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Predictive clothing insulation model based on outdoor air and indoor operative temperatures

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Abstract

Clothing affects people's perception of the thermal environment. In this research two predictive models of clothing insulation have been developed based on 6,333 selected observations taken from ASHRAE RP-884 and RP-921 databases. The database has been used to statistically analyze the influence of 20 variables on clothing insulation.

The results show that the median clothing insulation is 0.59 clo (0.50 clo (n=2,760) in summer and 0.66 clo (n=3,580) in winter). Clothing insulation is correlated with outdoor air temperature (r=0.45), operative temperature (r=0.3), relative humidity (r=0.26), air velocity (r=0.14) and metabolic activity (r=0.12).

Two mixed regression models were developed. In the first one clothing insulation is a function of outdoor air temperature measured at 6 o'clock in the morning and in the second one the influence of indoor operative temperature is also taken into account. The models were able to predict only 19 and 22% of the total variance, respectively. These low predicting powers are better than the assumption of constant clothing insulation for the heating (1 clo) and cooling (0.5 clo) seasons.

Key words

Clothing, behavior modeling, thermal comfort, occupant behavior, weather

Introduction

The amount of thermal insulation worn by a person has a substantial impact on thermal comfort (ANSI/ASHRAE, 2010). Clothing adjustment is a behaviour that directly affects the heat-balance (De Dear & Brager, 1997). The thermal insulation provided by garments and clothing ensembles is expressed in a unit named clo, where 1 clo is equal to 0.155 m^2°C/W. For near-sedentary activities where the metabolic rate is approximately 1.2 met, the effect of changing clothing insulation on the optimum operative temperature is approximately 6°C per clo. For example, adding a thin, long-sleeve sweater to a clothing ensemble increases clothing insulation by approximately 0.25 clo. Adding this insulation would lower the optimum operative temperature by approximately 6°C/clo × 0.25 clo = 1.5°C (ANSI/ASHRAE, 2010). The effect is greater with higher metabolic rates

(ANSI/ASHRAE, 2010). Clothing adjustment is perhaps the most important of all the thermal comfort adjustments available to occupants in office buildings (Newsham, 1997).

Clothing is one of the six variables that affect the calculation of the predicted mean vote (PMV) and predicted percentage of dissatisfied (PPD) (Fanger, 1970) and therefore is an input for thermal comfort calculation according to American (ANSI/ASHRAE, 2010), European (CEN, 2007) and International (ISO, 2005) thermal comfort standards. In the standards thermal comfort ranges are usually calculated for clothing insulation equal to 0.5 clo and 1 clo. If other information is not available, thermal comfort evaluations for the cooling season are performed with a clothing insulation equal to 0.5 clo, and for heating season with a clothing insulation equal to 1 clo. The selection of the clothing insulation for thermal comfort calculations affects the design (sizing and analysis) of HVAC systems, the energy evaluation and the operation of buildings. In a yearly energy and thermal simulations there are no standardized guidelines on how to set clothing insulation schedules. Often, just two values are used (0.5 and 1 clo) and the change from 0.5 to 1 or vice-versa is done suddenly (from one day to another) and arbitrarily (Hensen & Lamberts, 2011). These simplifications may lead to systems that are incorrectly sized and/or operated. A model that is able to predict how building occupants change their clothing would greatly improve HVAC system operation. Previous attempts to develop a dynamic clothing model demonstrated that the ability to more accurately predict variations in clothing leads to improved thermal comfort (Newsham, 1997), smaller HVAC size and lower energy consumption (De Carli et al., 2007).

de Dear and Brager (De Dear & Brager, 2001) and de Dear (De Dear & Brager, 1997) analysed the relationship between clothing insulation and mean indoor operative temperature and mean outdoor effective temperature in the publicly available database developed within ASHRAE Research Projecet-884. To study the relationships between clothing level and indoor and outdoor temperatures they used the average building value (160 buildings) and not the value for each occupant (22,346 occupants), i.e. the regression analysis was done with 160 statistical units (one value for each building) and not with 22,346 statistical units. They used the building and not the occupant as unit of the statistical analysis to ensure some homogeneity of conditions affecting each subset of data, but there was not an explicit verification of linear regression assumptions. In figure 5b a risk of leverage effect due to four data points (probably outliers) is visible. (De Dear & Brager, 2001). Using the building as the statistical unit artificially reduces variance and increases the coefficient of determination (R^2). This implies a loss of information. As explained later in the paper, it is possible to take into account the variance caused by the building and use each occupant as the statistical unit by applying regression analysis based on mixed models (fixed plus random effects) instead of linear model (only a fixed effect) (Faraway, 2006b). De Carli et al. (De Carli et al., 2007) developed single variable linear regression models to predict the clothing insulation as a function of the outdoor air temperature measured at 6 o'clock in the morning. Independent models were developed for naturally and mechanically air conditioned buildings and for three latitudes ranges. The models have been based on a publicly available database developed within ASHRAE Research Proget-884 (De Dear & Brager, 1997) and on field measurements performed by Feriadi et al. (Feriadi et al., 2002). Based on energy simulation, De Carli et al. (De Carli et al., 2007) concluded that in mechanically conditioned building a variation of 0.1 clo is sufficient to significantly change the comfort evaluation. The developed models have the following limitations: a) the homoscedasticity hypothesis of the developed linear models has not been reported, therefore it is possible that the regression coefficients are not correct (Faraway, 2006a); b) the variance introduced by the building has not been included in the models; c) all the data from ASHRAE RP-884 has been used regardless of the quality of the measurements of the single projects included in the final project and different standards has been used to assess the clothing insulation (De Dear & Brager, 1997); d) single variable regression models has been used, losing the opportunity to check for interaction effect and the combination of several variables at the same time; and e) probably other relevant variables, such as air velocity and relative humidity, have not been considered. Morgan and de Dear (Morgan & De Dear, 2003) examined clothing behaviour and its relationship with thermal environments in two indoor settings (shopping mall and call centre) located in Sydney, Australia. They found that day-to-day variation in clothing levels changed significantly in the shopping mall where a dressing code was not in place. Clothing varied less in the call centre where a dressing code was forced. For the shopping mall they develop a linear regression equation to relate the daily average clothing value with daily mean outdoor dry bulb temperature.

