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Minimising Overheating in Passive and Low Energy Buildings Using Kriging-based inverse modelling techniques

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Abstract: Preventing summertime overheating within passive buildings is important for the comfort of the occupants. The likelihood that a building will overheat depends on several factors, including the form of the building, the percentage glazing and the building's thermal mass and insulation. Furthermore, the amount of overheating depends on the criteria we use to measure it. We investigate the CIBSE TM52 overheating criteria and look at how they are affected by changes in the design of a *PassivHaus* style building. We calculate the percentage of possible buildings that pass each of the three CIBSE criteria using the *Gaussian process regression*-based *efficient global inversion* (EGI) technique. Our work is divided into two stages. First, we look at the sensitivity of the overheating criteria to the design (*i.e.* examining the building parameters that have the greatest effect on the overheating criteria). Second, we calculate the percentage of all possible building designs that meet these criteria using the EGI technique. This method provides an estimation of whether a building design will meet a criterion. This *surrogate modelling* method can be very accurate because the EGI technique 'tunes' the Gaussian process regression model to determine whether variables exceed a threshold. We explore the overheating criteria for 60,000 potential building designs. Our findings show that the relative glazed area has the greatest influence on the overheating criteria, whereas properties such as thermal mass and insulation have less effect than expected. Further work is needed to explore the effects on different building types in other climates.

Keywords: Overheating, Gaussian process, Inverse modelling, Design summer years

Introduction

To reduce the energy used by heating, many passive buildings are built with very low U-values. This minimises heat loss over the winter, but it can lead to overheating during the summer months. Since the form of the building affects overheating the most, buildings must be tested for problems before they are built (Jenkins et al., 2012). This means that we need to make use of computer simulations and simulated weather conditions so that design decisions can be made. Because of the need for computers in the design process, software simulations of buildings have a large influence on the building design.

The metrics used to measure overheating and the way that we measure overheating will influence the types of buildings that we design in the future. Our aim is to look at how *PassivHaus* style residential buildings might be affected by both the weather files and the parameters used to design them.

There are a potentially infinite number of building design parameters that can be adjusted, but some have been shown to be more important than others. These include the use (and size) of brise soleil, the amount of glazing, the orientation of the building and the relative amount of thermal mass (Eames et al., 2015; Banfill et al., 2012).

The weather files used for the dry in the simulation will also influence the building design. In the UK, design summer years (DSY) are used to test for overheating. In our work, we use the new CIBSE DSYs (Eames, 2016). These DSYs comprise of 42 weather years – 3 for each of 14 locations across the UK. The DSYs at each location each contain a moderate, and two separate near-extreme heat wave events (DSY1). One represents a year with a short more intense heat wave event (DSY2) and the other with a longer heat wave event (DSY3). We examine the effect of these extremes on the relative number of available building designs for each weather year.

We explore the effect of varying five continuous building feature on the potential overheating of the building as judged be various overheating criteria. However, as the building parameters are continuous, there are a potentially infinite number of combinations. Even if the features are limited to 20 discrete values each, the total number of simulations required would be 3.2 million. Therefore, to make this problem more tractable, we use a Gaussian process regression model to emulate the values for two of the three CIBSE overheating criteria from CIBSE TM 52 (Nicol, 2016)[1]. We have used GP models because the can be tuned to be very accurate at distinguishing between thresholds in a model. For example, if we know that we want one of our criteria to be below 3%, then we can tune the model to accurately predict whether certain building designs will be above or below this value.

Methods

Building model

The building model that we will analyse is a simple mid-terrace residential building. We simulate the results of the building model using *EnergyPlus v8.4* (US Department of Energy 2017). The building is designed to meet the standards required by *PassivHaus* (Hopfe & McLeod, 2015) and is shown in Figure 1.

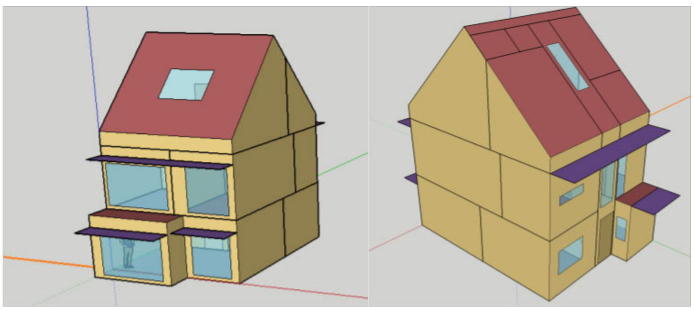


Figure 1: Building being modelled (maximum glazing and overhang shown)

The U-values for the building elements are shown in Table 1. The table also shows the glazing *g*-values, light transmission and the thickness of each of the elements used. We allow the glazed area, orientation, overhang distance, brick thickness, roof slab thickness and the position of the insulation to be varied. The maximum and minimum variables are shown in Table 2.

