Exploring the relationship between inhabitant actions and summer indoor overheating risk in the London housing stock: A mixed methods approach

Abstract

This paper presents an indoor overheating assessment study of 100 London dwellings during the summer of 2009. The study included physical building surveys, indoor dry bulb temperature monitoring and a questionnaire survey on occupant behaviour, including the operation of passive and active ventilation, cooling and shading systems. A theoretical London housing stock comprising 3,456 combinations of building geometry, orientations, urban patterns, fabric retrofit and external weather was simulated using the EnergyPlus thermal modelling software. A statistical meta-model of EnergyPlus was then built by regressing the independent variables (simulation input) against the dependent variables (overheating risk). The monitoring and questionnaire data were analysed to explore the relationship between self-reported behaviour and overheating, and to test the meta-model. The monitoring data indicated that London homes and, in particular, bedrooms are already at risk of indoor overheating during hot spells under the current climate. Around 70% of respondents tended to open only one or no windows at night mainly due to security reasons. An improvement in R^2 values between measured temperature and meta-model predictions was obtained only for those dwellings where occupants reported actions that was in line with the modelling assumptions, thus highlighting the importance of occupant behaviour for overheating.

Keywords

overheating; housing; occupant behaviour; monitoring; questionnaire; simulation

Introduction and background

Background

The last two decades have seen a growing research and policy interest in the assessment and mitigation of overheating risk for buildings in heating-dominated climates (ZCH, 2015). This has been driven by current climate change projections that predict an unprecedented rise in the frequency and severity of extreme heat episodes (Murphy et al., 2009), as well as recent events, such as the 2003 and 2006 European heat waves, which primarily affected elderly and socially isolated individuals (Fouillet et al., 2006; Kovats & Hajat, 2008). Significant emphasis has been placed recently on the role of the indoor environment (Buchin, Hoelscher, Meier, Nehls, & Ziegler, 2015; Vardoulakis et al., 2015); a large proportion of the deaths that occurred in 2003 in France were attributed to indoor heat exposure for individuals living alone at home (Fouillet et al., 2006). As 66% of the population is projected to live in cities by the middle of the century (UN DESA, 2015), tackling the issue of climate change-driven overheating in urban areas, where heat risk may be magnified by urban heat island effects and increasing urbanisation, emerges as a priority.

Another significant driver of indoor overheating risk is the unintended consequences of poorly applied energy efficiency principles in building construction (Shrubsole, Macmillan, Davies, & May, 2014). New and retrofitted dwellings need to meet increasingly strict energy efficiency standards, which is fundamental in order to deliver a thermally efficient building stock and a reduction in fuel poverty, thus achieving the Government’s carbon emission reduction targets and a transition to a low carbon economy. However, if high levels of thermal insulation and air tightness are not combined with appropriate climate change adaptation strategies, such as shading, natural ventilation and other passive cooling measures, the risk of uncomfortable or excessive summer indoor temperatures may be inadvertently increased (Dengel & Swainson, 2012).

Overheating may be already an issue even under the current climate; it has been estimated, for example, that it currently affects 20% of households in the UK (Beizaee, Lomas, & Firth, 2013; ZCH, 2015). In recent years, there has been a significant body of academic literature focusing on heat risk in UK homes comprising both:

(i) monitoring studies (Baborska-Narozny, Stevenson, & Chatterton, 2015; Beizaee et al., 2013; Firth & Wright, 2008; Ji, Fitton, Swan, & Webster, 2014; Lomas & Kane, 2013; Mavrogianni, Davies, Wilkinson, & Pathan, 2009; Mavrogianni, Taylor, Davies, Thoua, & Kolm-Murray, 2015; Morgan, Foster, Sharpe, & Poston, 2015; Oraiopoulos, Kane, Firth, & Lomas, 2015; Pana, 2013; Vellei, Ramallo-González, Kaleli, Lee, & Natarajan, 2016; Wright, Young, & Natarajan, 2005); and

(ii) modelling studies (de Wilde & Coley, 2012; Gul et al., 2015; Gupta, Gregg, & Williams, 2015; Gupta & Gregg, 2012; Holmes & Hacker, 2007; Mavrogianni, Wilkinson, Davies, Biddulph, & Oikonomou, 2012; McLeod, Hopfe, & Kwan, 2013; Oikonomou et al., 2012; S. M. Porritt, Cropper, Shao, & Goodier, 2012; S. Porritt, Shao, Cropper, & Goodier, 2011; J. Taylor et al., 2016; Tillson, Oreszczyn, & Palmer, 2013).

The UK Government and construction industry have responded to this challenge by launching a number of projects and reports that have emphasised the need to improve our understanding of heat risk across the UK's building stock and embed climate resilience in planning, building design and retrofit (Anderson, Carmichael, Murray, Dengel, & Swainson, 2013; CCC ASC, 2014; CIBSE, 2013; DCLG, 2012a, 2012b;

DEFRA, 2013; Garrett, 2014; NHBC Foundation, 2012; PHE, 2015; M. Taylor, 2014). A recent two-year project led by the Zero Carbon Hub (ZCH, 2015) quantified the extent to which the housing sector is preparing in order to address these challenges, and proposed necessary changes to policy frameworks and business procedures. There is also a growing trend towards the development of urban heatwave vulnerability indices for urban environments, such as London, that allow the mapping of overheating risk and identification of prioritisation areas by public health policymakers (Mavrogianni, Davies, Chalabi, et al., 2009; J. Taylor et al., 2015, 2016; Tomlinson, Chapman, Thornes, & Baker, 2011; Wolf, McGregor, & Analitis, 2013; Wolf & McGregor, 2013).

It is evident, however, from the review of the literature presented above that the influence of human behaviour on heat risk exposure is less well understood, and that the various existing modelling frameworks are very rarely validated against actual monitored data from large building samples.

Study aims and objectives

The aims of this study were two-fold:

(i) to develop an empirically tested indoor overheating prediction method entailing a set of simple rules that will enable the mapping of building-specific determinant factors of indoor overheating in London homes based on the limited data that are usually available at the citywide level; and

(ii) to quantify the potential impact of uncertainties surrounding occupant behaviour on these predictions.

The specific objectives of this study were:

(i) to quantify the extent to which summer overheating occurs in London dwellings under the current climate;

(ii) to analyse monitored summer indoor thermal conditions in London homes in relation to occupant behaviour with a focus on the operation of shading devices, windows and other ventilation sources;

(iii) to construct a simplified, physics-based tool for the estimation of relative indoor overheating risk in London dwellings that can be run with the reduced data readily available and easily extractable from existing Geographic Information System (GIS) databases and imputed building fabric characteristics as a function of known attributes; and

(iv) to empirically test its predictions based on measured data on the summer thermal performance of a large sample of London dwellings and information about the home energy use and ventilation behaviour of their occupants.

Methods

This section offers an overview of the mixed methods approach that was employed in this study. The work was divided into four distinct parts:

(i) an empirical study involving the physical survey and indoor thermal monitoring of 100 household spaces in London, and a questionnaire survey on occupant behaviour with respect to the operation of home energy appliances, shading and ventilation systems;

(ii) the generation of a large set of dynamic thermal simulations of the summer thermal performance of archetypical London dwellings;

(iii) the development of a multiple linear regression meta-model based on the above simulations; and

(iv) the comparison of the meta-model indoor overheating risk predictions against measured data.

The entire process is summarised in Figure 1.

