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Dynamic Thermal Comfort Optimization for Groups

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Abstract— **Automatic optimization of individual thermal comfort in indoor spaces shared by multiple occupants is difficult, because it requires understanding of the individual thermal comfort preferences, modeling of the room thermodynamics, and fast online optimization to account for movements of the occupants. We explore an approach to optimizing individual thermal comfort subject to the seating arrangement of a group of individuals through temperature set-point optimization of Heating, Ventilation, and Air Conditioning (HVAC) equipment. In this paper, we learn both the individual thermal comfort preferences using a weakly supervised approach and the room thermodynamics via static approximations. Finally, we use optimization to determine the HVAC set points that maximize individual thermal comfort subject to the current seating arrangement. The proposed method is tested on a real data set obtained from workers in an open office. The results show that, on average, the temperature in the room at each user's location can be regulated on average to within 0.85^oC of the user's desired temperature, with a standard deviation of 0.12^oC.**

I. Introduction

Thermal comfort is an individual's feeling as to how cold, comfortable, or hot they are [1]. Each person has a unique set of physiological factors such as ethnicity, body composition, gender, and state of health that shape their perception of thermal comfort. These perceptions are manifested as unique responses to the question of how comfortable the individual is to environmental factors such as temperature, humidity, airflow, and the weather outdoors. When modeled, individual thermal comfort is typically described using easily measured variables of temperature and humidity [1], [2], [3]. A person's comfort zone is the set of temperature and humidity values for which that person is comfortable. Engineering bodies such as the American Society for Heating Refrigeration and Air-conditioning Engineers (ASHRAE) define zones that should be common to the majority of individuals [1], [2].

Traditionally, maintaining thermal comfort has been an individual's own responsibility. Individuals maintained their comfort by changing clothes, opening windows, or adjusting thermostats. However, these traditional routes of comfort optimization require the individual to have both learned the properties of the room within which they are sitting, as well as to be empowered to make changes to the environment. These requirements do not necessarily hold in the modern office environment, where the windows usually do not open, the thermostat is controlled centrally, and the individual's wardrobe choices are limited to their predictions of the indoor environment that morning. In addition, while the individual may learn the expected temperature in a particular location of the room, the individual may move later, because of new seating arrangements, such as those that take place in open offices with fluid seating plans, or because of meetings throughout the day. The inherent restrictions on the user actions brought on by the office environment, along with the possible variance of user locations throughout the day, often impair personal thermal comfort. Yet, studies show improving comfort is the key to improved work performance and satisfaction, and increased social happiness [4]. Improving comfort can also lead to greener buildings and important energy savings [5]. This motivates us to seek automatic solutions to improving individual thermal comfort in the group setting. Interest in this problem is also growing in the literature [6].

In this paper, similar to our previous work [7], [8], we leverage the Internet of Things (IoT), and specifically the ability to place multiple low-cost temperature and humidity sensors throughout the room. We utilize these sensors to learn a model of the individuals thermal comfort, subject to the temperature and humidity experienced by the user at his or her seat, and to learn static mappings from the Heating, Ventilation, and Air Conditioning (HVAC) set points (system inputs) to each seating location in a room. These static mappings help us to learn the temperature field produced in the room in response to the HVAC system and the external conditions. We leverage the learned models in an optimization across all users that determines the set of HVAC set points that minimize the deviation of temperature observed at each user's location from the user's desired temperature. Our approach is evaluated on data collected from 18 users in an open office in Japan.

A. Background

There is a large body of literature in the thermal comfort modeling community and the thermodynamic modeling community. We review here relevant works and focus mainly on work that contrasts with our approach.

1) Thermal Comfort Modeling: The extensive work in the field of thermal comfort estimation and optimization can be subdivided into three approaches. The first approach focuses on cost of computing the most popular model, Predicted Mean Vote (PMV) [9], and tries to improve (simplify) the computation [10], [11], [12], [13]. The second approach notes weaknesses in thermal comfort standards: small cohort sizes, homogeneity in the cohorts, and averaged model outputs. To overcome these weaknesses, authors lean on user surveys and interaction to learn personalized models. These works yield either population models over many users with

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as little as 1 data point [14], or individual models with many collected data points per user [15], [16], [17], [7], [18], [19], [20], [21], [22], [23]. The third approach is to use a standard method of thermal comfort modeling and focus on the HVAC control.

