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Predictive thermal comfort model:
Are current field studies measuring the most influential variables?

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Thermal comfort has widespread implications, including health and energy consumption, yet little is known about the interrelation between thermal-discomfort response and physical dependencies. Empirical research on occupants' interaction with their home environment calls for a holistic socio-technical approach. The aim of this paper is to report on an evaluation of the sensitivity of the predictive thermal-comfort model, as described in the BS EN ISO 7730 standard. In light of the results of this analysis, this paper presents a methodological framework to measure the occupants' activity levels. One of the key aims is to gather accurate measurement while using 'discreet' observatory systems to have minimum impact on the occupants' behaviour. With recent emergence of, and advancements in, more accurate and affordable sensing technologies, this problem can potentially be overcome.

Keywords: Activity level, Thermal comfort, Predictive model, Sensitivity analysis

I. Introduction

An accepted definition of thermal comfort, proposed by ASHRAE-55, is 'that condition of mind which expresses satisfaction with the thermal environment'. This definition holds psychological and physiological significance where people's opinions validate their state of comfort or discomfort. There are three kinds of response to this state: involuntary mechanisms of thermoregulation, voluntary action-response and habituated behaviour. To record these responses, mixed-method approaches are commonly used, including recording environmental parameters and carrying out questionnaires and observations. The results of these studies are compared against benchmarks contained within the heat-balance approach or the adaptive approach. This paper is focusing on the first one, the heat-balance approach developed by Fanger (1970).

Developed from laboratory experiments in climate chambers, the heat-balance approach combines knowledge of the human body's physiology and of the heat-transfer theories (Darby & White, 2005). It forms part of the International Standard Organisation in ISO 7730. This standard states that a 'human being's thermal sensation is mainly related to the thermal balance of his or her body as a whole'. This thermal balance is associated to:

- Four measured environmental factors, including: ambient air temperature (T_a), mean radiant temperature (T_r), relative humidity (RH) and air velocity (V_a).
- Two estimated personal factors, including: metabolic rate (M) and thermal insulation of clothing (I_{cl}).

By determining these six factors, the overall satisfaction of the occupants with the environment can be predicted using the Predicted Mean Vote model. Predicted Mean Vote (PMV) can be described as a measure of satisfaction, contained in a seven-point index that indicates the average response of a group of people in given environmental conditions. The PMV model comprises of one dependent variable, PMV, and six independent variables, T_a, T_r, RH, V_a, M and I_{cl}, combined in the ISO 7730 Basic algorithm (Annex D). It can be summarised under the following equation:

$$PMV = PMV\ (T_a, T_r, RH, V_a, M, I_{cl})$$

Methods for the measurement and the estimation of the six independent variables are set in following standards:

- ISO 7726 addresses the minimum characteristics of instrumentation to be used to measure the four environmental factors.
- ISO 8996 reviews four methods used to assess metabolic rate.
- ISO 9920 determines the assessment of thermo-physical properties of clothing ensembles.

Yet, only a few sensitivity analyses on the PMV index have been completed and little is known on levels of influence played by each of the six independent variables in the calculation of PMV. In previous studies (Alfano, 2001; D'Ambrosio Alfano, 2011) differential sensitivity analyses have been employed to evaluate the accuracy of the independent variables. However, this analysis technique has limitations, including:

- Establishing a base level where PMV = 0, and list of associated input-values for each variable. The justification for these chosen inputs remains questionable.
- Assuming that the model is linear or additive.
- Assuming that the input variables are independent from one another.

To address some of these issues, the following sensitivity analysis of the PMV model uses global-sensitivity techniques. It aims to evaluate which independent variable has the most and the least influence on the model. This study will determine where the model uncertainty is coming from. It will also expand current knowledge and confidence in the PMV model and its output.

The following analysis reveals that the most influential input variable is metabolic rate. Consequently this paper goes on to review current methods used to estimate this variable. These present some limitations in terms of accuracy and of usability in fieldwork. To address those issues, this paper then explores alternative methods to measure, to observe and to analyse the occupant's activity. Finally, it presents the preliminary results of a field study, carried out on a small sample of UK households during the winter of 2012. This new set of data will enable the validation of the PMV model to be extended.

II. Global sensitivity analysis of the predictive model

This paper reports on an evaluation of the sensitivity of the predictive thermal comfort model, as described in the ISO 7730 standard. First the study provides an insight of how the model dependent variable, the PMV value, responds to changes in the six independent variables. Further analysis assesses which inputs have the most and the least influence on the output PMV.

