Personalizing Individual Comfort in the Group Setting

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Abstract

Maintaining individual thermal comfort in indoor spaces shared by multiple occupants is difficult because it requires both intuition about the thermal properties of the room and an understanding of the thermal comfort preferences of each individual. We explore an approach to optimizing individual thermal comfort within a group through temperature set-point optimization of HVAC equipment. We propose a weakly-supervised algorithm to learn the individual thermal comfort preferences and an autoencoding framework to learn static approximations of room thermodynamics. We further propose two approaches to learn a control law that sets the HVAC set-points subject to the preferred user temperatures. 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 to within 0.5^oC of the user's desired temperature.

Introduction

At any given time, a person's feeling of thermal comfort is somewhere on a continuum from cold to hot (ASHRAE 2013). The conditions that make a person comfortable are unique and dependent on physiological factors such as ethnicity, body composition, gender, and state of health, as well as environmental factors such as temperature, humidity, airflow, and weather. As a consequence of the difficulty in measuring many of these variables and the computational complexity of using many measured variables, individual thermal comfort is commonly summarized by the easily measured variables of temperature and humidity (ASHRAE 2013; CEN 2006; Haldi 2010). The set of temperature and humidity values for which a person is comfortable is commonly called their comfort zone, and zones common to many individuals are defined by engineering standard bodies (ASHRAE 2013; CEN 2006). These comfort zones provide an imperfect method to attempting to optimize user comfort that so far has been the best approach available for mass deployment.

Traditionally, maintaining thermal comfort has been an individual's own responsibility. Comfort is usually maintained through clothing adjustments or adjustments in the environment, such as opening a window or adjusting a heating, ventilation, and air conditioning (HVAC) device. Yet, each of these actions represents a learned intuitive model that is more complex than readily apparent. In search of an easily deployable method, here we focus on setting HVAC set-points, which in practice means learning the complicated non-linear relationship between the thermal conditions at an individual's location in the room and the temperature at a measurement point that controls the HVAC device. Users typically do not approximate these relationships very well. Most often, users learn heuristics on how to set the HVAC set-point or learn the most acceptable compromise on their thermal comfort. The problem is further complicated in common spaces, such as offices and living rooms. Here, choosing how to set the room temperature acquires a social/political component, and users may try to satisfy immediate desires by overshooting their perceived set-points, resulting in more discomfort for themselves and other occupants, as well as wasted energy. Yet, studies show that it is exactly in these environments where improving comfort is most important, leading to improved work performance and satisfaction, as well as increased social happiness (Hedge, Wafa, and Anshu 2005). Thus, the ability to improve comfort automatically is very desirable, particularly in group settings. This is reflected in the recent increased interest in solving this problem (Smith et al. 2017).

Background

Modern methods in sensing and learning offer the promise of developing the ability to automatically improve and maintain personal comfort. Here, we briefly review the state of the art in several fields relevant to this application, focusing mainly on thermal comfort modeling and thermodynamic modeling of the room.

Several recent papers have explored the problem of modeling personal thermal comfort (Laftchiev and Nikovski 2016; Ranjan and Scott 2016; Huang, Yang, and Newman 2015; Jiang and Yao 2016; Farhan et al. 2015; Yi, Jia, and Ler 2019; Kim, Schiavon, and Brager 2018). An important focus of this work has been on reducing the need for human feedback (Natarajan and Laftchiev 2019; Hu et al. 2019). This is because we know that, given sufficient feedback from the users, it is possible to learn a personalized model of the user's thermal preferences using statistical machine learning techniques. Unfortunately, users are not likely to provide the (typically) hundreds of labeled data points needed to learn these models in full detail. Furthermore, it is unclear how to combine multiple individual thermal comfort models to optimize the overall group comfort for a room.