We generally agree (and have observed in our experiments in the US and Japan) that the standard models of thermal comfort (ex. PMV, comfort zones) are inadequate for many people [7]. And we have learned through several projects that collecting supervised thermal comfort data via user surveys is difficult, resulting in small and specific existing datasets. This has been observed by many authors: in [15] 58 data points and 20 data points; in [16] a single user in a single room testing 5 strategies in 14 days; and in [19] making personalization optional with a reduced 1D linear model based on PMV; OccuTherm [22], Spot Monitoring [14] 1 label provided per user; Ranjan and Scott [18] between 8 and 33 labels per user over 5 weeks of data collections; and [24] combining multiple small data sets across cities; and others referenced herein. Survey methods also suffer from important issues such as granularity of the thermal comfort scale [22], [25], while detailed comfort models suffer from difficulties like measuring critical values such as Mean Radiant Temperature (MRT) [12].

It has been our experience from prior publications [7] that deployment of sensor setups commonly described such as for example the Kinect, Raspberry Pi, Adafruit sensors are a strong deterrent to the adoption of improved thermal comfort technology. Similarly, we found strong resistance, particularly in Japan, to accepting the intrusion of labeling. This is problematic because the best personalized individual comfort models are found by tracking and interacting with an individual [7], [23]. We conclude that methods that rely on models with multiple difficult measurements, or surveys/direct user queries, despite being very accurate, have low chance of practical impact. Similarly, we have found that transfer learning methods [8], [24] although promising, represent an initial investment that may be too large to speed adoption.

2) Room Thermodynamic Modeling: Similar to thermal comfort models, thermodynamic modeling has a long history. Each room exhibits a temperature gradient. This gradient means that each user experiences a different temperature and this temperature is not the same as the HVAC set point. Therefore, modeling the room thermodynamics at the locations of the users is essential for automatic thermal comfort optimization of a room. In this paper we make a distinction between learning a truly dynamical thermodynamic model, which models the temporal evolution of temperatures in response to the HVAC system operation at all user locations, and static (or quasi-static) models that learn the relationships between discrete room locations in the equilibrium (steady) state. Thermodynamic systems have been modeled using the broad categories of white-box models [26], [27], which model the physical processes from first principles; grey-box models [28], which rely on reduced-order physical models, simulation and optimization; and black-box models [29], which are purely data-driven models, and include statistical models.

White- and grey-box models that simultaneously model many room locations are still difficult to deploy rapidly and at scale in the commercial setting because they usually either exhibit large computational costs or require individualized tuning by an expert for each deployment. On the other hand, black-box models, and in particular neural networks, have recently been shown [30] to perform well in the absence of external knowledge such as room geometry or layout. Because of this, and because of the relatively easier problem of inferring static relationships from data, in this paper we will use neural networks to approximate static thermodynamic relationships.

B. Contributions

In search of a more easily deployable method we propose two contributions. First, we propose a weakly supervised approach to learning thermal comfort models that extends the logic embedded in the ASHRAE comfort zones and does not require any new behavior or behavioral change in the users' routine. Second, the thermal comfort of the users is improved via an optimization problem over the given seating arrangement of the users considering the learned desired user temperatures and static mappings that describe the room thermodynamics.

Our contributions emphasize weakly supervised learning to minimize the disruption to the users, and to avoid requiring users to change their behavior (ex. learn to use a new system/device or provide any additional feedback). We further emphasize static modeling of the relationship between multiple room locations and the HVAC set point(s). Such modeling is simpler than requiring the use of truly dynamical models over a multitude of location in a given room. Lastly, we leverage the existing HVAC controller and simply provide input to this system. Thus the proposed approach, controls the HVAC units in a given shared space such that user comfort is maximized while avoiding thermodynamic modeling and new controller derivations.

II. Problem Formulation

Consider an indoor space occupied by K users for an extended period of time, e.g. a shared office with assigned desks. The indoor space is equipped with N HVAC devices distributed over the space, which can heat or cool the environment, and with M sensors at fixed locations that can measure the local temperature and level of humidity.

With a slight stretch of notation, let $i \in 1,\dots,M$ denote one sensor and its location in the space, and let $x_i(t) = [x_{T,i}(t), x_{H,i}(t)] \in \mathbb{R}^2$ be the measurement of the i^{th} sensor at time t, called the thermal state, where $x_{T,i}$ and $x_{H,i}$ are the temperature and humidity measurements, respectively. The room thermal state is denoted by $X(t) = [x_1(t),\dots,x_M(t)]^T \in \mathbb{R}^{2M}$. The thermal state perceived by the k^{th} user, $k \in 1,\dots,K$, is approximated by the measurements of the closest i^{th} sensor.