The aim of this research is to develop a dynamic predictive model of clothing insulation typically used by office occupants to be applied in thermal comfort calculation, HVAC sizing, building energy analysis and building operation.

Method

Database

The data to develop the model has been taken from the ASHRAE RP-884 (De Dear & Brager, 1997) and from ASHRAE RP-921 (Cena & de Dear, 1999) databases. All the data from the ASHRAE RP-921 have been used. Data in ASHRAE RP-884 were classified by the authors of the report into three levels of quality (from Class I, the best, to Class III, the lowest data quality). In this research only data of Class I have been used because they were collected with 100% compliance with the specification set out in ASHRAE Standard 55-1992 and ISO 7730-1984 (see Paragraph 2.2.2 of (De Dear & Brager, 1997)). ASHRAE RP-921 complies with the same standards, and therefore it fits with Class I.

Thermal comfort standards (e.g. ISO 7730 and ASHRAE 55) provide techniques to evaluate the clothing insulation. A problem faced in ASHRAE RP-884 (De Dear & Brager, 1997) was related to the fact that standards, in their various revisions, have used different techniques. This led to the situation where quite different clo estimates would be calculated for a given set of clothing, depending on which standard and which edition was used. To solve this problem, the researchers converted the different clo estimation technique into equivalent ASHRAE Standard 55-92 (ANSI/ASHRAE, 1992) clo estimates. For the data used in this research ASHRAE Standard 55-81 (ASHRAE, 1981) and ASHRAE Standard 55-92 (ANSI/ASHRAE, 1992) have been used (see Table 1). The conversion from ASHRAE Standard 55-81 to 92 caused an error, and thus de Dear et al. (De Dear & Brager, 1997) estimated that for male and female the regression equation was able to explain 81% and 61% of the variance (R^2=0.81), respectively. In this current research it has been decided to keep data collected with the two methods in order to have a bigger sample (6333 observations instead of 3298). The clo values used here are calculated according to ASHRAE Standard 55-92 (ANSI/ASHRAE, 1992) and do not include the insulation caused by the chair. For all the used data, outdoor climatic information was gathered from meteorological stations located close to the building.

Variables

The ASHRAE RP-884 and 921 reported a large number of variables. In this research, only a subset of variables has been used. From a review of the possible independent variables that may affect the clothing insulation, 20 variables were identified. The variables included in the analysis are summarized in Table 1. Where not otherwise noted, the abbreviation follows the same of (De Dear & Brager, 1997).

Table 1 Variables included in the analysis

Variable	**Abbreviation**
Ensemble clothing insulation [clo]	clo
subject's gender [M=male, F=female]	sex
Metabolic activity [met]	met
Indoor operative temperature [°C]	top
Relative humidity [%]	rh
Air velocity high height (1.1 m) [m/s]	vel_h
Air velocity medium height (0.6 m) [m/s]	vel_m
Air velocity low height (0.1 m) [m/s]	vel_l
Outdoor 3pm (max) air temp on day of survey [°C]	day15_ta
Outdoor 6am (min) air temp on day of survey [°C]	day06_ta
Outdoor average of min/max air temp on day of survey [°C]	dayav_ta
Conditioning system (Mechanical = 1) (Natural=2)*	bldgtype
Year	year
Month of the (Jan=1, Feb=2, etc.)	month
Day of the month	day
Nation	location
File identification number referred to RP-884	file
Building identification number referred to RP-884 and RP-921	blcode
Season (dry season, summer, etc)*	season
Building identification number in this research*	blcodeNew
Season aggregate (summer, winter)*	Season1

*Abbreviation and variable name different from (De Dear & Brager, 1997)

Statistical analysis

The data distributions are reported as frequency histograms and as box-plots when more than one variable is plotted. A box-plot is a way of graphically summarizing a data distribution. In a box-plot the thick horizontal line in the box shows the median. The bottom and top of the box show the 25th and 75th percentiles, respectively. The horizontal line joined to the box by the dashed line shows either the maximum or 1.5 times the interquartile range of the data, whichever is smaller. Points beyond those lines may be considered as outliers and they are plotted as circles in the boxplot graphs. The interquartile range is the difference between the 25th and 75th percentiles (Crawley, 2005). The normal distribution of the data was tested with the Shapiro-Wilk normality test (Shapiro & Wilk, 1965). Correlation between variables is reported with Spearman's rank coefficient if the variable does not have a normal distribution, and with the Pearson correlation if it has a normal distribution. The description of the methods and tools used for the development of multivariable linear and mixed models is reported in the section "Development of the regression model". To compare means and to test statistical difference, t-test and ANOVA were used when appropriate. For all tests the results were considered statistically significant when $p<0.05$. The statistical analysis was performed with R version 2.10.1 (R Development Core Team, 2010).

