Toward Assessing the Sensitivity of Buildings to Changes in Climate

Initial work on a novel performance methodology

PARAG RASTOGI,
Interdisciplinary Laboratory for Performance-Integrated Design (LIPID),
École Polytechnique Fédérale de Lausanne (EPFL),
Lausanne, Switzerland, parag.rastogi@epfl.ch

SOENKE F. HORN,
LIPID, EPFL, Lausanne, Switzerland, sonke.horn@epfl.ch
MARILYNE ANDERSEN
LIPID, EPFL, Lausanne, Switzerland, marilyne.andersen@epfl.ch

Substantial numbers of existing and new buildings are expected to survive long enough to experience perceptible shifts in climate 'normals' (averages). To predict a building's response to changes in typical weather, two inputs are required: weather data representing this change, and suitable metrics to compare building performance across different climate normals. This paper presents initial work on a proposed method for assessing the sensitivity of new or existing buildings to climate change. This method begins with a selection of weather files to represent climate change, then quantities a building's passive performance in those climates using an enthalpy-based metric, and ends with a graphical analysis of the performance of the building in different climates to assess its robustness. In this paper, we propose an objective performance metric based on the extent to which a building creates indoor conditions passively, i.e. without auxiliary systems. Initial work suggests that the performance assessment carried out here is reproducible and applicable for indoor environment design and evaluation in different ranges of climate change. This approach enables a comparison of building performance without the bias introduced by inherent differences in climatic conditions.

Keywords: energy, passive performance, climate change

Toward Assessing the Sensitivity of Buildings to Changes in Climate

Initial work on a novel performance methodology

PARAG RASTOGI[1], SOENKE F. HORN[1], MARILYNE ANDERSEN[1]

[1] Interdisciplinary Laboratory for Performance-Integrated Design (LIPID), École Polytechnique Fédérale de Lausanne (EPFL), Lausanne, Switzerland

ABSTRACT: Substantial numbers of existing and new buildings are expected to survive long enough to experience perceptible shifts in climate. To predict a building's response to changes in typical weather, two inputs are required: weather data representing this change, and suitable metrics to compare building performance across different climate normals. This paper presents initial work on a proposed method for assessing the sensitivity of new or existing buildings to climate change. This method begins with a selection of weather files to represent climate change, then quantities a building's passive performance in those climates using an enthalpy-based metric, and ends with a graphical analysis of the performance of the building in different climates to assess its robustness. In this paper, we propose an objective performance metric based on the extent to which a building creates indoor conditions passively, i.e. without auxiliary systems. Initial work suggests that the performance assessment carried out here is reproducible and applicable for indoor environment design and evaluation in different ranges of climate change. This approach enables a comparison of building performance without the bias introduced by inherent differences in climatic conditions.
Keywords: energy, passive performance, climate change

INTRODUCTION

Putting aside political wrangling, this paper accepts the premise that climate change is a reality we have to confront in the near future. While climate scientists do not necessarily agree about what that change will be, various national and international bodies publish probabilistic scenarios for reference and adaptation. There is a general consensus in the building engineering community that the built environment, as a major user of energy and materials, has contributed substantially to the problem [1]. As building designers, we are not trying to predict changes in climate, only what it means for the buildings we construct. Rightly or wrongly, a lot of research has focussed so far on mitigating climate change rather than adapting to it. Buildings are usually designed for a functional lifespan of 50-100 years, with some level of anticipated renovation. External economic pressures remaining the same, the lifespan of a building strongly depends on its ability to maintain a desirable indoor climate. A building that does not meet expectations is liable to be torn down as soon as it is feasible to do so. If buildings are to perform well, i.e. maintain a comfortable indoor environment, in a climate different from the one they were designed for, we need to know their robustness or sensitivity to changes in typical weather or climate. Good design for the present climate is no guarantee of performance in a different climate, since individual design features and components behave differently when subjected to varying kinds of environmental stress. Current predictions of the robustness of the "more energy efficient building variants [are mixed]: Crawley [2] states that they are less sensitive to change [than regular buildings], whereas Wang et al [3] come to the opposite conclusion." [1]

