Predicting Thermal Comfort for Diverse Populations

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Abstract
Most thermoregulatory models used to understand human comfort are based on a standard human physiology — a 172 cm-tall man weighing 74.1 kg whose body composition is 15% fat. However, this body type is not representative of the world’s population, and variation in body build may significantly affect human perception of temperature. We use diverse, rapidly generatable body type models to predict the thermal sensation and comfort of populations. Our simulation method uses multi-nodal thermal models of the human body that can be adjusted parametrically to different body types. This gives us more flexibility than the single-node Predicted Percent Dissatisfied model, including the capacity to handle non-uniform and time-varying conditions. In our case study, analysis of the standard body type failed to detect discomfort in conditions where population analysis found 16% of tested individuals feeling uncomfortably warm and 31% of tested individuals feeling uncomfortably cold.

Key Innovations
- Human thermoregulatory model with dynamically adjustable physiology
- Method for rapid generation of a population with representative physiologies
- Case study of improved decision making based on population thermal comfort analysis

Practical Implications
Our method allows us to specify thermal comfort interventions that work for entire populations, rather than average members of those populations. By doing so, we avoid both oversized systems and occupant complaints.

Introduction
Building designers and engineers consider thermal comfort with the goal to reduce occupant complaints while minimizing the energy used to control interior temperatures. In order not to use excessive energy by rigidly controlling temperatures where not necessary, and to avoid complaints from controlling to the wrong temperature setpoints, they need to predict how a wide segment of the population will perceive the thermal environment. For typical cases, researchers have amassed survey data that demonstrates comfortable temperature ranges from many individual studies (Földváry Ličina, et al., 2018). However, in atypical cases, such as transient conditions, non-uniform environments, or where occupants have elevated metabolic rates, mathematical models of human thermal comfort are required.

Many human physiological models exist for predicting thermal comfort. The Predicted Mean Vote (PMV) and Predicted Percentage Dissatisfied (PPD) describe thermal sensation of a standard individual in uniform steady-state conditions and predict dissatisfaction in populations using a modified normal distribution (Fanger, 1972). Methods that allow for transient and non-uniform conditions (e.g. Stolwijk, 1971; Tanabe, et al., 2002; Fiala, et al., 1999; Huizenga, et al., 2001) model heat storage and exchange by different bodily tissues, and therefore depend on the overall mass of and distribution of tissues within the body. This physiological data is a fundamental part of all such thermal comfort models.

We wish to point out a common problem in the application of these models. Calculations based on these models almost invariably use the same standard physiological parameters — those describing a fit 74-kg male. In reality, thermal sensation is related to physiological parameters of individual bodies, most especially the amount of body fat. This paper presents a method for creating thermal comfort models to represent a wide spectrum of the population. Our method allows us to identify interventions in the thermal environment that improve comfort for most or all individuals, rather than basing designs on a single “standard” body type.

Background
Researchers have developed a variety of methods to predict the satisfaction of building occupants with their thermal environments. Most widespread are surveys in which occupants report their comfort “right-here-right-now,” of which 81,846 have been consolidated to elucidate trends (Földváry Ličina, et al., 2018). Extended monitoring of individual comfort preferences has also been used to train machine learning models of comfort (Kim, et al., 2018). These methods rely on gathering large amounts of empirical data and are therefore limited in application to typical thermal conditions.

In cases where limited data is available or human subject tests are impractical, mathematical models serve to predict thermal sensation. These models can be divided in two parts: thermoregulatory models predict body temperatures based on the environment, and psychophysiological models predict sensation based on body conditions.
Thermoregulatory Models

Human thermoregulatory models allow thermal sensation and comfort to be evaluated in a larger range of conditions by calculating heat transfer between the body and its surroundings. In the PMV calculation, the body is treated as a single node that exchanges heat with the environment through an insulated clothing layer (Fanger, 1972). The Pierce Standard Effective Temperature (SET) model divides the body into two nodes – skin and core – allowing skin temperature to be controlled by both internal and environmental factors (Gagge, et al., 1986). These one- and two-node models assume uniform and steady state conditions; they do not allow the environment to vary with space or time.

