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ROOM MATCH: ACHIEVING THERMAL COMFORT THROUGH SMART SPACE ALLOCATION AND ENVIRONMENTAL CONTROL IN BUILDINGS

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ABSTRACT

The thermal comfort of individuals is considered an important factor that affects the health, well-being, and productivity of the occupants. However, only a small proportion of people are satisfied with the thermal environment of their current workplace. Therefore, this paper proposes a novel framework to simulate and optimize thermal comfort by controlling room conditions and matching them with occupants. The method is developed based on personalized thermal comfort prediction models and the Large Neighborhood Search (LNS) algorithm. To illustrate and validate the algorithm, a case study is provided. The results compare the thermal comfort of the occupants before and after the optimization and show a significant improvement in the thermal comfort. The proposed simulation method is proven to be feasible and efficient in providing an optimal match of occupants and rooms with specific settings, and therefore, can be of great value for the decision-making of the building management.

1 INTRODUCTION

According to an epidemiological survey, people in the USA and Canada on average spent more than 90% of their time indoors (Leech et al. 2000). Thermal comfort of individuals is considered an important factor affecting the overall indoor experience of the occupants, as it is associated with their health (Lan et al. 2011; Ormandy and Ezratty 2012), well-being (Lan et al. 2011), and productivity (Akimoto et al. 2010; Lan et al. 2011). However, a recent study has shown that only 38% of the occupants are satisfied with the thermal environments of their workplace while 43% of them are thermally dissatisfied (Karmann et al. 2018).

The conventional methods for maintaining thermal comfort rely on adaptive models (e.g., PMV) (Gan et al. 2019; Gan et al. 2021; Yao et al. 2009) or design standards (ASHRAE 2017; Deng, Menassa, and Kamat. 2021), which try to adopt a one-size-fits-all approach for different occupants (Sood et al. 2020). Nevertheless, different people may have distinct preferences of the thermal environments, leading to variations of the thermal perception of the occupants in the same indoor environment (Cheung et al. 2019; Földváry Li ina et al. 2018). In order to satisfy occupants based on their own thermal preferences, several previous studies have investigated the personal environmental control (PEC) systems to achieve improvement of personal thermal and visual comfort. The PEC systems need to apply extra small-size devices to control the micro-environment for the individuals (Godithi et al. 2019). Nevertheless, PEC systems are not flexible and responsive enough as they have low spatial resolutions, and they will lead to extra maintenance and energy consumption due to the additional equipment (Veselý et al. 2017). Moreover, the concept of Activity Based Workplace (ABW) is becoming more and more common in modern buildings, which aims to provide flexible workplaces for the occupants depending on their preferences or tasks (Appel ‐ Meulenbroek et al. 2011). However, the number and capacity of the rooms are limited, thus it may not be possible to satisfy all occupants if we consider the ABW individually. For example, a room

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with a specific indoor environmental setting may be suitable for many occupants, while it cannot accommodate all of them due to the limited capacity. In this case, the occupants with similar thermal preference need to be separated into different rooms with suitable environmental settings. To achieve this, an optimization algorithm that can match and group different occupants to a suitable room with an appropriate indoor environment is needed. Therefore, the objective of this paper is to propose a novel framework to simulate and optimize thermal comfort by controlling room conditions and matching them with occupants. Moreover, the proposed framework is demonstrated and validated comprehensively by a case study.

Recently, personalized models regarding the evaluation of individuals' status are attracting attention (Deng, Wang, and Menassa. 2021; Kandasamy et al. 2018; Ma et al. 2019). Similarly, personalized thermal comfort models are required in this study to perform the optimization. To obtain personalized thermal comfort models, a series of environmental data and feedback from each individual are required (Li et al. 2017). Based on the environmental parameters and the occupants' personal feedback, machine learning (ML)-based personalized thermal comfort models can be built for them. For each of the models, the inputs should be the environmental parameters and the outputs are the perception of the thermal environment. The personalized models allow the estimation of each occupant's thermal preferences instead of providing an overall evaluation of the thermal environment. The indoor environment parameters such as temperature, humidity, and air velocity are proven to be the major factors that affect the thermal comfort of an occupant (Ma et al. 2019). In addition, the personal parameters including age, gender, height, weight, clothing level are also proven to be relevant to personal thermal comfort. Therefore, this study uses the typical parameters of the indoor environment and human factors as the inputs of the personalized thermal comfort prediction models. Assume that there are n rooms with different controllable indoor environments, and there are m people ($m > n$) we would like to assign to the rooms so as to maximize the overall indoor thermal comfort of them. We need to formulate and solve the occupants-room matching and room condition control task as a joint optimization problem. This is a non-trivial optimization problem as both the objective function and the decision variables contain continuous and discrete parts, and the model contains non-parametric machine-learned components.