[1] We have not included CIBSE criterion 3 because we are not considering short temperature peaks.

Table 1: Thermal design of building

Variable	Value	Unit
U-Value Wall / Roof / Ground	0.10	$Wm^{-2}K^{-1}$
U-Value Door and $Window_{limit}$	0.85	$Wm^{-2}K^{-1}$
U-Value $Window_{real}$	0.76	$Wm^{-2}K^{-1}$
g-value	0.59	Ratio
Light Transmission	0.69	Ratio
Window layers (triple glazed)	5 / 12 / 4 / 12 / 5	mm / mm / mm / mm / mm

Table 2:Variables changed in the building model

Variable	Min	Max
Glazing area	2.6 m^2	26.0 m^2
Orientation (from North)	-90°	90°
Overhang distance (m)	0.1 m	0.9 m
Wall and roof thermal mass thickness (T_{thick})	100 mm	400 mm
Roof slab thickness	100 mm	400 mm
Relative size of internal to external wall leafs (R_{rel})	0.1	0.9

We use R_{rel} to calculate the relative thicknesses of the external (W_{ext}) and internal wall leafs (W_{int}) using the following equations:

$$W_{\text{ext}} = T_{\text{thick}} \times R_{\text{rel}} \quad \text{and} \quad W_{\text{int}} = (1 - T_{\text{thick}}) \times R_{\text{rel}}$$

CIBSE TM52 Criteria

To test the buildings for overheating, we have used the new CIBSE design summer years (DSYs) for the UK (Eames, 2016). We used the DSY1, DSY2 and DSY3 weather files for Plymouth, London and Manchester and used them to calculate CIBSE 1 and 2 criteria (Nicol, 2016). CIBSE criterion 1 measures the number of hours where the internal operative temperature is above the maximum acceptable temperature (H_e) and CIBSE criterion 2 measures the *maximum daily weighted exceedance* (W_e). Both criteria are calculated based on a variable known as ΔT.

ΔT measures the exceedance of the maximum acceptable internal temperature. It is calculated on every time step of the simulation and is related to the operative temperature, T_{op}, that is in turn based on the air temperature, T_a, and the mean radiant temperature, T_r:

$$\Delta T = T_{op} - T_{max} \qquad \text{Where } T_{op} = \frac{T_a - T_r}{2}$$

The maximum acceptable temperature T_{max} is dependent on the *running mean* temperature, T_{rm}:

$$T_{max} = 0.33T_{rm} + 21.8$$

(where T_{rm} is defined as: $T_{rm} = (1 - \alpha)T_{od-1} + \alpha T_{rm-1}$)

Where T_{od-1} is the outdoor daily mean temperature for the previous day, T_{rm-1} is the running mean temperature for the previous day and α is an empirically derived coefficient (typically 0.8). These equations can be used to derive ΔT for each time step.

- **CIBSE Criteria 1: Hours of exceedance (H_e)** - Criterion 1 sets a limit on the number of hours where ΔT is greater than 1 between 1st May and 30th September. This is the number *hours of exceedance* and provides measure of the *duration* of the overheating periods. The criterion is expressed as a percentage of the occupied hours. To pass criterion 1, the percentage of occupied hours where ΔT is greater than 1, should be 3% or less.

- **CIBSE Criteria 2: Daily weighted exceedance (W_e) -** Where criterion 1 measures the duration of overheating, criterion 2 measures the relative *severity* of overheating events. The daily weighted exceedance, W_e, measures the daily overheating severity: $W_e = \sum_{h=1}^{24} \Delta T_h$ where h is the hours of the day. This criterion is satisfied if W_e is less than 6 for all days during the year.

Seeing the building as a mathematical function

The building model can be viewed as a function. This is because the computer model takes input variables (a vector of inputs, **x**, which describe the design of the building) and converts them into two outputs, CIBSE criterion 1 and CIBSE criterion 2. We can represent these outputs as $f_1(\boldsymbol{x})$ and $f_2(\boldsymbol{x})$. Note that the choice of weather file also affects the output (Figure 2).