Building physical survey, indoor thermal monitoring and questionnaire survey

The empirical data collection process consisted of two stages. The first stage (May-June 2009), included the recruitment of study participants and the calibration and installation of indoor and outdoor thermal monitoring equipment. A convenience sample of London householders was recruited following a call for participation circulated through the Bartlett School of Graduate Studies staff mailing list and online construction industry networks. To maximise research participation, a free Energy Performance Certificate (EPC, HM Government, 2016) was offered to all participants. This included information on the energy and environmental impact rating of a dwelling and a recommendation report with suggestions on how energy use and carbon emissions could be reduced if energy saving measures were put in place. An initial group of 111 participants were selected out of 350 who originally responded to the call. The main selection criteria were the type of the dwelling and its location within the London urban heat island. In order to achieve a wide spread of building geometries across the Greater London Area (GLA), a minimum of one mid-terraced house, one semi-detached house, one detached house and one purpose-built flat was chosen within each postcode area, wherever this was possible. The distribution of built form and construction age of the 94 dwellings for which reliable EPC data were obtained at the end of the study is illustrated in Figures 2 and 3. The distribution of dwelling types in the study sample is compared against the Energy Saving Trust's Home Energy Efficiency Database for London (EST HEED, EST, 2016) in Figure 4. Although it appears that mid-terraced houses were overrepresented and flats underrepresented in the present study, HEED also contains a significant proportion of missing data, thus not allowing a full comparison. Unsurprisingly, whilst a varied sample of housing characteristics was achieved, the sample is relatively homogenous as regards to its socioeconomic characteristics: Approximately 80% of participants were academic, research or administrative staff, or graduate students at the Bartlett School of Graduate Studies.

Dry bulb air temperature was measured in the participating dwellings at ten-minute intervals during the summer months using Onset HOBO U12-012 data loggers (Onset, 2016) with accuracy ± 0.35 °C between 0 °C and 50 °C. The loggers were calibrated by being exposed to constant thermal environmental conditions for 24 hours using an 8-point calibration method in a thermal chamber at the Bartlett School of Graduate Studies. Study participants received two data loggers each by post and were asked to place one in the main living area and one in the main sleeping space of their dwelling, in convenient locations at approximately eye level and away from sources of direct light and heat, such as radiators, light bulbs, televisions or other large electronic appliances. In addition, 10 participants were asked to mount a data logger on their garden walls, which was protected by a solar radiation shield (Stevenson screen), in order to measure external temperature. Of these externally installed loggers, 8 were deemed reliable at the end of the study; their locations are indicated with triangles in the map of Figure 3.

The summer period of 2009 was not typical of UK conditions and slightly cooler than normal. It was characterised by unsettled weather, with a number of cold spells and very wet days. According to the MetOffice, July 2009 was the wettest July on record (in a series from 1914). However, external temperatures above 25 ^{o}C were also recorded on a number of days. The only particularly hot spell occurred early in the summer, from 29th June to 3rd July. This five-day period was particularly hot and cloudless with an average external ambient temperature, as recorded in London Heathrow, of 23.1 ^{o}C (maximum 31.0 ^{o}C, minimum 15.0 ^{o}C). A detailed comparative analysis of their indoor thermal performance during this more extreme heat event has been presented elsewhere (Mavrogianni et al., 2010).

The second stage of the study (September 2009 - January 2010) involved the on-site visits to the participating dwellings. Building inspections were completed by two surveyors in 94 out of 111 dwellings due to 17 participants dropping out of the full survey. During these visits, the monitoring equipment was collected, and detailed questionnaire and EPC surveys were simultaneously conducted. The physical surveys followed the Government-approved and industry-agreed standardised Reduced Standard Assessment Procedure (RdSAP) 2005 method for the creation of EPC for existing dwellings (BRE, 2009). Following this method, a reduced number of data items were collected during the inspection of the property. Missing data were inferred by using default data contained in look-up tables in the approved RdSAP software (NES Ltd., 2016). Where possible, gas and electricity meter readings were obtained, and detailed architectural sketches of the interior layout were produced.

The participants underwent a detailed 16-page interviewer-assisted questionnaire, thus ensuring a very high response rate (80%, 89 out of 111 participants). The design of the questionnaire built upon an existing extensively-researched questionnaire (Shipworth, 2011; Shipworth et al., 2010), initially designed for the longitudinal home energy surveys undertaken within the context of the ‘Carbon Reduction in Buildings’ (CaRB, 2016) research project. The questionnaire was modified by removing questions related to the winter thermal performance of the dwelling and adjusted for summer by adding a number of questions on the operation of passive and active ventilation, cooling and shading systems. Its completion took 20 minutes on average and it included a variety of both close-ended (multiple choice, categorical, Likert-scale, numerical and ordinal) and open-ended questions on energy consumption habits, ventilation behaviour and systems operation during the monitoring period. Optional questions on the occupant's socioeconomic profile were also included at the end. The questions related to summer cooling, heating and ventilation behaviour are provided in the Appendix.

A number of participating dwellings were removed from the final dataset for a variety of reasons (participants dropping out or unable to arrange a visit, logger data judged as unreliable etc.). The survey completion rates are given in Table 1.

Dynamic thermal modelling of the theoretical London housing stock

The intermittent nature of indoor overheating phenomena necessitates the use of dynamic thermal models that function at a fine spatiotemporal resolution. The London housing typology originally developed by Oikonomou et al. (2012), and subsequently applied in studies by Mavrogianni et al. (2012), Taylor et al. (2014) and Mavrogianni et al. (2014), were used in the present study (Table 2 and Figure 5). The typology includes 15 main geometries and three variants for purpose-built flats (ground, mid and top floor flat), resulting in 27 dwelling types in total. In brief, these representative dwelling types were created using GIS analysis by identifying the most frequently occurring combinations of construction age and built form, and average values of height and footprint area across London areas for which such data were available. The rest of the input data items required for a complete thermal modelling simulation (building storey height, roof type, insulation levels, air permeability, glazing ratio etc.) were inferred as a function of known variables from the analysis of existing databases such as the English Housing Survey (EHS, DCLG, 2016) and HEED (EST, 2016), as described in Oikonomou et al. (2012). Two different levels of energy efficiency were considered in the present study: (i) as-built; and (ii) retrofitted by current standards. Two separate insulation levels were, thus, considered for each construction element. The corresponding U-values were extracted from look-up tables contained in RdSAP. The thermal insulation and capacity characteristics of the modelled archetypes are given in Table 3. Building fabric permeability was also estimated based on construction age using the most comprehensive UK air leakage cohort study undertaken in the late 1990s (Stephen, 2000). The same standard occupancy, window opening schedules, domestic hot water, lights and appliances use were assumed for all modelled dwellings as specified by Oikonomou et al. (2012) based on the review of existing studies. With regard to occupant-controlled ventilation, it was assumed that occupants will tend to open windows when the temperature reached a threshold temperature (25 ˚C for living rooms and 23 ˚C for bedrooms) and leave them open for as long as the external temperature remained below the internal. The specified thresholds are in line with the recommendations on general summer indoor comfort temperatures for non-air conditioned dwellings assuming warm summer conditions contained in the 7th edition of the Chartered Institution of Building Services Engineers (CIBSE) Guide A (CIBSE, 2007). It was also assumed that all windows would remain closed during the night time or when the dwelling was unoccupied. This was deemed a plausible assumption as this study focuses on urban areas with potential security and noise issues. The use of internal or external shading as a means to limit solar heat gains was not included in the assumptions. The thermal performance of the notional building stock was tested using a standardised weather file, the CIBSE Design Summer Year (DSY) for London Heathrow (CIBSE, 2016). This weather file represents a year with a hot, but not extreme, summer. It consists of an actual one-year sequence of hourly data that was selected from 20-year datasets based on dry bulb temperatures during the period April-

September. The selected year corresponds to the mid year of the upper quartile and is widely used by UK building professionals to assess indoor overheating. Two different building patterns were considered in order to take into account the urban overshadowing and wind sheltering effects or lack thereof: (i) urban; and (ii) rural. In the rural pattern, all dwellings were modelled as stand-alone buildings, whereas in the urban pattern, each archetype was multiplied in order to create a uniform urban structure in the 3D environment of the thermal modelling software. For example, mid-terraced houses formed rows with adjacent buildings.

