Building Simulation

Thermal responses of built forms on existing near-extreme summer weather data

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Thermal responses of built forms on existing near-extreme summer weather data

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Abstract:

There have been a number of attempts in the past to define 'near extreme' weather for facilitating overheating analysis in free running buildings. The most recently efforts include CIBSE latest release of Design Summer Year (DSY) weather using multiple complete weather years and a newly proposed composite DSY. This research aims to assess how various built forms respond to these new definitions of near extreme weathers. A single zone office was used for parametric studies where 4 sampling sets of building models were employed to examine the thermal responses of dry bulb temperature, global solar radiation & wind speed collectively. London weather data from 1976 to 1995 were used and the overheating assessments were made based on CIBSE Guide A & BS EN 15251. The research discovers that solar radiation and wind both influence the predicted indoor warmth with solar radiation has obvious stronger impacts than wind. No perfect correlation was found from observation and Spearman's rank order analysis on the ranks between the weather warmth and the predicted indoor warmth. The ranks made using multiple weather parameters show better correlation than some of the dry bulb temperature only metrics. The research also discovers that the Test Reference Year weather behaves warmer than expected. It is found that no single complete year can always represent near-extreme for various built forms and there is no evidence a composite DSY is better statistically. These findings support the notion of using multiple complete warm weather years for overheating assessments.

Keywords:

Design Summer Year, Test Reference Year; Overheating in buildings, EnergyPlus, Parametric study

1. Introduction

In assessing potential overheating in free running buildings, near-extreme weather data were often used. The methods for generating these standardized weather datasets vary but essentially fall within two main categories: either using 'a complete weather year' or using 'a composite weather year'. The complete weather year method was used by the Charted Institution of Building Services Engineers (CIBSE) since early 2000 when the Design Summer Year weather data were released for three sites (London, Manchester & Edinburgh) in the UK (CIBSE Guide J 2002). Later release included 14 cities (16 sites) in total using the same selection criteria – the third warmest year among a 20 year source weather datasets, or the mid-year of the upper quartile if more than 20 years (Levermore & Parkinson 2006). The warmth of a weather year was judged by the average Dry Bulb Temperature (DBT) April to September. The appropriateness of this averaged DBT method was criticized on the fact that at some locations in the UK the predicted indoor warmth using DSY is cooler than its corresponding Test Reference Year (TRY) which represents a typical weather (averaged condition) among the same source weather years (CIBSE TM48 2009; Nicol et al 2009; Smith & Hanby 2012). A detailed analysis on this averaged DBT method discovered a number of issues which could cause the chosen DSY less likely being representative as a near-extreme weather (Jentsch et al 2014). The latest release of CIBSE weather data in early 2016 (Virk & Eames 2016) was following the updated method discussed in TM49 – Design Summer Years for London (CIBSE TM49 2014). TM49 uses a definition called "weighted cooling degree hours (WCDH)" to judge the outdoor warmth. And as a result three complete weather years were selected from a much larger source weather datasets (1950 to 2006). The three complete weather years are intended to represent: inner urban (1976 – a year *with a long period of persistent warmth*), rural (2003 – a year with *a more intense single warm spell*) and intermediate urban & sub-urban (1989 – *a moderately warm summer*). WCDH is based on adaptive comfort temperature (CIBSE Guide A 2006; BS EN 15251 2007), and it is closely related to the likelihood of thermal discomfort (Smith & Hanby 2012). However, this DBT only selection method and the 'conceptual free running building' analogy used in TM49 can be problematic in practices as argued in recent research (Jentsch et al 2015; Ji et al 2016): other weather parameters such as solar radiation and wind should also be included in selecting DSY; assuming operative temperature is the same as outdoor temperature for the 'conceptual building' could be unrealistic.

The composite year method was often used for generating typical weather data, for example, CIBSE Test Reference Year is using Finkelstein-Schafer (FS) statistical method to choose the most representative months from source weather data and combine the chosen 12 months as a full year (Finkelstein & Schafer 1971). Similar approach was used in the US to generate Typical Meteorological Year (TMY) datasets (Wilcox & Marion 2008; Oko & Ogoloma 2011). For near-extreme weather year consideration, the composite year near-extreme weather can either be the combination of 12 near-extreme months as a 'warm reference year' (Frank 2005), or the hottest summer combined with the coldest winter as an 'extreme meteorological year' (Ferrari & Lee 2008), or a set of near-extreme summer data on top of its corresponding TRYs, these are thoroughly reviewed by Jentsch et al (2015). For CIBSE near-extreme weather data, the DSY, it has been always a complete year as discussed above. The work of Ji et al (2016) attempted to propose a new warmth ranking metric (sol-air temperature) which takes into account temperature, solar radiation and wind speed but this metric did not show noticeable improvement in terms of selecting a complete near extreme year compared with other existing metrics. In this particular work a parametric study using five different domestic house types was also carried out and it discovered that no single complete year weather data can always represent near-extreme condition in terms of the predicted indoor warmth. Therefore a composite year may better represent the near-extreme weather. A new sophisticated method was developed by Jentsch et al (2015) following their previous work which discussed the limitation of CIBSE DSYs (Jentsch et al (2014). This latest development accepts the method used to generate TRYs is robust. The proposed near-extreme weather, which is called summer reference year – SRY, is generated by shifting weather parameters during summer period (from April to September) of the existing TRYs. It is therefore a morphed composite near-extreme weather (Jentsch et al 2015). Considering how this new near-extreme weather is generated (October to March unchanged, April to September mathematically adjusted), a SRY will always be consistently warmer than its corresponding TRY, which is clearly illustrated by their benchmark model results.

In the efforts of generating both typical weather year and near-extreme weather year datasets for building simulation applications, various methods have been attempted to judge measured historical weather data in terms of outdoor warmth. These methods range from simple averaged DBT (CIBSE Guide J 2002) to six order polynomial regression TRY adjustment (Jentsch et al 2015), and others (CIBSE TM49 2014; Watkins et al 2011). One aspect that has not been explored is the role of buildings in the assessment of historical weather data. Since the purpose for developing (or selecting) weather data sets is to analyse building's performance, how various built forms respond to weather data is clearly a question in need of answering. For any particular building design in question, it is expected that a warm year should have higher likelihood of causing overheating (in case of free running buildings) or have higher cooling demand (in case of air conditioned buildings).

Some researchers made recommendation on creating standardized weather data without any verification using building models (Levermore & Parkinson 2006; Smith & Hanby 2012; Belcher et al 2005; Eames et al 2011), whereas others attempted to verify their proposals using either a particular building model (Jentsch et al 2008), or simplified benchmark building models (Jetsch et al 2015; Nicol et al 2009). The work of Ji et al (2016) used various built forms derived from five house types to verify the proposed Sol-air parameter alongside other existing ranking metrics. However, with these whole building models (UrbanArea 2012), it was not possible to isolate and assess the contributions of individual weather parameter in terms of predicted indoor warmth.

This research herein attempts to examine how various built forms of a single zone office respond to the existing proposals of near extreme weather conditions. This single zone office model was made in such a way that individual weather parameters such as DBT, GSR and WS can be examined individually or collectively in terms of their contributions to the indoor warmth prediction. Standard near extreme weathers are often used to assess the likelihood of overheating, while overheating happens indoors, therefore it is important to use various built forms to verify whether these data perform as what they are expected to be in terms of indoor warmth prediction.

2. Weather data analysis

In this study, the London historical weather data from 1976 to 1995 were used. The key weather parameters within these source weather years include: global solar irradiation, diffuse solar irradiation, cloud cover, dry-bulb temperature, wet-bulb temperature, atmospheric pressure and wind speed. For free running buildings, dry-bulb temperature (DBT), global solar irradiation (GSR) and wind speed (WS) are thought to have direct influence on indoor operative temperature. Hereinafter, they will be referred as DBT, GSR and WS.

For the purpose of generating standard near extreme weather data, various analyses have been used in assessing the historical weather data. Some analyses were focusing on DBT only (CIBSE Guide J 2002; Smith & Hanby 2012; CIBSE TM49 2014), others considered parameters such as GSR and WS in addition to DBT (Jentsch et al 2015; Ji et al 2016). Here we show some new analyses using Finkelstein-Schafer statistics on DBT, GSR and WS, number of hours and accumulated degree hours on DBT, and peak coincidence probability of DBT-GSR and DBT-WS. The ranking of weather years from these analyses are used to compare the parametric modelling results later.

2.1 Finkelstein-Schafer statistics

Cumulative distribution functions (CDFs) of daily mean weather parameters were often used to select candidate months of a typical weather year. The three parameters used for typical weather year selection are DBT, GSR and WS when generating CIBSE TRYs (Levermore & Parkinson 2006). The most average months were judged by the smallest Finkelstein-Schafer (FS) statistics (the sum of FS for the three parameters with equal weighting) by comparing CDFs of each individual month to the overall CDFs of the whole source weather parameters. By examining the nature of the FS statistic, it may also be used to judge extremes, i.e. the largest departure from the overall statistical average. The probability density functions (PDFs) of DBT, Radiation and Wind speed show different forms, i.e. DBT is more of a normal distribution, while radiation and wind speed data are more close to a Weibull distribution (Figure 1, left). While the FS statistic relies on the CDFs of the concerned parameter, which distribution the data fall within does not matter, as the CDF, by definition, is the percentage possibility of data equal or smaller than that particular datum. Figure 1 (right) shows the CDF of weather parameters for all the source weather years, Dry Bulb Temperature, Global Solar Radiation, and Wind speed. In Figure 1, the overall CDF represents the average, and some extreme years are highlighted.

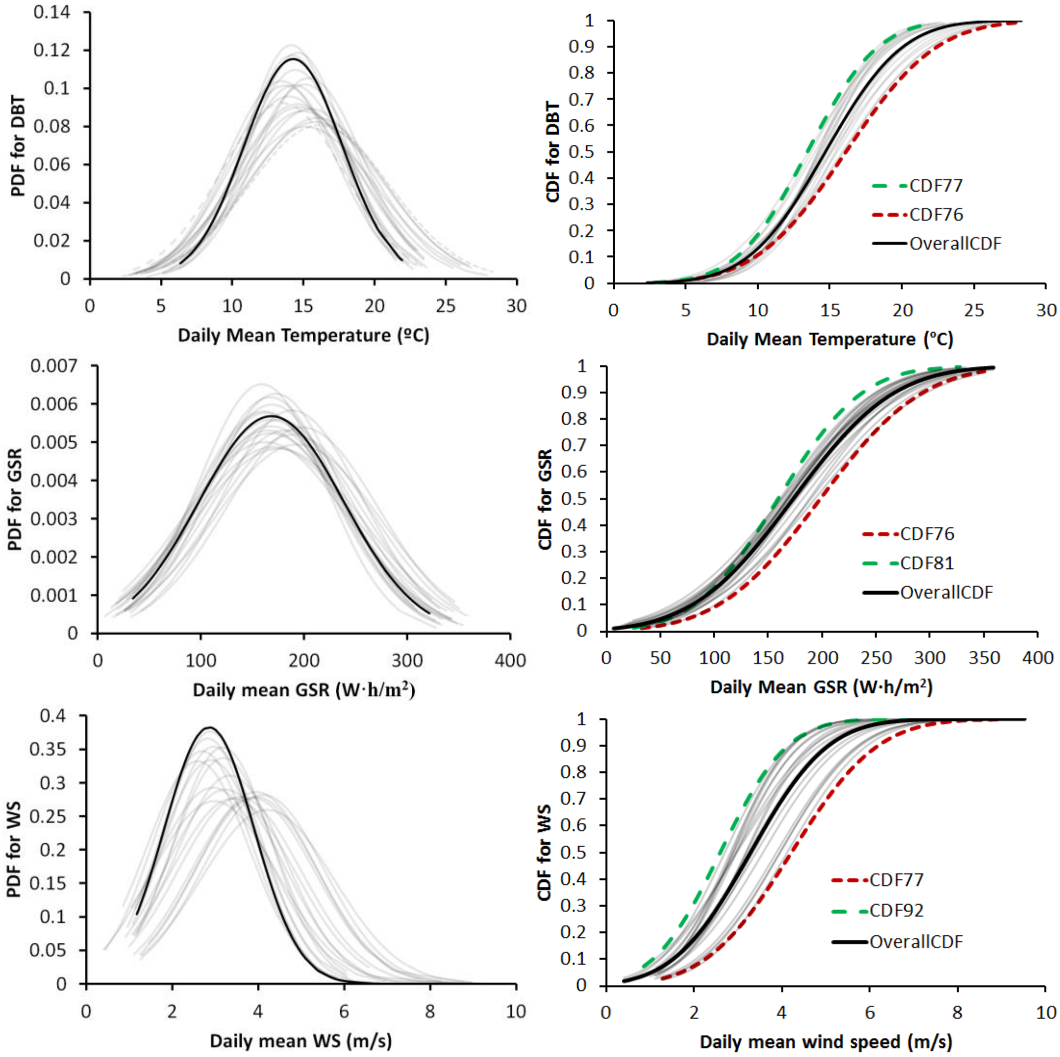

Figure 1 Probability density functions (PDF) and Cumulative distribution functions (CDF) of weather parameters – DBT, GSR & WS