This study uses a type of global sensitivity analysis, the Monte Carlo analysis (MC). This statistical tool simulates the simultaneous movement of all inputs. It aims to quantify the uncertainty of the dependent variable caused by the uncertainty of the independent input variables (Lomas, et al. 1992; Saltelli, et al. 2004). This method allows us to determine the interaction among variables, while not making any assumption on the additive effects of the inputs. However, as the inputs are varied simultaneously, the sensitivity of an individual input parameter cannot be revealed. The following analysis uses a five-step process (Saltelli et al., 2000) as described below:

- Selection of the ranges and the distributions of the model variables.
- Generation of a random sample of the model variables.
- Evaluation of the model for each variable input.
- Uncertainty analysis.
- Sensitivity analysis.

2.1. Ranges and distributions of the six independent variables

2.1.1 Selection of the ranges

In this analysis, the ranges selected for each independent variable are derived from BS ISO 7730 (chapter 4.1), and described in Table 1.

Table 1. Summary of the independent variables selected ranges.

Independent variables		Selected ranges
Ambient air temperature	(T_a)	10 to 30 ºC
Mean radiant temperature	(T_r)	10 to 40 ºC
Water vapour partial pressure(1)	(Pa)	0 to 2700 Pa
Air velocity	(V_a)	0 to 1 m/s
Metabolic rate	(M)	46 to 232 W/m^2 or 0.8 to 4 met
With 1 met = 58.15 W/m^2		
Thermal insulation of clothing	(I_{cl})	0 to 0.31 $m^2.K/W$ or 0 to 2 clo
With 1clo = 0.155 $m^2.K/W$		

(1) With RH = Pa / [10 * exp (16.6536 - 4030.183 / T_a + 235)]
The study will assumed a range of relative humidity (RH) of 0 to 100%

2.1.2 Selection of the input values

The input values to the environmental variables were determined by reviewing the required accuracy in ISO 7726. These were then used to determine the increment values, as described in Table 2.

Table 2. Summary of the independent environmental variables selected increments.

Independent environmental variables		Increment values	No. of possible inputs values
Ambient air temperature	(T_a)	0.5 ºC	41
Mean radiant temperature	(T_r)	2 ºC	16
Water vapour partial pressure(1)	(Pa)	0.15 kPa	21
Air velocity	(V_a)	(0.05+0.05V_a) m/s	15

(1) With 0.15 kPa, the study will assume an increment value of relative humidity (RH) of 5%

For the personal variables, the increment of each input value was determined by reviewing ISO 7730 Annex B and Annex C; as described in Table 3.

Table 3. Summary of the independent personal variables selected increments.

Independent personal variables		Increment values	No. of possible inputs values
Metabolic rate	(M)	0.1 met	33
Thermal insulation of clothing	(I_{cl})	0.1 clo	21

2.1.3 Selection of the distributions

The analysis includes the sensitivity of the PMV model as taken from the standard and does not assume any prior distribution of its variables. Therefore uniform distributions were assumed for all independent variables. It is worth noting that sensitivity analysis is more responsive to the selected ranges than the distribution of the variables (Saltelli et al., 2000). By following the assumption taken for the ranges, the increment values and the distributions, the total number of possible combinations of the 6 independent variables amounts to 143,201,520. This defines the space where the sample can be drawn from.

2.2 Sampling

The second step in the analysis involves the selection of a sample drawn from the selected distributions. Assuming that the variables were independent of each other, the same weighting was given for each input value. Then a random sample of 4,000 inputs for each variable was generated. The advantage of random sampling is to estimate unbiased mean and variance of the dependant variable, PMV.

2.3 Evaluation of the predictive model

Then the selected sample inputs were supplied to the PMV model, generating a sequence of outcome PMV values. These are summarised in Figure 1 and Table 4.