Multiple combinations of the parameters listed below led to the creation of a theoretical dwelling stock database comprising 3,456 variants (Table 4):

(a) 15 dwelling archetypes (27 variants including ground, mid and top floor level flats);

(b) 2 insulation levels (as-built and post-retrofit) for 4 construction elements (external walls, windows, ground floor, roof/loft);

(c) 4 orientations of the principal facade (0^{o}, 90^{o}, 180^{o} and 270^{o} East of North);

(d) 2 building patterns (whether a stand-alone building or part of a larger building structure); and

(e) 1 weather file (CIBSE DSY for London Heathrow).

The summertime dry bulb and mean radiant temperature of these 3,456 dwelling variants was simulated at hourly intervals in batch mode using the EnergyPlus thermal modelling software v. 3-1-0 (US DoE, 2016), an extensively tested and validated program. An in-house customised automation Microsoft Excel tool was used to generate EnergyPlus Input Definition Files (IDF) in batch mode, which allowed for the quick input insertion of multiple building configurations.

Development of a meta-model of indoor overheating risk in the London housing stock

A key restriction of dynamic thermal modelling tools when applied at the building stock level is the significant computing time that they require. To counteract this problem, a statistical meta-model was developed for the purposes of this study that replicates the building thermal simulation process in a time effective manner based on a set of representative London dwelling archetypes. The main aim of this analytical step was to build a set of simple rules/equations that could then be applied to rank the propensity to overheat of any random set of London dwellings for which only their building fabric properties are known without the need to perform detailed, time-consuming EnergyPlus simulations for each individual building. The input and output items of the extensive theoretical housing stock modelling described in the previous section was organised in groups of independent variables (regressors/predictor variables) and dependent variables (controlled variables). A statistical multiple linear regression model of EnergyPlus was then built by regressing the independent variables of the modelled theoretical housing stock (simulation input) against the dependent variables (simulation output) using the Statistical Analysis Software v. 9 (SAS, SAS Institute Inc., 2016). Following a preliminary sensitivity analysis, a total of 36 EnergyPlus inputs were selected as independent variables in the multiple regression analysis. These are the main parameters that are thought to affect the indoor temperature profiles in the modelled dwellings and are summarised in Table 5. Whilst the modelled theoretical stock is a non-experimental dataset, it was ensured that the selected independent variables varied to a satisfactory degree, thus reflecting real-world distributions. Defining the dependent variables involved a higher level of complexity as their selection highly depends on the chosen definition of overheating. Informed from a review of existing overheating criteria and epidemiological studies at the time of the study (Mylona, Mavrogianni, Davies, & Wilkinson, 2015), the series of indoor temperature statistics were considered to be of interest from a thermal comfort or epidemiological point of view and were hence used as dependent variables in this analysis. These included:

(i) the daytime (8 am to 8 pm) mean, maximum and minimum living room operative temperature;

(ii) the night time (8 pm to 8 am) mean, maximum and minimum bedroom operative temperature;

(iii) the number of occupied hours with living rooms above 28 ^{o}C; and

(iv) the number of occupied hours with bedrooms above 26 ^{o}C.

Each one of the dependent variables was then regressed against independent variables, so that for each dependent variable *i* regressed against *n* dependent variables, a linear equation with the format of Equation (1) was created:

$$y_i = a_0 + a_1x_1 + a_2x_2 + a_3x_3 + \ldots + a_nx_n \quad (1)$$

where:

y_i	:	the dependent variable, i.e. a marker for overheating, such as, for example, maximum daily summer temperature
$x_1, x_2, x_3, \ldots, x_n$	:	independent variables, i.e. building fabric properties such as U-values, thermal mass, glazing ratio etc.
a_0	:	the intercept of the multiple regression model
$a_1, a_2, a_3, \ldots, a_n$	:	the parameter estimates of the multiple regression model

The stepwise forward selection regression technique in SAS was used for the multiple regression analysis. This selection was dictated by the fact that the dataset considered in this modelling study is artificial, i.e. non-experimental. In other words, the simulated building stock was created by arbitrarily assigning fabric properties to the 15 base dwelling types until all possible combinations were made. As a result, it is likely that the independent variables are not truly independent and are correlated with each other. It can, therefore, be expected that in a simple non-stepwise regression analysis the calculated parameter estimates may be significantly affected by that particular subset of correlated independent variables in the regression equation and the resulting collinearity issues. Stepwise regression is hence applied in order to select the optimum set of statistically significant explanatory variables. This approach finetunes the prior selection of variables and eliminates the ones that do not yield significant improvements in the coefficient of determination (R^2) values (no additional benefit in R^2 would be gained by entering the next best independent variable). Only parameter estimates with significance levels $p < 0.15$ were accepted. Following this, only the equations with R^2 higher than 0.50 were considered to provide reliable predictions and were, therefore, kept in the model. Approximately 85% of the simulation runs (2,938 runs) were randomly selected to train the model (i.e. build the regression equations). The ability of the model to mimic the behaviour of EnergyPlus was first assessed by validating the regression predictions against the remaining 15% of the simulation output (518 runs).

Comparison of meta-model predictions against monitored data

The ability of the meta-model to rank random groups of London dwellings based on their summer overheating levels was then tested by comparing its predictions against the summer 2009 monitored indoor temperature data.

The core multiple regression equations used operative temperature as the basis of the indoor overheating metrics, in line with the CIBSE Guide A guidelines against overheating in domestic environments. However, as only dry bulb temperature was recorded by the HOBO data loggers, a similar set of equations was also generated for dry bulb temperature to allow the direct comparison of modelled temperature rankings against the ones derived from the monitored data.

The EPC survey data was translated into a format suitable for input into the EnergyPlus meta-model. Quantitative building fabric properties (e.g. U-values, thermal admittance values) were assigned to each surveyed dwelling based on the corresponding qualitative descriptions of its building elements obtained from the survey, in conjunction with other known information, such as its construction age band. This included building fabric air permeability, wall, roof, floor and window U-values and specific heat capacity. The meta-model was finally employed to estimate relative overheating risk in each one of the 100 dwellings in the field study.

Results

Monitored thermal performance of London dwellings in relation to occupant behaviour

The distribution of mean and maximum indoor dry bulb temperatures in the main living and sleeping areas in the 100 monitored dwellings during August 2009 is illustrated in Figure 6. On average, across all dwellings, the living room daytime (8 am to 8 pm) mean temperature was 23.1 ^{o}C (95% C.I. 22.9-23.4 ^{o}C) and the peak temperature was 26.1 ^{o}C (95% C.I. 25.7-26.5 ^{o}C). In bedrooms, the average mean night time (8 pm to 8 am) temperature was 23.4 ^{o}C (95% C.I. 23.1-23.6 ^{o}C) and the maximum temperature was 26.2 ^{o}C (95% C.I. 25.9-26.6 ^{o}C). Quantifying the actual levels of overheating is challenging in this analysis due to the lack of detailed occupancy pattern information on a daily basis, which does not allow the estimation of occupied hours. For example, it is likely that some dwellings were unoccupied for parts of August when people might have been on holidays etc. However, it is worth noting that despite the fact that 2009 was a mild summer, a significant number of living rooms and, in particular, bedrooms appear to have experienced temperatures above established indoor overheating thresholds (CIBSE, 2007), which is in agreement with the findings of other UK domestic overheating monitoring studies (Beizaee et al., 2013; Lomas & Kane, 2013).