This paper describes the initial development of a methodology to assess the robustness of a building's performance in a changing climate. It consists of three parts: a performance metric based on the concept of an energy 'distance' or 'gap', a protocol for selecting files to simulate future weather conditions, and finally a graphical method for assessing the robustness of a building to changes in climate. Since the methodology is in its initial phases of development, the number of case studies is limited. The graphical analysis is made from a relative perspective, comparing case studies to one another in terms of their correspondence to physical phenomenon and expectation. A proper quantification of the shapes of the resulting graphs, which we call 'response surfaces', will be carried out in future work. The response surfaces are single-dimensional as of now, i.e. they are response 'curves', since we were only able to make coherent analyses of the results along one of our intended dimensions (temperature).

Performance Metric

The performance of buildings is usually expressed in terms of such metrics as energy use, if they have auxiliary HVAC systems, or number of (un)comfortable hours. These metrics are perfectly valid for capturing the performance of a building in a given climate to explore design options, or to compare the performance of different buildings in the same climate. However, these comparisons rely on starting from the same baseline – the prevailing climate and its unique effect on a building. If the baseline climate itself shifts during the course of an analysis, then the resulting numbers for energy use or discomfort hours are less informative about the performance of the building itself. Rather, they are coloured by the inherent nature of the climate and its relation to human comfort. This concept of a climate-defined baseline has been explored in other contexts, as the idea of a 'climatic energy burden'. Emmanuel et al [4] carried out a review of historical and recent efforts to quantify this burden (of energy demands) that a climate places on a building. They themselves proposed a Climate Energy Index (CEI), which is very similar to one component of the performance metric proposed in this paper, the 'outdoor energy distance' (detailed below). They calculate the CEI as "an annual sum of unit energy required to condition $1m^3$ of air at any weather hourly ordinate to the nearest boundary of a human comfort zone [i.e. sensible and latent load]".

Future Weather Data

Guan [5] reviewed extant methods to create future weather data for building simulation. She classified these methods into four main types: (i) extrapolating statistical [refs 1-3, *ibid*] and (ii) imposed offset methods [refs. 6-13, *ibid*], where average anticipated changes are mapped onto historical patterns; (iii) stochastic weather [refs. 15-16, *ibid*] and (iv) global climate models (GCM) [refs. 17-18, *ibid*], which localise our understanding of the underlying physics and statistical properties of the climate. Extant literature, however, suggests that the rise in global temperature predicted by GCMs is not useful *as is* for building simulation for two reasons: localising these models to the spatial and temporal resolution required for building simulation would overwhelm the computing power available for most simulation work, and the *average global rise* in temperature is not necessarily indicative of micro- or meso-scale changes in climate.

De Wilde and Coley [1] also mention the possibility of using historical data from other locations to represent climate change for a given (home) location, and this is the speculative approach adopted in this paper. Since future climate cannot, by definition, be compared to measurements, evaluating these methods against each other is problematic. Their representativeness may, for example, be compared with climate change projections from the Inter-governmental Panel on Climate Change (IPCC). In comparing different methods, their spatial and temporal resolution is important, as is the time required to generate time series for a given location. Maintaining the historical auto- and cross-correlation of several different time series when creating future weather data is a persistent problem noted in the literature.

Future Weather in Building Simulation

To produce hourly weather files for simulation, one can use any extant procedure for creating Design Reference Years from long term data. Examples of projects include those for specific applications, e.g. [6] for Passivhaus design and [2] for Urban Heat Island issues; or those for specific geographical areas, e.g. the Prometheus project based on the UKCP'09 predictions [7, 8, 9]. Software such as METEONORM [10] generate "future weather files" corresponding to an IPCC climate change scenario, though it is not transparent how these files are produced. Since this particular software relies on stochastic generation of hourly data from observed distributions of different parameters scaled by long term 'normals' (averages), it probably generates future weather data by extrapolation of these normals based on a chosen scenario.