The FS statistics here are to evaluate the accumulated differences between the CDF of each individual year and the CDF of all 20 source weather years, as shown in Eq. 01, where *x* represents weather parameters (DBT, GSR & WS), *N* is the number of days of that month and year, *i* is year number (1976 to 1995), *d* is day, *m* is month, & *y* is year.

$$FS(x) = \sum_{d=1}^{N}\{CDF(d,m,y_i) - CDF(d,m,y_{all})\} \qquad \text{Eq. 01}$$

Graphically, as shown in Figure 1 (right), warmer years (with higher DBT) stay towards the right hand side of the overall CDF, i.e. year L76. Similarly, cooler years stay on the left hand side. Statistically, as shown in Table 1, the FS statistics of the three weather parameters for the 20 years source weather data (from April to September only) can be used to rank source weather years. The ranking in Table 1 can identify the extremes, i.e. for DBT, the 5 warm years are 76, 95, 89, 90 & 92 while the 5 cooler years are 77, 86, 78, 79 & 88. The CDFs for the years in the middle, to some extent, intersect with the overall CDF, so the daily FS has both positive and negative values. Table 1 shows the sum of all the daily FS values.

Table 1 FS statistics for weather parameters DBT, GSR & WS.

FS DBT	15.7	13.9	13.8	9.7	8.2	5.0	4.6	3.4	-0.2	-1.2	-1.4	-3.5	-4.8	-6.5	-7.7	-9.0	-9.0	-13.2	-14.6	-16.5
Year	L76	L95	L89	L90	L92	L83	L82	L94	L84	L91	L93	L87	L81	L80	L85	L88	L79	L78	L86	L77
FS GSR	16.8	13.0	10.7	10.6	5.8	2.3	1.1	-0.5	-2.2	-3.2	-3.3	-3.6	-3.7	-4.0	-4.3	-5.6	-7.1	-7.3	-8.5	-10.3
Year	L76	L89	L90	L95	L84	L83	L94	L82	L92	L91	L80	L85	L86	L93	L79	L78	L77	L87	L88	L81
FS WS	31.9	30.7	24.8	24.7	21.7	10.4	4.4	2.7	-1.8	-3.1	-3.3	-11.6	-11.8	-12.3	-13.9	-15.1	-15.8	-17.4	-22.1	-25.4
Year	L77	L80	L79	L76	L78	L85	L81	L83	L94	L88	L90	L86	L84	L91	L82	L87	L89	L95	L93	L92

2.2 Hours over temperatures

The number of hours over a base temperature can be a good indicator for judging the warmth of weather. A base temperature of 25°C was used to examine the selected DSYs for the 14 cities in the UK (Jentsch et al 2015). TM49 (2014) used 28°C as the base temperature which mirrors its ‘conceptual free running building’ definition by assuming outdoor temperature equals indoor operative temperature, and 28°C is the single overheating criterion of CIBSE Guide A (2006) for free running buildings. The work of Ji et al (2016) used multiple base temperatures (from 21°C to 28°C) to rank source weather years and the ranking was not always consistent. For free running buildings, the built form, operation, incidental heat gains, solar radiation gain and wind condition will all influence the indoor thermal responses of a building. The combination of these factors will cause a ‘difference’ between indoor and outdoor temperature. If this temperature ‘difference’ were known, it would be straightforward to know what the correct base temperature should be. For example, if the indoor and outdoor temperature difference is 6°C, using the CIBSE single temperature criterion (number of hours over 28ºC) the base temperature will be 22ºC and this base temperature will provide an accurate judgement in terms of the warmth ranking of outdoor temperature for that particular design. Practically this temperature ‘difference’ is always unknown and it is never a parallel shift in terms of outdoor and indoor temperature difference. Table 2 shows the ‘number of hours over’ a wide range of temperatures and the ‘accumulated degree hours (adh) over’ for the 20 years source weather data. For base temperature higher than 19°C the year of 1976 has the biggest ‘number of hours over’ numbers, smaller base temperatures show a different story, as in Table 2a, the year 1976 is no longer the warmest when the base temperature is smaller than 18ºC. Table 2b shows the similar shifting.

Table 2a Ranking with 'number of hours over' base temperatures from 15ºC to 30ºC (bottom row is the highest rank)

15°C	16°C	17°C	18°C	19°C	20°C	21°C	22°C	23°C	24°C	25°C	26°C	27°C	28°C	29°C	30°C
L77	L77	L77	L77	L77	L77	L77	L88	L88	L88	L78	L78	L78	L93	L93	L93
L86	L86	L88	L88	L88	L88	L88	L78	L78	L78	L80	L88	L88	L78	L88	L92
L78	L78	L86	L86	L85	L85	L85	L77	L77	L80	L88	L80	L93	L77	L81	L91
L88	L88	L78	L85	L78	L80	L78	L85	L80	L77	L85	L79	L79	L80	L80	L88
L85	L85	L85	L78	L80	L78	L80	L80	L85	L85	L77	L85	L85	L88	L78	L87
L87	L79	L81	L80	L86	L86	L86	L86	L79	L93	L79	L93	L80	L91	L77	L85
L79	L81	L79	L79	L79	L79	L79	L79	L93	L79	L93	L77	L77	L85	L92	L82
L81	L87	L80	L81	L81	L87	L87	L93	L86	L81	L81	L81	L81	L81	L91	L81
L80	L80	L87	L93	L87	L93	L93	L87	L87	L87	L87	L91	L91	L82	L87	L80
L93	L93	L93	L87	L93	L81	L81	L81	L81	L86	L91	L92	L82	L79	L85	L79
L91	L91	TRY	TRY	TRY	TRY	TRY	TRY	L82	L91	L86	L87	L92	L92	L82	L78
TRY	TRY	L91	L84	L82	L82	L82	L82	L91	L82	L82	L82	L87	L87	L79	L77
L84	L84	L84	L91	L91	L91	L91	L92	L92	L92	L92	L86	L86	TRY	L86	TRY
L94	L94	L94	L82	L84	L92	L92	L91	TRY	TRY	TRY	TRY	TRY	L86	TRY	L86
L83	L83	L82	L92	L94	L84	L94	L84	L84	L84	L84	L84	L84	L84	L84	L84
L90	L82	L92	L94	L92	L94	L84	L94	L94	L94	L94	L94	L94	L94	L94	L94
L82	L90	L83	L83	L83	L83	L90	L90	L90	L90	L90	L83	L90	L89	L89	L89
L95	L92	L90	L90	L90	L90	L83	L83	L83	L83	L83	L90	L89	L83	L83	L83
L92	L95	L95	L95	L95	L95	L95	L89	L89	L89	L89	L89	L83	L90	L90	L90
L76	L76	L76	L76	L89	L89	L89	L95	L95	L95	L95	L95	L95	L95	L95	L95
L89	L89	L89	L89	L76	L76	L76	L76	L76	L76	L76	L76	L76	L76	L76	L76

Table 2b Ranking with accumulated degree hours (adh) over base temperatures from 15ºC to 30ºC (bottom row is the highest rank)

15°C	16°C	17°C	18°C	19°C	20°C	21°C	22°C	23°C	24°C	25°C	26°C	27°C	28°C	29°C	30°C
L77	L77	L77	L88	L88	L88	L88	L88	L78	L78	L78	L78	L78	L93	L93	L93
L88	L88	L88	L77	L77	L77	L78	L78	L88	L88	L80	L88	L77	L78	L88	L92
L78	L78	L78	L78	L78	L78	L77	L80	L80	L80	L88	L80	L93	L77	L81	L91
L85	L85	L85	L85	L85	L80	L80	L77	L77	L85	L85	L93	L88	L80	L80	L88
L86	L86	L80	L80	L80	L85	L85	L85	L85	L77	L77	L77	L80	L81	L78	L87
L80	L80	L86	L79	L79	L79	L79	L79	L79	L79	L79	L85	L81	L88	L77	L85
L79	L79	L79	L86	L86	L93	L93	L93	L93	L93	L93	L79	L85	L85	L92	L82
L81	L81	L93	L93	L93	L86	L86	L81	L81	L81	L81	L81	L91	L91	L87	L81
L87	L93	L81	L87	L87	L87	L87	L87	L87	L87	L91	L91	L79	L82	L82	L80
L93	L87	L87	L81	L81	L81	L81	L86	L91	L91	L87	L82	L82	L87	L91	L79
TRY	TRY	TRY	TRY	TRY	L82	L91	L91	L86	L82	L82	L92	L92	L92	L85	L78
L91	L91	L91	L82	L82	L91	L82	L82	L82	L92	L92	L87	L87	L79	L79	L77
L82	L82	L82	L91	L91	TRY	L92	L92	L92	L86	L86	L86	L86	TRY	L86	TRY
L84	L92	L92	L92	L92	L92	TRY	TRY	TRY	TRY	TRY	TRY	TRY	L86	TRY	L86
L92	L84	L84	L84	L84	L84	L84	L84	L84	L84	L84	L84	L84	L84	L84	L84
L94	L94	L94	L94	L94	L94	L94	L94	L94	L94	L94	L94	L94	L94	L94	L94
L83	L83	L83	L83	L83	L83	L83	L83	L83	L83	L89	L89	L89	L89	L89	L89
L90	L90	L90	L90	L90	L90	L90	L90	L90	L89	L83	L83	L83	L83	L83	L83
L95	L89	L89	L89	L89	L89	L89	L89	L89	L90	L90	L90	L90	L90	L95	L95
L89	L95	L95	L95	L95	L95	L95	L95	L95	L95	L95	L95	L95	L95	L90	L90
L76	L76	L76	L76	L76	L76	L76	L76	L76	L76	L76	L76	L76	L76	L76	L76

2.3 Coincidence of peak values

Another factor to consider when judging the likelihood of weather causing overheating in buildings is the coincidence of high DBT, GSR and WS. Some research has shown that the coincidence of warm and sunny days is low, i.e. Chicago weather data (Levermore & Chow 2006) and the projected future (2050) DSY of Manchester (Watkins et al 2011). For London data, we considered the number of coincidence hours when 'DBT and GSR', and 'DBT and WS' are both above their respective 87.5 percentile. The results, after being normalized against the total number of occupied hours (9am - 5pm), are shown in Table 3. Relatively, the coincidence of high temperature and solar radiation does not vary significantly (ranging from 21.5% to 42.3%), while the coincidence of high temperature and high wind speed does vary from 0.8% to 30.8%. Year 1976 has significantly higher peak coincidence between DBT and GSR than that of year 1989 and 1990. On the other hand, the coincidence between the peaks of DBT and WS for 1976 is much lower than 1995 and 1989.

Table 3 Hourly coincidences of GSR and WS with DBT at 87.5 percentile.

GSR %	42.3	40.8	38.5	38.5	36.2	35.4	35.4	34.6	33.1	33.1	33.1	30.8	30.8	29.2	27.7	26.9	25.4	24.6	22.3	21.5
Year	93	92	78	76	86	94	87	77	95	91	79	83	81	88	90	89	80	82	85	84
WS %	30.8	20.8	20.8	19.2	18.5	15.4	15.4	13.1	11.5	10.8	9.2	7.7	7.7	6.9	6.9	5.4	3.1	2.3	0.8	0.8
Year	95	86	84	91	89	93	77	88	87	92	90	78	76	80	79	83	85	94	82	81

3. Methodology

This work uses a parametric thermal simulation model of a free-running office space to evaluate the indoor conditions under different weather, and uses the predicted indoor warmth to verify the selection of near extreme weather years. Three steps are involved in this methodology: creating a parametric model that represents a wide variety of free-running office spaces in the UK; creating a number of sample sets for analyzing the impact of weather parameters, in particular, DBT, GSR and WS; and performing simulations and statistical analysis on predicted indoor warmth.

