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Management of thermal performance risks in buildings subject to climate change

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ABSTRACT

This article reports on the use of building performance simulation to quantify the risks that climate change poses to the thermal performance of buildings, and to their critical functions. Through a number of case studies the article demonstrates that any prediction of the probable thermal building performance on the long timeframes inherent in climate change comes with very large uncertainties. The same cases are used to illustrate that assessing the consequences of predicted change is problematic, since the functions that the building provides in themselves often are a moving target. The article concludes that quantification of the risks posed by climate change is possible, but only with many restrictions. Further research that is needed to move to more effective discussion about risk acceptance and risk abatement for specific buildings is identified.

1. Thermal performance risks

Climate change impact assessment studies for buildings endeavour to quantify the impact that future climate conditions will have on the thermal performance of buildings [1]. Such predictions of future performance have inherent uncertainties, pertaining to climate conditions, the future operational conditions of the building, as well as interventions in the building fabric and systems [2]. However, most of the emerging work in this area still takes a deterministic approach, and does not quantify uncertainties, risk, or the acceptability of risk; at best it accounts for some uncertainties in the climate change predictions. This article reports on a study that pioneers a probabilistic approach to quantify and manage the risks that climate change poses to the thermal performance of buildings, and to their critical functions, using building performance simulation. It provides an overview of various sub-studies conducted in this project, tying together the various strands and presenting overall conclusions.

Risk management entails the prediction of the future behaviour of systems, allowing humans to reduce the chance of unwanted events [3]. Risk is generally seen as the product of two contributing factors: the probability of an occurrence and the consequences of that occurrence. A universal formula to represent this is:

$$RF = P \times C \tag{1}$$

where *RF* is the risk factor, *P* is probability, and *C* is consequence [3]. Typical risk management studies start with a study of probabilities, which is named *risk assessment*. This is then followed by a study of the consequences, which is named *risk analysis*. Once both probabilities and consequences are known they are combined into *risk quantification*. This then can be used to study *risk acceptance* and *risk abatement* options [3].

Following this generic approach, quantification and management of the risk that climate change poses for the thermal performance of buildings requires [4]:

- Projection of long-term changes that will affect the thermal behaviour of buildings. This projection includes but is not limited climate change, and comes along with uncertainties inherent in prediction of any changes and the time scale on which these changes are expected to take place.
- Development of risk-based performance indicators that allow to measure how the thermal performance of buildings might be affected by climate change. These performance indicators need to reflect the consequences of the building not meeting its primary functions.
- Implementation, testing and evaluation of the incorporation of complex change scenarios in building simulation to predict future performance and risks. This will involve the handling of changes in operational conditions, building system configuration, and various relevant performance indicators. Note that current building simulation tools in themselves do not accommodate such multi-facetted evaluations.
- Identification and quantification of the main risks that long term (climate) change poses for thermal building performance.

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This will make explicit the links between change scenarios, the building energy use and thermal comfort, and crucial performances like: occupant health, productivity, and carbon emissions.

- Analysis and discussion of the acceptance of these risks, both under present and future conditions, establishing threshold criteria and how these criteria might – or might not – change over time. This in time can lead into an investigation of prospects of interventions on a building (sub)system level that might abate such risks, and their impact on both risks and risk acceptance.

In order to explore this approach for studying the risk posed by climate change to thermal building performance, a series of case studies has been analyzed. Initially two cases were selected that are both aligned with previous work on climate change impact assessment by CIBSE TM36 [5] and which represent both a domestic (Case D2: new-build house) and commercial office building (Case O2: modern mixed-mode office). Two additional cases were added to investigate additional research dimensions and to further expand the range of building types covered in the project. One of these cases was a real educational building, allowing for interaction with the design team, facility managers and users of the building, and moving beyond a theoretical reference design. The other additional case was a supermarket building, which was selected due to a reasonable knowledge base on building fabric and services degradation as a function of time. All cases were studied under climate change conditions for the United Kingdom. Key information for developing thermal models of the case study buildings is sourced from authorative resources like the ASHRAE Handbook of Fundamentals [6], CIBSE Guide A [7], and the UK's National Calculation Method [8].

This article first presents the general methodology applied to quantify climate change risks for the thermal performance of the cases, which is based on building performance simulation. It then presents key aspects of risk assessment, risk analysis and risk quantification and risk management, using the various case studies for reference.

2. Methodology for computational assessment of climate change risks

The principal tool for quantifying climate change related risk to the thermal building performance is transient building simulation. A computational approach is the only available option to make equivalent comparisons between both the present and future climate conditions, based on climate data as developed by meteorological and climate change experts. Transient simulation is required as the interest lies with two key thermal performance aspects: energy use for heating and cooling (plus the related greenhouse gas emissions) and overheating risk. For both aspects the risk that is to be quantified is related to fluctuations in heat flows and internal/external temperatures over time, making more generic methods like monthly averages unsuitable. For all work reported in this article use has been made by subsequent versions of the simulation engine EnergyPlus (V.3.0 – V5.0) [9]. This specific tool was selected because of its extensive validation, capacity to model advanced building systems and components, extensive validation, and free availability. Additionally EnergyPlus has the advantage of access to a large set of climate files (EnergyPlus Weather Files) [10] for locations all over the globe, and of access to a series of detailed reference models [11].

In assessing the risk posed to thermal building performance by climate change a probabilistic approach is required, which accounts for uncertainties in both the present and future situation. Previous work on uncertainty analysis within building simulation has identified the following key sources of uncertainties as impacting simulation results: specification uncertainties, scenario uncertainties, modelling uncertainties, and numerical uncertainties [12,13]. Of these, specification and scenario uncertainties need to be taken into account. Assuming variations of the same building model are used to analyze both present and future risk the modelling and numerical uncertainties can be ignored. The specification uncertainties concern the definition of the object under investigation, in this case the building and its (sub)systems. Uncertainties in this category can stem from various sources, such as natural variation in material properties and likely differences between as-designed and as-constructed. Scenario uncertainties cover unknowns in climate conditions, occupant behaviour, building control settings, as well as facility management and renovation interventions.

The specification and scenario uncertainties require representation by a significant number of parameters (typically in the order of 20–25 parameters). Uncertainties then need to be represented by providing a typical distribution for each of these parameters [13]. Given the number of parameters and parameter values needed to describe typical distributions, sampling is needed to keep the sample size within manageable dimensions; this has been addressed by using Latin Hypercube sampling. Sample sizes for the studies thereby have been kept in the order of 60–2400 variants, depending on the complexity of the case. Furthermore, the process has been automated through use of the SIMLAB package [14].