Several projects have explored the practicality of using probabilistic climate projections in building simulation [4, 5, 6, 7]. The general trend seems to be to try and cover as many probable scenarios as possible without computational overload. Since computationally-intensive and comprehensive risk analyses are not feasible for industrial application, various simplifying measures have been proposed (e.g. regression equations [15, 16, 17] or preselection of future typical weather years [13]).

METHODOLOGY

Our methodology, which is equally applicable for new or existing buildings, consists of the following steps:

1. Simulate a building in its home environment, without an HVAC system. We remove HVAC systems to understand the buildings' passive response, since that is what we are trying to measure with our performance metric.
2. Locate contours of temperature gradients around the home location (or contours of any other pivotal weather parameter of interest). For example, cities with a one degree centigrade difference in mean annual temperature, and so on.
3. Simulate sub-sample of locations at each contour of interest, preferably with a variety of humidity and solar radiation patterns.
4. Plot simulation output of interest against the pivotal parameter. In this methodology, we plot a building's passive performance (in terms of the performance metric defined below) against temperature increments. We make a case below for why the proposed performance metric is a better indicator than say, total uncomfortable hours.

Future Weather

As discussed before, it is problematic to predict the complete set of future values and interactions for a given climate [5]. In this method, we bypass the question of the predictive accuracy and suitability of future climate generation with a speculative approach. We hypothesise a temperature change and simulate several locations with that difference of temperature, but an otherwise different climate. This way, we do not restrict ourselves to a particular prediction and are able to consider various probable developments instead. We use *existing* weather files from different locations in the vicinity of the home location. This allows us to examine the passive response of a building as the hypothetical future climate changes by increments of a chosen parameter. In this case we picked annual average outdoor dry bulb temperature as our pivotal parameter, although any parameter of interest could be used instead. For example, we intend to also analyse changes in building performance against a range of changes in solar radiation and humidity conditions. So, a given temperature contour line represents a range of annual temperature patterns and other meteorological parameters. In this project, we used hourly weather files from the METEONORM software (Meteo) based on historical data (like TMY files). The source of these design reference year weather files is less important, so long as they are considered representative of the climates being studied.

Performance Metric

The most commonly used metrics to evaluate a building's performance are its energy consumption and/or the number of (un)comfortable hours (based on any preferred comfort zone). These are complementary metrics, since a higher use of energy is generally associated with a climate that will also produce a high number of uncomfortable hours. Energy consumption is, however, highly dependent on the predominant outdoor conditions and the HVAC system used (type, efficiency, etc.). This means that the comparison of buildings in different climates or with different HVAC systems is not straightforward, and the behaviour of a building's design and materials could be masked in such a comparison. In this project, we propose a metric which measures performance as the ability of a building, acting passively and without an auxiliary system, to mitigate the impact of outdoor climatic conditions. The metric proposed in this paper represents the difference between two quantities: the enthalpy (energy) distances of indoor and outdoor conditions from a given comfort zone.

$$\Delta H = \Delta H_{vap} + \Delta H_{sensible} \tag{1}$$

$$P = \sum_{t=1}^{T} \Delta H_{out,t} - \Delta H_{in,t} \tag{2}$$

ΔH is composed of a sensible and latent term, each representing the distance of a state of atmosphere (i.e. temperature and humidity), plotted on a psychrometric chart, from a comfort zone in terms of the difference in (sensible

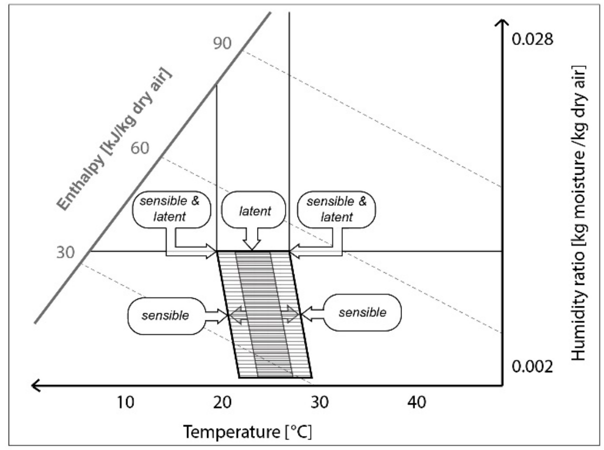

***Figure 1**: The idealised energy distance we use to calculate performance in this method. The hatched parallelograms represent static or dynamic comfort zones.*

