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Towards smart buildings with self-tuned indoor thermal environments – A critical review

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Previous studies show differences in thermal comfort among individual occupants and suggest solutions that incorporate building occupants in sensing and control frameworks (a.k.a., human-in-the-loop) and tune heating, ventilation, and air conditioning (HVAC) systems based on their preferences to enable self-tuned thermal environments. The objective of the review presented in this paper is to discuss two key aspects of self-tuned thermal environments: (i) learning individual occupants' thermal comfort; (ii) HVAC control based on the learned comfort profiles. The review is conducted considering practical issues associated with the implementation of such modeling and control approaches in real buildings. We found that research on learning personalized comfort profiles has rather focused on developing and testing the adopted methods assuming that it is feasible to collect a large amount of training data in real buildings. In addition, previous research has given less attention to the validity of methods for collecting occupants' feedback responses. Hence, we focus our discussion on data collection, input variable selection, and performance evaluation considering the data efficiency. Regarding HVAC systems control, we found that arbitrary rules have been used to operate the systems with the learned occupant comfort profiles, and we discuss their validity and consistency for different occupants and buildings.

Contents

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1. Introduction

Thermal comfort is defined as "the condition of the mind in which satisfaction is expressed with the thermal environment" [1]. Providing thermal comfort to occupants has been one of the main building functions because of its significant influence on occupants' overall satisfaction with indoor environments [2,3], productivity [3–8], and health [9]. Previous studies have shown that temperature and moisture sensations from the skin, deep body temperatures, and the level of physiological efforts, e.g., vasodilation, vasoconstriction, sweating, and change in muscle tension, required to thermoregulation are the major factors resulting in thermal comfort or discomfort in addition to psychological and other processes [10]. Various building heating, ventilation, and air conditioning (HVAC) systems have been developed to provide thermally comfortable conditions for building occupants.

In this regard, to provide guidelines for the HVAC design and operation, there have been numerous studies to develop empirical models predicting occupants' thermal comfort [11–15] in HVAC conditioned buildings. For example, Fanger [11] developed the PMV model which is based on the heat balance of the human body and data collected through extensive laboratory experiments. The PMV model calculates the thermal load on the human body in steady-state conditions, defined as the difference between internal heat production and heat loss to the actual environment for a person hypothetically kept at comfort values of mean skin temperature and sweat rate at the actual activity level. The PMV model became the basis for standards such as ASHRAE 55 [1], ISO 7730 [16], and EN 16798-1:2019 [17] for air conditioned buildings; as of now, it is the most widely accepted and used thermal comfort model in building design and control. Overall, empirical thermal comfort models successfully predicted the average comfort-related responses of large populations and were adopted in international standards for the design and operation of HVAC systems in typical office buildings [1,16].

However, individual differences in thermal comfort have been observed through controlled lab experiments and field studies [15,18]. It was reported that thermal preferences vary among individuals and may change due to seasonal variations or acclimation [18]. Furthermore, it was claimed that what was seemed to be comfortable for a group or occupant may be uncomfortable for others [19]. For example, Fountain et al. [20] reported differences in responses of individual occupants to comfort queries (on a 7-point thermal sensation scale) greater than 1 scale unit. Similar differences with a standard deviation of around 1 scale unit (on the 7-point ASHRAE's thermal sensation scale), corresponding to approximately 3 °C difference in preferred indoor temperature values, were found by Humphreys and Nicol [21]. Studies have been conducted to identify causal factors for these differences: age, weight, gender, historical thermal experiences, etc. However, a literature review by Wang et al. [18] showed that there were no consistent conclusions that could explain the inter-group differences amongprevious studies. For example, among 36 studies on the significance of gender difference, 11 studies found that the difference was significant, while 14 studies did not. Some studies argued that individual differences in thermal comfort are not directly caused by the aforementioned factors but by differences in physiological characteristics which relate to heat gain and heat loss of the human body [22–26]. Unfortunately, there has been no method that can consider all the physiological characteristics in predicting one's thermal comfort. Moreover, it may be impossible to measure the characteristics of each individual in real buildings. Therefore, although research studies have reported individual differences in thermal comfort for a long time, the conventional thermal comfort models, which cannot accurately predict the thermal comfort of individual occupants, have been used in the HVAC design and operation. Consequently, typical HVAC systems have not been able to achieve high levels of occupants' satisfaction. Moreover, there has been a high chance of energy waste due to the conservative control settings intended for "widely acceptable" conditions [27–30].