Room thermodynamics are complex. The temperature experienced by the user may be different than that specified at the HVAC set point because of the spatial location of the user or delays in the room's thermodynamic response. Therefore, modeling the room thermodynamics is essential for automatic thermal comfort optimization of a room. Here, a distinction can be made between learning a truly dynamical thermodynamic model, where the temporal evolution of temperatures in response to the HVAC system operation is modeled at all locations in the room, and static (or quasi-static) models that learn the relationships between room locations in the equilibrium (steady) state. Thermodynamic systems have been modeled using the broad categories of white-box models (Deng et al. 2010; Oldewurtel et al. 2010), which model the physical processes from first principles; grey-box models (Hu and Karava 2014), which rely on reduced-order physical models, simulation and optimization; and black-box models (Amasyali and El-Gohary 2018), which are purely data-driven models and include statistical models.

White- and grey-box models 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 been shown (Delcroix et al. 2020) to perform well without external knowledge. 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.

Contributions

This paper proposes an automatic thermal comfort optimization system for public spaces such as open offices, where improved comfort has been directly linked to improvements in economics (Hedge, Wafa, and Anshu 2005; Taub 2008). Our approach combines personal thermal comfort modeling with static thermodynamic models and proposes a data-driven approach to learning how to control one or more HVAC units to optimize room comfort for one or more individuals. The approach we choose is specifically guided by the need for easy deployment in real, and existing, environments. To this end we test the proposed approach in a large field experiment in an open office environment in Japan. We make the following AI model contributions that facilitate easy deployment:

- We propose a weakly-supervised neural network approach to learning individual thermal comfort models that minimizes the burden of feedback on the users.
- We learn predictive models relating the HVAC sensor and measurement sensors throughout the room, using an auto-encoding framework with a customized loss function that promises a black-box modeling approach that is easily deployable in new settings.
- We design a loss function that combines the user preference models with the learned thermal models and use this loss function to learn the final control law. This control law is a set of HVAC set points that leverage the existing HVAC system and its controller.
- We demonstrate that the learned model achieves optimal per-point performance, thus allowing for computationally cheaper online comfort optimization which is suitable for low power field devices.

AI 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, 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 $x^*_{T,k,i}$ the optimal temperature of user k at location i. The vector of optimal temperatures desired by the occupants is denoted as X^*_T. No assumptions are made regarding the number of users associated with each sensor. We assume that each user has the capability of providing 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 $j \in 1, \dots, N$ 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 $H(t) = [h_1(t), \dots, h_N(t)]^T$.

Our goal is to learn a control law $H^* = \pi(X^*_T)$ that, given the preferred temperature $x^*_{T,k,i}$ for each user k, maximizes the comfort probability of all the users denoted by $y_c = [y^1_c, \dots, y^k_c]^T$.

User Model Learning

For the k^{th} user, associated with the i^{th} sensor, there exists an unknown function, $y^{k,i}_c = \tilde{f}^{k,i}(\tilde{x}_i)$ that maps the user's thermal state, $\tilde{x}_i(t)$ at time t, to their personal probability of comfort, $y^{k,i}_c(t) \in (0, 1)$ 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 (Laftchiev and Nikovski 2016; Ranjan and Scott 2016; Huang, Yang, and Newman 2015; Jiang and Yao 2016; Farhan et al. 2015), we aim to learn an approximation to $\tilde{f}$ using the measurable quantities $x_i(t)$:

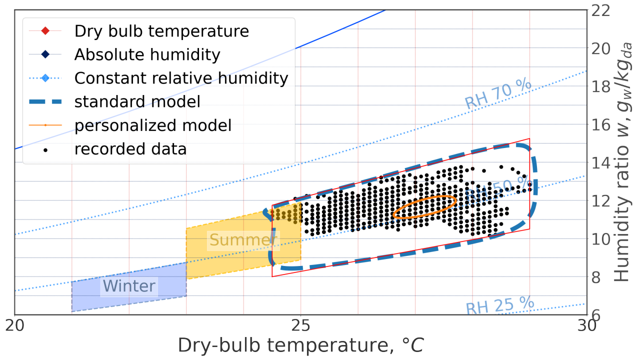


Figure 1: Psychrometric chart illustrating default comfort zones, learned models, and collected data.

$$y_c^k(t) = f^k(x_i(t)). \quad (1)$$

where we dropped the superscript i for ease of notation. To minimize the burden of providing feedback on the users, we propose a weakly supervised approach. First, a standard model, f^0, is learned using synthetic data. Then, the standard model is adapted using feedback provided by each user. The model for the k^{th} user is denoted as f^k.