We denote by $x^*_{T,k}$ the optimal temperature of user k. Then, let $X^*_T(t)$ be a time-varying vector of optimal temperatures desired by the occupants, such that the i^{th} element in the vector corresponds to the i^{th} location in the room, and contains the optimal temperature $x^*_{T,k}$ for k^{th} user seated in the i^{th} location. We note that in this work, the user seated in the i^{th} location may change for any given time t and that multiple users may be seated near the same sensor. When multiple users are seated near the same sensor, the optimal temperature at this sensor is the average of the optimal temperatures for each user near the sensor. We assume that each user has the capability of providing identifiable feedback regarding their perceived thermal comfort by changing the temperature set point of an appropriate HVAC unit. By associating the user's feedback with the measurement of the closest sensor, we can determine if the user feels hot, cold, or comfortable at that time instant. Finally, let $j \in 1,\ldots,N$ denote a given HVAC device, and $h_j(t) \in \mathbb{R}$ be the temperature set point of the j^{th} HVAC device at time t. The vector of set points for all devices is denoted as $H(t) = [h_1(t),\ldots,h_N(t)]^T$.

Our goal is to learn a control law $H^*(t) = \pi(X^*_T(t))$ that, given the preferred temperature $x^*_{T,k,i}$ for each user k, maximizes the comfort probability of all the users denoted by $y_c = [y_c^1,\ldots,y_c^k]^T$. We note here that this control law is time varying because users are allowed to change locations. However, if the users are given a fixed seating assignment, then the control law is not time varying, and instead has the form $H^* = \pi(X^*_T)$.

III. Model Learning

For the k^{th} user, associated with the i^{th} sensor at time t, there exists an unknown function, $y_c^{k,i} = \tilde{f}^{k,i}(\tilde{x}_i(t))$ that maps the user's thermal state, $\tilde{x}_i(t)$ at time t, to their personal probability of comfort, $y_c^{k,i}(t) \in (0,1)$ at time t. In practice, the user's thermal state $\tilde{x}_i(t)$ is defined by an extended set of parameters that include age, gender, metabolic rate, ethnicity, clothing, and others. Because many of these parameters are not measurable, it is not possible to learn $\tilde{f}$. Here, as in prior works [7], [18], [13], [31], [17], we aim to learn an approximation to $\tilde{f}$ using the measurable quantities $x_i(t)$:

$$y_c^k(t) = f^k(x_i(t)). \tag{1}$$

where we dropped the superscript i for ease of notation. It is important to note that while the location of the user may change, the model $f^k(x_i(t))$ remains the same, because the user's preferences do not depend on the seating location of the user, but rather on the temperature and humidity experienced by the user in the seating location. In this paper, the burden of providing feedback by the users is reduced by taking two steps. First, a standard default model, f^0, is learned from unsupervised data recorded in the room. Then, the standard model is adapted using feedback provided by each user, if available. The model for the k^{th} user is denoted as f^k.

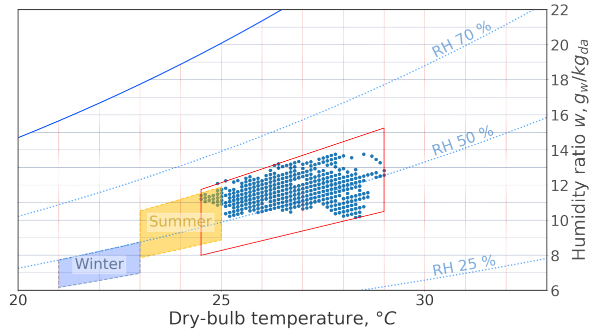

Fig. 1: Possible methods of specifying thermal comfort zones on the psychrometric chart.

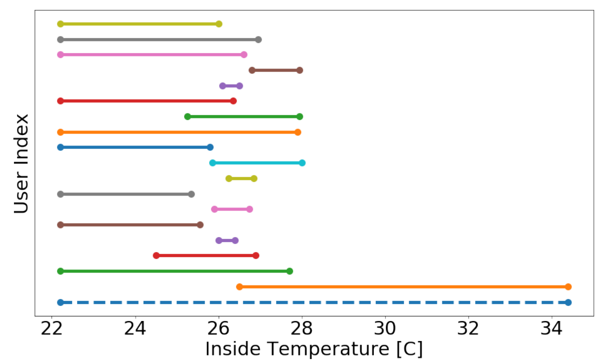

Fig. 2: Standard and personalized models based on indoor temperature. User index is used to denote users and make the plot clearer.