Summertime cooling in UK dwellings currently relies on natural ventilation. A very small number of study participants had air conditioning units in their home (only 3.4%, 3 out of 89 dwellings, 2 of which had a fixed unit and 1 of which had a portable unit that was not used). This is in line with the data contained in the EHS Energy Follow-Up Survey (EFUS) 2011 (Hulme, Beaumont, & Summers, 2011), which found that domestic air conditioning use is currently very rare across England with less than 3% of households using fixed or portable air conditioning units in the summer. Interestingly, it was found that ceiling fans are fairly uncommon; they were installed in only 4.5% (4 out of 89) dwellings. Pedestal/oscillating fans were much more common as they were used in around 60% (53 out of 89) dwellings. Where fans existed, they were switched on for 2.5 hours on a typical day and for 5.1 hours on a hot day on average. External shading devices are also uncommon; whilst the windows in almost all dwellings had some form of internal blinds or curtains, other types of shading, such as external shutters, awnings, overhangs, low emissivity glazing or vegetation were found in only 5 dwellings. As shown in Figure 7, internal blinds or curtains are used for solar protection and/or privacy by the majority of householders on summer days although it is worth noting that around one fourth of respondents do not tend to use them even on very warm days.

As part of the questionnaire survey, the occupants were asked to report on their ventilation habits on typical and very warm days. Figure 8 summarises the main drivers for opening windows in the surveyed households, in conjunction with parameters that might have hindered the use of natural ventilation. More than one third of participants typically open windows when cooking and more than half when bathing or showering (57 and 51 out of 89 respondents, respectively). The need for fresh air was shown to be the main driver for window opening (85%, 76 out of 89 respondents). Importantly, a little less than half of householders (41 out of 89) reported that high indoor temperatures was a key reason for opening windows, even under the current climate. Dwellings where occupants stated that they were led to open windows because of overheating were marginally warmer. Small but statistically significant differences ($p < 0.05$) of 0.8 ^{o}C and 1.3 ^{o}C in average and maximum living room air temperatures during August were observed, respectively; no statistically significant differences were found as regards to their night time thermal performance, however. Other reasons for opening windows included the removal of odours from bedrooms or smoking, moisture from drying clothes indoors and condensation, as well as the maximisation of daylight.

What is revealing in the analysis of the questionnaire results is that, overall, observed window opening behaviour for cooling seems to differ from standard modelling assumptions in theoretical indoor overheating assessment studies. More than half of all respondents (48 out of 89) stated that they were unable to open windows when they needed it due to security reasons, whereas more than one third (33 out of 89) would not open windows due to high external noise levels (Figure 8). A striking result to emerge from this study is that, on a very hot day, more than 1 in 5 respondents (10 out of 88) would not tend to open any windows at night, whilst around 1 in 10 (16 out of 85) would also keep all windows closed during the daytime (Figure 9). The majority of the participants stated that, if it was a very hot day, they would open most windows during the daytime (38%, 33 out of 88 respondents) and keep only one window open during the night (53%, 45 out of 85 respondents). In total, 72% of respondents stated that they open only one or no windows at night, mainly due to security reasons, which potentially highlights the limited potential for night cooling through purge cross ventilation in London urban dwellings.

The summertime thermal performance of the monitored dwellings was examined in relation to the self-reported ventilation behaviour of the occupants in order to assess the effectiveness of daytime rapid ventilation and/or night ventilative cooling. Figure 10 illustrates the cross comparison of the ventilation behaviour questionnaire responses and various metrics of thermal performance calculated for the August month. (Of the 100 dwellings shown in Figure 6, Figure 11 only includes the 89 dwellings for which questionnaire responses were also available.) The relatively small sample size of the study does not allow definitive conclusions to be drawn and no clear pattern emerges in the summertime thermal performance of living rooms in relation to window opening habits. However, there appears to be a clear trend of increasing temperatures with the number of open windows in bedrooms during the night time. There are also small but potentially statistically significant differences in both the mean and maximum night time temperature of bedrooms without purpose-provided natural ventilation and bedrooms where all windows remained open at night (of 1.5 ^{o}C and 2.7 ^{o}C, respectively). Disentagling causes and effects is challenging when dealing with the complex issue of indoor overheating; it is not apparent if the higher temperatures in these bedrooms resulted in occupants opening all windows, or if the ingress of warmer external air did not provide any cooling benefit, thus further increasing indoor overheating.

Stepwise multiple linear regression model

The predictors, regression coefficients and probability statistics of the multiple regression meta-model, which was trained on 85% randomly selected simulations, are presented for the CIBSE DSY weather file in Tables 6 and 7. Interestingly, R^2 values obtained for daytime maxima and night time minima were systematically higher than the ones calculated for daytime minima and night time maxima, respectively.

It has to be kept in mind that the parameter estimates of the model are not directly comparable unless their linked variables are expressed in the same units. Bearing this in mind, the following can be concluded from Table 6 on the daytime thermal performance of the modelled building stock:

(i) Wall and floor insulation levels appear to be positively correlated with peak temperatures, with wall insulation having the largest impact of all measures. This is potentially due to the fact that the insulation was placed internally in the dwelling archetypes with solid walls, which is likely to lead to trapped internal heat gains (Mavrogianni et al., 2012). Roof and window insulation generally appear beneficial for the alleviation of overheating, with window thermal upgrades being more effective. This could be partly explained by the lower solar radiation levels transmitted through double glazed windows compared to single glazed ones.

(ii) Increasing the wall thermal mass appears to stabilise the internal temperatures by increasing the minima, dropping the peaks and decreasing the number of hours above 28 ^{o}C. The thermal admittance of roof elements is negatively correlated with temperature, that is the more heavyweight a roof, the lower the indoor temperatures overall. This is potentially due to the slow solar heat absorption and rerelease rates through the roof as a result of its high thermal inertia.

(iii) The analysis of the parameter estimates of opaque and glazed surface areas offers some intuitive results: Smaller rooms and dwellings with large exposed roof areas tend to overheat more in the daytime. Increasing the external wall area also leads to a rise in overheating risk for all orientations apart from the North facing wall areas, which are not exposed to solar radiation throughout the day. Window areas are generally negatively correlated with indoor temperature, possibly due to the fact that they provide means of daytime ventilation, apart from West facing glazing areas that appear to slightly increase temperature peaks.

Broadly similar relationships appear to hold true for the general impact of insulation, thermal mass and geometry on night time operative temperature averages and peaks (Table 7):

(i) However, the daytime relationships with minima appear inverted: Unsurprisingly, insulating any construction element is expected to increase minimum bedroom temperatures.

(ii) In addition, large wall or window areas in bedrooms are associated with lower minimum and higher maximum temperatures at night, as they increase the room thermal responsiveness.

In both living rooms and bedrooms, temperatures are positively correlated with dwelling floor level, which is in accordance with existing literature indicating that top floor dwellings are more prone to overheating (Vandentorren et al., 2006).

