The Impacts of Climate Change on The Electricity Demand

of archetypal office buildings

A thesis submitted to the University of Manchester for the degree of Doctor of Philosophy in the Faculty of Science and Engineering

2021

Vasco dos Santos Zeferina

Department of Mechanical, Aerospace and Civil Engineering

Tyndall Centre for Climate Change Research

Page intentionally left blank

Contents

Total word count:73,704

List of Tables

List of Figures

Abstract

Mitigation and adaptation to climate change impacts will be one of the most important challenges to societies over the twenty-first century. Global average temperatures are likely to increase above the 2°C threshold, probably around 3°C. Therefore, it is vital to prepare and develop approaches to adapt to the impacts of climate change and design for climate resilience.

The effect of warming climates in buildings drives additional cooling requirements in them, leading HVAC (Heating, Ventilation and Air-Conditioner) systems to their capacity limits and then to indoor thermal discomfort. In addition, heatwaves can lead to a sharp increase in the daily peak electrical demand, hindering and stressing the power grid operation, while the ongoing energy transition is already driving multiple challenges to its operation.

This thesis set out to explore the potential effects of future climate change impacts on the cooling demand of office buildings, and quantified the implications for power network operation, in different regions of the world. It examines the impacts of climate change upon cooling requirement and total and peak electricity demand for three type of office buildings (small, medium and large office reference models) in six different cities (Singapore, Cairo, Athens, Beijing, Lisbon and London). Firstly, an assessment was conducted of the sensitivity of cooling and electricity demand of existing office building model to changes in building design assumptions. Secondly, the effects of potential weather variability on the total electricity demand of office buildings was analysed. Finally, a climate pathway framework was developed to capture the uncertainty in the future weather data, and used to quantify the impacts of climate change for the cooling demand of office buildings and evaluate the reduction effect of potential adaptation strategies. The effectiveness of six adaptation measures was analysed: increasing cooling set-point temperature to 27^{o}C, reducing lighting and equipment densities, increasing the HVAC system coefficient of performance, reducing the ventilation rate and the solar heat gain coefficient of windows.

The research findings showed that lighting and equipment density, cooling set-point temperature, coefficient of performance and ventilation rate, make a significant contribution to the total electricity demand in office buildings. In general, the response of peak electricity demand (total and for HVAC end-use) is larger than for annual demand for all office buildings across most of the locations analysed. In addition, the findings show that a uniform 5°C increase (shift) in dry-bulb temperature variable values lead to rise up to 26.8% and 38%, respectively for peak and annual total electricity. The effects on the electricity demand of offices under the climate pathway lead to an increase from baseline in total annual electricity demand, can reach up to 38%, and for peak total demand can go up to 62%, associated with maximum dry-bulb temperature increase of 12.7°C. For HVAC demand, the level of change from the baseline was found that could be much larger (182% for annual and 158% for peak). However, using the combination of six adaptation measures, the total electricity demand can be maintained below current baseline demand levels, both for annual (results are below baseline at least by 8%- large, 16% - medium or 27% - small offices) and peak demand (13% - large, 11% medium or 29% - small). In all model simulation

runs, the HVAC systems were automatically sized to respective correspondent weather data scenarios.

The research findings provide a better understanding of the overall energy demand implications of the modelling uncertainty for offices, both by design assumptions and weather variability. These findings also intend to propel building energy modellers and building designers to further interrogate the implication of these uncertainties across different climates and different types of buildings with different building characteristics. The research framework introduces a systematic and openly available procedure to assess the effects of climate change in buildings, incorporating uncertainty in the generation of future weather data. In addition, the framework enables the systematic assessment of the effectiveness of multiple adaptation measures under a span of future weather conditions.

Declaration

No portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institutes of learning.

Acknowledgements

First of all, I would like to thank my supervisors for having allowed pursuing this project and the vital support during the journey. Both Ruth and Rodger provided much appreciated and valuable support throughout the entire project. In addition, professor Xi provided great support under his supervision during my placement at Tsinghua university.

To my mentors, Anthony and Eugene, who have given valuable support, made me reflect and challenged multiple doubts and concerns along the PhD journey. The multiple talks with Gonçalo and Brendan, that were also essential to re-charge and relax my anxieties. Alys provided valuable coaching sessions during the challenging last year of PhD, while facing the novelties of lockdowns.

I would also like to highlight the insights and boosts that I got from multiple conversations with other academics in the building energy area, who kindly spared some of their time to discuss the research challenges that I faced to achieve the aims of my PhD. I would like to show my special appreciation to Hamed Yassaghi, that kindly spend multiple hours of his time discussing topics around our very similar PhD topics enthusiastically. To Wei Tian, who always kindly discuss and answer my queries about sensitivity and uncertainty analysis and contributed to the paper we published.

I would also like to show my appreciation for the good memories with my teammates in the UMBC Men's third team during the last four seasons. A great shout to Andrea for his contagious passion for sports and team bonding and for his comrade during our PhD journeys. To all UMBC's board members that I worked with during the last three seasons: Yeler, Jango, Jinnie, Ivelin and Kris. It was a pleasure to work with you all and feeling that I was contributing to develop the club.

To my office mates in the engine room, a great thanks. In the end, I concluded that there is no favourite, both of you were a great buddies in the journey. Please keep in mind: "Our PhD journeys are over, but the invitation to come to Portugal is always on. To James, for being a writing partner in the last weeks of the journey and always a cheerful presence in the office. To the Tyndall group, for the warming social atmosphere and opportunities to learn from interdisciplinary research.

A massive thanks to everyone that gave me feedback and proofread this manuscript. Your feedback is deeply appreciated and made this manuscript way better. Thanks all of you: Simon, Matthias, Christina, Angela, Nuno, Charlotte, Samira, Andrea, Alexandre, Hamed, Wei, James, Sérgio, Idalina, Tim, Claire and Christopher. To João and Sónia, that always made me feel that I could count on someone when it was indispensable.

To my friends, that in multiple different ways make me feel that my presence and actions matter for them. To the Jabardolas, for their presence, which makes me feel supported wherever I go and are always fun to be with.

A special thanks to Matthias and Nathalie for providing tremendous support during a whole pandemic year and the long months of writing in lockdown.

To my family and especially to my parents for their unconditional love. To my sister that always admires me, not for what I have achieved, but simply because, whatever, she enjoys my presence.

Abbreviations

AC	Air Conditioning
AMY	Actual Meteorological Year
ANOVA	ANalysis Of VAriance
AR5	Fifth Assessment Report
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
BEM	Building Energy Model
BPA	Building Performance Analysis
BPS	Building Performance Simulation
CBECS	Commercial Buildings Energy Consumption Survey
CCWG	Climate Change weather Generator
CDD	Cooling Degree Days
CIBSE	Chartered Institution of Building Services Engineers
CMIP	Coupled Model Intercomparison Project
COP	Coefficient Of Performance
CV	Coefficient of Variation
DAE	Differential Algebraic Equation
DBT	Dry Bulb Temperature
DHR	Diffuse Horizontal Irradiation
DNR	Direct Normal Radiation
DOE	Department Of Energy
EE	Elementary Effect
EPW	EnergyPlus Weather file
EU	European Union
FAST	Fourier Amplitude Sensitivity Tests
FEC	Final Energy Consumption
GCM	Global Climate Model
GDP	Gross Domestic Product
GIS	Geographic Information System
GSA	Global Sensitivity Analysis
HB	Heat Balance
HDD	Heating Degree Days
HIR	Horizontal Infrared Radiation
HVAC	Heating Ventilation and Air Conditioning
IAQ	Indoor Air Quality
IDF	Input Data File
IEA	International Energy Agency
IHG	Internal Heat Gains
IMF	Input Macro File
IPCC	Intergovernmental Panel on Climate Change
IQR	InterQuantile Range
IRENA	International Renewable ENergy Agency
NCM	National Calculation Methodology
RCM	Regional Climate Model
RCP	Representative Concentration Pathway

RQ	Research Question
SA	Sensitivity Analysis
SDG	Sustainable Development Goals
SHGC	Solar Heat Gain Coefficient
TMY	Typical Meteorological Year
TN	Thermal Network
TRY	Test Reference Year
UA	Uncertainty Analysis
UBEM	Urban Building Energy Model
UKCP	The UK Climate Projections

Page intentionally left blank

Page intentionally left blank

1 Introduction

This PhD research project explores the potential effects of future climate change impacts in the cooling demand of office buildings, for different climates, different cities, in different regions of the world, and quantify the implications for power network operation.

In December 2015, the Paris agreement on climate change mitigation, adaptation and finance was adopted by 196 parties at the UNFCCC COP 21 (Intergovernmental Panel on Climate Change (IPCC), 2018). The Paris agreement is a legally binding international treaty on climate change. The goal is to limit global warming to well below 2°C, preferably to 1.5°C, compared to pre-industrial levels. Hence urgent political action is necessary to mitigate climate change impacts. Mitigation and adaptation to climate change impacts will be one of the most important challenges to societies over the twenty-first century. Addressing these challenges, the United Nations defined climate action as the 13th goal in the 2030 agenda for sustainable development (SDG) (Assembly, 2015). Climate action is defined by reducing greenhouse gas emissions and increasing resilience and adaptive capacity to climate-induced impacts (United Nations Development Programme (UNDP), 2021). In recent years, youth movements have propelled strikes against climate change, namely Friday For Future, and have propelled large and wide protests for climate action, which have driven significant media, societal and political traction for the topic.

The declaration of climate emergency taken by several local and national governments is a response to this call for urgent action (The Climate Emergency Declaration and Mobilisation, 2021). Several major emitting countries have recently announced net-zero emission pledges to be reached by the mid-century (2050-2060) (United Nations, 2020). However, carbon emissions have increased on average, 1.3% per year between 2010 and 2019. The 2020 UN emission gap report (United Nations, 2020) highlights a significant gap between emissions on current global nationally determined contributions by the Paris agreement and the carbon budgets to reach the agreed goals. The IPCC special report on the impacts of Global warming of 1.5°C (Masson-Delmotte, et al., 2018) shows that the emission pathways to restrain climate change below 1.5°C are extremely challenging, as global net anthropogenic CO_2 emissions decline by about 45% from 2010 levels by 2030.

The Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) (Pachauri, et al., 2014) estimates that mean global surface temperature will increase by 1°C from 1990's baseline with a likely range between 0.3°C and 1.7°C for scenario RC P2.6 by the end of the century (2081-2100) (Allen, et al., 2013). The change is estimated to be 1.8°C (1.1°C - 2.6°C), 2.2°C (1.4°C - 3.1°C) or 3.7°C (2.6°C - 4.8°C) respectively for emission scenarios RCP 4.5, 6.0 and 8.5. Furthermore, it is expected that in Europe and North America will occur more frequent and intense periods of heat waves (Meehl, 2004). The world might be heading to increases in global average temperatures above the 2 degrees Celsius threshold. Therefore, it is not only necessary to mitigate climate change, drastically reducing carbon emission, but it is also necessary to prepare and develop approaches to adapt to the climate change impacts. Climate resilience studies consider how to reduce disruptions by the acute effects that more frequent and intense extreme events can have on the built infrastructure's operation (Nik, Perera, et al., 2020).

Heatwaves create high deadly heat risks for vulnerable population groups (Mora, et al., 2017), in buildings that are not adapted for extreme warm climate conditions. Heatwaves have become more frequent and intense, and both are expected to increase even more in the future (Smith, et al., 2015). Overheating in buildings is ever more frequent in the existing building stock, and it has been estimated that this effect will be exacerbated by future climate projections (Kolokotroni, et al., 2012). Current building designs may be inappropriate in the future, as the expected refurbishment rate of stocks is low, so they have high risks to underperform in more severe warmer conditions. Similarly, the rising temperatures can lead to a substantial increase in cooling demand and cooling peak loads, both due to an increase in air conditioning (AC) penetration and more intense demand from existing space cooling systems (Chandramowli, et al., 2014).

When reviewing the implications of climate change impacts on the electricity system, the power demand of buildings has been indicated as one of the most vulnerable sectors to warming climates (Chandramowli, et al., 2014; Andrić, et al., 2019). The built environment is vulnerable to the impacts of climate change, and the energy demand in the building sector is expected to face the highest levels of impacts across all sectors (Andrić, et al., 2019). The future shifts in cooling and heating energy demand are predicted to be larger for hot climates than cold climates (Li, et al., 2012; Andrić, et al., 2019). However, there are reports of differences between studies due to discrepancies in building modelling assumptions, weather dataset sources, building modelling tools and the approaches on the generation of future climates (de Wilde and Coley, 2012; Andrić, et al., 2019; Yassaghi, et al., 2019). Therefore, it is critical to further assess the multiple types of implications of climate change, for a variety of buildings, considering multiple modelling assumptions, and across representative climate across different world locations.

The growth of space cooling in buildings is a challenge to the future operation of energy systems (International Renewable Energy Agency (IRENA), et al., 2018). The additional demand for cooling creates additional stress on power grids, resulting in failures and blackouts (Burillo, et al., 2017). Meeting such additional demand may lead to potential shortfalls in transmissions and supply on the power network (Vine, 2012). In the USA and Europe, the sharp uptake of AC units during the last few decades have brought significant additional peak demand during summer peak periods (Auffhammer, et al., 2014). In the future, the power grid will operate in significantly different operative requirements and loads. The future challenges for the power network are massive due to new generation flows and the integration of new demand loads (Henderson, et al., 2017). The balancing of new types of supply profiles and new types of demand profiles present a considerable challenge for the design and planning of networks. At the same time, future and existing technologies in buildings can provide additional power flexibility to the power network (International Renewable Energy Agency (IRENA), et al., 2018; International Energy Agency (IEA), 2019). For example, buildings can be a source for thermal storage and demand response services. These new technologies embedded in buildings may be an asset to balance grids during generation shortages or surpluses. Therefore, it is required more detailed assessment of climate change impacts over the electricity peak loads, not only from cooling requirements, but for the overall building use.

The modelling and simulation of buildings are critical to assess the implication of all these different future conditions. In the last decades, building simulation has evolved significantly with the increasing computational resources availability (Hensen, et al., 2011). However, there are concerns with the credibility of the results generated by building performance simulation (BPS) tools, as significant performance gaps have been reported between these and actual energy measurements (de Wilde, 2014). Thousands of model parameters determine the accuracy of building models, and on the other hand, there are limited data measurements on the energy performance of buildings (Hong, et al., 2018). Therefore, the calibration and accuracy of building models become an under-determined and over parametrized system problem. Another major challenge that BPS tools face is integrating various parameters and complexity of factors such as non-linearity, discreteness, and uncertainty (Hopfe, et al., 2011). Further integration of uncertainty and sensitivity techniques are expected to enable BPS tools to provide a means to pursue more robust building designs and operation of systems (Clarke, et al., 2015). The field has acknowledged the limitation of the processes and approaches used in the community and it is claiming for better and more holistic methods to address the inherent complexity of the systems modelled (Hensen, et al., 2011).

The purpose of this PhD project was to better understand the effect of climate change on cooling demand of office buildings. This study set out to insightfully analyse the sensitivity of building modelling methods, the effects of weather uncertainty in cooling demand, and the effects of a future climate pathway. Secondly, cooling requirements and related electricity consumptions are estimated, under climate pathway scenarios and possible building design adaptation measures. This is made to have an insightful study of climate change overall impact upon the overall energy demand and the possible consequences to the power network.

The remainder of this chapter describes the research background and the research rationale of the thesis. The aims and objectives of the research are then presented. After that, the research methodology is summarised, a short description of the research's scope and limitations are analysed, and finally, a summary of the chapter is given.

1.1 Research background

Climate projections estimate significant changes in temperatures and indicate that extreme weather events such as heatwaves, will become more frequent and longer-lasting (Jenkins, *et al.*, 2009; Lowe, *et al.*, 2018). In urban areas, the effects of temperature increase could be even more accentuated by the Urban Heat Island (UHI) effects (Watkins, *et al.*, 2007), a phenomenon whereby the urban area temperature is higher than in the surrounding countryside areas (Met Office, 2014). Future extreme weather conditions raise many concerns for public health (Mora, *et al.*, 2017), as observed during the 2003 heatwave period over Europe (Robine, *et al.*, 2008).

Impacts of climate change are critical for the built environment (Li, *et al.*, 2012; Andrić, *et al.*, 2019), and they have been the sector of energy demand where climate change impact research has focused the most (Chandramowli, *et al.*, 2014). For buildings, warmer climate conditions and more intense and extreme hot periods present multiple challenges for the operation of buildings and related services. The effect of warming climates in buildings drives additional cooling requirements of buildings, leading HVAC (Heating, Ventilation and Air-Conditioner) systems to their capacity limits and then to indoor thermal discomfort. In addition, heat waves can lead to a sharp increase in electrical peak demand, due to additional cooling requirements to keep acceptable thermal comfort. Therefore, hindering and stressing the grid operation, which may potentially cause power outages (Vine, 2012; Burillo, *et al.*, 2017).

Studying the effects of additional cooling demand in buildings for power networks is necessary to understand the climate resilience of the power grid and the building stock. A systematic assessment of risks is required for revealing vulnerabilities in systems operations (Hall, *et al.*, 2019). In the following sub-sections, some aspects of the research backgrounds of this PhD research will be further analysed. The impacts of climate change on buildings are expected to be significant, as presented before; However, the coverage of the effects is challenging to model and quantify and get a broad scope of the problem. At the same time, the building sector represents a large share of energy use and carbon emissions, and the growth of cooling services is expected to be significant in the future. The growth of cooling demand creates additional stress to the power grid, which is already facing significant infrastructural challenges. The office building type, the future of building technologies, and the progress of the building stock are important to be further analysed as they may drive modelling assumptions in the research approach. Finally, climate resilience of the built environment is required but challenging to achieve due to the highly uncertain future conditions.

1.1.1 The building sector

Operational energy by buildings accounts for almost 30% of the total final energy consumption (FEC) in the world (International Renewable Energy Agency (IRENA), *et al.*, 2018). The building sector accounted for 28% of total energy-related CO_2 emissions. In the UK, the building sector's FEC represents around 50% of the UK total FEC (Department for Business Energy & Industrial Strategy, 2016). Therefore, the energy consumption for buildings becomes one of the main foci for energy efficiency policies. However, it has been found that there are higher risks of overheating during summer in newer buildings constructions and especially in high rise buildings. Recently constructed buildings are better insulated and present lower air infiltration, minimizing heat losses, and so buildings with higher internal heat gains can act as heat sinks (Beizaee, *et al.*, 2013). On the other hand, older buildings respond slowly to variations in the thermal balance and present smoother swings in internal temperatures as these buildings have larger thermal masses (Beizaee, *et al.*, 2013). Therefore, further improvement in the envelope insulation and airtightness of buildings may negatively impact the overall energy performance of buildings due to the increasing requirement for cooling.

In itself, cooling energy services represents around 3.4% of the total FEC, and it is the fastest-growing energy consumption end-use in the building sector (International Energy Agency (IEA), 2018). For example, the AC electricity demand worldwide more than tripled, between 1990 and 2016, increasing from 600 TWh to 2,020 TWh (International Energy Agency (IEA), 2018). The IEA estimated that 1.6 billion AC units were in use in 2016, and in the period 1990-2016, the total cooling capacity almost tripled, from 4,000 GW to 11,675 GW. In the next decades, cooling energy services are expected to keep a rapid growth. However, the access to cooling services by population is disproportional around the world and, to some extent, is linked to affluence. In India, only 7% of the population owns AC units, where the same number for the USA is 90% (Campbell, *et al.*, 2018). Therefore, it is from developing countries in hot climates that cooling demand growth is expected to be more significant. The IEA moderate scenario for space cooling estimates that by 2050, the FEC demand for space cooling will reach 6,200 TWh, which more than triples current levels (International Energy Agency (IEA), 2018).

