discourages the application of ML techniques in building control and optimization. A possible solution to this problem is to encourage the use of semi-supervised [109] or unsupervised [26] learning methods, which do not rely entirely on labeled data to train the required predictive models. Similarly, the use of reinforcement learning [110], which trains the model through a trial and error approach as opposed to via example, should be further explored to overcome the shortcomings of supervised learning methods in the building sector. There have been recent efforts to employ reinforcement learning methods in the modeling and control of thermal comfort [111,112]. However, these studies are still relatively few and are mostly validated via simulation programs, for example, Gao et al. [111]. Many of such studies, conducted in actual buildings are still necessary to solidify the benefits of reinforcement learning methods in accurately modeling thermal comfort while at the same time reducing building energy consumption. Moreover, Future studies should also look into the complex and specific mechanisms of how diverse machine learning algorithms work and how these mechanisms would translate into the application of ML in the modeling of thermal comfort and thermal control in buildings. A clear and detailed analysis of such mechanisms would make it less challenging when choosing which algorithm to employ in thermal comfort modeling.

Step 4—Lack of generalization, transparency, and deterministic conclusions

While ML techniques have reached impressive milestones over the years, most ML models still lack the ability to generalize conditions. For example, a thermal comfort predictive model developed using data from one building and which performs quite adequately may perform poorly when utilized to predict thermal comfort using a new dataset from a different building, despite the new set of data being similar to the data used in training the model. Problems associated with the lack of generalization of ML models require that several ML models be developed for each specific case that exists (e.g., for each building). This individualistic approach in modeling incurs huge burdens in terms of costs, computational loads, data collection, personnel, etc., An alternative is the use of transfer learning [113], which involves using knowledge gained from pre-trained models to solve new tasks. Transfer learning methods have been successfully employed, e.g., in tasks dealing with web-documenting [114,115]. Therefore, future studies should explore the use of transfer learning techniques in developing ML models for building operation purposes. Also, to further understand the current limitations of ML applications in the building sector, especially in thermal comfort modeling and thermal control of indoor environments, future studies should further explore limitations of employing ML methods in the modeling of occupant thermal comfort at different stages of modeling, for instance, at each step presented in Fig. 2 and subsequently, propose practical solutions to address the said limitations.

In addition, most AI-based predictive models are black-box models and thus lack an element of transparency. While we are able to judge the performance of the model as good or bad, it is nearly impossible to understand why a given model makes the choices that it does. There are simplified statistical methods such as path analysis that have been used in comfort studies to improve thermal modeling [116]. However, it is should be noted that while path analysis methods are certainly more informative than traditional statistical methods (e.g. multiple linear regression) in, for instance identifying, optimum models in cases where we have multiple models developed using many variables, it is still difficult to prove causality between variables using path analysis [117].However, of late, there have been attempts to solve this issue using novel techniques such as the local interpretable model-agnostic explanations (LIME) [118]. LIME attempts to identify which parts of the training dataset are responsible for most of the predictions made by the developed model. It does this by feeding developed model inputs similar to those used in the training and observing variances in the predicted outcome. Consequently, future studies in this area should explore the use of such novel techniques in ML models developed for building-related purposes. Such techniques would provide further insights into how different factors interact with a building or space;this would have significant implications in terms of space design, building regulations, policies, etc.

Additionally, the insights provided by most ML-based models are exploratory as opposed to deterministic. They merely inform whether certain attributes are correlated with an observed outcome; they are unable to shine light on the cause–effect relationship between variables [119]. Current research efforts leantoward using ML to discover cause–effect relationships in data sets. For example, Athey and Imbens [120]proposed several methods to use a cross-validation technique with supervised learning to solve cause–effect tasks. Consequently, future research should explore ways of adapting such novel technologies to building science. For example, through ML technologies, designers should be able to explore which physical or non-physical elements are likely to result in occupant discomfort and how they can be properly controlled to provide thermally comfortable conditions while minimizing energy use.

Step 5—Tuning, parameters, and model optimization techniques

While the variety of parameter tuning techniques and optimization techniques that exist for ML models are beneficial overall, they can also lead to inaccurate and unnecessarily computationally-expensive models when improperly employed. There remains a need for studies that explore optimum parameter tuning and optimization techniques that consider both accuracy and computational costs simultaneously.

Step 6—Deployment of comfort models in building control systems

As explained earlier, most existing studies on the use of AI-based techniques in thermal comfort modeling report on the ability of AI-based techniques to predict comfort levels in comparison with traditional models such as the PMV/PPD model [11]. The deployment of the developed comfort predictive models is often not discussed or at times neglected. It would be beneficial for future studies to place more emphasis on discussions regarding the integration of AI-based predictive models into building energy management systems (BEMS). Below (Fig. 3), we show a simple example of how a comfort predictive model can be integrated into a BEMS system for comfort control.

Step 7—Quantifying the benefits of AI-based comfort control systems

There are few studies that discuss the implications of using AI-based methods for the control of thermal comfort on building energy use and occupant thermal satisfaction. Moreover, most of those few studies rely on simulation results to quantify the benefits of AI-based thermal comfort control methods. While the use of computer simulation software is beneficial to study such complex tasks in terms of time, this approach is prone to many errors, and studies that explore the benefits of AI-based thermal comfort control systems through actual field and experimental studies are necessary.

