THE IMPLICATIONS OF TRANSPORTING ARCHITECTURE ON HUMAN HEALTH

Matt Eames[1], Mike Wood[1], Peter Challenor[1]
[1]College of Engineering, Mathematics and Physical Sciences, University of Exeter, North Park Road, Exeter, UK, EX4 4QF.

ABSTRACT

Where modern buildings are unable to maintain the internal environment to within comfort levels they often rely on mechanical systems to become habitable. This could be due to bad design or putting the building in an environment for which it is not suited. Due to climate change it is likely that all buildings will in effect and time be moved to an environment for which it is not suited. In this work the effects of changes in climate on the internal environment will be explored and an index to define how moveable a construction might be, will be developed.

INTRODUCTION

There is no end of examples where particular architectural movements have not had an influence on building design around the world. For example the Georgian symmetry of the 18th century and the gothic style of the Victorians, originating from the UK spread throughout the English speaking countries. Even these styles were not completely original with the Georgians taking influence from classical Italian Architecture and the Victorians from the Middle East and Asia(Ching, Jarzombek, & Prakash, 2010). These movements were not constrained by regional and national boundaries and the buildings were often constructed with little or no regard for the local climate. PassivHaus is a relatively new movement, which originated in Germany but now has many thousands of certified units around the world with the majority constructed in Europe. Although modelling of such buildings must take into account the local environment, the principles of the design are common – using passive means to regulate the internal environment (Feist, W, Pfluger, R, Scnieders, J, Kah, O, Kaufman,B, Krick, 2013). Where such buildings are optimised to maximise heat gains in the winter, there is a chance of overheating in the summer (McLeod, Hopfe, & Kwan, 2013) which could be further exacerbated by climate change in the future.

Previous work has shown that there is a strong correlation between a given building's internal environment (mean internal temperature) and its external environment (mean external temperature) over a period of significant length such as the six summer months (Coley et al., 2010). The work also showed that the correlation was invariant to the degree of climate change such that a building which performed well with an optimistic prediction of climate change, also performed well with a more pessimistic prediction. This was in part due to the nature of the application of climate change. In this case different climate scenarios were created using a set of transformations (Belcher et al., 2005), so it was no surprise that the correlation was so good. Further work demonstrated the same linear trend using stochastic weather data using representations of the current and future climates and a range of different weather file types (Eames et al 2010). However, in each case only a small subset of buildings was investigated and a single measure for characterising the building was considered – mean internal temperature against mean external temperature.

Here we ask in a general way what the restrictions might be in terms of the indoor environmental parameters to changes in external climate, and how this sensitivity can be measured for a design. There are links here with the question of how different buildings will fair under climate change, particularly more extreme climate change where weather systems may fundamentally change with areas experiencing very different temperatures, wind speeds and levels of humidity (Eames et al., 2010; Stocker et al, 2013). There are also links with the mitigation of climate change and the need to provide buildings that do not rely on energy intensive systems to achieve reasonable internal conditions. In this work, a number indices will be investigated to define how moveable/resilient a construction might be. The buildings parameters and cooling strategies are typical for moderate and temperate northern European climates. The buildings will then be tested in a number of different climates for their resilience. The most appropriate indices to define resilience will then be combined to provide a multidimensional optimisation strategy indicating the most resilient constructions. Unlike the previous studies, which are restricted to a few discrete changes in the building parameters such as whether the building is lightweight or heavyweight, a surrogate model is used to estimate the thermal response of many thousands of buildings. There has been much recent interest in the use of statistical models to model buildings due to the computational advantage at searching for optimum solutions to reduce cooling or heating energy use or improve thermal comfort (Eisenhower et al., 2012; Tian et al, 2014). In each case a building construction is parameterised so that regression analysis can be used to search for solutions which weren't originally part of the initial training set (Van Gelder et al, 2014). Ideally, the external environment would also be parameterised to be an input for the surrogate model. However, such a model would typically require the weather to be parameterised so that certain parameters could be selected to be space filling and create the best surrogate model (Van Gelder et al., 2014). Also, this would enable the derivative of the surrogate model surface to be determined directly (Roustant et al., 2012). Weather data is much more likely to be discrete such that a simple space filling parameterisation is a non-trivial process. Furthermore, it is unknown how the weather file should be parameterised to create such a surrogate model for building simulation. As an extension to the building surrogate model, the external weather is parameterised in terms of the number of cooling degree hours (CDH), the mean external summer temperature, and weighted hours above the adaptive comfort temperature (WCDH) for various locations around the world. The effects on the thermal internal environment is then investigated using a simplified regression analysis. The focus of this work is how changing the external environment effects the internal environment using a comprehensive building set and how the external environment can be parametrised to define this effect. As similar work, the building strategy will be handled in a simplistic manner i.e. the occupants will behave in the new climate in the same manner as in all the other climates. For of a particular construction resilience to changes in climate it is not the absolute change in any metric which is important, but the rate of change.