2 METHODOLOGY

2.1 Optimization problem description

In this section, we formulate an optimization problem for thermal comfort. We first add binary variables x_{ij} to indicate the occupant-room assignment: if occupant i $(1 \leq i \leq m)$ is in room j $(1 \leq j \leq n)$, $x_{ij} = 1$; otherwise, $x_{ij} = 0$. The index of thermal comfort is a discrete number following a standard 7-scale metric (i.e., -3, -2, -1, 0, 1, 2, 3)(ASHRAE 2017). For a specific occupant, it is a non-linear function of multiple indoor environmental parameters, including room temperature (RT), relative humidity (RH), and air velocity (AV). Suppose occupant i $(1 \leq i \leq m)$ is in room j $(1 \leq j \leq n)$, we assume its thermal comfort, TC_i, can be computed as follows:

$$TC_i = \sum_{j=1}^{n} g_i\left(T_j, H_j, V_j\right) x_{ij} \tag{1}$$

$g_i(\cdot)$ is the thermal comfort function of occupant i that returns $\{-3,-2,-1,0,1,2,3\}$, while T_j, H_j, and V_j are the room temperature, relative humidity, and air velocity of room j, respectively.

A separate $g_i(\cdot)$ is used to capture the personality of each occupant. Rather than an analytic function, $g_i(\cdot)$ is learned from data. From the perspective of the optimization process, a differentiable model $g_i(\cdot)$ is preferred, such as Support Vector Machines (SVM) and Artificial Neural Networks (ANN). In this study, we assume all of the input indoor environmental parameters (T_j, H_j, V_j) are continuous and controllable within a fixed range. We want to optimize the overall thermal comfort of the occupants. Therefore, we penalize the sum deviation of the thermal comfort from zero, F_C, in Eq. (3). Note that c_i is a weight on occupant i.

$$f_i(T_j, H_j, V_j) = |g_i(T_j, H_j, V_j) - 0| \tag{2}$$

$$F_C = \sum_{i=1}^{m} c_i \sum_{j=1}^{n} f_i(T_j, H_j, V_j) x_{ij} \tag{3}$$

In objective function (4), the decision variables are T_j, H_j, V_j, and x_{ij} $(1 \le i \le m, 1 \le j \le n)$. The constraint (5.1) limits the minimum and the maximum number of occupants in a room. The constraint (5.2) indicates that a person can only be in one room. (5.3), (5.4), (5.5), and (5.6) set up the variable ranges. M_j refers to the maximum capacity of the room j . T_j^{min} and T_j^{max} defines the allowable range of the room temperature, H_j^{min} and H_j^{max} defines the allowable range of the relative humidity, V_j^{min} and V_j^{max} defines the allowable range of the air velocity.

$$\min_{x_{ij}, T_j, H_j, V_j} \sum_{j=1}^{n} \sum_{i=1}^{m} c_i f_i(T_j, H_j, V_j) x_{ij} \tag{4}$$

subject to

$$0 \le \sum_{i=1}^{m} x_{ij} \le M_j \tag{5.1}$$

$$\sum_{j=1}^{n} x_{ij} = 1 \tag{5.2}$$

$$x_{ij} \in \{0, 1\} \tag{5.3}$$

$$T_j^{min} \le T_j \le T_j^{max} \tag{5.4}$$

$$H_j^{min} \le H_j \le H_j^{max} \tag{5.5}$$

$$V_j^{min} \le V_j \le V_j^{max} \tag{5.6}$$

The schematic diagram of the optimization problem is shown in Figure 1. The circles with different colors represent different individuals with distinct characteristics and the cuboids represent different rooms with specific environmental settings. The results should be able to maximize the overall thermal comfort of people. Therefore, the indoor environment parameters T_j, H_j, V_j and the room assignments x_{ij} are simultaneously perturbed and optimized.

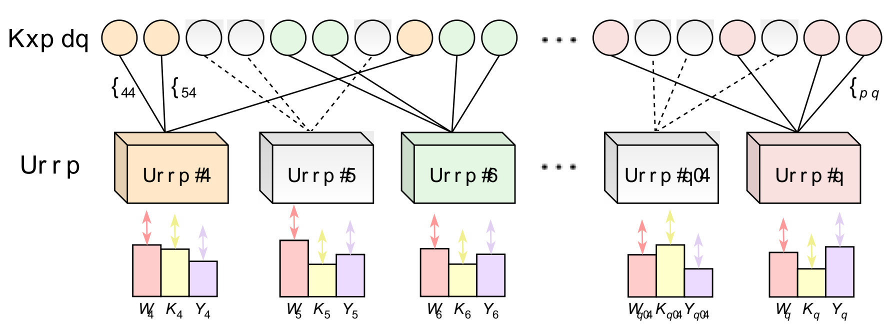

Figure 1: The schematic diagram for the original optimization problem.

2.2 Optimization algorithm

The Large Neighborhood Search (LNS) algorithm has proven to be very efficient in solving scheduling problems (Pisinger and Ropke 2010), it explores complex neighborhoods using heuristics. Here, based on the idea of LNS, the optimization process is divided into two separate steps in each iteration, and the pseudocode is shown in Algorithm 1.