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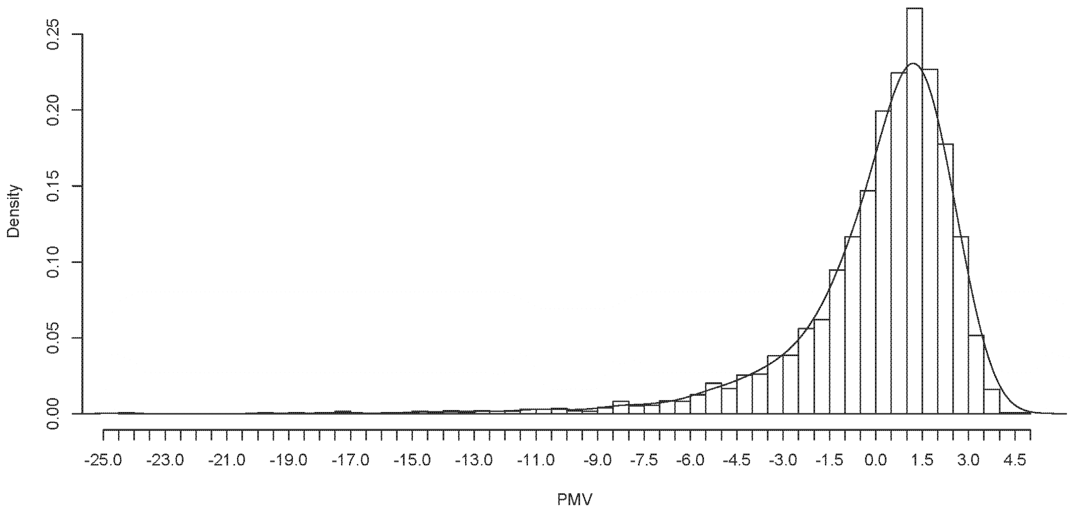

Figure 1. Density distribution of Predictive Mean Vote (PMV).

Table 4. Summary of the statistical characteristics of the distribution of Predictive Mean Vote (PMV).

Sample	No. of possible outcome	143,201,520
	Sample Size (n)	4,000
Central Tendency	Mean	0.06
	Median	0.71
Spread	Variance	7.06
	Standard deviation	2.66
	Maximum	4.55
	Minimum	-24.49
	Range	29.04
	Quintile (.75)	1.68
	Quintile (.25)	-0.79
Shape	Skewness	-2.4
	Kurtosis	9.51

Figure 1 shows the results of the predictive model, with indicative distribution inferred from the density trends. The resultant density distribution of PMV, given the input values described in section 2.1, can be compared with the PMV values prescribed in ISO 7730. First, the resultant range of [-24.49 to +4.55] is greater than the standard range of [-3 to +3]. This might be due to the fact that all six input variables in the analysis are assumed to be independent of each other; also extreme values can be randomly selected in the same combination. However, in 86.4% of cases the resultant PMV values are within the standard range of [-3 to +3]. Also, the resultant mean value [+0.06] is very close to the standard mean value [0].

2.4 Uncertainty analysis

The PMV uncertainty refers to the error expressed by its variance and its nominal value. For a large number of iterations, the predicted output is likely to be normally distributed. Thus the total uncertainty of the predictive model is expressed by estimation of:

- The mean: 0.06
- The variance: 7.06
- The standard deviation (sigma, σ): 2.66

Under the rules set through this analysis, PMV-limit variations can be expressed as: PMV = 0.06 ±2.66. It is important to note that this value is contained within the seven-point index set by ISO 7730.

2.5 Sensitivity analysis

The PMV sensitivity to the six independent variables is shown in Figure 2. These scatterplots provide an insight of how the model dependent variable, the PMV value, responds to changes in the six independent variables. It also reveals characteristics of the PMV model inputs, such as their ranges and thresholds.