5. Conclusions

AI methods, particularly those based on ML algorithms, offer enhanced opportunity to analyze data that is dynamic and highly variable. Subsequently, they are better suited for the analysis of the non-linear nature of the interactions between buildings and their occupants. The current review shows theoretical evidence, arising from several field and experimental studies, illustrating the potential benefits (i.e., in terms of accuracy) of ML algorithms in the prediction of occupant thermal comfort compared with traditional methods such as the PMV/PPD. Moreover, the advances in IoT wireless technologies offer simplified methods to collect the occupant-related data necessary to develop thermal comfort predictive models. Via building control techniques, the combination of the accuracy offered by machine algorithms and the ease of data collection from IoT-based devices makes predictive modeling the ideal approach for optimizing building energy performance without sacrificing occupant thermal comfort. However, while the idea is promising, there are still significant challenges that are likely to delay the adoption of AI-based methodologies in the building industry. For instance, there remains a lack of solid evidence demonstrating the usefulness of AI-based thermal comfort control based on in-situ experiments. While there is strong theoretical evidence regarding the potential usefulness of artificial intelligence-based predictive modeling on occupant thermal comfort and the associated building energy benefits, there is a lack of field and experimental studies to quantify the benefits of AI-based methods over traditional building control methods in terms of both thermal comfort and building energy use. Furthermore, we found that the AI methods currently being used in the building sector are lacking in several aspects, e.g., in the type of learning methods being employed; this may further prevent the transition from the traditional approach to thermal comfort and building control to modernized and potentially more beneficial methods based on AI. We have discussed several approaches that we believe can help in the integration of AI into buildings; these could potentially result in the provision of adequate comfort levels while minimizing energy use.

A further important discussion that has been largely ignored in the literature is that dealing with the financial costs associated with the development of AI-based thermal comfort predictive models and their deployment in building control systems. This issue is even more pronounced for personal comfort models as they are likely to require personalized devices for data collection during the development and training of the models and later during the deployment of said models in thermal control systems. Consequently, studies addressing the initial costs associated with the development and deployment of AI-based thermal comfort models in comparison with the long-term benefits in terms of costs through reduced energy usage, occupant thermal satisfaction, and reduced CO_2 emissions, would go a long way toward encouraging the use of AI-based methodologies for thermal control in buildings.

Besides the lack of studies discussing the benefits and financial costs of AI-based thermal comfort control, the lack of multidisciplinary collaboration in building research is also likely to result in unnecessary delays in the adoption of AI-based thermal comfort control methodologies. Most research in the built environment field is conducted by researchers in the hard engineering fields (e.g., civil and architectural engineering). However, the study of AI and its deployment in built environments requires the adoption of concepts and methodologies from many other academic

