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Translating probabilistic climate predictions for use in building simulation

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Abstract

With the onset of global climate change it is necessary, when designing buildings, to understand how a change in ambient conditions might affect the performance of a building. This requires the integration of future climate predictions with appropriate building simulation software. Previous approaches to this have used deterministic predictions of climate, essentially design years that provide a single prediction for what a future year might look like. The UK Climate Projections '09 (UKCP'09) have presented predictions in a probabilistic format – through multiple iterations of climate models, a large dataset of climate predictions can be constructed for specific scenarios, where each climate has a certain probability of occurrence. The Low Carbon Futures project described by this paper will suggest a methodology for translating this information into a building context. Not only will this provide a range of building performance predictions relating to a range of climate predictions, but also the effect of this predicted climate change on the "failure" of that building at some time in the future can be discussed. Such a failure may involve overheating in a naturally ventilated building, or a cooling plant becoming insufficiently sized. Through the simulation of multiple climates for specific buildings (accounting for occupancy, location, operation and construction), the project will demonstrate the link between specific climate metrics and overheating criteria, and the probability of this occurring. The project will use this methodology to discuss the failure probability of buildings including naturally ventilated offices, dwellings without mechanical cooling and also schools, though this paper will focus on overheating in the domestic sector. Where simulation techniques identify a potential issue with overheating, adaptation scenarios will be suggested (and simulated) to look at the possibilities of "future-proofing" these buildings against climate change. The methodology relies on applying established statistical methods to the climate data, to allow this information to be integrated into ESP-r dynamic building software and to develop simplified statistical models capable of estimating building performance, that closely approximate the predictions of ESP-r, in relation to climate data.

1. Introduction

In UK buildings, the main energy consumption is often (particularly in dwellings) that used for space heating (Shorrock and Ultey, 2003). The consequence of this is that approaches towards energy-saving refurbishments are often, usually quite rightly, centred on insulating the buildings and making it more air-tight. However, when a warming climate is accounted for, the danger of the building becoming too warm in the summer is likely to become an issue unless adequate design decisions have been made to accommodate this. To assist this design requirement, it is necessary to obtain an appropriate understanding of future climate change and to define suitable overheating criteria for that specific building.

Furthermore, these two assumptions need to be integrated into a design process such that buildings can be specified (both new buildings and refurbishment projects) with a low risk of failure in future summers.

The latter point of comfort criteria will be mostly assumed in this paper rather than investigated in detail, based on previous research as to the point at which an individual might act to change the internal environment in a dwelling due to them feeling too warm. Specifically, the study will look at periods where the bedroom temperature at night exceeds 23.9ºC, justified elsewhere (Peacock et al, 2009; He et al, 2005), though different comfort/overheating criteria may yield subtly different results (which will be investigated in due course by the project).

Therefore, this paper will be more concerned with the methods of integrating probabilistic climate projections, based on UKCP’09 (Murphy et al, 2009), into building simulations for overheating analyses (where the overheating definition can vary by building characteristics as well as user assumptions). Such climate projections will offer a range of possibilities (based on multiple iterations of climate models) for future climates in various locations. The result can be many thousands of climate files and simulating such a broad climate description within building software will usually be too time-consuming and impractical for building designers. The challenge is to gain an understanding of how future climate change will affect the risk of a building, or building services, becoming poorly specified.

The project will be looking at both domestic and non-domestic buildings, but this paper will be concerned with the former. Using a basic house design, and the previously stated overheating definition, an approach will be described for simplifying the relationship between climate and overheating metrics, such that the information in a probabilistic database can be efficiently transposed into an output describing the performance of that building in a future, and warmer, climate.

The work is part of the Low Carbon Futures project based at Heriot-Watt University as part of the Adaptation and Resilience to Climate Change (ARCC) programme (Low Carbon Futures, 2010).

2. Simulation of domestic building

Figure 1 shows the ESP-r model used for the simulation, a 3-bed house with a baseline infiltration rate of 0.7ac/h (with small variations due to wind-induced pressure changes). Air movement throughout the building is modelled using an airflow network, which is particularly important when modelling the effect of window openings. The house is modelled with an unheated loft, not shown in the diagram.

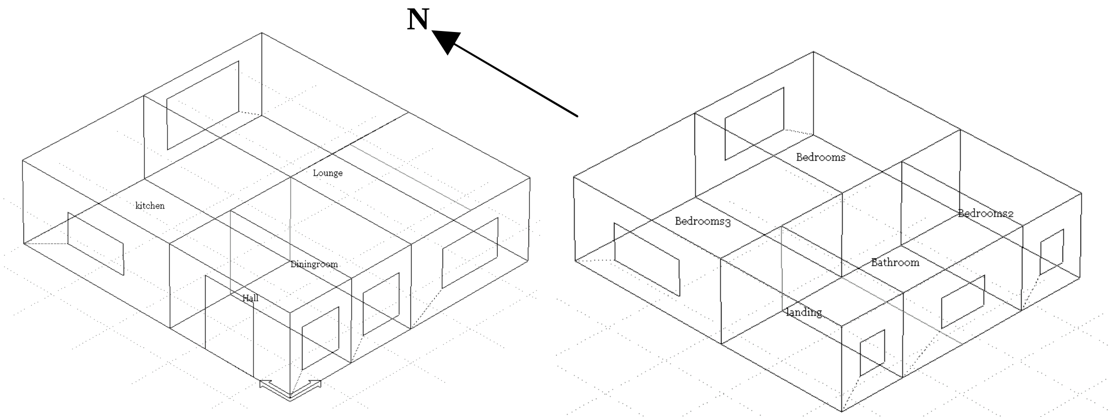

Figure 1 – ESP-r diagram of ground floor (left) and first floor (right) of modelling dwelling

The building model has a wall U-value of $0.37W/m^2K$, corresponding to a filled cavity wall construction. The floor areas and heating setpoints are summarised in Table 1. Additional information relating to the detailed internal activity, lighting and appliances assumptions can be found elsewhere (Peacock et al, 2009).

Table 1 – Dimensions and heating set-points of case-study buildings

Room	Floor area (m2)	Internal heating setpoint (degC)
Hall	8	21.5
Lounge	36	21.5
Landing	8	21.5
Dining	8	21.5
Kitchen	20	18
Bedrooms	48	18
Bathroom	16	26.5
Total	144	20.4 (average)

For the purposes of simplifying the simulation results, the analysis will focus on the average temperature of the "Bedrooms" zone, i.e. the North-East zone of the top floor. It is important to split the entire bedroom area ($48m^2$) into three zones representing actual rooms, as the simulation will be running a window opening schedule (if the bedroom zone was just one zone then there would be unrealistic air movement from windows of other zones). However, zonal temperatures of one bedroom will still be affected by the temperatures of the other bedroom zones (which will also have controlled window openings).