Over the last decade, with the extensive development of wireless sensor networks, mobile devices, and data-driven models (machine learning) as well as the significant increase in computational power [18,31], research studies suggested solutions that incorporate building occupants in sensing and control frameworks (a.k.a., human-in-the-loop) and tune the HVAC systems based on personal preferences. Initial studies have been conducted to verify the feasibility of this concept for customized indoor environments. The results have shown that HVAC systems tuned based on individuals' preferences can improve occupants' satisfaction and reduce HVAC energy consumption [32–37]. However, despite the successful demonstration of early studies, major components necessary for the robust implementation of self-tuned environments, i.e., learning occupant preferences, and incorporating their preference feedback into HVAC controls, are still quite anecdotal [31].

Previous literature reviews discussed various components required to realize the smart systems in a generic and comprehensive sense. Kim et al. [31] discussed the key components, such as data collection, input variable selection, performance evaluation, and long-term adaptation, along with the information and communication infrastructure, e.g., sensor and device networks, integration with Building Management Systems (BMS), and the corresponding cost. Jung and Jazizadeh [38] and Park et al. [39] reviewed literature within the context of occupant-centric or human-in-the-loop building system operation, including occupancy-driven control.

The objective of the review presented in this paper is to focus on two key aspects of self-tuned thermal environments: (i) learning individual occupants' thermal comfort, personalized thermal comfort modeling; (ii) HVAC control based on the personalized comfort models. This review focuses on anticipated issues when these modeling and control approaches are implemented in real buildings and elaborates on their feasibility from this practical point of view. In section 2, we introduce studies that developed learning methods. Then, we discuss data collection processes, model input variables, prediction performance evaluation methods, and data efficiency. In Section 3, we introduce HVAC operation strategies based on the personalized comfort models. We present how the HVAC controllers developed in different studies achieved the target thermal environment conditions in private or open-plan offices, and we discuss studies that utilized advanced building control techniques.

2. Personalized thermal comfort modeling

In this section, we introduce studies that developed learning methods, and Table 1 summarizes the information with regard to the data source, occupant feedback collection, input variables, performance evaluation, and data efficiency. In [40], one of the early studies for learning individuals' thermal comfort, Liu et al. proposed training a neural network model to predict thermal sensation. The study exposed each subject to 20–40 conditions, which are different combinations of air temperature and velocity, and requested their thermal sensation. Neural network models having 5 hidden layers were trained with occupants' responses and measured air temperature, mean radiant temperature, humidity, and air speed. The trained models showed high prediction performance (accuracy of 80%) with 20 training data points. However,

Table 1
Summary of personalized thermal comfort modeling studies.

Ref.	Data Source	Occupant Feedback Collection	Input Variables	Performance Evaluation	Data Efficiency
[33]	10 people (office)	Participatory	Ta, RH	Reduced number of participations	NA
[34]	39 people (office)	Participatory[†]	Ta	Reduced number of participations	~1 month
[36]	1 person (office)	Participatory	Ta, MRT, RH, V, Met, Clo	Root mean squared error[††], Pearson correlation	NA
[37]	6 people (office)	Participatory (asked to provide at least four times per day)	Ta	Increased thermal comfort ratings	NA
[40]	113 people (office)	Requested	Ta, MRT, RH, V, Met, Clo	Veracity	NA
[41]	6 people (office)	Requested	Ta	NA	~90 points
[42]	4 people (office)	Participatory	Ta	Average error[††]	~40–50 points
[43]	9 people (office)	Requested	Ta, MRT, RH, V	Mean square error[††]	NA
[44]	ASHRAE RP-884 DB	Requested	Top, RH, Tout, the day of the year	Root mean squared error[††]	~10–20 points
[45]	13 people (chamber)	Requested	Ta	Mean square error[††], coefficient of determination[††]	NA
[46]	33 people (office)	Participatory (limited the number of votes per day)	Ta	Accuracy, specificity	NA
[47]	20 people (chamber)	Requested	Ta, MRT, RH, V, Met, Clo	Accuracy	NA
[48]	21 people (office)	Requested & participatory	Ta	NA	NA
[49]	7 people (office)	Participatory[†] (informed the importance of feedback)	Ta, RH, CO2, window state, Tskin, heart rate, activity level, Tout, RHout	Accuracy	~50 points
[50]	10 people (office)	NA (requested feedback data were used for the validation)	Tskin	Specificity, precision, recall	NA
[51]	34 people (office)	Requested	22 features related to occupant behavior, time, indoor and outdoor environments, and HVAC system	Area under the ROC curve	~60 points
[52]	9 people (office) & ASHRAE RP-884 DB	Requested	Ta, MRT, RH, V, Met, Clo (with a method for handling uncertain values)	Area under the ROC curve, expected operational cost[††]	~12–18 points
[53]	5 people (office)	Requested & participatory	Ta	Qualitative evaluation with the quantified model uncertainties	NA

