Thermal Comfort Metabolic Rate and Clothing Inference

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Abstract. This paper examines the implementation of an algorithm for the prediction of metabolic rate (M) and clothing insulation (I_{cl}) values in indoor spaces. Thermal comfort is calculated according to Fanger's steady state model. In Fanger's approach, M and I_{cl} are two parameters that have a strong impact on the calculation of thermal comfort. The estimation of those parameters is usually done, utilizing tables that match certain activities with metabolic rate values and garments with insulation values that aggregate to a person's total clothing. In this work, M and I_{cl} are predicted utilizing indoor temperature (T), indoor humidity (H) and thermal comfort feedback provided by the building occupants. The training of the predictive model, required generating a set of training data using values in pre-defined boundaries for each variable. The accuracy of the algorithm is showcased by experimental results. The promising capabilities that derive from the successful implementation of the proposed method are discussed in the conclusions.

Keywords: thermal comfort · metabolic rate · clothing insulation.

1 Introduction

In modern societies people spend almost 90% of their time indoors [6]. Studies have shown that indoor thermal conditions may impact on the occupants' attendance and cognitive performance [10]. Consequently, indoor thermal conditions should be regulated so that they do not have any negative effect to the occupants' feeling or execution of activities. The American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) defines thermal comfort as "the condition of the mind in which satisfaction is expressed with the thermal environment" [1]. The definition emphasizes to the fact that it refers to a state of mind and not a standard condition. As such, it is different for every person and it is influenced by many factors such as age, gender, mood or culture.

Generally, comfort occurs when human temperature remains between a certain range, skin moisture stays low and human body makes a minimal effort for regulation. Lack of comfort is noticed when changes in human behavior are observed [2]. Changing clothes, changing posture, altering activity or just complaining are that type of behaviors. The parameters that affect thermal sensation were defined by MacPherson in 1962 [9]: air temperature, air speed, humidity, mean radiant temperature, metabolic rate and clothing insulation. Those six factors were later incorporated into a steady state heat transfer model developed by Fanger, utilizing experimental results from 1296 human subjects in a controlled climate chamber [4]. In these studies, participants were dressed in standardized clothing and completed specific activities, being exposed to different thermal environments. In some cases, the thermal conditions were chosen, while participants were recording their thermal sensation using the 7-point ASHRAE thermal sensation scale ranging from cold (-3) to hot (3) with neutral conditions at (0).

Analyzing the parameters that compose Fanger's comfort equation, it becomes obvious that measuring temperature, humidity and air speed can be done effortlessly using sensors. On the other hand, clothing habits and activity are more subjective factors and may as well require more complex equipment for their continuous registering. Thus, clothing insulation is either measured from human subjects or mannequins [3], or an initial assumption is made using ASHRAE tables. Metabolic rate is measured either by telling human subjects to perform certain activities, or assumed from tables similarly with clothing [8]. The current work attempts to personalize the thermal comfort computation process, by predicting different clothing insulation and metabolic rate values for every subject, depending on the thermal comfort feedback that they provide. This way, the thermal comfort computation becomes more accurate, without the need of ASHRAE tables, that significantly deviate from real-life indoor thermal comfort conditions.

The remaining of the paper is structured as follows: section 2 elaborates on Fanger's thermal comfort model. Section 3 describes the algorithm that was formulated for M and I_{cl} prediction. In section 4, experimental results that showcase the effectiveness of the algorithm are presented while conclusions are drawn in section 5.

2 Thermal comfort calculation

As long as the users provide no feedback, their comfort is calculated from Fanger's equation which uses the Predicted Mean Vote (PMV) index in order to quantify the degree of thermal discomfort on the 7-point ASHRAE scale. Fanger's equation is based on the general heat balance equation that describes the process of heat exchange between a man and his environment [7]:

$$M - W = C + R + E_{sk} + (C_{res} + E_{res}). \tag{1}$$

The external work W (W/m^2) in the equation is small and is generally ignored under most situations. The internal energy production M (W/m^2) is determined by metabolic activity. C (W/m^2) is the heat loss by convection. R (W/m^2) is the heat loss by thermal radiation. E_{sk} (W/m^2) is the heat loss by evaporation from the skin. C_{res} (W/m^2) and E_{res} (W/m^2) are the sensible and the evaporation heat losses due to respiration respectively.