The space program made it necessary to consider environments with highly non-uniform and rapidly changing temperatures. The Stolwijk (1971) model was commissioned by NASA to simulate biological response to hostile dynamic thermal environments without subjecting human subjects to those conditions. This model divides the body into a network of ten cylindrical and spherical segments for the trunk, limbs, and head, each containing nodes for the core, muscle, fat, and skin. The model was based on a 172 cm-tall male body weighing 74.1 kg and composed of 15% fat by weight, in line with typical astronauts of the time.

Various subsequent studies have improved upon Stolwijk’s model by subdividing body parts (Tanabe, et al., 2002), allowing non-cylindrical body parts (Ferreira & Yanagihara, 2009), adding detailed blood flow (Kobayashi & Tanabe, 2013), and considering aging (Takahashi, et al., 2021) and orientation for radiant heat exchange (Al-Othmani, et al., 2008). Any physiological parameters can in theory be applied to these algebraic models, and in fact, the Center for the Built Environment’s model (Huizenga, et al., 2001) allows an arbitrary number and connectivity of nodes. Nonetheless, Table 1 shows that researchers have been hesitant to stray from the original body defined by Stolwijk (with the recent exception of an update to the Fiala model (Fiala & Havenith, 2015)).

Table 1: Physiological data from various models, adapted from Shitzer, et al. (2015)

<table>
<thead>
<tr>
<th>Source</th>
<th>Height (cm)</th>
<th>Weight (kg)</th>
<th>Body Fat (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stolwijk (1971)</td>
<td>172</td>
<td>74.1</td>
<td>15</td>
</tr>
<tr>
<td>Werner &amp; Webb (1993)</td>
<td>170</td>
<td>78</td>
<td>16 ± 3°C</td>
</tr>
<tr>
<td>Wolf &amp; Garner (1997)</td>
<td>168.7</td>
<td>70</td>
<td>10</td>
</tr>
<tr>
<td>Fiala (1999)</td>
<td>171.6</td>
<td>73.5</td>
<td>14</td>
</tr>
<tr>
<td>CBE (2001)</td>
<td>175.5</td>
<td>74.4</td>
<td>14.05</td>
</tr>
<tr>
<td>Tanabe (2002)</td>
<td>171</td>
<td>74.43</td>
<td>15</td>
</tr>
<tr>
<td>Fiala (2015)</td>
<td>169.7</td>
<td>71.4</td>
<td>22.6</td>
</tr>
</tbody>
</table>

In contrast, physical data from the civilian population of the United States (CDC, 2020) shows significantly broader ranges of height (Figure 1), weight (Figure 2) and body fat (Figure 3). Among this population, the body fat contents of the models listed in Table 1 all fall within the leanest 1%, rather than within the more typical ranges in Table 2. To illustrate this bias, we compare the body fats from Table 1 to the predicted body fats of typical men and women with the same height and weight (according to Equations 2 and 3 below) in Figure 4. In using the Stolwijk model and its decedents to predict occupant thermal comfort without adjusting these parameters, we design buildings for astronauts.

Table 2: Physiological data for the middle 80% of American civilians, based on 2005-2006 and 2015-2016 National Health and Nutrition Examination Survey data

<table>
<thead>
<tr>
<th></th>
<th>Height (cm)</th>
<th>Weight (kg)</th>
<th>Body Fat (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Men</td>
<td>165.6 – 184.5</td>
<td>65.9 – 116.3</td>
<td>19.1 – 36.5</td>
</tr>
<tr>
<td>Women</td>
<td>152.5 – 170.1</td>
<td>54.4 – 105.1</td>
<td>31.5 – 49.1</td>
</tr>
</tbody>
</table>