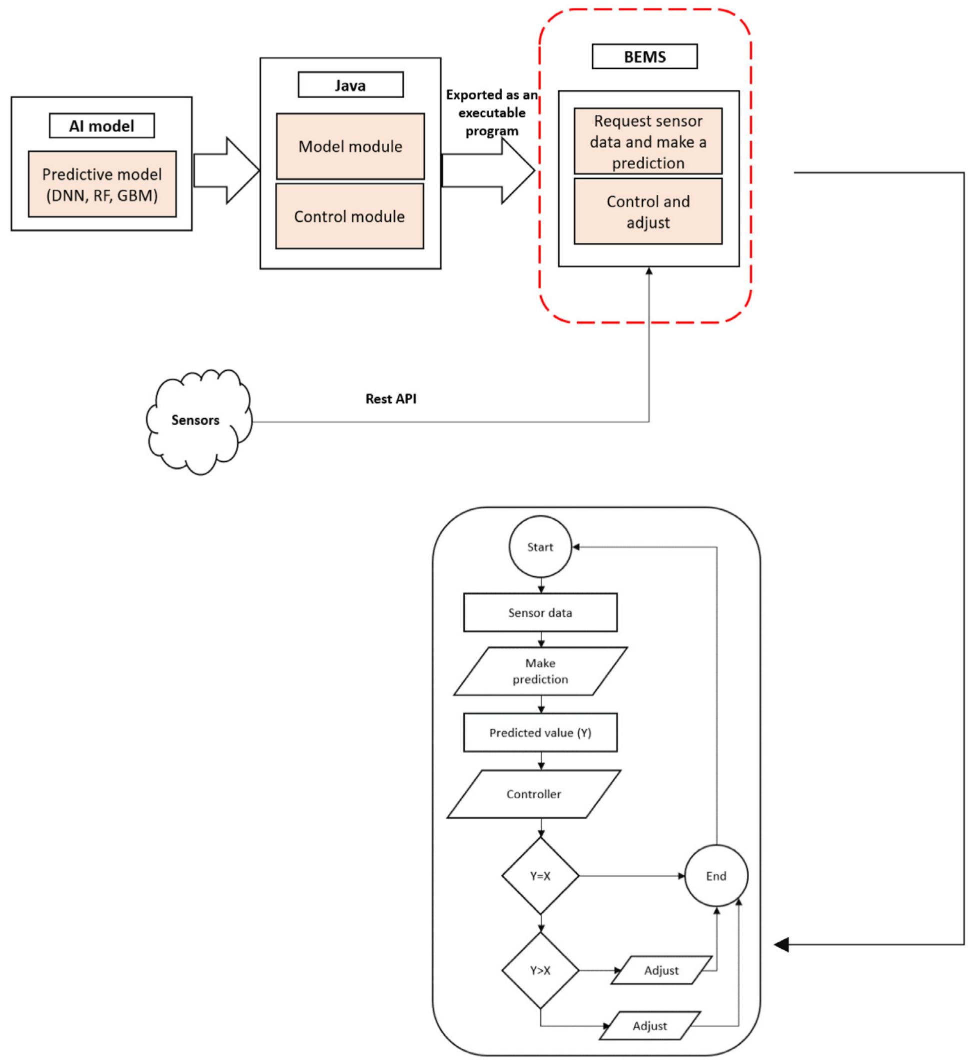

Fig. 3. Implementation of thermal comfort models in BEMS (building energy management system).

disciplines, primarily the computer science field. Consequently, this limited collaboration between these two disciplines (i.e., built environment engineering and computer science) is likely to further stunt the chances of discovering less complex and cheaper means of integrating AI-based thermal comfort control schemes into building control systems.

Declaration of Competing Interest

The corresponding author confirms on behalf of all authors that there have been no involvements that might raise the question of bias in the work reported or in the conclusions, implications, or opinions stated

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References

[1] M.Z. Jacobson, Review of solutions to global warming, air pollution, and energy security, Energy Env. Sci. 2 (2009) 148–173, doi:10.1039/B809990C.
[2] P.H. Shaikh, N.B.M. Nor, P. Nallagownden, I. Elamvazuthi, T. Ibrahim, A review on optimized control systems for building energy and comfort management of smart sustainable buildings, Renew. Sustain. Energy Rev. 34 (2014) 409–429, doi:10.1016/j.rser.2014.03.027.
[3] A.J. Marszal, P. Heiselberg, J.S. Bourrelle, E. Musall, K. Voss, I. Sartori, A. Napolitano, zero energy building – a review of definitions and calculation methodologies, Energy Build 43 (2011) 971–979, doi:10.1016/j.enbuild.2010.12.022.
[4] D. D'Agostino, P. Zangheri, L. Castellazzi, Towards nearly zero energy buildings in europe: a focus on retrofit in non-residential buildings, Energies 10 (2017) 117, doi:10.3390/en10010117.
[5] N.E. Klepeis, W.C. Nelson, W.R. Ott, J.P. Robinson, A.M. Tsang, P. Switzer, J.V. Behar, S.C. Hern, W.H. Engelmann, The National Human Activity Pattern Survey (NHAPS): a resource for assessing exposure to environmental pollutants, J. Expo. Sci. Environ. Epidemiol. 11 (2001) 231–252, doi:10.1038/sj.jea.7500165.
[6] D. Mitchell, C. Heaviside, S. Vardoulakis, C. Huntingford, G. Masato, B.P Guillod, P. Frumhoff, A. Bowery, D. Wallom, M. Allen, Attributing human mortality during extreme heat waves to anthropogenic climate change, Environ. Res. Lett. 11 (2016) 074006, doi:10.1088/1748-9326/11/7/074006.
[7] Y. Geng, W. Ji, B. Lin, Y. Zhu, The impact of thermal environment on occupant IEQ perception and productivity, Build. Environ. 121 (2017) 158–167, doi:10.1016/j.buildenv.2017.05.022.
[8] D. Ormandy, V. Ezratty, Health and thermal comfort: From WHO guidance to housing strategies, Energy Policy 49 (2012) 116–121, doi:10.1016/j.enpol.2011.09.003.
[9] O.B.Kazanci, D.Coakley, B.W.Olesen, A Review of Adaptive Thermal Comfort Implementation in International Thermal Comfort Standards, (n.d.) 4.
[10] L. Yang, H. Yan, J.C. Lam, Thermal comfort and building energy consumption implications – A review, Appl. Energy 115 (2014) 164–173, doi:10.1016/j.apenergy.2013.10.062.