Space cooling services are mainly provided by electricity, and for buildings, it represents a large share of the total electricity annual consumption (20%) (International Energy Agency (IEA), 2018). However, cooling services may represent an even larger share during peak demand periods, representing a constraint for the operation and design of power networks. Worldwide, demand for space cooling of buildings represents 14% of the electricity peak demand (International Energy Agency (IEA), 2018), but in the USA, this value is 40% and in India is only 10%. For hot climates, 50 to 80% of peak demand may be driven by space cooling (Ezzedine Khalfallah, Rafik Missaoui, Samira El Khamlichi, 2016). This creates significant pressure on additional capacity on the power network. For example, in 2017, 100 GW of the electric power generation added to the grid were estimated to be related to additional cooling service requirements (Campbell, *et al.*, 2018). By 2050, 2,000 GW of electricity generation is expected to have been added to the power network due to cooling requirements.

1.1.2 Effects of climate change on building performance

In the future, overheating risk and cooling demand of buildings may increase substantially in future warmer climate conditions, if current designs are maintained. However, the impacts of climate change on buildings are seasonal. For example, the annual total buildings' energy demand may remain steady considering the effects of climate change impacts, as reductions in heating demand are significantly offset by the increase in cooling demand. Active cooling measures may be necessary to maintain thermal comfort within an acceptable range and to avoid the overheating of buildings (Guan, 2012; Gupta, *et al.*, 2012; Kolokotroni, *et al.*, 2012). In addition, under future climate conditions, the electrical demand for cooling requirements in buildings with mechanical cooling systems may rise steeply (Chow, *et al.*, 2010; de Wilde and Tian, 2012).

Building energy models are required to estimate the effect of climate change impacts in buildings, allowing the simulation of their energy performance under future climate projections. However, due to the complexity associated with modelling and simulation, these research problems usually are simplified and the number of building designs considered tends to be minimized (Hensen, *et al.*, 2011). One previous systematic review of the literature on the impacts of climate change on building energy performance using BPS (Moazami, *et al.*, 2019), has shown that 66% of the studies are based on only typical future weather conditions. This shows that most studies use a few data samples, which exclude the assessment of future extreme weather conditions. However, Herrera et al. (2017) emphasized that the availability of climate projections data prepared for building simulation weather datasets is essential to promote research on the impacts of climate change on building energy performance. For example, most of the previous studies that included extreme climate conditions are from the UK, where the UKCP09 weather generator provided hourly weather data (Jones, *et al.*, 2009), allowing for extensive investigation of the implications of climate change on building energy performance (e.g. (Gupta, *et al.*, 2012; Short, *et al.*, 2012; Jenkins, *et al.*, 2013)). This shows the importance of having reliable and accessible weather datasets at national levels to produce building simulation research studies assessing climate change implications.

1.1.3 Energy consumption in offices

In the UK, the domestic and service sector represented 44% of FEC and 68% of the total electricity consumed in 2019 (Department for Business, 2020). In addition, from 1990 to 2019, the overall FEC changed little in the UK. However, there was a steep expansion on FEC for the services sector (+13%), while the industry sector reported significant reductions (-42%). In the same period, and the electricity demand in the services sector rose by 26% (Department for Business, 2020). In 2015, the office sub-sector represented 8% of the total electricity consumed in the UK (Department for Business Energy & Industrial Strategy, 2016). Furthermore, in 2015, the electricity for cooling and ventilation requirements in the office sub-sector was estimated to have been in itself 1.5% of the total electricity consumed in the UK.

Office buildings in the UK generally present a high intensity of internal heat gains per floorspace area (over 40 W/m^2) (Energy, 2003) and large floor space areas (over 1,000 m^2) (Abela, *et al.*, 2016), which leads to higher cooling requirements. It is estimated that 65% of the UK's total office floor space area is covered with mechanical cooling (Abela, *et al.*, 2016). Furthermore, there are risks that cooling demand will increase significantly in offices buildings in the UK under future climate projections as indicated in the literature (Chow, *et al.*, 2010; Kolokotroni, *et al.*, 2012; Jenkins, *et al.*, 2013). Li et al. (2012) also concluded that for non-domestic buildings with significant internal heat gains, the overall energy demand is likely to increase due to the effects of climate change. Similarly, it is estimated that the frequency and intensity of overheating inside buildings will increase substantially in current office building constructions. Therefore, to understand the extension of the effect on cooling demand of buildings due to climate change impacts, it is necessary to evaluate building energy performance in a vast set of parameters.

1.1.4 Future stock scenarios

In future scenarios, the energy demand in buildings may alter significantly due to the integration of new technologies, materials, and design approaches into building systems. These will be considered in this research project. The development of HVAC technologies and passive cooling technologies integrated into buildings design can significantly minimize buildings' energy demand (International Energy Agency (IEA), 2018). Despite all of the expected technological progress in cooling systems and building technologies, the increase in electricity demand for space cooling requirements may be significant in future warmer conditions, as AC technologies may be adopted in a large share of buildings that do not currently have mechanical cooling provision.

Finally, smart building operations will be more responsive to the electric grid condition, reducing power demand during peak periods and shift loads when there is excess power capacity (Nemtzow, 2017). Demand-side response (DSR) mechanisms as part of a building's operation could enhance the network's reliability and avert system stress, so deferring the upgrade of the power network. This type of demand response strategy is estimated to have the potential to reduce the peak demand during summer periods (Wilkinson, 2004; Liu, 2016). One potential demand response mechanism could be to relax the thermal set point temperature level in buildings, compromising the occupants' thermal comfort. However, it is exceptionally challenging to integrate the uncertainty of such adaptation measures further when quantifying the long-term climate resilience of buildings already considering climate variation uncertainty (Nik and Perera, 2020).

1.1.5 Downscaling climate change projections

Global climate projections estimate that average annual temperatures may increase between 1.0°C and 3.7°C by late 21st century relative to the 1986-2005 reference period (Allen, *et al.*, 2013). However, changes in climate are expected to be significantly different across different parts of the globe. The understanding of climate processes that drive global circulation models is well known but cannot be fully represented in the models. When applying climate change projections data in research analysis, it is critical to acknowledge uncertainty and assumptions. Similarly, it is necessary to understand the different accuracy levels for the different components of climate projections. Atmospheric science and global climate models can represent large scale processes that inform changes at the regional level but are weaker when modelling local scale surface climate phenomena (Hewitson, *et al.*, 2014).

The uncertainty of climate patterns and the availability of all-weather variables required to run BPS is a significant challenge to produce the required input weather files (Herrera, *et al.*, 2017). The energy modelling of buildings requires hourly or even more frequent weather data to input the simulation process (Barnaby, *et al.*, 2011). Historically, information was collected hourly due to difficulties in the collection process, and weather stations were limited to airports and other meteorological sites. Therefore, climate data was sparse, and simplifications would be used to avoid a lack of data. Currently, the collection of weather data has been deployed to many sites. However, future climate conditions are not possible to project based on current weather patterns (Herrera, *et al.*, 2017). In addition, the spatial and temporal scale of projections does not match the scales of observed local data. Therefore, the generation of future weather data for building simulation presents technical challenges and complexities that limit the evaluation of impacts of climate change impacts, based on BPS.

The availability of large sources of climate data and the availability of computational capacity also creates the opportunity to explore building models' uncertainty response to changes in climate variables. Building modelling is mainly based on temperature correlations that were used in more simplified modelling tools. However, in dynamic building simulation, the interaction between building models and the external weather conditions is much broader than average mean temperatures. For example, solar radiation heats the thermal mass of the building envelope and is transmitted through the building glazing into the internal space. Wind speed, precipitation, relative humidity, and the daily temperature amplitudes lead to different effects in the occupants' indoor thermal comfort and HVAC systems' operation. So it is important to incorporate the uncertainty of weather conditions, considering a wider range of weather data when evaluating the future heating and cooling demand of offices using BPS.

1.1.6 Power grid challenges

The power grid will face a sharp increase in electricity demand over the near future (PSERC, 2016), due to the addition of new customers (especially in developing countries), to supplying further energy services (for example, cooling, heating, cooking, and entertainment) and the efforts to decarbonise energy services currently provided by fossil fuel will also contribute the sharp increase in demand. The technological means and the energy vector used to achieve decarbonisation may still be unclear now. However, either directly or indirectly, the decarbonisation of these energy services will significantly increase electricity consumption as a consequence of displacing fossil fuels from direct building use (Henderson, *et al.*, 2017).

The power network is facing multiple challenges in the upcoming decades. In the past, power grids were designed into one-flow systems, where electricity would flow from large generation to transmission, into distribution and to the end-user. However, the power network operation is rapidly progressing to a much more interactive operation (Henderson, *et al.*, 2017). The fast proliferation of distributed generation and the rapid integration of storage and flexible loads have driven this transition. Indeed, the power grid is becoming a two-flow direction system, where electricity flows from large generators to consumers in large periods and from consumers and distribution networks when it is necessary to compensate for dips from the unavailability of renewable energy generation (Henderson, *et al.*, 2017). Some of these challenges are related to the impacts of climate change, an increase in the share of climate-sensitivity energy sources, and ever-growing societal needs for reliable energy supply (European Environment Agency (EEA), 2019).

Due to all these challenges, the direction of the power network operation will require a profound re-engineering of the power grid (PSERC, 2016). The power grid will move into a computerised and smarter grid to accommodate the additional demand and the requirements brought by new renewable energy sources. Additional grid flexibility will be required. Storage capacity, better grid control and management are required to balance the generation and demand loads. These transformations are already occurring in energy systems, and at a rapid pace. In addition, more reliable, resilient and safer grids are expected (Henderson, *et al.*, 2017). The infrastructure is also required to be more climate-resilient, as it is expected that climate change and extreme weather events are increasingly impacting all components of energy systems (European Environment Agency (EEA), 2019). For example, these effects will affect the availability of primary energy sources, the transformation, transmission, distribution, storage and final energy demand. The potential increase in electricity demand from AC end-use, responding to additional cooling requirements, especially during peak demand periods, is one of the main factors that should be considered when planning the sizing and operation of power networks.

1.1.7 Climate resilience

Over the next decades, investments in the infrastructure are expected to be on the level of 57 to 95 trillion dollars worldwide, to deliver SDG and to limit climate change according to the Paris agreement goals (Bank, *et al.*, 2021). In contrast, the global GDP (gross domestic product) was almost 85 trillion dollars in 2020 (Bank, 2021). Building up infrastructure resilience must be a policy priority, as it is cheaper to act sooner than deferring action to future opportunities (Bank, *et al.*, 2021). In addition, opportunities to build resilience decline with time. Hall et al. (2019) concluded that to improve the climate resilience of systems, it is necessary to invest in climate risk information, collect and make available more data, and build up the technical capacity to use climate information to enhance resilience.

Planning for resilience requires the ability to predict the future and understand the infrastructure's governing systems (Nik, Perera, *et al.*, 2020). In the future, the impacts of climate change could trigger cascading risks, which have knock-on effects throughout other sectors, besides the ones firstly considered (Bank, *et al.*, 2021). It is necessary to analyse both short and long-term effects of climate risks to improve infrastructure reliability, namely energy systems (Nik and Perera, 2020). In the same way, Hall et al. (2019) identified that it is critical to have climate-proofing design infrastructure solutions. It is necessary to develop methods that accommodate sophisticated uncertainty to achieve this, including the uncertainty from climate variation, namely pathway approaches (Nik and Perera, 2020). It is also relevant to consider the uncertainty of adaptation measures in assessing these scenarios (Nik and Perera, 2020). However, it is extremely difficult to execute these types of assessments, including such uncertainties.

In summary, the significant future contribution of cooling in buildings is accompanied by multiple challenges. Not only the rapid adoption of AC technologies in developing tropical regions drives rapid growth in cooling, but also the effects of global warming do. However, the future climate projections are highly uncertain, and there are multiple challenges on the generation of future weather datasets to be used in BPS. It is known that all this will create additional stress to the power grid, which is ever more required to be reliable. Therefore, it is important to develop approaches, and tools that help to provide and guarantee the climate resilience of built infrastructure. An overview of the research background was given, and in the following section, the motivation of this research work is going to be presented.

1.2 Motivation

The motivation of this work is established around three main ideas/topics: the inherent uncertainty of building energy modelling, the uncertainty of future climate conditions and the potential effects of climate change for buildings (especially for peak conditions).

The uncertainty on the effects of climate change impacts in buildings includes not only the uncertainty inherent to climate change projections, but also the unpredictable assumptions upon future scenarios of the building stock and building technologies. The effects of climate change, depending on their magnitude, could have important implications on the energy infrastructure, building design and system operation (Wood, *et al.*, 2015), and so further research is required to quantify it. The effects of climate change upon the building stock may have implications on the overheating of buildings, the increase in cooling capacity requirements and the electricity peak loads for cooling demand. The literature highlights the implications upon overheating of buildings (Gupta, *et al.*, 2012; Kolokotroni, *et al.*, 2012), the cooling and heating demand end-use in buildings (Chow, *et al.*, 2010; Tian, *et al.*, 2011b, 2011a; de Wilde and Tian, 2012) or annual energy use (Robert, *et al.*, 2012; Short, *et al.*, 2012; Zheng, *et al.*, 2020). However, there is a lack of research evidence that quantifies the possible change in cooling capacity or electricity peak loads.

The aim to reduce heat losses of buildings has been raising the need for cooling demand in buildings during the summer season, as levels of insulation and airtightness also may minimise opportunities for free cooling during summer. Therefore, it is necessary to evaluate the drawbacks, and counterproductive effects on the set of energy performance indicators for the different building design approaches, especially under warmer climate conditions. These different building design measures may include increased building envelope insulation, increased thermal mass of building fabric, and additional thermal storage capabilities in buildings. It is also relevant to consider design measures such as renewable driven HVAC systems, or the use of adaptive envelopes, and utilising demand response mechanisms. Understanding the implication of these factors in the energy demand of buildings considering the climate change impacts is essential for planning future design of building stocks and the energy network infrastructure.

The effects of climate change impacts in the building stock may be unlike for the different types of buildings, as they may present specific disparate characteristics. For example, office buildings have great potential to trap heat within the building as they generally have smaller proportions of heat losses through their envelope and larger intensity of internal heat gains (Energy, 2003; Beizaee, *et al.*, 2013). Therefore, the majority of office buildings floor space area in the UK is mechanically cooled (Abela, *et al.*, 2016). Thus, during the summer peak times, the energy consumption for cooling requirements in offices is estimated to represent 6-8% of the total power network load (Pout, *et al.*, 2008). Moreover, the office sub-sector presents a stable electricity energy demand profile and a sharp distinction between working and non-working periods (Kavgic, *et al.*, 2015). The composition of the office building stock is relatively homogeneous and facilitates the creation of broad office energy models, which can estimate a representative energy profile of buildings in the stock.

In order to assess the implications for the power network and the thermal comfort of buildings at a whole stock level, it is necessary to have an overall modelling approach that can represent the entire building stock. In addition, the outcome of simulations from this model approach should be sufficiently detailed to allow an analysis of implications on the peak load and HVAC capacity sizing. It is also important that the results capture the physical and operational differences among the existing type of buildings, as seen in (Wang, *et al.*, 2014; Dirks, *et al.*, 2015). The evaluation of effects of climate change impacts upon energy demand in buildings should also consider scenarios that incorporate adaptation strategies, as they are plausible to be undertaken in response to changing climates to minimise the effects on operation of buildings.

Sensitivity analysis (SA) and uncertainty analysis (UA) allow risks to be better characterised and the testing of different scenarios, which are essential to better building design decisions (Clarke, *et al.*, 2015). The performance gap that has been diagnosed in the literature corrodes the credibility of the simulation, and efforts are necessary to bridge this gap (de Wilde, 2014). The development of BPS tools has increased the sophistication of physical models, so the uncertainty of results also increased as the number of input model parameters grew. Current approaches in building design decision making do not incorporate uncertainty in case studies analysis (Hopfe, *et al.*, 2013). A priori assessment of uncertainty is critical to understand the relevant parameters in any system and explore the modelling methodology's limits (Kim, *et al.*, 2013). These statistical techniques improve the robustness of model results (Clarke, *et al.*, 2015). Therefore, it is essential to explore the uncertainty of input assumptions in the office building stock and assess the differences between results for different archetypes representing distinct shares of the building stock. Identifying the key input parameters of the building office models used enables tracking the parameters that should be more carefully prepared in further analysis. In addition, it can indicate the type of adaptation measures that can be the most effective in reducing cooling demand and total demand in the stock. Similarly, this type of analysis allows the study of the interaction between different types of demand loads in buildings (peak vs annual, and space cooling/HVAC versus total).

The study of weather data uncertainty in the cooling demand of buildings is critical to investigate the effects of climate change on building's energy demand. The weather is a critical factor for the energy use of buildings, and it is one of the single factors with the largest implication for the energy consumption of buildings (Yoshino, *et al.*, 2017; Chen, *et al.*, 2020). Additionally, future weather data generation is a complex and challenging task (Hall, 2014; Trzaska, *et al.*, 2014). A clear understanding of the implications and distinction of effects for peak and annual demand of total, HVAC and space cooling requirements are necessary to inform and prepare strategies to generate future weather datasets based on climate change projections. This information is essential to create approaches to assess the building design in future robustly. This will also suggest different suitable types of design options according to the differences in climate conditions.

Climate resilience is an emerging concept to represent the durability and stable performance of built infrastructure against extreme climate events (Nik and Perera, 2020;

Nik, Perera, *et al.*, 2020). Modern society requires a reliable operation of energy systems and building technologies, and for that it is necessary to account for variations and uncertainties in planning assumptions, including climate conditions. Planning for resilience requires exploring future scenario assumptions and understanding the systems' physic fundamentals (Nik and Perera, 2020). It is necessary to assess that designs are robust for multiple potential types of future assumptions. Relatively to resilience to climate change impacts, it is necessary to consider the deep uncertainty of climate variation (Nik and Perera, 2020). Therefore, it is important to develop strategies that evaluate the pathway that include a range of scenarios, and the effect of the whole range of conditions is studied.

1.3 Aim and research questions

This research aims to study the implications of climate change upon the space cooling requirement for office buildings in different regions of the world, operating in different representative future climates over this century (up to 2100). In order to pursue the aim, several research questions will be addressed in the current work as listed below:

1. How sensitive is office building energy modelling to different operational and design input parameters?

It is important to assess the contribution of different input parameters to cooling loads and electrical demand for office buildings. The sensitivity of the energy model results (total and HVAC electricity demand, space cooling both for peak and annual resolution) should be analysed in this context, considering a variation on input model parameters that drive buildings' energy consumption.

2. What is the relative impact on peak and annual HVAC and total electricity demand of office buildings as cooling requirements differ with changing building design and operational conditions?

When analysing the simulation results from BPS cases, a wide range of metrics can be evaluated. In this research, aimed at understanding the effects upon buildings' space cooling requirements, the research analysis looked specifically at space cooling demand as measured by electricity demand for HVAC end-use, and the total electricity demand. In addition, two time-resolutions of the performance are critical on the assessment of performance, the annual demand as a metric of overall demand and the peak demand that quantifies maximum demand, and it is also critical for the sizing of systems. Therefore, to have an overall understanding of the effects on the performance of the buildings, it is necessary to compare the implications for the different metrics, time resolutions, and types of buildings and climates analysed. Different locations and type of buildings are utilised in the research analysis to explore the effect of different building cooling requirements.

3. How does the morphing of weather timeseries influence the peak and annual total electricity demand in a case study of archetype office buildings?

The weather is one of the main factors for the energy use of buildings, and with climate change, in the long-term, there exists a large uncertainty on the weather data-sets required to evaluate the future performance of buildings. Therefore, it is necessary to assess the implication of different main weather parameters in BPS weather datasets for the energy use of buildings. It is necessary to evaluate each weather factor's (morphing procedures) individual contribution before understanding the implication of the changing climate (all factors).

4. To what extent could the peak and annual electricity load of archetype office buildings be affected by changes in cooling demand associated with the impacts of climate change?

It is necessary to acknowledge the massive uncertainty of the climate change impacts to address this question. Therefore, a pathway is developed to evaluate a sequence of potential climate states, which collect a broad spectrum of the potential weather that will exist in the future and quantify the extent of this impact. In addition, the quantification of the effect must be analysed on a broader spectrum, not only focused on one performance metric but on the impacts for at annual and peak level, for total electricity, HVAC end-use and space cooling requirements. Similarly, this analysis should support inquiry if the effects are similar across different buildings and climates.