3.1 Parametric models of single zone offices

Various built forms are represented by a single zone dynamic thermal model with a fixed height of 3 metres, and varying widths and depth between 3 and 6 metres, respectively, to represent a wide range of cellular and open-plan office spaces. Deriving from the four towns survey, such side lit spaces may account for over 45% of all offices (Steadman et al 2000a).

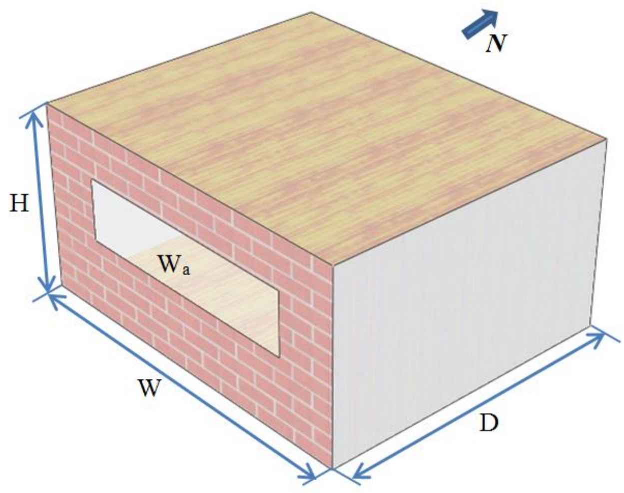

Figure 2 The single zone office model

Figure 2 is the graphic representation of the single zone model. This single zone space is assumed to be taken from a free running office building. Only the façade with a window is exposed to the ambient environment. The rest are either internal roof/ceiling or partition walls. Adiabatic condition is assumed for these internal surfaces. The cellular office is occupied from 9am to 5pm during which ventilation is provided by opening the window. A fixed night time ventilation schedule may be enabled, so that ventilation is employed when internal temperature is above 22°C between 1am and 8am.

The model is created using EnergyPlus. In order to cover the wide variations of office spaces in the UK, parameters including orientation, wall construction, insulation level, window type, window sizes and openable area, internal heat gain, and night ventilation operation are applied to the model. Table 4 shows the parameters of the model, and their variations. The number of all variations resulted from the combinations of different parameter values are in the order of 10^6.

Table 4 Model parameters and their selected values

Parameters	Values	Count
Geometry	Height (m): 3.0	1
	Depth (m): 3.0, 4.0, 5.0, 6.0	4
	Width (m): 3.0, 4.0, 5.0, 6.0	4
Orientation	45°, 90°, 135°, 180°, 225°, 270°, 315°, 360°(0°)	8
Construction type	Light – timbre frame wall and wooden floors Heavy - concrete block wall and cast concrete floors	2
Insulation thickness (mm)	0, 25, 50, 81.4, 100, 150, 200	7
Glazing/wall ratio	0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8	7
Window type	Single pane, double pane, triple pane	3
Window percentage open (for ventilation during occupancy only)	5%, 10%, 20%, 30%, 40%, 50%	6
Internal gains (W/m^2)	20, 30, 40, 50, 60, 70	6
Infiltration (ACH)	0.3	1
Night time ventilation	Allowed, disallowed	2

3.2 Sampling index description

To examine the impact on indoor warmth of naturally ventilated offices from temperature, solar radiation and wind, four sampling scenarios are devised. Sample "i" examines the combined influence of temperature, solar radiation and wind using complete random building models from table 4. Sample "ii" is also using the complete random building models but focuses on the sole influence of temperature, excluding the impact of solar radiation and wind completely. For solar, a spectrum filter applied as a shading device that stops all solar irradiance on the facade is employed. This setting prohibits visible light through the window for the whole simulation period. The internal lighting is scheduled instead of being controlled with lighting sensors therefore ‘no visible light’ does not affect the internal gains of the model. For wind, the weather data is filtered to remove wind speed, so that natural ventilation is only driven by buoyancy.

Sample "iii" examines the maximum possible impact of solar radiation. The random building models are filtered by the ‘maximum window to wall ratio’ and the ‘south east window’ (315°) where it receives the most solar gains during occupancy period compared with other orientations. Influence of wind is also disabled using the same method as in Sample "ii". Sample "iv" assesses the maximum possible wind influence without the presence of solar radiation. By examining London's weather data, the prevailing wind direction is south west. Therefore the random building models have the following fixed conditions: south west facing (45°), maximum window to wall ratio (80%) and maximum openable area (50%), whereas solar is blocked using the shading device. Table 5 is a short summary of the sampling conditions.

Table 5 Descriptions of the samples

Sample index	Descriptions
i	Full parametric building models (complete random sample)
ii	Full parametric building models but the influence of wind and solar is removed
iii	Influence of wind is removed; random models are filtered by maximum glazing and south east facing
iv	Influence of solar is removed; random models are filtered by maximum glazing, maximum opening area, and south west facing

3.3 Overheating criteria and predicted indoor warmth

There are various criteria which can be used to examine the thermal responses of buildings under the influence of environmental conditions. In this study, we selected single overheating criterion as defined in CIBSE Guide A (2006), and the adaptive overheating criteria from BS EN 15251 (2007).

CIBSE single temperature criterion assesses number of hours the indoor operative temperature over 28°C, i.e. for office setting such as this work, overheating is judged if there is more than 1% occupied hours (which corresponds 20 hours over a year) when operative temperature is over 28°C. Adaptive overheating criteria are based on extensive field studies that examine the relationship between indoor comfort conditions and the outdoor environment (Humphreys & Nicol 1998). The limiting comfort temperature T_{comf} defined as BS EN 15251 by:

$$T_{comf} = 0.33Max(10, T_{rm}) + 18.8 \text{ where} \quad \text{Eq. 02}$$

$$T_{rm} = \alpha T_{rm-1} + (1 - \alpha) T_{dm-1} \quad \text{Eq. 03}$$

(T_{rm-1} and T_{dm-1} are the running mean and daily mean temperature previous day)

T_{comf}, as shown in Eq. 02, is no longer a fixed temperature, it varies with the daily running mean temperature (Figure 3). The overheating limiting temperatures in BS EN 15251 were divided into three categories (Category I, II & III) and the upper limit temperatures for these categories are 2°C, 3°C and 4°C, respectively, above the comfort temperature calculated using Eq. 02. Similarly as CIBSE single temperature criterion, the number of hours over these limiting temperatures can be used as a measure of overheating, i.e. number of hours over these upper limiting temperatures should be no more than 3% of total occupied hours (which corresponds around 61 hours) for that specific category the assessment falls within.

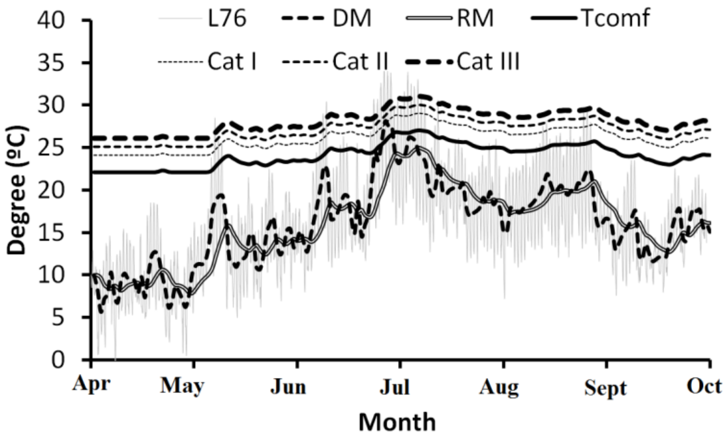

Figure 3 The limiting comfort temperature for the year of 1976 using Eq. 02 for April to September (the upper limits of Category I, II & III would be a parallel shift of T_{comf} by 2, 3 & 4 degree Celsius).

As discussed in CIBSE TM52 (2013), overheating occurrence does not always reflect the actual overheating severity which is the accumulated degree hours over limiting temperatures (either a fixed temperature as CIBSE Guide A or varying ones as BS EN 15251). In this work the accumulated degree hours (adh) is calculated the same as CIBSE TM52.

The predicted indoor warmth (including both overheating occurrence and severity) is ranked for each individual parametric model from the intended sampling (i to iv in Table 5). A criteria index list is made to facilitate the organization of the indoor warmth assessment (as shown in Table 6).

Table 6 Overheating assessment criteria

Index	Description	Unit
c0	Number of hours over 28C during occupancy	[hrs]
c1	adh over 28C during occupancy	[deg.hrs]
c2	BS EN 15251 Category I exceeded during occupancy	[hrs]
c3	adh over Category I during occupancy	[deg.hrs]
c4	BS EN 15251 Category II exceeded during occupancy	[hrs]
c5	adh over Category II during occupancy	[deg.hrs]
c6	BS EN 15251 Category III exceeded during occupancy	[hrs]
c7	adh over Category I during occupancy	[deg.hrs]

3.4 Statistical ranking and sampling method

The method for analysing the data is statistical ranking, i.e. to use statistics on the ranking orders of the results. The statistical ranking process is following the method used in Ji et al (2016):

1) A random sample of simulation cases is generated from the parametric model.
2) Simulations are carried out on the set of sample cases, with each of the 20 London weather years (1976-1995) and the Test Reference Year, respectively.
3) Using the results of each simulated case, the 20 weather years are ranked by the predicted indoor warmth using the overheating criteria defined in Table 6.
4) The ranks of the weather years of each simulation case, according to each criterion, are collated, so that for each weather year, frequency histograms of the ranks are calculated.

Given the number of building parametric models is over 2 million, sampling is necessary to represent the whole model population. In this work, the Latin Hypercube Sampling (LHS) method is used (Stein 1987). With LHS, a sample size of normally 10 times of the number of variables is sufficient for estimating mean values of the population. As a result, 100 random building models for each weather year will be enough for producing reliable estimation of the average overheating profiles. For the analysis where statistical ranking of the weather years is of interest, the relationship between built form characters and their overheating risks under different climatic conditions need to be examined, a larger sample is therefore required. After experimenting, a Quasi-Monte Carlo sample of 2,000 designs for each weather year, generated using the Sobol sequence, was used. Sampling and simulation of the parametric model is managed using the jEPlus tool (Zhang 2009). In total, 42,000 simulations have been performed for the years 1976-1995 plus TRY weather data.

4. Results and discussions

With 4 sets of samples (Table 5), 8 criteria (Table 6) and 20 source weather years (London 1976-1995), in total 32 groups of histograms were produced to illustrate the ranking probability of predicted indoor warmth for each weather year. Figures 4 & 5 are the typical representation of these graphs. Presenting 32 similar graphics like Figures 4

& 5 for all the samples (Table 5) and overheating criteria (Table 6) is deemed unnecessary, therefore the analysis is primarily carried out against those warm weather years of interests: the top 6 warmer years and the TRY (Figures 6 to 10, and 12), with the assumption that one of these weathers must be able to represent the 'near-extreme' weather, i.e. being the third warmest.

4.1 Typical modelling outputs

Figure 4 shows the full parametric sampling results of indoor warmth ranking probabilities against the CIBSE single temperature (number of hours over 28ºC) criterion using the statistical ranking process discussed in section 3.2. The ranking probabilities can be interpreted as the percentage likelihood of appearance on a particular ranking position among all sample cases (i.e. Sample "i" with 2000 random building models) simulated for a particular weather year, i.e. there is 37% chance the year 1989 weather is the warmest (1^{st} position), and the chance of being the 5^{th} warmest position for 1983 is about 46%. In terms of predicted indoor warmth ranking the general observation from Figure 4 is that the outdoor warmth of these weather years defined by various methods (DBT only or multiple parameters) does not seem to be well correlated, for example, the year 1976 has been consistently rated the warmest year, however, with the predicted indoor warmth, this year being warmest has only about 32% chance with the 2000 random building sample.