At the next stage, this surrogate model of EnergyPlus was validated against the remaining 15% of the simulations. Simple linear regression was performed to assess the level of fit between actual and predicted values for various overheating metrics derived from the simulated time-series of daytime living room operative temperature of the CIBSE DSY weather file (Figure 11). A relatively good agreement between the EnergyPlus and its meta-model has been achieved, with the latter being better at replicating maximum values ($R^2 = 0.7633$, $p < 0.0001$). Although a certain level of scattering is present in all plots, the regression of minimum temperatures reveals distinct clusters of data, potentially representing groups of dwellings with similar thermal and ventilation behaviour.

Comparison of the meta-model against monitored data

For testing purposes, a modified version of the meta-model that was presented in the previous section was created by replacing operative with dry bulb temperature as the dependent variable. In the first stage, the monitored minimum, mean and maximum daytime living room and night time bedroom dry bulb temperature of the entire monitored housing sample (100 dwellings) in August 2009 was regressed against the corresponding predictions of the meta-model. It is worth noting that the comparison investigates the relationship of the relative positioning of values, i.e. the ranking rather than absolute values. Thus, the R^2 rather than the slope of the best fit line is the most suitable performance assessment criterion. The results of this analysis are summarised in Table 8. It is unclear whether the poor performance of the EnergyPlus meta-model should be attributed to weaknesses of the linear equations per se, limitations of the EnergyPlus algorithm, fabric input data used (both due to inaccuracy during the physical survey data collection process, as well as during the inference of the missing data items) or the impact of occupant ventilation and shading, occupancy patterns and the local urban climate on indoor temperature. With regard to the latter, no correlation was found between mean dry bulb temperature against distance of each dwelling from the centre of London ($R < 0.0$). Although this does not exclude the possibility of modifying effects caused by local microclimates, it does suggest that urban heat island effects are not dominant.

At the second stage, to investigate the potential influencing role of occupant behaviour on temperatures, the surveyed dwellings were divided into sub-sets based on the occupant responses to questions related to the frequency of window opening and operation of shading systems, such as curtains, blinds or external shutters (Table 9 and Figure 12). Both EPC and completed occupant questionnaires were available for 85 participating households. The two dwellings that reported the use of an active cooling systems in the summer of 2009 were removed from the analysis at this stage leaving 83 points of analysis. Rather interestingly, an improvement in R^2 values was obtained only for those dwellings were occupants reported a behaviour that was in line with the modelling assumptions, namely that they kept 'all windows open during the daytime' on a very hot day in summer (16%, 14 out of 83 homes) and had curtains or blinds drawn 'none of the time' on a typical summer day (26%, 23 out of 83 homes). The strongest relationship was observed for monitored and modelled minimum temperature in dwellings with all windows open ($R^2 = 0.5757$, $p = 0.003$). Importantly, nevertheless, in the majority of the other sub-sets, R was significantly lower.

Discussion

Study implications

This paper discussed the creation of a multiple linear regression meta-model based on a large number of EnergyPlus simulations. The results of this validation were encouraging and it was shown that the meta-model can broadly replicate the simulation output. The model predictions were then also compared to monitored data obtained from a set of London homes in summer 2009.

The results of the study are significant in at least five major respects. First, it was found that even though the summer of 2009 was rather mild, excess temperatures above established overheating thresholds occurred in a large number of living rooms and, in particular, bedrooms. The existing housing stock also currently lacks the passive cooling strategies necessary to mitigate overheating and the constraints of living in an urban environment (noise, pollution, security concerns) limit the potential to cool rooms through ventilation means. This suggests that London dwellings are likely to experience major overheating problems in the future, as a result of climate change and urban warming trends. The integration of climate resilience strategies into building design and retrofit hence needs to become a priority for architects, engineers, developers and retrofit providers.

Second, it was shown that it is generally possible to replicate the predictions of detailed thermal simulation programs through the use of a limited set of key variables/proxies related to the building dimensions and physical properties of the construction materials. High Pearson coefficients of determination of up to R^2 = 0.7633 were achieved for regression of values of maximum daytime temperature obtained from actual

EnergyPlus simulations and the linear meta-model of EnergyPlus. The meta-model was found to perform better when attempting to replicate maxima rather than minima. This could potentially be explained by the fact that the mean radiant component of peak operative temperature is highly dependent on the building fabric properties. The maximum temperature distribution is also characterised by a wider spread across the stock, i.e. a larger variation to be explained by individual differences across the dwelling variants. This is of particular relevance to researchers and practitioners who aim to develop simplified, quick-to-run indoor overheating assessment tools. Such tools, when applied at the building stock level and embedded in GIS mapping platforms, could become invaluable in the co-ordination of efforts between public health and urban planning departments, which is essential for the successful mitigation of urban heat risk (Fernandez Milan & Creutzig, 2015).

It was also demonstrated that individual building fabric characteristics are significant determinant factors for indoor overheating levels. In other words, if dwellings are exposed to the same external weather conditions and operated in the same way by their occupants, features such as geometry, thermal insulation and thermal mass levels of the building fabric are able to describe a large proportion of the variance in their thermal behaviour. As discussed previously in other studies (Oikonomou et al., 2012), this finding is particularly important to building designers and retrofit providers, as well as planners, who seek to identify the most efficient course of action to minimise urban heat risk.

Another key finding of this study was that occupant behaviour is a critical factor for indoor overheating. Significant differences were observed between indoor temperatures predicted by the meta-model and field monitored temperature data collected from 100 London homes during the summer of 2009. Arguably, there are many possible explanations for the observed discrepancy, including local microclimatic variations, epistemic uncertainties in the initial EnergyPlus simulations on which the multiple regression equations were based, as well as the high level of uncertainty in the fabric input data used. However, a factor that appears to alter results to a certain extent was self-reported occupant ventilation and shading habits. Although no agreement between modelled and monitored indoor overheating risk rankings was found across the entire surveyed stock, a statistically significant medium strong correlation was reported for the sub-set of dwellings with self-reported occupant ventilation and shading behaviour similar to the settings of the original EnergyPlus simulations. The samples are too small to draw any definitive conclusions, but this finding is clearly an indication of the potential significant modifying effect of behaviour on indoor overheating risk, which has been shown in other studies (Mavrogianni et al., 2014). This suggests that although building fabric characteristics are likely to explain a large proportion of the variance in overheating risk across the building stock, risk levels could potentially be significantly altered by individual behaviour.

Last but not least, an important finding is that the analysis of the questionnaire survey indicates that people in urban environments behave in a considerably different way to that assumed not only by standard indoor overheating modelling studies but also by the recommendations of policy documents that aim to protect the UK population from adverse heat-related health effects. For instance, Public Health England's *Heatwave Plan of England* (PHE, 2015) suggests that windows that are exposed to the sun remain closed during the day and night ventilation occurs when the external temperature has dropped. However, a significant proportion of Londoners interviewed in this study stated that opening windows at night was not an option even when indoor temperatures were uncomfortable due to security and noise reasons. The *Heatwave Plan* also recommends the use of curtains to block solar gains, but their use is also limited; the use of alternative, more effective shading options, such as external shutters (Gupta & Gregg, 2012), was also very rare in the participating dwellings. It is recommended that public health policymakers take these issues into account when designing best-practice guidance for urban areas.

Study limitations and suggestions for future research

Indoor overheating in housing is a complex phenomenon with multiple confounding factors. There are a number of epistemic uncertainties in the development of the EnergyPlus meta-model, such as inherent limitations of the core calculation engine used (in the specific case, of the EnergyPlus thermal modelling software and its simplification into multiple linear regression equations); and errors due to the lack of building stock information. EnergyPlus, as is the case with any building physics model, can only be expected to function as an approximation to reality. Testing of the underlying physics algorithms and constant validation against real world monitored data are essential tools for the refinement of thermal performance models. It is important to bear in mind, however, that there will always be a trade-off between the level of output accuracy and the amount of input required to run a simulation. A certain amount of error will hence be pertinent in modelling work based on reduced data, such as GIS-based building stock models.

