Topic A7: Thermal comfort

GENERATING EMPIRICAL PROBABILITIES OF METABOLIC RATE AND CLOTHING INSULATION VALUES IN FIELD STUDIES USING WEARABLE SENSORS

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SUMMARY

This research introduces a mixed-method framework to estimate *metabolic rate* and *clothing insulation* as objective and quantitative variables. Methods included automated visual diaries and both environmental and wearable sensors. Applying this framework in an exploratory study, during the winters of 2012 and 2013, allowed empirical probabilities of metabolic rate and clothing insulation values to be generated. The results indicate that current standards overestimate winter clothing insulation by 22% but underestimate residential metabolic activity by 9%. Beyond reviewing the standards thresholds, these probability distributions may be used as input to building energy simulation (BES) programs.

INTRODUCTION

The need to identify occupants' behaviour-responses to thermal discomfort during the heating season has become one of the priorities in the quest to reduce energy demand. Drawn from physical and physiological principles, the current predictive models are based on environmental and personal variables; the latter of which, metabolic rate *(M)* and thermal insulation of clothing (I_{cl}), have been identified as being the most influential ones (Gauthier and Shipworth, 2012). In field studies, these personal variables are often estimated with a great degree of error, and in building simulation studies these variables are given constant values as a function of the season, building and room types (Schiavon and Lee, 2013). Considering that these personal variables are the most influential variables, this high level of error will undoubtedly reduce both accuracy and precision of the results of the predictive models.

METHODS

To address these two issues, this paper introduces a mixed-method framework drawn from psychological and physiological studies. Automated visual diaries with wearable sensors (including: tri-axis accelerometers, heart-rate monitors, light intensity sensor, and temperature sensors) provided measured input from which (*M*) and (I_{cl}) were ascertained over a continuous period of time. The wearable sensors included:

- A SenseCam manufactured by Vicon Motion Systems (Microsoft, UK). It comprises of a tri-axial piezoresistive accelerometer (Kionix KXP84), a light intensity sensor, and a temperature sensors.

- Heart-rate (HR) monitors manufactured by Kalenji - Sensors and transmitter (Kalenji CW 300 coded), and Receiver and datalogger (Kalenji Cardio Connect).

This mixed-method was applied to 20-participants living in 19-different dwellings over a minimum period of 10-consecutive days, in the South-East of England during the winters of 2012 and 2013. Concurrently, environmental variables were recorded, and interviews conducted at the end of each monitoring period to gain an understanding to occupants responses to thermal discomfort, which included 'putting on/off an item of clothing' or 'changing body position or location'. The sampling frame was defined by the 3-physiological attributes prescribed by ISO 8996:2004, Annex C, as gender, age and weight. The sample frame was populated across combinations of categories using a mixture of convenience and snowball sampling.

The aim for this research was to develop methods to estimate metabolic rate and clothing insulation values as objective, quantitative and continuous data. Following on, the results from mixed-method framework allowed empirical probability distributions to be generated. These may be used as input in building simulation.

RESULTS AND DISCUSSION

Estimation of the thermal insulation of clothing

To estimate the thermal insulation of the clothing (I_{cl}), the ASHRAE 55:2013 - Appendix B can be applied as a preliminary estimate of the surface temperature of clothing (Equation 1 and 2). For this to apply two conditions should be met: (1) v_a should be equal to, or lower than, *0.1m/s*, and (2) participants should be sedentary.

$$T^a_{clo} = T^a_a + \frac{(35.5 + T_a)}{(3.5 \times (6.45 \times I_{cl} + 0.1))} \qquad (1)$$

$$I_{cl} = [([(35.5 - T_a) \div (T^a_{clo} - T^a_a)] \div 3.5) - 0.1] \div 6.45 \qquad (2)$$

where T^a_{clo} is the surface temperature of clothing in Kelvin, T^a_a is ambient air temperature in Kelvin, T_a is ambient air temperature in Celsius, I_{cl} is thermal insulation of clothing in m^2K/W. (note $0.155\ m^2K/W = 1clo$, ISO 7730:2005).