Based on the personalized thermal models and the room conditions, the first step tries to match the occupants with the room that optimize their thermal comfort. Because the room parameters (i.e., T_j, H_j, V_j) are fixed temporarily, the objective function in Eq. (4) reduces to Eq. (6). It is an integer linear programming (ILP) problem, as the only variables are x_{ij} and the objective function and the constraints are all linear. For this specific ILP, we can replace the constraints (5.3) with $0 \le x_{ij} \le 1$, solve the reduced linear program (LP) using Simplex-based algorithms, and the solutions to x_{ij} are guaranteed to be integers. Because Simplex-based algorithms have polynomial computational costs, this step will be conducted efficiently.

A brief proof that the solutions, x_{ij}, to the reduced LP will be integers:

Because this problem falls in the category of bipartite matching if it is converted to the form $\min \boldsymbol{c}^T\boldsymbol{x}$ with $\boldsymbol{Ax} \le \boldsymbol{b}$ and $\boldsymbol{x} \ge \boldsymbol{0}$, the incidence matrix $\boldsymbol{A}$ will be totally unimodular (Keller and Tompkins 1956), and therefore, all the extreme points of the feasible region (a polytope) defined by the linear constraints will be integers. Since the Simplex-based algorithm searches through extreme points, the solutions will be integers.

$$\min_{x_{ij}} \sum_{j=1}^{n} \sum_{i=1}^{m} c_i f_i(T_j, H_j, V_j) x_{ij} \tag{6}$$

subject to

$$0 \le \sum_{i=1}^{m} x_{ij} \le M_j, \tag{7.1}$$

$$\sum_{j=1}^{n} x_{ij} = 1, \tag{7.2}$$

$$x_{ij} \in \{0, 1\} \tag{7.3}$$

The second step of the algorithm optimizes the indoor environment parameters T_j, H_j, V_j, with the currently fixed room assignments. After matching the occupants with the rooms in step 1, the room conditions (i.e., T_j, H_j, V_j) are perturbed so as to further reduce the objective function in Eq. (6). Since the room assignments, x_{ij}, are fixed in this step, the optimization problems of different rooms are decoupled, the large nonlinear optimization problem in Eq. (6) is further split into n small non-linear programming problems (NLP) with only three variables T_j, H_j, V_j.

For each room, the thermal comfort of the occupants in that room is optimized according to Eq. (8). The constraints limit the ranges of T_j, H_j, and V_j. The n problems could thus be solved with a gradient-based algorithm. Here we choose a trust-region algorithm.

$$\min_{T_j, H_j, V_j} \sum_{i=1}^{m} c_i f_i\big(T_j, H_j, V_j\big) x_{ij} \tag{8}$$

subject to

$$T_j^{min} \le T_j \le T_j^{max} \tag{9.1}$$

$$H_j^{min} \le H_j \le H_j^{max} \tag{9.2}$$

$$V_j^{min} \leq V_j \leq V_j^{max} \tag{9.3}$$

Algorithm 1: Large Neighborhood Search for Thermal Comfort

Input: initial room parameters $T_j^0, H_j^0, V_j^0 \quad \forall j = 1, \cdots, n$
initial room assignment $x_{ij}^0 \quad \forall i = 1, \cdots, m, \quad \forall j = 1, \cdots, n$

Output: optimal room parameters $T_j^*, H_j^*, V_j^* \quad \forall j = 1, \cdots, n$
optimal room assignment $x_{ij}^* \quad \forall i = 1, \cdots, m, \quad \forall j = 1, \cdots, n$

$F^* = +\infty$
for $l = 1, \cdots, l_{\max}$ **do**
  // Step1: optimize x_{ij}, while T_j, H_j, V_j are fixed
  // Simplex-based algorithm
  Solve the linear program: $\min_{x_{ij}^l} \sum_{j=1}^{n} \sum_{i=1}^{m} c_i f_i(T_j^{l-1}, H_j^{l-1}, V_j^{l-1}) x_{ij}^l$
  Update x_{ij}^l
  // Step2: optimize T_j, H_j, V_j, while x_{ij} are fixed. Rooms are decoupled
  for $j = 1, \cdots, n$ **do**
    // Trust-region algorithm
    Solve the nonlinear program: $\min_{T_j^l, H_j^l, V_j^l} \sum_{i=1}^{m} c_i f_i(T_j^l, H_j^l, V_j^l) x_{ij}^l$
    Update T_j^l, H_j^l, V_j^l
  end for
  $F^l = \sum_{j=1}^{n} \sum_{i=1}^{m} c_i f_i(T_j^l, H_j^l, V_j^l) x_{ij}^l$
  if $F^l < F^*$ **then**
    $F^* = F^l, T_j^* = T_j^l, H_j^* = H_j^l, V_j^* = V_j^l, x_{ij}^* = x_{ij}^l \quad \forall i = 1, \cdots, m, \quad \forall j = 1, \cdots, n$
  end if
  if Termination condition reached **then**
    return $T_j^*, H_j^*, V_j^*, x_{ij}^*$
  end if
end for

The two steps, considered together, is an LNS algorithm, as both step 1 and step 2 search through large neighborhoods within the feasible region. The LNS algorithm decomposes the large nonlinear program into two simpler sub-problems that are easier to solve. In each iteration, it tries to find better room assignments and room parameters by solving either the LP or the NLP problem. The algorithm keeps iterating until converges. Finally, the algorithm outputs an optimized matching between occupants and rooms, as well as the environmental conditions. Considering the complexity of the optimization (a learned nonlinear function in the objective with integer constraints), we empirically evaluate the optimality and computational time.