Results

The database includes 6,333 observations. Statistical summaries are reported for categorical variables in Table 3 and for numerical variables in Table 4.

Table 2 Statistical summary of categorical variables

Name	**Level**	**Observation**	**Percentage [%]**
Conditioning system	Mechanical	5584	88.2
	Natural	749	11.8
sex	Female	3547	56
	Male	2786	44
location	Australia	2429	38.3
	California	2950	46.6
	Canada	869	13.7
	Michigan	85	1.3
season	Dry season	627	9.9
	Summer	2153	34
	Wet season	604	9.5
	winter	2949	46.6
season1	Summer	2757	43.5
	Winter	3576	56.5

Table 3 Statistical summary of numerical variables

Name	**Factor**	**Measuring unit**	**Max**	**Min**	**Mean**	**Stand. Dev.**	**Median**
clo	No	[clo]	1.94	0.13	0.6239	0.22	0.59
met	No	[met]	2.58	0.990	1.21	0.20	1.2
top	No	[°C]	31.67	16.64	23.11	1.24	23.10
rh	No	[%]	77.95	10.00	45.22	13	45.30
vel_h	No	[m/s]	1.71	0	0.1161	0.088	0.1
vel_m	No	[m/s]	1.97	0	0.1063	0.085	0.09
vel_l	No	[m/s]	1.55	0	0.0968	0.084	0.08
day15_ta	No	[°C]	41.2	-22.6	20.5	9.7	20.9
day06_ta	No	[°C]	26.2	-27.2	10.8	8.7	11.7
dayav_ta	No	[°C]	31.7	-24.9	15.6	8.9	15.9
year	No		From 1986 to 1997				
month	No	1…12	From January to December				
day	No	1..31	From 1 to 31				