The building is modelled for two behaviour scenarios: i) "No adaptation", with the occupants not reacting to high bedroom temperatures and ii) "Window opening", which refers to a simple control algorithm where the window in each bedroom is opened at $0.5m^2$ if the bedroom temperature of that respective zone exceeds 23.9ºC. If the temperature drops below this level, the window is closed. While this behaviour is very idealised, and relies on the occupant being present whenever an overheating event occurs, it does indicate the maximum potential of the openings (as sized) for reducing the bedroom temperature. In reality, the detrimental noise and air-change issues associated with such an opening might cause the occupant to close the window while the bedroom temperature is still uncomfortably high.

Also, a building designed to optimise natural ventilation might have vents and windows in a position to utilise buoyancy effects. However, as the dwelling in question is an existing building, not designed with overheating as a main concern, this effect will not be simulated.

The $0.5m^2$ opening is found, following simulation, to provide a substantial increase in the air-changes in the bedroom zones. The results of the window opening algorithm on the air-changes in one of the bedroom zones (relating to the topmost zone in the right diagram in Figure 1) is shown in Figure 2. It can be seen for much of the year that the air-change is close to 0.7ac/h (i.e. the base infiltration rate) and then, at specific times, reaches almost 1.2ac/h for that room when the window is opened. It should be noted that the relatively constant infiltration rate is a result of modelling this as a fan, with slight variations due to wind speed fluctuations. Clearly, infiltration can be modelled in a more fundamental way, assigning cracks and gaps to the walls to account for the "leakiness" of the building and allowing the simulation engine to calculate the resulting air changes per hour. However, the desire was to specify this infiltration rate at an exact value to be, in some way, typical of this type of building – therefore a “virtual” fan was deemed the most effective way of doing this. The window ventilation, however, is defined merely by the opening size and the simulation engine performs the calculation to estimate the effect on zonal air change.

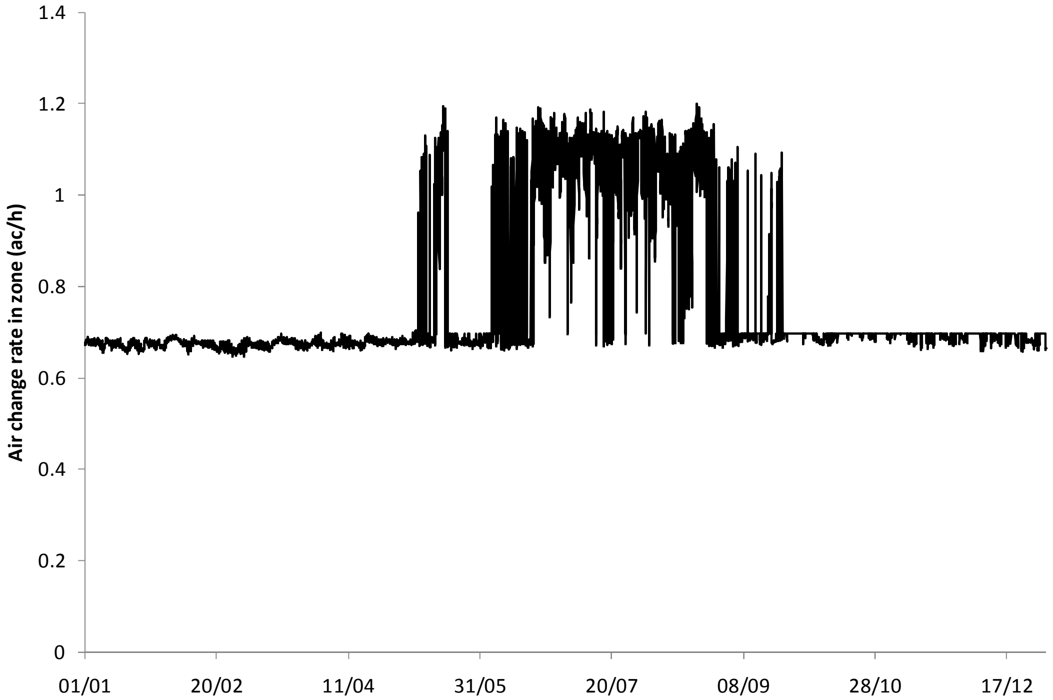

Figure 2 – Total air change rates (ac/h) throughout the year for the bedroom zone