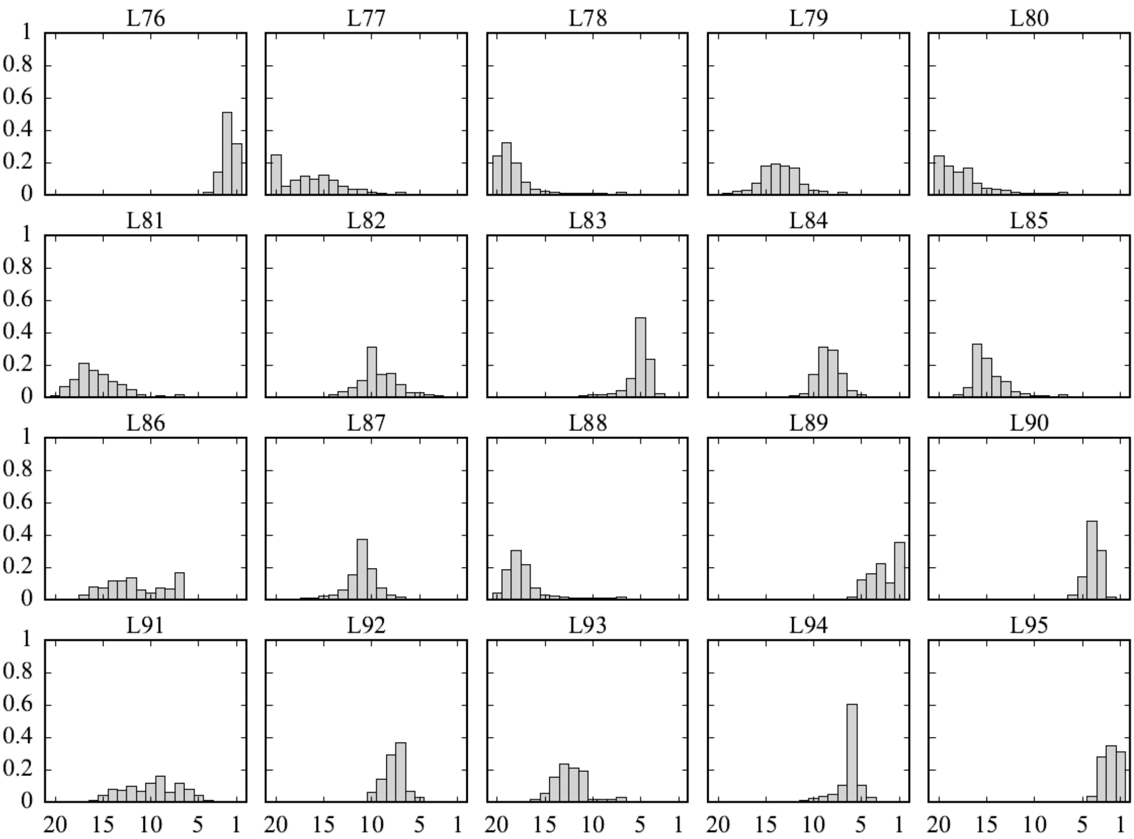

Figure 4 [sample i + c0] – Ranking probability by the number of hours over 28ºC for the single zone office space during occupancy (x-axis is ranking position and y-axis is the probability of being that position for a particular year, same hereafter)

The overheating severity (accumulated degree hours over 28°C) ranking probability in Figure 5 shows better statistical significance for these warm weather years, i.e. the year 1976 has a much higher chance of being the warmest (above 90%), followed by the year 1995 with 84% of being the second warmest. However the year of 1989 does not seem to sustain a strong position. The years of 1983, 1990 and 1994 positioned relatively strong but all the other years do seem to be arbitrary.

The random nature of the predicted indoor warmth ranking probabilities was observed in the previous study of Ji et al (2016) with different types of dwelling models. As reviewed earlier in section 1, these models do not have the flexibility to distinguish the level of contributions from individual weather parameters in terms of predicted indoor warmth.

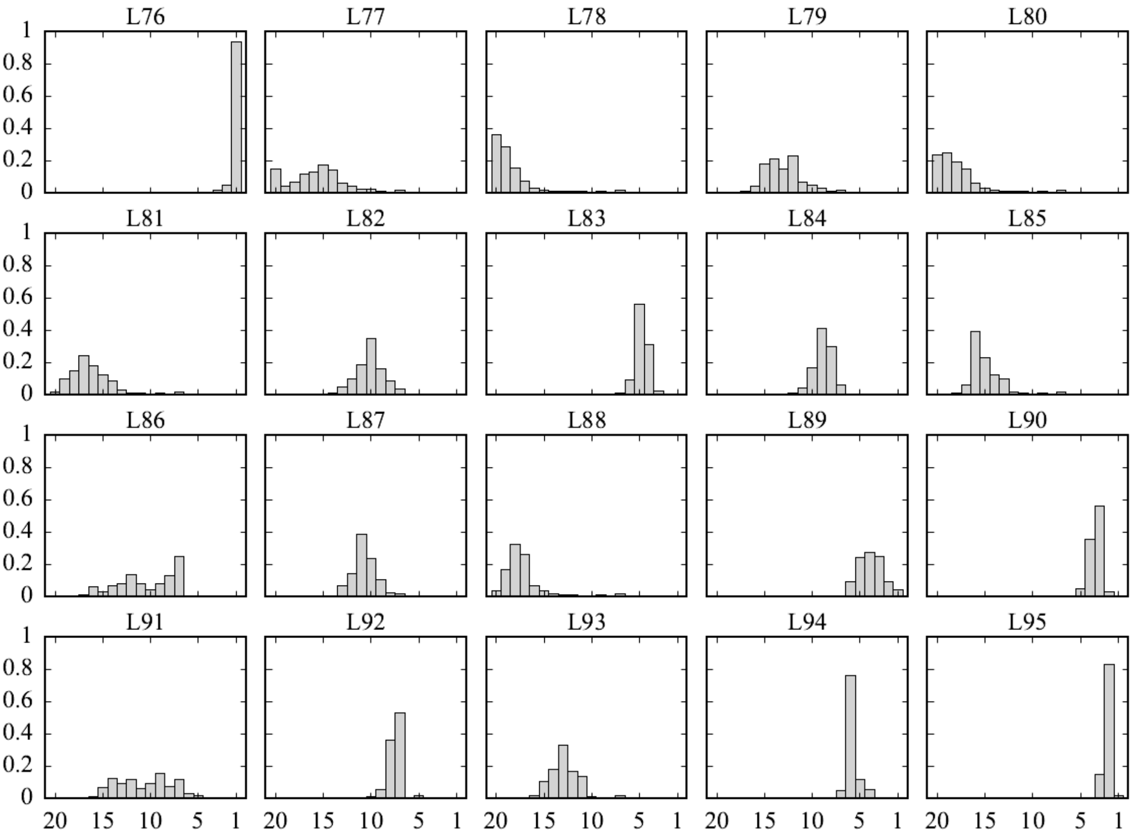

Figure 5 [sample i + c1] – Ranking probability by the number of accumulated degree hours over 28°C for the single zone office space during occupancy.

4.2 Analysis on the warmer years

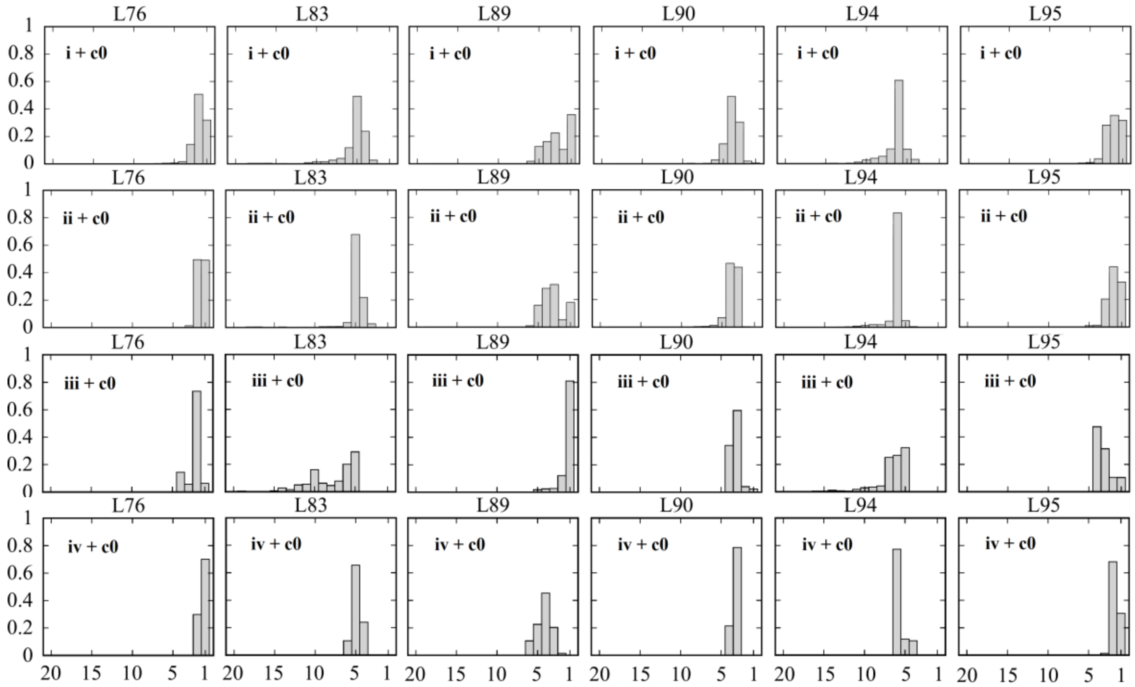

Figure 6 [samples i to iv + c0] Ranking probabilities by the 'number of hours over' 28°C (*ref*: Table 6) for the single zone office space during occupancy.

In Figure 6, i to iv + c0 are the ranking probabilities of the 4 sample sets in Table 5 by the number of hours over 28°C for the single zone office space during occupancy. For the year 1976, the probability of being the warmest in terms predicted indoor warmth is only about 32% for the full parametric Sample "i"; while this probability increases to 48% when excluding influences of both solar radiation and wind condition (Sample "ii" – only dry bulb temperature is the key driver for possible overheating), and to 74% for Sample "iv" where the random models have a maximum possible influence of wind speed and direction on top of Sample "ii". There seems to be a tendency that the probability of being the warmest for 1976 increases when the sampling conditions can lead to less number of hours over the limiting temperature. On the contrary, significantly less probability (6%) of being the warmest for the year 1976 was resulted by Sample "iii" where the solar radiation is maximized as well as removing the influence of the counter factor of wind in terms of predicted indoor warmth. The year 1989 does not seem to sustain a ranking position with statistical significance apart from for sampling iii where its probability of being the warmest is over 80%. For the c0 criterion, it is more likely for the year 1990, 1983 & 1994 to be in the 4th, 5th & 6th ranking position and same is true for the year of 1995 to be in the 2nd ranking position although this is less obvious and with exception of Sample "iii". For all those concerned years Sample "iii" creates a more random order in terms of their ranking probabilities.

Looking at the characteristics of these historical weather files some of the above phenomena may be explained to some extent. The FS statistics of DBT, GSR & WS in Table 1 show that these warm weather years tend to have higher values for DBT & GSR. These higher values should have led to higher predicted indoor warmth which is reflected on their ranking probabilities although their ranking positions vary towards the warmer end. The FS statistics of WS, these six examined weather years have both high (i.e. windy year 1976) and low values (less windy years 1989 & 1995). It is not obvious how this statistic is reflected on Figure 5 broadly but for the case of ‘iv + c0’, low wind condition could have contributed the 30% chance of the year 1995 being the warmest (or in other words, the probability of being the warmest for the year 1976 could be higher than its current stands 70%). In principle, with the single zone office setting and London climate, wind promotes natural ventilation which effectively brings down the indoor temperature (*ref*: Figure 11).

For these six warm years, their hourly coincidences of GSR and WS with DBT at 87.5 percentile (Table 3) do not seem to influence the results explained above significantly. For the coincidence level between GSR and DBT, the changes are small as the range is only from 26.9% (1989) to 38.5% (1976). For the coincidence level of WS and DBT, less windy years (1995 & 1989, *ref*: Table 1) have higher percentage hourly coincidence while the windy year 1976 only has 7.7% coincidence level with DBT during occupancy time. It is therefore unlikely these coincidence levels can significantly alter the predicted indoor warmth.

Sample "iii" random models emphasize the maximum influence of solar radiation and in the meanwhile excluding wind. This would result the highest level of overheating (by the number of hours over limiting temperatures) among the 4 sampling sets i to iv. The year of 1989 has the highest probability of being the warmest (slightly over 80%). This is ‘unusual’ as the year of 1989 has long been used as a near extreme year, never been deemed the warmest by any of the previous analysis (CIBSE Guide J 2002; Jetsch et al 2014; CIBSE TM49 2014; Ji et al 2016). In Table 2a, when varying the base temperatures, the year 1989 has the highest number of hours over 18ºC (as well as small base temperatures, 17 ºC, 16 ºC, 15 ºC, etc). The random models from Sample "iii" have the largest glazing ratio, facing south east (the highest solar gain orientation during occupancy), and no wind. These models may have caused overheating (i.e. indoor operative temperatures are higher than 28ºC or the upper limits of the adaptive comfort criteria) when outdoor temperature is below 18°C and this could be the reason why the year 1989 has the highest probability of being the warmest in terms of the predicted indoor warmth.