A. Learning an Initial User Model

The standard model, f^0, common to all users, is a model that describes the range of measurements that are comfortable for all users. Thus, selecting these ranges is an important design choice. There are at least two methods of choosing these ranges. The first method, defined on the measurements of temperature and humidity, is through expert opinion. An example of expert opinion (also based on past experimental studies) are the summer and winter comfort regions published by ASHRAE [1]. These are visualized by blue and yellow rectangles, respectively, on the psychrometric chart [32] shown in Fig. 1. The second method is to define a region on the psychrometric chart that encompasses the actual observed data points at a given location. This latter method extends the logic used in the ASHRAE zones. This can be conveniently captured in a quadrilateral region on the psychrometric chart by finding the observed $T_{min}, T_{max}, RH_{min}$ and RH_{max} from measurements in the room. An example of such a region is shown in the red rectangle in Fig. 1. The points plotted inside the rectangle represent data collected for the verification of this paper. Note that these fall largely outside of the expert-defined comfort zones. This method is convenient, because it does not require prior knowledge or hand engineering.

During the course of developing this work, we experimented with both approaches suggested above. Because

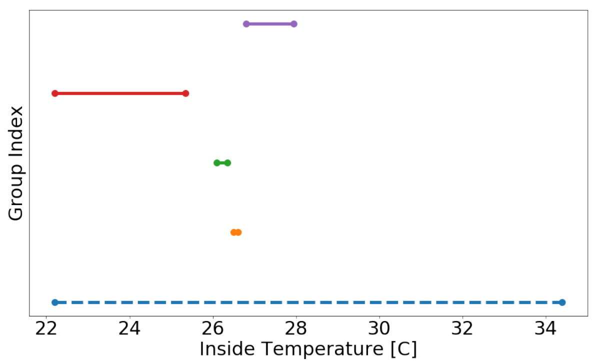

Fig. 3: Standard and combined personalized models based on indoor temperature. Group index is used to denote groups of users with overlapping preferences and make the plot clearer.

of the international nature of this project, it was observed that the standard ASHRAE zones might not apply to the thermal comfort preferences of individuals outside of the United States. We also observed that while users seemed to react to temperature changes in the office environment, there was little reaction to changes in humidity. Thus keeping track of humidity adds complexity to the model but does not materially improve the model quality. For this reason, we suggest a third approach, that defines an initial user comfort zone corresponding to the interval encompassing the observed maximum and minimum indoor temperature. This 1-Dimensional model is simple to learn and maintain for each user, easy to initialize using room measurements, and provides an extensible foundation for incorporating outdoor temperature (or other sensors) into the comfort model in the future.

In this third approach, a standard comfort zone based on indoor temperature, is shown by the blue dashed line in Fig. 2. The initial model shows that the maximum and minimum indoor temperatures. This shows a wide range of temperatures recorded indoors which might be because some sensors are located such that they are irradiated by the sun near a window, or because the indoor temperature is allowed outside of its regulated range outside of the regularly scheduled office hours. The initial comfort interval is customized for each user based on the feedback provided, and represents the learned thermal comfort model of the user. For the 18 users in this study, the standard comfort model and the customized model for each user are shown in Fig. 2. Note here that while we choose to have a 1-Dimensional user comfort interval, the number of measurements can be expanded using a similar approach for each measurement. In addition, the interval could be indexed to a time measurement such as day (or month) of the year, or a seasonal measurement such as outdoor temperature, to learn, over the course of a year, a time-varying interval of comfort preferred by a user.

An interesting observation from Fig. 2 is that there is significant overlap between the individual models of the user. One assumption of our models is that a user is comfortable for all temperature measurements inside the determined comfort interval. If the user is not comfortable, then user would have adjusted the HVAC set point and thus altered the comfort interval. Leveraging this assumption greatly simplifies finding a common optimal temperature for the users. Specifically, when the comfort intervals of two individuals overlap, a new comfort interval is created for each individual that is the intersection of the two comfort zones. Repeating this merge operation for all 18 users and all feedback points provided, we observe in Fig. 3 that the number of comfort zones to reconcile in the final optimization problem has been reduced from 18 to 4. Thus the number of parameters against which we optimize is greatly reduced. An interesting extension of this method is that individuals of similar thermal preferences can be co-located in parts of the room based on their shared thermal preference. We now elaborate on how the thermal comfort zones are optimized.