3. Description of methodology

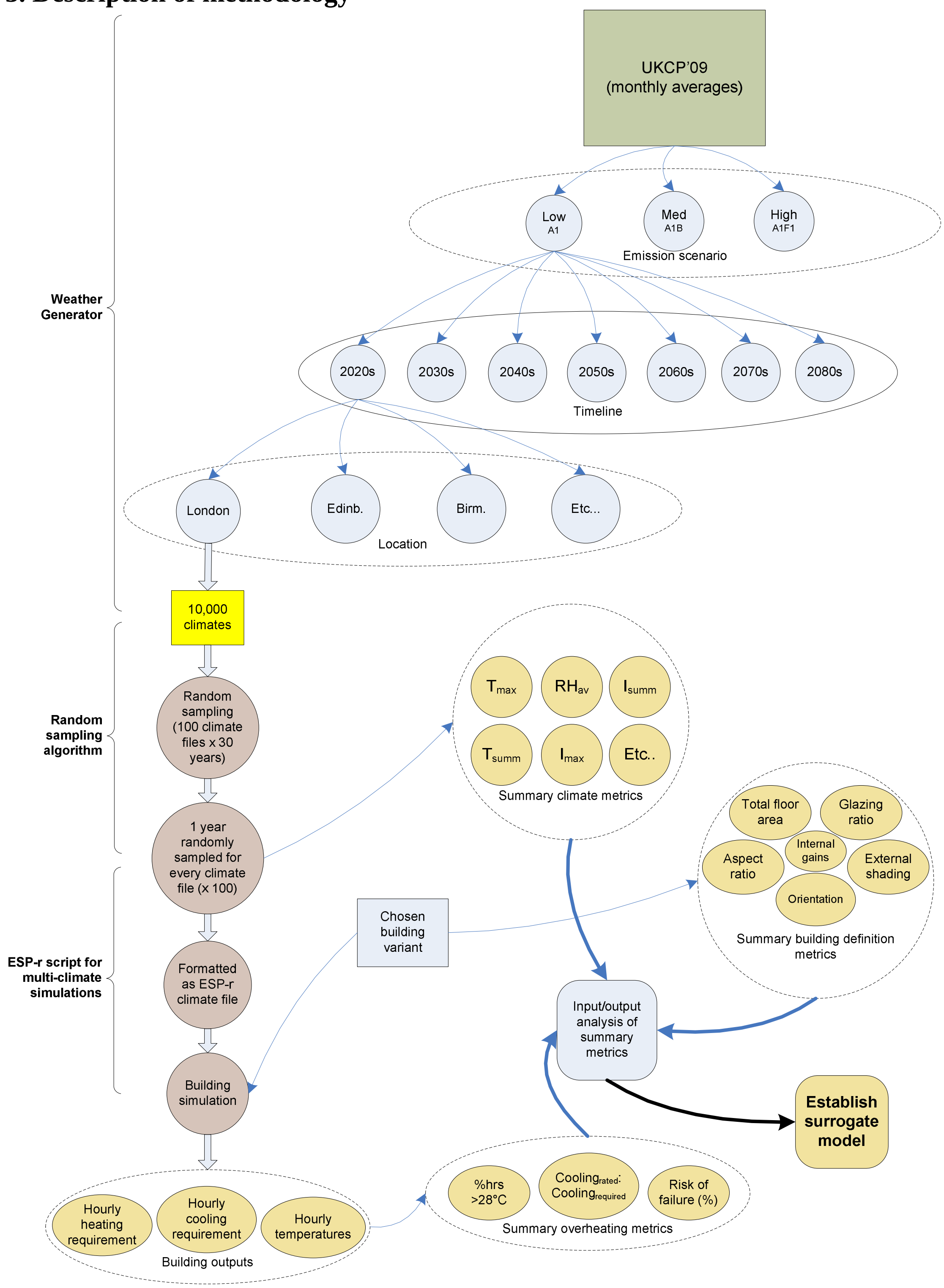

Figure 3 – Diagram of proposed methodology for assimilating probabilistic climate data into building simulation practices

3.1 Summary of approach

The steps proposed for producing a simplified design tool from simulation output are summarised as follows, and shown diagrammatically in Figure 3:

i. Select climate scenario from Weather generator defined by:
   a. Emission scenario

b. Timeline
c. Location

ii. Randomly choose 100 annual climate files from the above dataset
iii. Simulate chosen building in ESP-r (Clarke et al, 2007) to produce hourly temperature for the zone(s) concerned, for identified climate file(s)
iv. Formulate regression equation to predict the hourly temperatures of one climate year, with regression coefficients calibrated by ESP-r output (see section 3.3)
v. Validate hourly temperature regression equation for other climates from step (ii)
vi. Repeat for adaptation scenarios, re-calculating regression equation (or adding corrective factor) as necessary
vii. Produce overheating metrics from hourly simulated and hourly regression equation temperatures.
viii. Compare these results to confirm suitability of regression equation for predicting overheating for any climate scenario for a specific building, i.e. "surrogate model", a design tool for overheating estimations
ix. Further steps include, from the point of view of the user of such a design tool, providing a means of running the tool without the need of resorting to hourly climate files. This will involve simplifying the chosen climate through "summary climate metrics", essentially averaged information of that climate. Likewise, allowing the regression tool to automatically account for "summary building metrics" (e.g. floor area, glazing/wall ratio) would allow for greater application of the tool, and even reduce the reliance on simulation in the first place (currently needed to calibrate the regression equation for any change in the building definition). Both these options are currently being investigated, though are not included in this paper.

The detail of the above is described in section 3.2 and 3.3. This should be read as a generic process, though the case-study of section 2 is used as a template for this approach. The hypothesis is that when carrying out a dynamic building simulation, and faced with hundreds (or thousands) of climate files that represent a probabilistic climate dataset, it is acceptable to produce a regression equation, train (i.e. calibrate the regression coefficients) this through a single building simulation, and then use that regression equation for any number of other climate files for that same building.

3.2 Selection of climate scenarios

To begin our investigation we need information on the UK's possible climate in the near future. For any user-specified UK location at 5 by 5 grid square resolution, future time period (seven future 30-year periods, overlapping every 10 years, from 2010–2039 to 2070–2099 are available) and emission scenario (three "Low", "Medium" and "High" emission scenarios are available), "Weather Generator", a tool provided by UKCP09 (UKCP'09, 2009), can create 100 statistically equivalent hourly time series of weather variables. Each of these time series are of 30 years in length and represent the possible future climate for the user-defined conditions. The weather variables generated at hourly scales are: total hourly precipitation in mm, mean hourly temperature in ºC, vapour pressure in hPA, relative humidity in %, sunshine fraction of an hour, downward diffuse radiation and direct radiation (both in W/m^2).

In the present work, for the selection of one UK location (Central London), we will investigate the performance of the domestic building case-study (section 2) at a future time period [2020 – 2049], referred to as “2030”, and at three available emission scenarios (“Low”, “Medium” and “High”). Further we will compare our findings with the baseline time period [1961 – 1995]. For each of the three different emission scenarios at the time line of 2030 we need to run three different sets of Weather Generator simulations, while only one run for the baseline time period (which is not, by definition, categorised by a future emission scenario). Notably each run will produce 3000 equally probably representative climate years at an hourly scale for the desired period of 30 years of time. The information that can be produced by the Weather Generator tool is therefore potentially vast and necessarily requires simplification for use with a building model simulation (such as ESP-r), while maintaining the essential features that are important for defining the hourly climate conditions.

To serve this purpose an algorithm is prepared based on statistical methods. From each of the 100 time series of 30 year duration, a single year is selected at random to generate a representative sample of size 100 from the distribution of future climates with hourly resolution. These 100 hourly climate data files provide the input for a series of ESP-r building simulations and ultimately identify the probability of occurrence of climate conditions that may cause a certain building to overheat.

3.3 Formulation of regression equation

3.3.1 Prior to adaptation

To develop a simple probabilistic model capable of performing a quick and easy assessment of the likely impact of climate on the performance of the selected building, the outputs from ESP-r are carefully analysed against corresponding climate information. Bedroom temperatures were used as a metric to assess the comfort of residents inside the building under investigation.