5. To what extent could a potential increase in electricity demand due to cooling provision be limited in future scenarios by adaptation measures?

In order to cope with the effects of climate change impacts, several adaptation measures may be undertaken, namely, to mitigate the escalation of the peak load in the power network due to the warmer climate. Thus, it is important to quantify the potential adaptation measures have in coping with the effects of climate change upon buildings energy performance. Rather than an exact quantification of the effects, this wants to evaluate the general effectiveness of a range of basic measures on reducing additional demand from the impacts of climate change.

1.4 Thesis outline

This thesis is composed of eight chapters and appendixes. This first chapter (1), the research background is introduced (Section 1.1), followed by the research motivations (Section 1.2), aim and objectives (1.3), and the outline of the thesis (1.4). In Chapter 2, a review of the existing research literature is presented, first looking at topics related to the building energy modelling (Section 2.1), and then on the research topics related to the implications of climate change on cooling demand (Section 2.2). In Chapter 3, the research methodology is presented.

Chapter 4, Chapter 5, and Chapter 6 are the result chapters of this thesis. Chapter 4 presents and discusses the result findings on the office models' sensitivity analysis. Chapter 5 reports the results on analysing the impacts of the uncertainties associated with climate data on the electricity demand of office buildings. Chapter 6 presents and discusses research results on the implications of a future climate pathway on the electricity and space cooling demand of office buildings and adaptation measures' effectiveness. Chapter 7 discusses the overall findings of this research work, limitations, judgments and future research pathways. Finally, Chapter 8 summarises research findings, identify contributions and potential future work.

1.5 Chapter summary

This chapter, presents the background and motivation for the research work done in this thesis. First, an analysis of the research background is presented (Section 1.1), covering the background research topics to office buildings' cooling demand due to climate change impacts and the effects on the power network. Secondly, the research motivations (Section 1.2) are explained, and after which the aims and research questions (Section 1.3) are presented. Finally, an outline of the thesis chapter is given (Section 1.4).

The analysis of the research background presented in this chapter identifies the multiple challenges involved in analysing climate change impacts on building energy performance, namely, on building energy demand modelling, the rapid growth of cooing energy services, challenges of the power grid, or climate projections. This analysis emphasises the relevance of growing cooling energy services in the building sector and how this trend creates additional stress to the future energy infrastructure. In the following decades, the power network is expected to face multiple other challenges to comply with decarbonisation goals. Simultaneously, to guarantee the built infrastructure's climate resilience, it is necessary to assess designs in a more systematic and resilient way and develop new approaches to do it.

The chapter introduces the reader to the research background of “The impacts of climate change on the electricity demand of archetypal office buildings”. This chapter serves as a segue to interpret the research motivations, and the research focus/process pursued. The takeaways from this chapter help the reader place the different steps of the research in the context of the research challenges identified.

2 Literature review

The analysis and the quantification of the effects of climate change on a building's internal environment incorporate multiple challenges. First, building energy modelling (BEM) and aggregate stock level demand modelling aim to simulate very complex phenomena. There are ever more detailed and complex physical BEM, but there is still a gap between real building energy measurements and the energy consumptions estimated by virtual models, which can only provide approximations of the real system's performance (Hensen, *et al.*, 2011; Clarke, *et al.*, 2015). On the one hand, the increasing computational capacity available to execute simulations has increased the number, complexity and scope of the building simulations performed. But on the other hand, there is always a compromise between the resources and costs associated with the creation of new models and the new information their simulation can provide.

Second, the impacts of climate change on the building environment are broad, and there is a significant amount of literature investigating these. In particular, the focus on cooling demand in buildings is essential since, for example, global warming may increase mortality due to overheating in buildings. In fact, mechanically cooled buildings may face the frequent failure of HVAC systems, and additional electricity demand during peak power network loads may lead to power network disruptions.

Now, an accurate estimate of the impacts of climate change requires accurate weather forecasts. In turn, the generation of future weather datasets requires the availability of climate change projections at the regional grid point representative of the sites analysed, current weather data, and awareness of the limitations and requirements of downscaling approaches. Climate projections are inherently uncertain, creating additional challenges for impact studies which also rely on inherently uncertain building models. Adaptation measures in building design and its operations may minimise the effects of climate change in buildings. Hence, it is also relevant to quantify the effectiveness of these measures' potential effects.

In this chapter, a review of the relevant literature is presented on the effects of the impacts of climate change upon the cooling demand of buildings. The first section of the chapter (2.1) will be looking at different aspects of BEM, covering, in each subsection, different types of modelling, scopes, and related techniques. In the second section (2.2), research studies looking at the implications of climate change on the cooling demand of buildings are reviewed. The sub-sections look at different scopes of study: broadly at energy performance (2.2.1) or, more specifically, at cooling demand (2.2.2), analysing the challenges on generating future weather data (2.2.3) and possible adaptation measures (2.2.4). Finally, a discussion section (2.3) analyses, discusses and summarises the findings of the literature review performed.

2.1 Building energy modelling (BEM)

2.1.1 Building stock modelling

There are two main types of approaches to estimate the energy consumption at the large whole stock level: top-down and bottom-up, as has been discussed and identified in several reviews of modelling techniques for this purpose (Swan, *et al.*, 2009; Kavgic, *et al.*, 2010; Fumo, 2014). The terminology of these two categories is based on the hierarchical position of the modelling data inputs relative to the building stock as a whole (Swan, *et al.*, 2009). Figure 2.1 presents a diagram showing the two main categories and examples of methods within these. Top-down approaches estimate the energy consumption of the entire building stock considering the attributes of the whole sample. On the other hand, the bottom-up approach accounts for buildings' energy consumption separately, considering each building's particular parameters, which may be extrapolated to the stock's aggregated scale.

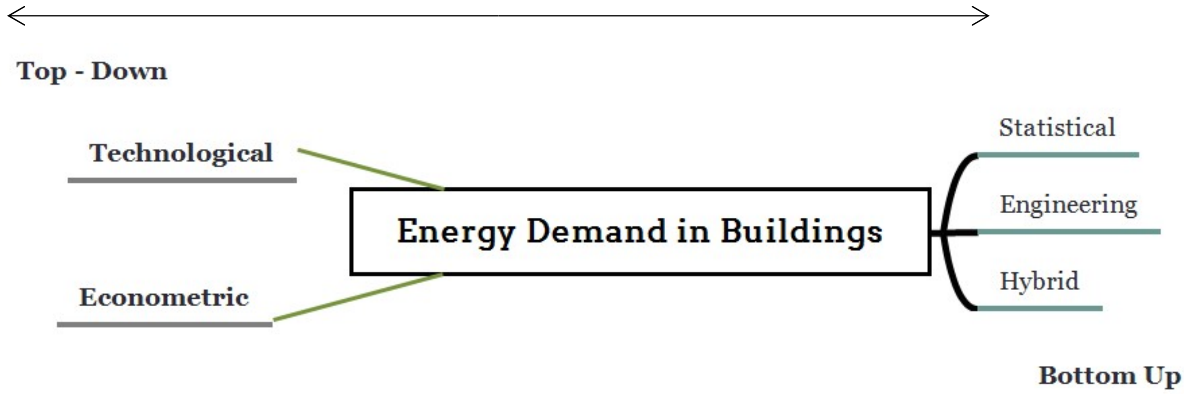

Figure 2.1 – Top-Down versus Bottom-up approaches adapted from (Swan, et al., 2009; Fumo, 2014; Brøgger, et al., 2018)

Bottom-up methods present a more detailed, informed and broader modelling scope and are, therefore, more relevant to this research's methodology. The independent modelling and simulation of individual buildings enabled by bottom-up approaches allow the investigation of the critical parameters for cooling demand in buildings (research objective 1). The modelling approach also allows assessing the energy performance of different representative office building models under different input parameterisation scenarios. Statistical methods are a particular category of bottom-up approach techniques. Tools such as regression analysis, neural networks or principal component analysis are used to estimate buildings' energy consumption. Similarly, engineering methods rely on the representation of the physical and thermal systems in buildings to estimate the energy end-use consumption.

Archetype modelling technique is an engineering method that scales up representative buildings simulation results to an aggregated level, based on the weight of these building classes in the stock population (Swan, *et al.*, 2009; Reinhart, *et al.*, 2016). These classes group similar buildings, e.g. by use, vintage, size or a combination of these. Many studies in the literature have applied weighted archetype modelling approaches to model large building stocks, as in (Caputo, *et al.*, 2013; Wang, *et al.*, 2014; Dirks, *et al.*, 2015; J. Huang, *et al.*, 2016a; Tarroja, *et al.*, 2018; Burillo, Chester, Pincetl, Fournier, *et al.*, 2019; Zheng, *et al.*, 2019). In Sub-section 2.1.4, the archetype modelling technique is reviewed in further detail. Reinhart et al. (2016) also concluded that this type of approach has been broadly used to estimate the aggregated impacts on energy demand, using regional or nationwide bottom-up stock models.

Bottom-up engineering methods are well suited to investigate different scales and aspects of the energy performance of the building stock. This is in contrast to top-down approaches, which provide a simpler and straightforward characterisation of the building stock, by modelling and analysing the building stock's overall energy demand using broad scenario assumptions (Lipson, *et al.*, 2019; Mata, *et al.*, 2019). Bottom-up models are more complex to model and simulate, allowing a more flexible set of simulation targets. They can address research questions looking at the occupants' thermal comfort and at the implications for peak or annual cooling demand. In particular, archetype modelling efficiently scales up the results from the detailed modelling of building representatives to a stock level. Therefore, it allows a user to address research questions looking at larger spatial scopes and provides the flexibility to look at different variables and incorporate different assumption conditions (stock, weather, or technological) as done in (Dirks, *et al.*, 2015; J. Huang, *et al.*, 2016b; Burillo, Chester, Pincetl and Fournier, 2019; Zheng, *et al.*, 2019).

Bottom-up data-driven or statistical type approaches can be used for a group of buildings as done in (Miller, *et al.*, 2008; Parkpoom, *et al.*, 2008; Constable, *et al.*, 2013; Davis, *et al.*, 2015; J. Huang, *et al.*, 2016a; Auffhammer, *et al.*, 2017; Zheng, *et al.*, 2020). Data-driven methods allow rapid and simplified modelling of the whole building stock, reducing the computational requirements and enabling extensive screening of the implications of input parameters to a single output. However, data-driven models of the whole building stock demand are set only for estimating single output, due to limited data available to train and to validate the models, which undermines the accuracy of the model estimations. Thus, the ability to adapt modelling approaches to analyse several output variables and address different research questions is limited. Lastly, future conditions may differ substantially from the initial training conditions, thus compromising the model's validity.

The urban building energy model (UBEM) is a nascent field and an emerging simulation method for bottom-up stock building energy analysis. UBEM is a type of simulation-based method with a building operational-oriented approach, which calculates the hourly energy use of a building stock at an urban scale (Abbasabadi, *et al.*, 2019). Reinhart et al. (2016) leverages UBEM to predict the operational energy use of a group of buildings, applying a physical model base to model the heat and mass flow and estimate indoor and outdoor environmental conditions. UBEMs modelling procedures are based on the identification of geometric data, shape, and geospatial position of buildings through 3D models of a city that are stored and further analysed on geographic information systems (GIS). Additional building model assumptions, for HVAC systems, construction systems and materials, operational schedules, internal gains are defined according to building typologies, known as "archetypes" (Reinhart, *et al.*, 2016; Johari, *et al.*, 2020). Each building included in the city model is characterised by one of these typologies.

UBEM is central to evaluating and managing energy performance at city level scale (Abbasabadi, *et al.*, 2019). However, to make BEM viable to an urban realm, it is still necessary to automatise much of the required steps for generating building models. It is also essential to improve the whole process integration between modelling conceptualisation to the highly intensive computation of the models (Hong, *et al.*, 2018). For a detailed insight into this research area and its applications, refer to the review papers (Reinhart, *et al.*, 2016; Abbasabadi, *et al.*, 2019; Ferrando, *et al.*, 2020; Johari, *et al.*, 2020).

In this sub-section, several techniques were identified that quantify the energy consumption at the whole building stock level. Sub-section 2.1.2 reviews the modelling methods for estimating an individual building's thermal and energy performance, and Sub-section 2.1.3 specifically reviews dynamic models, as they provide a deeper understanding of energy consumption.

2.1.2 Whole-building energy simulation

In this sub-section, the different types of building energy modelling categories will be analysed. Firstly, to clarify the terminology related to BEM, it is necessary to state a clear distinction between building model and simulation. A building model is a description, often a mathematical one, of the building system to be simulated, attributing input parameters to describe the building system characteristics and interactions (Clarke, *et al.*, 2015). Wetter (2011) described modelling as the creation of a mathematical model as a means to present knowledge about a physical system. On the other hand, a simulation instantiates the model to compute the system response (Wetter, 2011; Clarke, *et al.*, 2015).

One distinction between building energy model simulations is the time-scale of their analysis, steady or dynamic (ASHRAE, 2013b). The steady-state building simulation assumes that modelling parameters are constant over time, simplifying the complexity of the analysis. On the other hand, the dynamic simulation of buildings considers the transient properties of models along the simulation period, often increasing the complexity and the computational effort of the simulation, see Figure 2.3. Building energy models, like the stock models above, can too be classified based on the description of the building system and interaction effects included in the building. Thus, they are often divided into three categories (Swan, *et al.*, 2009): physical, data-driven and hybrid.

Physical models, also referred to as forward-models or white-box models, represent the building system using a mathematical description to calculate its energy use (Foucquier, *et al.*, 2013). Data-driven models, also denominated as black-box models, are building system models trained to replicate the existing relationship in a data-set between building characteristics and energy end-use (Swan, *et al.*, 2009). The hybrid or grey box model mixes features from both physical and data-driven methods, as seen in (Tian, *et al.*, 2011a; Patidar, *et al.*, 2012, 2014; Jenkins, *et al.*, 2013, 2014; Shen, *et al.*, 2019). This uses simulation results from complex physical models to train and validate a data-driven model, replacing the more complex physical model with less computational effort.

For energy performance assessment and HVAC capacity design, it is fundamental to estimate a building’s thermal load response. Spitler (2011) defined the building thermal load as the required amount of heat to be added (heating load) or removed (cooling load) from a zone to maintain a constant temperature. To conduct a thermal analysis within a zone, it is necessary to evaluate all three heat transfer modes: conduction, convection, and radiation. Figure 2.2 is a simplified representation of the main heat transfer mechanisms in a building zone considered in typical BEM.

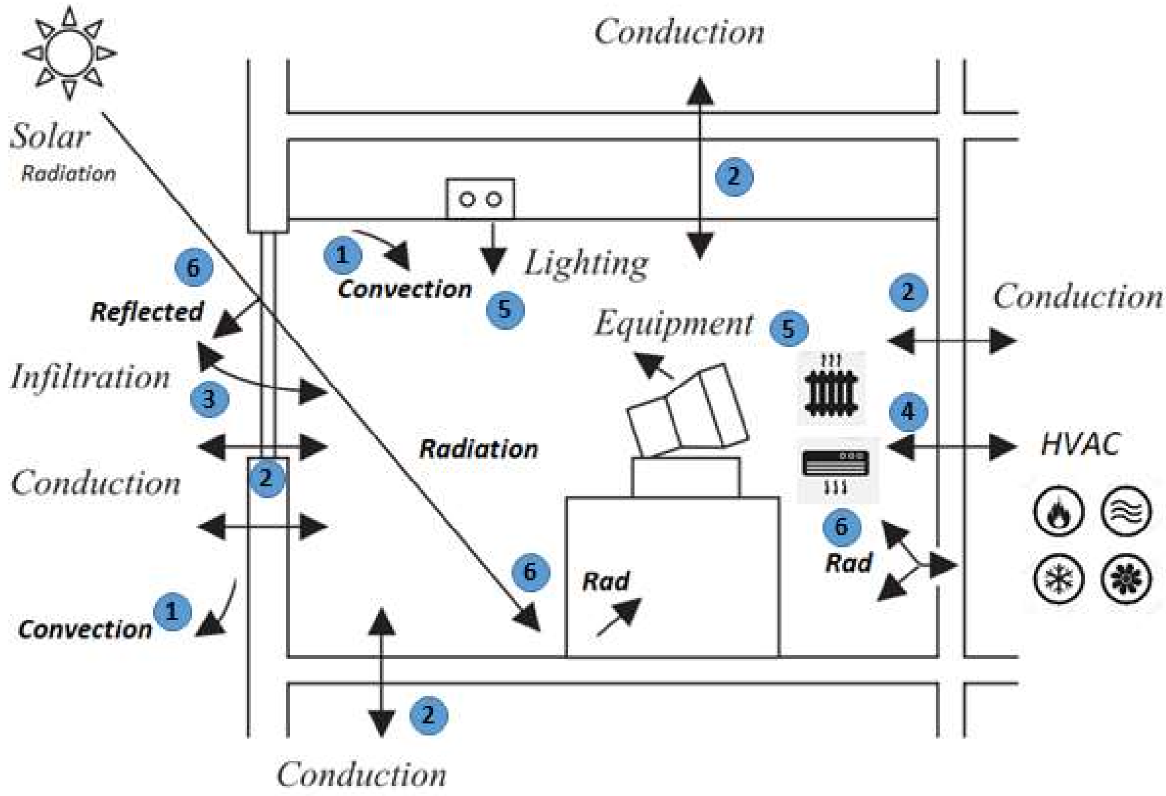

Figure 2.2 – Diagram of heat transfer mechanisms in a building zone, adapted from (Underwood, *et al.*, 2004, fig. 1.1)

The main heat transfer mechanisms within and across the boundaries of a typical zone can be grouped as follows (Underwood, *et al.*, 2004):

1. Convection of air flows at the zone's external and internal surfaces;
2. Conduction from all envelope surfaces, including roof, walls, floor and glazing;
3. Convection from all inflows in the building system, namely the air inlets from infiltration;
4. Sensible and latent loads from HVAC systems;
5. Sensible and latent heat dissipation load from internal occupancy, including equipment, people and lighting;
6. Thermal energy radiation between building components, and between the building and external surroundings (solar, sky, other buildings or ground surface).

A more detailed analysis of the heat transfer mechanisms at sub-component level of the building system is described in Appendix A - Heat transfer mechanisms. Besides the heat transfer mechanisms, the heat balances in the different surfaces of the building envelope and into the air zone are also presented.

The majority of physical BEM methods estimate cooling and heating loads in building zones, calculating the heat balance in each zone's surface and the convective zone's heat balance (ASHRAE, 2013a). On the contrary, data-driven building models do not precisely represent the heat transfer mechanisms within buildings. These models are trained to calculate outputs based on the regression of single or multiple system parameters. However, even when data-driven models are trained including multiple details on the building's envelope characteristics, these models still do not represent the existing physical heat transfer modes.

To estimate space cooling/heating loads within an internal building space, it is necessary to analyse each heat mechanism's balance in the space simultaneously. There are three different classes of physical models: heat balance, thermal network and transfer function models. The heat balance (HB) method is a state-of-the-art method that considers the whole heat transfer process in the building zone to calculate heating and cooling loads (Spitler, 2011; ASHRAE, 2013a). The balances in the method consider all the heat transfer among space’s surfaces, including radiation, conduction and convection. To proceed with the calculation of loads, the model assumes the uniformity of the air and each surface temperatures, uniform irradiation, diffuse radiating surfaces and one-dimensional heat conduction (Spitler, 2011; ASHRAE, 2013a).

The thermal network (TN) method represents buildings as a network of nodes connected by heat transfer paths, further increasing the HB method's detail (Spitler, 2011). Advanced TN models with refined discretisation use sets of algebraic and differential equations. One way to solve these differential heat equations is to apply numerical methods to obtain approximate solutions. As presented in Figure 2.3, there are two categories of numerical calculation methods: direct and iterative. The direct method yields a solution for a certain number of computational steps. On the other hand, iterative methods start with an educated guess. An iterative calculation is conducted until the residue is under a threshold value, and are often applied to a set of equations that are sparse or converge rapidly. Several different techniques can be applied: Gauss-Seidel, Jacobi and Newton Raphson (Clarke, 2001). Another option is to use (time or frequency) response factors to quantify the system's dynamics characteristics.