METHOD

Coley developed a measure for quantifying the change in internal temperature in unconditioned spaces as a function of the change in external temperature(Coley et al., 2010). This measure is estimated by modelling (over a period greater than any relevant time constant, usually the whole summer period) the building in question in a dynamic thermal model then by using the relationship:

$$\frac{\delta internal\ variable}{\delta external\ variable} = C \qquad (1)$$

where C is the buildings amplification coefficient. Surprisingly for changes in mean internal/external temperatures and changes in maximum internal/external temperatures, C was found to be constant for any zone within a building and invariant to the level of external temperature change. For an architecture to be truly resilient, it would need to mitigate changes in not only small perturbations in the local weather, but to whole scale changes in the weather one might experience.

The key to habitability is the level of thermal comfort within the building. The original work focussed on mean temperatures. While mean temperatures could be used to inform construction resilience, overheating is usually defined as a period where the internal temperature is above what is considered by an occupant to be comfortable. As such, it is more typical to experience overheating with shorter periods of weather, which are extreme compared to the typical conditions (Nicol et al, 2002). Ensuring a building minimises the change in mean internal temperature with a change in mean external temperature does not necessarily imply that the risk of overheating is reduced. In this work measures of thermal comfort will be considered here over the six summer months which are defined as the six warmest months in the weather year.

Comfort Criteria

PPD is a common measure which establishes a quantitative prediction of the thermally dissatisfied people by predicting the mean value of the thermal votes of a large group of people exposed to the same environment(BS EN ISO 7730, 1995). The PPD can be determined from

$$\mathrm{PPD} = 100 - 95e^{-(0.03353\mathrm{PMV}^4 + 0.2179\mathrm{PMV}^2)}. \qquad (2)$$

Where PMV is an index that predicts the mean value of the votes of a large group of people on a seven-point scale ranging from hot (+3) to cold (-3). More details and explanation can be found elsewhere (BS EN ISO 7730). A well-functioning building should minimise the number of hours where the PMV lies outside the range of -0.5 to 0.5 (or minimise the number of hours where PPD is above 10.2%). The first internal comfort criteria will consider the number of hours where the PMV is greater than 0.5 (PMVH).

The number of PMVH gives a measurement of exceedance of the internal environment over a comfort level. However, it does not include a measure of intensity as all hours of exceedance have the same weight. The weighted cooling degree hours (WCDH) is a measure of how far the internal temperature deviates from the thermally neutral temperature. Using adaptive comfort criteria the thermally neutral temperature is related to the running mean external temperature (BS EN 15251) which is given by

$$T_c = 0.33T_{rm} + 18.8 \qquad (3)$$

where T_c is the predicted comfort temperature on a given day and T_{rm} is the running mean external temperature which is given by

$$T_{rm} = 0.8T_{rm-1} + 0.2T_{mean-1} \qquad (4)$$

where $T_{rm\text{-}1}$ is the running mean external temperature on the previous day and $T_{mean\text{-}1}$ is the mean temperature on the previous day. For free running buildings Nicol developed a criterion to weight the number of hours above the comfort temperature termed the Potential Daily Discomfort (PPD) (Nicol et al., 2008) given by the expression