Abbreviation: Ta = indoor air temperature, Top = indoor operative temperature, Tout = outdoor air temperature, Tskin = skin temperature, MRT = mean radiant temperature, RH = indoor relative humidity, RHout = outdoor relative humidity, V = indoor air velocity, Met = metabolic rate, Clo = clothing level, CO2 = indoor carbon dioxide concentration, ROC = Receiver operating characteristic.
[†] The authors assumed that occupants were comfortable if there was no participation for a while and added hypothetical data points in their training dataset.
[††] Metrics that penalize mispredictions considering the distance with the true values.

unreported data distribution and lack of clarity of the validation process degrades the reliability of the results. Feldmeier and Paradiso [33] demonstrated a personalized HVAC control system learning occupants' sensation with their participatory votes. Unlike [40], the controller did not intentionally expose the occupants to different conditions for the learning purpose. A linear discriminant algorithm was used with air temperature and humidity as inputs. To accommodate the adaptation of the comfort algorithm, only nine data points, which took 2–3 weeks to collect, were used with new points replacing the old. However, the predictive performance of the models was not evaluated. Daum et al. [41] trained univariate multinomial logistic regression models to predict occupants' thermal sensation using the air temperature as an input variable. They collected data for the subjects' thermal sensation up to 4 times a day. 22 synthetic data points were included in the training dataset, which formed a starting profile to boost the learning process and to allow the control to work from the beginning. Different models were developed for different subjects, but their prediction performance was not evaluated. A remarkable point was that the models required around 90 data points to be converged, which might take a long time (e.g., more than three months) to collect in actual office buildings. They also suggested replacing data points older than 30 days for Ta ± 0.25 °C with new data to adapt to long term changes in individuals' thermal comfort. Erickson and Cerpa [34] estimated time-varying air temperature correction factors for specific groups of occupants by comparing computed PMV values and actual sensation votes from them. The correction factors were used to adjust the setpoint temperature. Occupants' thermal sensation responses were collected through a participatory voting interface. It was assumed that no vote from occupants during a period implied they were in neutral (comfortable) since occupants would seldom participate in the system under comfortable conditions but would be eager to participate under uncomfortable conditions. Gao and Keshav [35,36] proposed to use a linear regression model trained with data from a target occupant to correct the discrepancy between computed PMV values and the occupant's actual thermal sensation votes. Although the prediction performance of the developed model was promising (RMSE 0.5377 with 12 training data points), since the study was conducted with only one subject, further validation is required. Jazizadeh et al. [42] collected more than 60 thermal preference votes over 3 weeks from each of the 4 test-subjects relying on their participations. The air temperature was varied between 18 and 29 °C so that each participant was exposed to different conditions. In addition, to encourage subjects' participation, the average of the responses was used in adjusting the room temperature. Using the collected data, the authors trained personalized models with the Wang-Mendel fuzzy rule extraction algorithm. The results showed that the method required about 40–50 data points to train a converged model. Zhao et al. [43] proposed a model structure derived based on the heat balance of the human body. The inputs were air temperature, mean radiant temperature, and humidity, and the output was thermal sensation. A personalized comfort model was developed by estimating four parameters in the model structure with data from each occupant with the recursive least-square (RLS) method. The forgetting factor in RLS helped adaptation of a model to long-term variation in individual occupant thermal comfort. The method was evaluated with data collected from 9 test-subjects. The thermal sensation was requested by the participants every one hour. Personalized models showed lower mean square error and bias over the testing data compare to PMV model. Auffenberg et al. [44] developed personalized models using a Bayesian network in which the observed variables are the operative temperature, humidity, outside temperature, the current day of the year, and the thermal sensation. A subset of the ASHRAE RP-884 database was used to validate the method. The trained models showed 17.5–23.5% higher performance in terms of RMSE compared to the PMV model and the adaptive model described in [54]. Also, the RMSE converged after 10 observations. Unlike other studies, Chen et al. [45] proposed a method for developing personalized dynamic thermal comfort models with a state-space Wiener model structure with a logistic output function. The authors conducted an experiment in which 13 subjects experienced