[11] P.O. Fanger, Analysis and Applications in Environmental Engineering, McGraw-Hill Book Company, New York, 1970.
[12] B.W. Olesen, K.C. Parsons, Introduction to thermal comfort standards and to the proposed new version of EN ISO 7730, Energy Build 34 (2002) 537–548, doi:10.1016/S0378-7788(02)00004-X.
[13] R.J. de Dear, G.S. Brager, Thermal comfort in naturally ventilated buildings: revisions to ASHRAE Standard 55, Energy Build 34 (2002) 549–561, doi:10.1016/S0378-7788(02)00005-1.
[14] M. Castillo-Cagigal, E. Caamaño-Martín, E. Matallanas, D. Masa-Bote, A. Gutiérrez, F. Monasterio-Huelin, J. Jiménez-Leube, PV self-consumption optimization with storage and Active DSM for the residential sector, Sol. Energy 85 (2011) 2338–2348, doi:10.1016/j.solener.2011.06.028.
[15] M.A. Humphreys, J. Fergus Nicol, The validity of ISO-PMV for predicting comfort votes in every-day thermal environments, Energy Build 34 (2002) 667–684, doi:10.1016/S0378-7788(02)00018-X.
[16] Richard De Dear, Gail Schiller Brager, Developing an adaptive model of thermal comfort and preference, ASHRAE Transactions 104 (1) (1998) 67–75.
[17] P. Ole Fanger, J. Toftum, Extension of the PMV model to non-air-conditioned buildings in warm climates, Energy Build 34 (2002) 533–536, doi:10.1016/S0378-7788(02)00003-8.
[18] J.J. Aguilera, O.B. Kazanci, J. Toftum, Thermal adaptation in occupant-driven HVAC control, J. Build. Eng. 25 (2019) 100846, doi:10.1016/j.jobe.2019.100846.
[19] Comite'Europe'en de Normalisation, C. E. N., "Indoor environmental input parameters for design and assessment of energy performance of buildings addressing indoor air quality, thermal environment, lighting and acoustics.", EN (2007) 15251.
[20] Bjarne W. Olesen, "International Standards for the Indoor Environment. Where are we and do they Apply Worldwide.", ASHRAE Distinguished Lecturer Talk, ASHRAE Singapore, 2006 Chapter.
[21] T. Cheung, S. Schiavon, T. Parkinson, P. Li, G. Brager, Analysis of the accuracy on PMV – PPD model using the Ashrae global thermal comfort database II, Build. Environ. 153 (2019) 205–217, doi:10.1016/j.buildenv.2019.01.055.
[22] J.Y. Park, Z. Nagy, Comprehensive analysis of the relationship between thermal comfort and building control research - A data-driven literature review, Renew. Sustain. Energy Rev. 82 (2018) 2664–2679, doi:10.1016/j.rser.2017.09.102.
[23] KiamHeong Ang, G. Chong, Li Yun, PID control system analysis, design, and technology, IEEE Trans. Control Syst. Technol. 13 (2005) 559–576, doi:10.1109/TCST.2005.847331.
[24] J Ang, H. Kiam, Gregory CY Chomg, "PID control system analysis and design. problems, remedies and future directions.", IEEE Control Syst. Mag. (2006) 32–41.
[25] D. Enescu, A review of thermal comfort models and indicators for indoor environments, Renew. Sustain. Energy Rev. 79 (2017) 1353–1379, doi:10.1016/j.rser.2017.05.175.
[26] Y. LeCun, Y. Bengio, G. Hinton, Deep learning, Nature 521 (2015) 436–444, doi:10.1038/nature14539.
[27] J. Schmidhuber, Deep learning in neural networks: An overview, Neural Netw 61 (2015) 85–117, doi:10.1016/j.neunet.2014.09.003.
[28] Bekir Karlik, A. Vehbi Olgac, Performance analysis of various activation functions in generalized MLP architectures of neural networks, International Journal of Artificial Intelligence and Expert Systems 1 (4) (2011) 111–122.
[29] Rich Caruana, Alexandru Niculescu-Mizil, "An empirical comparison of supervised learning algorithms.", in: Proceedings of the 23rd International Conference on ML, ACM, 2006.
[30] Adam Coates, Andrew Ng, Honglak Lee, An analysis of single-layer networks in unsupervised feature learning, in: Proceedings of the fourteenth international conference on artificial intelligence and statistics, Fort Lauderdale, Florida, USA, Microtome publishing, 2011, pp. 215–223.
[31] L.P. Kaelbling, L Michael, W.M. Littman, "Reinforcement learning: A survey.", J. Artific. Intell. Res. 4 (1996) 237–285.
[32] J.M. Mendel, Fuzzy logic systems for engineering: a tutorial, Proc. IEEE. 83 (1995) 345–377, doi:10.1109/5.364485.
[33] F.Pedregosa, G.Varoquaux, A.Gramfort, V.Michel, B.Thirion, O.Grisel, M.Blondel, P.Prettenhofer, R.Weiss, V.Dubourg, J.Vanderplas, A.Passos, D.Cournapeau, Scikit-learn: Machine Learning in Python, Mach. Learn. PYTHON. (n.d.) 6.
[34] J.W. Moon, S.-H. Yoon, S. Kim, Development of an artificial neural network model based thermal control logic for double skin envelopes in winter, Build. Environ. 61 (2013) 149–159, doi:10.1016/j.buildenv.2012.12.010.
[35] J.W. Moon, S.K. Jung, Algorithm for optimal application of the setback moment in the heating season using an artificial neural network model, Energy Build 127 (2016) 859–869, doi:10.1016/j.enbuild.2016.06.046.
[36] J.W. Moon, J.-J. Kim, ANN-based thermal control models for residential buildings, Build. Environ. 45 (2010) 1612–1625, doi:10.1016/j.buildenv.2010.01.009.
[37] A. Ashtiani, P.A. Mirzaei, F. Haghighat, Indoor thermal condition in urban heat island: Comparison of the artificial neural network and regression methods prediction, Energy Build 76 (2014) 597–604, doi:10.1016/j.enbuild.2014.03.018.
[38] T.G. Özbalta, A. Sezer, Y. Yıldız, Models for prediction of daily mean indoor temperature and relative humidity: education building in Izmir, Turkey, Indoor Built Environ 21 (2012) 772–781, doi:10.1177/1420326X11422163.
[39] L. Mba, P. Meukam, A. Kemajou, Application of artificial neural network for predicting hourly indoor air temperature and relative humidity in modern building in humid region, Energy Build 121 (2016) 32–42, doi:10.1016/j.enbuild.2016.03.046.