Once the sample for each risk quantification has been identified, the handling of files is automated as much as possible using Excel VBA (Visual Basic of Application), which is essential given the number of files to be handled. Furthermore, grid computing has been used to speed up calculation times. Each variant in itself is a stand-alone simulation in EnergyPlus, requiring mainly an input file (IDF), weather data file (EPW) and access to key program files like the executable (.exe), initiation (.ini) and input data directory (.idd). This makes EnergyPlus simulations very suitable for parallel computing. Specifically use has been made of Condor, a high-throughput computing (HTC) software package [15], which speeds up the number of jobs completed on a system rather than the speed of individual jobs, which is the key objective of high-performance computing (HPC). The specific grid used in this instance allowed access to 200 desktop computers on the user's campus. As not all machines are continuously available and as the Condor grid is shared by other researchers, the actual simulation times have been reduced with about a factor 15 in comparison to running the same simulations consecutively on a single desktop PC.

Results from the simulations are again handled by Excel VBA, automating the process. They then have been subjected to various sensitivity analysis approaches, using Standarized Regression Coefficients (SRC), Standardized Rank Regression Coefficients (SRRC), Multivariate Adaptive Regression Splines (MARS) and Adaptive COmponent Selection and Smoothing Operator (ACOSSO) [16,17].

3. Climate change predictions underpinning the research

For climate change impact studies, climate predictions are a key ingredient. Initial work in this research project employed the UKCIP02 data [18]. This was considered the state-of-the-art data for the United Kingdom during 2002–2009. In essence, the UKCIP02 dataset extrapolates past climate observations into the next century (2000–2100), giving a range of predictions based on a range of greenhouse gas emission scenarios that include low, medium–low, medium–high and high. Whereas deterministic studies typically focus on one of these scenarios (generally the medium–high emission scenario), the probabilistic approach used in this work has taken into account all four scenarios through Monte Carlo analysis, assigning each scenario an equal likeliness [19]. In order to generate EnergyPlus Weather (EPW) files, use was made of the original climate data for Birmingham, UK (International Weather for Energy Calculations (IWEC) data, 1982–1997). The IWEC data was converted into EPW data using the UKCIP02 projections and the Climate Change Weather File Generator [20].

Subsequent work in the project shifted to the newly-released UKCP09 dataset [21]; this is a more complex dataset that includes probabilities with the climate change projections. The UKCP09 provides projections relative to baseline 30-year period (1961–1990) for a total of seven overlapping 30-year periods, starting with the 2020s (2010–2039) and ending with the 2080s (2070–2099) by stepping forward by a decade at a time. According to the IPCC Special Report on Emissions Scenarios three emission scenarios embedded UKCP09 are high, medium, and low levels, which cannot currently be assigned probabilities. UKCP09 also provides a weather generator utility that can be used to directly generate synthetic daily and hourly files for relevant weather variables, which then can be used to run EnergyPlus. Typically this weather generator produces a sample of 100 weather files for each year to represent the likely distribution; with a time span of 30 years this yields a total of 3000 weather files. This would require substantial computational power, as demonstrated by Fig. 1, which shows cumulative distribution functions (CDF) of the mean annual temperature as predicted within the UKCP09 data. In Fig. 1, each sub-plot represents the CDF of annual mean temperatures over a time span of 30 years. For the 2030s the mean is around 12.6 °C with a standard deviation in the order of 0.5 °C. Moving towards later timespans the mean shifts upwards to 13.3 °C for the 2050s, while the standard deviation almost doubles. This trend continues for time scales to the 2070s. Note that each point of the plot in fact represents a full year of weather data, in other words 8760 hourly values. In order to manage the 3000 files statistical reduction has been applied, using Finkelstein–Schafer statistics, and yielding a set of 100 representative weather files for use with EnergyPlus. Further details about the application of UKCP09 data for building performance simulation studies can be found in Tian and de Wilde [22]. The UKCP09 data was applied to all cases studied in this project; various time horizons have been used in different case studies.

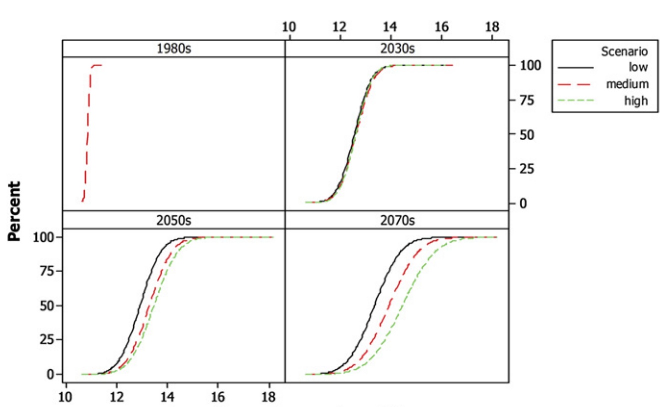

Fig. 1. Cumulative distribution functions (CDF) of annual mean temperatures for various time slices as generated by the UKCP09 Weather Generator (1980s: 1961–1990, i.e. baseline period; 2030s: 2020–2049; 2050s: 2040–2069; 2070s: 2060–2089).

4. Risk assessment: probability of the impact of climate change on buildings

The feasibility, as well as some of the limiting factors, of conducting climate change risk assessments is presented through the review of the study of the two reference buildings which were selected from the earlier CIBSE TM36 report on climate change [5].

4.1. Case 1: modern mixed-mode office

Initial efforts to conduct a risk assessment focussed on the CIBSE TM36 Case O2: Modern mixed-mode office. This building is an open plan office, providing a total of 3864 m^2 of floor space, putting it in the medium size category. It has mechanical ventilation as well as low-energy active cooling. The building operates in natural ventilation mode when the internal operative temperature is below 25 °C; above that threshold the windows are closed and mechanical ventilation and cooling are turned on. This mixed-mode approach makes the building interesting for a climate change impact study: it is to be expected that climate change will cause a shift from the natural ventilation mode towards the mechanical mode. Fig. 2 presents a 3D view of this office.

As noted, a risk assessment of this building requires the identification of the specification and scenario uncertainties. While the building is well specified in parameters that are key to building performance simulation, one still needs to account for likely variation in dimensions, material properties, infiltration rates, metabolic rate of occupants, heat gain of equipment and lighting, and efficiency of the heating system. An overview of values used for the analysis, mainly based on the work by Macdonald [13] is provided in Table 1.