Multiple regression techniques are used to identify the relationship between bedroom temperature and corresponding weather variables. It is clear that present bedroom temperatures inside the house must depend on the outside weather conditions at that time and at some time in past (due to the thermal mass and heat retention of the building). All weather variables and corresponding ESP-r output (particularly bedroom temperature) is recorded at an hourly scale for each of the 100 possible climates. One climate file is randomly select and a multiple regression model fitted to the chosen period (from May to October, i.e. a potential domestic overheating season suggested elsewhere (Peacock et al, 2009)). The model can efficiently predict bedroom temperature at an hourly resolution based on present and past hourly weather variables by means of a simple linear model given as:

$$\begin{aligned} T_{bed}(t) &= C + \sum_{i=0}^{71} m_i T_{ext}(t-i) + m_{72} R(t) + m_{73} P(t) \\ &+ m_{74} RH(t) + m_{75} SF(t) + m_{76} I_{diff}(t) + m_{77} I_{dir}(t) \end{aligned} \qquad (1)$$

where bedroom temperature at any time *t* hour $T_{bed}(t)$ can be estimated as a linear combination of 72 hrs of previous external air temperature $T_{ext}(t-i)$ (*i* varying from 0 to 71), present value of total hourly precipitation $R(t)$, vapour pressure $P(t)$, relative humidity $RH(t)$, sunlight fraction of an hour $SF(t)$, downward diffuse radiation $I_{diff}(t)$ and direct radiation $I_{dir}(t)$.

Constant C and coefficients m_i (i varying from 0 to 77) of Equation 1 were estimated using "R" (software environment for statistical computing and graphics ("R" software package, 2010) and are listed in the Appendix.

Equation 1 directly predicts the hourly temperatures across the potential overheating season. This means that, if this equation is validated for the scenarios discussed, any overheating metric should be similarly validated, providing that metric is based on hourly temperatures (e.g. percentage of hours over 28ºC (CIBSE, 2005), peak temperature at night etc).

3.3.2 Accounting for adaptation scenarios

To model adaptation scenarios, it is argued that the bedroom temperature with window openings permitted, at any time t, should have some dependencies on the bedroom temperature with windows assumed closed, estimated by Equation 1, at time t and at some time in the past $(t - i)$. These dependencies were analysed by considering multiple regression techniques and a simple "Window Open" addition to the model is proposed:

$$T_{bed\_wo}(t) = C + \sum_{i=0}^{2} T_{bed}(t-i) m_i \qquad (2)$$

where bedroom temperature (with window open) at any time t, $T_{bed\_wo}(t)$ can be predicted as a linear combination of 3 hrs of previous and present bedroom temperatures (windows closed) $T_{bed(t-i)}$ (i varying from 0 to 2).

Notably, to formulate Equation 2, hourly summer data was used, which has been randomly selected from the sample of 100 representative years for "Medium" emission scenario. This data was fitted using the same "R" software as previously described, where estimated constant C and coefficients m_i (i varying from 0 to 2) of Equation 2 are given in Table 2.

Table 2 – List of coefficients for window opening algorithm adaptation

Coefficients	Estimate
C	2.50727
m_0	0.55068
m_1	0.04694
m_2	0.25962

4. Regression model validation

The building is simulated for a London climate, for a baseline and "2030" scenario (specifically, the UKCP'09 2020-2049 timeline), in three future emission scenarios, and with or without an adaptation choice of opening the windows to cool the building. With 100 climates describing each scenario, the model in section 2 is effectively simulated across 800 climate scenarios (with the baseline not being applicable to the three different future emission scenarios).

The following section will document the results of the ESP-r simulations for the various scenarios, the application of the regression equation (detailed in section 3) in attempting to abbreviate this simulation process, and also the correlation between the two techniques.

4.1 Internal temperature profiles

The first, and most detailed, validation exercise is to compare the hourly temperatures in the bedroom zone that is predicted by the ESP-r simulation and calculated by the regression analysis. Due to the large amount of data involved from all the scenarios analysed, the most appropriate method for visualising the comparison between the two methods is graphical residual analysis. Figures 4 and 5 are frequency plots for the difference in predicted temperature for the two scenarios, Figure 4 referring to the "no adaptation" case (i.e. Equation 1) and Figure 5 displaying the results where window openings are permitted (i.e. implementing Equation 2).

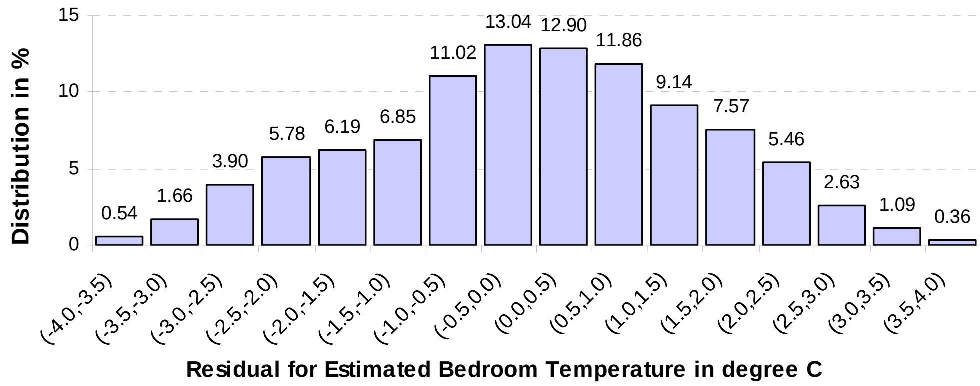

Figure 4 – Graphical residual analysis of correlation between ESP-r and regression equation predictions, for no adaptation

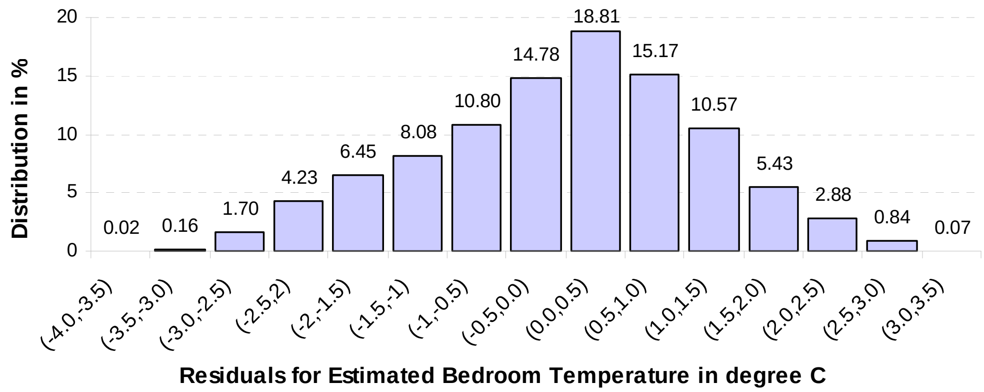

Figure 5 – Graphical residual analysis of correlation between ESP-r and regression equation predictions, with window openings permitted

These plots show correlations that are centred around a zero error (i.e. a match between ESP-r predictions and regression equation) but also showing errors of significant size (i.e. greater than ±1ºC) occurring at a significant frequency. In Figure 4, the regression equation is within 1ºC of the ESP-r values for 49% of compared values, and within 2ºC for 79% of the compared values. In Figure 5, which permits window opening as an adaptation, the equivalent numbers are 60% (for ±1ºC) and 90% (±2ºC).