Having determined the method of estimation, each term of the equation was estimated as follows. First, ambient air temperature (T_a) was measured using HOBO U12-012 dataloggers. Three set of 4-dataloggers were placed in living-rooms and in bedrooms, fastened to wooden-poles, and positioned at 0.1m, 0.6m, 1.1m and 1.7m from the ground, to comply with the requirements set by ISO 7726:2001. For the purpose of the analysis, T_a represents the temperature monitored in living room while standing calculated as the mean temperature over three heights: 0.1m; 0.6m; and 1.7m. As the monitoring frequency was set at 5-minutes, the data was re-sampled to a 1-minute sampling rate, with each 1-minute data-point taking on the value of the nearest 5-minute data-point.

Relative air velocity (v_a) was measured during the first visit. For all participants, the results were equal to or below *0.1m/s*. Therefore a relative air velocity of *0.1m/s* was assumed for all cases on a basis that in winter, openings, such as windows, tend to remain closed (Hong et al., 2009).

Finally, the surface temperature of clothing (T_{clo}) was estimated using the wearable temperature sensor recordings. First, readings were averaged over the chosen temporal unit of analysis of 1-minute. Then a normalising process was carried out, including:

- Identifying and discounting the time taken for the SenseCam to reach thermal equilibrium with its environment. This is a function of the observed thermal resistance and initial temperature of the SenseCam when switched-on and worn. To estimate this temperature rise-time, a calibration study was undertaken, and concluded that it takes, on average, 22-minutes when first worn.
- To fulfil the second condition of the equation, it was necessary to identify when participants were sedentary and to discount T_{clo} values when participants were in motion. To do this, the mean linear acceleration (LA) over the 1-minute epoch was estimated using the tri-axis accelerometer recordings, and compared to the images of the visual diary. Results show that participants were sedentary when the measured mean linear acceleration over 1-minute was within the range: $-0.075\ g$ to +0.075 g or $-0.735\ m/s^2$ to $+-0.735\ m/s^2$. Based on this observation, a data filter was written that identified T_{clo} when sedentary.
- Identifying and discounting other artefacts including the SenseCam been taken-off but left switched on, and SenseCam been worn under an item of clothing. The first of these was identified by using the accelerometer recordings, i.e. if $-0.01\ g < LA < +0.01\ g$ then T_{clo} was discounted. The second was identified by using the light sensor data (CLR). The efficacy of both filters were established by comparing the respective sensor data to the visual diary output.

As the monitoring was carried-out on the chest, only the upper-body thermal insulation level was measured. Lower body thermal insulation was taken as a constant value of *0.3 clo* based on the aggregation of lower body garments including underwear, trousers or skirt, and socks. This was added to the final I_{cl} value (ISO 9920:2007). The resultant I_{cl} is summarised in Figure 1 and Table 1, with an indicative gamma-distribution inferred from the histogram.