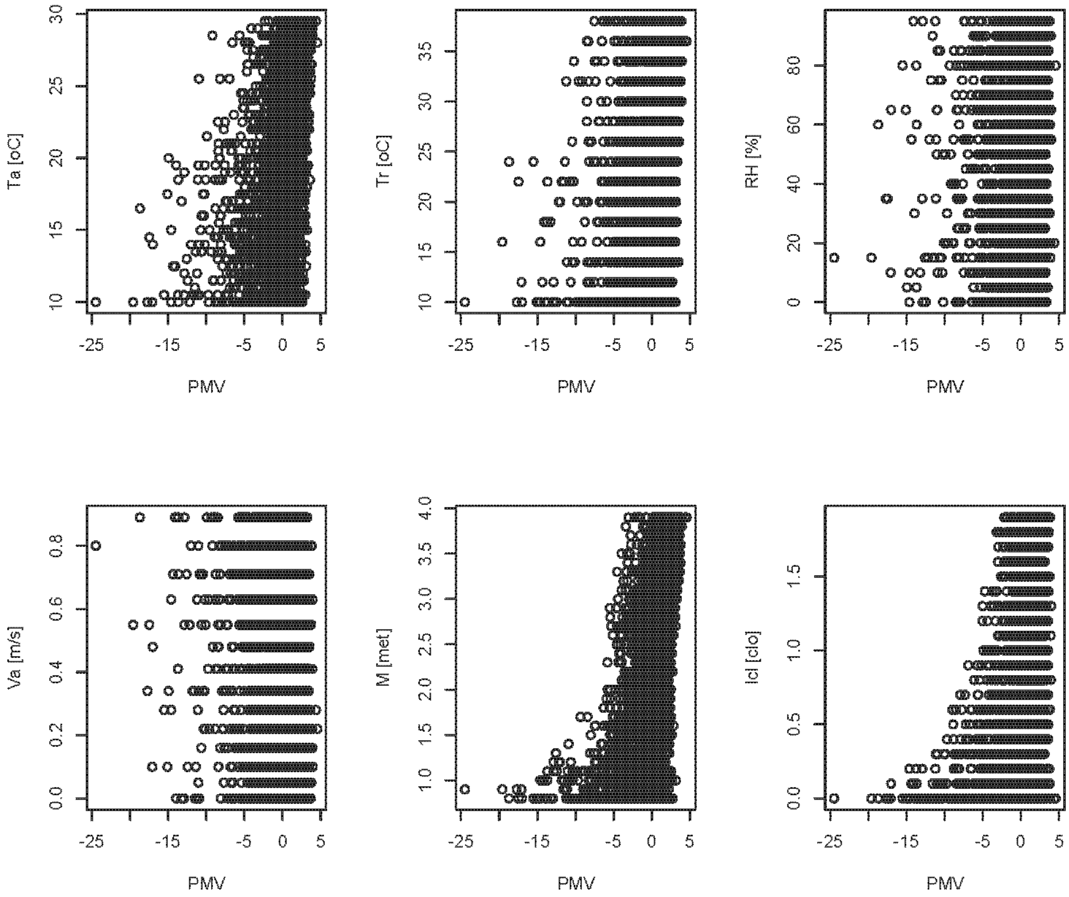

Figure 2. Scatterplot of the relationship between Predictive Mean Vote (PMV) and the six independent variables (T_a, T_r, RH, V_a, M, I_{cl}).

To follow this analysis, Pearson product moment correlation coefficients are quantified, see Table 5.

Table 5. Summary of correlation coefficients (R) between Predictive Mean Vote (PMV) and the six independent variables (T_a, T_r, RH, V_a, M, I_{cl}).

	T_a	T_r	RH	V_a	M	I_{cl}
PMV	0.36	0.28	0.05	-0.11	0.55	0.46

These correlation coefficients (R) assess which independent variables have the most and the least influence on PMV (Cohen, 1988). The obtained results are summarised as follows:

- Ambient air temperature (T_a): with a correlation coefficient of 0.36, influence of T_a on PMV is considered moderate.
- Mean radiant temperature (T_r): with a correlation coefficient below 0.3, the influence of T_r on PMV is present but limited.
- Relative humidity (RH): with a correlation coefficient of 0.05, effect of RH on PMV is negligible. It is assumed that RH has a reduced effect on thermal sensation in an indoor environment.
- Air velocity (V_a): with a correlation coefficient of -0.11, influence of V_a on PMV is negligible. Although of less significance, V_a shows a negative

correlation with PMV; hence the higher the air velocity, the lower level of comfort experienced.
- Metabolic rate (M): with a correlation coefficient of 0.55, PMV appeared very sensitive to M.
- Thermal insulation of clothing (I_{cl}): with a correlation coefficient of 0.46, the influence of I_{cl} on PMV is considered high.

In conclusion the human body is more sensitive to ambient air temperature variation than any of the other environmental variables. Also, based on the results of the sensitivity analysis, both personal variables, as metabolic rate (M) and thermal insulation of clothing (I_{cl}), are the most influential variables.