and latent) energy. $\Delta H_{out,t}$ and $\Delta H_{in,t}$ represent this distance/gap for a single outdoor/indoor point (i.e. one reading or simulation output). P is performance, arrived at by summing the individual outdoor and indoor enthalpy gaps over a whole year (t = 1,…,T). We assume a constant pressure and chemical composition of the air, and that no work is done on the system. This means that the 'distance' on a psychrometric chart, which is calculated in terms of enthalpy, represents the theoretical latent and sensible load, or the amount of energy (per unit mass) that would be needed to close the gap to the comfort zone. [18]

Indoor climatic conditions are obtained from simulating a building without an HVAC system. The outdoor and indoor states can be plotted on a psychrometric chart as 'clouds' of points. The distance between individual points in these clouds and a specific comfort zone is what we call the energy distance of each point. This is, in essence, the theoretical sum of latent and sensible energy addition/removal required to 'move' a point into the comfort zone. We chose to not calculate a straight-line distance, since HVAC systems and human comfort models treat sensible and latent energy differently. The performance

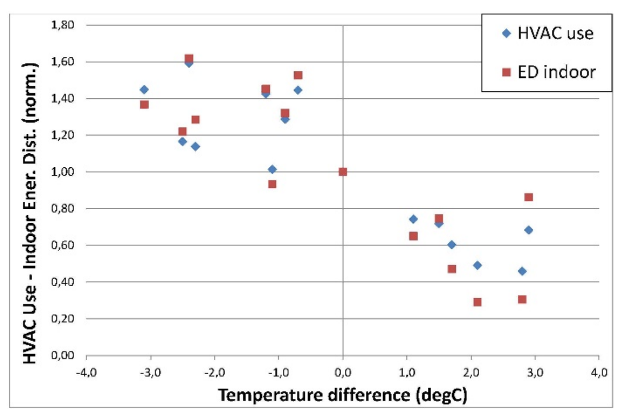

***Figure 2**: Indoor energy distance and HVAC energy use plotted against temperature change for Chambéry.*

metric we report is the difference of the sums of outdoor and indoor energy distances for each hour of the year. This idealised concept of energy gap is illustrated in Figure 1. The indoor enthalpy distance is representative of expected HVAC energy consumption, as demonstrated by Figure 2 later. Enthalpy distance is an idealised measure of the theoretical loads that an HVAC system would have to meet, and these can be treated as equivalent metrics. Figure 2 shows a plot of HVAC energy use and Indoor Energy distance implemented in the Chambéry building. As is visible from this plot, the trends of the two are very similar. Some differences arise due to the non-linear of the response of any HVAC system.

Our metric is conceptually similar to heating and cooling degree days. The disadvantage of the degree day approach is that it measures the distance to the comfort zone in one dimension only – temperature. It is unable to capture the energy distance between over-humid climatic states and the upper humidity limit of the comfort zone. In contrast, the notion of enthalpy offers the possibility of describing the location of each point around the comfort zone in two dimensions. In this iteration of our method, comfort is taken to be adaptive but in the boundaries of the standard ASHRAE winter and summer comfort zones [18]. In keeping with the adaptive comfort approach originally developed by de Dear and Brager [19], and later adopted by the ANSI/ASHRAE Standard 55-2004 [20], the comfort temperature is assumed to depend linearly on the preceding month's mean temperature. We chose a standard definition of comfort since it is not the main emphasis of this project. The idea of an adaptive comfort zone is appropriate to this analysis since we are simulating naturally ventilated residential buildings [21]. To examine the quantities generated by our metric against existing performance metrics, we present below the results of a comparison with discomfort hours and indoor enthalpy distance (theoretical HVAC loads).