significant temperature changes. During the experiment, the test-subjects' thermal sensation was recorded. Personalized models were developed with the measured air temperature and the subjects' responses. The trained models showed better results in terms of R-square compared to the PMV model and a model proposed in [55]. The authors proposed using the Extended Kalman Filter to update the offset parameter in models in order to account for environmental and/or occupant variability. Since this method is not updating the dynamics of the model but a parallel translation of the output, its reliability is questionable. Ghahramani et al. [46] developed a learning method using a Bayesian network with the air temperature and the thermal sensation as the input and output variables. Data from each occupant were used to estimate the probability threshold as well as model parameters to convert the probability to a prediction. To detect long-term comfort variation and to update models accordingly, the Kolmogorov-Smirnov test was introduced in the method. To validate the method, the thermal sensation of 33 test-subjects was collected through their participatory votes. The validation results showed that the model prediction performance was higher than that of alternative methods. The authors claimed that the improvement was due to the Kolmogorov-Smirnov test. Hu and Li [56] proposed a classification algorithm that was evaluated with synthetic data. Although the algorithm worked as expected, the authors did not discuss the necessity of using it compared to other approaches. Jiang and Yao [47] used a C-support Vector Classification algorithm to develop personalized comfort models. Model inputs were the air temperature, mean radiant temperature, humidity, air speed, clothing level, and metabolic rate, and the output was the thermal sensation. To collect data to evaluate the method, 20 subjects were exposed to different conditions, and their thermal sensation was collected every 10 min. The developed models showed very high prediction performances (accuracy of 89.8%). However, the testing conditions and distribution of responses were not reported. Sarkar et al. [48] modeled individuals' thermal comfort with a Gaussian formulation, i.e., estimation of mean and variance of a Gaussian form for each occupant. Although the method was implemented in a controller, it was not evaluated analytically. Li et al. [49] demonstrated the use of the Random Forest algorithm. Different variables, i.e., clothing level, heart rate, skin temperature, activity level, air temperature, humidity, CO_2 level, window state, outdoor temperature, and outdoor humidity, were tested as model inputs. The model output was the thermal preference. To collect the preference votes, a participatory voting interface was developed. For the natural ventilation mode, when the outside air temperature was appropriate, subjects were asked to open the window (also set back the HVAC system) twice per day. Similarly with [34], the authors in [59] assumed that if no feedback was received from an occupant, he/she experienced comfortable conditions. The results showed that human physiological and behavioral data are important to increase models' prediction performance (accuracy of 70–80%). In [50], to eliminate the necessityof occupants' actual responses in the learning process, Ghahramani et al. used hidden Markov model with face skin temperature as the observed variable. Estimated hidden states were expected to reflect occupants' thermal preferences. To measure the face skin temperature, an eyeglasses frame on which four infrared sensors were installed was used. Although the results were promising, i.e., overall specificity of 82.8% over 10 subjects, there are two unclear points that make the reliability of the results doubtful: 1) hyper-parameters in the algorithm were selected arbitrary; 2) the metric specificity was not enough to show the validity. Kim et al. [51] tested six machine-learning algorithms and different variables with data collected 3 times daily from 38 occupants. All the personalized models developed showed higher prediction performances compared to PMV model and the adaptive model in [1]. They reported that (i) the algorithms required over 60 survey responses for the model to provide reliable predictions; (ii) the algorithms required data of all the three classes, i.e., 'want warmer,' 'no change,' 'want cooler'; (iii) considering occupants' behaviors as model inputs increases the prediction performance significantly. Lee et al. [52,57] proposed a Bayesian clustering and online classification algorithm for learning individual occupants' thermal preferences. This algorithm enabled effective and efficient learning by solving two sub-problems: (i) discovery of thermal preference clusters using a large dataset collected from various people (developing general knowledge); (ii) online classification of new occupants,' i.e., inferring their thermal preference clusters (using the general knowledge for specific problems). The idea behind the proposed approach was in line with the concept of transfer learning [58]. The authors showed that much fewer observations were needed for the inference compared to developing different personalized comfort models from scratch.