In general, specification uncertainty will be expected to increase over time, given the view that it is more difficult to predict the future with increasing time horizons. This is clearly the case for climate predictions, with standard deviations increasing over time as shown in Fig. 1. However, this effect can be compensated by being framed within trends that impose smaller overall margins, for instance where one can expect building regulations to become increasingly stringent. This is the case for U-values and infiltration rates over the last decades. Internal heat gains show a continuous decrease as more energy-efficient appliance may be installed in buildings, which can be projected forward with some confidence. Initially values for specification uncertainty can be attributed to natural variation and a lack of knowledge of how the building properties will relate to the specified values. Two aspects of scenario uncertainties have been studied for this case: interventions in the building, and climate change. The first scenario results in an increase of uncertainty in the same parameters that are

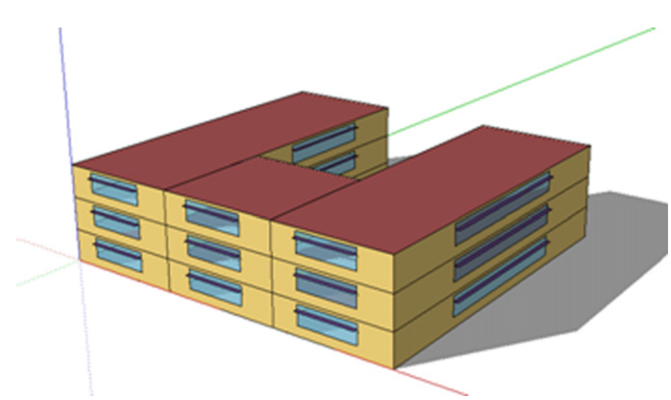

Fig. 2. CIBSE TM36 Case O2 Reference Building (Modern mixed-mode office).

Table 1
Uncertainty of specification parameters of the CIBSE TM36 O2 Office.

Variable	Unit	Initial distribution	Standard deviation	Distribution shift over time	2020s	2050s	2080s
Metabolic rate	W/person	Normal	50	None	–	–	–
Wall U-value	W/m^2 K	Normal	10	Uniform continuous	0.15–0.3	0.1–0.2	0.05–0.15
Floor U-value	W/m^2 K	Normal	10	Uniform continuous	0.1–0.22	0.08–0.18	0.05–0.1
Roof U-value	W/m^2 K	Normal	10	Uniform continuous	0.1–0.22	0.08–0.18	0.05–0.1
Window U-value	W/m^2 K	Normal	10	Uniform continuous	1–2	0.8–1.5	0.5–1.0
Infiltration rate	ACH	Normal	50	Uniform continuous	0.1–0.25	0.05–0.15	0.02–0.1
Equipment heat gain	W/m^2	Normal	15	Uniform continuous	8–12	5–10	4–8
Lighting heat gain	W/m^2	Normal	20	Uniform continuous	6–12	4–9	2–6
Boiler seasonal efficiency	–	Normal	5	Uniform continuous	0.8–0.9	0.9–0.95	0.92–0.96

already subject to specification uncertainty due to systems having a decreasing performance and then being replaced in a series of interventions (upgrades and renovations). While some literature on risk makes a point of distinguishing between aleatory (natural, inherent) uncertainty and epistemic uncertainty (resulting from a lack of knowledge) [23] the risk assessment of the CIBSE TM36 O2 Office combines both categories into one. This scenario uncertainty also captures technology developments like increases of efficiency of lighting systems and heating and ventilation plant. The second change scenario concerns the obvious changes in climate conditions that are at the core of the research. Two datasets have been used to represent climate conditions: the United Kingdom Climate Impact Programme's UKCIP02 [18] and UKCP09 data [21]. Further details about this case study are provided in earlier publications by the authors [24–26].

After identification of the uncertainties that might impact the future thermal performance of the CIBSE TM36 O2 Office, the next step in risk assessment is the identification of potential areas of risk. Obvious performance aspects that are deemed to be directly at risk from climate change are the annual energy use for cooling and building thermal comfort. Yet deeper analysis demonstrates the need for investigation of further factors. It is likely that, for a temperate climate like the United Kingdom, climate change will result in a shift in energy use where annual heating energy decreases, while annual cooling energy increases, so both need to be captured. Additionally various system efficiencies will impact the primary energy use for heating or cooling and need to be taken into account; the same applies if energy use is to be translated into greenhouse gas emissions. These more complex performance indicators then also introduce additional uncertainties; for instance the computation of greenhouse gas emissions requires assumptions about volatile parameters that describe the electricity energy mix [26]. A similar issue is found for prediction of overheating risk, where the underlying thermal comfort model and whether this is static or adaptive has a large impact on predicted results [25]. Another issue that might lead to risk is a discrepancy between design and actual peak loads for heating and cooling. On the heating side, reduced peak loads might lead to system inefficiency. On the cooling side, increasing peak loads might mean that the installed capacity becomes insufficient, leading to overheating risk.

4.2. Case 2: new-build house with PV and GSHP

Augmenting the study of the office building, the project also analyzed a domestic project. Again this is aligned with the previous work by CIBSE TM36, this time taking a new-build house as starting point. For the purpose of this study the building has been equipped with state-of-the-art HVAC systems: for heating purposes it is modelled with a ground–source heat pump (GSHP) and a single vertical U-type borehole with a depth of 76 m. Part of the electricity needed to drive the heat pump is provided by a photovoltaic array (PV system). The combination of GSHP and PV is presently very popular in continental Europe and the UK, and is considered to be a good way to provide energy-efficient, low-carbon heating. The house is a typical detached property, with four bedrooms; it has two storeys and provides a total of 148 m^2 floor area. A simple representation of the building is given in Fig. 3; for a more extensive description see Tian and de Wilde [27].

Again a series of uncertainties has been identified via a risk assessment study. They include specification uncertainties pertaining to building envelope and its properties, equipment gains, as well as heating temperature set points. Furthermore, the specific HVAC systems come with their own specification uncertainties like PV typical system loss or potential variations in soil temperature due to both climate conditions and the extraction/insertion of heat. Note that in the case the focus is on space heating and cooling only; domestic hot water production has been ignored. Scenario uncertainties of course include the predicted climate change effects. Additionally, the case study considers the potential use of passive cooling methods like application of shading devices and specific ventilation regimes aimed at cooling. Furthermore, the potential of continuous versus intermittent heating and variation of thermostat set point values has been taken into account.

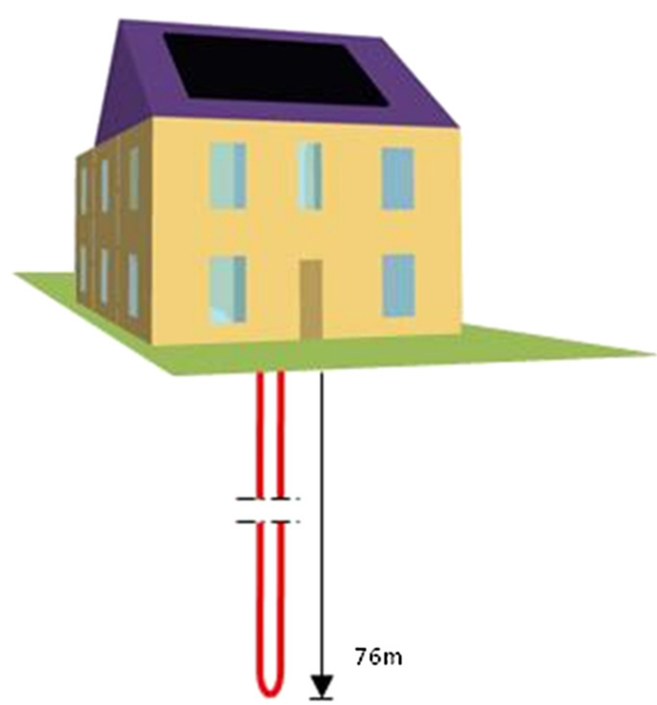

Fig. 3. New-build home with GSHP, U-borehole and PV array.