3 CASE STUDY

3.1 Personalized thermal comfort models and loss function

In order to validate the performance of the proposed optimization algorithm, a case study is demonstrated in this section. To obtain $g_i(\cdot)$ as the prediction model for different occupants with distinct profiles, ASHRAE Global Thermal Comfort Database II (Földváry Li ina et al. 2018) is used to establish representative personalized models. As thermal sensation is a subjective thermal metric that has been most widely used (Wang et al. 2020), it is applied in this study to represent the thermal comfort of the occupants. It evaluates the feeling of the occupants within a 7-scale metric, which uses discrete numbers from -3 to 3 to indicate that people feel cold, cool, slightly cool, neutral, slightly warm, warm, and hot, respectively. Besides thermal sensation, we selectively filter the database based on the required input data. The filtered data includes the human profiles (i.e., gender, age, height, weight, clothing level, and metabolic rate) and the environmental parameters (i.e., RT, RH, and AV). The details of the data samples are summarized in Table 1. Based on the example dataset, the computation of the $f_i(T_j, H_j, V_j)$ of the optimization problem is shown in Figure 2. Two most typical differentiable algorithms: support vector machine (SVM), and artificial neural network (ANN) are applied to build the prediction models. Note that this actual $f_i(\cdot)$ is slightly different from the one defined in Eq. (2). The one in Eq. (2) is conceptual and indicates that we penalize the situation when the thermal comfort is not zero. However, since the $f_i(\cdot)$ in Eq. (2) is discrete, which introduces challenges to the optimization process, we replace it with the definition in Figure 2. As the goal is to achieve the distribution as close to 0 as possible, the sign of the weight corresponds to 0 is set to be negative while others are set to be positive. For example, the "$+$" and "$-$" in Figure 2 indicate that a predicted result of "0" will reduce the function loss while others will increase the function loss. In addition, each predicted thermal sensation value was assigned a weight indicated by S_i with i represented the corresponding value. In this case, the final function loss will be the weighted sum of the probabilities of each possible predicted output (-3 to 3). Therefore, the function becomes continuous and also penalizes the non-zero thermal comfort while rewards zero thermal comfort.

We test the accuracies of SVM and ANN for the prediction of thermal sensation using the selected data samples. The overall accuracy is indicated by the fraction of the predictions our model gets right. The results show that the accuracy of SVM could reach around 0.706, which significantly outperforms ANN (around 0.540). Therefore, the SVM is selected to be $g_i(\cdot)$ for the optimization process.

Table 1: Details of the example database.

Count	5339
Age range	16 ~ 70
Gender	Male/Female
Height (cm)	122 ~ 206
Weight (kg)	35 ~ 116
Clothing Level (Clo)	0.04 ~ 1.49
Air Temperature (°C)	13.9 ~ 37.9
Relative Humidity (%)	10.4 ~ 95.3