[40] J.W. Moon, Integrated control of the cooling system and surface openings using the artificial neural networks, Appl. Therm. Eng. 78 (2015) 150–161, doi:10.1016/j.applthermaleng.2014.12.058.
[41] G. Mustafaraj, G. Lowry, J. Chen, Prediction of room temperature and relative humidity by autoregressive linear and nonlinear neural network models for an open office, Energy Build 43 (2011) 1452–1460, doi:10.1016/j.enbuild.2011.02.007.
[42] G. Mustafaraj, J. Chen, G. Lowry, Thermal behaviour prediction utilizing artificial neural networks for an open office, Appl. Math. Model. 34 (2010) 3216–3230, doi:10.1016/j.apm.2010.02.014.
[43] Jian Liang, Ruxu Du, Thermal comfort control based on neural network for HVAC application, in: Proceedings of the IEEE Conference Control Appl CCA, Toronto, Canada, IEEE, 2005, pp. 819–824, doi:10.1109/CCA.2005.1507230.
[44] S. Atthajariyakul, T. Leephakpreeda, Neural computing thermal comfort index for HVAC systems, Energy Convers. Manag. 46 (2005) 2553–2565, doi:10.1016/j.enconman.2004.12.007.
[45] Jian Yao, Jin Xu, "Research on the BPNN in the Prediction of PMV.", Appl. Mech. Mater., 29, Trans Tech Publications, 2010.
[46] C. Li, Q. Zhang, T. Mou, The Study of Neural Network in the Application of PMV Index, in: Proceedings of the International Conference System Science Engineering Des. Manuf. Informatiz, Yichang, China, IEEE, 2010, pp. 289–292, doi:10.1109/ICSEM.2010.85.
[47] M. Castilla, J.D. Álvarez, M.G. Ortega, M.R. Arahal, Neural network and polynomial approximated thermal comfort models for HVAC systems, Build. Environ. 59 (2013) 107–115, doi:10.1016/j.buildenv.2012.08.012.
[48] A. Garnier, J. Eynard, M. Caussanel, S. Grieu, Predictive control of multizone HVAC systems in non-residential buildings, IFAC Proc 47 (2014) 12080–12085, doi:10.3182/20140824-6-ZA-1003.01826.
[49] C. Buratti, M. Vergoni, D. Palladino, Thermal comfort evaluation within non-residential environments: development of artificial neural network by using the adaptive approach data, Energy Procedia 78 (2015) 2875–2880, doi:10.1016/j.egypro.2015.11.656.
[50] T. Chaudhuri, D. Zhai, Y.C. Soh, H. Li, L. Xie, Random forest based thermal comfort prediction from gender-specific physiological parameters using wearable sensing technology, Energy Build 166 (2018) 391–406, doi:10.1016/j.enbuild.2018.02.035.
[51] Z. Wang, H. Yu, M. Luo, Z. Wang, H. Zhang, Y. Jiao, Predicting older people's thermal sensation in building environment through a machine learning approach: Modelling, interpretation, and application, Build. Environ. 161 (2019) 106231, doi:10.1016/j.buildenv.2019.106231.
[52] S. Lu, W. Wang, C. Lin, E.C. Hameen, Data-driven simulation of a thermal comfort-based temperature set-point control with ASHRAE RP884, Build. Environ. 156 (2019) 137–146, doi:10.1016/j.buildenv.2019.03.010.
[53] S. Lu, W. Wang, S. Wang, E. Cochran Hameen, Thermal comfort-based personalized models with non-intrusive sensing technique in office buildings, Appl. Sci. 9 (2019) 1768, doi:10.3390/app9091768.
[54] A.A. Farhan, K. Pattipati, B. Wang, P. Luh, Predicting individual thermal comfort using machine learning algorithms, in: Proceedings of the IEEE International Conference Automation Science Engineering CASE, Gothenburg, Sweden, IEEE, 2015, pp. 708–713, doi:10.1109/CoASE.2015.7294164.
[55] S. Bin, H. Ke, Indoor thermal comfort PMV Index prediction based on particle swarm algorithm and least square support vector machine, in: Proceedings of the International Conference Intelligent System Des. Engineering Application, Changsha, Hunan, China, IEEE, 2010, pp. 857–860, doi:10.1109/ISDEA.2010.322.
[56] A.C. Megri, I. El Naqa, Prediction of the thermal comfort indices using improved support vector machine classifiers and nonlinear kernel functions, Indoor Built Environ 25 (2016) 6–16, doi:10.1177/1420326X14539693.
[57] T. Chaudhuri, Y.C. Soh, H. Li, L. Xie, Machine learning based prediction of thermal comfort in buildings of equatorial Singapore, in: Proceedings of the International Conference IEEE Smart Grid Smart Cities ICSGSC, Singapore, Singapore, IEEE, 2017, pp. 72–77, doi:10.1109/ICSGSC.2017.8038552.
[58] D. Li, C.C. Menassa, V.R. Kamat, Personalized human comfort in indoor building environments under diverse conditioning modes, Build. Environ. 126 (2017) 304–317, doi:10.1016/j.buildenv.2017.10.004.
[59] M.Kischkoweit-Lopin, AN Overview Of Daylighting Systems, (n.d.) 6.
[60] International Organization for Standardization, ISO 7730: Moderate Thermal Environments-Determination of the PMV and PPD Indices and Specification of the Conditions for Thermal Comfort, ISO, 1994.
[61] D. Int-Hout, Thermal comfort calculations/a computer model, ASHRAE Trans. (1990) 96-1.
[62] J.W. Moon, Performance of ANN-based predictive and adaptive thermal-control methods for disturbances in and around residential buildings, Build. Environ. 48 (2012) 15–26, doi:10.1016/j.buildenv.2011.06.005.
[63] A.E. Ruano, P.M. Ferreira, Neural network based HVAC predictive control, IFAC Proc. 47 (2014) 3617–3622, doi:10.3182/20140824-6-ZA-1003.01051.
[64] J. von Grabe, Potential of artificial neural networks to predict thermal sensation votes, Appl. Energy 161 (2016) 412–424, doi:10.1016/j.apenergy.2015.10.061.
[65] B.W. Olesen, Effect of body posture and activity on the thermal insulation of clothing: measurements by a movable thermal manikin, ASHRAE Trans. 88 (2) (1982) 791–805.
[66] M. Luo, Z. Wang, K. Ke, B. Cao, Y. Zhai, X. Zhou, Human metabolic rate and thermal comfort in buildings: The problem and challenge, Build. Environ. 131 (2018) 44–52, doi:10.1016/j.buildenv.2018.01.005.