B. *Personalizing the User Model*

Customization of the standard model for a given user begins when an uncomfortable user, k, adjusts the j^{th} HVAC device's set point. At this point, we observe the user's thermal state, $x_i(t)$, and the requested set point temperature, h_j. Each set point request reveals three levels of information. First, we know that the user is uncomfortable in the current state, $x_i(t)$. Second, the user is either hot or cold, depending on the direction in which the set point, h_j, is changed. And third, the user thinks that their optimal temperature might be h_j.

Of these three feedback components, we make use of the first two components. This is because we cannot be explicitly sure that the target set point chosen by the user is optimal. Thus, when a user adjusts the HVAC thermostat, we obtain a labeled data point that states that the user is uncomfortable in these conditions and whether the user is hot or cold.

To personalize f^0, we first check if the user is hot or cold. If the user is cold, we shift the minimum temperature of the user's comfort interval to be the current observed temperature. If the user is hot, we shift the maximum temperature of the user's comfort interval to be the current observed temperature. The updated model for the k^{th} user is denoted by f^k.

By updating the comfort interval in this fashion, we determine the range of indoor temperatures that motivate the user to provide feedback. We obtain estimates for the minimum indoor temperature for which the user felt hot, and the maximum indoor temperature for which the user felt cold. We expect that the comfortable temperature of the user will be the average of these two temperatures.

By personalizing models for each user and then choosing the overlapping intervals between users, we find that for the 18 users in the experimental data for this study, there are 4 comfort zones. These are shown in Fig. 3. Taking the weighted average over these 4 comfort zones, where the weight is equal to the fraction of users in a given comfort zone, we find that the average temperature for which the users would be comfortable is 26^oC. Interestingly, if the average temperature is found over the individual models, then

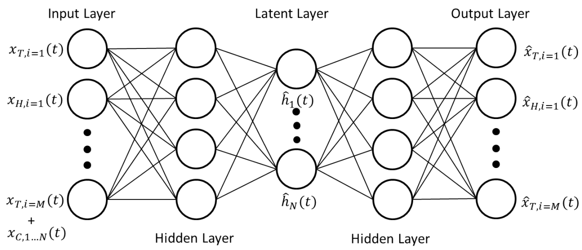

Fig. 4: The thermal sensor model and the thermal set point model shown in the autoencoding framework.

the average preferred temperature is 25.6^{o}C, which reflects the wide temperature range throughout which some users did not interact with the system. In other words, leveraging the individual models shows the effect of some outliers, or disinterested users, on the average comfortable temperature.

C. Approximating the Room Thermodynamics

In a given common room with M sensors and N HVAC units, at steady state, there exists a function $X(t) = g(H(t))$ that maps the forward (causal) relationship in the data from HVAC set points to room sensor measurements. In addition, there exists a function $H(t) = g^{-1}(X(t))$ that maps the inverse relationship, g^{-1}, in the data from room sensor measurements to HVAC set points. Ideally, one invertible model g can be learned from steady-state data. Unfortunately, collecting steady-state data is both time consuming and requires further thermodynamic modeling. For this reason, we focus on tightly controlled environments, such as an office, and accept that there will be some thermodynamic transients in the data. We learn two models. In the forward direction, we learn a model, herein called the thermal sensor model, that maps the HVAC set points to the resulting room thermal state X:

$$\hat{X}(t) = f_{sensor}(H(t)). \tag{2}$$

and in the inverse direction we learn a model, herein referred to as the thermal set point model, that maps the current room state to the best estimate of the input HVAC set points,

$$\hat{H}(t) = f_{SetPts}(X(t)) \tag{3}$$

We also observe that due to the nature of our data, the functions f_{sensor} and f_{SetPts} might be highly non-linear and non-convex. Noting that neural networks are particularly suitable for approximating such functions, we choose to model both the forward and inverse models with neural networks. Then, observing the symmetry in these models, and that the number of HVAC set-points N is usually strictly less than the number of sensors M, $N < M$, and the fact that these are black-box neural network models, we observe that these models can be trained as an autoencoder, where

$$\hat{X}(t) = f_{sensor}(f_{SetPts}(X(t))). \tag{4}$$

Fig. 4 shows the models linked in the autoencoding framework. From left to right, the input layer of the model corresponds to the room thermal state, $X(t)$. The hidden layers consist of a tunable group of layers with the usual non-linear activation functions. The latent layer has a dimension equal to the number of HVAC units controlling the room, and represents the learned set-point for each HVAC unit, h_j. Next comes a new set of hidden layers that translate the latent layer's outputs into an estimate of the room thermal state, $\hat{X}$. As shown in the figure, the model inputs can be further augmented using HVAC state conditions such as fan on/off state, fan speed, etc. We denote these as $x_{C,j}(t)$.