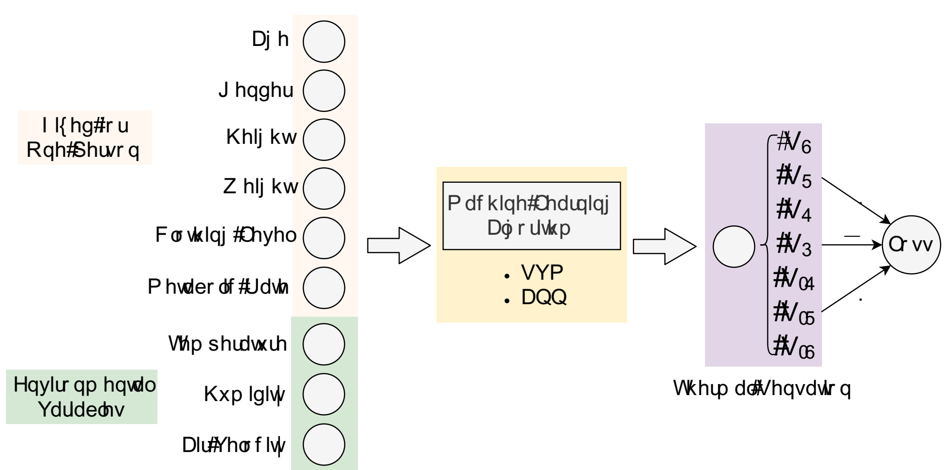

Figure 2**:** Computation of function loss**.**

3.2 Initialization of the algorithm

There are several approaches to set the initial conditions of the indoor environments. To ensure the best performance of the algorithm, three typical initial settings are examined: (1) Assign evenly distributed random values within the desired range to the indoor environmental parameters of different rooms; (2) assign Gaussian distributed random values centered at the mean of the desired range to the environmental parameters of different rooms; (3) assign the same mean values of the desired range to the environmental parameters of different rooms. The ranges of the environmental parameters in this study are also obtained from the ASHRAE database. In addition, as an illustrative example, it is assumed that there are 12 rooms and 120 people (randomly selected from the example database) for the optimization process. In addition, as each room in a real building will have a maximum capacity of occupants, the maximum number of occupants in one room is set to 15. Note that the setting for the illustrative example is flexible and here we just use these example settings to demonstrate the simulation. A preliminary evaluation is conducted to compare the final results of these three initialization approaches. The results indicate that the first initialization method can lead to the best performance based on the number of people at a thermal comfort index of zero.

3.3 Results

3.3.1 Distributions of thermal comfort

The comparison of the initial thermal comfort distribution of the occupants before and after the optimization is shown in Figure 3. As indicated in the plot, the original thermal comfort indices are distributed over the range from −3 to 3. Among the 120 occupants, only 54 of the occupants consider the indoor environments as comfortable. A significant amount of people (41) feels slightly cool, 4 of them feel cool, and 2 feel cold. In contrast, 18 of them feel slightly warm, and 1 of them feels warm. However, the thermal comfort is significantly improved after the optimization. Results show that all of the 120 occupants will consider the indoor environments as comfortable (with the thermal comfort index of 0). None of the people will consider the indoor environments as slightly cool, cool, cold, slightly warm, warm, or hot. Therefore, the algorithm shapes the distribution of the thermal comfort of the occupants to optimal.

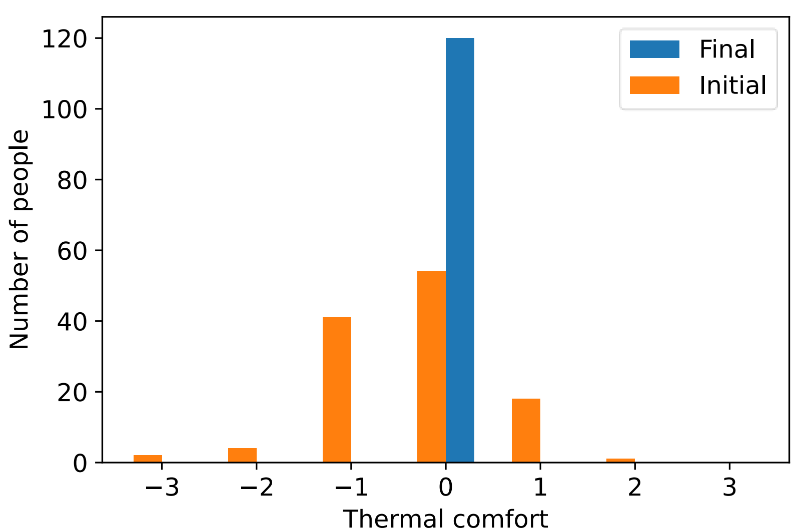

Figure 3: Comparison between the initial and optimized thermal comfort distribution.

3.3.2 Matches between occupants and rooms

Figure 4 shows the distribution of occupants in different rooms before and after the optimization. The double borders are used to represent the rooms and the circles refer to the occupants. Blue colors are used to represent cool environments (or negative thermal comfort indices) while orange/brown colors are used to represent the warm environments (or positive thermal comfort indices). In addition, deeper colors represent cooler/warmer environments (or the cooler/warmer feelings of the occupants). Following a similar logic, the white color is used to indicate that the occupants will feel neutral about the indoor environments. Moreover, in order to track individual occupants, each person is marked with a unique number tag between 1 to 120. The right part of the figure shows the changes of the loss function (value objective function) and distribution of thermal comfort distribution during the optimization process (consistent with Figure 3). Note that it is a 2-step optimization process, it can be seen that there are two points for each iteration. As seen from the upper left part of Figure 4, with an initial random assignment of the occupants and indoor environments, a lot of occupants are rendered blue or orange, indicating that they feel cool or warm. After the optimization (left bottom part), the results of the human-room match, and room temperature change significantly. All of the occupants are in white color after the optimization, and none of them is in orange or blue. As for rooms 3, 5, 9, and 11, the number of occupants reaches the maximum room capacity (15). The results and the visualization of the human-room match further prove the feasibility of the optimization algorithm.

3.3.3 Optimization of the indoor environmental conditions

Table 2 shows the indoor environmental conditions (i.e., RT, RH, and AV) before and after the optimization. Figure 5 (a) shows the change of RT during the optimization process. As for the initialization, each room is randomly assigned an initial temperature. The temperature is then updated as the algorithm goes forward. The temperature in each room converges by itself gradually. For most of the rooms, the convergence of the temperature avoids crossing the temperature range of other rooms during the optimization process. In addition, a general tendency can be observed that the temperature of the rooms converges closer to each other. For example, the original maximum and minimum temperatures are 37.0 °C and 13.7 °C, respectively. After the optimization, the temperature ranges from 18.4 °C to 33.9 °C. The results are considered reasonable as the temperature converges to a more commonly acceptable range.