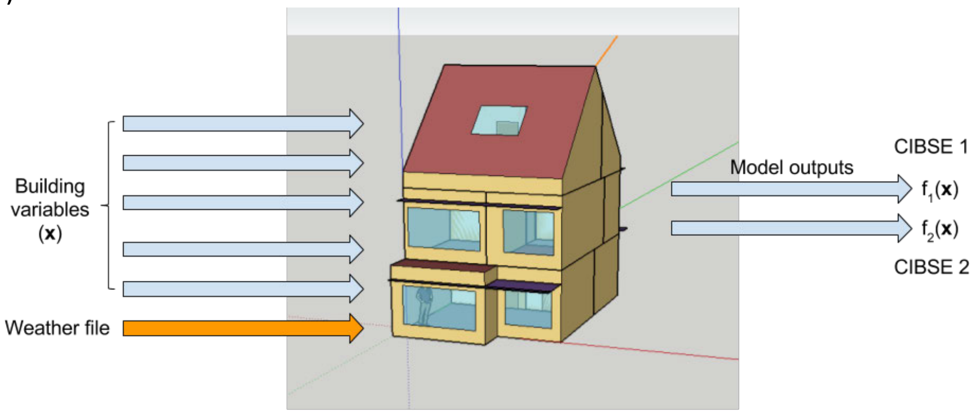


Figure 2: Representing the *EnergyPlus* building model as a function

Exploring the outputs of the building model using Gaussian process and Efficient Global Inversion

Since there is no analytic way to link $\boldsymbol{x}$ and $f(\boldsymbol{x})$, we need run the building simulator each time we want to obtain its output $f(\boldsymbol{x})$. It is possible to use the simulator alone for this, but if we want to explore a design space with more than 1 or 2 input variables, this quickly becomes a very large problem (see Bellman's curse of dimensions (Bellman 1957)). One solution to this problem is to use a surrogate model for the building model, $\hat{f}(\boldsymbol{x})$. Many different types of surrogate model can be used, but we use a Gaussian Process (GP) regression model.

We use GP regression in our model for two reasons. First, GP models allow us to explore a large sample of possible designs in a reasonable amount of time. The second is that GP regression models can be 'tuned' using a method called Efficient Global Inversion (Chevalier et al. 2014) to distinguish thresholds in the model with a relatively small number of training simulations. However, we first show how we create a regression model from the building.

GP regression has certain advantages over other regression methods. One of the nice properties of this method is that it requires relatively few training samples to provide good emulation, as little as 10 – 15 samples per input parameter (Loeppky et al., 2009) .

Efficient Global Inversion (EGI) iteratively improves the surrogate model and improves its ability to estimate a *threshold* within the model. This allow us to accurately predict whether a design will exceed an output value. In our case, we want to know whether the CIBSE criteria will be exceeded.

This is useful for our experiment in that we can build emulators with good accuracy at predicting whether the model has failed the criteria for the hours of exceedance (threshold at $H_e = 3\%$) or the daily weighted hours of exceedance (threshold at $W_e = 6$ degrees).

To improve the emulator at each threshold, EGI uses a three-step iterative process:

1. Create a surrogate model $\hat{f}(\boldsymbol{x})$ for the original building model $f(\boldsymbol{x})$
2. Predict the next sample $(\boldsymbol{x}_{n+1})$ that will improve the threshold estimate the most
3. Run the simulator at point $\boldsymbol{x}_{n+1}$ and return to step 1.

The surrogate model is created using a training set of inputs $\boldsymbol{D}$ (where $\boldsymbol{D} \in x$), which is created using a Latin hypercube design (Franco et al., 2011). This set of inputs are fed into the building simulator one at a time. This produces the *response* data $f(\boldsymbol{D})$. The input data and the response data are then used to *train* the surrogate model.

GP models are different from most linear regression methods as the outputs is represented as a multivariate Gaussian process:

$$\hat{f}(\boldsymbol{x}) \sim \mathrm{GP}(m(\boldsymbol{x}), v(\boldsymbol{x}, \boldsymbol{x}'))$$

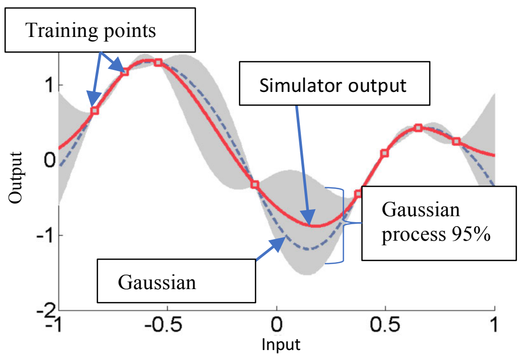


Figure 3: Gaussian process function and example realisation in one dimension

where $m(\boldsymbol{x})$ is the mean function and $v(\boldsymbol{x}, \boldsymbol{x}')$ is the variance function.