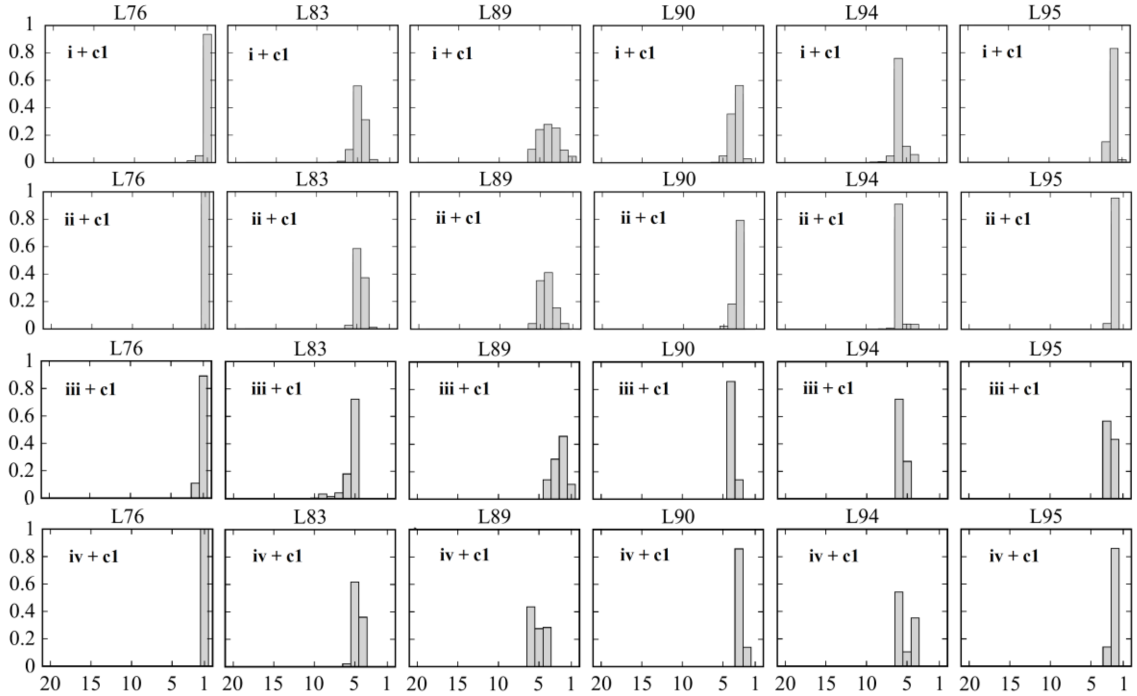

Figure 7 [samples i to iv + c1] Ranking probabilities by both ‘the accumulated degree hours (adh) over’ 28°C (*ref*: Table 6) for the single zone office space during occupancy.

Similarly as observed in Figure 6 above, when examining the overheating severity (accumulated degree hours over 28ºC) in Figure 7, the 4 sampling sets i to iv + c1 show better consistency in terms of predicted indoor warmth ranking probability. The year 1976 is consistently the warmest. Even with Sample "iii", its ranking probability of being the warmest is still as high as 90%. The ranking probability of the year 1989 spreads over 4 or 5 positions in Figure 7. Other years maintain their ranking position well with relatively higher percentage probabilities, in particular for sampling sets i, ii & iv. Unlike the other three sampling sets, the years 1990 & 1995 behave differently for Sample "iii", i.e. the year 1990 stands in the 4th position and the year 1995 has nearly 60% chance in the 3rd position. For all 4 sampling sets in Figure 7, the highest probability ranking position for the years 1983 and 1994 remain unchanged (5th and 6th in ranking). The above observations could be explained by Table 2b where the accumulated degree hours over various base temperatures for these 20 year historical weathers. In Table 2b, the year 1976 is consistently the warmest, while the year 1989 moving from the 5th to the second warmest when the base temperature is 15 ºC. The year 1995 is consistently the second warmest in Table 2b and Figure 7 with the exception of Sample "iii" where the parametric models of this sample group are prone to cause large number of overheating hours, i.e. when outdoor temperature is 15ºC the single zone office space may be already overheated due to maximum possible solar gain, internal heat gains and windless condition. In summary, to some extent Figure 7 does reflect Table 2b well.

Figures 8 to 10 show the ranking probabilities of the six warmer years using the adaptive overheating criteria from BS EN 15251 (Table 6). To a great extent, these ranking probabilities do behave similarly as those using the CIBSE fixed temperature criterion. For example, what has been discussed in Figures 6 & 7 can also be said with these histograms although variations do exist. With ‘the number of hours over limiting temperatures (c2, c4, c6 in Table 6), the year 1976 tends to have higher probability of being the warmest where sampling sets cause less number of hours over, i.e. Samples "ii" & "iv". Sample "iii" is still an ‘outlier’ as the year 1989 has the highest probability of being the warmest within this group of random models. For Sample "i", the histograms of ‘i+c0’ and ‘i+c2’ do look similar in shape although the exact probabilities differ. With the limiting temperature increases from Category I, II & III, there will be less number of hours over for all the sampling sets, it is then expected that the probabilities of being the warmest for the year 1976 will increase which is certainly the case by examining Figures 8 to 10 (i to iv + c2, c4, c6 for the year 1976). The probability of being the second warmest for the year 1995 increases from Category I to III for sampling sets i, ii & iv (i, ii, iv + c2, c4, c6) but it is not the case for Sample "iii" (iii + c2, c4, c6) where the random models in this group causes the maximum possible overheating. With the likely more number of hours over limiting temperatures of the three categories from BS EN 15251, the year 1989 was the warmest based on its ranking probability for this particular sampling set (iii). The years 1990, 1994 and 1983 holds their position (being the 4th, 5th, & 6th warmest) relatively better but do not always show statistical significance, i.e. histograms of i + c2, c4 & c6 for the year 1994, their highest probabilities are only about 20%, 37% & 32% respectively.

For the accumulated degree hours over the limiting temperatures of Category I to III, apart from 1976 which is consistently the warmest for all categories and all 4 sampling sets, the probability ranking position of other years do vary. For Categories I & II, the year 1995 was the second warmest for sampling sets i, ii & iv but for Category III, the case of ‘iv + c7’, it moved to the third warmest place, while the year 1990 (iv + c7) shows high probability of being the second warmest. This may be evidenced by Table 2b where when the outdoor base temperature is 29°C or 30ºC, there is more accumulated degree hours over these limiting temperatures for year of 1990 than the year of 1995. In Table 2a when the base temperature is 29°C or 30ºC the year 1995 is still the in the second warmest place, which explains why the year 1995 has the highest probability of being the second warmest for the case of ‘iv + c6’ when the ‘number of hours over’ criteria are used. To some extent there is alignment between the outdoor warmth defined by Table 2 and the predicted indoor warmth ranking probabilities in Figures 8 to 10, however, there is no strict correlation between any of the discussed outdoor ranking methods (in this work and existing literature such as CIBSE Guide J 2002; Nicol et al 2009; Jetsch et al 2014; CIBSE TM49 2014) and the predicted indoor warmth probability ranking. It is clear that thermal responses of various built forms can be very different against the tested historical weather data in terms of predicted indoor warmth. Judging by the probability ranking of the predicted indoor warmth it is impossible to choose a complete year which can always represent the ‘near extreme’ or the third warmest year.

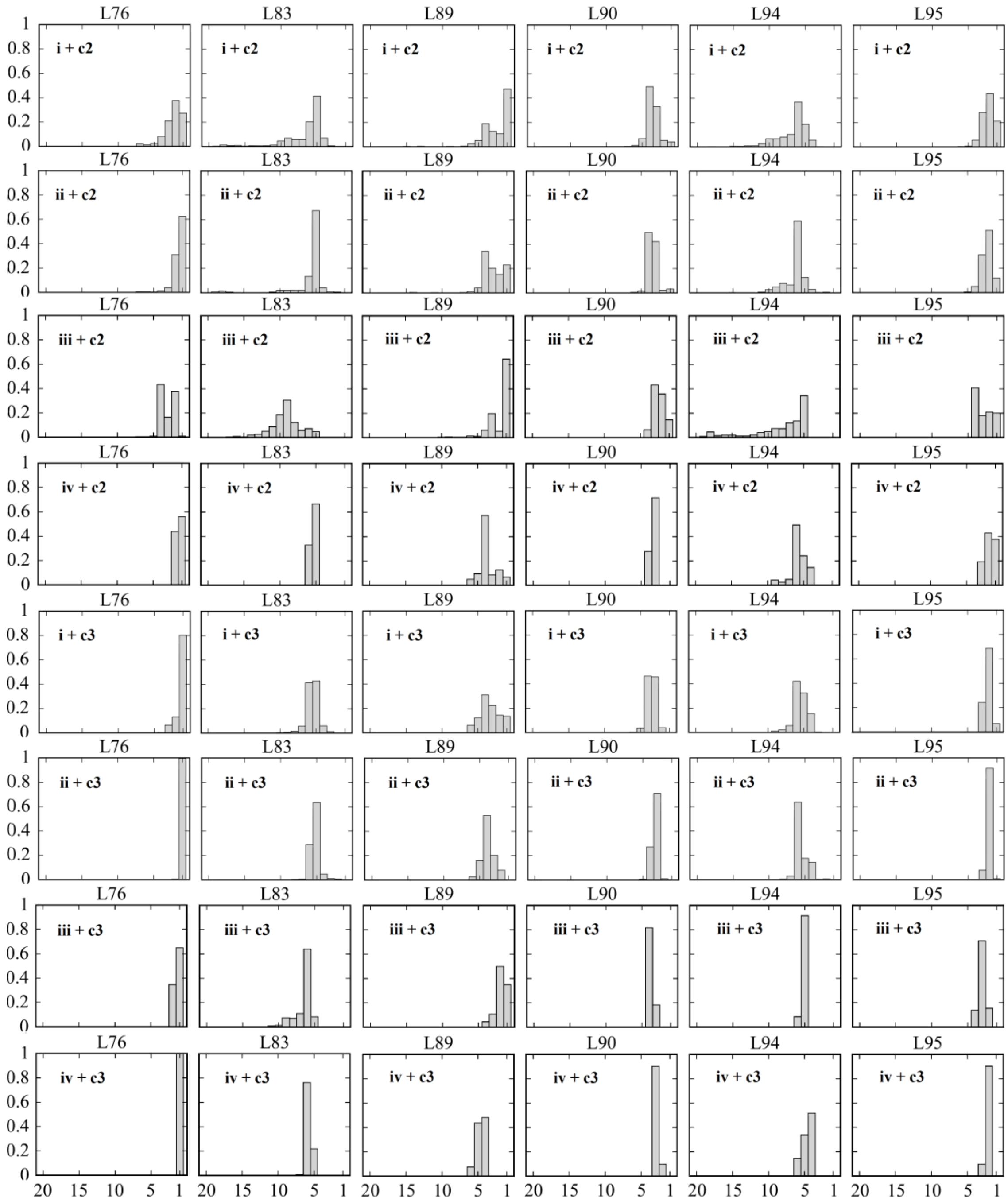

Figure 8 [samples i to iv + c2, c3] Ranking probabilities by both ‘the number of hours over’ and ‘adh over’ BS EN 15251 **Category I** upper limit (*ref*: Table 6) for the single zone office space during occupancy.