SIMULATION/EXPERIMENT

For our pilot case study we simulated three single family homes (Figure 3) in the towns of Braunschweig in north-central Germany (BS); Chambéry in south-eastern France

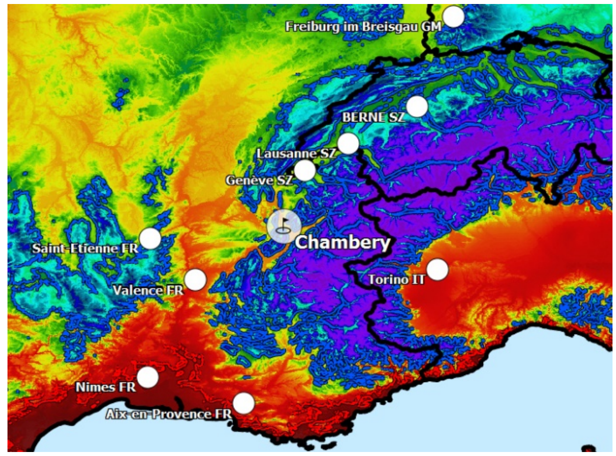

***Figure 4**: The temperature contour map for Chambéry. Red represents a change of around +2.5°C, while dark blue represents about -2.5°C. Green is roughly the same annual average temperature as the home location (Chambéry here).*

(CHM); and Rudrapur in north-central India (RDP). The first two buildings are in continental European climates and the last is in a hot and humid monsoon climate. While the homes in Germany and India are real buildings, the building in France is a theoretical high performance design. We selected the two real buildings because we had detailed data available about each and because they are

***Table 1**: Input parameters for the simulation of buildings in (1) Chambéry, (2) Rudrapur, and (3) Braunschweig.*

Parameter	**1 - CHM**	**2 - RDP**	**3 - BS**
ASHRAE Climate Type	4A	1B	5C
Floors	2	2	3
Un / conditioned Area (m^2)	101/96	179/58	0/311
Wall U-val. [W/m^2-K]	0.108	2.224	0.907
Window U-val. [W/m^2-K]	0.78	15/3	1.96
Window-Wall Ratio (%, South / Overall)	71/25	1.96	20/15

***Figure 3**: Renderings of the three buildings, from left to right: Rudrapur, Chambéry, Braunschweig.*

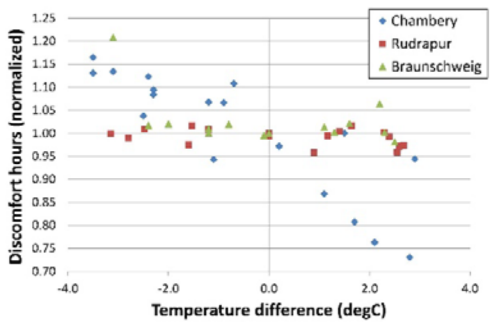

Figure 5*: Change in uncomfortable hours vs temperature change (normalised against value at home location).*

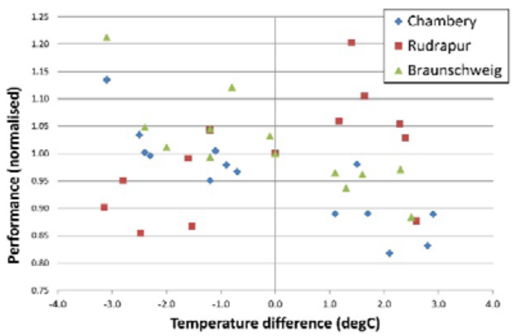

Figure 6: *Performance vs temperature change (normalised against value at home location).*

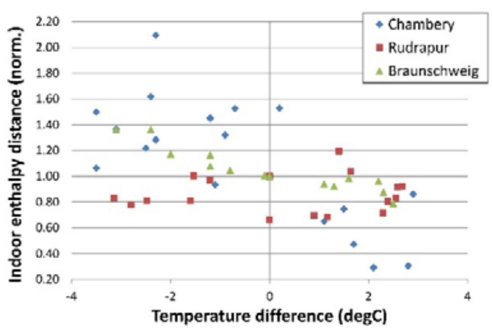

Figure 7: *Indoor energy distance vs temperature change (normalised against value at home location).*

sufficiently different in their construction and home climate. To simulate a high performance building, we selected a design we had already created for Chambéry because it is close enough to Braunschweig to serve as a useful comparison. We assumed that the houses have four occupants each, and similar standard schedules and average internal heat gains from lights and appliances. The occupants open the windows to maintain an average 0.6 ACH, or when the temperature reaches 23.4°C.