2.1. Feedback data collection

In most of the above studies, researchers used occupants' comfort-related feedback responses to train personalized models. However, the feedback data were collected in various ways, and there has been a lack of discussion about the impact of the data collection methods in real building applications. For example, we may need to think about (i) how practical a method is, (ii) how effective the method is in collecting qualitatively and quantitatively enough data, (iii) how reliable a learning algorithm is in developing personalized models with given data, etc.

Since thermal comfort is the condition of mind [1], the only way to measure it is by surveying occupants [59], assuming they are reliable. In this context, collecting occupants' responses by requesting feedback randomly or regularly [40,41,43–45,47,51] would be the ideal way to minimize the sampling bias [60]. However, frequent requests would be distractive for occupants, and therefore, not practical in real buildings, especially if continuous data collection is needed for the online model update [33,45,46,51]. On the other hand, if one reduces the request frequency, the models would underperform for a long time until it observes enough data. To detour this problem, participatory user-interfaces were used in [33,34,42,49], with which occupants voluntarily provide information on their thermal comfort states. However, occupants' participation, which is a type of behavior, may be affected by factors other than their thermal comfort. For example, people would actively report their feedback if they are dissatisfied with the current thermal conditions. On the other hand, if they are comfortable, they would not be as active. In other words, the feedback data collected with a participatory interface would be biased. If one develops a model with the biased data without any special processing, due to the lack of middle state responses (satisfaction/comfort/neutral), the predictive probability or corresponding score of the middle state will decrease as more data fed into the model, i.e., more data do not guarantee better model [53]. To resolve this, some researchers assumed that occupants were comfortable if there was no participation for a while and added synthetic comfort responses in their dataset [34,49]. However, the assumption may not be valid because occupants may not (or forget to) participate because of other reasons (e.g., high workload) even though they are uncomfortable [49]. Also, there are other factors (e.g., interface design, how occupants perceive or trust the system) that makes it difficult to devise heuristic methods for handling the biased data, which are generalizable [42]. Moreover, the proposed methods cannot distinguish the causal effects of occupants' thermal comfort and the level of occupants' activeness in using the interface on the data distribution. Hence, if the thermal condition in a shared space (e.g., open-plan office) is conditioned based on the personalized comfort models, the thermal condition would be biased towards the thermal preference of active occupants, which may not be fair. Besides, passively relying on a participatory interface would not assure the collection of sufficient data in a reasonable time [61]. Lee et al. [53] presented a modeling approach that can incorporate both voluntary feedback data, collected via participatory interfaces, and requested feedback data. In the model structure, the authors explicitly considered occupants' participation behavior, to handle the sampling bias. In addition, the concept of a smart feedback request algorithm was proposed to determine whether it is valuable to request feedback in order to query sufficient data less-intrusively. However, the authors discussed that the behavioral part of the model structure was rather simple and required further improvement.

There have been efforts to obviate the necessity of occupants' feedback using physiological information, e.g., skin temperature, with advanced sensing and estimation technologies [50,62,63]. Studies following this direction imply that one generalized estimation method can accurately predict individual occupants' thermal comfort. Hence, besides the feasibility of such approaches in real buildings [38], their effectiveness should be further examined with large populations.

2.2. Input variable (predictors) selection

It is well known that model input variables should be selected by their importance in making accurate predictions, i.e., prediction power as predictors, and the cost of collecting and using the data [49,51]. In [33,34,41,42,45,48,50], only one or two (i.e., air temperature, humidity) variables were used to minimize the data collection cost. In [49–51], occupants' physiological (e.g., skin temperature, heart rate) and behavioral data (e.g., window operation, PCS behaviors) were used to increase the prediction performance. However, another important point may need to be considered in the input variable selection: can we use the input variables to predict occupants' future thermal comfort? This question would become important when we design operation strategies for HVAC systems. For example, suppose that fan on/off behavior (or similarly skin temperature) at the current moment is used in predicting one's current thermal comfort. Since this information is directly related to the thermal comfort, the prediction performance of the model would be high. However, since it may be a cause of one's thermal comfort, we cannot know whether the occupant would act or not at a future moment. Therefore, the prediction power gained by having this variable may fade if the model is used for future predictions. In other words, although the variable would improve the performance of an HVAC system in a responsive way, it may not be notably helpful in terms of optimizing the operation over a longer period of time using advanced and predictive optimal control.