Figure 1: Height percentiles for men and women

Figure 2: Weight percentiles for men and women

Figure 3: Body fat percentiles for men and women

1 Werner & Webb (1993) do not specify fat in their model, but instead report it for a comparable pool of “healthy, physically active men.”
Recognizing the need for personalized comfort metrics, Zhang, et al. (2001) compiled methods to generate individualized physiological parameters from easily collected data. These methods include the ability to calculate body fat based on height and weight (Allen, et al., 1995) or more accurately from height and various circumferences (Hodgdon & Beckett, 1984a; 1984b). Even in these studies, the test subjects may not be representative of the overall population. Hodgdon and Beckett discovered their correlations among members of the United States Navy, for example.

**Psychophysiological Models**

Human psychophysiological models use the recorded or calculated nodal temperatures of the body to predict an occupant’s impression of the environment. Perhaps the best known, PMV rates this impression on a seven-point scale from “cold” (-3) to “hot” (+3). The accompanying PPD scale indicates the fraction of the population experiencing thermal discomfort given a certain PMV. Analysis of 81,846 thermal comfort observations shows that PPD overestimates discomfort, especially in cold conditions (Cheung, et al., 2019).

Zhang et al. (2010a; 2010b; 2010c) performed human subject tests to determine correlations between locally-applied thermal stimuli and subjective evaluations. Subjects reported sensations on a nine-point scale ranging from “very cold” (-4) to “very hot” (+4), with zero indicating neutral. As Table 3 indicates, the 15 women and 12 men in the study represent a broad physiological range, though still leaner than the general population.

Table 3: Physiological data for the subjects of Zhang (2003)

<table>
<thead>
<tr>
<th></th>
<th>Age (years)</th>
<th>Height (cm)</th>
<th>Weight (kg)</th>
<th>Body Fat (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Men</td>
<td>20 – 51</td>
<td>169 – 181</td>
<td>67.0 – 81.2</td>
<td>13 – 23</td>
</tr>
<tr>
<td>Women</td>
<td>21 – 47</td>
<td>149 – 176</td>
<td>47.5 – 81.4</td>
<td>17 – 49</td>
</tr>
</tbody>
</table>

Without involving thermoregulatory models, Zhang (2003) proposed the following equation to predict an individual’s local thermal sensation:

$$S_B = S_L + 0.025(F - 25.4) - 0.12(G - 7.78) + 0.016(A - 31.8)$$  \[(1)\]

where $S_B$ is the modified local sensation, $S_L$ is the local sensation calculated by the method in Zhang, et al. (2010a), $F$ is the body fat percentage, $G$ is 10 for women and 5 for men, and $A$ is age in years. Although Zhang (2003) notes that female core temperature varies with the menstrual cycle, it is unclear whether the gender term in Equation 1 is related to this or is a product of cultural acclimatization.

Previously, we combined Zhang’s work with the thermoregulatory model by Tanabe, et al. (2002) to predict thermal sensation from calculated rather than measured body temperatures (Jones, et al., 2019). Our work at the time included limited ability to adjust the body’s thermal capacitance and metabolic heat production proportionally to weight, body fat, and skin surface area (Du Bois & Du Bois, 1916).

**Method**

We have expanded our method to include several adjustments for individual physiology. In this section, we describe how we modify the body according to known parameters and then how we create populations of virtual test subjects to evaluate thermal comfort interventions.

**Adjusted Physiology**

Our main concern is to provide the correct thermal resistance to the fat node of each body segment, which acts as an insulator between the metabolic heat production of muscle and the environmental heat exchange at the skin. Given a body fat percentage, we adjust the masses of the core, muscle, fat, and skin layers of each body segment. We use the height and Du Bois surface area formula to determine how the altered mass affects the length and thickness of each node, assuming the tissue density of each node does not change. Then, given initial values for each node reported by Tanabe, et al. (2002), we modify thermal capacitance, conductance, metabolic heat production, and basal blood flow according to the mass and dimensions of each node.