Similarly, the multiple linear regression approach is characterised by significant limitations. Summarising the linkage between simulation inputs and outputs by a fitted linear relationship is bound to lead to loss of variation in results. The markers produced by equations with very low R^2 should be, therefore, treated with caution. Additionally, reducing the entire set of EnergyPlus input items to only a few key variables forms a major assumption of uniformity across the modelled stock with regard to secondary variables (e.g. all dwellings were modelled with exhaust fans). It could be argued, however, that this simplified surrogate model of EnergyPlus aims to only flag up ‘hot spots’ across the city and that detailed simulation models could be produced later for individual buildings within these identified high-risk areas.

Furthermore, the selection of the CIBSE single-temperature threshold exceedance overheating criteria to form the basis of the dependent variables of the regression model could be debated. Although the use of the adaptive thermal comfort criterion was initially examined (CIBSE, 2013), it was concluded that such a metric would be more appropriate for an occupant exposure risk model rather than a building-focused tool.

Another major source of uncertainty lies in the inference methods used to impute missing building fabric characteristics. Estimating unknowns (e.g. glazing areas, wall construction types, insulation levels etc.) as a function of known attributes will always be associated with a significant level of error risk. In turn, this depends on the quality of the data used to build these logical assumptions. In this particular case, the representativeness of the stock of the EHS or the BRE air leakage database is crucial. For instance, it is known that the latter was not the result of random sampling and cannot be, therefore, considered a fully accurate depiction of the construction age-fabric air permeability relationship. In addition, some of the assumptions contained in RdSAP, such as the U-values assigned to solid brick walls, have been found to be unreliable following field studies (Li et al., 2014).

A convenience sample was used in the monitoring and questionnaire survey and, as a result, the socioeconomic characteristics of the participating households fell within a narrow range and, thus, do not form a representative sample of the London population.

Moreover, owing to the volunteering nature of participation, it is highly likely that the participants that responded to the call were energy conscious individuals whose occupant behaviour is significantly different to the norm. One might argue, however, that summer ventilation behaviour does not vary with socioeconomic characteristics as it is not related to fuel consumption, cost and CO_2 emissions. In contrary with the operation of heating systems which may be linked to fuel prices, and given that no auxiliary cooling systems were installed in the majority of the surveyed households, income and socioeconomic status, in general, are not expected to have a significant influence on the ability of a household to combat overheating.

Participants in the monitoring study were not asked to keep detailed occupancy and thermal diaries during the entire monitoring study as it was thought that this might discourage participation. Any investigation of the variation between modelled and monitored data and its association with occupant ventilation behaviour relied on self-reported ventilation behaviour during different times of the day. Currently, there are no large scale datasets that combine detailed monitoring of the indoor environment during the summer period and occupant behaviour in dwellings. A national level housing stock survey of indoor overheating risk needs to be undertaken before the association between indoor heat exposure and human factors is more clearly understood.

An implication of the above notes on uncertainty is that it is not claimed that the meta-model presented in this paper is able to produce absolute indoor temperature predictions. It is suggested, nonetheless, that its output offers a relative ranking of dwellings in the specific case study area based on their propensity to overheat based only on their fabric properties and for a specific set of assumptions. An integrated multivariate energy-comfort-health citywide model with common units is envisaged in the future that will be able to map energy demand, outdoor and indoor thermal comfort, as well as cold- and heat-related health risk vulnerability indices as multiple interlinked layers of information across urban environments within the context of a changing climate.

Conclusions

Existing epidemiological studies tend to focus on the impact of external rather than internal climate on health risk. This work presented the development of a simple model that isolates the contribution of the building fabric on indoor overheating risk and associated health risk. Novel inference GIS-based methods from reduced datasets were applied in order to create a quick ranking prediction meta-model of citywide indoor overheating risk that could be easily applied in the future by epidemiologists and public health policy makers. It has been argued that this GIS-based building sample approach could become of central importance in the future in studies aiming to inform policy at the building stock level, i.e. city or neighbourhood level, due to its time and cost advantages over approaches based on onsite data collection methods. Such an approach lends itself to future citywide energy, comfort or health impact assessment studies. The relevance of this method is supported by the findings of this study. However, whilst it was shown that the meta-model successfully replicates the predictions of a detailed dynamic thermal model, its testing against monitored data demonstrated the importance of occupant behaviour for overheating risk. More building-specific information from the UK building stock, combined with detailed data on occupant behaviour, would help researchers to establish a greater degree of accuracy on modelled outcomes.

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Tables

Table 1. Survey completion rates

Count	%	Survey element
111	100%	participants initially recruited for indoor monitoring
10	9%	participants initially recruited for outdoor monitoring
101	91%	loggers with reliable data from living rooms
99	89%	loggers with reliable data from bedrooms
8	80%	loggers with reliable data from gardens
90	81%	EPC issued
94	85%	EPC survey notes collected
89	80%	questionnaires filled in

Table 2. Construction age and built form characteristics of the modelled dwelling archetypes

Dwelling type code	**Construction age band**	**Built form description**	
H01	1902-1913	Two storey terraced houses with large T	
H02	1914-1945	Two storey terraced houses with small or no T	
H03	1914-1945	Large semi-detached houses	
H04a	1960-1979	Tall purpose shared discrete houses and	ground floor
H04b		maisonettes	mid floor
H04c			top floor
H05	1902-1913	Two storey terraced houses with small or no T	
H06a	1946-1959	Tall purpose shared discrete houses and	ground floor
H06b		maisonettes	mid floor
H06c			top floor
H07a	1980-2008	Tall purpose shared discrete houses and	ground floor
H07b		maisonettes	mid floor
H07c			top floor
H08	1902-1913	Two storey linked and step linked houses	
H09	1914-1945	Bungalows and single storey houses	
H10	1960-1979	Two storey terraced houses with small or no T	
H11a	1960-1979	Three-four storey line built walk up flats and	ground floor
H11b		purpose built mews	mid floor
H11c			top floor
H12a	1914-1945	Three-four storey line built walk up flats and	ground floor
H12b		purpose built mews	mid floor
H12c			top floor
H13	1980-2008	Attached houses with shops below	
H14	1946-1959	Two storey linked and step linked houses	
H15a	1946-1959	Three-four storey line built walk up flats and	ground floor
H15b		purpose built mews	mid floor
H15c			top floor