The convection heat transfer C (W/m^2) from the human body to the environment is given by:

$$C = f_{cl} \cdot h_c \cdot (T_{cl} - T_a), \tag{2}$$

where T_{cl} (^{o}C) is the clothing surface temperature and T_a (^{o}C) is the ambient air temperature. The heat transfer coefficient h_c $(W/m^2 \cdot K)$ depends on the air velocity V_a (m/s) across the body and consequently also upon the position of the person and orientation to the air current while the clothing area factor f_{cl} depends on the clothing insulation.

The radiation heat transfer between the body and surrounding surfaces is given from:

$$R = \sigma \cdot \varepsilon_{cl} \cdot f_{cl} \cdot F_{vf} \cdot \left[(T_{cl} + 273.15)^4 - (T_r + 273.15)^4 \right], \tag{3}$$

where ε_{cl} is the emissivity of the clothing. F_{vf} is the view factor between the body and the surrounding surface. σ is the Stefan-Boltzmann constant, which has the numerical value of $5.67 \cdot 10^{-8}$ W/m^2K^4. T_r (^{o}C) is the radiant temperature. The surrounding surface temperature can be taken as approximately ambient air temperature T_a (^{o}C). The respiration heat loss is divided into evaporative heat loss (latent heat) and sensible heat loss. The rate of the heat transfer by respiration is usually at the lower level beside the other rates of the heat transfer. This rate is given by:

$$C_{res} + E_{res} = 0.014 \cdot M \cdot (34 - T_a) + 0.0173 \cdot M \cdot (5.87 - P_a), \tag{4}$$

where P_a (P_a) is the partial vapour pressure.

The rate of the heat loss by evaporation is the removal of heat from the body by evaporation of perspiration from the skin. The heat loss by evaporation is made up of two, the insensible heat loss by skin diffusion and the heat loss by regulatory sweating. This rate can be calculated by:

$$E_{sk} = 3.05 \cdot (5.73 - 0.007 \cdot M - P_a) + 0.42 \cdot (M - 58.15)). \tag{5}$$

Finally, the PMV value is determined from the following equation:

$$PMV = (0.303 \cdot e^{-0.036 \cdot M} + 0.028) \cdot L, \tag{6}$$

where L is defined as follows:

$$L = M - W - C - R - E_{sk} - (C_{res} + E_{res}). \tag{7}$$

The air speed is set to $0.1 m/s$, which is a typical value used by ASHRAE standard [1]. According to [11], the difference between air temperature and mean radiant temperature is negligible for indoor environments. Sensors are utilized for the acquisition of temperature and humidity data, while metabolic rate and clothing insulation are initialized according to ASHRAE standard [1], as shown in Figure 1 and Figure 2. The hypothesis for the metabolic rate and clothing insulation values begins by separating the day at five intervals. Regarding the metabolic rate, mild activities such as sitting, reclining, typing, reading are considered for each user during the day, while at night the user is considered to be sleeping. The clothing insulation takes into consideration the day interval in combination with the season of the year, in order to infer a user's clothing. Day and night separation is also made here, since during sleep the bed and the sheets provide some extra insulation.

TABLE A1 Metabolic Rates for Typical Tasks

Activity	Metabolic Rate		
	Met Units	W/m^2	(Btu/h·ft^2)
Resting			
Sleeping	0.7	40	(13)
Reclining	0.8	45	(15)
Seated, quiet	1.0	60	(18)
Standing, relaxed	1.2	70	(22)
Office Activities			
Reading, seated	1.0	55	(18)
Writing	1.0	60	(18)
Typing	1.1	65	(20)
Filing, seated	1.2	70	(22)
Filing, standing	1.4	80	(26)
Walking about	1.7	100	(31)
Lifting/packing	2.1	120	(39)

Fig. 1. Metabolic rates for typical tasks [1]

3 Metabolic rate and clothing insulation prediction from user feedback

User feedback is utilized in order to revise the initial metabolic rate and clothing insulation values and steadily converge to the user's objectives. The final goal is to create a different profile for each user, since every person may have different dressing preferences and may perform different activities in his/her house during the day. The feedback provided by the users refers to their thermal sensation in terms of the PMV index. The correction of the metabolic rate and clothing insulation values is made only for the specific interval that the feedback is given. The new M, I_{cl} are calculated according to the following methodology:

The first step towards building this model was the formulation of a training dataset. According to ASHRAE standards [1], M and I_{cl} have upper and lower limits. Discrete values were chosen within the respective boundaries for all of the variables that compose Fanger's equation (T, H, I_{cl}, M). The step that was used for the sampling of each variable, was selected considering the variable's impact on the final PMV outcome at the [-3, 3] scale of PMV (Table 2).