When body fat content is not known, we have two methods to calculate it. Given only height $H$ (in cm) and mass $M$ (in kg), the mass of fat $M_f$ is (Allen, et al., 1956):

$$M_{f,\circ} = 0.685M - 5.86\left(\frac{H}{100}\right)^3 + 0.42$$  \[(2)\]

$$M_{f,\circ} = 0.737M - 5.15\left(\frac{H}{100}\right)^3 + 0.37$$  \[(3)\]

For increased accuracy, the body circumferences at the neck ($C_n$), waist ($C_w$), umbilicus ($C_u$), and hip ($C_h$) (in cm) can be used to calculate body density $\rho$ (in g/cm$^3$) (Hodgdon & Beckett, 1984a; 1984b), which in turn relates to fat content (Siri, 1956):

$$\rho_{\circ} = -0.19077\log_{10}(C_u - C_n) + 0.15456\log_{10}H + 1.0324$$  \[(4)\]

$$\rho = -0.35004\log_{10}(C_w + C_h - C_u) + 0.211\log_{10}H + 1.29579$$  \[(5)\]
\[ M_p = M \left( \frac{4.95}{\rho} - 4.5 \right) \]  

Additionally, we adjust the basal metabolic rate and cardiac output. Mifflin, et al. (1990) provide basal metabolic rate \( (W \text{ in kcal/day}) \) calculation methods depending on the amount of available information:

\[ W = 9.99M + 6.25H - 49.2A + 166G - 161 \]  

\[ W = 19.7(M - M_p) + 413 \]

where gender \( G \) is 1 for male and 0 for female in this case. Cardiac output tends to be lower for individuals with stout build. Following Zhang, et al. (2001), we vary cardiac output linearly with body fat percentage between the values listed in Table 4 and cap it at those extremes.

Table 4: Cardiac output limits, adapted from Zhang, et al. (2001)

<table>
<thead>
<tr>
<th>Body Fat (%)</th>
<th>Men</th>
<th>Women</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>20.9</td>
<td>29.4</td>
</tr>
<tr>
<td>Cardiac output (cc/min/kg)</td>
<td>93.9</td>
<td>69.1</td>
</tr>
</tbody>
</table>

These values represent whole body basal metabolic rate and cardiac output. We distribute them to each body segment in the same proportion as Tanabe, et al. (2002) and divide them between the core, muscle, fat, and skin layers based on our adjustments to the mass of each layer.

Creating Populations

We implemented our method in object-oriented C++, which allows us to quickly run multiple iterations in series or parallel. Each iteration tracks the thermal sensation of an individual through a series of environments, with the following parameters defined for each environment:

- Duration
- Dry bulb temperature (DBT) at each body segment
- Mean radiant temperature (MRT) at each body segment
- Relative humidity (RH) at each body segment
- Air speed at each body segment
- Metabolic rate (MET)
- Clothing ensemble description

For any scenario, we consider all combinations of the parameter values in Table 5. This results in 108 simulations of thermal sensation for each scenario.

Table 5: Variables and default values considered in population studies

<table>
<thead>
<tr>
<th>Variable</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clothing</td>
<td>Typical Light Attire</td>
</tr>
<tr>
<td>Sex</td>
<td>Male</td>
</tr>
<tr>
<td>Age</td>
<td>25</td>
</tr>
<tr>
<td>Height</td>
<td>10th percentile</td>
</tr>
<tr>
<td>Body Fat</td>
<td>10th percentile</td>
</tr>
</tbody>
</table>

We select light and heavy clothing ensembles appropriate to the scenario, which we draw from a set of tested outfits (Lee, et al., 2013). Depending on the scenario, the selected ensembles may differ by gender. For example, the range of clothing worn in an event venue may range from t-shirts and slacks for staff to formal gowns and tuxedos for attending women and men. Note that the selection of outfits cannot be based on the overall insulation value alone, as two outfits with similar CLO values but different coverage of the body may produce vastly different thermal sensations.