$$\mathrm{PDD} = \frac{1}{24} \sum_{\substack{all\ hours \\ \Delta T > 0}} F \Delta T \tag{5}$$

where

$$F = (1 + e^{2.61 - 0.473\Delta T})^{-1} \tag{6}$$

and

$$\Delta T = T_{op} - T_c \tag{7}$$

ΔT is the difference between the operative temperature (T_{op}) and the comfort temperature. While this weighting gives higher values for greater departures from the comfort temperature, the weighting tends to one for the greatest departures (ΔT > 5.52°C). In this work to place more emphasis on the greater departures a simpler weighting was used where F is given by ΔT (TM49). The greatest discomfort is assumed for the largest values of ΔT and the total weighted degree hours is given by the expression

$$\mathrm{WCDH} = \sum_{\substack{all\ hours \\ \Delta T > 0}} (\Delta T)^2 \tag{8}$$

The WCDH approximation is related to the duration of the exceedance as well as giving emphasis to more extreme temperatures which therefore takes into account the severity of the exceedance.
As only unconditioned buildings are considered, we can expect any overheating metric to increase if a building is subjected to warmer conditions. What interests us here is the rate of change of these measures as a function of the change in external conditions, and in particular is the change linear and how it varies with the properties of the building construction.

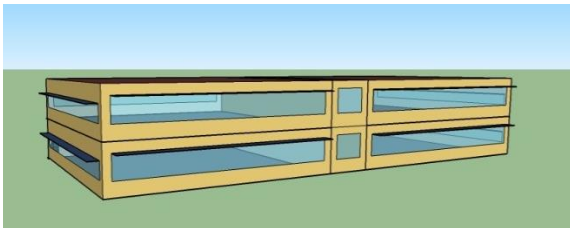

Figure 1: The building model consisting of five zones: four rooms and a corridor.

The building model

A multi storey building is considered (see figure 1) running in free running mode modelled using EnergyPlus (US Department of Energy, 2013). The building has a total floor area of 990m^2. The model was created with the OpenStudio plugin for Sketchup. Table 1 lists the inputs for the model. All distributions are uniform between the given limits. The building is occupied as for a typical open office. The fractional occupancy for each schedule and the fractional schedule for the heat gains are not variables and are as specified by the ASHRAE for an open plan office. The parameters listed in table are used to cover a range of possible building configurations covering the building construction, occupancy, and building use. Table 2 lists the building construction parameters. For each parameter specified in table 1, the required U-value is achieved by varying the thickness of the insulation. The U value of the external floor is 0.19 Wm^{-2}K^{-1} and the U value of the internal floor/ceiling is 0.84 Wm^{-2}K^{-1}. The windows are on all external walls with a U value of 1.39Wm^{-2}K^{-1} and g-value of 0.586. The infiltration rate is, as specified, the uncontrolled leakiness of the building. Ventilation is provided by opening the windows when the internal temperature goes above 24°C for all building models. The ventilation profile is also modulated by the occupancy profile, which is constant for all building models. The buildings are modelled using industry standard software. Although uncertainty in the construction has been considered, modelling uncertainties and assumptions such as discharge coefficients, static pressure distribution and static infiltration has not. These modelling uncertainties could be significant but are outside the scope of this work.

Table 1
Input parameters for the building model

PARAMETER	MINIMUM	MAXIMUM
Occupancy (m^{-2} per person)	1.2	16
Peak electrical gains (Wm^{-2})	2	15
Peak lighting (Wm^{-2})	5	12
Wall U-value (Wm^{-2}K^{-1})	0.05	0.6
Roof U-value (Wm^{-2}K^{-1})	0.05	0.4
Window opening area (%)	10	100
Overhang percentage North	0	100
Overhang percentage East	0	100
Overhang percentage South	0	100
Overhang percentage West	0	100
Glazing percentage North	10	60
Glazing percentage East	10	60
Glazing Percentage South	10	60
Glazing percentage West	10	60
Infiltration rate (ach^{-1})	0.05	2