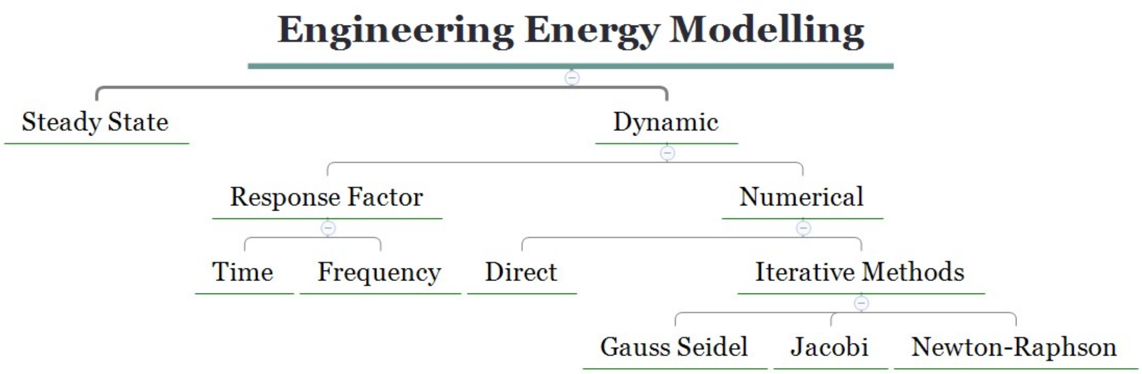

Figure 2.3 – Engineering modelling methods based on the type of solution, adapted from (Clarke, 2001)

It is important to highlight that a drawback of TN methods is a more significant requirement for computational effort and further demand for a detailed model characterisation. However, the method provides more flexibility to simulate different models and conditions (Spitler, 2011; ASHRAE, 2013b). In TN modelling tools, the solvers and building models are divided into different parts, to increase simulation flexibility. Therefore, the algorithm that calculates the building system model's solution (solver) is separated from the actual building model description so that several different solving techniques can be applied to the same model formulation.

In order to reduce the complexity of dynamic whole building simulation tools, the TN method can alternatively use transfer function models, like the RC-methodology which uses an electrical network analogy. A differential equation then governs each component of the electrical system and the number of capacitors sets the order of the model (Kampf, *et al.*, 2007). A typical simplified approach for building thermal models is the second-order electrical circuit, where the resistance represents the thermal resistance of the envelope structure and the capacitance, the thermal storage of the envelope material (ASHRAE, 2013b). The result is a simpler transfer function model that can be used to execute a large number of simulations.

2.1.3 Dynamic building performance simulation

Building performance simulation (BPS) programs are computer programs that aim to simulate building systems' energy performance (U.S. Department of Energy, 2020). Most of the whole/integrated BPS programs use dynamic building simulation, an hourly computer-based simulation, normally simulating a whole year. Integrated BPS programs present modelling approaches that leverage the HB method described previously in Sub-section 2.1.2. This type of software has an approach capable of simulating the whole building model with transient features and evaluating all the main components in the HB within a building system. Therefore, these tools incorporate multiple domain models that calculate different heat and mass transfer mechanisms. There exist several integrated BPS programs available, as reviewed by Crawley et al. (2005). However, few of them model the whole building in detail, offering simplified models for some sub-components.

In the following paragraphs, a short description of BPS programs that offer a detailed model for the whole building will be analysed: EnergyPlus, Modelica, IDA-ICE, ESP-r and TRNSYS. One of the most popular and complete BPS programs is EnergyPlus (Crawley, *et al.*, 2001), developed by the U.S. DOE (Department of Energy). As represented in Figure 2.4, EnergyPlus is primarily a building simulation engine with a modular structure with three core components, the surface HB, Air HB and the building systems, which are simulated iteratively and tight coupled. Several different modules are coupled with the core element representing different system components. The surface HB in the program is calculated simultaneously by solving the air mass balance through the building envelope. A relevant feature is that it offers different solving and modelling approaches for each module. Therefore it can improve the detail of analysis for particular components under evaluation.

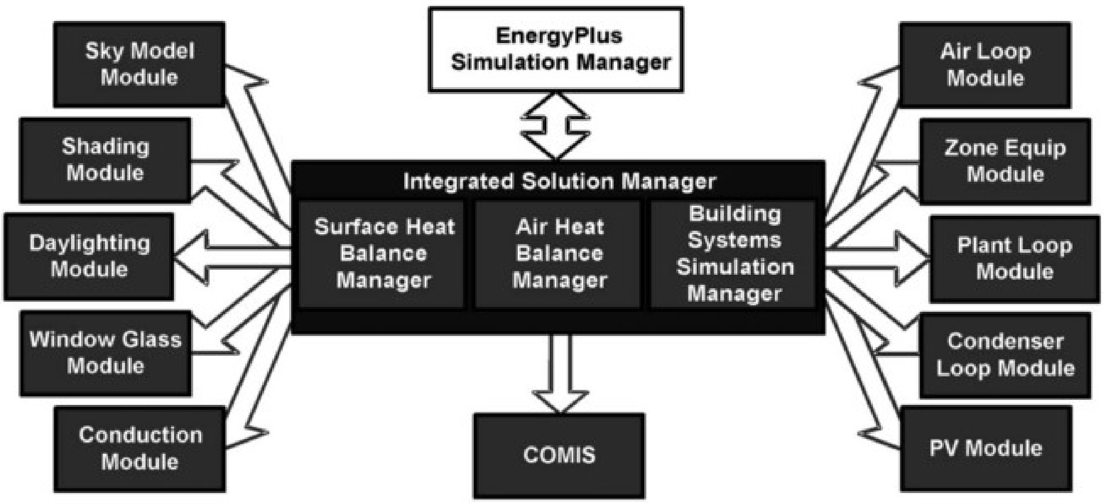

Figure 2.4 – Model components modules of EnergyPlus' Integrated Simulation Manager, source: (Crawley, et al., 2001)

Beausoleil-Morrison et al. (2014) stated that ESP-r was considered to be the most rigorous whole-building simulation software to represent the building physics of the envelope system and that TRNSYS has the best capabilities to simulate the HVAC system components. TRNSYS provides a detailed HVAC equipment library, the flexibility to incorporate multiple model components, and enables developing new components and applying different control strategies rapidly. In ESP-r (Strachan, *et al.*, 2008), for each modelled zone, the air volume, each fabric component and each surface, are discretised in finite difference equations. Therefore, all energy flow paths are represented by a set of equations in all system nodes in an algebraic and discrete form approximating partial differential equations, which are then solved simultaneously with only one iteration per time step (Jost, 2012). Therefore, this approach could risks of lack of congruency due to a mismatch between modules.

The state of the art modelling approach in dynamic whole building simulation are the differential algebraic equation (DAE) models, like the one used by the IDA-ICE BPS tool or Modelica models (Wetter, *et al.*, 2015, 2016). DAE models are intended to bring accurate physical phenomena modelling while keeping the flexibility on modelling multi-domain BPS (Sahlin, *et al.*, 2004). These models are mathematical representations of the systems, and so their physical meaning representation may be superior to other dynamic tools (Trcka, *et al.*, 2010). One of the most interesting features is that it allows a variable simulation time-step, which enables further detail in short transient periods and requires less computation effort over quasi-steady periods (Sahlin, *et al.*, 2004). However, as it is in an earlier development stage, the number of existing modules and their validation and integration level with other programs are inferior to other modelling tools.

2.1.4 Archetype modelling

The archetype modelling of the building stock was briefly introduced in Sub-section 2.1.1. This type of modelling approach has the capability to deeply analyse the energy performance of the building stock. For clarity of archetype modelling definition, it is necessary to distinguish between three different terms: archetype building, reference building and a buildings' benchmark data. An archetype (or representative) building is a synthetic representation of a building, which mimics the average performance of a group of buildings in the stock (Reinhart, *et al.*, 2016). A reference building is a synthesised model to establish a baseline comparison target against the actual buildings' performance (Moffatt, 2004; Deru, *et al.*, 2011). These models are developed based on the statistical treatment of observations of the building stock or building standards. Benchmarking is the practice of comparing the measured energy performance of an actual building, relative to similar or reference buildings, based on specific energy codes and standards (Pérez-Lombard, *et al.*, 2009).

The most reliable method to create archetype models is to use an empirical database of well-classified representative buildings of the stock (Moffatt, 2004). However, the empirical database's quality is often insufficient to establish proper modelling of the buildings' energy use. Therefore, other sources of input are often combined with these empirical databases to define the parameter characteristics of representative models. These include contributions from experts, surveys and detailed benchmark records, as was done for commercial building benchmark models in the USA (Torcellini, *et al.*, 2008).

Two specific steps make up the archetype models' generation: the segmentation or classification of archetypes and their characterisation (Reinhart, *et al.*, 2016). In the first step, segmentation, the building stock is divided into different groups, based on building form or shape, use, age, climates and systems. In the second step, archetype models are generated and characterised to represent each group defined in the previous step. The models' characterisation includes setting the building envelope characteristics, usage pattern (schedules, equipment, lighting, occupant loads) and the HVAC systems characteristics. According to Reinhart et al. (2016) and Ballarini et al. (2014), characterisation can be performed following two different methods: sample and virtual. The sampling method is based on real data from this stock group. The virtual building model is based on the statistical treatment of data for each parameter within this group of buildings. Sokol et al. (2017) refer to a third option, which considers probabilistic attribution of values for the generation of virtual archetype models.

For example, Shahrestani et al. (2014) identified that existing building benchmarks are first generally categorised based on the built form, building type occupancy, and the materials' thermal properties. Next, each model's representative locations and the weighting factors are defined. Finally, the modelled buildings' energy benchmark is defined, namely the floor space area, occupancy density or equipment loads intensity. In addition, Moffatt et al. (2004) concluded that 30 to 50 archetype form models are necessary to represent any given building stock.

Ye et al. (2019) presented a comprehensive review of US commercial buildings' energy-related data, analysing the different available data sources, namely surveyed data and simulation-based data. The creation and update of different sets of commercial virtual building models are also analysed. They concluded the most up to date model sets are: the commercial reference buildings by DOE (Deru, *et al.*, 2011; DOE, *et al.*, 2019), the DOE prototype building (U.S. Department of Energy, 2019a) and the OpenStudio open-gem (National Renewable Energy Laboratory (NREL), 2021). These three sets of models present

16 types of commercial buildings with the same form characteristics. However, the climate zones and the different energy codes/standards that are used to characterise the building models are different. There are three vintages for each type of DOE reference models, and input model parameters are collected from several sources: ASHRAE 90.1 (ASHRAE, American Society of Heating, 2013), standard 62.1 (American Society of Heating, Refrigerating and Air-Conditioning Engineers, 2007) and the Commercial Buildings Energy Consumption Survey (CBECS) (U.S. Energy Information Administration (EIA), 2021). The prototype DOE models present the same shape/form model configuration as the reference models, but they are characterised, so each version meets one of the eight different versions of the ASHRAE 90.1 and IECS energy code. Building models updated regarding different standard versions enables assessing the effects of upgraded regulations/standards and different building operation assumptions in buildings' energy performance.

The CBECS in the USA included a dataset of 4,820 commercial buildings (Griffith, *et al.*, 2008), which were used to create 16 building models to represent the US commercial building stock. There are three office building types in the set of buildings: small, medium and large. Several different research studies have continuously revised these benchmark reference models' descriptions as done in (Deru, *et al.*, 2006, 2011; Torcellini, *et al.*, 2008). The availability of the different types of building models enables comparing the energy performance of these as done by Hong et al. (2013) or Siu et al. (2020). The use of archetypes allows direct comparison of simulation results and their reproducibility. It substantially reduces the requirement to prepare and exhaustively validate building models, steering the focus to simulations addressing research topics such as the impacts of climate change in different types or building locations, as done by Huang and Gurney (2016a) and Wang and Chen (2014). In the UK, Mata et al. (2014) presented a model for the whole national building stock, using nine types of building reference models that were simulated considering seven different construction vintages and four different climate locations.

The built form of building models influences their energy performance (Shahrestani, *et al.*, 2014), and is therefore essential in their parameterisation. For example, CBECS benchmark reference models (Deru, *et al.*, 2006) are defined based on four parameters categories: form, fabric, program and equipment. These models' form parameterisation includes the number of floors, floor height, aspect ratio, shading, and building orientation. Similarly, Shahrestani et al. (2014) also identified that existing building benchmarks are generally categorised based on the built form, building type occupancy, fabric materials' thermal properties, and locations.

Office buildings generally present a significant proportion of glazing areas, large thermal mass and sharp, distinct operation periods (occupied, non-occupied) (Kavgic, *et al.*, 2015). In addition, the office building stock often presents more similarities among its buildings than what occurs in other buildings sub-sectors (Kavgic, *et al.*, 2015). Kavgic et al. (2015) also identified that the building characteristics with more significant implications on the thermal balance of indoor building zones are the thermal mass of buildings, glazing areas, the capability to oscillate temperature set-points and adapting ventilation rates. In the UK, Shahrestani et al. (2014) proposed a building benchmark structure that considered different glazing ratios, fabric types, HVAC equipment, and internal energy loads, which enhanced these parameters' relevance to the implications on the energy performance of buildings.

Korolija et al. (2013) also created four different office representative building models based on the benchmark information available for office buildings in the UK. Hence, they used these representative models to understand the sensitivity of different input parameters on the buildings' energy performance and estimate the impacts of several adaptation measures to reduce energy demand. The TABULA project (Ballarini, *et al.*, 2014; Mata, *et al.*, 2014; Loga, *et al.*, 2016) intended to create a harmonized data structure for European building typologies and to define an accessible set of representative buildings. This is aimed at analysis and comparison of retrofit measures across multiple countries, and it has the objective of ensuring transparency in calculations and communication of results. Thus, it facilitates data handling and the understanding of methodologies/results among different partners.

Building design regulations: In this thesis, a building simulation case study was prepared, which includes six locations in six different countries, which intend to represent different weather conditions. In Section 3.5, a more detailed explanation and reasoning behind the simulation case choice and modelling conditions is provided.

In the review of the literature, it was identified that most of building simulation research use modelling case studies conditions specific for only one country (e.g. (Asimakopoulos, *et al.*, 2012; Farrou, *et al.*, 2016; Duarte, *et al.*, 2018; Huang, *et al.*, 2018; Chai, *et al.*, 2019, 2020; Mahmoud, *et al.*, 2020)). In such cases, it is often utilised values from national building regulations, guidelines, or benchmark data to define building modelling assumptions. For example, as done by Huang et al (2018) for the USA, by Li et al. (2014) and Chai et al. (2019, 2020) for China, Farrou et al. (2016) and Asimakopoulos et al. (2012) for Greece, Mahmoud et al. (2020) and Ibraheem et al. (2012) for Egypt, or Ng et al. (2013) and Duarte et al. (2018) for Singapore.

In Table 2.1, a summary of building regulations, standards, and guidelines relative to the locations chosen for the simulation case study in this thesis is provided. Some of the values in these documents are binding, establishing minimum requirements and thresholds for the energy performance of buildings, as done in EU directive on the energy performance of buildings (Parliament, 2003; The European Parliament, 2010, 2018). National building regulations of EU member states transpose this directive for the national level, as done by the RCCTE in Portugal (Ferreira, *et al.*, 2006) or KENAK in Greece (T.O.T.E.E., 2014). However, there are also guidelines and guides that are only booklets that help modelling assumptions as for example (EMSD, 2007). By contrast, regulations often focus on different areas of building operation, as for example, lighting (Council, 2019), indoor air quality and ventilation requirements (Chartered Institution of Building Services Engineers, 2016), mechanical ventilation (American Society of Heating, Refrigerating and Air-Conditioning Engineers, 2007), thermal comfort (ASHRAE, American Society of Heating, 2003; Race, 2006, 2012; CIBSE, 2013) or building envelope thermal properties (China Standards, 2016). Therefore, research studies consider a mix of regulations/standards and guidelines to compile the modelling conditions of their simulation cases as done in (Duarte, *et al.*, 2018), (Du, *et al.*, 2012a) and (Tian, *et al.*, 2011a).

A minority of the studies analysed in the review have attempted to include in the simulation case different countries, as done in (Cellura, *et al.*, 2018; Ciancio, *et al.*, 2019, 2020; Bravo Dias, *et al.*, 2020). For example, Cellura et al. (2018) included a simulation case with 15 Mediterranean cities in five different countries (Turkey, Spain, Italy, France and Greece), considering the same form and operation conditions for all cases, only adapting the envelope thermal properties based on each local policy. In contrast, Ciancio et al. (2020) consider the same residential building in 19 European cities, but the only distinction made on the modelling assumptions is the carbon dioxide intensity of the power network, to account for the related emissions. In many simulation cases identified, specific existing building cases were selected, and modelling assumptions were based on such cases, and were then extrapolated to different locations, as done in (Ciancio, *et al.*, 2019). In some cases, modelling assumptions are reported, and the reasoning behind the values is omitted, as done in (Mahmoud, *et al.*, 2020).

In building simulation research, it is very challenging to create modelling cases that are representative of overall building stock conditions, which becomes even more, when considering different building cases in distinct locations/countries. Benchmark values and values defined in building standards are entirely indicative values that represent a generic building. By contrast, in the building stock, there exist a wide range of buildings, with multiple building case conditions, which are outliers from standards/benchmarks. Modelling assumption values utilised in research studies are merely indicative, as simulation results are not primarily intended to follow/represent existing performances, but on exploring differences between different technological/future scenarios, or analyse the contribution of different energy policies.

Table 2.1 – List of building regulations and guidelines for different countries

Country	**Regulation type**
European (EU)	DIRECTIVE 2002/91/EC on the energy performance of buildings, and following amendments 2010 and 2018 (Parliament, 2003; The European Parliament, 2010, 2018)
European Standards	EN 13779:2007 - Ventilation for non-residential buildings - Performance requirements for ventilation and room-conditioning systems
Singapore	SS 530 - Code of practice for energy efficiency standard for building services and equipment (Council, 2018) SS 531 - Code of practice for lighting of work places – Indoor (Council, 2019) SS 553 - Code of practice for air-conditioning and mechanical ventilation in buildings (Council, 2021a) SS 554 - Code of practice for indoor air quality for air-conditioned buildings (Council, 2021b) BCA Green Mark for New Non-Residential Buildings (BCA Green Mark, 2010) Code on Envelope Thermal Performance for Buildings (Building and Construction Authority, 2008)
Portugal	Regulamento das Características de Comportamento Térmico dos Edifícios,
Greece	Regulation on Energy Performance in the Building Sector—KENAK (T.O.T.E.E., 2014)
China	GB 50176 - 2016 - Code for thermal design of civil buildings (China Standards, 2016) GB 50189 - Design standard for energy efficiency of public buildings (China Standards, 2015) GB/T 51161- 2016 - Standard for energy consumption of buildings (Standards, 2016) GBT 50378-2014 Green Building Standard in China (Standards, 2012) Guidelines on Performance-based Building Energy Code (Guidelines) (EMSD, 2007) GB 50736 - 2012 - Design code for heating ventilation and air conditioning of civil buildings (China Standards, 2012)
UK	CIBSE Guide F - Energy efficiency in buildings (CIBSE, 2012) CIBSE Guide A – Environmental Design (Butcher, *et al.*, 2015) National Calculation Methodology (NCM) modelling guide (for buildings other than dwellings in England*) (Communities & Local Government, 2008) Energy Consumption Guide 019: Energy Use in Office (Energy, 2003) The Building Regulation 2010 : • Part L : Conservation of fuel and power (HM Government, 2010b) • Part F : Ventilation
USA	ASHRAE Standard 90.1 - Energy Standard for Buildings Except Low-Rise Residential Buildings (ASHRAE, American Society of Heating, 2013) ASHRAE Standard 62.1 - Standard for ventilation system design and acceptable indoor air quality (IAQ) (American Society of Heating, Refrigerating and Air-Conditioning Engineers, 2007) DOE/ASHRAE Prototypes (U.S. Department of Energy, 2019a) DOE Reference Models – CBECS info (Deru, *et al.*, 2011; DOE, *et al.*, 2019; U.S. Energy Information Administration (EIA), 2021)
Egypt	Survey and paper discussing Energy Performance Legislation (Ibraheem, *et al.*, 2012; Attia, *et al.*, 2015; Mahmoud, *et al.*, 2020)

2.1.5 Building performance simulation (BPS) validation

The validation of a simulation model is the process of determining the degree to which the model and its associated data are an accurate representation of the real-world behaviour of the system being evaluated (de Wilde, 2018). The requirement for BPS model validation exists due to significant and frequent reports of performance gaps on building design and real building performance (de Wilde, 2014, 2018; Shrubsole, *et al.*, 2018). The performance gap is the difference between a building's estimated energy performance during the design stage and actual performance achieved once a building is operated (de Wilde, 2018). Discrepancies between different building models simulations results are often significant (Coakley, *et al.*, 2014; Fabrizio, *et al.*, 2015). This is to be expected since a building model is a simplification of a real, multi-layered and interactive system, so each model misrepresents to some extent the actual performance of the building systems (Clarke, *et al.*, 2015). Several factors have been identified as potentially responsible for the energy performance gap, and there is a significant research effort to close this gap, as reviewed by De Wilde (2014).