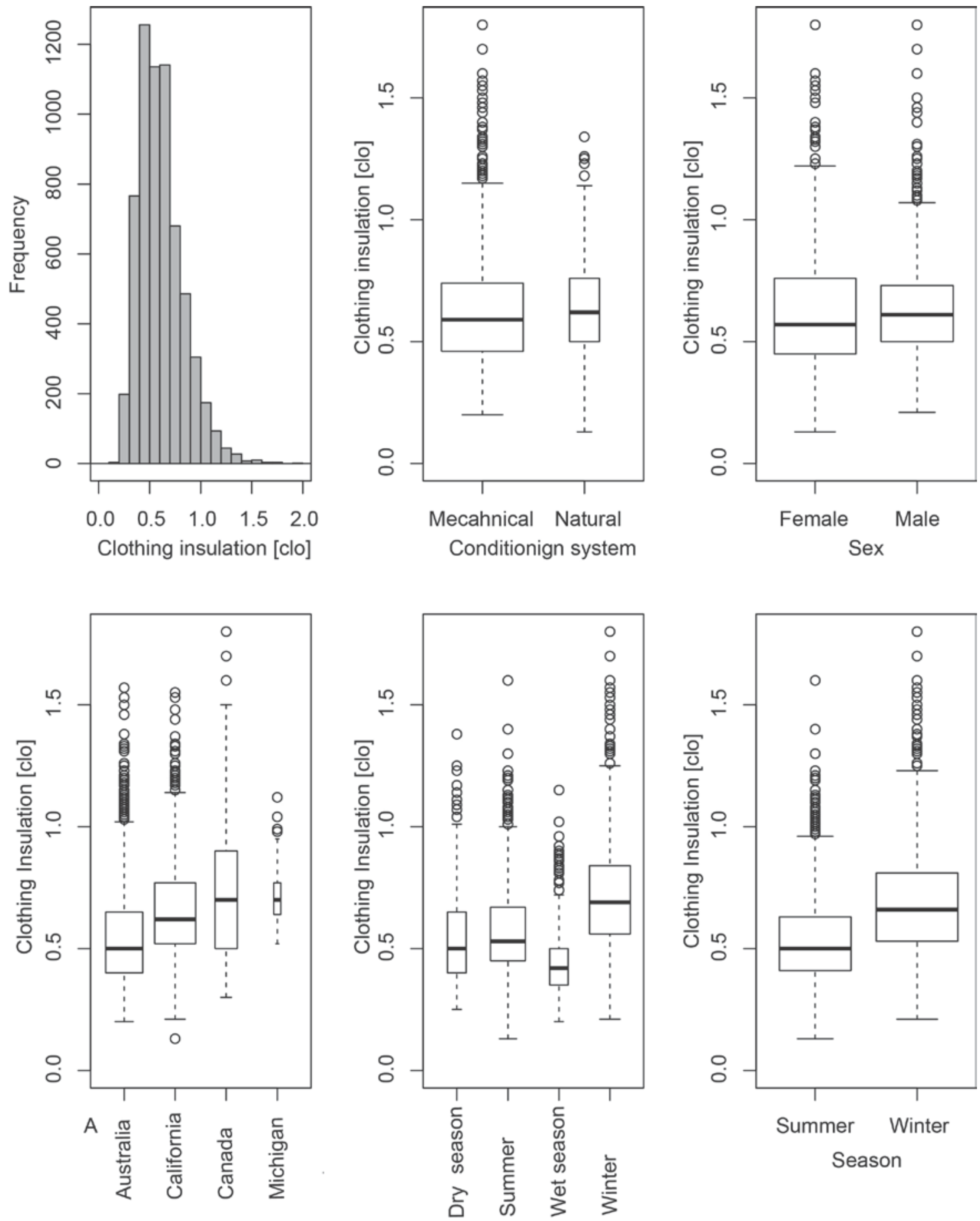

Figure 1 Frequency distribution of the clothing insulation and box-plots for the clothing insulation versus the air-conditioning systems (mechanical or natural), the sex of the occupant, the location of the building, the season divided into summer and winter or in four categories (wet season, summer, dry season and winter).

Analysis of the categorical variables

Figure 1 shows the frequency distribution of the clothing insulation and box-plots for the clothing insulation (without chair) versus the air-conditioning system (mechanical or natural), the sex of the occupant, the location of the building, and the season divided into summer and winter or in four categories (wet season, summer, dry season and winter). A detailed description and further analysis of each plot reported in Figure 1 is described in (Schiavon & Lee, 2012).

Analysis of the numerical variables

The outdoor air temperature is described by three variables: the minimum outdoor air temperature measured at 6:00, the maximum outdoor air temperature measured at 15:00 and the average daily temperature. The three variable are highly correlated (Spearman's rank -r 0.88-0.97, $p<0.001$). The correlation values are extremely high and therefore there is a high risk of collinearity. Variance Inflation Factor (VIF) is equal to 100 (much higher than the maximum acceptable value of 10 (Diamantopoulos & Winklhofer, 2001)) and therefore collinearity is present. To eliminate the collinearity, two of these variables can be taken out from the model. It is not necessary to keep all three variables in the model because one variable is sufficient to describe the other two. It is not important which one is kept. We arbitrarily preserved the minimum air temperature (6:00 am). A similar situation is true for the three air velocities. Air velocity at medium height, vel_m, was selected as representative of other velocities.

Figure 2 shows the correlation matrix of the following variables: metabolic activity, relative humidity, indoor operative temperature, air velocity at medium height, minimum outdoor air temperature (outdoor air temperature measured at 6am), and clothing. Bivariate scatter plots and the fitted lines are shown in the lower-left part of the figure; Spearman's rank correlation values and their significance level ($p<0.001$ for three stars and $p<0.01$ for two stars) are shown in the upper-right part. Clothing insulation is correlated with outdoor air temperature measured at 6am ($r=0.45$), operative temperature ($r=0.3$), relative humidity ($r=0.26$) and is slightly correlated with air velocity ($r=0.14$) and metabolic activity ($r=0.12$). In this graph it is possible to study the correlation between the dependent variables. This will be helpful to avoid the problem of multicollinearity. Outdoor air temperature is strongly correlated with relative humidity ($r=0.64$) and operative temperature ($r=0.3$).