The weather files used for the building simulation will be a geographical range of the typical weather data. This will be the CIBSE test reference years (Levermore et al., 2006) of London, Manchester and Southampton in the UK, weather files representative of climate change at Southampton for the 2080s for three percentiles of future climate (50th, 66th and 90th percentile) (Eames et al., 2010) , and example weather years for Beijing, Tokyo, Moscow and San Jose [DOE 2015]. The external weather will be parameterised in terms of the mean external summer temperature, the number of cooling degree hours with a base temperature of 15°C, 18°C and 21°C, and the external WCDH as given by equation 8 as typically used in more temperate climates. Similar to the internal environment there are a number of variables, which can be used and are important for influencing the internal environment. A different choice of external parameters could give different relationships with the internal environment.

For each weather file location a meta-model was produced with the same set of simulation points (the buildings are in effect moved to the new weather location). Kriging algorithms are used in R (Roustant et al., 2012) to create the meta-model in this analysis, as it has been shown to perform well to predict environmental performance of building models (Van Gelder et al., 2014).

The meta-model is designed using fifteen samples per input variable giving a total of 225 simulation points generated using an optimised Latin Hypercube design (Loeppky et al., 2009). From these meta-models, relationships between the external weather and the indices of human health are developed using 5,000 buildings (of the same form) with parameters sampled from table 1.

RESULTS

The results are presented in three ways. Firstly, the r^2 values for linear regression for metrics of mean internal temperature, internal WCDH and internal PMVH against the external mean temperature are shown (figure 2) to extend the analysis of Coley (Coley et al., 2010). Secondly, the regression r^2 values are shown for the most appropriate distribution for internal WCDH and PMVH metrics (figures 3 and 4). Finally, the coefficients of the regression are plotted against the key building parameters and each other to show relationships between the metrics and find the most optimally resilient buildings for this example (figures 5, 6 and 7).

The goodness of fit (r^2 values) for linear regression for external mean summer temperature against the internal mean temperature, internal WCDH and internal PMVH is plotted in figure 2. In the case of mean internal temperature, the linear nature of the results is evident with 100% of the buildings having an r^2 value greater than 0.84. In contrast, WCDH and PMVH is less well correlated with change in external mean temperature using linear regression. For WCDH, 84% of the buildings have r^2 values between 0.7 and 0.8 and the distribution is negatively skewed. For PMVH, 74% of all buildings have r^2 values greater than 0.8 but the negative skew demonstrates that for some buildings the linear fit is not as appropriate. The same non-linear trend is found for the internal number of cooling degree days with a range of base temperatures against the external mean temperature (not shown).

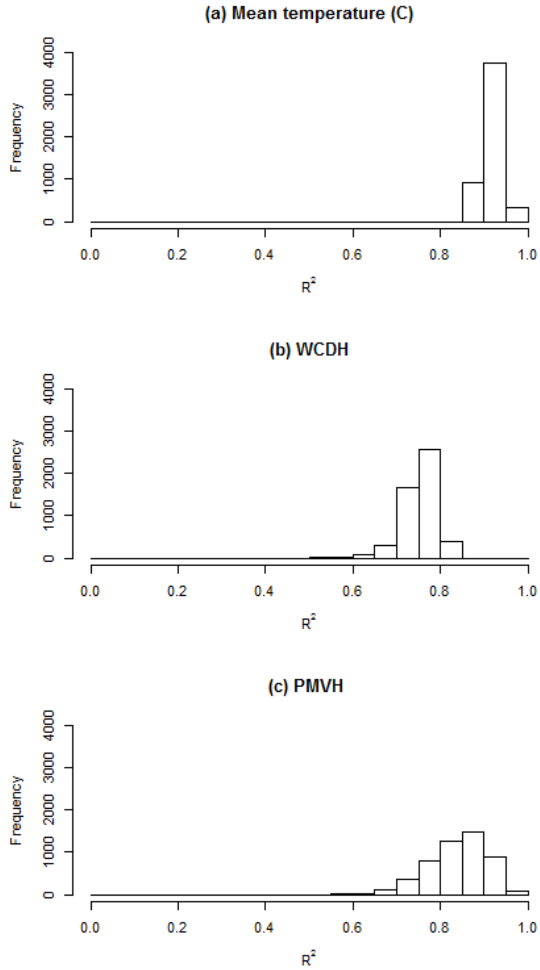

Figure 2: Histogram of the r^2 values for linear regression for (a) internal mean summer temperature, (b) internal WCDH and (c) internal PMVH against the external mean summer temperature