Learning an Initial User Model

The standard model, f^0, common to all users, is learned using labeled synthetic data sampled uniformly over the space of all possible temperature and humidity values that could be measured in a room. The labels for the data are derived from commonly accepted ranges of temperature and humidity that are thought to be comfortable for all individuals. If a given temperature and humidity data point falls within such a commonly accepted range, it is labeled comfortable. Otherwise, the point is labeled uncomfortable.

Selecting the ranges of humidity and temperature that constitute a comfortable range is an important design choice. There are at least two methods of choosing these ranges. The first method is through expert opinion. An example of expert opinion is the summer and winter comfort regions published by ASHRAE (ASHRAE 2013). These are visualized by blue and yellow rectangles, respectively, on the psychrometric chart (Balmer 2011) 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. Extending the logic used in the ASHRAE zones, here we suggest that the region should be rectangular, corresponding to the observed $T_{min}, T_{max}, H_{min}$ and H_{max}. An example of such a region is shown in the red rectangle in Fig. 1. The black points plotted inside the rectangle represent data collected for the verification of this paper. Note that these fall outside of the expert defined comfort zones. This method is convenient because it does not require prior knowledge or hand engineering.

In this paper, we adopt the second method for two reasons. First, this approach extends the well-known and accepted engineering logic used in determining the original ASHRAE zones of comfort. Second, a rectangular region immediately suggests a shape for the standard thermal comfort model, f^0, and the user's thermal comfort model, f^k, which matches our intuitive understanding of the personal comfort region: a neural network with four neurons in the hidden layer, an example of which is shown in Fig. 2. Conveniently, we can think of each neuron as learning a boundary on one side of the chosen comfort region: a temperature boundary cold to comfortable; a temperature boundary comfortable to hot; a humidity boundary humid to comfortable; and a humidity boundary dry to comfortable. To interpret the output of the model as a probability, we give each neuron a sigmoid activation. Using this neural network is advantageous not only because of its intuitive origin, but also because we know that the comfort region is highly dependent on the season. We expect that each user's model will be continuously tuned during exploitation.

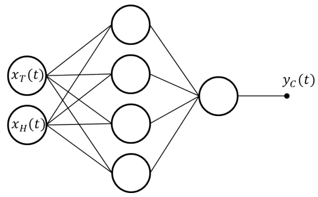
To learn the models, we sample uniformly over the set of all possible room conditions and label the samples using the boundaries of our newly defined comfort region shown in Fig. 2. We then train the standard model, f^0. This model is shown in Fig. 1. Here the red rectangle represents the comfort region, and the blue dashed line represents the learned model. The line is one of the level sets of the learned thermal comfort probability model, f^0.

Personalizing the User Model

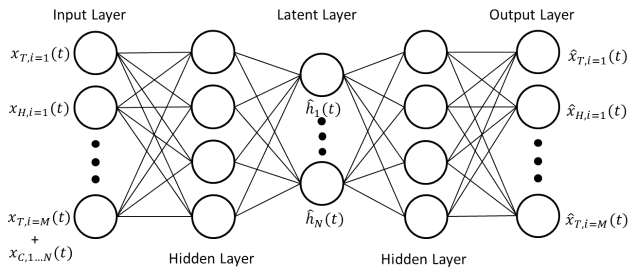
Customization of the standard model for a given user begins when an uncomfortable user, k, adjusts the j^{th} HVAC device's set point. At this point, we observe the user's thermal state, $x_i(t)$ and the requested set point temperature, h_j. Each set point request reveals three levels of information. 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. Third, the user thinks that their optimal temperature might be h_j.