The gap between building energy models and buildings' real energy performance is attributed to two primary sources of errors: internal and external (Judkoff, *et al.*, 2006). Internal sources of errors occur due to discrepancies in modelling the heat transfer mechanisms, inaccuracies in modelling the interactions within the simulation thermal engine's heat balance, or coding errors in the simulation program. On the other hand, external errors occur due to differences between the model's input data parameters and the buildings' actual characteristics and operating conditions, including weather data, occupant behaviour, or buildings' thermal and physical properties.

It is a research consensus that it is impossible to validate simulation results but only increase confidence in the building modelling (Clarke, *et al.*, 2015). Automated sensitivity analysis (SA) may increase the understanding and confidence on building simulation results (Clarke, *et al.*, 2015). However, building models inputs are often highly correlated, and so risks of large variances in uncertainty analysis (UA) may occur (collinearity), so modellers should acknowledge these facts and carefully interpret simulation results with sensitivity indices (Tian, 2013). In addition, the validation of building models is confined to a specific parameter space and set of conditions, meaning model extrapolation outside those conditions may lead to significant errors that were not identified during validation procedures (Judkoff, *et al.*, 2006).

2.1.6 Uncertainty and sensitivity analysis

Building energy model simulation is a powerful tool for the estimation and assessment of building energy performance. In recent years, the need for more detailed building models has led to a significant increase in the complexity of whole building simulation models (Wetter, 2011). The further complexity of building energy models has increased the detail and number of input parameters on building performance analysis and the number of output metrics that can be explored. Therefore, input model assumptions should not be deterministic, and these input conditions should be represented with probability density distributions to execute BPS (Tian, Heo, *et al.*, 2018). In fact, In the field of building performance simulation, it has become essential to identify the most critical parameters with the largest implications for simulation outputs. Tian et al. (2018) reviewed UA for building energy assessments andconcluded that UA is ready to become a mainstream method in this research area. Clarke et al. mapping of the effects of such variance on the simulation results would become more common. Thus, Incorporating uncertainty and sensitivity analysis in building performance simulation would contribute to close the existing building performance energy gap, as discussed in Sub-section 2.1.5.

In decision theory, uncertainty is defined as the information gap between certainty and the available information to the decision-maker (Aughenbaugh, 2006). Therein, uncertainty is a confidence range of the information available at the present state. There are two types of uncertainties: aleatory and epistemic (Helton, 2009). Aleatory uncertainty is due to inherent or natural random variations of the variable analysed. The lack of knowledge about the variable determines epistemic uncertainty. Uncertainty analysis studies the propagation of uncertainties in an experiment, exploring how the inputs' variation influences the outcomes (de Wilde, 2018). There are two types of uncertainty analysis: forward and inverse (Tian, Heo, *et al.*, 2018). Forward UA intends to quantify the uncertainty in the system outputs propagated from the considered uncertainties in the input parameters propagated through the simulation models. Inverse UA, which may be referred to as model calibrations, are made to determine the unknown variables through models from measurement data.

For building model simulation, Tian et al. (2018) has grouped the sources of uncertainty into four categories: weather data, envelope, HVAC systems and occupancy. Building simulation usually uses TMY files to describe weather conditions in simulations. It is known that typical year data is suited to represent long-term annual trends but is not appropriate to represent extreme conditions. Indeed, weather data can be a significant source of uncertainty (Barnaby, *et al.*, 2011; Huang, *et al.*, 2019). Building envelope uncertainty can be further divided into: thermal properties, surface properties and other envelope properties (e.g., infiltration rates or the thickness of materials). Occupant behaviour uncertainty has recently become a very active research topic, studying the impact of behaviour on buildings' energy demand (Tian, Heo, *et al.*, 2018). From all of them, HVAC system parameters uncertainty is studied the least for building energy consumption (Tian, Heo, *et al.*, 2018).

Tian et al. (2018) concluded that more effort is needed to rigorously quantify the uncertainty of input parameters for uncertainty analysis in BPA. A priori assessment of the critical uncertainties sources on a building model is required in order to acknowledge the potential uncertainty in the simulation results analysed (Kim, *et al.*, 2013). Indeed, the quantification of uncertainty in the probabilistic distribution of input parameters is the most difficult aspect of uncertainty analysis in building simulation (Sun, Gu, *et al.*, 2014; Tian, Heo, *et al.*, 2018).Tian et al. (2018) recommended that uncertainty analysis consider assessing different building types, weather conditions and building ages. For example, Huang et al. (2018) is one of the few studies that analysed the uncertainty for different building conditions, analysing peak load uncertainty on five different locations and for five different types of buildings. In addition, Huang et al. (2018) concluded that the hourly cooling distribution is affected by two main factors, the weather conditions and the building type.

However, these UA approaches cannot inform and quantify the sensitivity of changes in design (envelope and system) input parameters.

Sensitivity analysis (SA) is a statistical method used to evaluate and quantify the degree of change in output results, given a determined change of input parameters (Saltelli, et al., 2008; de Wilde, 2018). There are two main categories of sensitivity analysis: local and global (Saltelli, et al., 2008). Global sensitivity analysis explores the model's response to changes in all input parameters, varied simultaneously, while local sensitivity analysis evaluates the response of the model to one local parameter (Saltelli, et al., 2008). Global sensitivity analysis demands more significant computational effort than local methods; however, it provides more information about the effect of varying model inputs (Saltelli, et al., 2008).

Variance based sensitivity analysis is one type of global sensitivity method (other: screening, regression and meta-models), which decompose the model output deviation based on the uncertainty of input parameters (Saltelli, et al., 2008). Variance-based GSA methods for complex models, such as dynamic building energy models, require large computational capacity, as many sampling iterations are needed to guarantee stable and statistically robust results (Tian, 2013). On the other hand, variance-based SA methods become unstable, biased and extremely costly with many input parameters (more than 10) (Iooss, et al., 2015). Sobol and Fourier amplitude sensitivity tests (FAST) are the most widely used variance-based GSA methods (Saltelli, et al., 2008).

Another global method is the screening Morris EE (elementary effect) method that identifies the effect of one input parameter at a time and makes the changes from different starting points (Saltelli, et al., 2008). It is a very computationally efficient procedure, and it is a widely accepted technique used for different computational models. During the initial building design, when more/larger design uncertainties exist, screening methods like Morris EE are recommended (Iooss, et al., 2015), as they identify the most significant parameters out of a larger set, with minimum computation cost. This approach can reduce the number of parameters to be analysed during the following more complex analysis.

Multi-stage sensitivity analysis (with screening methods, followed by variance-based methods) on building energy performance have been performed to reduce computational requirements of these analyses (Sun and Augenbroe, 2014; Petersen, et al., 2019). In an initial stage, a screening method such as the Morris EE (Petersen, et al., 2019) or Lasso (Sun, Gu, et al., 2014) is applied, which identifies the most relevant parameters. In the following stages, more detailed and complex GSA methods such as Sobol or FAST are applied to evaluate a reduced number of parameters.

In BPA, sensitivity analysis has been applied to investigate different types of modelling outputs: total energy demand (Petersen, et al., 2019), peak electricity loads (Eisenhower, et al., 2012), cooling and heating demand (Labat, et al., 2018; Petersen, et al., 2019), carbon emissions (Tian, de Wilde, et al., 2018) and overheat frequency (de Wilde, et al., 2009). A smaller number of studies have looked at the sensitivity in peak cooling loads due to uncertainty on building model parameters (Domínguez-Muñoz, et al., 2010; Eisenhower, et al., 2012; Sun, Gu, et al., 2014). Dominguez-Muñoz et al. (2010) analysed the results of an office building model in Malaga, Spain, using a resistance-capacitance modelling method. Using an SRC for SA, the main contributors for peak sensible space cooling are thermal inertia parameters, thermal mass and internal convective coefficient over a group of 20 parameters. Eisenhower et al. (2012), for a building in Illinois, USA, used sensitivity decomposition indices based on analysis of variance (ANOVA) tests, and analyses the total sensitivity of total peak demand and annual consumption. Sun et al. (2014) used the ANOVA method to calculate sensitivity indices on the chiller's and boiler's design peak load capacity.

The existing literature examining sensitivity analysis of energy demand in building energy models have shown the implications on annual demand, either for total energy, heating, cooling or carbon emissions. Few studies have focused explicitly on the sensitivity regarding peak cooling demand, especially on electricity demand for HVAC end-use periods. However, peak demand is critical to defining HVAC systems' design capacities and analysing energy systems operation limits. Moreover, current research using SA methods to analyse cooling peak demand (Domínguez-Muñoz, *et al.*, 2010; Eisenhower, *et al.*, 2012; Sun, Gu, *et al.*, 2014) is only executed for a single building and a single climate. Although uncertainty related to the weather parameters requires further studies (Huang, *et al.*, 2019), there is also evidence from UA studies looking at peak cooling demand that building types and climate are significant sources of cooling demand uncertainty (Huang, *et al.*, 2018). For this reason, in this research UA and SA are utilised to explore further explore these uncertainties for different climates and different types of buildings.

2.2 Implications of climate change on cooling demand of buildings

The aim of this research focuses on the effects of climate change impacts upon the space cooling demand of office building stock, which, when actively supplied by cooling systems, is usually provided by electricity. Therefore, it is also essential to analyse the subsequent change in the electricity demand profile on the power network. Peak power network demand is highly correlated to cooling requirements during extremely hot conditions (Vine, 2012; Chandramowli, *et al.*, 2014; Burillo, *et al.*, 2017) where there are hot summers, such as in California or Australia. However, the effects of climate change upon buildings energy performance cover a much broad range of simulation conditions. Therefore, it is important to have a more comprehensive look at the literature covering these effects, to get some perspective on the different types of effects found and the different modelling approaches utilised, according to the various research objectives defined.

The main focus of this review is on the additional requirement for cooling in buildings due to the impacts of climate change. The additional need for cooling presents a multi-fold challenge that affects the design of building envelopes, building HVAC systems and power networks. The impacts of climate change will drive space cooling requirements to grow, which will lead to a rise in discomfort hours for occupants when space cooling is not satisfied due to lack of active cooling systems or ineffective ventilation. Similarly, these impacts may lead to frequent failure of active cooling systems that are not sized for future climate conditions, leading to increasing overheating. Finally, the additional cooling requirements will be followed by additional electricity demand to supply these requirements. This may be critical during extremely hot periods, as these may overlap with the periods of power network peak demand, creating substantial additional demand that may lead to power shortages.

Looking at the literature covered in this review, their broad aim is to evaluate the effects of climate change upon building performance. However, the set of specific objectives of each study may be completely distinct. One typical type of objective is to compare the energy demand during future scenarios and current climates, of specific buildings, namely the effect upon cooling and heating demand (Tian, *et al.*, 2011a; Jenkins, *et al.*, 2013) or the overheat (Jenkins, *et al.*, 2011). For example, in Tian et al. (2011b), the uncertainty and sensitivity in buildings' thermal performance are explored, taking into account the uncertainties in climate change projections and building envelope characteristics.

In the UK, research findings show broad agreement on the significant risks of overheating on existing buildings, especially in future warmer climates (Beizaee, *et al.*, 2013). In future climate scenarios, the overheat in the UK housing stock may be even more noticeable, especially in southern regions and more noticeably later in the century, as concluded by Gupta et al. (2012). Moreover, passive design measures in buildings may not eliminate the overheating in future scenarios considering climate change impacts, and so buildings will require to accommodate active cooling systems as concluded in (Gupta, *et al.*, 2012, 2015). However, the analysis of the increasing overheating in not actively cooled buildings due to the impacts of climate change is not possible to be extrapolated to the effects for buildings with active cooling systems. Research has shown that in the future, more buildings will be requiring active cooling systems (Bravo Dias, *et al.*, 2020), even in the UK (Mulville, *et al.*, 2016), with more energy consumption and larger system capacities (Cellura, *et al.*, 2018; Ciancio, *et al.*, 2019; Farah, *et al.*, 2019; Bravo Dias, *et al.*, 2020).

The present section looks into and examines current literature on the implications of climate change to building energy performance with the aim to identify, analyse and discuss the different types of research questions and approaches that have been employed in studying this vast research topic. After a brief overview, this section will analyse the research looking at the effects of climate change impacts on building energy performance (Sub-section 2.2.1), then more specifically, for the effects for cooling of buildings (Sub-section 2.2.2). It will also analyse the approaches to generate future weather files and the effects of weather variability on the energy demand of buildings (Sub-section 2.2.3). Finally, it will review building design adaptation measures that may reduce the effects of additional cooling demand due to the impacts of climate change (Sub-section 2.2.4).

2.2.1 Effects of climate change on building energy performance

The implications of climate change for space heating and cooling has been the most studied of all the impacts in the electricity demand market, as noted by Chandramowli et al. (2014). The assessment of the implications of climate change on building energy performance has been developing and progressing its detail and complexity. Most of the initial research studies applied data-driven model approaches, as discussed in Sub-section 2.1.2, and focused on the response to the short-run weather shocks as noted by Auffhammer et al. (2014) in his review empirical literature, measuring climatic impacts on energy consumption. Research looking at the implications of climate change in the energy performance of buildings has taken place across multiple spatial (single, district, regional or national building stock), and temporal resolutions (hourly, monthly, annual), as well as different performance outputs being analysed. The model outputs were equally diverse, ranging from total final energy demand, total energy demand by energy source (electricity or gas), energy by end-use (heating or cooling), or even total carbon emissions.

Many of the studies have looked at the implications for singular buildings (Chow, *et al.*, 2010; Huang, *et al.*, 2016, 2016), several different individual buildings (Du, *et al.*, 2012b, 2012a) or at whole sets of archetype buildings (Hong, *et al.*, 2013; Berardi, *et al.*, 2020). With increasing computational capacities available, analysis at a larger aggregated scale, based on building simulation approaches have been becoming more common (Wetter, 2011), at larger spatial scales such as a district area (Jenkins, *et al.*, 2015; Nik, 2016; Moazami, *et al.*, 2019) or even national (Dirks, *et al.*, 2015; J. Huang, *et al.*, 2016b). Hong et al. (2013) illustrated that office buildings' cooling and heating requirements can be substantially different across different types of archetype office buildings. This is caused due to differences in envelopes (glazing areas), but primarily due to IHG and occupancy patterns. For more detailed reviews on the effects of the impacts of climate change on the built environment, refer to (Yau, *et al.*, 2013), (Andrić, *et al.*, 2019), (Yassaghi, *et al.*, 2019), (Li, *et al.*, 2012) or (de Wilde and Coley, 2012).

In Appendix B1, a summary table is given Table A. 1, covering all studies analysed in this area and describing methods utilised in each. The summary of the literature information about the existing literature provided in this table is aimed to present the scope of the simulation and research methodologies identified in the studies analysed. The initial columns of the table describe the authors, year of publication and the country or countries utilised in the analysis. In the following columns, the type of building modelling technique utilised is categorised, and the geographic scale and the buildings typologies used in the analysis are described. The simulation output energy metrics analysed in the studies are described based on the type of outputs modelled (thermal comfort, space cooling or electricity demand) and the time resolution of the analysis is also identified (peak, annual, or monthly). Finally, it is identified if the studies analyse the effect of adaptation measures, and if they have utilised DOE reference or Prototype models.

In general, the literature on the effects of climate change impacts upon buildings energy performance agrees that the annual need for space heating and cooling will respectively decrease and increase in future scenarios due to warming climates (Andrić, *et al.*, 2019). Therefore, electricity demand is expected to increase and gas demand to fall (Chandramowli, *et al.*, 2014). Moreover, the effect on the net energy balance is gradually positive for cooling dominated buildings in warmer climates and negative for heating-dominated buildings in colder climates. Dirks et al. (2015) also agreed with the above. However, the annual demand increase does not necessarily present an additional challenge for buildings or power network systems. It is the increase during peak loads that may present the most difficult challenges to address for the design of building systems and the power network due to the impacts of climate change. Another point of agreement among the literature is that the increase of energy demand and overheating of buildings in the future due to climate change impacts, may potentially be offset by the implementation of adaptation strategies in the building stock (Chow, *et al.*, 2010; Jenkins, *et al.*, 2011, 2013; Gupta, *et al.*, 2012, 2015). Therefore, this type of literature has been intended to quantify to what extent adaptation measures can reduce energy consumption in buildings and if this is enough to offset the increase caused by climate change impacts. In Sub-section 2.2.4, studies using adaptation measures to minimise the effects of climate change are further analysed.

The space cooling requirements and energy performance of buildings are highly correlated with weather conditions, and building energy requirements are significantly different across different climate zones (Pyrgou, *et al.*, 2017; Yoshino, *et al.*, 2017). However, the majority of the studies reviewed looked to implications on a single location (Nik, *et al.*, 2013; Berardi, *et al.*, 2020), and others investigated multiple locations across one country (Chow, *et al.*, 2010; Jenkins, *et al.*, 2011; Gupta, *et al.*, 2015). A few studies analysed the impacts over multiple locations representing different climate zones (Hong, *et al.*, 2013; Bravo Dias, *et al.*, 2020). The majority of these studies focused on western developed countries (Europe, USA and Australia and Canada), with a substantial majority from the UK, as concluded by Moazami et al. (2019), and few have been concentrated in other parts of the world as highlighted in (Yau, *et al.*, 2013). Yau et al. (2013) have also identified that few studies have focused on the potential impacts for tropical regions. Thus, most of the research has analysed effects on cold climates, mild summers, and the findings may be substantially different for another type of climates, as concluded by Andric et al. (2019). For example, Berger et al. (2014) used different building types, when estimating the effects for building energy consumption of climate change impact projections in Wien, Austria. Quantifying the implication of different locations and building types is essential to reasonably quantify the effect of climate change upon the entire building stock.

A large number of the studies identified in this review intend to quantify the effects in single buildings' energy performance due to climate change impacts, but only explore this at a limited number of locations and cannot reasonably analyse the effects at larger spatial levels. Therefore, their objective is, for example, to quantify the effect of climate change projections in the annual and peak cooling requirement of offices buildings samples (Jenkins, *et al.*, 2013), the overheating of dwellings (Jenkins, *et al.*, 2011), or to quantify the effect on the annual heating and cooling demand of office buildings (Tian, *et al.*, 2011a). In these cases, the main focus is to quantify buildings' individual energy performance, considering the effects of different climate change projection scenarios. Nevertheless, the set of results in the buildings' energy performance is detailed and extensive, enabling the research to investigate multiple parameters and output results. However, this type of individual building analysis cannot be extrapolated to quantify the entire building stock's implication.