Table 3. Building fabric characteristics of the modelled dwelling archetypes

Archetype	Retrofit state	U-value (W/m^2K) walls	floor	win-dows	loft	roof	Thermal admittance (W/m^2K) walls	floor	roof
H01	As built	2.10	1.20	4.80	0.40	3.10	4.22	5.45	4.43
	Retrofitted	0.60	0.51	2.00	0.15	3.10	4.35	5.46	4.43
H02	As built	2.10	1.20	4.80	0.40	3.10	4.22	5.45	4.43
	Retrofitted	0.60	0.51	2.00	0.15	3.10	4.35	5.46	4.43
H03	As built	2.10	1.20	4.80	0.40	3.10	4.22	5.45	4.43
	Retrofitted	0.60	0.51	2.00	0.15	3.10	4.35	5.46	4.43
H04	As built	1.60	1.20	3.10	0.40	3.10	4.25	5.45	4.43
	Retrofitted	0.50	0.51	2.00	0.15	3.10	4.52	5.46	4.43
H05	As built	2.10	1.20	4.80	0.40	3.10	4.22	5.45	4.43
	Retrofitted	0.60	0.51	2.00	0.15	3.10	4.35	5.46	4.43
H06	As built	2.10	1.20	4.80	0.40	3.10	4.22	5.45	4.43
	Retrofitted	0.60	0.51	2.00	0.15	3.10	4.35	5.46	4.43
H07	As built	0.45	0.45	3.10	0.29	3.10	4.52	5.46	4.43
	Retrofitted	0.35	0.25	2.00	0.15	3.10	4.54	5.46	4.43
H08	As built	2.10	1.20	4.80	0.40	3.10	4.22	5.45	4.43
	Retrofitted	0.60	0.51	2.00	0.15	3.10	4.35	5.46	4.43
H09	As built	2.10	1.20	4.80	-	2.30	4.22	5.45	4.37
	Retrofitted	0.60	0.51	2.00		0.15	4.35	5.46	5.97
H10	As built	1.60	1.20	3.10	0.40	3.10	4.25	5.45	4.43
	Retrofitted	0.50	0.51	2.00	0.15	3.10	4.52	5.46	4.43
H11	As built	1.60	1.20	3.10	-	1.50	4.25	5.45	4.52
	Retrofitted	0.50	0.51	2.00		0.15	4.52	5.46	5.97
H12	As built	2.10	1.20	4.80	-	2.30	4.22	5.45	4.37
	Retrofitted	0.60	0.51	2.00		0.15	4.35	5.46	5.97
H13	As built	0.45	0.45	3.10	0.29	3.10	4.52	5.46	4.43
	Retrofitted	0.35	0.25	2.00	0.15	3.10	4.54	5.46	4.43
H14	As built	2.10	1.20	4.80	0.40	3.10	4.22	5.45	4.43
	Retrofitted	0.60	0.51	2.00	0.15	3.10	4.35	5.46	4.43
H15	As built	2.10	1.20	4.80	-	2.30	4.22	5.45	4.37
	Retrofitted	0.60	0.51	2.00		0.15	4.35	5.46	5.97

Table 4. Combinations of modelled dwelling variants

Dwelling archetypes		Wall insulation		Floor insulation		Windows insulation		Roof/loft insulation		Orientation		Building patterns		Weather files		TOTAL
27	×	2	×	2	×	2	×	2	×	4	×	2	×	1	=	3,456

Table 5. Modelling inputs selected as independent variables in the multiple linear regression analysis

Building descriptors
External wall U-value (W/m^{2}K)
Ground floor U-value (W/m^{2}K)
Windows U-value (W/m^{2}K)
Loft U-value (W/m^{2}K)
Roof U-value (W/m^{2}K)
External wall thermal admittance (W/m^{2}K)
Ground floor thermal admittance (W/m^{2}K)
Roof thermal admittance (W/m^{2}K)
Loft roof thermal admittance (W/m^{2}K)
Loft ceiling thermal admittance (W/m^{2}K)
Air permeability (m^3/m^{2}h @ 50 Pa)
Building height (m)
Living room and bedroom descriptors
Floor level (m)
Net storey height (m)
Ground floor area (m2)
Exposed roof area (m2)
Exposed North facing wall area (m2)
Exposed East facing wall area (m2)
Exposed South facing wall area (m2)
Exposed West facing wall area (m2)
North facing window area (m2)
East facing window area (m2)
South facing window area (m2)
West facing window area (m2)

Table 6. Multiple linear regression analysis of indoor overheating markers for the living room for the June-August period of the Design Summer Year

Dependent variable	**Minimum tempera-ture (°C)**	**Mean tempera-ture (°C)**	**Maximum tempera-ture (°C)**	**Count of occupied hours above 28 °C**
Statistics				
Number of regressors	14	18	17	17
Error degrees of freedom	2,923	2,919	2,920	2,920
Coefficient of determination (R^2)	0.572	0.616	0.765	0.710
Root mean squared error	0.455	0.475	1.197	23.934
Parameter estimates*				
Intercept	9.631	25.254	50.309	345.988
External wall U-value (W/m^2K)	0.230	-0.322	-1.101	-18.053
Floor U-value (W/m^2K)	-0.203	-0.127	-	-
Window U-value (W/m^2K)	-	0.131	0.533	8.582
Loft/roof U-value (W/m^2K)	0.027	0.071	0.460	13.160
External wall thermal admittance (W/m^2K)	2.421	-0.570	-5.618	-79.765
Roof thermal admittance (W/m^2K)	-0.208	-0.309	-0.726	-13.760
Dwelling floor level (m)	-0.011	0.060	0.228	2.846
Living room net storey height (m)	-1.667	0.585	2.292	29.739
Living room floor area (m)	-0.022	-0.020	-0.015	-0.309
Living room exposed roof area (m)	0.065	0.034	0.042	2.099
Living room exposed North facing wall area (m)	-0.011	-0.037	-0.032	-0.742
Living room exposed East facing wall area (m)	-	0.017	0.063	0.662
Living room exposed South facing wall area (m)	-	0.024	0.107	1.603
Living room exposed West facing wall area (m)	-	0.018	0.117	1.231
Living room North facing window area (m)	-0.063	-0.054	-0.049	-1.423
Living room East facing window area (m)	-0.073	-0.034	-0.131	-1.327
Living room South facing window area (m)	-0.071	-0.100	-0.168	-2.813
Living room West facing window area (m)	-0.049	-0.043	0.302	3.131

*Significance levels $p < 0.15$ for all parameter estimates.

Table 7. Multiple linear regression analysis of indoor overheating markers for the bedroom for the June-August period of the Design Summer Year

Dependent variable	**Minimum tempera-ture (°C)**	**Mean tempera-ture (°C)**	**Maximum tempera-ture (°C)**	**Count of occupied hours above 26 °C**
Statistics				
Number of regressors	18	16	16	15
Error degrees of freedom	2,919	2,921	2,921	2,922
Coefficient of determination (R^2)	0.648	0.496	0.631	0.505
Root mean squared error	0.478	0.418	1.131	61.19
Parameter estimates*				
Intercept	18.277	25.52	43.346	507.432
External wall U-value (W/m^2K)	-0.515	-0.380	-0.785	-39.753
Floor U-value (W/m^2K)	-0.050	-0.079	-	-6.706
Window U-value (W/m^2K)	-0.116	0.063	0.384	14.308
Loft/roof U-value (W/m^2K)	-0.120	0.090	0.541	23.435
External wall thermal admittance (W/m^2K)	-0.421	-1.192	-4.609	-179.515
Roof thermal admittance (W/m^2K)	0.298	-0.088	-0.381	-16.372
Dwelling floor level (m)	0.013	0.101	0.247	13.764
Bedroom net storey height (m)	0.982	1.310	1.934	150.525
Bedroom floor area (m)	0.004	0.022	0.087	3.173
Bedroom exposed roof area (m)	-0.064	-0.038	-	-3.859
Bedroom exposed North facing wall area (m)	-0.038	-	-	1.800
Bedroom exposed East facing wall area (m)	-0.067	-0.007	0.058	1.380
Bedroom exposed South facing wall area (m)	-0.031	-	-	-
Bedroom exposed West facing wall area (m)	-0.029	0.024	0.094	4.005
Bedroom North facing window area (m)	-0.104	-0.193	-	-19.821
Bedroom East facing window area (m)	-	-0.035	0.203	-
Bedroom South facing window area (m)	-0.184	-0.136	0.276	-7.287
Bedroom West facing window area (m)	-0.156	-0.099	0.239	-

*Significance levels p < 0.15 for all parameter estimates.