Another way of displaying this data is in a scatter plot, showing all the individual hourly values that have been compared across the different climate scenarios. Figures 6 and 7 show an example of this data for the "no adaptation" and "window opening" scenarios. An ideal match between simulation and regression predictions would show a linear trend about "y=x", which is indeed seen (or suitably close to this) for all figures. However, as suggested in Figures 4 and 5, the spread of the data is still quite significant, where a variation of just 1ºC can be important when assessing thermal comfort in a building. The data does suggest, however, that the regression equation is providing the correct trend in temperature predictions, if using the ESP-r simulation as the comparator.

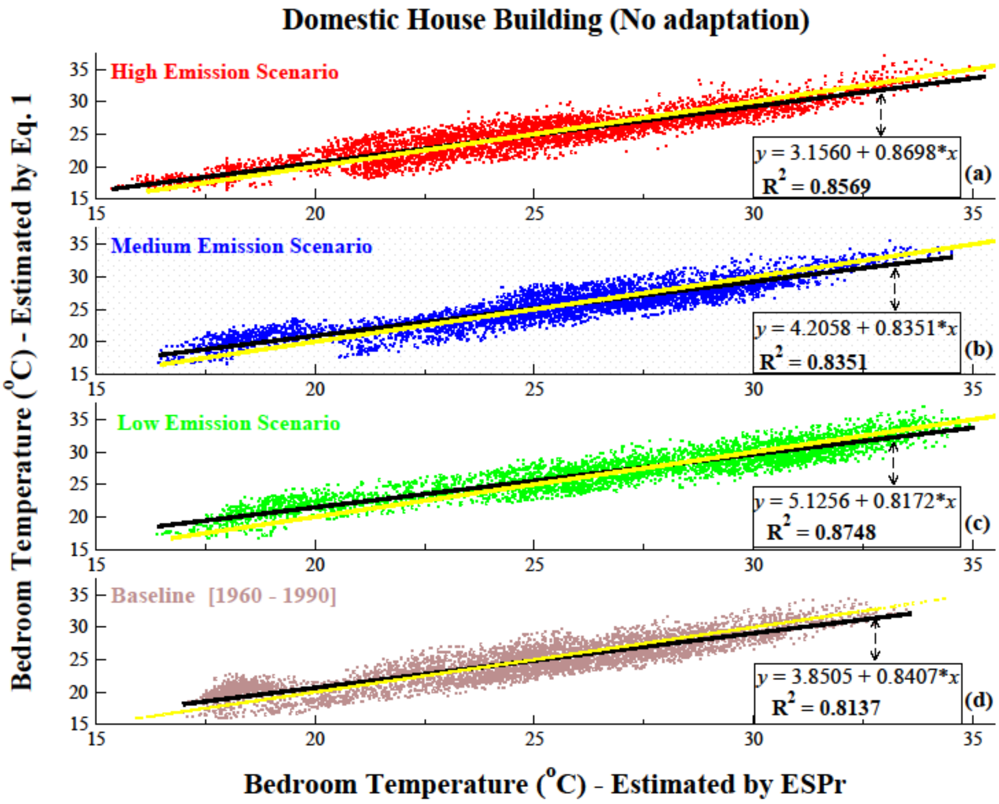

Figure 6 – direct comparison of simulated and regression hourly temperatures across four climate scenarios (no adaptation). *Yellow line represents "y=x"*

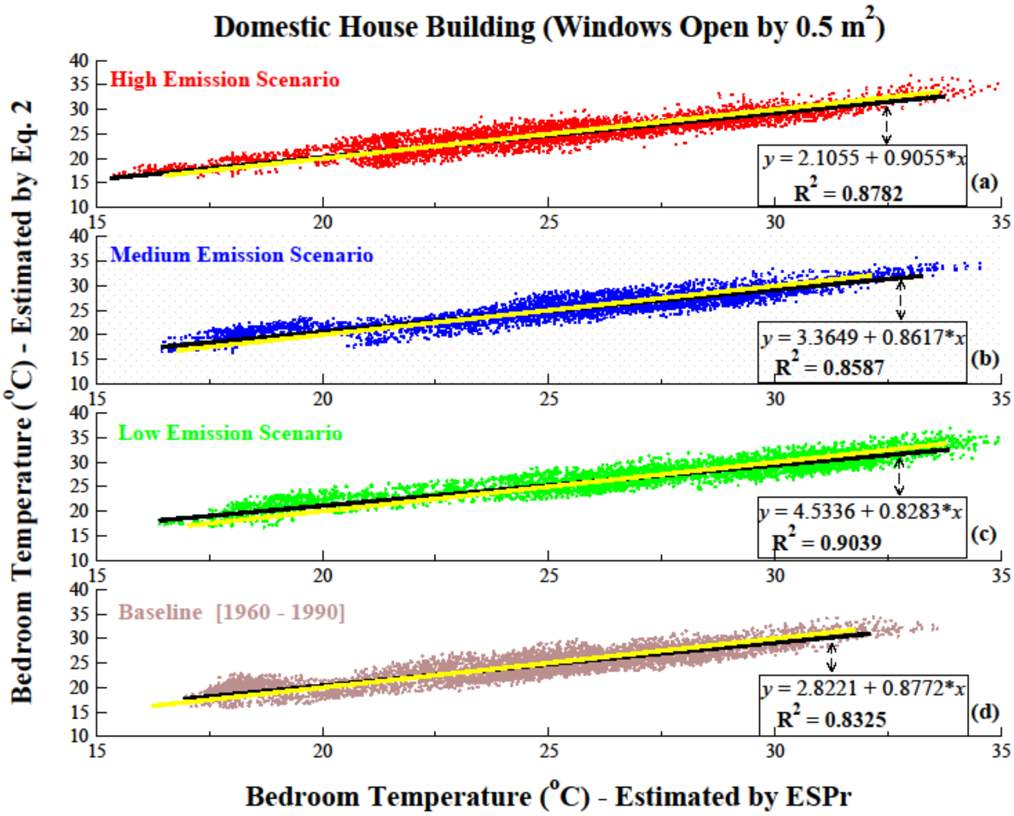

Figure 7 – direct comparison of simulated and regression hourly temperatures across four climate scenarios (window opening permitted). *Yellow line represents "y=x"*

In summary, it is suggested that the above comparison does not represent adequate correlation between simulation and regression for hourly temperature predictions. However, this process is currently undergoing additional statistical analysis (not included in this study) which will involve the use of auto-regression corrections techniques and principal component analysis (Jolliffe, 1982). It is believed that such additional manipulation can reduce the spread of values along the linear trends of Figures 6 and 7.