The next step requires solving Fanger's equation for all of the possible states that were generated. The combination of T, H, I_{cl}, M values generate a total

TABLE B2
Garment Insulation*

Garment Description†	I_{clu}, clo	Garment Description[b]	I_{clu}, clo
Underwear		**Dress and Skirts****	
Bra	0.01	Skirt (thin)	0.14
Panties	0.03	Skirt (thick)	0.23
Men's briefs	0.04	Sleeveless, scoop neck (thin)	0.23
T-shirt	0.08	Sleeveless, scoop neck (thick), i.e., jumper	0.27
Half-slip	0.14	Short-sleeve shirtdress (thin)	0.29
Long underwear bottoms	0.15	Long-sleeve shirtdress (thin)	0.33
Full slip	0.16	Long-sleeve shirtdress (thick)	0.47
Long underwear top	0.20	**Sweaters**	
Footwear		Sleeveless vest (thin)	0.13
Ankle-length athletic socks	0.02	Sleeveless vest (thick)	0.22
Pantyhose/stockings	0.02	Long-sleeve (thin)	0.25
Sandals/thongs	0.02	Long-sleeve (thick)	0.36
Shoes	0.02	**Suit Jackets and Vests††**	
Slippers (quilted, pile lined)	0.03	Sleeveless vest (thin)	0.10
Calf-length socks	0.03	Sleeveless vest (thick)	0.17
Knee socks (thick)	0.06	Single-breasted (thin)	0.36
Boots	0.10	Single-breasted (thick)	0.44
Shirts and Blouses		Double-breasted (thin)	0.42
Sleeveless/scoop-neck blouse	0.12	Double-breasted (thick)	0.48
Short-sleeve knit sport shirt	0.17	**Sleepwear and Robes**	
Short-sleeve dress shirt	0.19	Sleeveless short gown (thin)	0.18
Long-sleeve dress shirt	0.25	Sleeveless long gown (thin)	0.20
Long-sleeve flannel shirt	0.34	Short-sleeve hospital gown	0.31
Long-sleeve sweatshirt	0.34	Short-sleeve short robe (thin)	0.34
Trousers and Coveralls		Short-sleeve pajamas (thin)	0.42
Short shorts	0.06	Long-sleeve long gown (thick)	0.46
Walking shorts	0.08	Long-sleeve short wrap robe (thick)	0.48
Straight trousers (thin)	0.15	Long-sleeve pajamas (thick)	0.57
Straight trousers (thick)	0.24	Long-sleeve long wrap robe (thick)	0.69
Sweatpants	0.28		
Overalls	0.30		
Coveralls	0.49		

Fig. 2. Garment insulation [1]

Table 1. ASHRAE thermal comfort scale

Value	Sensation
+3	Hot
+2	Warm
+1	Slightly warm
0	Neutral
-1	Slightly Cool
-2	Cool
-3	Cold

of 770.400 different states. After solving the equation, a mapping table was formulated that will be utilized as the training dataset for the model (Table 3).

When a user decides to give feedback about the thermal comfort conditions in his/her house, the given value is considered to be the actual PMV value for the specific timestamp. The task of the model is to use the given feedback along with the sensor data and predict the clothing insulation and the metabolic rate. The formulated problem requires the estimation of multiple continuous variables y_i=(M, I_{cl}) from a vector of k input variables x_i=($PMV_{feedback}$, T, H). This is

Table 2. Variables sampling for the training dataset

Variable	**Interval**	**Step**	**Impact of variable's step change on PMV value**
Temperature	[18,31]	0.3	0.1
Humidity	[20,75]	5	0.05
Metabolic Rate	[44,164]	4	0.05-0.2
Clothing Insulation	[0.04,1.84]	0.04	0.02-0.2