Of these three feedback components, we only make use of the first component. This is because we cannot be explicitly sure that the target set point chosen by the user is optimal, and because the thermal comfort model chosen in this paper only determines the probability of comfort, not the direction of discomfort. Thus, when a user adjusts the HVAC thermostat, we obtain a labeled data point that states that the user is uncomfortable in these conditions.

To personalize f^0, we fit the newly acquired labeled data point using backpropagation on f^0 until the probability of comfort assessed at the present data point is below a given threshold, τ. The fitted model is termed f^k because it is the personalized model of the k^{th} user. This is updated as the user provides feedback. Note here that personalizing the model in this manner has the effect of altering the probability of comfort over all previously recorded data points. There are two reasons for this. First, because the overwhelming majority of points used in learning the model are synthetic, each new data point provides a more concrete indication of the user's actual preference. Second, we ideally want to learn a decision surface over which comfort probability can be determined from a collection of points. Yet we do not know when/if the user will interact with the system. Thus we treat



(a) Individual comfort model



(b) The thermal sensor model and the thermal set point model shown in the autoencoding framework.

Figure 2: Neural Network Models

each interaction as if it is the last for this user.

Lastly, when deploying this model we envision that at least during the first full year of exploitation the user model will be periodically learned from sets of recent feedback points, leading to a collection of seasonal personalized models f^k for a given user k. This initial method of deployment provides a bridge between the current experiment and the development of a seasonally adjustable thermal comfort model. Initial deployment in this fashion will motivate users to participate when they are readily observing the effect of their participation.

An example of a model f^k that is personalized over 15 feedback instants of a single user is shown in Fig. 1 as a yellow oval that represents one of the level sets of the personalized model. As expected, this model encompasses only a small subset of the data encompassed by f^0.

Approximating the Room Thermodynamics

In any given 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 a single invertible model g is 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, which means that learning a single invertible model might not be possible. Instead, here 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. 2(b) 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 nonlinear 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 $\mathcal{L}_\mathcal{T}(t)$, where $\mathcal{T}$ denotes that this is an approximation of the static thermodynamic relationships.

$$\mathcal{L}_\mathcal{T}(t) = \underbrace{\sum_{i=1}^{M} (\hat{x}_{T,i}(t) - x_{T,i}(t))^2 + (\hat{x}_{H,i}(t) - x_{H,i}(t))^2}_{\text{Reconstruction Loss on } X(t)}$$

$$+ \quad \underbrace{\sum_{i=1}^{N} (\hat{h}_j(t) - h_j(t))^2}_{\text{Embedding Loss on } H(t)} \tag{5}$$

The modeling approach presented here is attractive from the stand point of deploying this technology at real-world locations for two reasons. First, learning the room models together in an autoencoder leverages a well known unsupervised modeling approach that can be set to learn the on-site conditions without further human intervention. Second, using neural network models allows for online updates to the model as new data is recorded. This is advantageous because we expect that the model will have a seasonality that will shift the relationship between the room measurements and the HVAC set point slowly throughout the year.

Learning the Control Law

We now combine these models to learn a control law, $\pi(X_T^*)$, the set points of 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, we sample uniformly from the set of possible room conditions, and for each user k we choose the point with the highest probability of comfort. The temperature at this point is $x_{T,k,i}^*$ as described in the problem formulation.

Next, we propose two methods of learning the control law π. The first approach, herein called Retuned Inverse Model (RIM), is to choose the control law π to have the same architecture as the thermal set-point model, eq. (3). The model is warm started with the learned weights of the thermal set-points. Then the control law is trained such that the predicted HVAC set-points result in measurements $x_{T,i}$ at the user locations that correspond to $x_{T,k,i}^*$. This training is accomplished by using the forward model, and by tuning π using a loss function that penalizes deviations from the ideal user temperature at each user's location,

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

where $1(i) = 1$ if i corresponds to the sensor location closest to at least one user, and $1(i,k) = 1$ if i corresponds to the closest sensor location for the k^{th} user. This forces RIM to learn a new mapping that emphasizes user comfort over reconstruction of the room thermal state. The second approach, herein called Tuned Linear Map (TLM), is to define π as the thermal set-point model, eq. (3), with an additional linear layer of dimension N added to the output of the model. Here the inverse and forward models are fixed, and training is only performed on the added layer using eq. (). The advantage of this approach is that there are fewer model parameters to learn, resulting in a model that can be efficiently learned with few training data samples.