The r^2 values for linear regression for internal WCDH and external WCDH and CDH with a base of 21°C is plotted in Figure 3. For external WCDH 98% and 53% of all buildings have an r^2 value greater than 0.8 and 0.9 respectively. For external CDH less than 2% of all buildings have an r^2 value greater than 0.9. Figure 2 demonstrates that the relationship between internal PMVH and external mean temperature is not linear for a number of buildings. Similar is also true when comparing similar relationships with other external environmental parameters. Plotting the r^2 values for linear regression for the natural logarithm of the internal PMVH with the natural logarithm of the external parameters, as displayed in figure 4, shows a clear correlation. For both external WCDH and CDH with a base of 21°C, over 94% of all buildings have an r^2 value greater than 0.8. For external WCDH 34% have an r^2 value greater than 0.9. For external CDH the percentage of buildings increases to 54% with an r^2 value greater than 0.9. Figures 2, 3 and 4 demonstrate that the external mean

temperature is highly correlated to the internal mean temperature, the external WCDH is highly correlated to the internal WCDH and the natural logarithm of the external CDH is highly correlated to the natural logarithm of the internal PMVH. However it is not known whether a building which is more resilient according to one metric is also resilient to another; Buildings which are resilient to a particular metric will have a lower amplification coefficient (C from equation 1) from the linear regression. These amplification coefficients will be denoted as C_{Tmean}, C_{WCDH} and C_{PMVH}, with the name referring to the internal environment metric.
The relationship between C_{PMVH} and C_{WCDH} is plotted in figure 5 and the relationship between C_{Tmean} and C_{WCDH} is plotted in figure 6. It can be seen in Figure 5 that buildings which are resilient to changes in mean external temperatures (low value of C_{Tmean}) are also resilient to changes in external WCDH. However, there is a clear trade-off between resilience to changes in WCDH and resilience to changes in PMVH (figure 6).

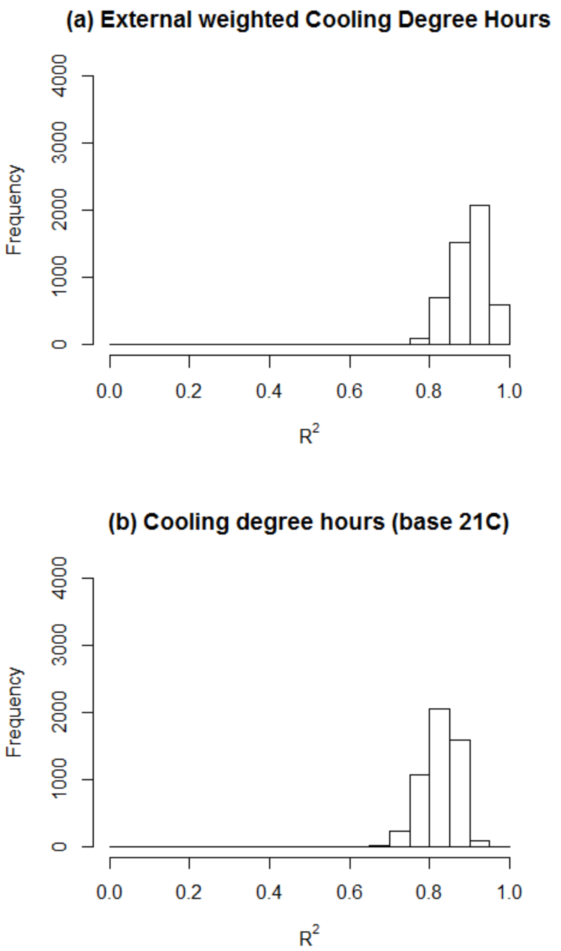

Figure 3: Histogram of the r^2 values for linear regression for internal WCDH *against (a) external* WCDH and *(b) CDH (base temperature of 21 °C).*