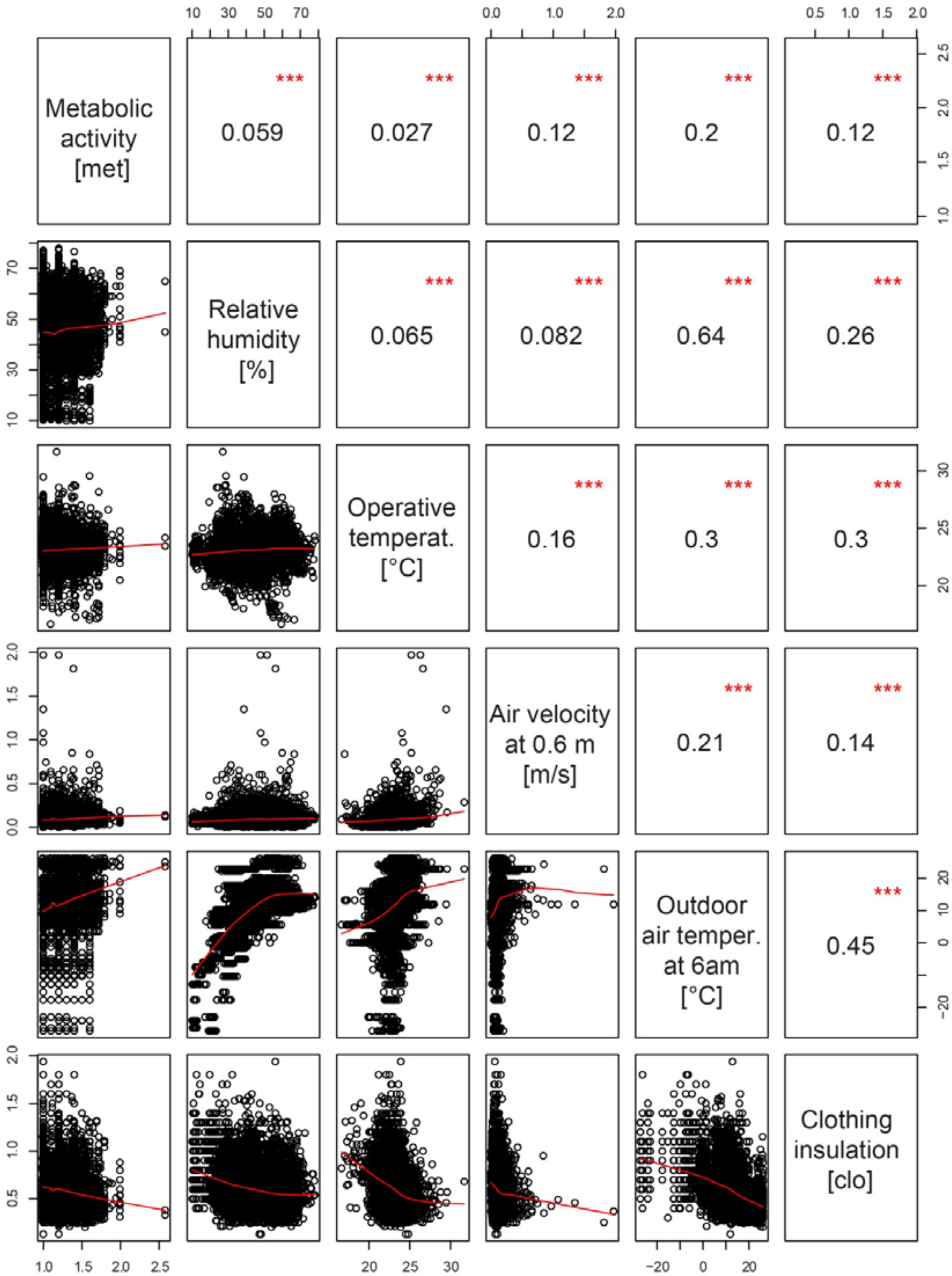

Figure 2 Correlation matrix of the following variables: metabolic activity, relative humidity, indoor operative temperature, air velocity at medium height (0.6 m), minimum outdoor air temperature (measured at 6am) and clothing insulation. Bivariate scatter plots and the fitted lines are shown in the lower-left part of the figure; Spearman's rank correlation values and their significance level ($p<0.001$ for three stars and $p<0.01$ for two stars) are shown in the upper-right part. An analysis of the influence of dress code on clothing insulation is reported in (Schiavon & Lee, 2012).

Development of the regression models

Multi-variable linear models have been developed. The best models were selected based on the R-squared adjusted method (R^2_{adj}), and the minimum number of explanatory variables has been used. If all the available variables are used, the obtained model has an R-squared adjusted value equal to 0.28. That is the maximum value achievable with a linear multivariable model. The regression linear hypotheses have been tested for all the studied models. The plot of residuals vs. fitted values was used to check the validity of the hypothesis of constant variance required for linear models. This showed that this hypothesis (aka heteroscedastic) was violated if a transformation of the dependent variable was not applied. The same problem was revealed in the plot of the square root of the standardized residuals versus the fitted values. Ignoring non-constant variance when it exists invalidates all inferential tools like p-value, confidence intervals and prediction intervals (Faraway, 2002). Therefore the models with this problem were transformed. To overcome non-constant variance a power transformation of the response variable was applied for each model. The Box-Cox method (Box & Cox, 1964) was used to find the exponent of the transformation. The results showed that applying a logarithm transformation of the dependent variable would remove the problem. All the tested models have been reported in (Schiavon & Lee, 2012).

In general, data may include both fixed effects and random effects. Fixed effects have informative variables whereas random effects are generally uninformative or not useful for predicting the dependent variable. In this case the building itself may have an influence on the clothing insulation but in the regression model it would be useless to have the specific building as an independent variable. For this reason a multivariable mixed model was used in order to take this effect into account. The R package "lme4" has been used (Bates et al., 2007)(Faraway, 2006a). It is not possible to use R-squared adjusted to compare mixed models. Here the Akaike Information Criterion (AIC) has been used (Akaike, 1974). The AIC is not a test of the model in the sense of hypothesis testing; rather, it provides a means for comparison among models. Given a data set, several candidate models may be ranked according to their AIC, with the model having the minimum AIC being the best. From the AIC values one may also infer that the top two models are roughly in a tie and the rest are far worse (Wikipedia contributors, 2011). Two valid mixed models are reported in equations (1) and (2). The relevance of the random effect is measured in term of interclass correlation coefficient. For the developed models the interclass correlation coefficient was equal to 0.17 and 0.13 respectively, meaning that the random effect explain 17% and 13% of the total variance. Therefore the mixed models have to be used instead of the linear models.