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 via an Apache Tomcat server that identifies the users and the HVAC units. No assumptions are made about additional heat loads in the room, such as computers or non-participating occupants. Data from the sensors is streamed to the same server, but we envision a cloud deployment to systems like AWS or Azure for commercial deployments.

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 little 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 (Kingma and Ba 2015) with standard parameters. AI model learning and testing is performed on a Linux desktop machine with an i7 processor.

Comparison Methods

The AI approach proposed in this paper invites comparison to several other methods. These methods include learning direct inverse models, distal learning (Jordan and Rumelhart 1992), and on-line optimization. To directly exploit the inverse model, eq. (2), as a control law, we input to the model the desired temperature measurements at each user's location x_i and predict the resulting set-points H. To make use of the distal learning framework suggested in (Jordan and Rumelhart 1992), we learn and fix the forward model and then directly learn the control law from the desired temperature measurements. For both of these models, an entire vector of desired temperatures at all M locations needs to be provided as input. Lastly, directly optimizing eq. (), i.e., solving $H^* = \arg\min_H \mathcal{L}_{C,I}(f_{sensor}(H), X_T^*)$, we can learn a global set of HVAC set-points that optimizes the temperature measurements only at the specific locations of users, for a fixed forward model learned ahead of time. In practice, we expect that directly using the inverse model as a control law will have worse performance than our approach, because the input vector composed of desired temperatures does not have to obey the physical correlation between room measurements, which would result in an out-of-sample condition for the inverse model. Similarly, methods that select one set of optimal set-points, such as the global optimization approach or the model learned from the distal framework, are also likely to under perform. This is because these approaches assume a static relationship in the underlying data, while some transients will inevitably be present in our data. Thus, these approaches likely yield an average solution.

Lastly, it is possible to use optimization in an online fashion by setting the initial value of the solution to set-points predicted by the inverse model, for a given value of $X(t)$. This approach uses the neural network model to identify the correct numerical sub-problem to optimize and should yield an optimal solution. However, this approach requires continuous online optimization, which is more computationally expensive than performing prediction using an advance tuned neural network model.

	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 1: Error rates of static thermodynamic models.

Numerical Experiments

Here we present numerical results and compare them to the aforementioned methods. All optimization experiments are implemented using back propagation in PyTorch. We begin by training the forward and inverse models that approximate the static thermodynamic relationships. Model performance is compared to baseline linear regression models trained in the forward and inverse directions. Table 1 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, as seen when comparing MAE to RMSE for this model.

Using the inverse and forward models with HVAC state conditions, we learn a control law π using the two approaches suggested in this paper. We compare the results to two baseline methods. The first uses the inverse regression model to predict optimal HVAC set-points directly, and the second uses a common HVAC set-point of 27^{o}C (the average preferred temperature of the users). The results are shown in Table 2. To gain further insight in Fig. 3, we plot a histogram of the RMSE and MAE of the control laws learned using both methods suggested in this paper. Each histogram is compared to the online optimization approach described at the end of the previous section.

	MAE	RMSE
Baseline Regression	1.11±0.70	1.41±0.68
Baseline 27C	1.08±0.36	1.32±0.36
Retuned Inv. Model (RIM)	0.49±0.17	0.63±0.18
Tuned Linear Map (TLM)	0.46±0.23	0.64±0.24

	MAE	RMSE
Direct Inv. Model	0.93±0.14	1.08±0.12
Global Optimization	1.04±0.46	1.35±0.50
Distal Learning	1.16±0.66	1.52±0.70

Table 2: Averaged error per user in ^{o}C $\pm$ standard deviation in ^{o}C. A comparison to (top) baseline methods and (bottom) competing modeling approaches.