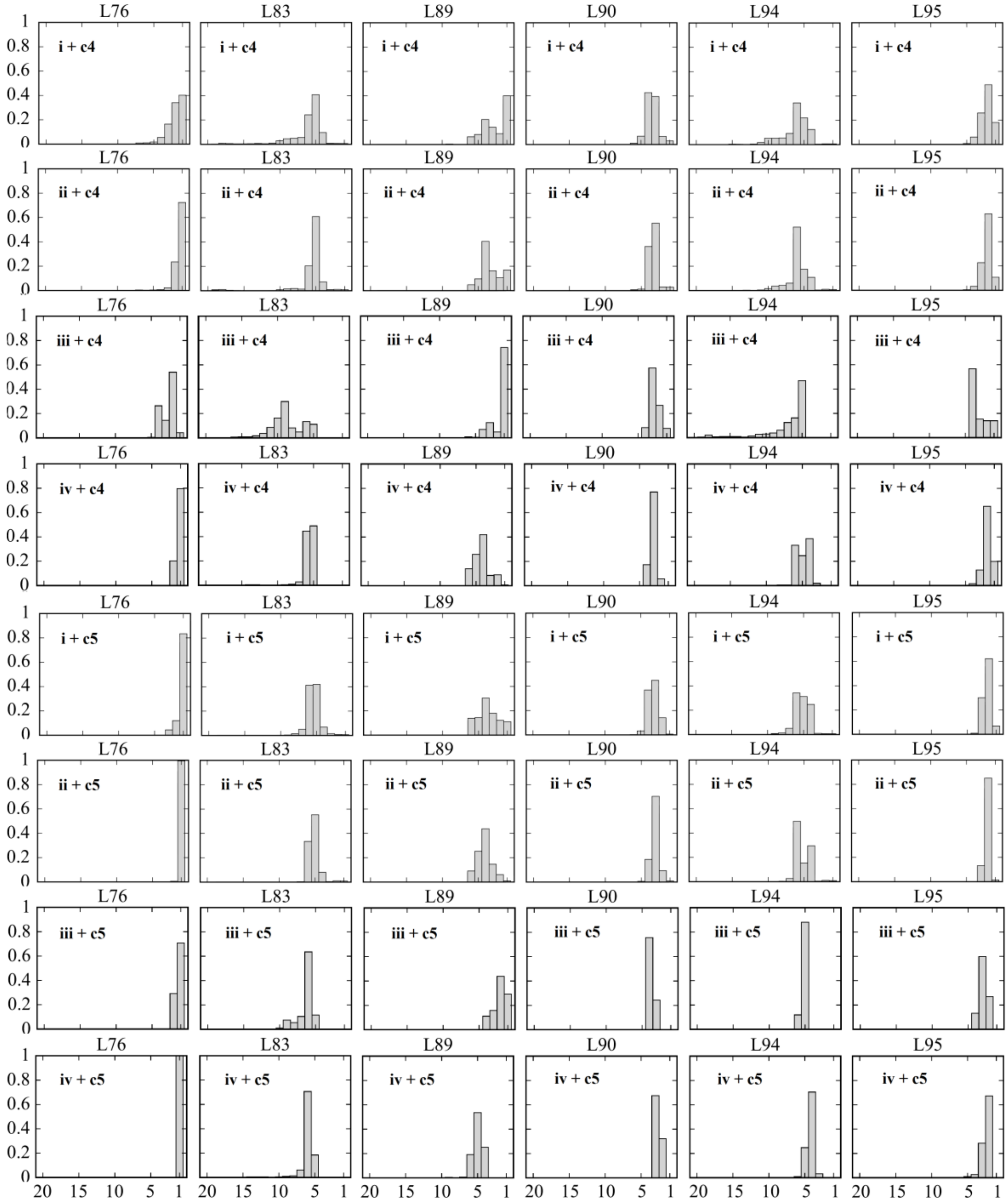

Figure 9 [samples i to iv + c4, c5] Ranking probabilities by both ‘the number of hours over’ and ‘adh over’ BS EN 15251 **Category II** upper limit (*ref*: Table 6) for the single zone office space during occupancy.

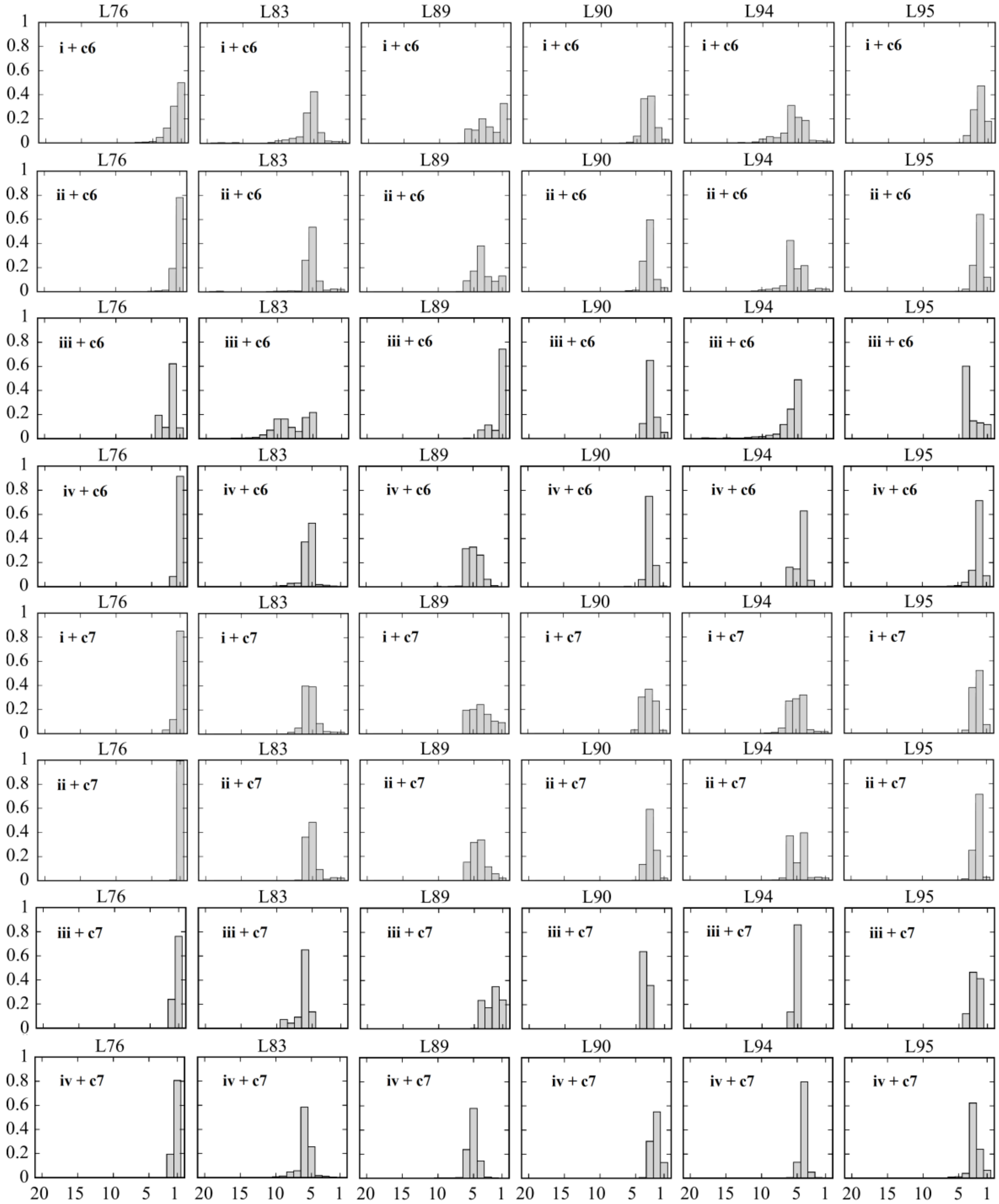

Figure 10 [samples i to iv + c4, c5] Ranking probabilities by both ‘the number of hours over’ and ‘adh over’ BS EN 15251 **Category III** upper limit (*ref*: Table 6) for the single zone office space during occupancy.

4.3 The averaged results

The averaged ‘number of hours over’ 28°C and the upper limiting temperatures from the adaptive Categories I, II & III for each sampling set (Table 5) are shown in Figure 11. Sample "i" is full parametric in terms of built forms while Sample "ii" excluded the influence of solar and wind condition so outdoor DBT becomes the only key driver for the indoor thermal response from weather data (*ref*: section 3.2 and Table 5). In Figure 11, the averaged ‘number of hours over’ for Sample "i" is consistently higher than

Sampling "ii" which indicates that the combined influence of wind and solar tends to increase the level of overheating. Solar gain is a contributing factor for overheating but for free running buildings wind is a counter factor. This increase of overheating level means solar radiation plays a more significant role to push the indoor temperature up than wind which tends to cool the indoor temperature down through ventilation. Although the exact quantity of overheating hours for each individual random model is arbitrary the general trend in average term is obvious. The filter conditions of creating random building models for sampling sets "iii" & "iv" are to maximize the influences of solar and wind individually alongside outdoor DBT. It is evident in Figure 11 that the level of increase in overheating hours for Sample "iii" is higher than the level of decrease in overheating hours for Sample "iv" when using Sample "ii" as a baseline (see table 5). This also confirms the stronger influence on overheating hours from solar than from wind. When examining the averaged ‘accumulated degree hours (adh) over’ in Figure 11, the observation on the relative influences of solar and wind in overheating prediction is the same. For absolute quantities of the averaged adh over 28ºC and adaptive Category I to III limiting temperatures, the year 1989 becomes the second warmest for Sample "iii" which is consistent with Figures 7 to 10. Similarly for the averaged ‘number of hours over’ of Sample "iii" in Figure 11, the year 1989 becomes the warmest (as in Figures 6, 8 to 10).

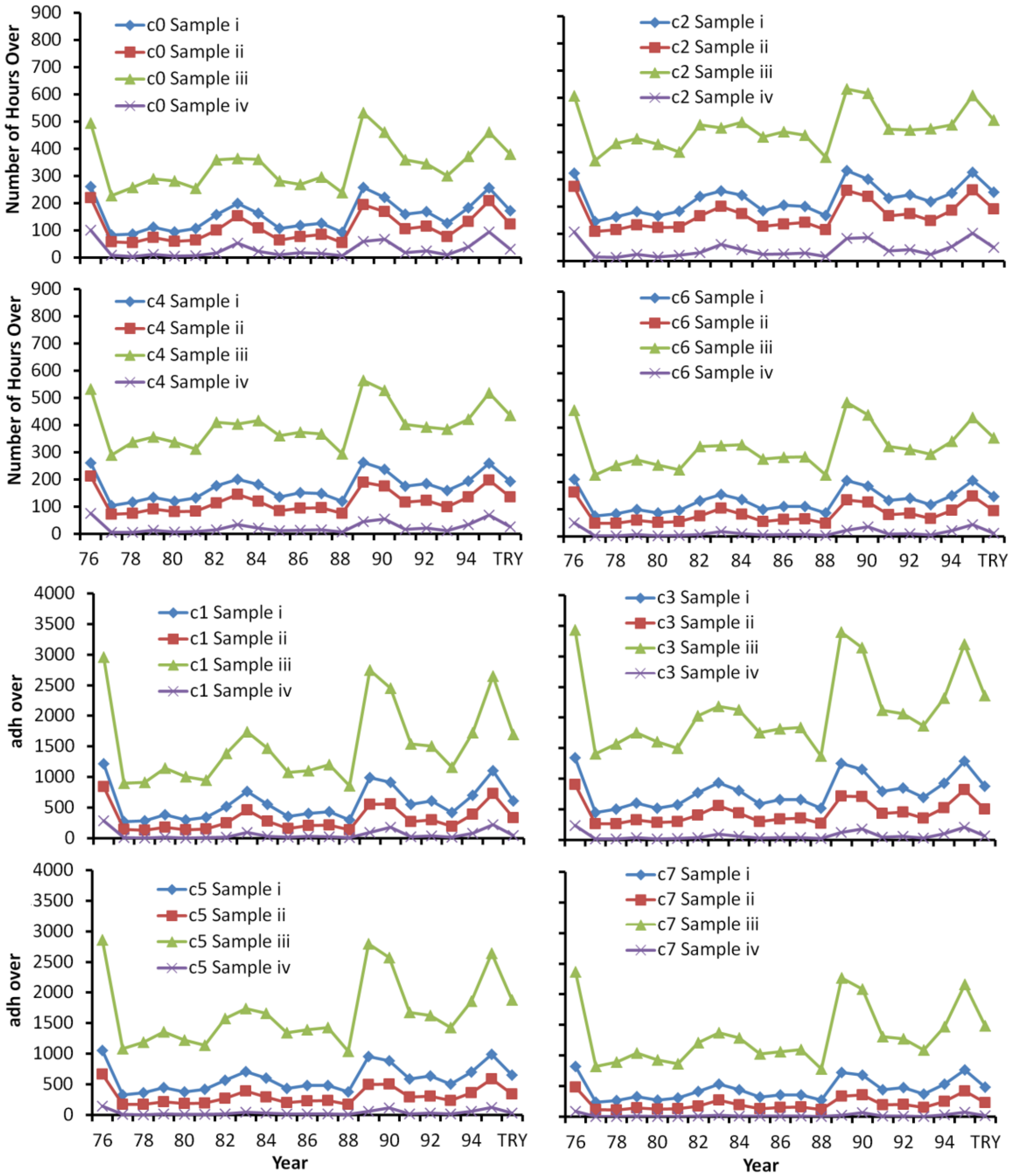

Figure 11 **Averaged** 'number of hours over' and 'adh over' for all 4 sampling sets of random building models (Table 5) against the 8 criteria (Table 6)

4.4 Spearman's rank order correlation

Spearman's rank order correlation measures the strength and direction of association between two ranked variables (Spearman 1904). The correlation coefficient, rho (ρ), is determined by the difference in rank order between two pair of datasets, as below Eq. 04 where d_i is the rank difference for each individual data and n is the total number of data in each dataset.