To learn the forward and inverse models together in an autoencoder, we augment the usual autoencoding loss function with a term minimizing the deviation of the embedding from the real HVAC set-points, h_j. The new loss function is denoted as $\mathscr{L}_{\mathscr{T}}(t)$, where $\mathscr{T}$ denotes that this is an approximation of the static thermodynamic relationships.

$$\mathscr{L}_{\mathscr{T}}(t) = \underbrace{\sum_{i=1}^{M}(\hat{x}_{T,i}(t) - x_{T,i}(t))^2 + (\hat{x}_{H,i}(t) - x_{H,i}(t))^2 +}_{\text{Reconstruction Loss on } X(t)} \\ \underbrace{\sum_{i=1}^{N}(\hat{h}_j(t) - h_j(t))^2}_{\text{Embedding Loss on } H(t)} \tag{5}$$

IV. Thermal Comfort Control Law

We now combine the models described in Section III to learn a control law, $\pi(X_T^*)$, that controls the HVAC units such that thermal comfort is optimized. To begin, we first leverage the personalized user models, f^k, to find the optimal temperature of each user. To do this, for each individual or joint comfort interval we obtain the average indoor temperature determined as $(T_{max} - T_{min})/2$. We record this temperature as the optimal temperature, $x_{T,k}^*$, preferred by the user(s) in this individual (joint) comfort interval.

Next, we obtain the control law by optimizing the loss function,

$$\mathscr{L}_{C,I}(\hat{X}(t), X_T^*) = \sum_{i \in M}\sum_{k \in K}(\mathbb{1}(i)\hat{x}_{T,i}(t) - \mathbb{1}(i,k)x_{T,k,i}^*)^2 \tag{6}$$

where $x_{T,k,i}^*$ is the optimal temperature of the k^{th} user who is currently sitting in the i^{th} location, $\mathbb{1}(i) = 1$ if i corresponds to the closest sensor location to at least one user, and $\mathbb{1}(i,k) = 1$ if i corresponds to the closest sensor location for the k^{th} user. The estimated value of the temperature at the i^{th} location is approximated by the thermal sensors model (eq. (2)). Optimization is performed using the Powell method, which is a derivative free optimization method [33]. Using this optimization method allows the static approximation to the room thermodynamics to take any form without constraining the function to have analytically tractable derivatives. In the future, if desired, a constrained optimization approach may be used to optimize energy efficiency or other desirable building parameters.

A key observation is that neither the static room approximation nor the objective function are expected to be globally convex. For this reason, it is important to begin the optimization at a point that is near the local optimum of the loss function. We use the thermal set points model, (eq. (3)), to provide this initial estimate of the solution.

V. Data Collection and Training Parameters

Data to test the proposed approach was collected in a large field experiment in an open office. The office is air-conditioned by $N = 5$ HVAC units, each of which directly cools or heats a particular part of the room.

The desks in the room are arranged in rows, and each desk has two sensors, one at each corner that abuts the next desk. Each sensor measures temperature and humidity. There are 39 such sensors in the room, resulting in $M = 78$ sensor measurements. There are 18 users in the room, who are actively participating by setting the set-points of the HVAC units. No assumptions are made about additional heat loads in the room, such as computers or non-participating occupants.

Data collection was performed continuously for 10 days in August of 2019. During this time, sensor and HVAC data was collected at 1-minute increments and the users were free to request a new set-point temperature at any time. This experiment resulted in $12,425$ measured data points and 136 user set-point change requests. We observed that the request data are not uniformly obtained from all users; some users were much more inclined to change the HVAC unit set-points, while others provided as few as one HVAC change over the course of the experiment. This distribution of interaction is common to this setting and fits the expected behavior of the users.

For the experiments in this paper, the data are split using an 80/20 (train/test) split. The thermal set point and thermal sensor models are each composed of a single hidden layer with 50 neurons. This number of neurons is chosen based on the number of available data points. Training is performed using the loss function in eq. (5) and using an Adam optimizer [34] with standard parameters. Model learning and testing is performed on a Linux desktop machine with an i7 processor.