Table 8. Comparison of modelled vs. monitored indoor overheating rankings for all surveyed dwellings (daytime living room and night time bedroom dry bulb temperature)

Dry bulb temperature		**R^2 between meta-model predictions and monitored data**
Daytime (living room, 8 am to 8 pm)	minimum	0.0774
	mean	0.1156
	maximum	0.1084
Night time (bedroom, 8 pm to 8 am)	minimum	0.0014
	mean	0.0005
	maximum	0.0127

Table 9. Comparison of modelled vs. monitored indoor overheating rankings for a sub-set of surveyed dwellings (daytime living room dry bulb temperature)

Dry bulb temperature		**R^2 between meta-model predictions and monitored data**	
		Dwellings with all windows open	Dwellings with no shading
Daytime (living room, 8 am to 8 pm)	minimum	0.5757	0.3038
	mean	0.2762	0.3241
	maximum	0.1828	0.1654

Appendix

(Part of the questionnaire)

1. Use of Cooling and Heating Systems

The first series of questions are about cooling and heating systems. Your answers will help us understand how you use energy to cool or heat your home.

1.1 *Are there any rooms where you had the central heating on during the monitoring period (June to September)?*

- ☐ Yes → Please specify approximate dates
- ☐ No → (Skip to 1.3)

1.2 *Which rooms were these?*

- ☐ 1. Main Living Room
- ☐ 2. 2nd Living / Dining Room
- ☐ 3. 3rd Living / Dining Room
- ☐ 4. 4th Living / Dining room
- ☐ 5. Conservatory
- ☐ 6. Kitchen
- ☐ 7. Other room for cooking
- ☐ 8. Main Bedroom
- ☐ 9. 2nd Bedroom
- ☐ 10. 3rd Bedroom
- ☐ 11. 4th Bedroom
- ☐ 12. 5th Bedroom
- ☐ 13. Main Bathroom
- ☐ 14. 2nd Bathroom
- ☐ 15. 3rd Bathroom
- ☐ 16. Toilet or WC
- ☐ 17. Main Hallway
- ☐ 18. 2nd Hallway
- ☐ 19. Stairs
- ☐ 20. Landing(s)
- ☐ 21. Other Room, please specify ____________________

1.3 *Was your boiler installed before the end of 1997, between 1998 and 2004 or after 2004?*

- ☐ 1. 1997 or earlier
- ☐ 2. 1998 to 2004
- ☐ 3. 2005 to 2009

1.4 *Does your home have any electric extractor fans or cooker hoods with external vents?*

- ☐ Yes
- ☐ No

1.5 *How many electric extractor fans or cooker hoods are there?*

0..7 ________________

1.6 *How often do you use it (them)?*

- ☐ 1. Every day
- ☐ 2. 5 or 6 days a week
- ☐ 3. 3 or 4 days a week

- ☐ 4. 1 or 2 days a week
- ☐ 5. 1 – 3 times a month
- ☐ 6. Less than once a month
- ☐ 7. No regular frequency, it depends

1.7 ***Is there any air conditioning (cooling) in use in your home?***
(INTERVIEWER INSTRUCTIONS: Please do not include fans)
- ☐ Yes
- ☐ No → (Skip to 1.12)

1.8 ***How many air conditioning units are in use in your home?*** **(MULTICODE OK)**
0..7 ________________ fixed AC units
0..7 ________________ portable AC units
0..7 ________________ portable evaporative coolers
0..7 ________________ other, please specify ________________

1.9 ***During a typical summer, for how many months would the air conditioning (cooling) be in use?***
0..7 ________________

1.10 ***During a typical month when the air conditioning (cooling) is in use, for how many days would the air conditioning (cooling) be in use?***
0..31 ________________

1.11 ***During a typical day when the air conditioning (cooling) is in use, for how many hours would it be turned on?***
0..24 ________________

1.12 ***How many cooling fans do you have in your home?*** **(MULTICODE OK)**
0…7 ________________ ceiling fans
0…7 ________________ oscillating/pedestal fans

1.13 ***During a typical day in summer, for how many hours would the fans be turned on?***
0..24 ________________

1.14 ***During a very hot day in summer, for how many hours would the fans be turned on?***
0..24 ________________

1.15 ***Do you regularly open kitchen windows when cooking?***
- ☐ Yes
- ☐ No

1.16 ***Do you regularly open windows when bathing/showering?***
- ☐ Yes
- ☐ No

1.17 ***What is the main reason for opening windows in summer other than cooking or bathing/showering?*** **(MULTICODE OK)**
- ☐ 1. High indoor temperatures
- ☐ 2. Need for fresh air
- ☐ 3. Other, please specify ____________________________

1.18 ***During a typical day in summer, how often were windows open in your home other than when cooking or bathing/showering?*** **(MULTICODE OK)**
- ☐ 1. Windows never open during the daytime

- ☐ 2. At least one window open during the daytime
- ☐ 3. Most windows open during the daytime
- ☐ 4. All windows open during the daytime
- ☐ 5. Windows never open at night
- ☐ 6. At least one window open at night
- ☐ 7. Most windows open at night
- ☐ 8. All windows open at night

1.19 ***<u>During a very hot day in summer</u>, how many windows were open in your home <u>other than when cooking or bathing/showering</u>?*** **(MULTICODE OK)**

- ☐ 1. Windows never open during the daytime
- ☐ 2. At least one window open during the daytime
- ☐ 3. Most windows open during the daytime
- ☐ 4. All windows open during the daytime
- ☐ 5. Windows never open at night
- ☐ 6. At least one window open at night
- ☐ 7. Most windows open at night
- ☐ 8. All windows open at night

1.20 ***Did any of the following prevent you from opening windows when you wanted to?*** **(MULTICODE OK)**

- ☐ 1. Security issues
- ☐ 2. External noise
- ☐ 3. External air pollution
- ☐ 4. High external air temperatures
- ☐ 5. Other, please specify _______________

1.21 ***Is it possible to close off the living room from neighbouring rooms by closing a door or doors?***

☐ 1. Yes, from all neighbouring rooms
☐ 2. Yes, from some neighbouring rooms
☐ 3. No

HELPSCREEN: The "living" room is that which is used regularly by the family for watching TV etc. Neighbouring rooms include stairs, hallways, etc.

1.22 ***<u>During a typical day in summer</u>, how often did you leave the internal doors open?***

- ☐ 1. All of the time
- ☐ 2. Most of the time
- ☐ 3. About half of the time
- ☐ 4. Some of the time
- ☐ 0. None of the time

1.23 ***<u>During a very hot day in summer</u>, how often did you leave the internal doors open?***

- ☐ 1. All of the time
- ☐ 2. Most of the time
- ☐ 3. About half of the time
- ☐ 4. Some of the time
- ☐ 0. None of the time

1.24 ***Do you have any shading systems installed in your home?*** **(MULTICODE OK)**

- ☐ 1. Internal blinds or curtains
- ☐ 2. External blinds or awnings
- ☐ 3. Low-e coated glazing
- ☐ 4. Other, please specify _______________

1.25 *<u>During a typical day in summer</u>, how often did you draw the internal curtains/blinds during the <u>daytime</u>?*

- ☐ 1. All of the time
- ☐ 2. Most of the time
- ☐ 3. About half of the time
- ☐ 4. Some of the time
- ☐ 0. None of the time

1.26 *<u>During a very hot day in summer</u>, how often did you draw the internal curtains/blinds during the <u>daytime</u>?*

- ☐ 1. All of the time
- ☐ 2. Most of the time
- ☐ 3. About half of the time
- ☐ 4. Some of the time
- ☐ 0. None of the time