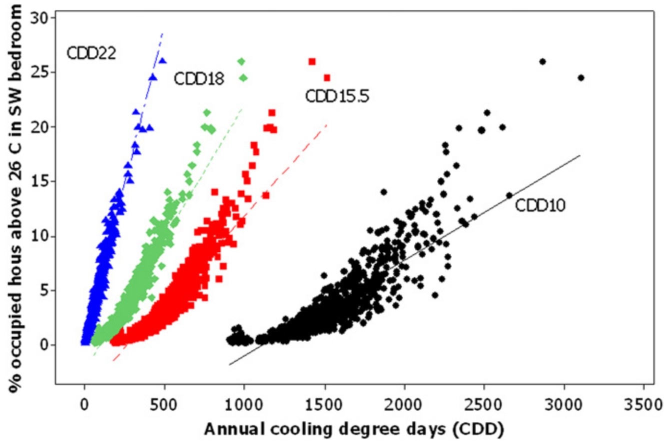

Fig. 4. Relationship between overheating risk and annual cooling degree days with different base temperature in Southwest bedroom.

The risk assessment study flags up overheating risk, which is widely believed to be an issue in modern, highly insulated buildings which minimise transmission, maximise internal and solar gains, and reduced ventilation rates. This risk needs to be studied at a high level of spatial resolution, requiring analysis of individual rooms: a bedroom facing southwest on the first floor runs a much higher overheating risk than a north-facing kitchen area on the ground floor. Complexity is added by the need to set threshold values for heating. By way of example Fig. 4 shows the relation between annual cooling degree days, as measured against various baseline temperatures, and the number of overheating hours over 26 °C as predicted for the South-western bedroom.

Furthermore, the risk assessment flags up the risk that variations in the electricity mix might lead to different emission factors for electricity use and thus having a large impact on the predicted environmental performance of the building.

Both the office and domestic case study demonstrate the depth required to do a meaningful risk assessment study. However, as these buildings are notional reference buildings, they do not allow access to actual stakeholders in the future building performance. This has been recognized as a problem in the identification of areas at risk: for instance, in a generic office model it is not possible to discuss whether expected overheating problems might affect key business processes or whether in fact the impact will be marginal and can be tolerated. As a consequence, a further case study has focussed on a real building, with access to users, facility managers and the design and engineering team that developed the building. This will be discussed in the next section.

5. Risk analysis: consequences of climate change for building performance

The feasibility of risk analysis in the context of climate change impact studies is presented through the review of two further case studies. One of these cases was selected with the aim to include a real, operational building in the project. The other case was included with the aim of investigating a building where a relative large amount of information was available on the degradation of systems during the building lifetime, allowing to conduct a longitudinal study.

5.1. Case 3: Roland Levinsky Building, University of Plymouth, UK

In order to be able to discuss areas of risk with actual users and facility managers, an existing building on the campus of the authors was selected as third case: the Roland Levinsky Building at the University of Plymouth, Devon, UK. This building is home to the local Faculty of Arts. It is a flagship building on a prominent location, providing the face of the building towards the city centre. The building offers about 13,000 m^2 of multi-purpose floor space over nine storeys, for University staff, students as well as the general public. Amongst others it includes teaching space, theatres, offices, and a café. The structure of the building consists of reinforced concrete. While it has a highly complex geometry, the basic design concept is to have glazed facades facing North and South, with low solar heat gains coefficients. The roof, East and West façade are based on copper cladding wrapping around the remainder of the building. See Fig. 5 for a photo and a model of the building.

The building is mechanically ventilated in order to cope with the noise and pollution in the city centre. In terms of systems this is

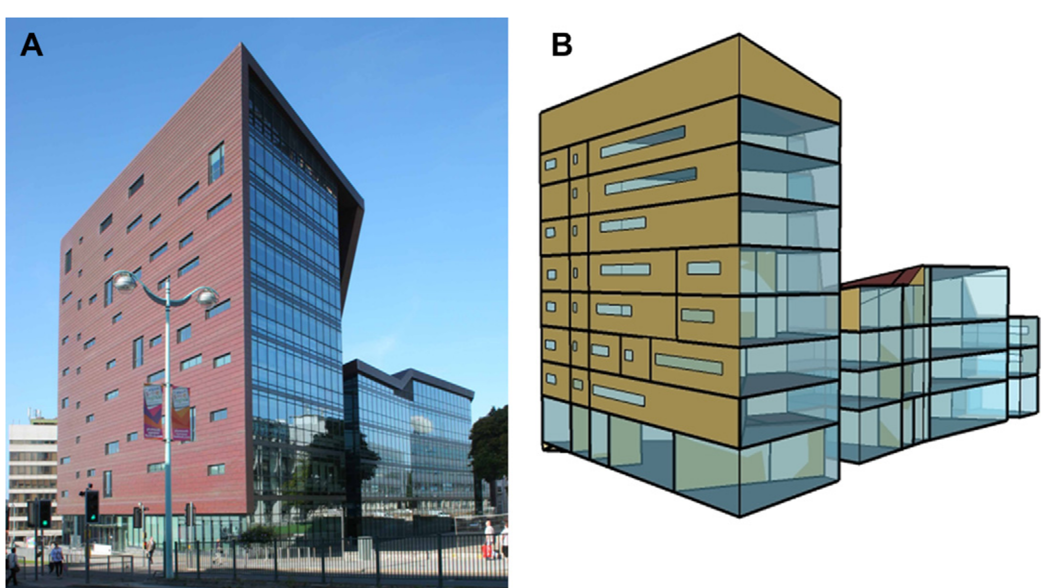

Fig. 5. Roland Levinsky Building, University of Plymouth. Left: Photo. Right: OpenStudio Model.

provided by variable speed fans and multiple air handling units. Furthermore the building has air-cooled chillers provide chilled water to cooling coils in the air handling units, and fan coil units; it has gas-fired condensing boilers supplying hot water to heating coils in the air handling units, to perimeter trench system and to wall-mounted radiators. Apart from the climate change impact study, the building has also been subject to (separate) post occupancy evaluations studies and a building engineering process analysis. Further details about this case study are provided in yet another separate publication by the authors [28].