(SI) $$log_{10}\, clo = -0.1635 - 0.0066 * \text{day06\_ta} \tag{1}$$

(SI) $$log_{10}\, clo = 0.2134 - 0.0165 * top - 0.0063 * \text{day06\_ta} \tag{2}$$

(IP) $$log_{10}\, clo = -0.0460 - 0.00367 * \text{day06\_ta} \tag{3}$$

(IP) $$log_{10}\, clo = 0.6189 - 0.00916 * top - 0.0035 * \text{day06\_ta} \tag{4}$$

In these equations, day06_ta is the outdoor air temperature measured at 6:00 and top is the operative temperature. These models are valid within the following boundary: day06_ta should be between -27.2°C and 26°C [-17 and 78.8°F] and top should be between 16.6°C and 31.7°C [61.9 and -89°F]. These models have been developed with a mixed model approach that does not allow to calculate R^2_{adj}. In order to assess the ability of the models they have been tested in the database. The results of this process are plotted in Figure 3. For equation (1) R^2_{adj} is equal to 0.19 and for equation (2) it is 0.22.

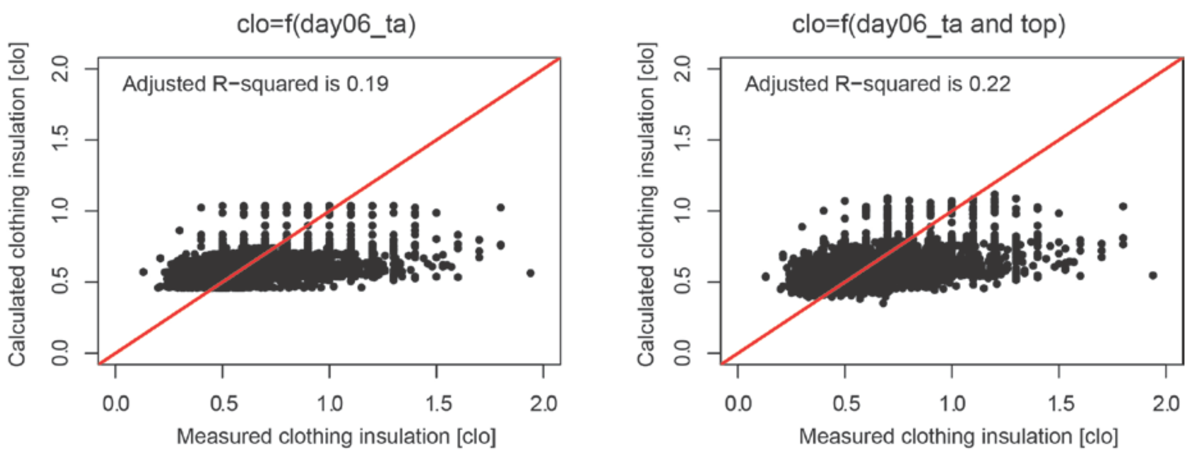

Figure 3 Measured versus fitted clothing insulation values calculated with the two models.

To assess the predictive ability of the two models, the entire dataset has been randomly divided into two parts: a training dataset and a test dataset. Two multivariable mixed models with the same structure of equations (1) and (2) have been fitted for the training dataset. The models were tested in the test dataset. The model with only day06_ta had a R-squared adjusted (R^2_{adj}) of 0.18 and the model with day06_ta and top had a $R^2_{adj}$of 0.21. The developed models have regression coefficients very similar to the model developed in the whole database and the calculated clo values have a difference that is negligible (less than 0.025 clo between the models (1) and (3) and less than 0.02 clo between the models (2) and (4)) and therefore it is acceptable to use models obtained in the whole database. The predicting power of these two models is small, only 19 and 22% of the total variance is described in the model. This is due to the fact that people do not dress only based on climate but mainly on other social and cultural parameters. These parameters are have not been measured in the thermal comfort database and thus they cannot be included in the analysis. These low predicting powers are better than the assumption of constant clothing insulation for the heating (1 clo) and cooling (0.5 clo) seasons.

Figure 10 reports the graphical representation of the regression model developed to predict the clothing insulation when only the outside dry bulb air temperature is known (equation (4)). In all the models reported here, the chair is not present and should be added to the calculated value if present. Figure 11 reports an example of the application of equation (4). The outside dry bulb air temperatures measured at 6 o'clock have been extrapolated by the EnergyPlus EPW weather file of Chicago O'hare International Airport.