Although that output of the Gaussian process is essentially random Gaussian noise (with a mean of $m(\boldsymbol{x})$ and a variance of $v(\boldsymbol{x}, \boldsymbol{x}')$), this doesn't mean that we think the original simulator output is random. Instead, we are using the Gaussian process to allow us to express uncertainty in the output as demonstrated in Figure 3 above. The mean and variance functions of the Gaussian process model are estimated using a training set (shown in Figure 3). Standard functions govern the mean and variance. However, these functions require the tuning and estimation of hyper-parameters, who's derivation would be too lengthy to detail here. There interested reader is referred to *Gaussian Processes for Machine Learning* (Rasmussen & Williams 2006).

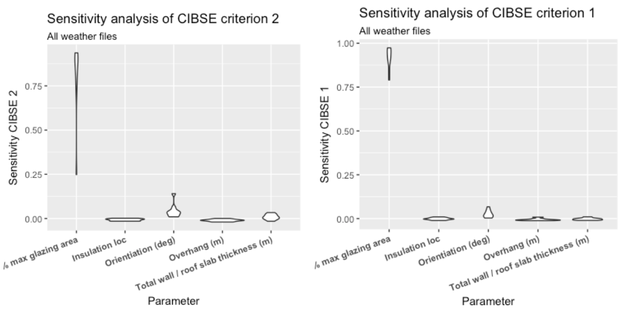
Results

Table 3 shows the percentage of buildings passing for both CIBSE criterion 1 and criterion 2 for each of the weather files tested.

Table 3: Proportion of emulated buildings passing the CIBSE criteria

Weather file	% passing CIBSE 1	% passing CIBSE 2	% passing both
London DSY1	49.8	5.4	5.4
London DSY2	86.5	66.0	66.0
London DSY3	43.6	0.4	0.4
Manchester DSY1	96.6	35.7	35.7
Manchester DSY2	90.9	27.2	27.2
Manchester DSY3	60.9	0.8	0.8
Plymouth DSY1	100.0	96.3	96.3
Plymouth DSY2	100.0	75.3	75.3
Plymouth DSY3	96.4	32.6	32.6

Figure 4: a) Sensitivity analysis of CIBSE 1 (left) of CIBSE 2 (right) for all weather files



The results of the sensitivity analysis show that the main first order effects on both CIBSE criterion 1 and CIBSE criterion 2 are the orientation and the % maximum glazing area. The analysis was conducted using the *sobol* function of the *sensitivity* package for *RStudio* (R Core Team, 2017; Sobol, 1993) . Figure 4 a) and Figure 4 b) shows a violin-plot of the sensitivities of the parameters across all the weather files tested. Figure 5 shows the compliant designs.