Figure 5 (b) shows the convergence of RH during the optimization process. Similar to RT, random initial RHs are assigned to the rooms and the changes are relatively stable, for most of the rooms, the changes are retained within 6%. Figure 5 (c) shows the convergence of AV during the optimization process. The AVs in the different rooms, in general, become lower. The best values of AV ranged from 0 to 2 m/s as shown in the results.

Overall, the RTs, RHs, and AVs of the rooms converge within 10 iterations and the overall thermal comfort is improved during this process.

Table 2. Room environments before and after optimization

Room	Before Optimization			After Optimization		
	RT (°C)	RH (%)	AV (m/s)	RT (°C)	RH (%)	AV (m/s)
1	31.0	39.7	2.9	24.7	41.3	0.4
2	13.7	50.8	3.7	24.3	54.8	1.5
3	37.0	24.0	2.1	30.2	27.2	1.3
4	20.0	36.6	3.4	25.3	36.9	0.5
5	30.2	90.8	1.0	24.3	74.6	1.0
6	21.6	48.7	2.1	25.2	53.0	2.0

7	32.7	13.9	2.9	33.9	12.3	1.4
8	19.7	13.0	0.3	18.4	26.0	0.0
9	35.5	56.7	2.1	29.6	60.0	0.8
10	22.3	50.8	0.3	21.8	56.0	1.2
11	28.1	72.9	2.0	27.6	67.4	0.0
12	15.0	36.2	2.0	26.5	46.0	0.7