[67] F. Haldi, D. Robinson, Modelling occupants' personal characteristics for thermal comfort prediction, Int. J. Biometeorol 55 (2011) 681–694, doi:10.1007/s00484-010-0383-4.
[68] J. Ngarambe, G.Y. Yun, G. Kim, Prediction of indoor clothing insulation levels: A deep learning approach, Energy Build 202 (2019) 109402, doi:10.1016/j.enbuild.2019.109402.
[69] H. Na, J.-H. Choi, H. Kim, T. Kim, Development of a human metabolic rate prediction model based on the use of Kinect-camera generated visual data-driven approaches, Build. Environ. 160 (2019) 106216, doi:10.1016/j.buildenv.2019.106216.
[70] Z. Wang, R. de Dear, M. Luo, B. Lin, Y. He, A. Ghahramani, Y. Zhu, Individual difference in thermal comfort: A literature review, Build. Environ. 138 (2018) 181–193, doi:10.1016/j.buildenv.2018.04.040.
[71] W. Liu, Z. Lian, B. Zhao, A neural network evaluation model for individual thermal comfort, Energy Build 39 (2007) 1115–1122, doi:10.1016/j.enbuild.2006.12.005.
[72] J. Kim, Y. Zhou, S. Schiavon, P. Raftery, G. Brager, Personal comfort models: Predicting individuals' thermal preference using occupant heating and cooling behavior and machine learning, Build. Environ. 129 (2018) 96–106, doi:10.1016/j.buildenv.2017.12.011.
[73] Frederik Auffenberg, Sebastian Stein, Alex Rogers, A personalised thermal comfort model using a Bayesian network, in: Twenty-Fourth International Joint Conference on Artificial Intelligence, Buenos Aires, Argentina, AAAI press, 2015, pp. 2547–2553.
[74] A. Ghahramani, C. Tang, B. Becerik-Gerber, An online learning approach for quantifying personalized thermal comfort via adaptive stochastic modeling, Build. Environ. 92 (2015) 86–96, doi:10.1016/j.buildenv.2015.04.017.
[75] S. Lee, I. Bilionis, P. Karava, A. Tzempelikos, A Bayesian approach for probabilistic classification and inference of occupant thermal preferences in office buildings, Build. Environ. 118 (2017) 323–343, doi:10.1016/j.buildenv.2017.03.009.
[76] L. Jiang, R. Yao, Modelling personal thermal sensations using C-Support Vector Classification (C-SVC) algorithm, Build. Environ. 99 (2016) 98–106, doi:10.1016/j.buildenv.2016.01.022.
[77] A.I. Palmero-Marrero, A.C. Oliveira, Effect of louver shading devices on building energy requirements, Appl. Energy 87 (2010) 2040–2049, doi:10.1016/j.apenergy.2009.11.020.
[78] S.S. Shetty, D.C. Hoang, M. Gupta, S.K. Panda, Learning desk fan usage preferences for personalised thermal comfort in shared offices using tree-based methods, Build. Environ. 149 (2019) 546–560, doi:10.1016/j.buildenv.2018.12.040.
[79] E. Gratia, A. De Herde, The most efficient position of shading devices in a double-skin facade, Energy Build 39 (2007) 364–373, doi:10.1016/j.enbuild.2006.09.001.
[80] International Organization for Standardization, Ergonomics of the Thermal Environment: Analytical Determination and Interpretation of Thermal Comfort Using Calculation of the PMV and PPD Indices and Local Thermal Comfort Criteria, International Organization for Standardization, 2005.
[81] P.M. Ferreira, A.E. Ruano, S. Silva, E.Z.E. Conceição, Neural networks based predictive control for thermal comfort and energy savings in public buildings, Energy Build 55 (2012) 238–251, doi:10.1016/j.enbuild.2012.08.002.
[82] P.M. Ferreira, S.M. Silva, A.E. Ruano, Model based predictive control of HVAC systems for human thermal comfort and energy consumption minimisation, IFAC Proc 45 (2012) 236–241, doi:10.3182/20120403-3-DE-3010.00085.
[83] P.M. Ferreira, S.M. Silva, A.E. Ruano, Energy savings in HVAC systems using discrete model-based predictive control, in: Proceedings of the International Joint Conference Neural Network IJCNN, Brisbane, Australia, IEEE, 2012, pp. 1–8, doi:10.1109/IJCNN.2012.6252538.
[84] P.M. Ferreira, S.M. Silva, A.E. Ruano, A.T. Negrier, E.Z.E. Conceicao, Neural network PMV estimation for model-based predictive control of HVAC systems, in: Proceedings of the International Joint Conference Neural Network IJCNN, Brisbane, Australia, IEEE, 2012, pp. 1–8, doi:10.1109/IJCNN.2012.6252365.