The risk assessment for the Roland Levinsky Building resulted in the definition of a series of input scenarios as represented in the histograms in Fig. 6. Note that this figure represents four intervention scenarios: a base case, which represents like-for-like interventions and in fact assumes the building stays unchanged over time, and intervention scenarios named case A, B and C which make the building increasingly energy efficient. These cases each represent a future which is defined by interlinked set of probable parameter value distributions. As an example, in the base case the mean chiller COP is 2.8; in cases A, B and C the COP is increased to 3.0, 3.2 and 3.4 respectively, in line with similar changes to other building parameters.

For the climate change impact study, the risk analysis focussed on the typical performance aspects of the annual energy use for heating and cooling and their associated greenhouse gas emissions; since the building is mechanically ventilated thermal comfort was not seen as a direct risk. In terms of peak heating and cooling loads the modelling of a real building flagged up a typical discrepancy between notional reference buildings, and an actual facility: whereas the reference buildings typically have an optimal HVAC system that is sized to just meet demands, a real building normally contains back-up systems to allow for maintenance. A typical sizing might then be to design both systems at 75% of anticipated peak load, providing a total of 150% of required peak capacity and a safety factor of 1.5. This building engineering approach means that most concerns about climate change causing buildings to overheat are unfounded. It also means that potential inefficiency of heating systems running at part load is less likely. However, the risk of a shift from heating to cooling resulting in an overall increase of emissions remains. Interestingly, preliminary results of post occupancy evaluation studies of the building show that, contrary to assumptions, overheating is already an issue at present; this is believed to be due to economies being made on plant installation in the final stage of construction, with some chillers and ductwork having left uninstalled. Discussion of the operation and maintenance planning of the Roland Levinsky Building with the local estate department showed that climate change does not rank amongst the key concerns. Given the current economic conditions and general carbon reduction targets priority is given to running the building as efficient as possible under current conditions. Adaptation to climate change did not feature in the design or construction stages of the building, nor does it feature in the maintenance and capital cost planning of the building. Discussion with the estate department also indicated another interesting point: the lifetime expectancy of most systems is relatively short in comparison to the gradual effects of climate change, only in the order of 15–20 years. This would allow regular interventions and systems replacement to take into account any change in climate conditions to be incorporated, maintaining the building within operational specifications.

5.2. Case 4: supermarket building

The findings from the university building led to a final case study, which attempted a novel climate change related performance indicator. The underpinning thought is that the life expectancy of systems might be shortened due to climate change, bringing the need for capital investments forward. To this end, an effort was made to predict thermal performance over decades, taking into account both climate change and systems degradation. For this work a supermarket building was selected as case, due to the fact that supermarkets are highly repetitive buildings; as a consequence this is a building type for which system degradation and interventions are relatively well-documented. In order to align the project with other simulation efforts, use was made of the EnergyPlus benchmark supermarket model. Fig. 7 shows an image of a real supermarket as well as the reference model.

Apart from the typical uncertainties, maintenance and system degradation now become key issues in the risk assessment. Various maintenance strategies exist: reactive, preventive, predictive, and reliability-centred maintenance; these of course have a direct relation with system deterioration. Various strategies allow to

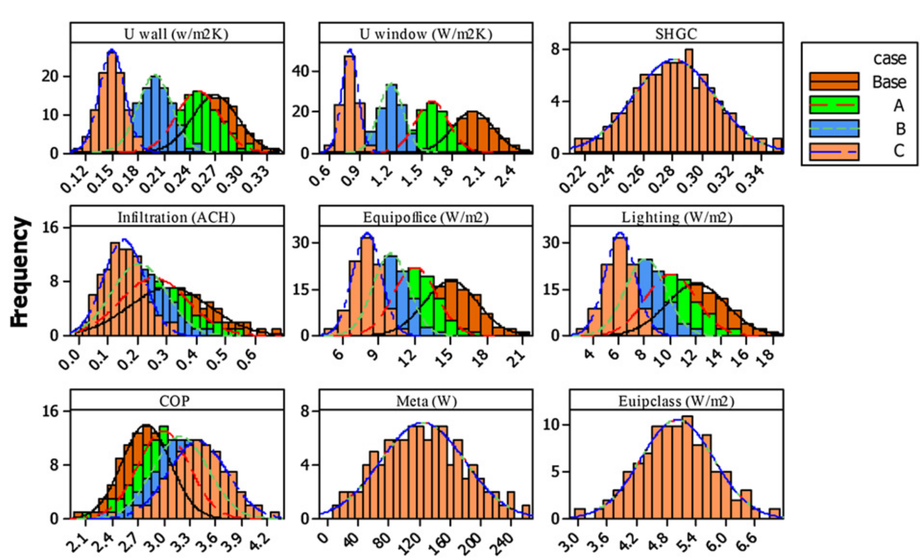

Fig. 6. Histograms for input scenarios for the Roland Levinsky Building. (SHGC: solar heat gain coefficient for windows; infiltration: ACH, air exchange per hour; Equip office: peak equipment heat gain in office; Lighting: peak lighting heat gain in office and classroom; COP: coefficient of performance for chillers; Meta: metabolic rate for occupants; Euipclass: peak equipment heat gains in classroom).

model maintenance and deterioration: failure rate functions, Markov chains, Brownian motion, and Gamma processes. Further details about this case study can be found in de Wilde et al. [29].

The risk analysis for the supermarket still takes into account the typical thermal performance aspects (energy use, emissions) but now uses the changes in the overall building performance to predict the impact of climate change on life expectancy of systems. This is closely related to financial planning, and combines a full control of thermal risks with financial risks.

6. Quantification and management of thermal performance risks

Risk quantification, via propagation of uncertainties in building performance simulation using the methodology described in Section 2, has been carried out for all four case studies. This section only provides a sample of salient results; more detailed results are reported in separate papers on each case study [24–29]. The domestic case study shows very trends to the other buildings and does not yield any new information that adds to the handling of risk quantification and management of thermal performance and therefore is not discussed here.