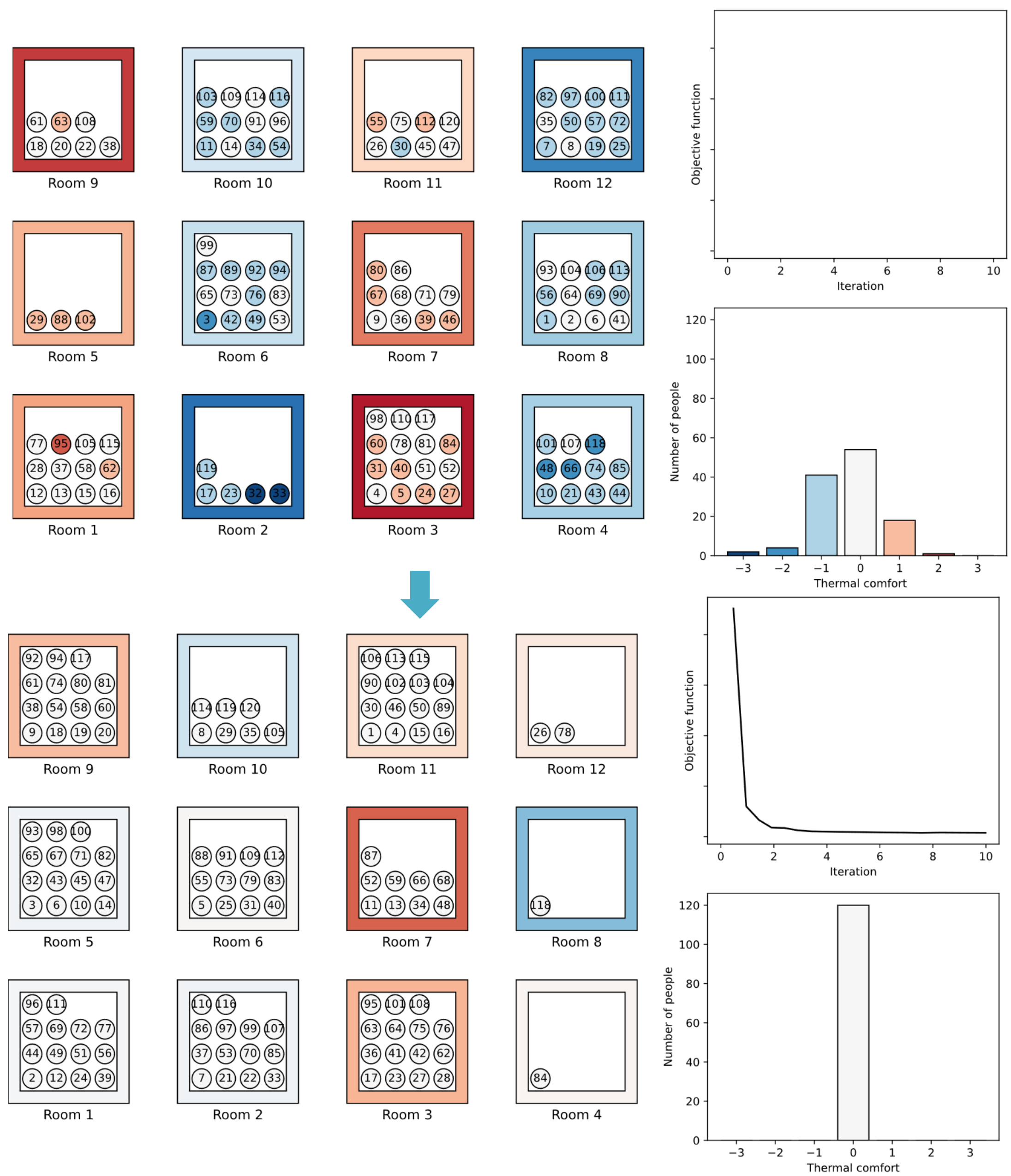

Figure 4: Matches between occupants and rooms before (upper) and after the optimization (bottom).

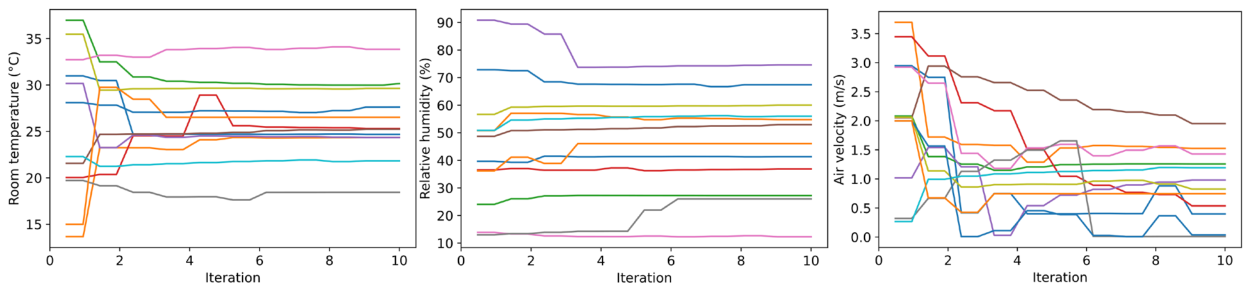

Figure 5: Changes in (a) air temperature, (b) relative humidity, and (c) air velocity during the optimization process.

4 CONCLUSION

This study proposes an NLS-based optimization algorithm to simulate the thermal comfort of the occupants. The problem is formulated as a joint optimization problem to achieve the optimal allocation of the occupants into different rooms and the corresponding room environmental parameters. In order to satisfy the indoor thermal comfort of all individuals, rather than the adaptive models, personalized thermal comfort prediction models are used to estimate the thermal comfort of different occupants. Based on the personalized models, an overall objective function is formulated, and the optimization problem is defined. Then, in the proposed algorithm, this problem is divided into two sub-problems and solved in two steps. The first step is to optimize the matches between the occupants and rooms, which is achieved by solving a linear program. The second step is to adjust the indoor environments of each room. The goal is also to improve the thermal comfort of the occupants in the rooms. This part of the problem is formulated as a nonlinear program.
To validate and demonstrate the proposed algorithm, a case study is given. The personalized thermal comfort prediction models for the occupants are trained from an example dataset using the SVM algorithm. The results of indoor environment changes and thermal comfort of the occupants before and after the optimization are obtained and discussed, and a significant improvement of the thermal comfort of the occupants is shown. Therefore, the algorithm can be used as an assistant tool for building environment management and can facilitate decision-making to improve the overall indoor thermal comfort. Furthermore, the thermal comfort, which is optimized in this study, is only an example, the proposed algorithm is generalizable and can also be applied to the optimization of other types of indoor comforts, such as visual comfort and acoustic comfort, as long as the personalized models are provided.

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REFERENCES

Akimoto, T., Tanabe, S.-i., Yanai, T., and Sasaki, M. (2010). "Thermal comfort and productivity - Evaluation of workplace environment in a task conditioned office." *Building and Environment*, 45(1), 45-50.

Appel-Meulenbroek, R., Groenen, P., and Janssen, I. (2011). "An end-user's perspective on activity-based office concepts." *Journal of Corporate Real Estate*, 13(2), 122-135.

ASHRAE (2017). *Standard 55-2017, Thermal Environmental Conditions for Human Occupancy, Atlanta USA*.

Cheung, T., Schiavon, S., Parkinson, T., Li, P., and Brager, G. (2019). "Analysis of the accuracy on PMV – PPD model using the ASHRAE Global Thermal Comfort Database II." *Building and Environment*, 153, 205-217.

Deng, M., Menassa, C. C., and Kamat, V. R. (2021). "From BIM to digital twins: a systematic review of the evolution of intelligent building representations in the AEC-FM industry." *Journal of Information Technology in Construction (ITcon)*, 26(5), 58-83.

Deng, M., Wang, X., and Menassa, C. C. (2021). "Measurement and prediction of work engagement under different indoor lighting conditions using physiological sensing." *Building and Environment*, 203, 108098.