[85] K. Mařík, J. Rojíček, P. Stluka, J. Vass, Advanced HVAC Control: Theory vs. Reality, IFAC Proc 44 (2011) 3108–3113, doi:10.3182/20110828-6-IT-1002.03085.
[86] L. Ciabattoni, G. Cimini, F. Ferracuti, M. Grisostomi, G. Ippoliti, M. Pirro, Indoor thermal comfort control through fuzzy logic PMV optimization, in: Proceedings of the International Joint Conference Neural Network IJCNN, Killarney, Ireland, IEEE, 2015, pp. 1–6, doi:10.1109/IJCNN.2015.7280698.
[87] S. Hussain, H.A. Gabbar, D. Bondarenko, F. Musharavati, S. Pokharel, Comfort-based fuzzy control optimization for energy conservation in HVAC systems, Control Eng. Pract. 32 (2014) 172–182, doi:10.1016/j.conengprac.2014.08.007.
[88] M. Collotta, A. Messineo, G. Nicolosi, G. Pau, A dynamic fuzzy controller to meet thermal comfort by using neural network forecasted parameters as the input, Energies 7 (2014) 4727–4756, doi:10.3390/en7084727.
[89] W.-T. Sung, S.-J. Hsiao, J.-A. Shih, construction of indoor thermal comfort environmental monitoring system based on the IoT architecture, J. Sens (2019) 1–16 2019, doi:10.1155/2019/2639787.
[90] B. Thomas, M. Soleimani-Mohseni, P. Fahlén, Feed-forward in temperature control of buildings, Energy Build 37 (2005) 755–761, doi:10.1016/j.enbuild.2004.10.002.
[91] S.C. Bengea, P. Li, S. Sarkar, S. Vichik, V. Adetola, K. Kang, T. Lovett, F. Leonardi, A.D. Kelman, Fault-tolerant optimal control of a building HVAC system, Sci. Technol. Built Environ. 21 (2015) 734–751, doi:10.1080/23744731.2015.1057085.
[92] S.R. West, J.K. Ward, J. Wall, Trial results from a model predictive control and optimisation system for commercial building HVAC, Energy Build 72 (2014) 271–279, doi:10.1016/j.enbuild.2013.12.037.
[93] F. Salamone, L. Belussi, L. Danza, M. Ghellere, I. Meroni, An Open Source "Smart Lamp" for the optimization of plant systems and thermal comfort of offices, Sensors 16 (2016) 338, doi:10.3390/s16030338.
[94] Y. Ma, S. Vichik, F. Borrelli, Fast stochastic MPC with optimal risk allocation applied to building control systems, in: Proceedings of the IEEE 51st IEEE Conference Decision Control CDC, Maui, HI, USA, IEEE, 2012, pp. 7559–7564, doi:10.1109/CDC.2012.6426251.
[95] M. Wallace, R. McBride, S. Aumi, P. Mhaskar, J. House, T. Salsbury, Energy efficient model predictive building temperature control, Chem. Eng. Sci. 69 (2012) 45–58, doi:10.1016/j.ces.2011.07.023.
[96] K.I. Katsigarakis, G.D. Kontes, G.I. Giannakis, D.V. Rovas, Sense-think-act framework for intelligent building energy management: sense-think-act framework for intelligent building energy management, Comput.-Aided Civ. Infrastruct. Eng. 31 (2016) 50–64, doi:10.1111/mice.12173.
[97] F. Jazizadeh, A. Ghahramani, B. Becerik-Gerber, T. Kichkaylo, M. Orosz, User-led decentralized thermal comfort driven HVAC operations for improved efficiency in office buildings, Energy Build 70 (2014) 398–410, doi:10.1016/j.enbuild.2013.11.066.
[98] A. Ghahramani, F. Jazizadeh, B. Becerik-Gerber, A knowledge based approach for selecting energy-aware and comfort-driven HVAC temperature set points, Energy Build 85 (2014) 536–548, doi:10.1016/j.enbuild.2014.09.055.
[99] M. Mokhtar, X. Liu, J. Howe, Multi-agent Gaussian Adaptive Resonance Theory Map for building energy control and thermal comfort management of UCLan'sWestLakes Samuel Lindow Building, Energy Build 80 (2014) 504–516, doi:10.1016/j.enbuild.2014.05.045.
[100] F. Behrooz, N. Bin Mariun, M. HamiruceMarhaban, M.A. MohdRadzi, A.R. Ramli, New design approach to MIMO nonlinear controller for direct expansion air conditioning system in building automation system, in: Proceedings of the IEEE 15th International Conference Environment Electrical Engineering EEEIC, Rome, Italy, IEEE, 2015, pp. 1706–1712, doi:10.1109/EEEIC.2015.7165429.
[101] J. Drgona, M. Kvasnica, Comparison of MPC strategies for building control, in: Proceedings of the International Conference Process Control PC, StrbskePleso, Slovakia, IEEE, 2013, pp. 401–406, doi:10.1109/PC.2013.6581444.