Typical probabilistic computational results are exemplified by Fig. 8, which shows box-and-whisker plots for predicted annual heating energy, cooling energy and carbon emissions for the Roland Levinsky Building. Fig. 8 contains information for four time horizons: the baseline, which represents the current condition, and the future time slices centred on the 2030s, 2050s and 2070s under medium emission scenario. For every time horizon and scenario, the graph also distinguishes for the various inputs (intervention) scenarios as represented in Fig. 6. The trends in Fig. 8 are according to expectations. First of all, moving from the building as-is to intervention scenarios A, B and C overall annual energy use and carbon emissions decrease. Over time, with increased global

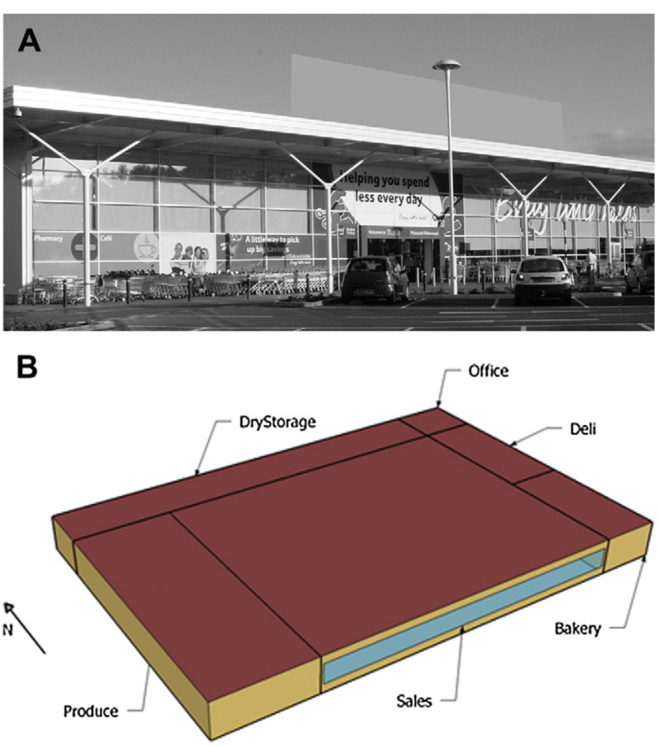

Fig. 7. Supermarket. Left: Photo of an actual building. Right: EnergyPlus Benchmark model.

warming, annual energy use decreases, while annual cooling energy use shows the opposite trend. The combination of both heating and cooling energy into annual carbon emissions shows an undesirable effect: over time, the carbon emissions of the building will increase. The whiskers in Fig. 8 show the uncertainty in the results; typically uncertainty increases when moving further into the future.

As noted in Section 2, computational results have been subject to various sensitivity analysis methods. Table 2 shows typical results, again for the Roland Levinsky Building and focussing on the predictions for the 2050s under a medium emission scenario. Two sensitivity analysis methods, SRC and ACOSSO, have been used side by side; this is a standard approach in sensitivity analysis in order to increase confidence in the outcomes. Both techniques rank the various input parameters, providing an insight into which parameters have the most impact on the performance aspect under investigation and hence cause the most uncertainty. SRC (standardized regression coefficient) is widely used in sensitivity analysis as it is fast to calculate and easy to understand although this method is only appropriate for linear model in the case of independent inputs. The higher absolute values of SRC, the more important the variable is. Negative SRC values suggest that the input and output variables tend to move in opposite directions. ACOSSO (Adaptive COmponent Selection and Smoothing Operator) is one of non-parametric methods, which do not require predetermined form for regression, and consequently it can be suitable for non-linear models. The drawback of this approach is that it takes much longer time to obtain the results compared to SRC. S.cum in this table is a measure of the incremental increase in the proportion of the uncertainty explained by including the new variable in a stepwise manner. T.hat from this table indicates the contribution of the total variance explained by the input and any of its interactions with other inputs. Hence, a higher value of T.hat indicates a more important factor in the model. As can be seen from this table, the results from SRC and ACOSSO approaches are very consistent although there are slight differences in ranking key factors for annual heating energy. For the time horizon of the 2050s, climate conditions are the driving factor, as represented by Heating Degree Days (HDD) or Cooling Degree Days (CDD) since the HDD or CDD have the largest SRC or T.hat for all three performance indicators (heating, cooling, and carbon emissions). This is followed by window properties (Solar Heat Gain Coefficient or SHGC), infiltration, and lighting gains. Hence more attention should be focused on window performance, infiltration, and lighting during the refurbishment in order to improve the thermal performance in this campus building. This type of ranking can be conducted for each building type and time horizon; it allows to identify the key parameters that need to be addressed in order to make a building more robust and/or adaptable to the future conditions.

Results obtained for the supermarket case are presented in Fig. 9 and show how predictions as from Fig. 8 can be studied over a continuous time series, yielding a longitudinal prediction – provided sufficient data is available on performance degradation of the building systems. Since a supermarket has a shorter life expectancy, typically of 40 years only, the time horizon only stretches to 2040. Note that the figure is based on an exact timing, where systems are upgraded after exactly 20 years. Also note that the figure shows trends with and without maintenance; as is to be expected, without maintenance energy use increases faster.

Finally, Fig. 10 shows a combination of risk quantification with a complex performance indicator, now for the O2 Reference Office. In this case, hourly prediction of indoor temperatures has been converted into a quantification of expected relative office work performance, using an empirical correlation that has been