2.6 Conclusion of the sensitivity analysis

To combine the results of the sensitivity analysis the most influential variables are the two personal variables, metabolic rate (M) and thermal insulation of clothing (I_{cl}). In current field studies, the values given to these variables are usually estimated from observation (DeDear, et al., 1998). This estimation holds great uncertainty, which undermines the PMV model's results. Consequently, it is critical to be able to determine those factors with greater precision and accuracy. In the following chapter, this paper presents a comprehensive exploration of methods used to determine metabolic rate (M). This may contribute to the research design of future empirical studies in the choice of measuring methods and instruments.

III. Method to determine metabolic rate

In light of the sensitivity analysis presented above, this paper will now review the current methods used to estimate the most influential variable, metabolic rate (M). Conclusions will inform the methods and the measuring instruments chosen for future field studies.

3.1 Current methods

In previous studies (DeDear, et al., 1998; Parsons, 2001; Humphreys, and Nichol, 2002; Hong, et al., 2009), metabolic rate (M) has been estimated by using screening or structured observation methods. ISO 8996 provides the methodological framework to estimate this variable. It includes four levels, screening (1), observation (2), analysis (3) and expertise (4), summarised below:

[Level 1] Screening. Metabolic rate is estimated by considering the subject mean workload for a given occupation (level 1A) or for a given activity (level 1B). For example, the following lists of activities are included within the range specified in the sensitivity analysis (0.8 to 4 met):

- Resting (55-70 W/m^2 or 0.95-1.2 met): resting, sitting.
- Low MR (70-130 W/m^2 or 1.2-2.2 met): light manual work.
- Moderate MR (130-200 W/m^2 or 2.2-3.4 met): sustained hand, arm and leg work.
- High MR (200-260 W/m^2 or 3.4-4.5 met): intense arm and trunk work.

This estimation method only provides rough information and is associated with a high risk of error.

[Level 2] Observation. Metabolic rate is estimated by observing the subject's work at a specific time. Information such as time and motion are required for this type of study, including body posture, type of work, body motion related to work speed. It holds a high risk of error and the accuracy of the results is estimated to be within ± 20% (ISO 8996).

[Level 3] Analysis. Metabolic rate is determined from recordings of the subject heart-rate over a representative period. This method uses an indirect determination of M, based on the relationship between oxygen uptake and heart-rate under defined conditions. This method shows an accuracy of ± 10% (ISO 8996).

[Level 4] Expertise. Metabolic rate is determined by experts using three different types of methods and requiring specific measurements. It includes:

- Oxygen consumption measured over short periods (10 to 20 minutes).
- 'Doubly labelled water' method or isotopic method characterising the average metabolic rate over longer periods (1 to 2 weeks).
- Direct calorimetry method.

These methods are used to calculate metabolic rate with an accuracy of ± 5%. Unfortunately their application in field studies is limited, as they employ protocols and equipment, which are not yet suitable for monitoring 'day-to-day' life in dwellings over longer periods.

In summary most studies estimate metabolic rate by employing method Level 1 and Level 2. These methods are associated with a great risk of error, which is an issue when incorporating their estimated results within the PMV model. Considering that metabolic rate is the most influential variable within the PMV model, this high inaccuracy will undoubtedly undermine its results.

Moreover in field studies, interaction between the researcher and the participants must be kept to a minimum, so as not to influence the subjects' responses to the thermal environment. Level 1 may be able to do so, whereas Level 2 implies the use of a diary. Activity levels will often be recorded using 'pen-and-paper' where the participant fills a preset schedule. Alternatively, an observer is present in the home and takes notes when required. Both methods are intrusive and may have an impact on the participant's activity. Monitoring systems should be designed to have minimum influence while measuring each factor accurately. With the recent advancements in more accurate and affordable sensing technologies, this problem might be overcome.

3.2 Proposed methods

Drawn from literature on wearable ubiquitous sensor technologies, two instruments used to determine metabolic rate are reviewed in detail in the following chapter.

3.2.1 The SenseCam

In this study SenseCam is used as an automatic diary method. Its aim is to support the evaluation of metabolic rate in field experiments over longer and continuous periods of time (3 to 10 days). Primarily used in the field of cognitive psychology, this tool has been used as an external memory aid for patients with neurodegenerative disease and brain injury (Hodges, et al., 2006). Of similar size to a badge, the SenseCam takes photographs when triggered manually and automatically by timer or by changes in the sensors' readings. The camera trigger-options and associated sensors are summarised in Figure 3.