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \qquad \text{Eq. 04}$$

By definition $-1 \leq \rho \leq 1$, value of -1 or 1 indicates a perfect negative or positive correlation, with no correlation when $\rho=0$. Table 1 (section 2.1) can be used as a quick example of this particular correlation analysis. Using Eq (04) the FS statistic ranking of DBT and GSR results a correlation coefficient of $\rho=0.8391$. This is a relatively strong correlation between DBT and GSR which implicates that a warmer year tends to have higher solar radiation or vice versa. The FS ranking of DBT and WS results a correlation coefficients of $\rho=-0.4947$ which is a weak negative correlation indicating that a cooler year may or may not have a stronger wind speed.

The early analysis on the ranking probabilities (Figure 4 to 10) was not able to examine the strength of their correlation between the pre-determined outdoor warmth (Table 1 & 2) and the predicted indoor warmth from the source weather years. Spearman's rank order correlation analysis provides a mean of assessing this strength. Table 7 shows the correlation coefficients between ranks in table 1 & 2a and the ranks from the averaged predicted indoor warmth using various criteria (Table 6) for all four sampling sets (Table 5). FS Ave is the rank by the arithmetic average of FS statistics between DBT and GSR shown in table 1. Three other ranks from early studies, such as Ave.DBT (averaged DBT from CIBSE Guide J 2002), Sol-air (Ji et al 2016) & WCDH (CIBSE TM 49 2014) are also included.

From the first 6 rows in Table 7 stronger correlations are observed for the ranks involving both DBT and GSR (i.e. FS Ave & Sol-air) than the DBT or GSR only ranks. However, below the first 6 rows - the ranks by the number of hours over base temperatures show that some base temperatures have stronger correlation with the averaged predicted indoor warmth. In general, correlations are less strong for Samples "iii" & "iv" compared with Samples "i" & "ii" with a few exceptions towards the bottom of the table. Samples "i" & "ii" are both complete random building models but Sample "ii" excluded solar and wind influence (DBT becomes the only driving factor for indoor thermal response). From the table it is obvious that Sample "ii" correlates well with those base temperatures from 19°C to 24ºC (refer the ***bold italic*** numbers) but less well with Sample "i". This indicates that the impact from solar and wind does alter the probability ranks of the predicted indoor warmth. For Sample "i", apart from the 'c0' criterion (operative temperature 'number of hours over 28°C), the correlations for rows between 17ºC to 25°C and Sol-air are in similar range. The strong correlations with these base temperatures are consistent with the early observation of the probability ranking changes against Table 2 (Figures 6 to 10). However, It is still difficult to be conclusive from Table 7. There seems to be a tendency that the ranks by the number of hours over a particular base temperature can correlate well with the overall predicted indoor warmth ranking, however, it is difficult to decide which base temperature, in particular, against the four overheating criteria. And the exact influences from solar and wind are not obvious.

Table 7 Spearman's rank order coefficients between ranks of outdoor weathers and the averaged predicted indoor warmth

	Sampling i				Sampling ii				Sampling iii				Sampling iv			
	c0	c2	c4	c6	c0	c2	c4	c6	c0	c2	c4	c6	c0	c2	c4	c6
FS DBT	0.9338	0.9278	0.9233	0.9188	0.9233	0.9308	0.9308	0.9308	0.9158	0.8632	0.8797	0.8932	0.8361	0.8977	0.8977	0.8541
FS GSR	0.8707	0.8782	0.8902	0.8842	0.8812	0.8902	0.8902	0.8902	0.9188	0.9038	0.9233	0.9233	0.8586	0.8707	0.8677	0.8406
FS Ave	0.9474	0.9353	0.9398	0.9383	0.9429	0.9489	0.9489	0.9489	0.9564	0.8917	0.9083	0.9308	0.8647	0.9188	0.9158	0.8782
Ave. DBT	0.9293	0.9263	0.9218	0.9158	0.9188	0.9278	0.9278	0.9278	0.9113	0.8647	0.8767	0.8887	0.8301	0.8902	0.8887	0.8451
WCDH	0.8947	0.8692	0.8737	0.8767	0.9023	0.8827	0.8827	0.8827	0.8376	0.8120	0.8421	0.8481	0.9263	0.9188	0.9188	0.9158
Sol-air	0.9459	0.9564	0.9534	0.9444	0.9338	0.9383	0.9383	0.9383	0.8977	0.8947	0.9068	0.9068	0.8752	0.9218	0.9218	0.8872
Over 15°C	0.8932	0.8857	0.8872	0.8812	0.8767	0.8887	0.8887	0.8887	0.8932	0.8316	0.8511	0.8556	0.7820	0.8406	0.8421	0.7835
Over 16°C	0.9188	0.9083	0.9083	0.9023	0.9053	0.9143	0.9143	0.9143	0.9218	0.8602	0.8767	0.8872	0.8105	0.8707	0.8707	0.8195
Over 17°C	0.9504	0.9323	0.9353	0.9323	0.9398	0.9504	0.9504	0.9504	0.9594	0.9008	0.9143	0.9278	0.8556	0.9083	0.9053	0.8617
Over 18°C	0.9594	0.9338	0.9338	0.9353	0.9429	0.9534	0.9534	0.9534	0.9549	0.8857	0.9113	0.9263	0.8632	0.9173	0.9143	0.8812
Over 19°C	***0.9835***	0.9579	0.9594	***0.9684***	***0.9684***	***0.9789***	***0.9789***	***0.9789***	0.9504	0.9008	0.9248	0.9398	0.9128	0.9489	0.9414	0.9188
Over 20°C	***0.9699***	0.9474	0.9459	0.9549	0.9504	***0.9639***	***0.9639***	***0.9639***	0.9383	0.8962	0.9218	0.9323	0.8992	0.9398	0.9293	0.9128
Over 21°C	***0.9684***	0.9444	0.9429	0.9519	0.9504	***0.9609***	***0.9609***	***0.9609***	0.9368	0.8887	0.9113	0.9263	0.8947	0.9383	0.9263	0.9068
Over 22°C	***0.9684***	0.9398	0.9368	0.9474	***0.9654***	***0.9609***	***0.9609***	***0.9609***	0.9353	0.8737	0.9023	0.9233	0.9158	0.9519	0.9429	0.9293
Over 23°C	***0.9729***	0.9549	0.9504	0.9564	***0.9714***	***0.9654***	***0.9654***	***0.9654***	0.9188	0.8767	0.9083	0.9233	0.9398	***0.9624***	0.9579	0.9474
Over 24°C	***0.9699***	0.9549	0.9549	0.9594	***0.9744***	***0.9639***	***0.9639***	***0.9639***	0.9113	0.8872	0.9188	0.9248	***0.9684***	***0.9729***	***0.9699***	***0.9624***
Over 25°C	***0.9609***	0.9549	0.9534	0.9564	***0.9654***	0.9504	0.9504	0.9504	0.8842	0.8767	0.9038	0.9068	***0.9714***	***0.9669***	***0.9609***	0.9579
Over 26°C	0.9128	0.9098	0.9053	0.9023	0.9263	0.9008	0.9008	0.9008	0.8406	0.8556	0.8782	0.8797	0.9459	0.9293	0.9218	0.9323
Over 27°C	0.8872	0.8677	0.8632	0.8647	0.9023	0.8707	0.8707	0.8707	0.8105	0.7820	0.8195	0.8361	0.9233	0.9083	0.9068	0.9158
Over 28°C	0.8647	0.8391	0.8436	0.8496	0.8662	0.8466	0.8466	0.8466	0.7805	0.7549	0.7925	0.8015	0.9113	0.9098	0.9143	0.9248
Over 29°C	0.8030	0.7850	0.8000	0.8045	0.8256	0.8105	0.8105	0.8105	0.7910	0.7820	0.8135	0.8105	0.8842	0.8647	0.8677	0.8782
Over 30°C	0.5414	0.5263	0.5308	0.5368	0.5564	0.5474	0.5474	0.5474	0.5504	0.5383	0.5609	0.5549	0.6301	0.5895	0.5789	0.6045

4.5 Responses of TRY on random models

By definition TRY represents an averaged weather condition of the historical weather data from which it is generated. The 11th ranking position in Figure 12 with a higher probability is where ideally it should be. It is clearly not the case. For random model Sample "i", TRY is more likely being 7th warmest based on its highest probability ranking with the 20 source weather years, although for cases ‘i + c0’ (53%) and ‘i + c2’ (35%) the highest probabilities are not statistically significant. With the adh over ‘i + c1’ & ‘i + c3’, its probabilities of being the 7th warmest are both higher (around 60%). Sample "iv" shows more consistent high ranking probability of being the 7th warmest position for all criteria (c0 to c3, table 6). TRY’s probability ranking positions vary for random models in sampling sets ii & iii, changing from the 5th warmest position (iii + c2, c3), the 6th warmest position (iii + c0) to the 7th warmest position for remaining cases with the case ‘ii+c1’ show 90% probability in Figure 12. The above observations on the probability ranking of the predicted indoor warmth for TRY do not correlate well with the earlier analysis with the weather data. For example, in Table 2a & 2b, the highest ranking position for TRY is the 8th warmest in terms of outdoor warmth. With lower base temperatures, the TRY tends to move the middle. The FS statistics of the TRY weather data using Eq. 01 would give FS(DBT)=0.18, FS(GSR)=1.05 & FS (WS)=0.2 (*ref*: Table 1). If TRY were included in Table 1, its position would be either 9th for DBT and WS, or 8th for GSR. While in Figure 12, it is in the 7th or warmer position. When coincidence of weather parameters is calculated (*ref*: Table 3), the hourly coincidences of GSR and WS with DBT at 87.5 percentile are 26.1% and 15.4% respectively. These do not seem to justify the TRY’s position in probability ranking either. From the above observation the probability ranking of the predicted indoor warmth for TRY does indicate that TRY is warmer than expected.

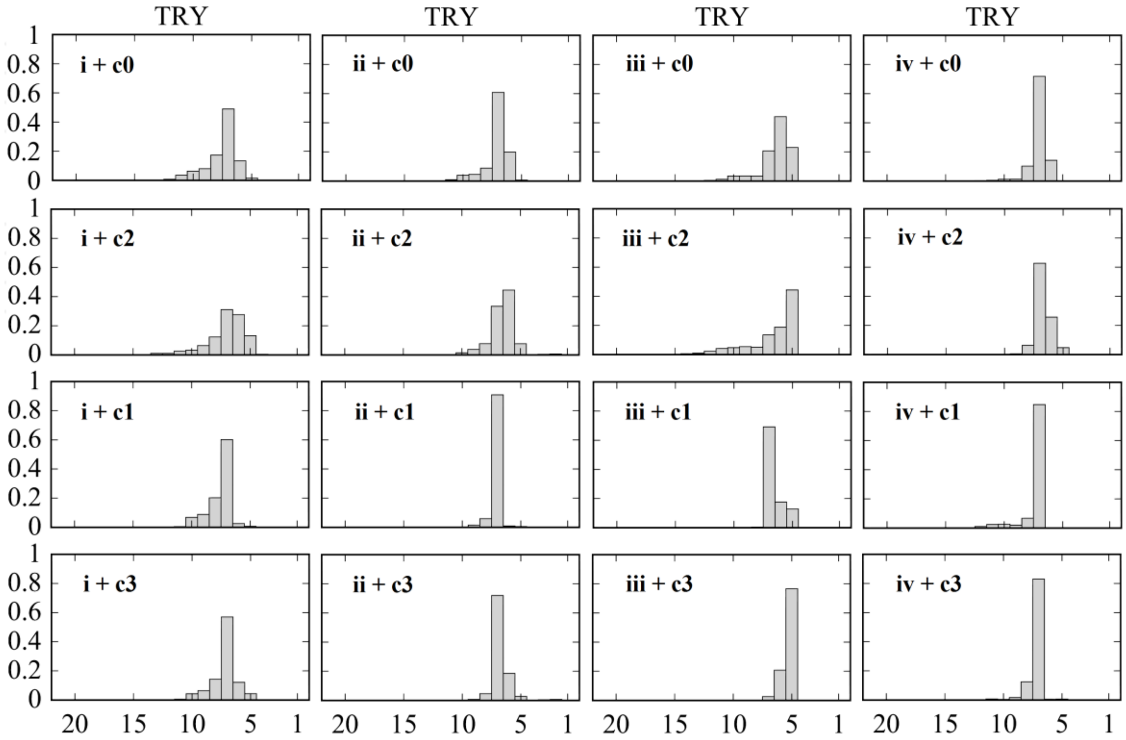

Figure 12 Ranking probabilities for TRY (21 ranking positions) by both 'the number of hours over' and 'adh over' CIBSE Guide A single temperature criterion 28ºC and BS EN 15251 Category I upper limit (*ref*: Table 6) for the single zone office space during occupancy.