Table 3. Mapping table

Temperature	**Humidity**	**Clothing Insulation**	**Metabolic Rate**	**PMV**
23.4	40	0.84	52	-0.58
23.4	40	0.84	56	-0.41
23.4	40	0.84	60	-0.25
23.4	40	0.84	64	-0.17
23.4	40	0.84	68	-0.09
23.4	40	0.84	72	0.21
23.4	40	0.84	76	0.32
23.4	40	0.84	80	0.42
23.4	40	0.84	84	0.50
23.4	40	0.84	88	0.58
23.4	40	0.84	92	0.65
23.4	40	0.84	96	0.72
23.4	40	0.84	100	0.78
23.4	40	0.84	104	0.84
23.4	40	0.84	108	0.91
23.4	40	0.84	112	0.97
23.4	40	0.84	116	1.02
23.4	40	0.84	120	1.09
23.4	40	0.84	124	1.15

a multi-target regression (MTR) problem so an appropriate regressor is selected. To this end, extremely randomized trees (extra trees), presented by Geurts et al [5] were utilized. Extra trees is an algorithm for ensemble tree construction based on extreme randomization. It belongs to the global methods of MTR, which means that all of the target variables are predicted simultaneously using one model in contrast to the local methods that predict each target variable separately. Global methods exploit the dependencies that exist between the target variables and result in better predictive performance.

The extra trees regression algorithm builds an ensemble of unpruned regression trees according to the classical top-down procedure. It has two main differences with other ensemble tree-based methods:

- The procedure of selecting cut-points for splitting the tree nodes is performed randomly.

– The trees grow using the whole learning sample and not just a bootstrap replica.

The splitting procedure for numerical attributes includes the following parameters:

– K, which denotes the number of attributes selected at each node;
– n_{min}, which refers to the minimum sample size for splitting a node;
– L, which represents the number of trees of the ensemble.

The final prediction in regression problems is given by aggregating the predictions of all trees and then using the arithmetic average. From variance point of view, extra trees are able to reduce variance more strongly than other randomization tree methods, using explicit randomization of the cut-point and attribute, combined with ensemble averaging. Bias is also minimized by the usage of the full original learning sample, in contrast to methods that use bootstrap replicas. Assuming balanced trees, the complexity of tree growing is of order $N \cdot logN$ with respect to learning sample size. The parameters K, n_{min}, L can be adjusted manually or automatically, however it is suggested by Geurts that the default settings are used in order to maximize the computational advantages and autonomy of the method. The above claim is empirically confirmed at our case, since different settings of the algorithms were used, but finally the default settings were selected as they provided more accurate results. The default criteria for measuring the quality of a split is mean squared error.

The users are able to give their feedback through a mobile application. Then, the model uses the feedback along with temperature and humidity data and finally predicts the new values of M and I_{cl} for the current user. Those values refer to the time interval in which the feedback is given. Metabolic rate and clothing insulation values are finally stored, updating previous ones. From that point on, the user's thermal comfort will be estimated with these new M and I_{cl} values.

Summarizing, the comfort inference algorithm is executed as a whole, as described in the following steps:

1. All the necessary data are retrieved from the database. This includes: temperature, humidity, metabolic rate, clothing insulation.
2. Data are pre-processed in order to handle abnormalities such as null or duplicate values.
3. It is checked whether the user has provided feedback. If there is feedback, then the comfort feedback predictive model is loaded and new values for M and I_{cl} are calculated.
4. Thermal comfort is being calculated using Fanger's Equation.

4 Experimental Results

The algorithm is tested for the whole possible range of feedbacks, from -3 to +3. The feedback was set to change with a step of 0.05 at each observation, while

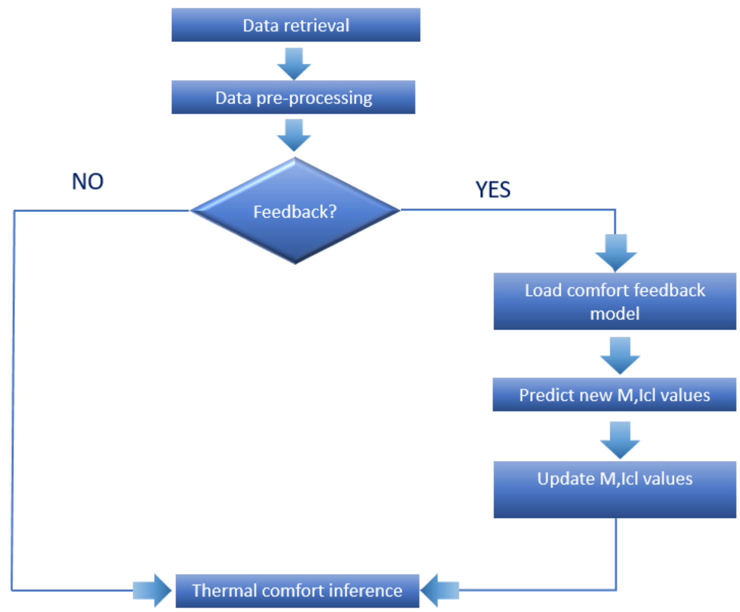

Fig. 3. Thermal comfort inference flow chart

T and H were randomly chosen to be between certain intervals. A total of 120 observations were created, that were utilized as inputs to the pre-trained predictive model, which generated a pair of M, I_{cl} predictions for each observation. The predicted M, I_{cl} values were then inserted into Fanger's equation and PMV value was calculated. Finally, the feedback was compared to the calculated PMV value for each observation in order to test the accuracy of the M, I_{cl} predictions. The comparison between thermal comfort feedback values and predicted PMV values is shown in figure 4.