While the above suggests that the regression formula does not (currently) have a high accuracy for predicting exact temperatures at specific hours, the regression method might still be suitable for predicting general overheating metrics, as demonstrated below.

4.2 General overheating characteristics

As discussed, it is difficult to select a definitive metric for overheating. However, two measures that indicate the temperature/overheating in a bedroom might be the average temperature throughout the day, and the occurrences of an "overheating event" (defined as greater than 23.9ºC) during the night. It is therefore a useful exercise to validate the regression equation for these parameters.

Firstly, Figures 8 and 9 show, for different scenarios, the number of hours above 23.9ºC taken across the whole day, and also during the night-time (11pm to 7am), which is arguably the period at which discomfort in the bedroom might be most prevalent as the adaptation scenarios of the occupant will be restricted. The scenarios refer to the baseline climate and the three future climate projections of low, medium and high emissions for the timeline of 2020-2049. The calculations are taken across a potential “overheating” season of May to October, as suggested elsewhere (Peacock et al, 2009).

Figure 8 shows the estimations where the occupants do not make any adaptations or changes in their environment, while Figure 9 allows the occupant to open the bedroom window (by $0.5m^2$) when the temperature in that zone exceeds 23.9°C. “ESP-r” refers to the simulation package of the same name and “RegEq” refers to the regression equation of section 3 for the same scenario.

The results for each scenario (i.e. base, low, medium and high) are averages across the 100 random climates chosen within each climate projection – however, these are based on hourly results for each individual climate (with Figures 6 and 7 in section 4.1 being examples of this).

Similarly, Figure 10 shows the average bedroom temperature, across all 100 climates (per scenario), throughout the overheating season (N.B. ESP-r simulations are run for a full calendar, but the overheating metrics are only calculated for the potential domestic overheating season of May to October). This, in itself, is not necessarily suitable as an overheating metric on its own – averaging across all 100 climates and all hours in the season will result in a loss of resolution for short-term (i.e. hourly) variations in temperature (which again emphasises the importance of carrying out validation, firstly, on an hourly basis). However, this metric is useful for validating the more generic output of the regression equation where, if producing a design tool, hourly resolution might not actually be desirable or necessary.

The comparison between the ESP-r simulation and regression output is reasonable across all metrics and scenarios. It is noticeable that the regression equation consistently under-predicts the overheating criterion in the baseline (by up to 6.5% across all results in Figures 8 and 9), and slightly over-predicts the future projections (by up to 6.4%). The predictions for average temperature show greater correlation than the other overheating metrics – which is to be expected for the reasons mentioned above.

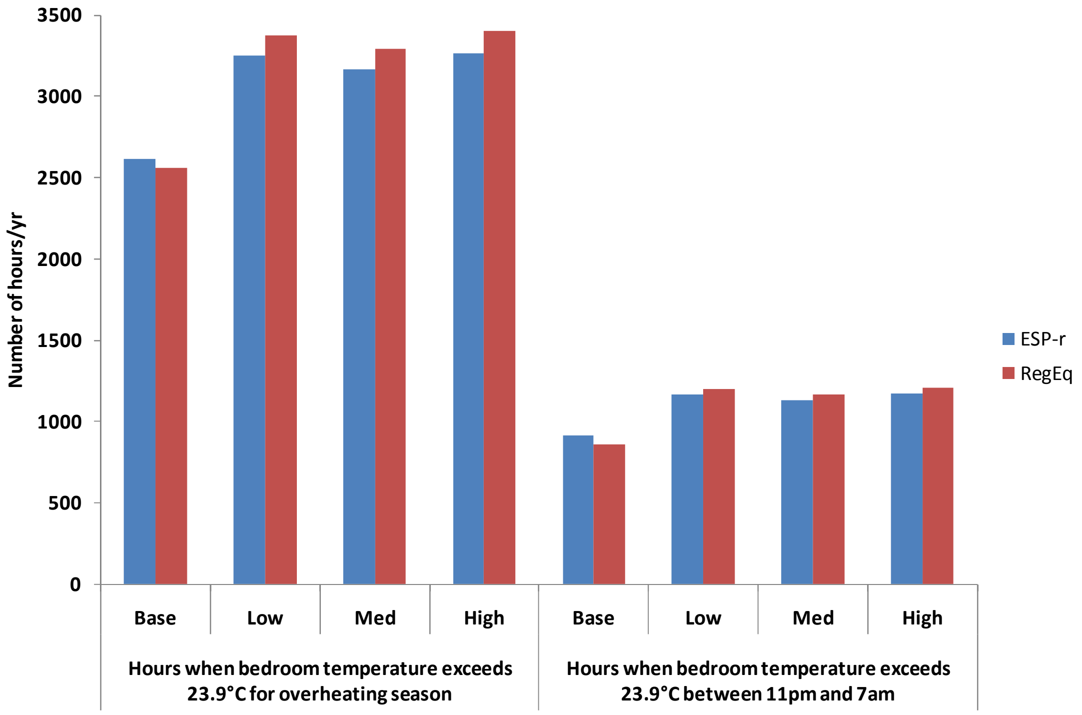

Figure 8 – ESP-r and regression equation results of overheating in the domestic case-study across all scenarios, without adaptation