The response of the building to a change in external conditions depends on the building parameters. The response of C_{WCDH} and C_{PMVH} with the total heat transfer coefficient (sum of all U values multiplied by the respective surface area and the air exchange rate) is shown in Figure 7 and figure 8 respectively. In each case, buildings with a smaller heat transfer coefficient are more resilient to changes in the external environment but the changes with external WCDH is much greater with amplification coefficients varying between 1 and 12 (compared to 0.2 and 1.3 for PMVH). The 33 buildings which might be considered optimal from figure 6 are shown as dark circles. The optimal buildings, which are more resilient for this example, each have a reduced glazed percentage on all sides, have thicker insulation and have more solar shading.

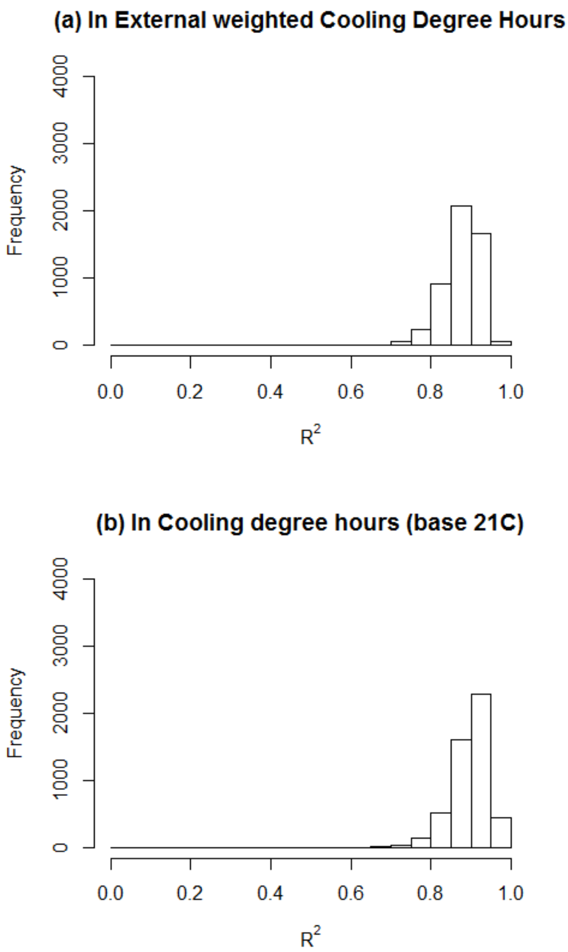

Figure 4: Histogram of the r^2 values for linear regression for ln internal PMVH *against (a) external* WCDH and *(b) cooling degree days (base temperature of 21 °C).*

DISCUSSION AND CONCLUSION

In this work, the effects of changing the external environment are correlated to changes in the internal environment. Previous work has found that for a free running building, the mean summer internal temperature is linearly correlated to the mean summer external temperature (Coley et al., 2010; Eames et al., 2010) regardless of the form of the climate. However, this metric does not consider the effects to the occupants, which are more typically described in terms of the number of hours exceeding a threshold or predicted mean vote. Also mean conditions do not predict peak conditions and therefore the true implications to occupants. A strong correlation was found between the mean internal temperature and mean external temperature, as expected. Furthermore, a strong correlation was found between the external WCDH and internal WCDH – a measure of the intensity of the internal temperature above the predicted comfort temperature – and the external weighted cooling degree hours and the internal PMVH – the number of hours where greater than 10.2% of occupants is dissatisfied. While the change in PMVH was not found to be linearly correlated to the cooling degree hours, the natural logarithm of the PMVH was found to be linearly correlated to the natural logarithm of the cooling degree hours. This result is not so surprising as when all hours have greater than 10.2% of all occupants dissatisfied, a warmer climate will make no further difference to the total so the power law is more appropriate.