2.3. Prediction performance evaluation

Different metrics have been used to evaluate the prediction performances of models. The metrics can be categorized into two groups: (i) metrics designed for classification problems (e.g., accuracy, specificity, precision, recall, and area under the Receiving Operating Characteristics (ROC) curve) [40,47,49–51], (ii) metrics considering the magnitude of errors (e.g., root-mean-square error, mean absolute error) [36,42–44]. Lee et al. [52] claimed that the use of metrics in the first group requires special attention since the metrics usually penalize different misprediction/misclassification cases equally. The authors argued that the cost/penalty of mis-predicting an instance of "warmer" as "cooler" should be higher than the cost/penalty for mis-predicting the same instance as "no change." If one agrees with that, categorizing occupant thermal comfort states into three classes (e.g., warm/comfort/cool) instead of two classes (e.g., comfort/discomfort) would be preferred. The authors also suggested evaluating the prediction performance with the expected benefit or cost of using the model to control an actual HVAC system.

Another issue in the prediction performance evaluation is that there is no metric that can guarantee whether the model is good or not by itself since a value of a metric is affected by not only the goodness of the model but also the characteristics of the data. In other words, naively comparing reported numbers for the predictive performance does not provide much information. Therefore, a comparative evaluation with alternative models or methods will be needed to draw meaningful conclusions. In [44–46,51], researchers used Fanger's PMV model and adaptive models [64,65] as the baseline for the comparison. However, since the studies showed that personalized models developed with data from individuals far surpass the conventional comfort models, comparing with competitive data-driven models, e.g., linear logistic regression [51,52], would be more meaningful.

2.4. Data efficiency

It is well known that data with sufficient quantity and quality are required to train a reliable model. Lee et al. [52] showed that personalized comfort models trained with insufficient data, i.e., over-fitted models, can make significantly wrong predictions. Daum et al. [41] reported that their method required approximately 90 data points to train a converged model. Li et al. [49] reported that their comfort models showed acceptable accuracy with around 50 data points. Kim et al. [51] showed that their comfort models needed over 60 data points to train a model that provides stable predictions. In real buildings, a collection of over 50 to 90 data points could take a few months [41,61,66].

The problem here is that personalized models would underperform until sufficient data become available, and subsequently, the HVAC operation would not be optimal during this period. If a model needs to be continuously updated to maintain a certain performance level, i.e., online learning, [37,41,43,46] and requires a large dataset to converge, it may not provide reliable predictions. Therefore, the data efficiency of a learning method should be thoroughly examined. Lee et al. [52] claimed that the data efficiency is closely related to the model complexity and highlighted the importance of the regularization to improve the efficiency.

3. Control based on personal thermal comfort models

In this section, we introduce HVAC operation strategies based on the personalized comfort models and Table 2 summarizes the approaches used with regard to the target conditions, control integration, and aggregation strategy A relatively small number of

Table 2
Summary of control studies based on personalized thermal comfort models.

Ref.	Target Condition	Control Integration	Aggregation Strategy
[33]	Decision boundary (a line on the Ta-RH space)	PI control around a small deadband	Normalize based on the distance between a condition to one's decision boundary
[34]	Time-varying Ta setpoint	PID control with a setpoint	Create one set of correction factors for multiple occupants
[35,36]	Range of thermal conditions	Reactive control [35] MPC [36]	NA
[37,42]	Ta setpoint	Proportional control with a set of setpoints	Use the sum of deviations from the preferred temperatures to room temperatures
[48]	Range of temperature	Heuristic rule-based control	Calculate the range with which all the occupants would be comfortable
[49]	Ta setpoint	Heuristic rule-based control	Heuristic rule-based aggregation
[67]	Range of temperature	Solve optimization problems to find the optimal daily setpoint temperature (heuristic rules were used for infeasible optimization cases)	Include multiple occupants' models into the optimization
[68]	Range of temperature	MPC	Compute the optimal temperature bounds that minimize the expected operational cost with personalized models
[69]	Range of temperature	Heuristic rule-based control	Compute a quantity representing the comfort sensitivity of an individual occupant and apply a rule to find a range for multiple occupants
[70]	NA	Multi-objective optimal control with a singular perturbation approach	Include multiple occupants' models into the optimization
[71]	NA	Multi-objective MPC	NA
[72]	Range of temperature	MPC	NA
[73]	NA	Tabular Q-learning control	NA