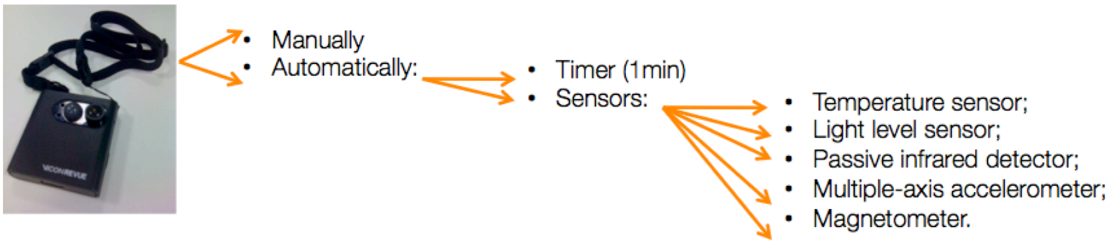

Figure 3. SenseCam image recording triggers.

The SenseCam provides two types of outputs: (1) a record of measurements taken by each sensor and (2) a visual diary of the participants' activity in their home. To process this information, two approaches can be used; automatic and manual segmentation (Lee, 2008). The automatic segmentation process reviews the readings from the accelerometer and the magnetometer to detect speed and distance. These readings were then analysed to determine the 'cut-in' and 'cut-off' time when participants were:

- Seated or standing (vertical axis).
- Static or moving (horizontal axis).

Next the picture series associated with these time-frames were drawn out to be reviewed through a manual segmentation approach. Each image was visually inspected and labelled using six criteria; which included: (1) image number, (2) when and (3) where the image was taken, (4) how many persons were in the room, (5) clothing and (6) activity levels. The participants' metabolic rate was estimated as a function of their activity level, using the Level 2 approach. The SenseCam facilitates an automatic' electronic-diary collection by logging occupants' activities in a systematic approach. Its results enabled the estimation of participants' metabolic rate in their home throughout a record period of three to ten days.

3.2.2 Heart-rate Monitor (HRM)

To evaluate metabolic rate with more accuracy, the Level 3 approach may be used to provide continuous recording of heart-rate. Heart-rate monitors have become more accessible and reliable in recent years as the demand for training tools in endurance sports increased (Achten, Jeukendrup, 2003). The instruments involved are in two parts:

- Sensors and a transmitter are fitted in a chest strap belt recording the electric activity present in the heart, electrocardiography.
- Receiver and datalogger are fitted in an independent device which can be fitted to the belt or kept in the participant's pocket.

With memory capacity, the datalogger records heart-rate (HR) every 2 seconds over 35 hours and is able to store information from multiple sessions. Once the information is gathered, it is analysed using a Level 3 approach. Metabolic rate is ascertained by proxy, based on the relationship between oxygen uptake and heart-rate under defined conditions. These vary with participants' personal attributes, gender, age and weight (ISO 8996, table C.1).

3.3 Preliminary results from field studies

Using the two empirical methods described above, metabolic rate was monitored on a small sample of UK households during the winter of 2012. Using a case-study approach, a purposive sample of nine residents from nine different dwellings was monitored over a period of ten consecutive days. The sample of interest was defined by the three personal attributes prescribed in ISO 8996, as gender, age and weight. Located in London, the dwellings were built during different periods, dating from 1850 to 2008. Some incorporated features such as retrofitted central or communal heating systems.

Initial results from monitoring heart-rate were used to estimate metabolic rate, by following the method set out in ISO 8996, Table C.1. Figures 4 and 5 illustrate an example of a 2-hour sequence over lunchtime for one of the participants. The average metabolic rate over this period is 80 W.m^{-2}, or resting state. Following ISO 8996, Table A.2, classification of activity, the participant was in resting position 87% of the time, carrying out light manual work 25% of the time and sustaining moderate work 2% of the time.