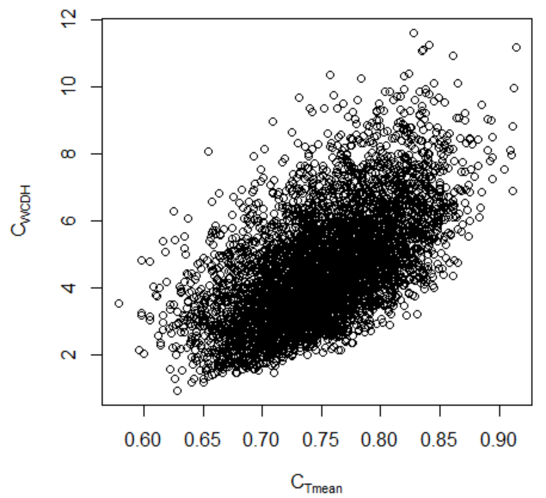

Figure 5: C_{WCDH} against C_{Tmean}. for all 5000 building.

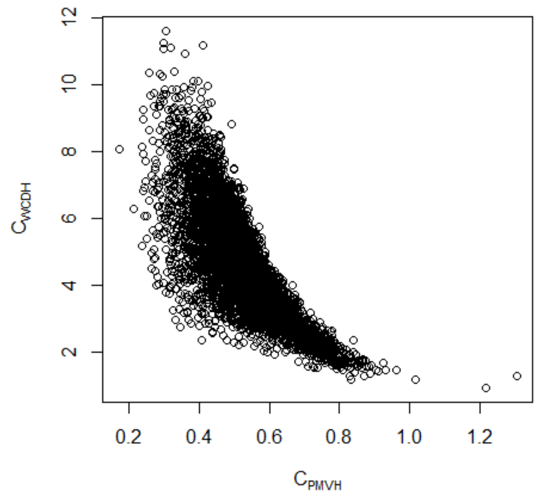

Figure 6: C_{WCDH} against C_{PMVH}. for all 5000 buildings

For a building to be considered resilient to a range of climates, either through using the same architecture and moving its location or through the effects of climate change, the effect of the external environment on the internal environment should be minimised such that potential risk of overheating is minimised. However minimising the buildings amplification coefficients (*C*) with regards to a single metric does not guarantee that the overheating risk has been minimised (figure 5 and figure 6). In the original work of Coley the building was considered resilient if the change mean temperature amplification coefficient was reduced. Although the amplification coefficient for WCDH is linearly correlated to the mean temperature amplification coefficient (figure 5), it is not linearly correlated to the PMVH amplification coefficient (figure 6). Looking at the indices in more detail this result might be expected. The absolute number of WCDH for a building provides a measure of the level at which the comfort temperature has been exceeded. The weighting puts an emphasis on large departures from the comfort temperature. Optimising a building to flatten out the peaks in the temperature would therefore be key to minimising the amplification coefficient such as reducing peak gains and increasing thermal mass. The absolute number of PMVH is a measure of the number of hours at which the internal environment is uncomfortable for occupants. The metric in effect lumps together key weather parameters of mean radiant temperature, relative humidity, air temperature and airflow to give an equivalent environment. Optimising a building to reduce the number of PMVH would require minimising the heat gains and increasing its thermal insulation while maintaining adequate ventilation. Overall, using a single metric to measure the resilience to changes in climate is not appropriate and multiple indices must be used where by the building can then be optimised. In this case the overall metric for resilience would minimise the amplification coefficient for both the WCDH and PMVH. Given the trend in figure 5, an equal metric might consider the amplification coefficients in terms of PMVH and mean temperature. In either case, the measure of resilience does not depend on the magnitude of any index. It is the relative change of the internal conditions given a change in external conditions, which is important. Such buildings do not amplify the effect of overheating on the occupants if the climate changes. Therefore, when design teams have a choice between different options, the building which is more resilient, would have the lowest amplification coefficients. This work also has implications for locations where there is little appropriate weather data or weather files, which include climate change. The linear nature of the metrics shows that the resilience of the building is independent of the external weather, level of climate change or building location. As a result, very few weather files would need to be modelled to establish the amplification coefficients and thus determine the resilience of the building design and these do not necessarily need to be representative of the building location.