The data in Table 2 and Fig. 3 show that the proposed approaches, RIM and TLM, outperform baseline methods by improving RMSE and MAE by a factor of at least 2 when compared to the baseline regression method and the average set-point baseline. The results in Table 2 also show that competing modeling approaches have error rates on par with the error observed by setting the HVAC set-points to an average desired value. Lastly, comparing the resulting error histograms, we find that both RIM and TLM find solutions similar to those in the online optimization approach. But the methods presented in this paper have a clear computational advantage with an average run time of 3.7ms, while online optimization has an average run time of 4.7s.

The results in this section and the model choices throughout make the developed approach a practical AI modeling approach to user comfort optimization. Our approach is greatly facilitated by modern IoT sensing and cloud technology. Still, to deploy this application, a long term study must be performed to learn about the seasonality of the AI models and model improvements that this will require.

Conclusion

We propose a new easily deployable data driven approach to learning how to determine HVAC set-points in order to optimize user comfort in a room. Our work proposes a new approach to learning personalized thermal comfort models that reduce the burden of collecting labeled user data. We also propose to learn a static model of the relationship of temperature and humidity readings between the HVAC sensor and room sensors using an autoencoding framework with a custom loss function. We propose two methods of learning an HVAC control law based on a custom loss function that incorporates the desired temperature of multiple users simultaneously. Our approach is tested using real data from an open office in Japan, achieving a mean absolute error of 0.5^oC and a root mean square error of 0.6^oC per user location.

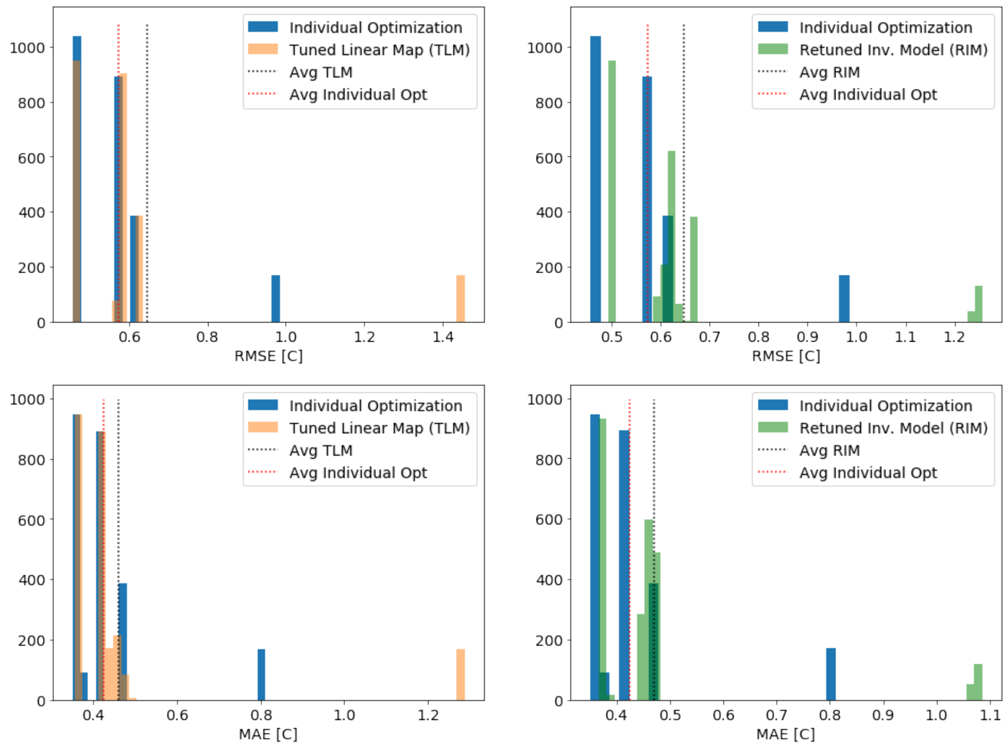


Figure 3: Histograms illustrating model performance over the test set. (left) Tuning a linear layer between the forward and inverse models. (right) Retuning the inverse model to optimize user comfort.

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