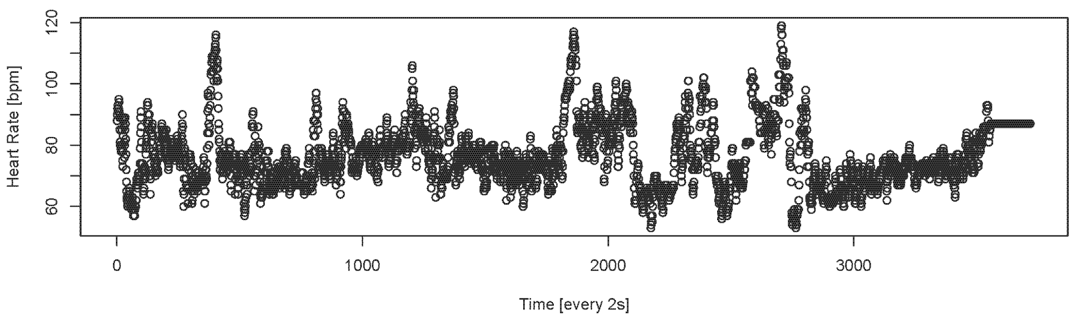

Figure 4. Heart-rate recordings in beats per minute every 2 seconds over a 2-hour monitoring period.

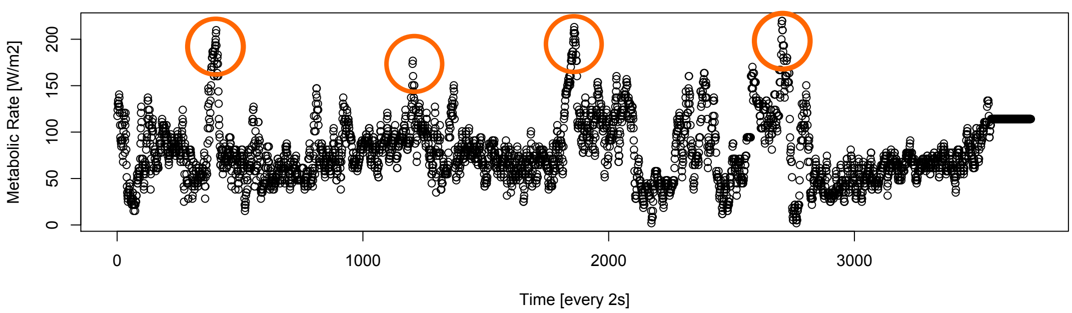

Figure 5. Metabolic rate in W.m^{-2} every 2 seconds over a 2-hour monitoring period.

When reviewing the metabolic rate profile together with the SenseCam visual diary the participant's activity level can then be validated. For example, the four peaks highlighted in Figure 5 correspond to the highest levels of activity in this sequence. These are above 165 W.m^{-2} and correspond to sustained moderate work (ISO 8996, Table A.2). The review of the SenseCam visual diary did confirm these levels of activity. The first peak corresponds to the participant setting up lunch, the second peak was to start clearing the dining table, and finally the third and the fourth peaks were attributed to climbing up the stairs to the first floor.

In conclusion this proposed method allows the evaluation of activity levels throughout the monitoring period, with great granularity and precision. Having readings of metabolic rate every 2 seconds allows future studies to use this high-frequency information in the calculation of PMV. Then the resultant PMV values could be plotted throughout the monitoring period. When PMV values are outside the comfort ranges prescribed by ISO 7730, Table A.1, then we may anticipate that the participant might act upon his/her state of discomfort and formulate a response. In this instance the SenseCam visual diary will be reviewed to validate the predictive model results.

3.4 Conclusion of the review of methods to determine metabolic rate

The methodological framework developed in this paper includes variants of existing methods and evaluation techniques for measuring metabolic rate. The two proposed methods linked together to form an alternative tool, offering a number of advantages, including:

- A rich picture of the participants' activity pattern, through the visual diary.
- A measured value for metabolic rate, with an accuracy of ± 10%.
- Longer and continuous periods of monitoring, which allow us to monitor the variability of a person's thermal sensation in time.
- A collection method, which has minimum impact on the participants' activity, through the use of automated tools.

Despite all these benefits, some sources of uncertainty remain, namely the accuracy of the equipment and only a partial understanding of the subject. This method should be supported by a questionnaire or an interview with the subject to review unaccounted variables, such as previous experiences. For the purposes of this research, this method was used essentially in dwellings over the winter period, however it may be applied to different settings and seasons.