To create a realistic representation of potential changes in climate for each location, we selected locations (with different climatic conditions) that are located near and around the three investigated locations. The locations were chosen by using high-resolution temperature maps with ‘contour’ lines of a specified temperature difference (e.g. Figure 4). By choosing a variety of locations on these lines, the mean annual temperature difference (factor of interest) is uniform for a given contour but the individual climates have a variety of other characteristics (humidity, seasonality, etc.). From simulations of the investigated buildings in these locations, we extracted hourly values for the average temperature and humidity over the occupied zones to calculate performance (based on our metric). The final step was to plot the buildings' performances against (mean annual) temperature change to ascertain the shape of their response surfaces/curves.

RESULTS

Figure 5, Figure 6, and Figure 7 give an overview of the results. Figure 7 is a plot of the indoor energy (enthalpy) distances rather than HVAC energy use, since simulating buildings without mechanical systems saved us considerable computational time.

For BS and RDP the number of uncomfortable hours and the HVAC energy requirement do not give conclusive results. In both graphs, BS and RDP show no discernible trend. CHM shows an overall negative slope (increase of energy use and uncomfortable hours for falling temperatures and vice versa), though without a high coefficient of determination (R^2). These graphs are normalised with respect to the values in the respective home locations. So, they do not show that the overall magnitudes of uncomfortable hours are much higher for RDP and BS (about 6000) than CHM (about 2500), which is expected since the former are real buildings which were not highly optimised in the design phase. In any case, we are more interested in changes rather than absolute numbers at this point. The plots of uncomfortable hours and indoor energy distance show two results. Firstly, the highly optimised building is not peaking in its home climate. And, secondly, its performance seems to be worse in a slightly colder climate (i.e. increase in uncomfortable hours and theoretical energy use) and better in a warmer climate. These two inferences are not necessarily indicative of the performance of the building. That a cold Alpine climate is pleasanter if mean temperatures rise is obvious. Experience from heat-waves in continental Europe and North America would suggest that the performance of cold-climate buildings deteriorates during warm episodes. The very features that make a building retain heat to maintain warmer indoor temperatures during cold spells should cause it to overheat during warmer spells.

Looking at the curve of our performance metric, however, we see that the optimised building does show a somewhat flat peak at and near its design location. It is more sensitive to an increase in mean annual temperature than a decrease, which is probably due to its large glazing fraction on the southern facade. We are also able to see regions of similar behaviour in both the BS and RDP buildings. The cold climate buildings seem to perform worse with a rise in temperature than a drop, which seems intuitive. If a building has been designed for cold climates, it is likely to continue performing well for small decreases in temperatures, though the effects are not straightforward. For a building with average insulation and solar harvesting potential, the effectiveness of the design seems to be enhanced noticeably with colder outdoor temperatures. For the highly optimised building, though, performance does not improve dramatically. This could be because the optimised building is already exploiting passive measures as much as possible, so it leaves little scope for improvement. However, the insulation and air tightness that serve these buildings well in a colder climate cause performance to drop when average outdoor temperatures rise. The cold climate designs are optimised to reduce heating demand by allowing in more sunlight and retaining heat, and they cannot do the opposite (i.e. reject/remove heat) when temperatures rise.

The reverse is true for the hot climate building, which has less insulation, more shading, and more thermal mass (due to a largely concrete-based construction). Colder conditions decrease performance, whereas warmer conditions increase performance up to a certain point. This could be a somewhat misleading result since it assumes virtually no adaptation on the part of the occupants (like opening the blinds more often or shifting more activity outdoors in the winter). The performance of the hot climate building drops off after a certain temperature increase. As the metric measures the difference in energy gap between indoor and outdoor conditions, a decrease in performance could mean that the cooling requirement indoors is increasing faster than the heating requirement is decreasing in this case.