We do not consider body mass explicitly because it depends to some extent on the individual’s height. Instead, we vary body fat percentage, which is more independent of height, and calculate mass for each iteration by solving Equation 2 or 3 in reverse. This calculation produces a set of 108 time series representing thermal sensation on Zhang's scale from “very cold” (-4) to “very hot” (+4). We consider sensation ratings between “cool” (-2) and “warm” (+2) to indicate comfort, while sensations colder than “cool” and hotter than “warm” are cause for complaint. In the case study, we show how we visualize and interpret the results.

User Interface

As part of our previous work, we developed a web tool that allows scenario testing of transient environments on occupant thermal sensation (Jones, et al., 2019). We added population analysis capabilities to this tool to provide quick access to this method of analysis with minimal setup required (Figure 5). The new population control tab allows users to specify sets of individuals based on the sex, age, and body fat percentile values specified in Table 5 and display them simultaneously on a thermal sensation timeline. For simplicity, the web tool ignores height in the population, as it has the least effect. Clothing is specified elsewhere in the interface. The web tool may be accessed at comfort.arup.com.

![Figure 5: User interface for specifying members of a population to display in the web tool](https://doi.org/10.26868/25222708.2021.30601)

Case Study

To demonstrate our method, we consider the case of arrival at a climate-controlled building on a hot day. This scenario includes three phases:

1. The individual walks outdoors. Outdoor air and mean radiant temperatures are set to the ASHRAE 0.4% cooling dry bulb temperature for Boston. The duration of the walk is 10 minutes, with an additional 10 minutes of warm-up prior to the simulation start.
2. The individual arrives at the building and performs a typing activity for one hour. Solar gains result in the potential for local heating, for which we consider...
three options: the “do nothing” approach, addition of a fan coil unit (FCU), and addition of shading.

3. The individual moves to an interior location away from the window and continues work.

Conditions for each phase are listed in Table 6. We selected two clothing ensembles to bookend the range of outfits worn in the space (an academic building): a T-shirt, jeans, socks, and sneakers providing 0.57 CLO insulation, and a thin dress shirt, slacks, blazer, tie, belt, socks, and formal shoes providing 0.93 CLO insulation. We assigned these ensembles to both male and female cases in all environments. We consider the ensembles to be unisex and ignore the fact that CLO values were measured on a female manikin that wore a bra (Lee, et al., 2013), as undergarments provide negligible insulation.

Table 6: Environmental conditions for the three phases of the case study

<table>
<thead>
<tr>
<th>Outside</th>
<th>Do Nothing</th>
<th>Arrival</th>
<th>Add Shading</th>
</tr>
</thead>
<tbody>
<tr>
<td>DBT</td>
<td>32.6 °C</td>
<td>23.9 °C</td>
<td>23.9 °C</td>
</tr>
<tr>
<td>MRT</td>
<td>32.6 °C</td>
<td>34.4 °C</td>
<td>24.2 °C</td>
</tr>
<tr>
<td>RH</td>
<td>50%</td>
<td>50%</td>
<td>50%</td>
</tr>
<tr>
<td>Air Speed</td>
<td>0.5 m/s</td>
<td>0.1 m/s</td>
<td>0.1 m/s</td>
</tr>
<tr>
<td>MET</td>
<td>2</td>
<td>1.1</td>
<td>1.1</td>
</tr>
<tr>
<td>Interior</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The “Standard” Man

Considering only the “standard” male body used by Stolwijk and others, all three options for the arrival phase appear comfortable. As shown in Figure 6, during the arrival phase between 10 and 70 minutes, the occupant experiences only sensations between “slightly cool” (-1) and “slightly warm” (+1). From only this information, a designer might reasonably conclude that the least expensive alternative, “do nothing,” is sufficient.