Földváry Li ina, V., Cheung, T., Zhang, H., de Dear, R., Parkinson, T., Arens, E., Chun, C., Schiavon, S., Luo, M., Brager, G., Li, P., Kaam, S., Adebamowo, M. A., Andamon, M. M., Babich, F., Bouden, C., Bukovianska, H., Candido, C., Cao, B., Carlucci, S., Cheong, D. K. W., Choi, J.-H., Cook, M., Cropper, P., Deuble, M., Heidari, S., Indraganti, M., Jin, Q., Kim, H., Kim, J., Konis, K., Singh, M. K., Kwok, A., Lamberts, R., Loveday, D., Langevin, J., Manu, S., Moosmann, C., Nicol, F., Ooka, R., Oseland, N. A., Pagliano, L., Petráš, D., Rawal, R., Romero, R., Rijal, H. B., Sekhar, C., Schweiker, M., Tartarini, F., Tanabe, S.-i., Tham, K. W., Teli, D., Toftum, J., Toledo, L., Tsuzuki, K., De Vecchi, R., Wagner, A., Wang, Z., Wallbaum, H., Webb, L., Yang, L., Zhu, Y., Zhai, Y., Zhang, Y., and Zhou, X. (2018). "Development of the ASHRAE Global Thermal Comfort Database II." *Building and Environment*, 142, 502-512.

Gan, V. J. L., Deng, M., Tan, Y., Chen, W., and Cheng, J. C. P. (2019). "BIM-based framework to analyze the effect of natural ventilation on thermal comfort and energy performance in buildings." *Energy Procedia*, 158, 3319-3324.

Gan, V. J. L., Luo, H., Tan, Y., Deng, M., and Kwok, H. L. (2021). "BIM and Data-Driven Predictive Analysis of Optimum Thermal Comfort for Indoor Environment." *Sensors*, 21(13).

Godithi, S. B., Sachdeva, E., Garg, V., Brown, R., Kohler, C., and Rawal, R. (2019). "A review of advances for thermal and visual comfort controls in personal environmental control (PEC) systems." *Intelligent Buildings International*, 11(2), 75-104.

Kandasamy, N. K., Karunagaran, G., Spanos, C., Tseng, K. J., and Soong, B.-H. (2018). "Smart lighting system using ANN-IMC for personalized lighting control and daylight harvesting." *Building and Environment*, 139, 170-180.

Karmann, C., Schiavon, S., and Arens, E. (2018). "Percentage of commercial buildings showing at least 80% occupant satisfied with their thermal comfort."

Keller, I., and Tompkins, C. (1956). "An Extension of a Theorem of Dantzig's. Linear Inequalities and Related Systems." *Annals of Mathematics Studies*, 38, 247-254.

Lan, L., Wargocki, P., and Lian, Z. (2011). "Quantitative measurement of productivity loss due to thermal discomfort." *Energy and Buildings*, 43(5), 1057-1062.

Lan, L., Wargocki, P., Wyon, D. P., and Lian, Z. (2011). "Effects of thermal discomfort in an office on perceived air quality, SBS symptoms, physiological responses, and human performance." *Indoor Air*, 21(5), 376-390.

Leech, J., Burnett, R., Nelson, W., Aaron, S., and Raizenne, M. (2000). "Outdoor air pollution epidemiologic studies." *American Journal of Respiration Critical Care Medicine*, 161(3), A308.

Li, D., Menassa, C. C., and Kamat, V. R. (2017). "Personalized human comfort in indoor building environments under diverse conditioning modes." *Building and Environment*, 126, 304-317.

Ma, G., Liu, Y., and Shang, S. (2019). "A Building Information Model (BIM) and Artificial Neural Network (ANN) Based System for Personal Thermal Comfort Evaluation and Energy Efficient Design of Interior Space." *Sustainability*, 11(18), 4972.

Ormandy, D., and Ezratty, V. (2012). "Health and thermal comfort: From WHO guidance to housing strategies." *Energy Policy*, 49, 116-121.

Pisinger, D., and Ropke, S. (2010). "Large Neighborhood Search." *Handbook of Metaheuristics*, M. Gendreau, and J.-Y. Potvin, eds., Springer US, Boston, MA, 399-419.

Sood, T., Janssen, P., and Miller, C. (2020). "Spacematch: Using environmental preferences to match occupants to suitable activity-based workspaces." *Frontiers in Built Environment*, 6, 113.

Veselý, M., Molenaar, P., Vos, M., Li, R., and Zeiler, W. (2017). "Personalized heating – Comparison of heaters and control modes." *Building and Environment*, 112, 223-232.

Wang, Z., Wang, J., He, Y., Liu, Y., Lin, B., and Hong, T. (2020). "Dimension analysis of subjective thermal comfort metrics based on ASHRAE Global Thermal Comfort Database using machine learning." *Journal of Building Engineering*, 29, 101120.

Yao, R., Li, B., and Liu, J. (2009). "A theoretical adaptive model of thermal comfort – Adaptive Predicted Mean Vote (aPMV)." *Building and Environment*, 44(10), 2089-2096.

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