The building modelling approach used to analyse the effects of climate change can be the simplified steady-state model (Hekkenberg, *et al.*, 2009), or a simplified building dynamic model applying the RC-method (Frank, 2005; Nik, *et al.*, 2013; Fonseca, *et al.*, 2015). As discussed in Section 2.1, RC-methods enables faster calculations and enables the possibility to analyse more modelling assumptions. Using an RC-method, Chow et al. (2010) investigated the effects of climate change on heating and cooling demands in office buildings in the UK. On the other hand, dynamic BPS requires much more computation effort, but the amount of output metrics that can be explored is much larger. EnergyPlus (Crawley, *et al.*, 2001; U.S. Department of Energy, 2017), IES-VE (Strachan, *et al.*, 2008) and TRNSYS (TESS – Thermal Energy System Specialists. LLC, 2021) are some of the most used software for this as discussed in section 2.1.3. The initial application of the dynamic simulation-based approach to assessing the effects of climate change used parametric simulation studies of single buildings (Guan, 2009; Gupta, *et al.*, 2012). No studies have been identified using the UBEM methodology that investigates the effects of the impacts of climate change at a building stock level. UBEM methods are already widely used to demonstrate compliance with energy codes/standards and evaluate the effect of retrofit measures (Reinhart, *et al.*, 2016). However, the modelling approach requires substantial detailed building characteristics and consumption measurements to validate and calibrate models.

Top-down approaches, such as in Isaac et al. (2009) and Zhou et al. (2013, 2014), were essential to identify and analyse the impact of different technological scenarios and initial climate change model projections, and quantify the implication at system levels. Isaac et al. (2009) quantified that global energy demand for AC may increase from 300 TWh in 2000, to 10,000 TWh in 2100, in the considered median technological scenario, mainly driven by developing countries uptake. An estimation of the possible electricity demand for space cooling of the whole building stock in the UK in 2050 was done in (HM Government, 2010a), and annual electricity demand for cooling for the whole building stock may reach up to 150 TWh. However, these findings are based on top-down technological modelling approaches and do not directly investigate the impacts of climate change on building energy performance.

Similarly, overall estimations of the energy demand of a sample of buildings can be achieved with data-driven models using the buildings' current data set (Miller, *et al.*, 2008; Constable, *et al.*, 2013; Auffhammer, *et al.*, 2017). Data-driven models present advantages in analysing stock level trends and quickly assessing climate dataset’s impacts on the aggregated level. However, these approaches miss a detailed analysis of buildings' thermal performance, as regression models usually only correlate to a single dependent variable. Moreover, regression analysis models of the building stock usually only use the outdoor air temperature as the predictor, so neglect the analysis of other parameters that may significantly impact the building stock's overall energy consumption. For example, the building stock composition will change, with changes in the floorspace area, the share of type of buildings, different occupancy, or the HVAC technology's progress or changes in internal heat gains.

One other category in the studies looking at the effects of climate change impacts upon buildings is looking at district stock spatial scale. For example, Moazami et al. (2019) aggregated the simulation results of a residential and commercial building model mix to assess the magnitude of impacts at a neighbourhood scale in Geneva, Switzerland. Similarly, Zheng et al. (2019) have used a GIS-based approach to combine individual building level model simulation, using DOE archetypes, to evaluate the impacts of climate change on different districts at Los Angeles county, in the USA. Three studies have used RC-lumped methods to model district building stocks in Sweden, in Stockholm (Nik, *et al.*, 2013, 2021; Nik, 2016), and Gothenburg and Lund (Nik, *et al.*, 2016). These assessed the impact on heating and cooling demand of a district building stock composed by selecting multiple existing residential buildings. In the UK, Jenkins et al. (2015) quantified the climate associated risk for a selected virtual district stock in Edinburgh based on weighted archetypal simulation of 1,271 dwellings. These studies aimed to investigate the effect of climate change at district levels to evaluate the robustness of energy networks in future extreme conditions.

Wang et al. (2014) also systematically assessed the climate change impacts for the different DOE archetype buildings across different US climate zones. Using DOE archetype models and weighting factors to aggregate to national or regional level this approach, (Xu, *et al.*, 2012; Wang, *et al.*, 2014; Dirks, *et al.*, 2015; J. Huang, *et al.*, 2016b) explore the effects upon the energy consumption of the whole building stock in the USA due to climate change impacts. To do this, the results from archetype reference models are weighted based on their composition share in the building stock analysed. These studies used several of the main representative building form models of the stock. These are simulated in all representative national climate zones and with different input building parameters based on their construction vintage and operational characteristics. Therefore, the number of simulations runs can be large in some cases, reaching almost 180,000, as done in Dirks et al. (2015). Using dynamic BPS, the research can quantify the effects upon the whole building stock's energy consumption, exploring the contribution of such a variety of parameters. This approach permits extensive detail on output parameters investigated (up to final energy end-uses) and temporal resolutions spanning from annual to peak conditions (hourly). Furthermore, it enables exploring the implications of climate change impacts across both different spatial zones and building characteristics clusters.

2.2.2 Effects on cooling demand

Many research studies that assessed the implications of climate change for both annual and peak space cooling demand in the building stock had used single building modelling approaches. For example, Chow et al. (2010) estimated that space cooling demand in an office building goes almost from not requiring any cooling, to a total annual requirement of 230 kWh in an office located in Heathrow, in the UK. Guan et al. (2009), using a sample office building model in different cities in Australia, estimated a possible growth in cooling consumption of between 36.3% up to 52.9%, under the high future (2070) weather scenario option. Guan et al. (2012) further concluded that total energy consumption might increase by between 6.4% to 15.1% for the same modelling conditions. The cooling capacities required, as shown in (Guan, 2009), will go from the current level of 131 $W.m^{-2}$ up to 208 $W.m^{-2}$ in the high weather scenario conditions by the 2070s, in Sidney. It is an increase of up to 59%, which is the largest among all cities considered. For Japan, Shibuya et al. (2016)

estimated that annual cooling consumption might increase by 19.8% in Naha, and by up to 47% in Sapporo, by 2090s from 1990s levels.

The literature reviewed concerned with potential effects of climate change impacts in the UK buildings is primarily focused on the risk of overheating in buildings, with less focus on the impact on energy demand for cooling. This may justify Wood et al. (2015) conclusion that there is limited literature looking at the effects of climate change impacts on the overall energy demand in buildings. However, the majority of the office stock floor space area in the UK is actively cooled (Abela, *et al.*, 2016). A great deal of previous research into the implications of climate change impacts in the UK for cooling demand of buildings investigated office buildings (Chow, *et al.*, 2010; Tian, *et al.*, 2011a; Jenkins, *et al.*, 2013) or university buildings (Tian, *et al.*, 2011b). In these cases, the uptake of annual electrical consumption for cooling requirements by the end of the century was found to might increase between 60% (Jenkins, *et al.*, 2013) , and over 100% (Tian, *et al.*, 2011b, 2011a). Hence, these studies showed significant uptake on annual HVAC electricity demand end-use; it is impossible to quantify the effect on the buildings' total annual electricity demand, or for peak demand and sizing of the HVAC or the total electricity demand.

The implications at an aggregated building stock level are more challenging to assess using simulation-based approaches, due to requiring much more complex simulation approaches, as is discussed in Sub-section 2.1.1. Some research studies have been using data-driven models to assess the effects of climate change on building energy consumption as done in (Miller, *et al.*, 2008; Auffhammer, *et al.*, 2014; J. Huang, *et al.*, 2016a; Fan, *et al.*, 2019). Some of the literature scoping building stock level show that cooling capacities and electrical peak loads will rise in future scenarios due to climate change impacts (Miller, *et al.*, 2008; Parkpoom, *et al.*, 2008; Dirks, *et al.*, 2015; Auffhammer, *et al.*, 2017). However, the extent of the increase at a large spatial scale is not clear. Miller et al. (2008) for California and Auffhammer et al. (2017) for the whole USA estimated that the peak demand in the electrical system might rise almost by 20% during future extreme weather events using regression analysis techniques.

Whole building stock research studies utilising engineering modelling methods can further assess the effects of climate change for the stock; however, they are more complex to develop and perform analysis. On a district spatial scale, Nik et al. (2013) concluded that by the end of the century, annual cooling demand would double for most of the climate scenarios considered, but there is a large discrepancy (up to 500%) between scenarios. However, even increasing substantially in the future, the amount of cooling demand is rather low. Moazami et al. (2019) estimated that peak cooling demand (space or electricity) of a district in Geneva, Switzerland, can increase up to 16.8% by the end of the century.

At the national spatial scale level, few studies have looked at the implications using simplified models, as Gouveira et al. (2012) did for the residential building stock of Portugal. Gouveia et al. (2012) used an energy services bottom-up approach with a technological model, and estimated the cooling services in the residential sector would increase more than 200%, which leads to an increase in electricity demand for cooling larger than 100% by 2050. Dirks et al. (2015) found that annual cooling demand might increase 15% for the whole US, leading to an increase of 17% in electricity demand and an increase in peak electricity load of 42%, considering scenario A2 in the CASCaDE dataset. Zhou et al. (2014) found that among the US states, the change in annual electricity demand can vary from a reduction of 10% to an increase of 20% by the end of the century considering IPCC scenario A2. Similarly, Xu et al. (2012) found that total electricity demand in the US might increase by 2%, 5% or 8%, respectively for IPCC emission scenario B1, A2 or A1F1, while the electricity demand for cooling increase 25% or 50% respectively for A2 and A1F1 scenarios. However, it is found that the implications for cooling demand are significantly different for different buildings, as large office buildings can have an increase up to 70% and only 20% for warehouse buildings, for the A1F1 scenario, on cooling demand (Xu, *et al.*, 2012). Similarly, Huang et al. (2016b) also found that there is a significant difference across the relative changes in energy consumption across different US climate zones, where the electricity for Minnesota could increase 136%.

The effects of climate change impacts on cooling demand have associated an extensive range of uncertainty and often report to different variables. However, it is clear that for cooling demand, implications are substantial, both annually and for peak demand. Some report results relative to annual demand (Guan, 2012; Nik, *et al.*, 2013; Zhou, *et al.*, 2013; Huang, *et al.*, 2016), and another report to peak demand (Auffhammer, *et al.*, 2017; Burillo, Chester, Pincetl, Fournier, *et al.*, 2019; Zhai, *et al.*, 2019). Similarly, some present the implications at a global scale (Zhou, *et al.*, 2013; Dirks, *et al.*, 2015; Auffhammer, *et al.*, 2017), others only compare the results between different regions (Guan, 2012) or different types of buildings (Wang, *et al.*, 2014). The majority have reported that the stock or buildings' technological assumptions are kept the same as the current status. However, this is extremely unlikely due to changes in the building stock, progress in technologies, and the likelihood of buildings adapting to climate change, as discussed in Sub-section 2.2.4. In addition, results are often presented to a limited number of scenarios, which may not match, or comparisons are made from different base levels. Probabilistic projections have enabled uncertainty in the weather projections and to explore the impacts for a more extensive range of climate conditions. However, to include this uncertainty on top of exploring different building types, climate zones, and building vintages, the computational costs often become prohibitive.

2.2.3 Generation of future weather data

In this section, the use of weather datasets for building thermal simulations is going to be discussed. First, the fabrication of current weather files will be discussed, and second, the generation of future weather datasets that include future climate projections will be reviewed. Weather files are used in building simulation to assess built environment designs' performance, especially during planning stages (Herrera, *et al.*, 2017). Future weather datasets are required to assess the impacts of climate change on buildings, using simulation to assess the performance of building design solutions in these conditions (CIBSE, 2009). This type of analysis also allows for creating adaptation measures to enable buildings to operate in such conditions.

To start, it is essential to distinguish the definition of both weather and climate that are often used in the alternative. Weather is the description of the short-term phenomenon of climate variables. Climate is the long term description of the weather in a particular location, generally over 30 years (Shamash, *et al.*, 2014). In the building energy simulation field, EPW files invented by the U.S. DOE, are the most common type of weather file used, which can be read by TAS, IES, ESP-r and EnergyPlus. In these type of files, the values of 35 variables are kept for a sequence of 8,760 hours (EnergyPlus, 2010, 2015). However, only 14 variables are used internally in the thermal engine. In typical weather files, the main weather variables covered are air temperature, dew point, global horizontal radiation, diffuse solar radiation, wind speed and wind direction (Herrera, *et al.*, 2017).

Weather files for building simulation programs are divided into two main categories, regarding the construction method used, typical and extreme conditions. It is first necessary to understand the features that these files must have to perform building simulations to understand the pursuit for such distinction. Herrera et al. (2017) identified that seven features are essential in these files to perform accurate building energy simulation: detailed time resolution (hourly), geographically meaningful, included urban-micro climate patterns, typical and extreme weather conditions, future possible conditions and finally, being credible in the community. Typical weather files are constructed weather files that intend to represent a typical weather data year for a specific location. Some examples of these fabricated files are CIBSE test reference year (TRY), typical meteorological year (TMY), weather year for energy calculations (WYEC) or international weather for energy calculations (IWEC-ASHRAE). Extreme weather files are constructed weather files that select extreme weather records, which are primarily intended to test the resilience of HVAC systems. Some examples are the CIBSE design summer year (DSY), hot summer year (HSY) or extreme meteorological year (XMY). Weather files are typically constructed based on a composite selection of different years of weather records. For example, TMY files select composite months based on Finkelstein – Schafer statistics (Finkelstein, *et al.*, 1971).

In BEM, it is standard practice to simulate buildings energy performance using single weather year data (CIBSE, 2009). For example, simulations using TMY are a good indication of long-term annual energy consumption (CIBSE, 2009; Barnaby, *et al.*, 2011; Herrera, *et al.*, 2017). However, weather datasets present a significant limitation (Herrera, *et al.*, 2017), as they may represent large spatial areas, and so its applicability may be less appropriate in some positions, significantly further away from the collection point (weather station). Also, as weather datasets are created based on composite construction, these files create an improbable time series. Similarly, extreme weather files are based on observed weather data, which is not long enough to enable these files to replicate weather conditions' potential natural variability. In addition, these weather sets do not include information on climate change. Some research has been studying the effects of using TMY files on the energy performance gap's existence (Drury B. Crawley, 2008; Bhandari, *et al.*, 2012; Hong, *et al.*, 2013; Grudzińska, *et al.*, 2015). These studies use long timeseries of actual meteorological year (AMY) weather data, which are actual measurements of multiple years. Even considering a long time series, it is impossible to estimate future extreme conditions and future years' sequences accurately.

A climate projection is the climate system's simulated response, derived based on climate models (Intergovernmental Panel on Climate Change (IPCC), 2018). A climate model aims to simulate the physical, biological and chemical processes that governate the climate system (Intergovernmental Panel on Climate Change (IPCC), 2018). These models are complex and intend to understand climate change's potential trajectories and understand climate changes in past events (CIBSE, 2009). These models simulate all the land-sea processes at high resolutions, including all earth-system components (CIBSE, 2009; Moazami, *et al.*, 2019). Climate projections consider a baseline period, which is the representative base climate for a location for 30 years. Climate projections are related to emission scenarios and timelines (Herrera, *et al.*, 2017). An emission scenario is a hypothetical trajectory of anthropogenic factors (due to greenhouse and other radiative factors) affecting the climate. A timeline is usually a period of 30 years, in which the respective results in the projections are averaged for the central point of this horizon period. Climate projection scenarios in IPCC assessment reports were first defined as emission scenarios and have now evolved for representative concentration pathways (RCP) (Herrera, *et al.*, 2017).

Climate projections found a generic likelihood for average temperatures to increase in the future (Pachauri, *et al.*, 2014). In the future, It is expected that the frequency and intensity of extreme events will increase (Herrera, *et al.*, 2017). It is also expected that the duration of these events will be longer. Herrera et al. (2017) concluded a growing need to simulate buildings in extreme conditions. This is especially important to evaluate the risks when morbidity and the failure of HVAC systems may occur. It is also expected that changes are more considerable during summer than in winter (CIBSE, 2009). Maximum temperatures are expected to rise more in summer than winter; however, this is not followed by similar patterns in minimum temperatures. Thus, it is expected a substantial increase in the daily amplitude of temperatures.

The IPCC has set up the coupled model intercomparison project (CMIP) to create a procedure for systematic comparison between climate model outputs (Intergovernmental Panel on Climate Change (IPCC), 2018). The output results of these models are used to inform the IPCC assessment reports. For example, the CMIP6 (Eyring, *et al.*, 2016; IPCC, 2020a) compares and analyses 23 global climate models' outcomes to understand climate change phenomena better. These climate model results will be informing the sixth assessment report (AR6) due to release in 2022 (IPCC, 2020b). CMIP5 provides a multi-model context for the climate change assessment in the IPCC AR5 (Taylor, *et al.*, 2012; IPCC, 2021). For the UK, the Met Office Hadley Centre climate programme has been producing the most up-to-date assessment of changes in the UK climate over the 21st century, the United Kingdom Climate Projections (UKCP). The HadCM3 is the coupled atmosphere-ocean GCM developed at the Hadley Centre, that has been used to produce UKCIP02 (Hulme, *et al.*, 2002), UKCP09 (Jenkins, *et al.*, 2009) and then for UKCP18 (Lowe, *et al.*, 2018).

The UKCP18 (Lowe, *et al.*, 2018) includes a more recent generation of results from Met Office Hadley Centre global and regional climate models included in CMIP5. The climate projections presented in the UKCP18 report uses four RCP scenarios and one SRES scenario. The global model projections' spatial resolution is 60 km grids, probabilistic projections at 25 km resolution, presenting regional model projections at 12 km grid cells resolution and local model projections at a 2.2 km scale resolution. The UKCP 09 showed similar distinct levels of spatial resolution. The UKCP09 made available a local weather generator (Jones, *et al.*, 2009), based on the RCM model outputs. However, the UKCP18 will not present such a tool as it considers that climate change results for such temporal resolution have limited application in impact studies (Lowe, *et al.*, 2018). For the UK, the Prometheus project (Eames, *et al.*, 2011; Exeter, 2020) was set to develop risk probability weather datasets for 51 locations in the UK. A methodology was developed to downscale UKCP09 projections with different likelihood levels for the different emission scenarios, time slices and locations (Eames, *et al.*, 2011).

Climate projections based on GCM are spatial and temporal coarse. Grid cells resolutions are generally between 100 km to 500 km, and these results' temporal resolution is at best on a few hours scale (CIBSE, 2009; Yassaghi, *et al.*, 2019). The current good understanding of the climate relationship could enable better resolutions, but a lack of computational resources and data storage forces resolution to be coarse. However, for impact studies using building simulation, finer spatial and temporal resolutions are required. To achieve this, downscaling is often used. Downscaling of climate change projections outputs generates data at lower temporal or spatial levels than the original projections (CIBSE, 2009; Trzaska, *et al.*, 2014). The temporal downscaling derives finer temporal resolutions from coarser original datasets.

On the other hand, spatial downscaling derives information at a lower spatial resolution, assuming that relationships between larger and local climates are kept. There are two major types of downscaling: statistical and dynamic. Dynamic downscaling is made using finer spatial climate models (RCM, or Local), which are iterated coupled with assumptions from GCMs and can be executed in finer temporal scales/resolutions (CIBSE, 2009; Trzaska, *et al.*, 2014; Herrera, *et al.*, 2017; Bravo Dias, *et al.*, 2020). Statistical downscaling derive climate change projection outputs using existing statistical relationships in observed data. Dynamical downscaling can potentially model extreme conditions that can only be accurately modeled at low spatial resolution modelling. However, these require enormous computational resources, produce larger amounts of data and require a high level of expertise in setting up simulations and interpreting results (Trzaska, *et al.*, 2014). Statistical downscaling is simpler to execute, but future climate trends will contain the current trends observed as they are based on observed data.

Statistical downscaling can be further divided into stochastic and morphing methods. The morphing method was developed by Belcher et al. (2005). It consists of generating a time series of weather data set from a base series dataset, using three basic operations to derive new weather variables: shift, stretch and a combination of stretch and shift. Stochastic generation of weather data sets is produced by random generation of weather variables based on statistical properties from observed data and meteorological rules (CIBSE, 2009; Herrera, *et al.*, 2017; Moazami, *et al.*, 2019). The majority of future weather datasets used to analyse climate change 's impacts on buildings utilised statistically downscaled data (Bravo Dias, *et al.*, 2020). Both statistical methods are based on observed historical data, and projections assume that historical trends will be kept, which may not be the case (Trzaska, *et al.*, 2014; Herrera, *et al.*, 2017). It is recognised that morphed data may exacerbate extreme conditions (Herrera, *et al.*, 2017), and once it deals with each variable independently, it loses the prevalent inter-link between variables in historical data. Stochastically generated data has the flaw that it reduces the extreme realisations to keep current trends. Synthetic stochastic weather generated data is considered the most reliable method for BPS, considering the available options for future weather generation (Herrera, *et al.*, 2017).