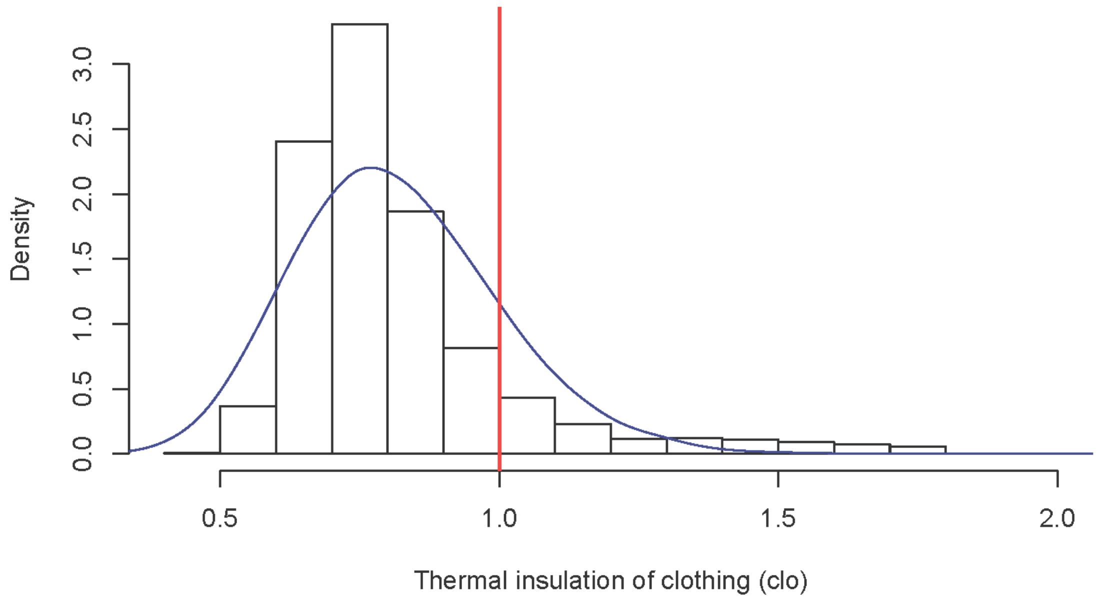

Figure 1. Density distribution of estimated thermal insulation of clothing for all participants and minimum clothing level for winter of *1 clo* prescribed by EN 15251:2007 (Table A.2).

Table 1. Summary of the statistical characteristics of estimated thermal insulation of clothing for all participants.

Sample	Sample size (no. of observations)	18,559
Central Tendency	Mean	0.82
	Median	0.77
	Mode	0.77
Spread	Variance	0.04
	Standard deviation	0.20
	Maximum	1.99
	Minimum	0.43
	Range	1.56
	Quintile (.75)	0.86
	Quintile (.25)	0.69
Gamma distribution	Shape	19.92
	Rate	24.42

The estimated range of *0.43* to *1.99 clo* is within the expected standard values as described in ISO 7730:2005 (4.1) as *0* to *2 clo*. However the mean value of *0.82 clo* is lower than the assumed winter value of *1 clo* given as constant in building energy simulation (Schiavon, 2013) and the minimum clothing level for winter of *1 clo* prescribed by EN 15251:2007 (Table A.2).

Estimation of the metabolic rate

Participants' activity level was estimated from the output of the SenseCam tri-axis piezoresistive accelerometer. Participants' total acceleration (*TA*) was calculated as the normalized magnitude of the acceleration vector including the earth's gravity; see equation 3 (Shala and Rodriguez, 2011). Then the linear acceleration (*LA*) was estimated as the difference between *TA* and the acceleration due to Earth's gravity; see equation 4.

$$TA = \sqrt{(x^2 + y^2 + z^2)} = LA + g \tag{3}$$

$$LA = \sqrt{(x^2 + y^2 + z^2)} - g \tag{4}$$

where TA is the total acceleration in m/s^2, LA is the linear acceleration in m/s^2, x is acceleration in the x-axis in m/s^2, y is acceleration in the y-axis in m/s^2, z is acceleration in the z-axis in m/s^2, and g is the acceleration due to Earth's gravity of *9.81* m/s^2.

The linear acceleration (*LA*) was then integrated over a 1-second interval to estimate participants' speed. The results were then averaged over the each 1-minute epoch. Assuming that participants walked between locations in their home Ralston's equation (1958) may be applied; see equation 5.

$$E_w = 29 + 0.0053v^2 \tag{5}$$

where E_w is the energy expenditure in cal/min/kg, and v is velocity in m/min.
After converting the variables in the Ralston's equation to SI units, power was calculated and divided by the participants' body surface area using Du Bois formula (ISO 8996:2004, 7.1.2)

to estimate metabolic rate (*M*) in W/m^2 and then in *met*; where *1 met = 58.2 W/m2* (ISO 7730:2005). This estimation does not take into account the energy required to sit, or to climb/descend stairs; such activities may be incorporated in further analysis (Rassia et al., 2009). The resultant *M* is summarised in Figure 2 and Table 2, with indicative gamma-distribution inferred from the histogram.