Abbreviation: PI = proportional-integral, PID = proportional-integral-derivative controller, MPC = model predictive control.

studies demonstrated self-tuned HVAC systems that increased occupant satisfaction and reduced HVAC energy consumption. Feldmeier and Paradiso [33] implemented their smart HVAC system that operated based on personalized comfort models and actual occupancy in real offices. The authors reported that the system saved energy consumption by up to 24% and improved occupants' thermal comfort. Erickson and Cerpa [34] implemented their control logic tuned with occupants' feedback and reported that occupants were fully satisfied while the HVAC energy consumption was 10% lower. Gao and Keshav [35,36] developed a controller with preference learning, clothing level estimation, and occupancy detection. They reported energy-savings was up to 60% compared to a controller with a fixed-temperature setpoint. Jazizadeh et al. [37] implemented an HVAC system that could learn occupants based on the method presented in [42]. They reported that the HVAC energy consumption was reduced by 39% while occupants' comfort was improved. Ghahramani et al. [67] presented an optimal controller operating based on personalized comfort models and room energy models. The study demonstrated up to 12% reduction in energy consumption for cooling. = Sarkar et al. [48] incorporated personalized profiles in a rule-based controller, which resulted in up to 39% reduction of the HVAC energy use. Li et al. [49] reported that their controller, which adjusted the room setpoint temperature with personalized comfort models developed with the Random Forest algorithm, reduced the number of uncomfortable responses by 54%. Lee et al. [68] developed a self-tuned HVAC controller that learned individual occupants' thermal preference with the method discussed in [52,57]. The authors developed a model predictive control algorithm with bounds calculated with the personalized models. The controller was implemented in an actual open-plan office to operate a radiant floor cooling system with eight independently controlled water loops that provide localized thermal conditions, thereby satisfying the diverse occupant thermal preferences. The field implementation showed that the occupants' daily thermal dissatisfaction decreased notably with the self-tuned controller. Also, a simulation study reported in [67] showed that (i) building managers' ad hoc decisions on control bounds could result in significant energy waste or occupant dissatisfaction; (ii) the level of occupant satisfaction and energy consumption can be controlled by adjusting a single parameter in the self-tuned controller.

3.1. Single condition vs. range of conditions

The personalized models proposed in the previous studies output a set of quantities for given input values. In the studies, these quantities (a.k.a. predictive score) correspond to the probability of a person being satisfied/dissatisfied, the level of satisfaction, or the probability of a person reporting comfort/discomfort votes via an interface. In [33,34,37,42,49], the authors operated the HVAC systems to provide a specific condition (i.e., setpoint tracking) that maximized the predictive score. This approach may be conservative as it guarantees occupants' thermal comfort but may compromise the potential for energy-savings [67]. In other studies [35,36,48,67], the researchers decided a range of conditions in which the selected comfort-related parameter was higher than a threshold. One problem is that this range does not always exist. The predictive score could always be lower than a threshold that a user or a building manager sets in advance [46]. Jung and Jazizadeh claimed that this problem could be solved by re-scaling the parameter [69]. However, the scaled parameter would loose its original probabilistic meaning; consequently, the HVAC operation may become inconsistent over different occupants and buildings. Lee et al. [68] proposed a decision-making method to compute an optimal set of temperature control bounds that minimizes the expected operational cost with personalized preference models. To compute the operational cost, they used a misclassification cost matrix that penalized different misclassification cases differently. The method always provides a solution without modifying the output of personalized comfort models nor solving a computationally heavy optimization problem. However, the simplified misclassification cost matrix may require improvement. A multi-objective optimization problem to maximize occupant comfort and minimize energy consumption was formulated by Gupta et al. [70]. However, complex personalized comfort models and building energy models result in non-convex optimization algorithms, which could be computationally costly for real-time control.