There are some weather tools available to generate future weather files. For example, UKCP09 (Jones, *et al.*, 2009; Eames, *et al.*, 2011) has produced its stochastic weather generator, creating 100 iterations of 30 years of hourly weather data for all locations in the UK and considering four different scenarios for three timelines. However, this method is only available for the UK, as it is based on local RCM simulation for this specific geographic resolution. Therefore, it is not possible to use a similar approach to locations that have not similar detailed RCM projection results. CCWorldWeatherGen (Jentsch, *et al.*, 2013; University of Southampton, 2014) is a tool that morphs weather data for any world location, based on data HadCM3 GCM, and considering the A2 emission scenario. Meteonorm is a commercial tool based on a stochastic generator that produces weather data based on weather datasets' interpolation, combined with morphing technique considering GCM results (Meteotest, 2020). WeatherShift^{tm} (Dickinson, *et al.*, 2016; Troup, *et al.*, 2016; Arup, *et al.*, 2020) is another tool using morphing techniques to temporally and spatially downscale GCM results. This software uses an ensemble of the 14 GCM models from CMIP5, to generate six probability levels for two emission scenarios and timelines. Many studies that are looking at the impacts of climate change in building energy demand have been using WeatherShift data (for example Aijazi, *et al.* (2018), Dino, *et al.* (2019)*,* Troup, *et al.* (2019) *and* Berardi, *et al.* (2020)), as it can downscale data for any location in the world, and it incorporates some uncertainty.

Probabilistic projections that some of these weather tools create, incorporate uncertainty levels to the analysis of the impacts of climate change, which deterministic projections based on a single modification of representative weather files (TMY-TRY) do not include. However, probabilistic projections require a spatial detailed and a vast number of climate projections, that are only available for specific and limited geographies, like the UK or Sweden. Therefore, deterministic approaches are applied more often, when assessing the impacts for regions with limited number of climate projections data available. Nevertheless, incorporating uncertainty in future weather data is critical to extensively analyse climate risks.

Yassaghi et al. (2019) reviewed the multiple sources of uncertainty in assessing climate change impacts for buildings energy performance. It divides this uncertainty into three groups: the BPS, the climate projection and current weather data. It discusses that current weather data may be influenced by two types of uncertainties, the source and the procedure to generate these datasets. Future weather uncertainty may be driven either by the downscaling technique used or the inherent uncertainty from the climate projection itself. For example, it is clear that by the end of the century, the uncertainty driven by the emission scenario will lead to the most considerable differences in results (Yassaghi, *et al.*, 2019). However, climate models bias was acknowledged in the climate change research community (Maraun, 2016), and was defined as the systematic difference between climate model estimations and observed data. This bias is generally dependent on the time-resolution of the results analysed.

GCM projection results are the source of most knowledge on future climate change (IPCC, 2013), providing potential snapshots of future changes (Herrera, *et al.*, 2017). However, some climate phenomena are substantially sub represented, especially at lower spatial levels (IPCC, 2013). Climate models are often biased and may present implausible results. For example, extreme events are not well represented, as they can only be modelled at low-level resolutions. Model bias correction is used to overcome some of these limitations (Maraun, 2016). Bias correction is often used to match present observed data with model projections to calibrate them. However, these methods have limited function on downscaling global results and cannot change the global climate model's wrong sensitivities. Maraun (2016) discusses the correctness of using bias correction methods to correct climate models. It identifies that when trying to correct for lower levels, the patterns and interlinks in original global models are lost, so they should be used with caution.

For a realistic and comprehensive assessment of climate change impact for building energy performance, it is essential to have building simulation accounting probabilistic climate projections to quantify the implications of different impact levels considering its embedded risks levels as discussed by Huang et al. (2019). The UKCP09 WG have enabled incorporating uncertainty in future weather data (Jones, *et al.*, 2009), and several studies have utilised this approach to explore the impacts of climate change in buildings. However, this cannot be utilised for another type of climates, as discussed by Huang et al.(2019). However, for robust assessment of future climate scenarios, it is necessary to explore a broad range of outcomes, more than single projections. As reviewed in this sub-section, the weather datasets only indicate future scenarios, as there are multiple challenges for their generation and embedded bias. On the other hand, the sensitivity of buildings to weather status and the delicate correlation of weather parameters is known.

2.2.4 Adaptation measures to climate change in buildings

The energy performance of buildings in the future is highly uncertain for multiple reasons discussed in the previous sections of this chapter, namely BEM parameters (Section 2.1) or the weather conditions (Sub-section 2.2.3). However, it is important to assess the new challenges that building operations might face in the future. These challenges include the warmer and more extreme hot temperatures, the role in balancing power grids, and the need to reduce carbon emissions in all sectors. In this section, the implications of different building designs and related system options are analysed.

In the future, it is expected that buildings operations will have to adapt to more extreme external environmental conditions. Many research studies have looked at the impacts of different design solutions for the future performance of buildings, for example, on reducing the overheating risks (Jentsch, 2009; Gupta, *et al.*, 2012; Patidar, *et al.*, 2012; Moazami, *et al.*, 2016; Liu, *et al.*, 2020), minimizing additional cooling loads (Chow, *et al.*, 2010; Asimakopoulos, *et al.*, 2012; Jenkins, *et al.*, 2015; Gercek, *et al.*, 2019), shifting or shedding electricity peak loads or minimizing increase on cooling system design capacities (Jenkins, *et al.*, 2013; Sánchez-García, *et al.*, 2019).

The analysis of the effects of climate change impacts often includes analysing the effects of adaptation measures on minimising the additional effects of climate change. The IPCC (2018) defines adaptation as the process of adapting to climate conditions and the effects of climate change. Adaptation seeks to avoid or moderate the negative consequences or exploit the opportunities from these changes. On the other hand, in the context of the impacts of climate change, mitigation is defined as the human intervention to reduce the sources or enhance greenhouse gas capture (Intergovernmental Panel on Climate Change (IPCC), 2018). However, these terms are often used alternatively as adaptation measures are considered to mitigate additional demand effects.

On analysing the effects of climate change impacts for building energy demand, adaptation measures are considered alternative building design options. These are often called retrofit measures or energy conservation measures (Costa, *et al.*, 2020). The assessment of such measures' performance is executed compared to base case results, which are current/present-day design conditions. These assessments are executed by using BPA tools that evaluate buildings' energy performance, considering future weather datasets. Therefore, the assessment of adaptation measures is made by analysing alternative design conditions for the same weather conditions. Adaptation measures can be generically grouped into different group types: reduction of internal heat gains, reduction of solar gains, change in thermal resistance, change of thermal mass, ventilation strategies, the adaptation of set-point temperatures, and changes in the efficiency of HVAC systems.

Studies analysing the effect of adaptation to climate change in buildings energy performance have been using changes to the building envelope as one of the main measures to consider (Tian, *et al.*, 2011b; Gupta, *et al.*, 2012; Shibuya, *et al.*, 2016; Pérez-Andreu, *et al.*, 2018; Shen, *et al.*, 2019). Measures that change the envelope properties may include changes in different components and over different thermal properties. The aim to better insulate buildings' envelopes (wall, roofs, ground and glazing) is done due to the increase of the thermal resistance driven by lower U-values (thermal transfer coefficients). Another design solution often evaluated changes on the reflectance (absorptivity and reflectance) envelope properties to reduce solar gains into external buildings thermal mass (Gupta, *et al.*, 2012; Orehounig, *et al.*, 2014; Vasaturo, *et al.*, 2018). In addition, the effect of larger buildings thermal mass is often considered for adaptation (Gupta, *et al.*, 2012; Ouedraogo, *et al.*, 2012; Huang, *et al.*, 2016), as it can offer some dampening effect between weather heat loads and space cooling requirements.

Some of the most straightforward and common design strategies to reduce buildings' energy consumption are the retrofit of envelope design conditions, considering more stringent energy codes. Therefore, research studies assessed alternatives of envelope insulations, such as the U-Values of external walls (Shibuya, *et al.*, 2016; Shen, *et al.*, 2019), roofs (Tian, *et al.*, 2011b; Shen, *et al.*, 2019), infiltration rates (Nik, *et al.*, 2016; Mata, *et al.*, 2019), or window coefficients (Wan, *et al.*, 2011). Several studies have analysed the impact of such measures to mitigate the additional building energy consumption in the future with different climate change scenarios (Patidar, *et al.*, 2011; Wan, *et al.*, 2011; Asimakopoulos, *et al.*, 2012; Chen, *et al.*, 2017)). For example, Wan et al. (2011) concluded that total annual energy consumption for an office building in Hong Kong would be reduced by a maximum of 4%, considering the different individual envelope design measures analysed (shading coefficients, U-values or window to wall ratio). However, the total energy consumption would still be at least 4% larger in these scenarios than the base scenario. Similar findings were achieved in other research studies (Gupta, *et al.*, 2012; Vasaturo, *et al.*, 2018), indicating that increasing insulation or airtightness might be insufficient to mitigate the additional energy consumption due to future global warming.

Another primary type of adaptation measure is focused on reducing glazing solar heat gains. Different building design parameters may have effects on this, and so several different strategies are often studied. The most studied of these effects include shading design solutions over glazing envelope, to avoid direct solar radiation heat gains. An alternative design solution to reduce solar heat gains is to reduce the available glazing area, and it is quantified by reducing window to wall ratios (Wan, *et al.*, 2011, 2012; Guan, 2012; Ouedraogo, *et al.*, 2012). Yassaghi et al. (2019) has also identified adaptative glazing control solutions as options to reduce unintended solar heat gains. Adaptative coating solutions present encouraging results, blocking or allowing solar heat gains depending on weather and indoor conditions (Hoes, *et al.*, 2016).

There has been a strong focus on evaluating the impact of better building shading to reduce additional building heat gains through the envelope (walls and windows). Several studies have analysed how overhangs could reduce additional cooling loads and total energy consumption on buildings (Patidar, *et al.*, 2011, 2012; Gupta, *et al.*, 2012; Chen, *et al.*, 2017). As analysed by Asimakopoulos et al. (2012), building adaptation studies to climate change may also consider the impact of cooling paints to reduce the albedo factor of buildings or consider the effect of passive solar strategies in building facades as done by Huang et al. (2016). The increase in the building thermal mass coupled with some ventilation / AC strategies can be considered another adaptation measure, as it explores free cooling opportunities and might shift cooling peak loads.

The reduction of internal heat gains is another type of adaptation measure that has been significantly considered. In this type of measure, it is possible to reduce the contribution from different internal heat gains, such as lighting (Tian, *et al.*, 2011b; Nik, *et al.*, 2016; Mata, *et al.*, 2019; Shen, *et al.*, 2019), equipment (Tian, *et al.*, 2011b; Wan, *et al.*, 2012; Shibuya, *et al.*, 2016; Kotireddy, *et al.*, 2018), or occupancy. For example, measures considering reducing lighting densities follow the expectation that new lighting technologies will enable sharp drops in lighting densities. Similarly, reductions in equipment densities are considered using more efficient IT equipment, which will reduce waste heat from these appliances. There is a trend for increasing computational requirements in offices, which have raised the equipment densities in offices, but on the other hand, there is a trend for more centralised computing power, like cloud computing, which will reduce the local computing and so power densities. Some studies (Beddoe, 2012; Kotireddy, *et al.*, 2018) have looked at reducing occupancy densities and/or operation schedules.

The increase in HVAC systems efficiency is another primary type of adaptation measure, considering the increasing efficiency of cooling systems (changing the coefficient of performance (COP)) or the adoption of heat recovery systems. In addition, it can be considered that adaptations of ambient set-point temperatures can also be included under this type of measures. Multiple studies have been analysing the effects of increasing cooling set-point temperatures for buildings' space cooling and electricity demand (Wong, *et al.*, 2010; Wan, *et al.*, 2011, 2012; Nik, *et al.*, 2016; Pagliano, *et al.*, 2016; Shibuya, *et al.*, 2016; Hooyberghs, *et al.*, 2017; Wang, *et al.*, 2017; Jiang, *et al.*, 2018; Dino, *et al.*, 2019; Mata, *et al.*, 2019; Shen, *et al.*, 2019). In some studies, set-point temperatures changes are set based on thermal adaptive comfort temperatures (Pagliano, *et al.*, 2016; Liu, *et al.*, 2020). Thermal adaptive comfort is an approach based on the occupants' vote for comfort temperatures, considering the assumption that occupants react in reflection to the environment's situation experienced and are less likely to suffer discomfort (Nicol, *et al.*, 2002).

The configuration and operation of HVAC systems are other types of common adaptation measure that are analysed. In general, the adaptation of HVAC systems consider altering coefficient of performance (COP) (Wan, *et al.*, 2011, 2012; Jenkins, *et al.*, 2013; Nik, *et al.*, 2016; Chen, *et al.*, 2017; Mata, *et al.*, 2019; Shen, *et al.*, 2019). Including heat recovery in HVAC systems, has been also considered to reduce electricity demand for cooling (Chen, *et al.*, 2017; Pérez-Andreu, *et al.*, 2018; Mata, *et al.*, 2019). Changing on HVAC operation strategies can also be considered, such as changing ventilation strategies, to integrate more free-cooling (Patidar, *et al.*, 2012; Dodoo, *et al.*, 2016; Huang, *et al.*, 2016; Wang, *et al.*, 2017; Dino, *et al.*, 2019), namely through night ventilation (Frank, 2005; Shibuya, *et al.*, 2016; Hooyberghs, *et al.*, 2017). Impact studies evaluating adaptation may also consider the use of further ventilation rates to increase the use of free cooling using buildings thermal mass (Gupta, *et al.*, 2012; Ouedraogo, *et al.*, 2012; Dodoo, *et al.*, 2016; Huang, *et al.*, 2016). Integrating active storage systems in the HVAC system may also reduce energy consumption or obtain other types of design gains (economics of the operation, reduce system design capacity level). However, the evaluation of these measures' implications is often made at the aggregate level, and it is difficult to understand the individual impact of each measure.

Many research studies analysing the impacts of climate change on building energy performance (Tian, *et al.*, 2011b; Jenkins, *et al.*, 2013) have aimed to address a research question similar to: *"Is it possible to mitigate the additional demand with the adaptation option?"*. One or several sets of adaptation options are analysed, including a group of changes to the multiple design parameters. For example, this may include reducing internal heat gains, increased thermal resistance, improved cooling systems efficiency, and the analysis often compares the energy demand reduction of such conditions against base conditions in future scenarios. It often shows a design solution that presents similar demand levels in future scenarios as the base case in present-day weather conditions, as seen in (Tian, *et al.*, 2011b). However, Tian et al. (2011b) found that even considering adaptation options, for the most extreme weather samples of the scenarios analysed the future demand is found to be larger than at current levels. On the other hand, for overheating, adaptation options' effectiveness is not enough to avoid overheating for multiple conditions and cases as shown by Gupta et al. (2012).

In order to assess the effectiveness of different retrofit measures, some studies have developed systematic metrics to measure the savings compare to base cases and the robustness of the different options. For example, Nik et al. (2015, 2016) calculated the relative difference of the corresponding space heating demand before and after the retrofit for each measure and for each building, climate scenario and projection timeline. In addition, a standard deviation from the mean RD among all buildings is calculated to study the effectiveness of each measure. Pérez-Andreu et al. (2018) presented the percentage of savings of the annual energy demand of different modelled adaptation measures, considering all climate scenarios and timelines. Chinazzo et al. (2015) presented multiple energy conservation measures performance based on an energy-saving index based on the weighting between the relative difference of retrofitted and base case model results, across different time points for a determined climate scenario. It is now well established that adaptation measures contribute to reduce the impacts of climate change in buildings. However, only a few studies have developed systematic ways to assess these measures' effectiveness. Exactly how adaptation strategies contribute to effectively mitigate the additional demand due to the impacts of climate change remains poorly understood. In this research, the mitigative effect of these adaptation options will be systematically analysed (Section 6.4).

Regarding the ranking and identification of the most effective measures discussed previously, the COP improvement, reducing lighting and equipment densities, and cooling set-point temperature's relaxation seems to be the individual measures to have the largest impact. For example, Wan et al. (2011) have shown that annual energy use could be reduced by almost 15%, by reducing lighting intensity from 15 to 10 $W.m^{-2}$, for a generic office building in Hong Kong. In the same study, relaxing the cooling set-pointset-point from 24°C to 27°C, or the improvement of the COP from 4.7 to 6.5, led to a reduction of annual energy use by around 8%. Similarly, Shibuya et al. (2016) have found that improved lighting and equipment could reduce annual cooling demand by 25% in some cities in Japan, while the relaxation of set-pointset-point temperature could reduce around 15%. On the other hand, looking at the implication on heating demand, Nik et al. (2016) found that the relaxation of the set-pointset-point temperature by one or two degrees could lead to at least 20% reduction on annual heating demand, which is the most effective measure among the range of options analysed. More efficient equipment led to an increase in annual heating demand by around 10%. The consistency between results is robust, hence, it is important to point out that most of these results refer to locations in cold or mild climates, such as Sweden or the UK. Consequently, there is a lack of understanding of the robustness of these results across different sites.

Studies looking at the effects of adaptation measures as strategies to cope with the impacts of climate change are mainly focused on the effects on annual energy demand, and/or looking at the mitigation of thermal discomfort in future conditions. Existing research on energy conservation measures mainly focuses on annual demand rather than peak demand, as it intends to analyse the energy-savings, and the cost-effectiveness of these measures. One study by Jenkins et al. (2013) evaluated the effects of two adaptation solutions on reducing electricity annual and peak demand for cooling in an office building. It found that annual electricity consumption can be reduced by 33% and 44% for locations as Edinburgh and London, respectively. However, the peak electricity consumption is not reduced with both measures in comparison to the base design conditions. This may be the case as some design conditions may be sufficient to reduce cooling requirements for most of the year but might be ineffective during extreme conditions. This becomes a central challenge when it is known that the impacts of climate change are intensifying and increasing the duration of these extreme warmer conditions.

To date, only a few studies have analysed systematically the effectiveness of adaptation strategies in mitigating additional demand due to climate change impacts. Moreover, very few studies have analysed the effects for peak demand. This research is going to analyse the effects of a group of fairly standard adaptation options in attenuating both peak and annual HVAC and total electricity demand, for three different office types, for different cities. Six individual measures are analysed (on relaxing cooling set-point, lighting and equipment densities, COP, SHGC and reducing ventilation rate) and three combined measures (grouping two, four and all six measures).

2.3 Discussion of the literature review

Overall, the literature review in this chapter has covered challenges and methods in building energy modelling that may be detrimental when analysing the impacts of climate change on building energy consumption. For example, the cooling demand for buildings in the future is a challenge, especially on peak loads, that are driven substantially by extremely hot weather conditions. This has consequences for the sizing of HVAC buildings and the operation of power networks, which can fail more often in the future. However, it is possible to estimate the future weather conditions, and the impacts may differ from location to location and depending on buildings.

In the literature reviewed, there are several different methods to estimate the aggregated energy consumption of building stocks, divided into top-down and bottom-up approaches. For bottom-up approaches, the individual energy performance of buildings is modelled and then scaled up. The different types of research objectives in this research area constrain the selection of the modelling approaches. Physical energy models and, more specifically, dynamic building performance simulation is a modelling approach capable of explicitly calculating the end-use energy consumption, at different building levels, spatial and temporal, and considering different technological scenarios. Therefore, these methods enable the analysis of the potential implications of new technologies and adaptation measures in buildings, which are required to be considered when evaluating future long-term scenarios as aimed in this thesis.