DISCUSSION

A high performance building should lie at the peak of its response surface at its home climate (y-axis). That means its performance should be maximum in the climate it was designed for and drop or stay the same in all surrounding locations. The slope of this drop, however, is not guaranteed (i.e. we do not know *a priori* whether a building will perform better or worse if the average temperatures change). If the performance decreases steeply the building is very sensitive to changes in average climate, and if the slope is gentler, the building is more robust. But many buildings are not optimally tuned to their location, which may place the peak of the response surface off-centre (i.e. in another city). Nevertheless, it is still possible to forecast the building's sensitivity to changes in mean annual temperature.

The graphs show a spread of data points for each temperature difference. This is expected and even desirable, since the selection of multiple locations at each temperature increment represents a variety of possible climates (patterns, interaction with other weather parameters, etc.). This does, however, make it more difficult to extract deterministic trends. We expect that the results could be better represented with probabilistic confidence intervals (e.g. 95% CI) for the trends. The size of our current data set (sample) makes the calculation of confidence intervals for the population (of all possible climates) impractical because the actual coverage of CI limits obtained from such a small sample size would be inadequate. Therefore, the representativeness of the trend we estimated at this point was not statistically robust and could be misleading. This is a persistent problem when dealing with small records, and we expect to carry out further analysis of the trends with more simulations. The use of more robust techniques for calculating confidence intervals (e.g. bootstrapping) is also a potential avenue for further work. In any case, our preliminary understanding of the behaviour of our performance metric and its comparison with comfortable hours and HVAC energy use is discussed below. One initial result was that locations which are reached after a sharp topographic change from the locations (for example, crossing the Alps from Chambéry, France to Torino, Italy) seem to show different results from locations with a similar temperature increment on the same side of the topographical feature (the Alps). Whether these represent a realistic climate change scenario is not clear from this study. If they are considered realistic, then treating them as outliers would not be a conservative option. Rather, they could indicate limits of sudden and, perhaps, catastrophic changes in performance.

CONCLUSION

Our methodology allows the simulation of several hypothetical climate change scenarios, but because the weather files are composed from real climate data, the auto- and inter-correlations of the weather parameters are more realistic. There is a wide spread of data and several points that could be outliers in this study due to the paucity of data. We expect trends to become clearer with more data because the relative influence of outliers, noise, and erroneous data decreases in a larger sample size. As demonstrated by the projects discussed in the introduction, there is a balance to be struck between obtaining large amounts of data through impractically long computation on the one hand and confidence in the results on the other. Statistical methods like resampling can increase the coverage probability of confidence intervals without necessitating the generation of more data, though they are even further removed from the underlying physics of a building's response to its climate. Using indoor and outdoor energy distances represents the magnitude as well as duration of distance from the edge of a comfort zone. Using this metric seems to show a building's performance in a changing climate better than changes in uncomfortable hours. This could, for example, allow a designer to explore various design options based on their robustness to climate change. Each design strategy/change could be simulated in surrounding locations to ascertain its performance (in creating a comfortable indoor environment in a changing climate) without the change caused by the climate itself. The methodology we propose in this paper potentially covers a wide range of realistic climate change possibilities without the computational effort of a full Monte Carlo-style analysis.

REFERENCES

[1] P. de Wilde and D. Coley, "The implications of a changing climate for buildings," *Building and Environment*, vol. 55, pp. 1–7, Sep. 2012.

[2] D. B. Crawley, "Estimating the impacts of climate change and urbanization on building performance," *Journal of Building Performance Simulation*, vol. 1, no. 2, pp. 91–115, 2008.

[3] X. Wang, D. Chen, and Z. Ren, "Assessment of climate change impact on residential building heating and cooling energy requirement in Australia," *Building and Environment*, vol. 45, no. 7, pp. 1663–1682, Jul. 2010.