IV. Summary

The sensitivity analysis reported in this paper established which independent variable has the most and the least influence in the calculation of PMV. This has a critical impact on the way future studies may choose to assess those factors. In particular, this analysis found that metabolic rate (M) was the most influential input variable. Most thermal comfort field-studies only estimate this factor, using method Level 1 or method Level 2 prescribed by ISO 8996. Using this evaluation process, PMV may vary enough to make its results open to questioning. Therefore tools that will enable detailed measurement of metabolic rate will undoubtedly increase the understanding of thermal comfort and the relationship between participants and their environment. In response to this query, the paper suggested a method drawn from literature on wearable-ubiquitous sensor technologies. The use of heart-rate monitor and automatic visual diary allowed the gathering of precise and accurate measurements of activity level. This mixed-method was employed in a series of case studies in dwelling, during the winter of 2012. The preliminary results show that activity level can be validated over a 35 hours wearable period. Future studies may look at the potential application and practicality of this method.

Through this paper, multiple evaluations of the PMV model were carried out by randomly selecting the model inputs. It was assumed that factors were independent from one another; hence the interaction among factors cannot be determined at this stage. The results of future field studies may be able to answer this question by assigning prior distributions to each variable. Then Markov Chain Monte Carlo analysis will be able to suggest a close representation of the systems by conveying a distribution for PMV and the associated inter relationship between factors. This research into fundamental knowledge may suggest a need for a review of the measurements' protocols and the instruments used to assess PMV using new sensing technologies.

References

Achten, J. & Jeukendrup, A.E. (2003), Heart-rate Monitoring Applications and Limitations. Sports Medicine, 33(7), pp.517_538.

Alfano, G., Romana d'Ambrosio, F. & Riccio, G. (2001), Sensibility of the PMV index to variations of its independent variables. In Moving Thermal Comfort Standards into the 21st Century. Windsor, UK, pp. 158_165.

D'Ambrosio Alfano, F.R., Palella, B.I. & Riccio, G. (2011), The role of measurement accuracy on the thermal environment assessment by means of PMV index. Building and Environment, 46, pp.1361_1369.

The American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) (2004), Thermal environment conditions for human occupancy, Standard 55, Atlanta, USA.

Cohen, J. (1988), Statistical power analysis for the behavioral sciences, Second Edition. Lawrance Erlbaum Associates, New Jersey, USA.

Darby, C. & White, R. (2005), "Background Document C: Thermal Comfort." 40% House report. Environmental Change Institute.

Dear, R.D., Brager, G. & Cooper, D. (1998), Developing an Adaptive Model of Thermal Comfort and Preference. Final report on ASHRAE RP-884. ASHRAE, Atlanta, USA.

Fanger, P.O. (1970), Thermal comfort. Danish Technical Press, Copenhagen.

Hodges, S. et al. (2006), SenseCam: A Retrospective Memory Aid. In P. Dourish & A. Friday, eds. Springer Berlin / Heidelberg, pp. 177_193.

Hong, S.H. et al. (2009), A field study of thermal comfort in low-income dwellings in England before and after energy efficient refurbishment. Building and Environment, 44(6), pp.1228_1236.

Humphreys, M.A. & Fergus Nicol, J. (2002), The validity of ISO-PMV for predicting comfort votes in everyday thermal environments. Energy and Buildings, 34, pp.667_684.

ISO (2001), Ergonomics of the thermal environment - Instruments for measuring physical quantities. BS EN ISO 7726:2001.

ISO (2005), Ergonomics of the thermal environment - Analytical determination and interpretation of thermal comfort using calculation of the PMV and PPD indices and local thermal comfort criteria. BS EN ISO 7730:2005.

ISO (2004), Ergonomics of the thermal environment - Determination of metabolic rate. BS EN ISO 8996:2004.

ISO (2009), Ergonomics of the thermal environment - Estimation of thermal insulation and water vapour resistance of a clothing ensemble (ISO 9920: 2007, Corrected version 2008-11-01). BS EN ISO 9920:2009.

Lee, H. et al. (2008), Constructing a SenseCam visual diary as a media process. Multimedia Systems Journal, 14 (6). pp. 341_349.

Lomas, K.J. & Eppel, H. (1992), Sensitivity analysis techniques for building thermal simulation programs. Energy and Buildings, 19 (1), pp.21_44.

Parsons, K.C. (2001), The estimation of metabolic heat for use in the assessment of thermal comfort. In Moving Thermal Comfort Standards into the 21st Century. Windsor, UK, pp. 301_308.

Saltelli, A., Chan, K. & Scott, E.M. (2000), Sensitivity analysis. John Wiley & Sons, Chichester, UK.

Saltelli, A. et al. (2004), Sensitivity analysis in practice : a guide to assessing scientific models. John Wiley & Sons, Chichester, UK.