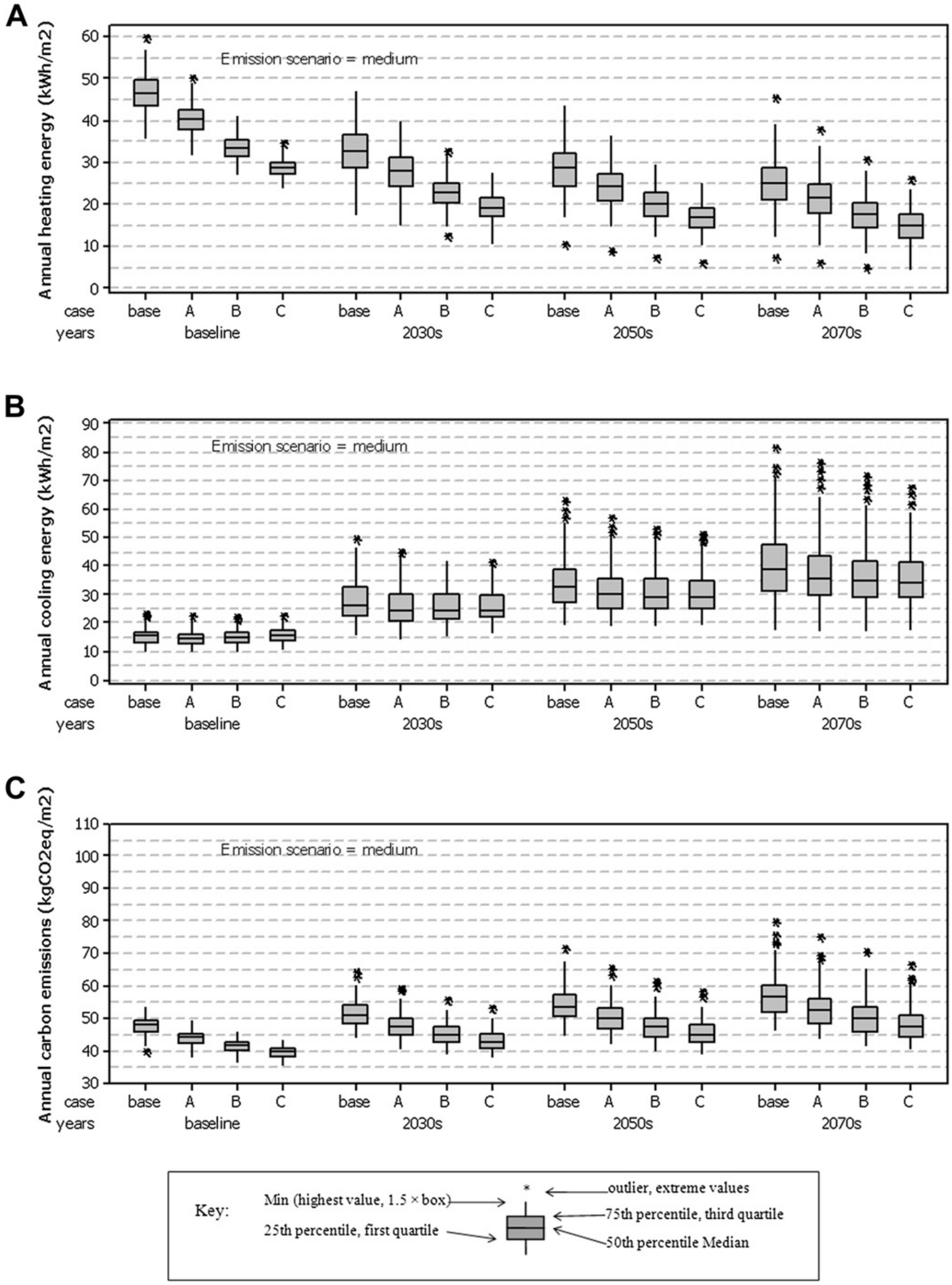

Fig. 8. Annual heating energy, cooling energy, and carbon emissions for Roland Levinsky Building as predicted for the present (baseline) and three future time periods under medium emission scenario.

developed by Seppänen et al. [30]. Again, results look at time horizons representing the present time, 2020s, 2050s and 2080s. They consider three scenarios for upgrading the building; the base case maintains the building in the original state, whereas cases A and B represent more aggressive interventions to make the building more energy efficient. As an example, the U-value for windows starts with a value of 2.0 W/m^2 K in the base case. Under intervention scenario of case A this is then lowered to 1.50 in 2020s and 2050s, and 1.0 in the 2080s. Under intervention scenario of case B it is lowered to 1.00 in 2020s and 2050s, and 0.50 in the 2080s. Similar impacts have been assumed for other construction U-values, infiltration rate, internal gains, and HVAC system efficiency. For full details on case definition see [26]. Fig. 10 provides the relative work performance on a room level of spatial resolution, which is important since actual overheating might differ from room to room and render average values less relevant. Rooms represented are positioned in key orientations, with results following the expectation that there will be minimal impact on work performance in rooms oriented to the North, slightly more impact on East facing rooms, and most impact on rooms facing SouthWest.

Information as conveyed by Fig. 10 is the type of quantification of risk that can presently be achieved by using probabilistic building performance simulation. It yields information of the type:

Table 2
Sensitivity analysis of results for the Roland Levinsky Building for the 2050s under the medium emission scenario, using SRC and ACOSSO.

Output	SRC			ACOSSO		
	Variables	SRC	R2	Variables	S.cum	T.hat
Annual heating energy	HDD15.5	0.792	0.562	HDD15.5	0.622	0.609
	Win U-value	0.407	0.743	Win U-value	0.794	0.188
	Infiltration	0.248	0.841	Win SHGC	0.881	0.082
	Win SHGC	−0.276	0.910	Infiltration	0.924	0.053
	Wall U-value	0.158	0.934	Boiler eff	0.971	0.026
	Boiler eff	−0.124	0.957	Equip office	0.971	0.017
Annual cooling energy	CDD18	0.855	0.723	CDD18	0.798	0.809
	Win SHGC	0.360	0.888	Win SHGC	0.925	0.151
	Win U-value	−0.155	0.908	Win U-value	0.963	0.049
	COP	−0.150	0.928	COP	1	0.017
	Equip office	0.101	0.938	Equip office	1	0.005
	Lighting	0.072	0.943	–	–	–
Annual carbon emissions	CDD22	0.740	0.564	CDD22	0.649	0.655
	Win SHGC	0.358	0.783	Win SHGC	0.823	0.170
	Lighting	0.323	0.866	Lighting	0.915	0.099
	Equip office	0.136	0.890	Equip class	0.941	0.047
	Equip class	0.172	0.913	Equip office	0.948	0.031
	COP	−0.142	0.933	COP	0.987	0.016
	Win U-value	−0.119	0.947	Boiler eff	0.988	0.011
	Infiltration	0.074	0.952	–	–	–

Note:
1. SRC: standardized regression coefficient, ACOSSO: adaptive component selection and smoothing operator.
2. For SRC, probability of F value for entering and removing the variable in the model is 0.001 and 0.005, respectively, and variables listed here in the order of entering into the model.
3. SRC is in the final regression model.
4. R2 (coefficients of determination) with entry of each variable into the model.
5. S.cum: the cumulative contribution of variance explained by the input and the others entered in the model.
6. T.hat: the contribution of the total variance explained by the input and any of its interactions with other inputs.

"there is a predicted drop of 5.0 percent, plus or minus 2.5, of relative work performance in the south-western room on the 2nd floor of the building for the 2080s". This is assuming there are no significant changes to the building systems and operations by that time". Whether such a finding is acceptable then needs to be discussed with the building owner/operator. Obviously this cannot be done for a notional reference building. However, it is worth bearing in mind that in most businesses the salary costs are a much larger cost than energy costs, so that a 5.0% drop in productivity might have serious consequences.

The computational results from the case studies were discussed with colleagues working in industry and academia in a series of workshops in order to gain input on the current position on the management (and need for abatement) of thermal performance risk that stem from climate change. Workshops were conducted, in various settings, in Plymouth, UK; London, UK, Atlanta, USA and Enschede, the Netherlands, in the 2009–2010 timeframe. This yielded the following key points:

- Over the lifetime of a building, it does not seem unreasonable to expect a shift in technology. For instance, a current gas-fired boiler might be replaced by a ground–source heat pump system. However, this seems too large an uncertainty to include in any modelling approach.
- From an estates point of view, building management is asset management, and is related to reserving funds for maintenance and interventions. Risk quantification, which explores when to intervene, seems very informative for that type of decisions.
- An extension of 'operating energy' to 'relative work performance' is relevant when taking a monetary view of decisions. An apparently small reduction in work performance of about 3% can equal the total cost of energy use per year when translated into investments.