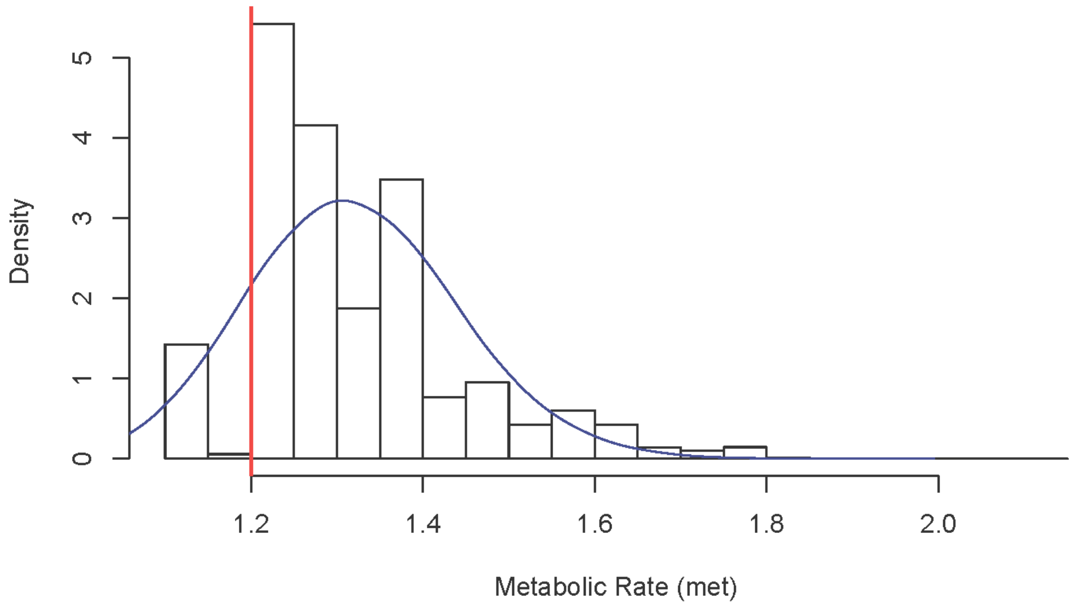

Figure 2. Density distribution of estimated metabolic rate for all participants, and activity level value of *1.2 met* prescribed by EN 15251:2007 (Table A.2) for residential building in living spaces.

Table 2. Summary of the statistical characteristics of estimated metabolic rate for all participants

Sample	Sample size (no. of observations)	31,444
Central Tendency	Mean	1.32
	Median	1.28
	Mode	1.13
Spread	Variance	0.02
	Standard deviation	0.13
	Maximum	2.12
	Minimum	1.11
	Range	1.01
	Quintile (.75)	1.37
	Quintile (.25)	1.24
Gamma distribution	Shape	116.79
	Rate	88.49

The estimated range of *1.11* to *2.12 met* is within the expected standard values as described in ISO 7730:2005 (4.1) as *0.8* to *4 met*. However the mean value of *1.32 met* is higher than the activity level value of *1.2 met* prescribed by EN 15251:2007 (Table A.2) for residential building in living spaces.

CONCLUSIONS

This mixed-methods approach allows for (M) and (I_{cl}) to be determined as objective, quantitative, and continuous data. In addition, results from this experimental investigation generated probability distributions for the levels of (M) and (I_{cl}) in residential settings during the winter season. Surprisingly, the mean (I_{cl}) level was *0.82 clo*, which is lower than the 1 *clo* prescribed by EN 15251:2007. On the other hand measured mean (M) was *1.32 met*, which is higher than the *1.2 met* also prescribed by EN 15251:2007. In summary the standard (M) and (I_{cl}) values differ from the measured values, although both are within the standard deviation of the mean as *1 clo* is within *0.82±0.2 clo* and *1.2met* is within *1.32±0.13 met*. However as (M) and (I_{cl}) are the most influential variables in the PMV model (Gauthier and Shipworth, 2012), these observed differences from the standard values may have great effect on output PMV as shown in Figure 3.