The error that corresponds to the observations of figure 4, is depicted in figure 5. This error represents the deviation of the observed value (PMV deriving from the predicted M, I_{cl}) from the true value (actual PMV feedback).

$$error = predicted\_PMV\_value - feedback \tag{8}$$

As seen in figure 4, the predictions are accurate for the whole range of feedback values. This is also confirmed from the errors that are below 0.2 for the majority of the observations. Mean squared error (MSE) and mean absolute error (MAE) remain very low, at 0.0108 and 0.0739 respectively. The model's worst prediction, results to an error of 0.28 which is translated to lower than 5% error in the [-3, 3] scale. It is deduced that the overall performance of the model is satisfying, as the predicted M, I_{cl} values approximate closely to the feedback (PMV value) from which they were derived, when inserted to Fanger's equation.

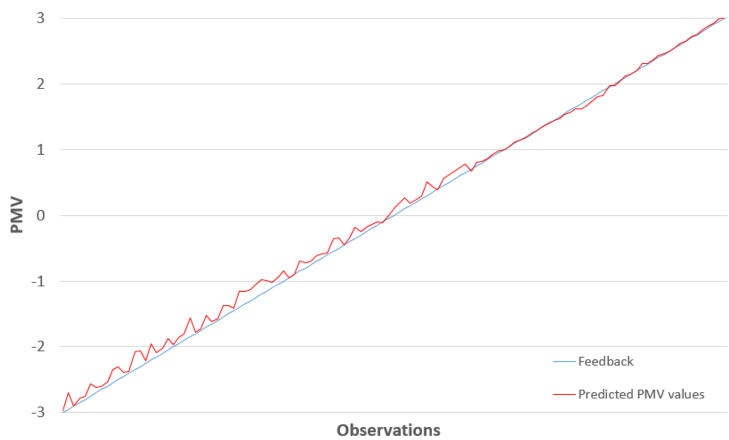

Fig. 4. Feedback and predicted PMV values comparison

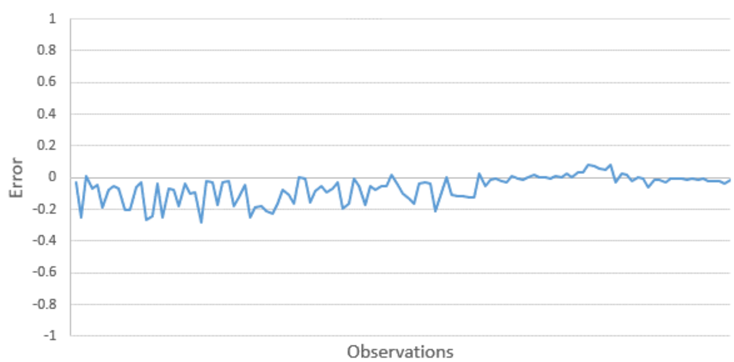

Fig. 5. Error of each observation

Table 4. Error Analysis of the tested observations

Error Analysis	
Mean Squared Error	0.0108
Mean Absolute Error	0.0739
Maximum Error	-0.28
Minimum Error	0.0009

5 Conclusions

This study elaborates on the two subjective factors that are part of the thermal comfort equation, clothing insulation and metabolic rate. The accurate prediction of these parameters, utilizing feedback provided by the study subjects, could be crucial in the field of indoor thermal comfort inference, as it allows the creation of flexible personalized models that can be more accurate as they eliminate the subjective factor enclosed in Fanger's static model. Experimental results were demonstrated that showcase the accurate prediction of M, I_{cl}. This allows the use of the proposed algorithm for the definition of M, I_{cl} values, thus enhancing the accuracy obtained by assuming initial M, I_{cl} values from ASHRAE tables. Future work may include experiments using subjects from different study groups in order to create thermal comfort models depending on age, gender etc.

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