Singe Variable Sensitivity Analysis

The effects of varying only clothing, age, height, and body fat content are shown in Figure 7 through Figure 10. In general, men feel warmer than women due to the term in Equation 1. Warm sensations also intensify with increased clothing insulation, increased age, increased height, and increased body fat. The last of these is the only factor that results in a sensation above “warm” (+2), theoretically resulting in a complaint by the male occupant at the 90th percentile for body fat (37% fat by mass). The spread among the six individuals with varying body fat shown in Figure 10 exceeds 1.9 units on the thermal sensation scale. None of the other variables have spreads exceeding 1.3 on this scale.
Whole Population Analysis

The analysis of single variable neglects that many individuals in the population differ from the “standard” body type in more than one way. All 108 members of the simulated population are shown together for each of the three design options in Figure 11 through Figure 13. Notably, only the case with shading provides thermal comfort to all members of the population. In the “do nothing” case, 16% of the population feels uncomfortably warm when seated by the window. With the addition of the FCU, 31% feel uncomfortably cold upon leaving the outdoors (a phenomenon termed “overshoot” by Arens, et al. (2006)), and 4% eventually become uncomfortably cold after prolonged exposure to the FCU.

Figure 11: All individuals for the “do nothing” case

Figure 12: All individuals with the addition of an FCU

Figure 13: All individuals with the addition of shading

Within the population, the coldest sensation generally belongs to the young female at the 10th percentile for height and body fat, although taller lean females occasionally feel colder. The warmest sensation in nearly all cases belongs to the oldest male with the 90th percentile for height and body fat. The maximum total spread in the population while seated at the window are 2.6 in the “do nothing” case, 3.1 in the shading case, and 4.4 with the FCU.

Discussion

In our case study, the judgement of which thermal comfort intervention to adopt depends on the amount of information obtained from simulation. Analysis of the “standard” man, even considering transient thermal comfort effects, indicates that no action is required. However, population analysis shows that only the addition of shading achieves thermal comfort for all occupants. We consider this a strong argument in support of the use of population analysis for transient thermal comfort problems where steady-state methods such as PMV and PPD do not apply.

Other factors may yet be incorporated into our model to produce more widely applicable results. For example, we do not consider personal temperature preferences that do not arise from physiology. Such preferences might stem from cultural habituation, acclimatization to seasons, occupant expectations, or other factors. Currently, our tool allows users to supply a PMV preference; for example, a user who prefers slightly warm conditions might input a PMV preference of +1, indicating that they are comfortable when the average person feels slightly warm. While this allows some personalization of sensation predictions, it does not specify a mechanism for comfort and has no scientific backing.

Additionally, more human subject studies are needed to validate physiological and thermal sensation predictions across larger segments of the population and outside of normal office activities. The use of physiology data collected by NASA and the military may not be representative of the civilian population, but at present it is the best data available. Additional thermal sensation data is also needed for activities with elevated metabolic rates, which have different user expectations and potentially chemical differences in thermal perception.

Conclusion

Thermal comfort systems, including building mechanical systems and personal thermal controls, must provide occupant comfort without using excessive energy. Calculation methods that are based on the standardized physiology of a fit male body do not detect conditions that may result in thermal comfort complaints, especially among women, older men, and the obese. In our case study of a transient environment, we simulated a population based on the physiology of the middle 80% of the United States civilian population. Depending on the thermal comfort intervention we applied, we found 16% of the population uncomfortably warm, and 31% of the population uncomfortably cold, even though the “standard” occupant remained comfortable in all cases. This supports our assessment that population analysis is necessary for making informed decisions on thermal comfort interventions.

Population analysis is fast and efficient. Our tool implementing both a thermoregulatory model with physiological variation and a psychophysiological model of thermal sensation allowed us to quickly model the entire population. The typical run time for the entire population was under a minute, and parallel processing introduced in our web tool provides results at interactive speeds. This is in keeping with our broader goal to create
a positive building user experience by making simulation data available at all stages of design.

Acknowledgments
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