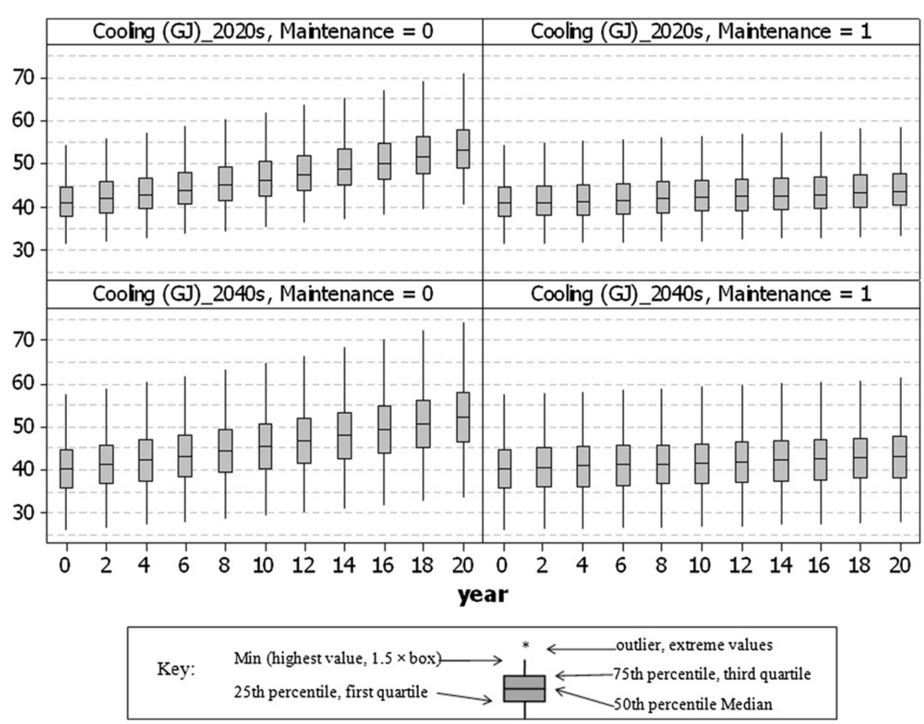

Fig. 9. Predicted development of annual energy use for cooling for the supermarket building, over a 40-year period. System intervention/upgrade takes place after 20 years. The first 20 years assume the 2020s climate conditions, the 2nd 20 years 2040s climate. The table shows versions with and without maintenance.

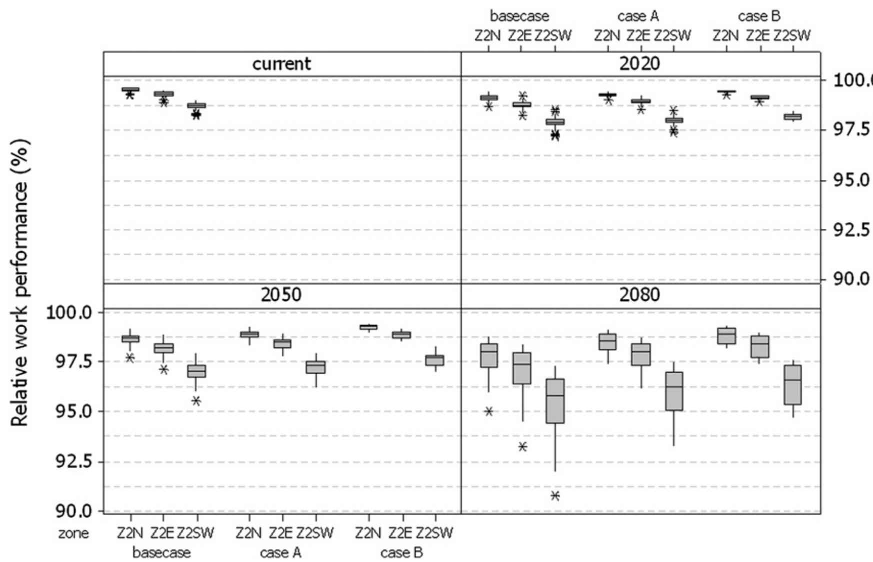

Fig. 10. Predicted relative work performance for the O2 Office Building for the current state, 2020s, 2050s and 2080s. A distinction is made between different intervention scenarios and zones within the building. Base case: building in present conditions; case A and B: building modified under increasingly efficient renovation scenarios. Zones: Z2N: Zone 2nd floor North; Z2E: Zone 2nd floor East; Z2SW: Zone 2nd floor SouthWest.

7. Conclusions and remarks

The following conclusions have been drawn from the research of which this paper presents an overall overview:

1. Current building simulation tools, when combined with automated sampling and output analysis and data aggregation techniques, allow making probabilistic predictions of the thermal behaviour of buildings subject to climate change. Yet care should be taken when setting up such predictive computations, and any results should be critically viewed. Specific assumptions made regarding maintenance, system interventions and renovation of the building over its lifetime need to be queried, as these assumptions will have significant impact on the results. These assumptions are hard to make on the long time scales associated with climate change, and typically run into a lack of information on system performance degradation and lifetime expectancy. As a consequence, a full probabilistic prediction of thermal building performance on a time scale of 50–80 years is likely to come with large uncertainties.
2. The regular approach of computing risk as a product of probability and consequences has been demonstrated to work for climate change impact assessment studies of individual case study buildings. However, the efforts described in this paper show that this requires a deep analysis of specific building functions at stake. Typically, identification of relevant performance indicators requires interaction with the building occupant, owner and/or manager. The primary indicators for heating energy use, cooling energy use, emissions and overheating provide a good basis but in many cases will require further work. Examples demonstrated in this project are the translation into ‘time to intervention’ and ‘relative work performance in specific building spaces/zones’.
3. Since appropriate performance indicators for climate change impact need further development, it is premature to set thresholds for acceptability of climate change risk. However, there appears to be interest in the industry to take these indicators and quantification of risk to a next level.
4. While climate change is a serious concern that needs to be taken into account when designing, constructing and managing buildings, the current building stock is likely to be much more resilient towards climate change than generally assumed. Once reason for this is the presence of back-up systems, which provide additional capacity for heating and cooling, and result in large safety factors. Another reason is the fact that the life expectancy of most building services is a lot shorter than that of the building itself. This means that these systems are likely to be replaced after about 15–20 years. On that time scale, climate change effects will be marginal, while it gives plenty of opportunity to install systems that can cope with the changes in conditions.
5. In order to reduce uncertainties in further climate change risk impact assessments of buildings, more work is in the areas of system performance degradation and life expectancy, maintenance, and interventions. Creation of a body of knowledge that allows simulations to take into account the likely timing and impact of changes to the building will increase the usefulness of predictions.

Overall, it will not be surprising that predicting the future is difficult due to the many uncertainties that need to be considered. However, the high level of detail of the most recent climate change predictions risks a skewed approach in building science and simulation that focusses on climate date and simulation that underplays some of the other issues. A balanced approach is needed to produce climate change impact studies on a building level that have sufficient resolution and focus to enable design teams, clients and facility managers to actually act on the information resulting from such studies.

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