NOMENCLATURE

C = Building amplification coefficient
PMV = Predicted mean vote
PMVH = Hours PMV is greater than 0.5.
PPD = Percentage of People Dissatisfied.
T_c = Comfort temperature.
T_{op} = Operative temperature.
T_{rm} = Running mean temperature.
WCDH = Weighted Cooling Degree Hours.

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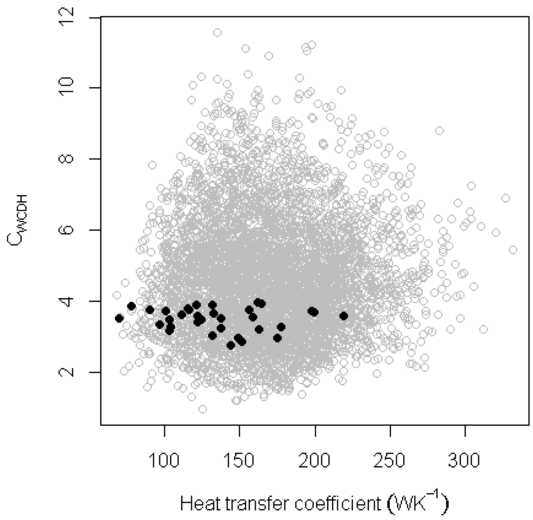

Figure 7: C_{WCDH} against the total heat transfer coefficient. The 33 optimal buildings in terms of minimizing C_{WCDH} and C_{PMVH} are shown by dark circles

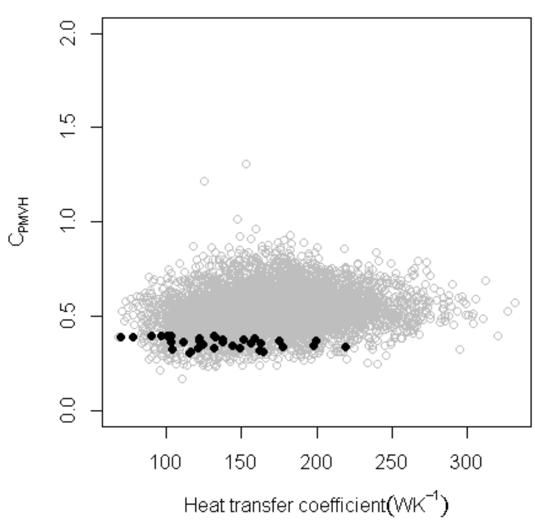

Figure 8: C_{PMVH} against the total heat transfer coefficient. The 33 optimal buildings in terms of minimizing C_{WCDH} and C_{PMVH} are shown by dark circles

Table 2
Building constructions parameters used in the building model

	MATERIAL THICKNESS (mm)	CONDUCTIVITY (W/m.K)	DENSITY (kg/m^3)	HEAT CAPACITY (J/K)
EXTERNAL WALL				
Brick	106	0.89	1920	790
Insulation	36-586	0.03	43	1210
Brick	106	0.89	1920	790
Plasterboard	12.5	0.21	700	1000
GROUND FLOOR				
Insulation	110	0.025	700	1000
Concrete	100	2.3	2300	1000
Cavity	100	-	-	-
Chipboard	20	0.13	500	1600
Carpet	10	0.04	160	1360
EXTERNAL ROOF				
Clay Tile	12.7	0.84	1900	800
Membrane	0.1	1	1100	1000
Insulation	69-594	0.03	43	1210
Plasterboard	12.5	0.21	700	1000
INTERNAL WALLS				
Plasterboard	12.5	0.21	700	1000
Brick	0.005	0.89	1920	720
Plasterboard	12.5	0.21	700	1000
INTERNAL FLOORS/CEILINGS				
Carpet	10	0.04	160	1360
Chipboard	20	0.13	500	1600
Cavity	50	-	-	-
Concrete	100	2.3	2300	1000
Cavity	50	-	-	-
Plasterboard	12.5	0.21	700	1000