3.2. Aggregation of different occupants' different preferences

In many cases, spaces of multiple occupants are conditioned by shared HVAC systems. In such spaces, the aggregation of multiple occupants' preferences is required. Erickson and Cerpa [34] proposed simply training a single model for a group of occupants by using all the data collected from them. However, there is a problem that if occupants' responses are collected via a participatory vote scheme, the model will bias to responses of occupants who actively participate [42]. The authors of [42,48,49] suggested learning individuals separately and aggregating them later. Jazizadeh et al. [42] calculated a single point with which the sum of deviations from occupants' preferred temperatures. Sarkar et al. [48] set a threshold for the score to gain occupants' comfort ranges and simply used the overlapped range. Li et al. [49] used a heuristic rule to determine the setpoint based on personalized models. Jung and Jazizadeh [69] proposed to define occupants' thermal sensitivity from the personalized comfort model and use it to compute the control range. Lee et al. [68] claimed that the optimal control range for multiple occupants can be computed naturally without an arbitrary rule by considering individual occupants' probability of dissatisfaction in the computation of expected operational cost.

3.3. Integration with advanced building controls

There have been a few studies that employed advanced control techniques such as model predictive control (MPC) into the human-in-the-loop framework to optimize the HVAC system performance. Previous studies reported that using MPC can significantly improve building energy efficiency while maintaining occupant thermal comfort [74–79]. In personalized thermal environment applications, Gao and Keshav [35,36] presented an MPC controller integrated with preference learning. However, the controller was tested with only one occupant. Majumdar et al. [71] and Zhao et al. [80] conducted simulation studies to evaluate an MPC controller that can learn individual differences in thermal comfort. Chen et al. [72] developed an MPC controller with a dynamic personalized thermal sensation model, which was tested using chamber experiments. However, the duration of the experiments was 3-hours, which may be too short. Lee et al. [68] presented a 16-day long experiment to demonstrate the implementation of a controller that integrated an advanced building control scheme and personalized thermal comfort models, in a real occupied office space. However, except for the operative temperature, other input variables for the personalized comfort models were rather simplified for the implementation. Lu et al. [73] showed that a reinforcement learning algorithm can learn control policies from occupants' responses through a simulation study. However, considering the huge amount of data points required to learn the policies, the feasibility and possible solutions for reducing the required data points would need to be investigated.

4. Summary and recommendations

This paper reviewed the literature on self-tuned thermal environments, specifically focusing on 1) learning individual occupants' thermal comfort; 2) HVAC system control based on the personalized comfort models. Our review shows that self-tuned HVAC systems can significantly improve the level of occupants' thermal comfort/satisfaction while saving HVAC energy consumption by 10–60 %, by deploying energy where demand actually exists. However, it also revealed that there is room for improvement.

Regarding learning methods, we found that a number of studies were conducted without considering the difficulty in collecting quantitatively and qualitatively sufficient data in real buildings. For leaning methods to be practical so they can be deployed in actual building management systems, their data efficiency needs to be carefully examined in their design and performance evaluation. In addition, previous research has given less attention to the validity of methods for collecting occupants' feedback responses. To minimize the level of intrusiveness and distortion in comfort profiles, one may need to rethink about the user interface, which in many studies was designed based on ad-hoc decisions. Holistic investigations of causal relationships over occupants' thermal comfort and comfort-related behaviors would be helpful for a systematic design of the interface system. Finally, we recommend thinking about the actual control strategy before designing the learning method so that it can be effective and, at the same time, efficient.

Regarding control approaches, studies have demonstrated clear benefits using smart systems. However, our review shows that various arbitrary and coarse rules have been employed for the control implementation, which may degrade the validity and consistency for different occupants and buildings. To come up with better rules, one may start from formulating a multi-objective optimal control problem with comfort and energy (and/or peak demand) as the objectives (or ensuring comfort as a constraint), i.e., from the ideal goal. In the formulation, one may need to rethink about what the output score of a personalized comfort model means. It could be the probability of a person being comfortable, the level of comfort, or the probability of a person voting a discomfort response. Based on this meaning, the appropriate formulation for the optimal control problem would vary. Here, it is important to emphasize that the probability of comfort-related behaviors (e.g., voting or overriding thermostat setpoint) and the level of comfort would be highly correlated with each other but not the same. Then, one may consider devising a controller that solves the optimal control problem directly. If solving the control problem is computationally too heavy, finally, one may start decomposing the problem into smaller problems that can be solved and/or simplifying some of the smaller problems. We think that this procedure would help to minimize the loss of optimality.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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