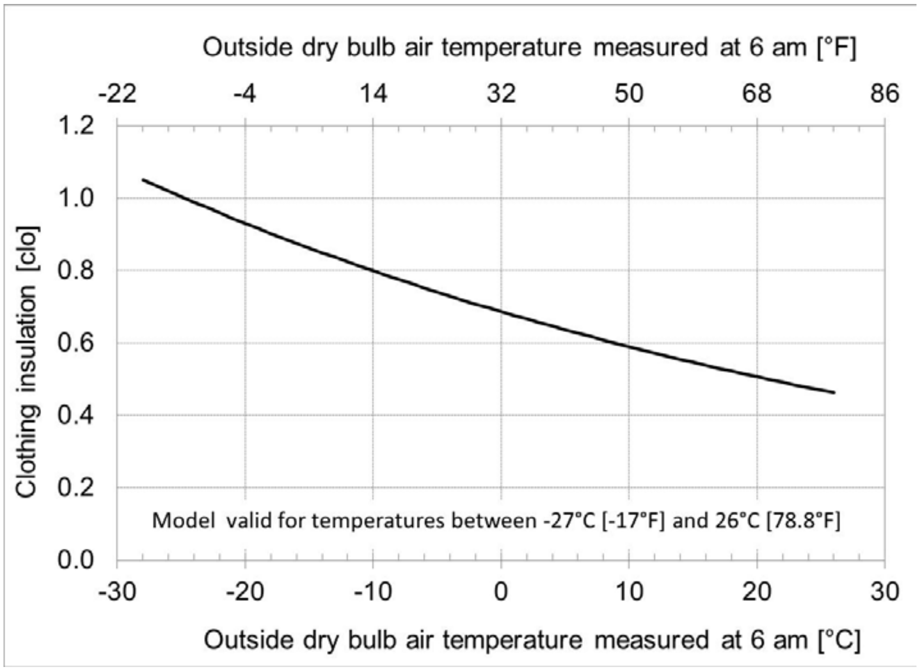

Figure 4 Graphical representation of the regression model developed to predict the clothing insulation when only the outside dry bulb air temperature measured at 6 o'clock is known.

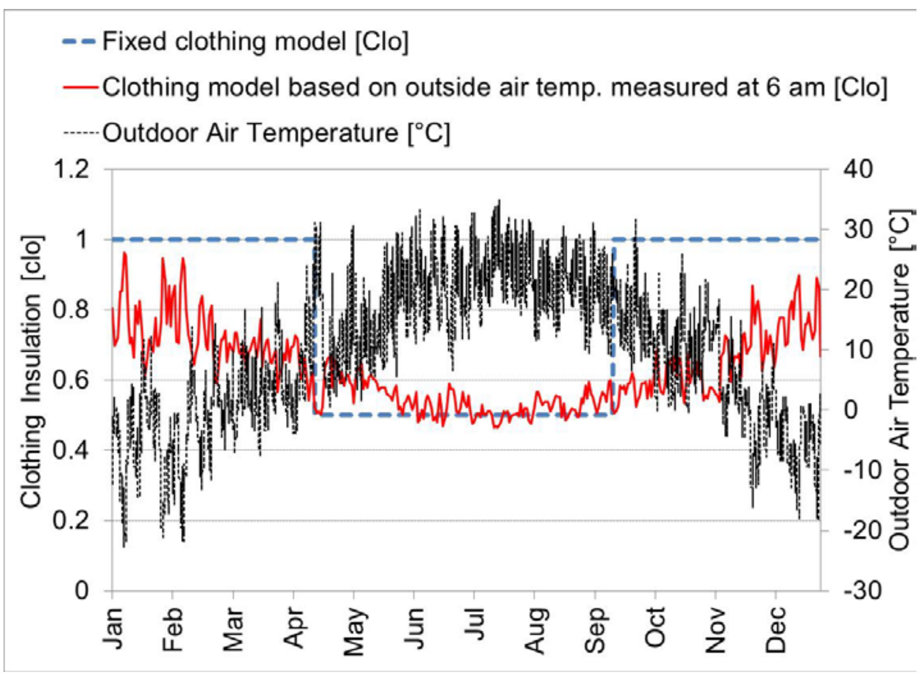

Figure 5 Clothing insulation schedule for a fixed model (blue) typically used in energy simulation software and for the clothing model based on outdoor air temperature measured at 6am. Climate data for Chicago O'hare International Airport has been used.

Discussion of the influence of indoor and outdoor temperatures on clothing insulation

Morgan and de Dear found that indoor operative temperatures are not statistically associated with clothing insulation levels, but they affirmed that the extremely limited variance in both the predictor (indoor temperatures) and the dependent (indoor clo) variables precluded any other finding being made with their data. Moreover, a significant part of the data comes from a cross-sectional study in a shopping mall where visitors stayed indoors for only a short time. It is possible that most of time the visitors had been exposed to outdoor conditions. In the study reported here, it was found that indoor operative temperature is the second most important variable affecting clothing insulation among the 20 observed variables. This result is based on a higher number of observations and it is supported by a larger variation of indoor temperatures and clothing insulations. This study support the idea that people, if allowed, change their clothing as a function of the indoor conditions that they are exposed to.

Morgan and de Dear (Morgan & De Dear, 2003) showed why outdoor temperature affects clothing insulation. They stated that "it is not difficult to understand how the temperature of the indoor microclimate surrounding the human body exerts an influence on clothing levels. Indoor temperature directly impacts the body's heat balance, skin temperatures and skin wettedness, which are, in turn, the main thermophysiological drivers for thermal discomfort. In conventional thermal comfort theory we regard the motivation for clothing selection and indeed, any other thermoregulatory behavior, as being proportional to the intensity of conscious sensations of thermal discomfort. Therefore if this is the casual chain linking indoor temperature to indoor clothing insulation levels, how can outdoor temperature exert an effect as well…?". Morgan and de Dear suggested that the timing (usually in the morning) of exactly when clothing decision are made is relevant for explaining the relationship between clothing and outdoor air temperature. They found that both previous day thermal experience and forecast of thermal experience are relevant factors (Morgan & De Dear, 2003). From the results and models reported in this study and from previous studies (De Carli et al., 2007; De Dear & Brager, 1997; Newsham, 1997) it can be concluded that there is common agreement about the relevant role of outdoor air temperature as climatic parameter that affect indoor clothing insulation.