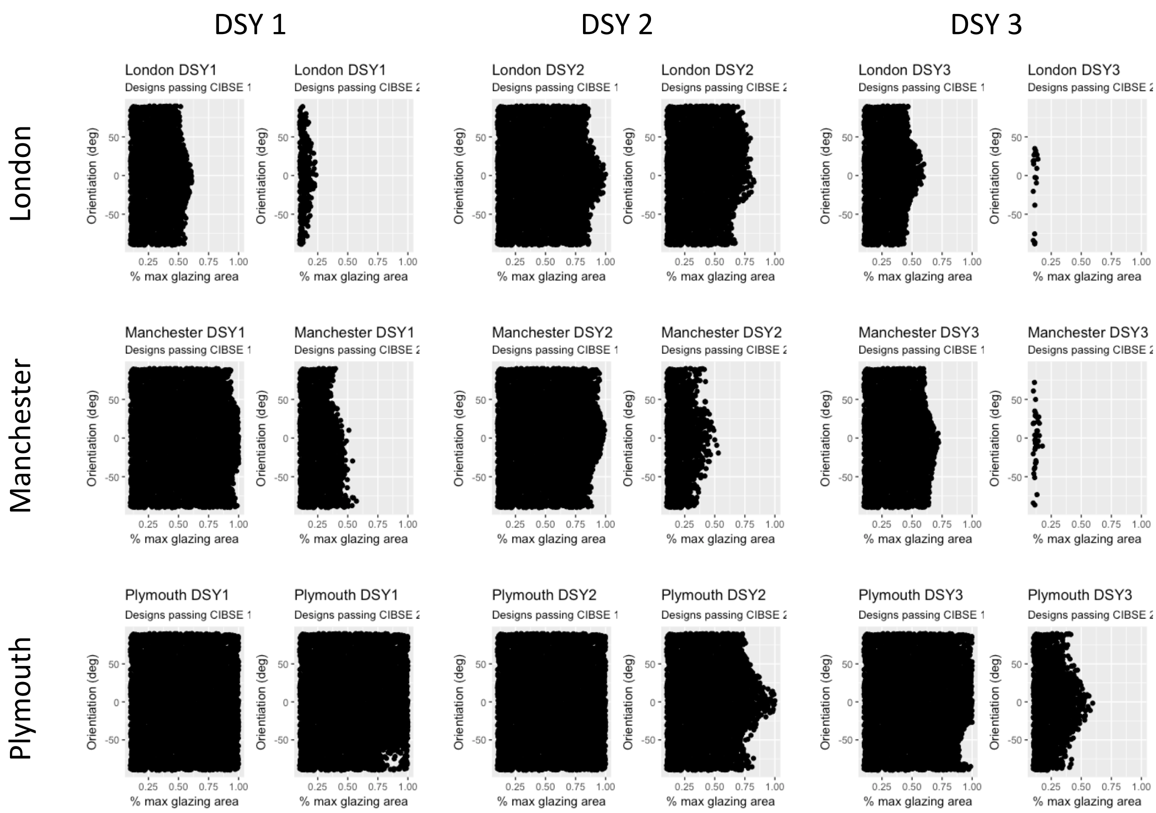


Figure 5: Plot showing the designs that pass the CIBSE 1 and CIBSE 2 criteria for each weather file

Discussion

The results in table 3 show that the % of buildings passing criteria 2 is overall less than those passing criteria 1. It also shows that a much larger percentage of buildings pass criteria 1 than criteria 2. The later as few as 0.4% of buildings pass criterion 2 for London DSY3. The percentage of buildings passing both criteria is the same as those passing criterion 2. Further investigation has shown that all buildings that passed criterion 1 passed criterion 2.

The results of the sensitivity analysis show how the biggest factor influencing both criteria 1 and criteria 2 was the glazing area. Across all weather files, the sensitivity of both criteria to the glazing area was between 0.79 and 0.97 (criterion 1) and 0.25 and 0.94 (criterion 2). Of the remaining variables, orientation has the greater influence, but this is not significantly more than the influence of the insulation location, overhang and the total wall / roof slab insulation thickness. Interestingly the amount of thermal mass appears to have limited influence on the overheating response in all cases (at least compared to the other variables).

Knowing that the orientation and the glazing were the biggest influencers of both overheating criteria, we plotted the buildings that pass each of these criteria in Figure 5.

The results of this analysis show a wide range of compliant designs. Not surprisingly, the buildings with the lowest glazing consistently pass both criteria in all cases. The exception is for London DSY3 and Manchester DSY3, where only a handful of buildings pass the criterion 2. The orientation also influences the overheating. In Figure 4, we can see a pattern where the number of compliant buildings increases for both criteria (though particularly criterion 2) where the lounge side of the building is facing due south (i.e. *orientation = 0 degrees*). This can best be seen for Plymouth DSY3 (criterion 2) and London DSY 3 (criterion 3).

It is well understood that solar radiation plays an important part in overheating. However, our results show that even with the same building designs, the pattern observed is different. For example, comparing the results of criterion 2 for Manchester DSY1 and DSY2 we see different patterns. Both have around the same number of compliant designs, but the *pattern* of where those designs lie is different (see Figure 4).

We expect the number of buildings passing DSY2 would be less, which is true (27.2% *vs.* 35.7%), but the pattern of building designs in DSY1 is more skewed to an orientation of -90 degrees, whereas the DSY2 has more high glazing options at orientations around 0 degrees.

Given that criterion 2 is based on a single day's-worth of overheating, there are several possible explanations for this pattern. One explanation is that cloud cover may play a major role. Since the hottest day will trigger criterion 2, then on this day, it may be that there is more cloud cover in the weather file during different periods of the day. There needs further investigation, but if cloud cover can influence the design in this way, then this has important implications for weather file design.

Conclusion

We have demonstrated the results for a *PassivHaus*-style building design. The results show that the glazing and orientation are the biggest determinants over the overheating risk. Further work is required to investigate these same relationships for other passive and low energy design methodologies. Also, these findings may also only be relevant to the CIBSE overheating criteria. Further work may also consider looking at other overheating criteria.

However, it is clear from the results that it is very likely that the relative glazing area is the biggest design parameter affecting the amount of overheating in passive-style buildings.

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