VI. Numerical Experiments

Here we present numerical results and compare them to a baseline linear model and using the inverse model directly. We begin by training the forward and inverse models. Table I shows the average performance of models quantified using both the Mean Absolute Error (MAE), and the effect of model output outliers quantified using Root Mean Squared Error (RMSE). When MAE is approximately equal to RMSE, model performance is consistent, with few outliers.

We note here that the neural network model with $x_{C,j}$ outperforms both other models when predicting temperature and set points. This is also true when comparing the per measurement (set point) standard deviation (σ) of this model with the linear regression model (MAE/RMSE): σ_{SetPt}: 0.23/0.27 vs. 0.70/0.80; $\sigma_{Temp.}$: 0.15/0.22 vs. 0.26/.34; and $\sigma_{Humid.}$: 0.48/0.66 vs. 1.13/1.27 (outliers omitted). Outliers notably exist in predictions of humidity measurements, which

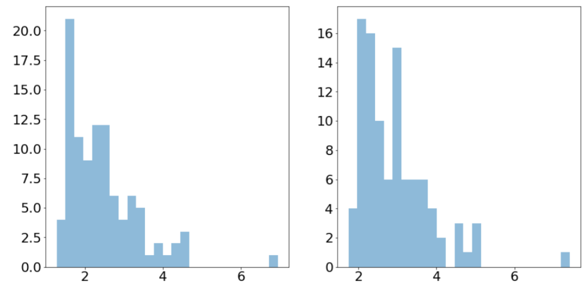

Fig. 5: Linear model performance histogram for individual comfort models. X-axis (left) MAE [^{o}C] (right) RMSE [^{o}C]

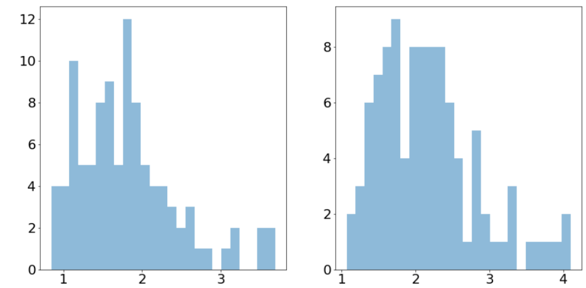

Fig. 6: Linear model performance histogram for combined comfort models. X-axis (left) MAE [^{o}C] (right) RMSE [^{o}C]

is seen when comparing MAE to RMSE for this model. We believe these will improve as the size and diversity of our data set grows.

For the remainder of the experiment, we use the neural network models that incorporate the HVAC conditions. Here, we learn a control law π using the described optimization method. We compare the proposed approach to linear modeling and using the inverse model directly. To use the inverse model directly we input to the learned inverse model, eq. (3), a measurement vector with the desired temperatures substituted at the correct temperatures. All approaches are tested over 100 randomly chosen seating arrangements of the 18 individuals, and 190 test points for each seating arrangement. We compare the models for the case where the user comfort zones are combined and the case where the comfort zones are left individually, Table II. We plot histograms of the RMSE and MAE, in Figs. 5-8, of the linear model and the proposed optimization method to gain better insight of the method performance.

The data in Table II and Figs. 5-8 show that the combined non-linear modeling and optimization method reduces the average error rate with respect to the desired temperature of an individual across the many seating arrangements by more 50% as compared to the linear regression model. In addition from the figures, we note that while the linear model error rates are left-skewed, they exhibit a long tail, indicating that in some seating arrangements, this approach fails to satisfy any of the users. In contrast, the optimization approach proposed in this paper exhibits a symmetrical Gaussian distribution about the mean, which indicates that

TABLE I: Error rates of static thermodynamic models.

	Set-Point (^oC)		Temperature (^oC)		Humidity (%)	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
Linear Regression	1.42	1.89	0.88	1.13	3.98	4.82
Thermal Model w/o $x_{C,j}$	1.15	1.53	1.96	4.54	10.94	19.24
Thermal Model with $x_{C,j}$	0.58	0.75	0.51	0.71	4.13	12.82

TABLE II: A comparison of modeling approaches for individual and combined user comfort zones. Averaged error per user in ^{o}C $\pm$ standard deviation in ^{o}C.