[102] V. Kirubakaran, C. Sahu, T.K. Radhakrishnan, N. Sivakumaran, Energy efficient model based algorithm for control of building HVAC systems, Ecotoxicol. Environ. Saf. 121 (2015) 236–243, doi:10.1016/j.ecoenv.2015.03.027.
[103] M. Sourbron, C. Verhelst, L. Helsen, Building models for model predictive control of office buildings with concrete core activation, J. Build. Perform. Simul. 6 (2013) 175–198, doi:10.1080/19401493.2012.680497.
[104] M. Klauco, M. Kvasnica, Explicit MPC approach to PMV-based thermal comfort control, in: Proceedings of the 53rd IEEE Conference Decision Control, Los Angeles, CA, USA, IEEE, 2014, pp. 4856–4861, doi:10.1109/CDC.2014.7040147.
[105] Y.M. Lee, R. Horesh, L. Liberti, Optimal HVAC Control as Demand Response with On-site Energy Storage and Generation System, Energy Procedia 78 (2015) 2106–2111, doi:10.1016/j.egypro.2015.11.253.
[106] A.E. Ruano, S. Silva, S. Pesteh, P.M. Ferreira, H. Duarte, G. Mestre, H. Khosravani, R. Horta, Improving a neural networks based HVAC predictive control approach, in: Proceedings of the IEEE 9th International Symposium Intelligent Signal Processing WISP, Siena, Italy, IEEE, 2015, pp. 1–6, doi:10.1109/WISP.2015.7139168.
[107] D. Sturzenegger, D. Gyalistras, M. Morari, R.S. Smith, Model Predictive climate control of a swiss office building: implementation, results, and cost–benefit analysis, IEEE Trans. Control Syst. Technol. 24 (2016) 1–12, doi:10.1109/TCST.2015.2415411.
[108] Geoff Hulten, Laurie Spencer, Pedro Domingos, "Mining time-changing data streams, in: Proceedings of the Seventh ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, ACM, 2001.
[109] Xiaojin Zhu, Zoubin Ghahramani, John D. Lafferty, Semi-supervised learning using gaussian fields and harmonic functions, in: Proceedings of the 20th International conference on Machine learning (ICML-03), Washington DC, USA, AAAI press, 2003, pp. 912–920.
[110] Richard S. Sutton, Andrew G. Barto, Introduction to Reinforcement Learning, 2, Cambridge: MIT press, 1998.
[111] G.Gao, J.Li, Y.Wen, Energy-efficient thermal comfort control in smart buildings via deep reinforcement learning, ArXiv190104693 Cs. (2019). http://arxiv.org/abs/1901.04693 (accessed January 12, 2020).
[112] J. Brusey, D. Hintea, E. Gaura, N. Beloe, Reinforcement learning-based thermal comfort control for vehicle cabins, Mechatronics 50 (2018) 413–421, doi:10.1016/j.mechatronics.2017.04.010.
[113] S.J. Pan, Q. Yang, A Survey on Transfer Learning, IEEE Trans. Knowl. Data Eng. 22 (2010) 1345–1359, doi:10.1109/TKDE.2009.191.
[114] M.M. Mahmud, Sylvian Ray, Transfer learning using kolmogorov complexity: Basic theory and empirical evaluations, in: 20th Annual Conference *Advances in neural information processing systems*, Vancouver, Canada, MIT press, 2008, pp. 985–992.
[115] D. Xing, W. Dai, G.-R. Xue, Y. Yu, Bridged Refinement for Transfer Learning, in: J.N. Kok, J. Koronacki, R. Lopez de Mantaras, S. Matwin, D. Mladenič, A. Skowron (Eds.), Knowl. Discov. Databases PKDD, Springer, Berlin Heidelberg, Berlin, Heidelberg, 2007, pp. 324–335, doi:10.1007/978-3-540-74976-9_31. 2007.

[116] Y. Peng, T. Feng, H. Timmermans, A path analysis of outdoor comfort in urban public spaces, Build. Environ. 148 (2019) 459–467, doi:10.1016/j.buildenv.2018.11.023.
[117] D.L. Streiner, Finding Our Way: An Introduction to Path Analysis, Can. J. Psychiatry 50 (2005) 115–122, doi:10.1177/070674370505000207.
[118] M.T.Ribeiro, S.Singh, C.Guestrin, Model-Agnostic Interpretability of Machine Learning, ArXiv160605386 Cs Stat. (2016). http://arxiv.org/abs/1606.05386 (accessed November 29, 2019).
[119] Nikhil Malik, Param Vir Singh, Deep Learning in Computer Vision: Methods, Interpretation, Causation, and Fairness, Operations Research & Management Science in the Age of Analytics. INFORMS (2019) 73–100.
[120] S. Athey, G.W. Imbens, Machine learning methods for estimating heterogeneous causal effects, stat 1050 (5) (2015) 1–26 arXiv.