Conclusion

The main conclusions of the analysis of the clothing insulation behavior are summarized below.

1. The median clothing insulation value is 0.59 clo (0.50 clo (n=2,760) in summer and 0.66 clo (n=3,580) in winter). The median winter clothing insulation value is significantly lower than the value suggested in international standard (1 clo).
2. Male and female have similar clothing insulation values.
3. Clothing insulation is correlated with outdoor air temperature measured at 6 o'clock in the morning (Spearman's rank correlation coefficient r = 0.45), indoor operative temperature (r=0.3), relative humidity (r=0.26) and only slightly correlated with air velocity (r=0.14) and metabolic activity (r=0.12).

4. Two mixed regression models were developed. In the first one, clothing insulation is a function of outdoor air temperature measured at 6 o'clock; in the second one, the influence of indoor operative temperature is also taken into account. The models were able to predict only 19 and 22% of the total variance, respectively.

The models will be implemented in energy simulation software (e.g. Energy Plus). The developed models are able to predict how office building occupants dress and how they will change their clothing as a function of the climate. The models will allow more accurate HVAC sizing, thermal comfort calculation energy analysis and building operation.

References

Akaike, H. (1974) A new look at the statistical identification model, IEEE transactions on Automatic Control, 19, 716-723.

ANSI/ASHRAE. (1992) ANSI/ASHRAE 55-1992: Thermal environmental conditions for human occupancy, American Society of Heating, Refrigerating and Air-Conditioning Engineers, Atlanta.

ANSI/ASHRAE. (2010) ANSI/ASHRAE 55-2010: Thermal environmental conditions for human occupancy, American Society of Heating, Refrigerating and Air-Conditioning Engineers, Atlanta.

ASHRAE. (1981) ANSI/ASHRAE Standard 55-1981: Thermal environmental conditions for human occupancy, American Society of Heating, Refrigerating and Air-Conditioning Engineers, Atlanta.

Bates, D., Sarkar, D., Bates, M.D. and Matrix, L.T. (2007) The lme4 package, R Package Version 2.4, 1.

Box, G.E.P. and Cox, D.R. (1964) An Analysis of Transformations, Journal of the Royal Statistical Society.Series B (Methodological), 26, 211-252.

CEN. (2007) EN 15251-2007, Criteria for the indoor environment including thermal, indoor air quality, light and noise, European Committee for Standardization.

Cena, K. and de Dear, R.J. (1999) Field study of occupant comfort and office thermal environments in a hot, arid climate, ASHRAE Transaction: Research, 105, 204-217.

Crawley, M.J. (2005) Statistics: an introduction using R, , Wiley.

De Carli, M., Olesen, B.W., Zarrella, A. and Zecchin, R. (2007) People's clothing behaviour according to external weather and indoor environment, Build Environ, 42, 3965-3973.

De Dear, R. and Brager, G. (1997) Developing an adaptive model of thermal comfort and preference, Final Report ASHRAE RP-884.

De Dear, R. and Brager, G. (2001) The adaptive model of thermal comfort and energy conservation in the built environment, Int J Biometeorol, 45, 100-108.

Diamantopoulos, A. and Winklhofer, H.M. (2001) Index construction with formative indicators: An alternative to scale development, J Market Res, 38, 269-277.

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

Faraway, J.J. (2002) Practical Regression and ANOVA using R.

Faraway, J.J. (2006a) Extending the linear model with R: generalized linear, mixed effects and nonparametric regression models, , CRC Press.

Faraway, J.J. (2006b) Extending the linear model with R: generalized linear, mixed effects and nonparametric regression models, , CRC Press.

Feriadi, H., Wong, N.H., Chandra, S., Cheong, K.W. and Tham, K.W. (2002) Redefining appropriate thermal comfort standard for naturally ventilated buildings in Tropics (Singapore and Indonesia perspective), Indoor Air, 110-115.

Hensen, J.L.M. and Lamberts, R. (2011) Building Performance Simulation for Design and Operation, , Taylor and Francis.

ISO. (2005) ISO 7730, Moderate thermal environment- Determination of the PMV and PPD indices and specification of the conditions for thermal comfort, International Organization for Standardization.

Morgan, C. and De Dear, R. (2003) Weather, clothing and thermal adaptation to indoor climate, Climate Research, 24, 267-284.

Newsham, G.R. (1997) Clothing as a thermal comfort moderator and the effect on energy consumption, Energy Build, 26, 283-291.

R Development Core Team. (2010) R: A language and environment for statistical computing, .

Schiavon, S. and Lee, K.H. (2012) Predictive clothing insulation model based on outdoor air and indoor operative temperatures, To be submitted to Building and Environment.

Shapiro, S.S. and Wilk, M.B. (1965) An analysis of variance test for normality (complete samples), Biometrika, 52, 591-611.

Wikipedia contributors. (2011) Akaike information criterion, , 2011.