	MAE	RMSE
Individual Comfort Models		
Baseline Regression	2.46±0.90	2.94±0.91
Direct Inverse Model	1.69±0.16	2.02±0.16
Online Optimization	1.09±0.16	1.41±0.22
Combined Comfort Models		
Baseline Regression	1.81±0.64	2.17±0.66
Direct Inverse Model	1.14±0.12	1.55±0.17
Online Optimization	0.85±0.12	1.07±0.14

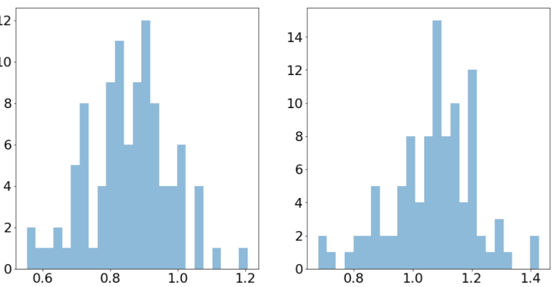

Fig. 8: Proposed model performance histogram for combined comfort models. X-axis (left) MAE [^{o}C] (right) RMSE[^{o}C]

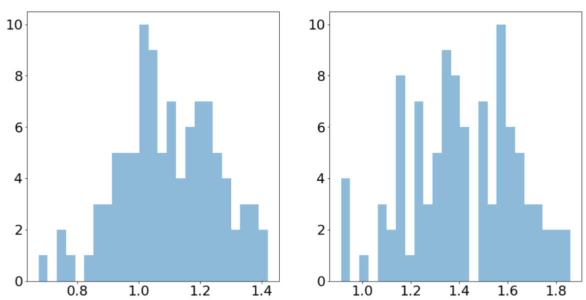

Fig. 7: Proposed model performance histogram for individual comfort models. X-axis (left) MAE [^{o}C] (right) RMSE [^{o}C]

the approach is performing well and that the higher error rates are likely due to an incompatibility of individuals seated next to one another.

This is expected for two reasons. First, the linear method is extrapolating from a few inputs to many outputs. Thus, the model is attempting to predict an average data point in a very large dimensional space. Furthermore, the input to the model suffers from an out-of-sample condition where the synthetic desired data point may not have been observed in the training data set. In contrast, the optimization approach uses physically learned models to predict the start point of the optimization, and then to learn the optimal room set points. Because the models are learned from physical data, and we assume that sufficient training data can be collected, the out-of-sample condition observed in the linear model is not likely to happen for our optimization based approach.

Comparing the performance of our approach to using inverse model directly shows a reduction in the error rates by about 1/3 or more. There are two likely reasons for the out performance of the optimization approach as compared to the direct inverse model. The first is that the inverse model learns to approximate a set of HVAC set points that is most likely to result in the observed temperature field. This solution is not connected to personal thermal comfort and thus the optimization algorithm is able to locally optimize for personal thermal comfort about the physical solution. The second, that inputting a modified measurement vector into the inverse model means that the model is receiving a temperature field that likely violates the physical relationships learned from the data. Such an input would result in an out-of-sample condition for the inverse model and thus reduce the fidelity of the model output.

Lastly, we note that the models learned in this work are expected to be at least seasonal. For example, given the training dataset in this paper, we only expect the learned model here to apply for the summer season. This seasonality can be accommodated in the neural network model through online adaptation, and through periodic relearning of the thermal comfort models. The seasonal thermal comfort models can then be saved in seasonal dictionaries per user and re-used when appropriate. We leave to future work the development of a single time varying thermal comfort model per user.

VII. Conclusion

In this paper, we proposed an online approach to learning how to determine HVAC set-points in order to optimize user's comfort in a room. We proposed a new weakly supervised learning approach that learns personalized thermal comfort models during ordinary HVAC operation. This approach does not require teaching new behaviors to the individuals or altering the individual behavior in any way. Then, we learned a static model of the relationship of temperature and humidity readings between the HVAC sensor and room sensors. This model enabled the prediction of state of the user's environment for given HVAC set points. Finally, we combined the static room models with the user models to learn a control law via optimization that improves the user thermal comfort subject to the learned individual models. We proposed two approaches to using the individual user models, either utilizing the models separately, or combining similar users into a single comfort model. Our approach was tested using real data from an open office in Japan for 100 randomly chosen seating arrangements of the users. The approach achieved a mean absolute error of 0.85^{o}C and a root mean square error of 1.07^{o}C per user location over all seating arrangements.

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