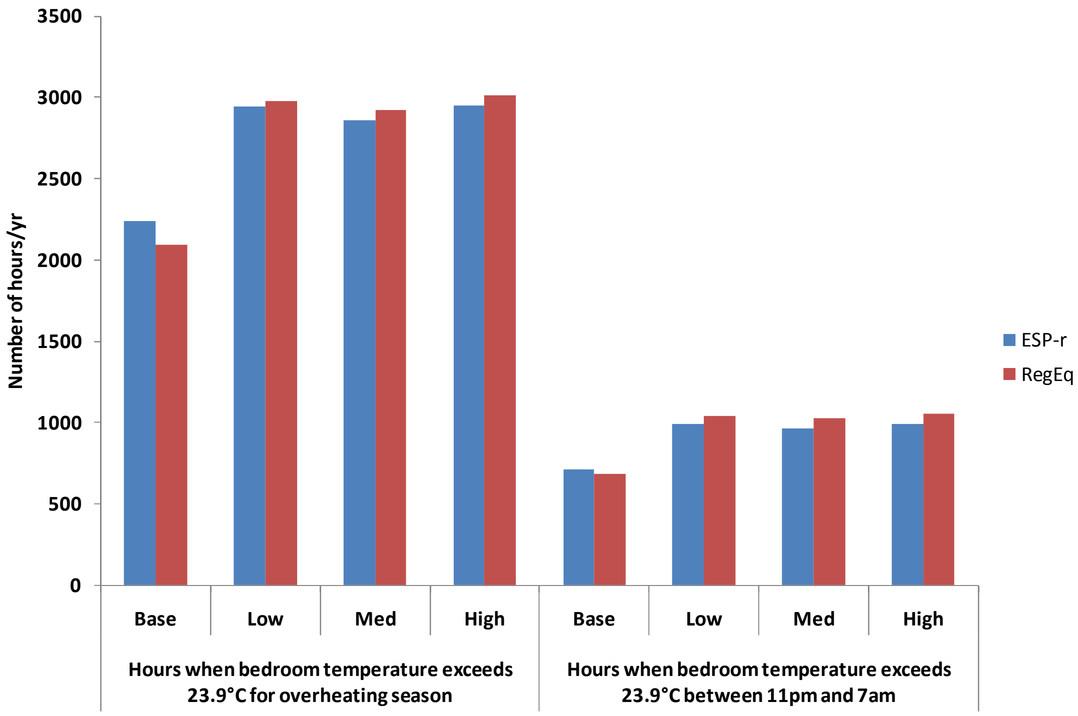

Figure 9 – ESP-r and regression equation results of overheating in the domestic case-study across all scenarios, with window opening adaptation permitted

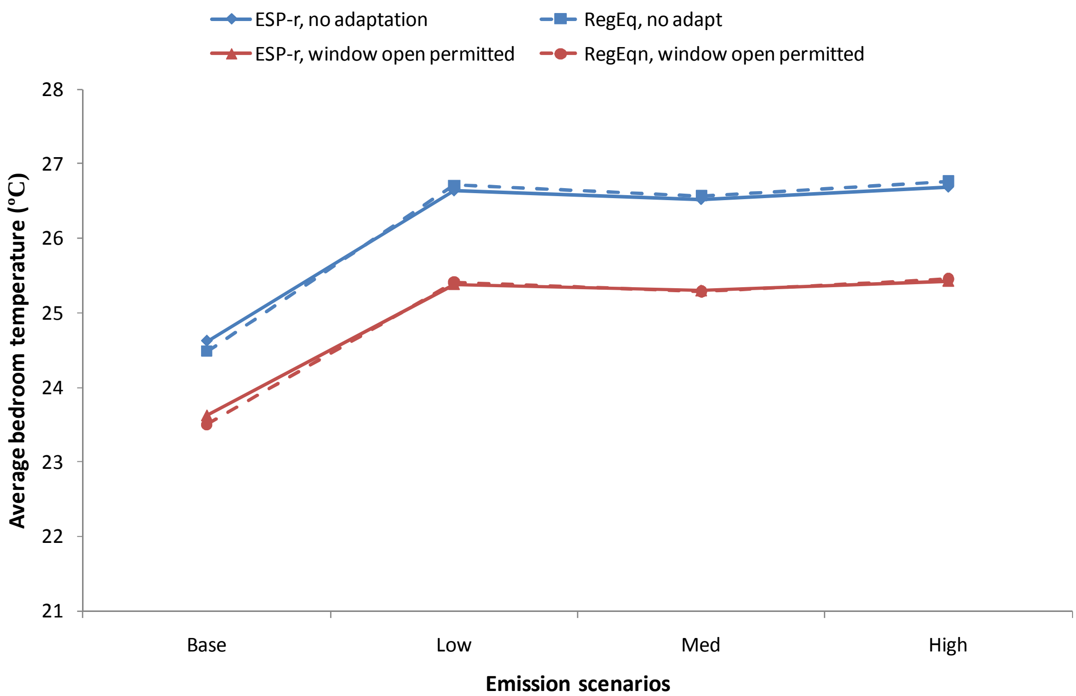

Figure 10 – Predicted average bedroom temperatures for different climate scenarios

The validation of both hourly temperatures and more generic overheating metrics seems to suggest that the regression equation method is an acceptable "short-cut" when attempting to carry out many climate configurations (i.e. hundreds or more) for a specific building model.

5. Application of results

It has already been mentioned that the precise definition of overheating can vary depending on the subjective view of an individual, as well as the nature of the building itself. However, if the described regression approach can be successfully formulated for hourly temperatures then, theoretically, any overheating metric should be successfully predicted through the regression equation. This means that the time-consuming process of building simulation need only be carried out once, to calibrate the regression tool for that specific building, and then any future climate from the weather generator can be run through the regression tool to predict both hourly temperatures and overheating metrics, whatever the latter may be.

The current limitations of the hourly predictions have been discussed in section 4.1. These issues will be resolved to provide a more reliable base for the general overheating risks that might be expected in the building concerned. With regards to these overheating metrics, Figure 11 provides an example of useful output that might be presented to a building designer or simulator. The procedure might be to simulate a building in a “current” or baseline climate, and then look at the change in overheating risk for future/alternative scenarios, which will be based on the regression equation (taking the form of an additional module attached to the simulation engine), rather than requiring hundreds of additional simulations across many climate files.