[4] R. Emmanuel, B. Kumar, Y. Roderick, and D. McEwan, "A universal climate-based energy and thermal expectation index: Initial development and tests," *Energy and Buildings*, vol. 58, pp. 208–218, Mar. 2013.

[5] L. Guan, "Preparation of future weather data to study the impact of climate change on buildings," *Building and Environment*, vol. 44, no. 4, pp. 793–800, Apr. 2009.

[6] R. S. McLeod, C. J. Hopfe, and Y. Rezgui, "A proposed method for generating high resolution current and future climate data for Passivhaus design," *Energy and Buildings*, vol. 55, pp. 481–493, Sep. 2012.

[7] M. Eames, T. Kershaw, and D. Coley, "On the creation of future probabilistic design weather years from UKCP09," *Building Services Engineering Research and Technology*, vol. 32, no. 2, pp. 127–142, Oct. 2010.

[8] University of Exeter, "Prometheus: The Use of Probabilistic Climate Change Data to Future-proof Design Decisions in the Building Sector." [Online]. Available: emps.exeter.ac.uk/research/energy-environment/cee/projects/prometheus/. [Accessed: 09-May-2013].

[9] M. Eames, T. Kershaw, and D. Coley, "A comparison of future weather created from morphed observed weather and created by a weather generator," *Building and Environment*, vol. 56, pp. 252–264, Oct. 2012.

[10] J. Remund, S. Mueller, S. Kunz, and C. Schilter, "METEONORM Handbook Part II : Theory," May 2012.

[11] D. P. Jenkins, S. Patidar, P. F. G. Banfill, and G. J. Gibson, "Probabilistic climate projections with dynamic building simulation: Predicting overheating in dwellings," *Energy and Buildings*, vol. 43, no. 7, pp. 1723–1731, Jul. 2011.

[12] M. Shamash, A. Mylona, and G. Metcalf, "What Guidance Will Building Modellers Require For Integrating," in *Proceedings of the 2012 Building Simulation and Optimization Conference*, Loughborough, UK, 2012, pp. 253–260.

[13] T. Kershaw, M. Eames, and D. Coley, "Assessing the risk of climate change for buildings: A comparison between multi-year and probabilistic reference year simulations," *Building and Environment*, vol. 46, no. 6, pp. 1303–1308, Jun. 2011.

[14] W. Tian and P. de Wilde, "Thermal building simulation using the UKCP09 probabilistic climate projections," *Journal of Building Performance Simulation*, vol. 4, no. 2, pp. 105–124, 2011.

[15] S. Patidar, D. P. Jenkins, G. J. Gibson, and P. F. G. Banfill, "Statistical techniques to emulate dynamic building simulations for overheating analyses in future probabilistic climates," *Journal of Building Performance Simulation*, vol. 4, no. 3, pp. 271–284, 2011.

[16] S. Patidar, D. P. Jenkins, G. J. Gibson, and P. F. G. Banfill, "Correlating Probabilistic Climate Projections With Cooling Demand In An Office Building," 2012, pp. 261–268.

[17] S. Patidar, D. P. Jenkins, P. F. G. Banfill, and G. J. Gibson, "Simple statistical model for complex probabilistic climate projections: Overheating risk and extreme events," *Renewable Energy*, pp. 1–6, May 2012.

[18] M. S. Owen, *ASHRAE Handbook: Fundamentals*. Atlanta, GA: ASHRAE, 2009.

[19] R. J. de Dear and G. S. Brager, "Developing an adaptive model of thermal comfort and preference," *ASHRAE Transactions*, vol. 104, no. 1, pp. 145–167, 1998.

[20] E. Halawa and J. van Hoof, "The adaptive approach to thermal comfort: A critical overview," *Energy and Buildings*, vol. 51, pp. 101–110, Aug. 2012.

[21] P. Tuohy, S. Roaf, F. Nicol, M. Humphreys, and A. Boerstra, "Twenty first century standards for thermal comfort: fostering low carbon building design and operation," *Architectural Science Review*, vol. 53, no. 1, pp. 78–86, Feb. 2010.