4.6 Discussions

The current release of the CIBSE weather data sets follows the proposed method of TM49 – probabilistic DSYs (pDSYs). This means that there are three DSYs per location aiming to represent summers with different characteristics of warmth, in London as explained earlier: long persistent warmth (1976), an intense single warm spell (2003), and a moderate warm summer (1989). The latest update on UK DSY introduced two new metrics on top of the weighted cooling degree hours (WCDH) concept used in TM49: static & threshold WCDH (SWCDH & TWCDH) (Eames 2016). The resulting London pDSYs for moderate warmth is 2013 although there is little variation for all three metrics between 1989 and 2013. The other two pDSYs are the same as in TM49: 1976 and 2003. It is worth noting that, for the current release, pDSYs for all 14 locations were selected from all available years per location (i.e. London from 1961, Leeds from 1989) based on a 'return year' concept which was established by the 30 year baseline weather from 1984 to 2013(CIBSE TM 49 2014; Eames 2016). These pDSYs by definition are therefore 'complete' years selected using DBT only metrics: WCDH, SWCDH & TWCDH. This latest update on UK DSYs acknowledges two aspects that may need further consideration. One is the verification of these pDSYs in real building models as DSYs were developed using a conceptual building model which assumes the outdoor temperature is the same as the indoor operative temperature. The other is the potential 'issue' for not considering solar radiation within the selection process, in particular, for heavily glazed buildings.

The single office model with its variants by changing size, glazing, orientation, and so on (Table 4) resulted a population of building models in the order of 10^6 and simulations were carried out on 2000 sample models selected by LHS sampling technique and there are 4 sampling sets were used. From the real building models perspective, work presented in this research clearly serves the purpose of verification. The 20 weather years used in this research is from London 1976 to 1995 among which the 1976 and 1989 were the two pDSYs for London. From the simulation outputs discussed earlier, the predicted indoor warmth is very much dependent on the built forms. There is no strict correlation on ranks between the warmth defined by CIBSE TM49 (or the latest update of DSYs in Eames 2016) and the predicted indoor warmth. The Spearman's rank order does show the relative strength of correlation but no 'perfect' correlation is found. For building models where solar radiation is less dominant the year 1976 has the highest chance of being the warmest, while for building models where solar radiation has its maximum influences the year 1989 has the highest probability of being the warmest. It is evident there is that the thermal responses of complete year weather data against various built forms do vary significantly.

It is true from the early analysis that extreme years defined by temperature are in the meanwhile having relatively higher solar radiation, for example, the FS statistics in Table 1 show that higher temperature years do have higher solar radiation as well. Even the coincidence of high temperature and high solar radiation is often low (Table 3 and Watkins et al 2011; Levermore & Chow 2006) , the accumulated effects of both temperature and solar radiation can play dominant role in terms of the resulted indoor warmth for various built forms. Broadly speaking, the warmer years among the 20 historical weather years of London do result high overheating occurrence and severity, however, which year is the warmest or the third warmest (near-extreme) in terms of predicted indoor warmth depends very much on built forms. As Eames (2016) rightly argues that it is indeed an issue for heavily glazed buildings. Sample "iii" models of this work are indeed the most heavily glazed building models and the resulted indoor warmth prediction shows that the year 1989 is the warmest rather than the year 1976. This is contradictory with most of the existing analysis on warmth ranking including the 'return year' concept, but with exceptions shown in Table 2 where when base temperatures are small, the year 1989 does have more 'number of hours over' than the year 1976. Based on the probability ranking in terms of the predicted indoor warmth, the outdoor warmth defined by temperature or multiple parameters does not strictly correlate. For free running buildings wind is the primary driving forces for space conditioning and it is a counter factor for overheating in buildings due to ventilation. This is clearly the case when comparing all four sampling sets in Figure 11. Overheating happens indoors and wind does clearly influence the thermal responses of buildings greatly although not at the same extent as solar radiation, it is still an important influencing factor.

For composite year methods, by definition a DSY will be always warmer than its corresponding TRY consistently (Jentsch et al 2016). From the predicted indoor warmth of TRY in this work (Figure 12), it is anticipated that the composite DSY (termed as SRY by Jentsch et al 2015) will behave similarly as TRY but with a shift towards the warmer end. It probably will not sustain any ranking position with statistical importance for all the built forms of the 4 sampling sets either. The SRY assumes the method used to generate TRY is robust. The previous analysis indicates that this TRY is not quite the 'average' as it is largely between the 7th to 9th position in the outdoor warmth ranking (Tables 1, 2 & 3) and the 5th to 7th position in the predicted indoor warmth ranking (Figure 12).

The above discussions emphasize the influence of built forms on the predicted indoor warmth. Thermal responses of various built forms to the same weather data can be significantly different. This essentially means that whatever methods used to define DSYs using existing weather data, either a complete year or a composite year, it is not always guaranteed it is actually the 'near extreme' from the predicted indoor warmth among the baseline or source weather data. It may not even be likely there is a perfect definition of DSY by evaluating source weather data which will always represents 'near extreme' for all the building types and forms in terms of predicted indoor warmth. The consideration of classifying built forms in terms of high solar gains and high ventilation does not result consistent ranking position of the source weather files from this research (sampling set iii & iv). It seems to be unlikely possible to anticipate the thermal responses of individual built form without simulating all the source weather years, or at least those warmer years defined by various means (i.e. the six years analysed in Figures 6 to 10). The pDSYs in TM49 and Eames (2016) already proposed 3 complete weather years. It is therefore logical to propose more than 3 complete years to make sure one of these warm weathers will definitely represent the near extreme in terms of the predicted indoor warmth for all the built forms. It is therefore sensible to use multiple weather years, as many as necessary from the baseline weather files, to simulate a particular design. With the latest advancement of hardware and software technologies, this exercise is easily achievable although adding some extra complexity.

4.7 Limitations

Due to license requirement the up to date weather data, such as used to develop DSYs in TM49 and Eames (2016), were not used in this research. The Summer Reference Year (SRY) proposed by Jentsch et al (2015) was also based on latest source weather data which the authors of this work do not have access to. This research is based on London weather data from 1976 to 1995 which is deemed largely representative as there are two pDSYs were selected from this time period. For TRY, the selection procedures were kept the same as the early release, for example the TRY generated from baseline years 1976 to 1995 used in this research. It would be better to use the more up to date weather data to evaluate the thermal responses with various built forms, however, the principles and key observations from the current research would still be valid.

The current research focuses on free running office building setting only. As a consequence weather parameters such as temperature, solar radiation and wind speed were assessed in detail. Humidity level has significant implications on plant size and operation if a building were air-conditioned but this is beyond the scope of this research. It is also worth noting that the TRY is often used to assess the overall energy performance of a building rather than overheating. From this perspective, whether TRY is ranked in the 'middle' in terms of overheating hours becomes less important as long as it results averaged energy consumptions among the baseline weather data. This aspect was not assessed in this research.

As reviewed earlier, many efforts have been attempted to define DSY. The work here therefore does not intend to propose a new definition, rather, it aims to assess the existing proposals and examine how consistent these definitions can be when using them to simulate various built forms.

5. Conclusions

This paper sets out to assess the existing definition of near extreme weather years using various built forms. Both complete year and composite year methods were discussed along with their selection metrics – either DBT only or multiple parameters. The variation of built form was made by a single zone office setting through which both physical changes (size, orientation, glazing, insulation, etc) and operational changes (window opening percentage, internal gains, with or without shading, etc) were randomly modified. The LHS sampling technique was used to generate 4 sampling sets and the building models from these sampling sets were used to examine the impact of built forms on overheating assessments. The 20 years historical weather data of London as well as their corresponding TRY were simulated on the sample models of each sampling set. These weather data were also analysed using FS statistics, number of hours over various base temperatures and the hourly coincidence level between solar radiation, wind speed and dry bulb temperature. Both single temperature overheating criteria from CIBSE Guide A and adaptive criteria from BS EN 15251 were used to assess overheating in these sample building models. This includes assessing overheating occurrence and severity. By using a statistical voting procedure, the ranking probability of each weather year on their predicted indoor warmth is presented against both overheating occurrence and severity.

The ranking probabilities of predicted indoor warmth for source weather years show no strict correlation with any existing ranking metrics discussed in this paper. The general observation of warmth from the examined weather years shows that the year 1976 is not always the warmest when using the ‘number of hours over’ criteria. There is a clear ranking position swap between 1976 and 1989 when the sampling models emphasize the maximized solar radiation scenarios, i.e. the year 1989 has highest probability of being the warmest for Sample "iii". This observation conflicts with most of the existing outdoor warmth definitions apart from the ‘number of hours’ over lower based temperatures of existing weather data (Table 2). For the ‘accumulated degree hours (adh) over’ criteria, the year 1976 has been largely consistent of being the warmest with higher ranking probability of predicted indoor warmth. For Sample "iii" the year 1989 can become the warmest with the adh over but its probability is much lower than the overheating occurrence cases. Other examined weather years such as 1983, 1990, 1994 & 1995 could not hold any particular ranking position either, but relatively, they are more chances for them to appear in the 5th, 3rd, 6th & 2nd position although they do swap positions with different sampling sets and different criteria used to judge overheating.

For all 4 sampling sets the averaged ‘number of hours’ and ‘adh’ over clearly indicates the strong influences from solar radiation and wind speed on the indoor thermal responses. Although the exact ‘number of hours’ over (for both overheating occurrence and severity) contributed by solar and wind could be random for individual built forms, the averaged ‘number of hours’ over shows that the influence from solar radiation does overweigh the counter influence from wind induced space conditioning through ventilation. The Spearman’s rank order between these averaged predicted indoor warmth and the outdoor warmth defined by various methods does indicate various correlation strengths, however, it is far from obvious to make conclusive judgement which outdoor ranking method is always better than others.

The ranking probabilities of predicted indoor warmth for TRY show that TRY is warmer than expected as its highest ranking probability happens most likely in the 7th position when compared with its 20 source weather years. Even with this 7th position, the statistical significance is not always maintained as for some cases the probability of being the 7th warmest is less than 40%. The TRY is examined to mirror its corresponding SRY developed recently. It is anticipated that SRY will behave similarly as TRY in terms of variations in ranking position based on how it is generated.

It is evident from this research that built forms have significant influences on indoor overheating and the near extreme definitions using historical weather data do not always correlate with the predicted indoor warmth. This lack of correlation is true for both complete year definition and composition year definition, and taking multiple weather parameters into account in the selection process does not show obvious advantages than the temperature only metrics due to the arbitrary nature of the thermal responses of individual built forms. As shown in this research, it is true that warmer years defined from historical weather data using various methods (i.e. averaged DBT, WCDH, SWCDH, TWCDH, FS statistics on DBT & Solar radiation, etc) are also warmer years based on their predicted indoor warmth ranking probability (1976, 1983, 1989, 1990, 1994 & 1995). However, the exact ranking sequence is often not maintained, i.e which year is the warmest and which year is the near extreme for individual built forms. This supports the notion of the CIBSE latest release of using pDSYs where multiple weather years are used to cover various types of warmth of historical weather. It is therefore sensible to suggest that more warmer years should be included to make sure one of which can always represent ‘near extreme’ weather for any individual built form.

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