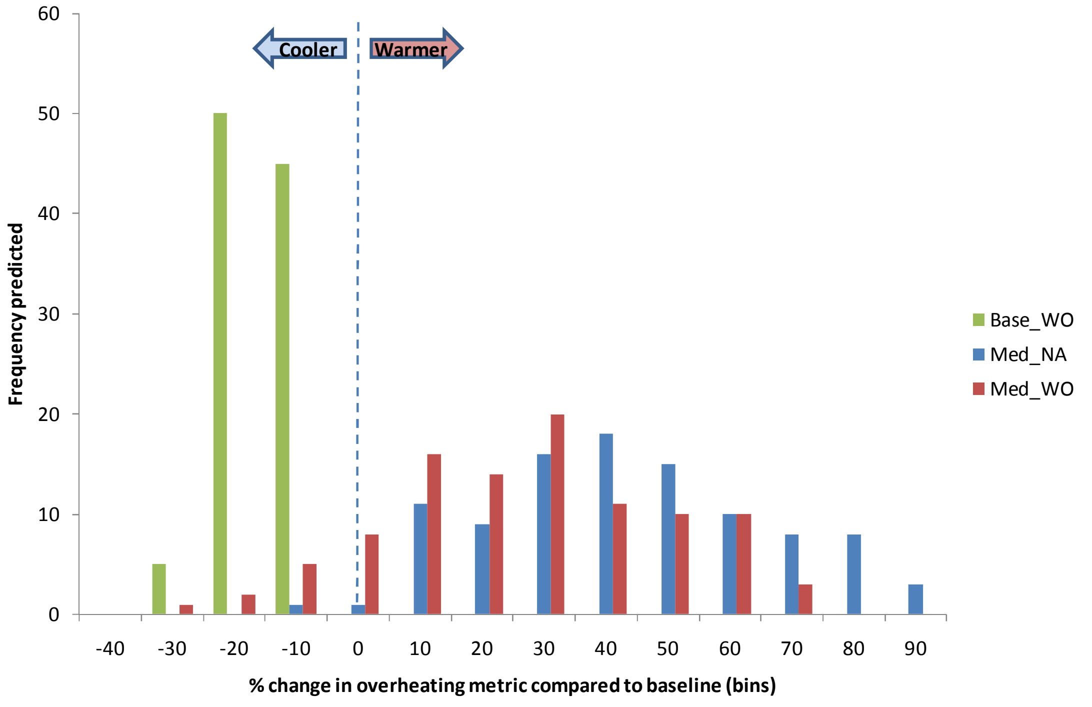

Figure 11 – Predicted (using regression equation) change in overheating metric (hours >23.9ºC during 11pm to 7am) compared to the baseline climate

Figure 11 uses the medium emission scenario as the future climate (defined by the randomly selected, equally probable, 100 climate files described in section 3). The “baseline” is the baseline climate without adaptation. The percentage change in the chosen overheating metric (in this case the number of hours above 23.9ºC between 11pm and 7am in the bedroom) is given for three scenarios, namely: the baseline climate with window openings permitted (“Base_WO”), the future climate without window openings (“Med_NA) and the future climate with window openings permitted (“Med_WO”). The results show, for example, the most “likely” effect of the future climate is a 40% increase in overheating, which is reduced to 30% if intelligent use of window openings (merely one adaptation possibility) is permitted. The same process can be carried out for other climate scenarios, as well as other adaptation choices (such as external shading, cooling methods etc), which might be chosen by the user.

Following these steps, a number of building variants will be investigated, requiring the methodology described in this study to be repeated for other simulated buildings. The format of the output will be, subsequently, disseminated to building professionals through focus groups, with feedback allowing any developed design tool to be tailored to suit industry and current practices of building design and simulation.

6. Conclusions

This study is based on the work currently being carried out by the ARCC-funded Low Carbon Futures project. The proposed methodology, based on a simulation-generated regression equation, aims to provide an efficient means to account for future climate projections in building design and simulation.

The results indicate that calculating general overheating risks, through regression formulae based on one climate, can be just as reliable as detailed simulations of many different climates. The prediction of specific hourly temperature profiles requires more analysis, but initial results suggest that this also might be possible through amended regression techniques. The advantage of validating the hourly predictions would be that any overheating criterion, based on temperature, would be as adequately described through the regression formula as through the detailed ESP-r simulation (once an initial simulation has been carried out to calibrate the regression formulae).

The significant simplification provided by the regression technique might allow the formulation of a design tool that is suitable for building professionals to assess the likelihood, and risk, of a specific building overheating in the future. This tool would also estimate the effect of basic adaptation choices for "future-proofing" the design against future climate change – a building might have a relatively low risk of overheating in the current climate but, for example, adding external shading might keep that risk level at a suitably low level for the next thirty years.

It is imagined that such a procedure would complement existing dynamic simulation packages and, indeed, actually rely on their output in the first case.

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Appendix – Regression coefficients relating to Equation 1

Coefficients	Value	Coefficients	Value
C	6.9591131	m_{39}	0.0173817
m_{0}	-0.027547	m_{40}	0.0406241
m_{1}	0.0808412	m_{41}	0.0134318
m_{2}	0.031773	m_{42}	0.0183002
m_{3}	0.0011261	m_{43}	0.0274299
m_{4}	0.0503898	m_{44}	0.0345959
m_{5}	0.0684512	m_{45}	-0.018704
m_{6}	0.0572569	m_{46}	-0.092068
m_{7}	0.0421012	m_{47}	-0.040946
m_{8}	0.0394333	m_{48}	-0.026114
m_{9}	0.0558224	m_{49}	0.0230136
m_{10}	0.0082685	m_{50}	0.036176
m_{11}	0.0017581	m_{51}	0.0122102
m_{12}	-0.001719	m_{52}	0.0527425
m_{13}	0.0011713	m_{53}	0.0560589
m_{14}	-0.003973	m_{54}	0.0223648
m_{15}	0.0206476	m_{55}	0.0031303
m_{16}	0.024711	m_{56}	0.0196094
m_{17}	0.0378183	m_{57}	0.0189426
m_{18}	0.0360358	m_{58}	0.0322428
m_{19}	0.017793	m_{59}	-0.010965
m_{20}	0.0289734	m_{60}	-0.016885
m_{21}	0.0084015	m_{61}	0.0303163
m_{22}	-0.054494	m_{62}	0.0515813
m_{23}	-0.088576	m_{63}	0.0559254
m_{24}	-0.051005	m_{64}	0.0266307
m_{25}	0.0299561	m_{65}	0.003148
m_{26}	0.033748	m_{66}	0.0105853
m_{27}	-0.00124	m_{67}	0.006762
m_{28}	0.0407536	m_{68}	0.0071595
m_{29}	0.0592041	m_{69}	-0.05874
m_{30}	0.0450379	m_{70}	-0.119354
m_{31}	0.0087487	m_{71}	0.2140646
m_{32}	0.0158841	m_{72}	0.1152178
m_{33}	0.0359563	m_{73}	-0.029354
m_{34}	-0.008983	m_{74}	-0.730503
m_{35}	-0.015487	m_{75}	0.3095552
m_{36}	-0.023128	m_{76}	0.0145201
m_{37}	0.0300079	m_{77}	0.003109
m_{38}	0.0057654		