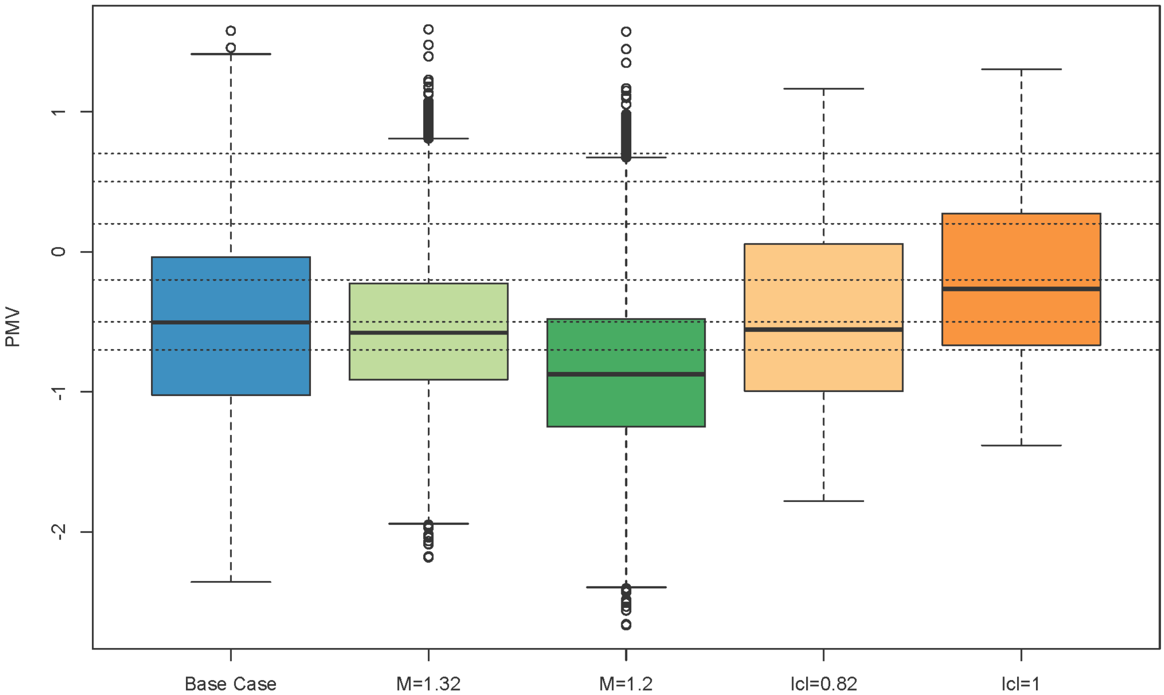

Figure 3. Distributions of PMV output for 5-senarios: (1) Base Case: input from the study for (M) and (I_{cl}) (Sample size – number of observations: 17,892), (2) Input from the study for (I_{cl}) and *M=1.32met*, (3) Input from the study for (I_{cl}) and *M=1.2met*, (4) Input from the study for (M) and I_{cl} *=0.82clo*, and (5) Input from the study for (M) and I_{cl} *=1clo*. (Note: thresholds PMV for categories A, B and C shown in dotted lines, ISO 7730:2005 –Table A.1).

The results illustrated in Figure 3 show that a reduction in (I_{cl}) from *1* to *0.82 clo* reduces the mean PMV from *-0.23* to *-0.51*; which is then outside the bound of category B acceptability. In parallel, an increase in (M) from *1.2* to *1.32 met* increases the mean PMV from *-0.87* to *-0.57*; which is still outside the bound of category B but inside the bound of category C. In conclusion using empirical and more informed input in the PMV model and building energy simulation may have great effect on the assessment of buildings.

Despite the important number of observations (31,444 for (M) and 18,559 for (I_{cl})), the number of participants in this research was relatively small; therefore the results may be strengthened by further studies adopting the same method in different seasons and regions.

In summary the (I_{cl}) value in winter was *0.18 clo* lower than the assumed typical value. This low clothing level may partially be compensated by higher observed metabolic rate. When combining these results with the environmental monitoring, the predicted mean votes are substantially below those expected in the standard model, with observed values of *-0.54± 0.65 PMV score*. This suggests that occupants maybe engaging in other adaptive behaviours, not currently accounted for within the standard model.

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