Future types of buildings' uses and functions make the modelling of future buildings a tremendous challenge, which brings additional complexity for simulation tools (Hensen, *et* *al.*, 2011). At the moment, these challenges seem still too complicated for most of the current modelling approaches and tools, as highlighted in the review by Hong et al. (2018). Some of these challenges are related to the limitations of building models and the challenges created by an increasing need for integrated and holistic modelling approaches as discussed in (Augenbroe, 2011; Hensen, *et al.*, 2011; Wetter, 2011; Clarke, *et al.*, 2015). The complexity and detail of physical building models have been evolving, with better computational processing capacity. However, even the most detailed and exhaustive models have difficulties ensuring the quality of simulation results (Hensen, *et al.*, 2011). Thus, it is essential to select the modelling approach based on the requirements for accuracy on the outputs and the costs of preparing and simulating the model.

Given all that has been reviewed, one can indicate that building stock energy models or stock aggregated energy models are still very reliant on the accuracy and weighting of individual building models. Thus, improving the accuracy of aggregated building stock demand requires improving the confidence and robustness of individual building models. Uncertainty and sensitivity analysis methods intend to analyse BPS results' robustness, identifying the embedded uncertainty in models used and the parameters contributing to these uncertainties. The evidence presented in this review suggests that it is important to understand further the uncertainty of building models simulation outputs and the contribution of different parameters for these changes, through sensitivity analysis.

Previous studies have failed to show the sensitivity of models relatively to peak electricity demand or peak space cooling requirements. In addition, there is a lack of understanding of how these measures compare among different climate base conditions and across different buildings. Thus far, sensitivity and uncertainty analysis often focus on singular case studies; however, it is crucial to have a broader understanding of the implications of these inherent modelling assumption uncertainties to critical outputs, such as peak electricity demand and peak space cooling requirements. In Chapter 4, the research analysis address research question 1 and 2 of this thesis that conveys the research gaps described above.

Overall, the research indicates that future climate conditions will be warmer and drier, showing significant uncertainty ranges and that climate projections present multiple sources of uncertainty. One of the primary sources of this uncertainty is the emission scenarios and the projections' time scale. Overall, these studies highlight the possibility of bias in the weather data generated due to the downscaling approach and the baseline conditions considered and the emission scenarios assumed. Therefore, there is a requirement to further incorporate uncertainty on the future weather data used in studies looking at the effects of climate change on the built environment. Downscaling methods have a different type of bias, and that the generation of extreme weather conditions is not well propagated in most of the methods. Extreme events are sensitive to the assessment of the effects, as they are critical for analysing the resilience of building systems. However, it is essential to acknowledge that future weather data-sets are still projections, and it will only be possible to use them as possible scenarios of climate conditions. Finally, quantifying cooling demand sensitivity due to different weather parameters uncertainty is required to understand the implications of future weather generation in measuring the effects of climate change in buildings on impact studies.

Each method for generating future weather data based on climate projections has its limitations; hence there is no best approach for downscaling, as concluded by Trzaska et al. (2014). Thus, it is important to be informed on the requirements of the approaches and the limitations of the results generated. For the assessment of impacts in buildings energy performance, it is still necessary to understand the implications of changes in different weather variables, especially for space cooling demand, both for annual and peak demand. Analysing the sensitivity of independent weather parameters on building simulations results is challenging to execute, as it is impossible to isolate weather variables due to their inherent inter-links. Some studies, however, have tried to analyse these sensitivities for building energy consumption, with findings that are limited and not possible to extrapolate to archetype models in other building simulation programs and locations. Therefore, a critical research gap relevant to be addressed is analysing the sensitivity of weather variables in building energy performance. Bridging this gap will allow to better understand the implications of these weather changes in the electricity demand for cooling demand. It is critical to realise how weather generation and changes in weather parameters can drive research findings on studies looking at the impacts of climate change in buildings performance.

In recent years, a more significant number of studies have investigated the impacts of climate change on building energy performance, as reviewed in (de Wilde and Coley, 2012; Li, *et al.*, 2012; Andrić, *et al.*, 2019; Yassaghi, *et al.*, 2019). Overall, these studies highlight that the impacts of climate change for buildings will drive overall annual reductions in heating demand and an increase in cooling demand. What remains unclear, however, is precisely how will be the implications for electricity peak demand and space cooling requirements. In addition, the assessments of these impacts lack incorporating different uncertainty levels of climate change projections, enabling robust approaches in evaluating the effects on climate change impacts. As Trzaska et al. (2014) discussed, it is necessary to incorporate quantitative levels of uncertainty to avoid the perception that climate projections results are scientific forecasts. Some studies have achieved robust assessments of the impacts of climate change, using future weather data generated based on dynamic downscaling from the outcomes of RCM. These studies are for locations in the UK, Sweden or Switzerland, where research on climate change has been significant. For example, a large share of the literature on the effects of climate change impacts on buildings energy performance has been done using locations in the UK, using large weather data-sets available, as concluded by Moazammi et al. (2019). Thus, this research area is mainly rooted in mild and cold climates and inherent assumptions. For different locations and climate conditions, research findings are likely to be different, as concluded in (Hong, *et al.*, 2013) and (Wang, *et al.*, 2014).

There are still several gaps in the literature, which are essential to address to fully understand the implications of climate change for the cooling demand of buildings. Flagging the most relevant: the need to fully incorporate the uncertainty of weather data-sets, to analyse the impacts of climate change, and analyse the effects on distinct locations representing a different type of base climate conditions. This thesis proposes a new methodology to generate a large sample of weather data, that mimics a pathway of possible future climate data. The specific objective of this approach was to study the effects of such uncertainty on a broad range of climates, addressing research question number 4 (Chapter 6).

Effects of climate change impacts on the built environment may be substantially reduced by adaptation measures on building design and operation. Research on the effects of adaptation measures to reduce the implications of climate change impacts on buildings performance are intended to quantify the reduction effect of adaptation strategies in buildings. Many of these studies have proposed a set of measures, and only a minority of them have quantified the implications of different individual strategies as conducted by Nik et al. (2016). As for research looking at the effects of climate change, these measures are mainly focused on reducing annual demand levels or overheating frequencies. Most of these design strategies are considered energy conservation measures , commonly incorporated on building design optimisation studies, aiming to reduce the energy consumption of buildings and consider the investment costs needed. Up to now, very little research has systematically analysed the implications of different measures, like Nik et al. (2016) or Mata et al. (2019). It is also evident that this analysis used snapshots of future climate conditions and cannot systematically analyse the effects of such measures across extensive uncertain future conditions.

This thesis will compare the effectiveness of different standard adaptation options and consider the whole uncertainty on future weather conditions, across different locations/climates and for different types of buildings. This is aimed to address research question number 5, and the results to answer this are presented in Chapter 6, specifically in Section 6.4. To sum up, it is important to understand further if these solutions can minimise the expected increase in energy demand due to additional cooling demand. It is also necessary to know if these solutions can reduce the sizing of HVAC solutions and if it is possible to control the increase in on-peak electricity demand.

2.4 Chapter summary

This chapter presents a review of the literature related to the research in this thesis. First, a review of previous studies related to building energy modelling is made (Section 2.1), covering building modelling approaches at stock and individual level. It also analyses archetype modelling, validation of building performance simulation and uncertainty and sensitivity analysis. Secondly, a review of the literature looking at the implications of climate change on cooling demand of buildings is made (2.2). The section looks specifically into the effects on building energy performance and then on cooling demand, but also analysis the generation of future weather data and adaptation measures. Finally, in Section 2.3, a discussion of this literature review is undertaken.

The review of the literature has highlighted some of the main research gaps in the analysis of the effects of climate change impacts for the cooling demand of buildings and identified some of the research challenges in this type of studies. This analysis has contributed to defining the research aim and the research questions to be addressed in this study. In addition, it serves as a segue to the definition of the research methodology presented in Chapter 3.

3 Methodology

3.1 Overview

The research methodology has three parts. First, a sensitivity assessment of building model simulation results employing parametric analysis of the building envelope and operational input parameters. Second, an assessment of the implications of weather uncertainty, through morphing procedures in weather timeseries, for the energy performance of buildings. Third, an assessment of the potential impact of climate change, using a novel climate pathway approach. In this thesis, each research analysis considers the simulation results of three DOE office reference building models in six locations. The metrics assessed in each simulation case were annual and peak electricity demand and the space cooling requirements of each office building model.

The first part of the research methodology assesses the sensitivity of different building design and operational parameters (Section 3.2, and research results presented in Chapter 4). This enabled to identify the effects of different office building energy model types, and locations on annual and peak electricity demand, together with the implications for different design outputs. The main novel contribution of this approach is that it systematically evaluates the sensitivity of results among different types of buildings and locations. The variability of the results in the simulation samples was quantified by the coefficient of variations of each output results analysed, and the sensitivity indices were presented for each parameter regarding each output analysed. In this research, a pre-analysis step was conducted with simplified building energy models to screen a larger number of parameters and identify which were the most important physical and envelope parameters. For this step. the Morris EE method was applied. Following this, a sensitivity analysis using detailed archetype models was conducted. It involved the application of the Sobol SA method to analyse a smaller number of parameters to better quantify the sensitivity of electricity demand to these parameters.

The second part of the method approach (Section 3.3) analyses the sensitivity of change parameters on future weather time-series through morphing procedures (research results are presented in Chapter 5). The approach assessed the effects of the potential weather uncertainty and the implications of different weather characteristics patterns on the energy performance of buildings. It evaluated the impact of individual variations on different weather variables, assessing the individual impact of the different morphing operations used to generate future weather data time series. This approach enabled assessing and comparing the different sensitivities to the weather change parameters commonly used to generate future hourly annual weather data for building energy simulation. The method proposed to study the effects of morphing procedures is pioneering in this research area. The methodology approach started by analysing 30 year series of actual weather data and the existing weather data downscaled from global climate model projections. It identified trends that are likely to occur to define/set the parameter ranges to be analysed in the weather sensitivity tests. After that, morphing operations were individually executed for multiple weather change parameters. For each distinct morphing operation tested in the case study, a linear sensitivity analysis was performed. A ranking of the indices for the different tests enabled identifying which operations had the most significant effect on the result analysed.

Finally, the third part of the research methodology proposed (Section 3.4) was aimed to study the effects of potential climate change impacts, developing an innovative approach (research results are presented in Chapter 5). A climate scenario pathway was developed to assess the effects of climate change impacts. The novelty of the approach is that it created a broad continuous set of future climate scenario conditions (a path), which was decoupled from the direct result of GCM and RCM climate projections and can be applied to any location and current weather file available. An extensive set of synthetic weather files must aggregated to compose a climate scenario pathway. In this research, 200 synthetic weather files were generated to create a climate scenario pathway for each location analysed. For each random iteration, the value of all-weather change parameters must be randomised to execute morphing operations on the annual weather -'data-set's main variables. The range limit for the weather change parameters to guide these operations should be defined based on climate 'projections' existing estimation values. After that, a set of adaptation measures was proposed and the effectiveness of these in reducing the additional demand due to the impacts of climate change was investigated.

For this thesis, a simulation case study was prepared to apply the research approach developed (Section 3.5). The three DOE reference office building models were adapted to utilise a model structure that enabled accessible parametric iteration, as some stages of the approach required. Six distinct locations were utilised as a part of the case study: C1-Singapore, C2-Cairo, C3-Athens, C4-Beijing, C5-Lisbon and C6-London.

To address the aim of this research project, the focus of the result analysis of the building models simulated was the electricity demand. , Total electricity demand, the HVAC end-use and the space cooling requirements of the building models were analysed. Both annual and peak demand results were analysed, especially focusing on peak demand, as this research aimed to evaluate the potential implications for the power network and the implications to HVAC systems design capacities.

The approach was aimed to evaluate the climate resilience of building designs, not only assessing the impacts of a large set of potential future climate conditions/scenarios but also evaluating the sensitivity of weather variability. Similarly, comparing the performance for different building design and operational model conditions across different buildings and locations. The approach was set on a three-stage method sequence; however, the methods can be used separately. Similarly, the methodology developed and proposed can be applied to a more extensive set of cases, with different sets of simulation outputs, locations and building models.

A general overview of the research methodology developed is given in the previous paragraphs. In the following sections of this chapter, more detailed insight is given into each part of the approach. First, the developed approach for large and broad sensitivity analysis for building simulation is presented in Section 3.2. Second, the approach developed to test the sensitivity of weather parameters is described in Section 3.3. Third, in Section 0, the developed method is described to generate the climate pathway scenario and evaluate the potential effect of climate change impacts. In Section 3.5, the particular simulation case study utilised for the research in this thesis is presented. The characteristics of the building office models used are presented in Sub-section 3.5.1, and the locations chosen for the simulation case are presented in Sub-section 3.5.2. The parametric details of the sensitivity studies executed are presented in Sub-section 3.5.3, and an explanation of the integrations of tools used to execute the approach is given in Sub-section 3.5.4.

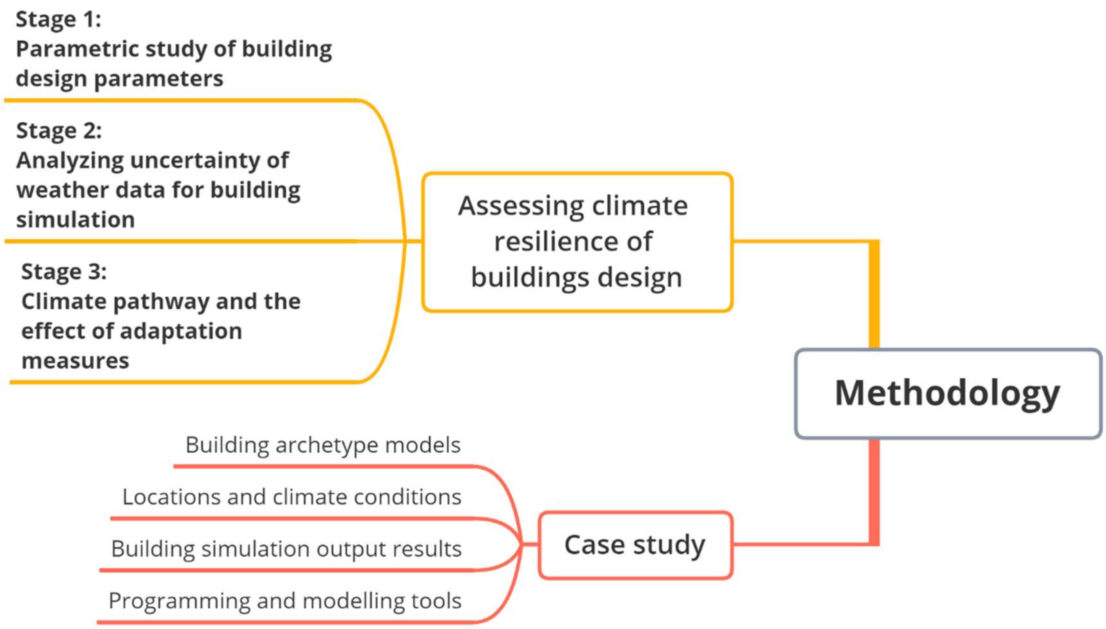

Figure 3.1 – Overview of the methodology framework developed

3.2 The systematic sensitivity analysis of building operation and building design parameters

The first part of the methodology developed aimed to evaluate the sensitivity of the energy performance of building designs modelled and so addressing research questions number 1 and 2 of this thesis. The approach was set to execute parametric studies of building energy models' design and operational input parameters to have insights on the effect for the energy performance metric or metrics of analysis. The step was subdivided into two main phases: a preliminary sensitivity study with simplified models and a sensitivity analysis study with a more detailed archetype model. The preliminary study was aimed to explore a vast number of parameters, with faster simulation runs and simplified iterations of design parameters and the results of the preliminary study were published in two conference papers: CLIMA (Zeferina, Birch, *et al.*, 2019) and CISBAT (Zeferina, Wood, *et al.*, 2019). The parametric study includes physical form geometric parameters, using a simplified one internal zone building model. The following phase, studying the sensitivity of archetype/prototype models, aimed to evaluate the variability of the performance in more detail, using a lower number of sets of parameters to iterate. It was intended to quantify the sensitivity for the energy performance metric(s) in analysis for different locations, time resolution and building types.

Tian et al. (2013) described a typical six-step sequence for implementing a sensitivity analysis in building performance simulation. The typical sequence starts by defining (1) input parameters variation, creating (2) and running (3) the model, collecting results (4), running the sensitivity analysis (5) and presenting the sensitivity result (6). In this research approach, similar steps were executed. In summary, the energy performance is assessed through dynamic simulation, parameters sensitivity is ranked, and the importance of each parameter is quantified to the contribution of the output metric analysed. The process is used to identify the building design parameters (occupancy, operational, HVAC and envelope) with the most significant contribution within the performance design constraints evaluated. A systematic comparison between different (but comparable) building types and locations is conducted to give insights on different performance characteristics and enhance design choices' distinct effectiveness for different simulation cases (conditions).

Using a dual-stage sensitivity analysis approach as proposed and presented in Figure 3.2 enables the application of a simplified sensitivity method to facilitate the execution of a broad parametric study with a smaller number of required simulation runs. After that, a reduction of the parameters in analysis can be made, and a more complex (i.e. a global method) can be used. In the following sub-sections, a more detailed explanation about the methods applied is made.

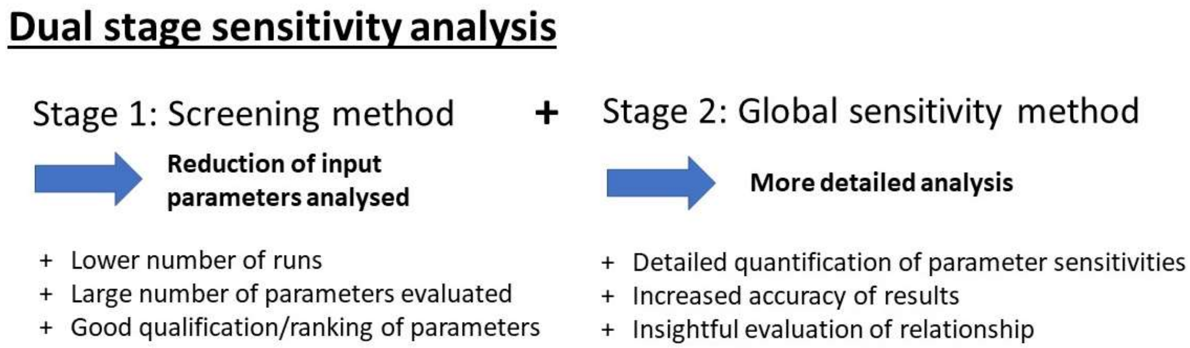

Figure 3.2 – Description of the dual–stage sensitivity analysis approach

The R sensitivity package (Iooss, *et al.*, 2020), which provides functions and routines to implement several global sensitivity methods, was utilised to prepare the sensitivity analysis executed in these studies. For the Morris method, the *morris* function implements the Morris elementary effects screening method (Morris, 1991). In addition, this implementation includes some improvements to the original method as the space-filling optimisation of the design (Campolongo, *et al.*, 2007) and simplex-based design (Pujol, 2009). For the Sobol method, the Martinez estimators (M. Baudin, K. Boumhaout, T. Delage, 2016) were used, which implements a Monte Carlo sampling-based procedure to estimate the Sobol indices.

3.2.1 Application of the Morris elementary effect (EE) method to screen input parameters

The Morris EE method is a screening method, a simple but efficient way to evaluate the contribution of the main input parameters to changes in the model outputs (Saltelli, *et al.*, 2008). This method determines two quantitative sensitivity measures, the mean (μ^*) and standard deviation (σ). The mean μ^* measures the overall influence of the input factor analysed on the model output and the standard deviation σ assesses the effect of factors due to the interaction with the other parameters (see Saltelli, *et al*. (2008) for an extended description of the method). The sampling method considers *k* independent inputs (X_i); where each parameter varies across *p* selected levels within the input range, creating equidistant spaces between input points. Thus, the method produces multiple trajectories (*r*), each with (*k+1*) samples, where two consecutive samples only differ in one input parameter value, which is changed by relative fix amount in that coordinate (X_i), Δ. The equations for evaluating the elementary effect (EE), the mean (μ^*), and standard deviation (σ) can be written as Eq. (3-1), (3-2) and (3-3), respectively.

$$EE_{i,j}(x_l\quad) = \frac{[y(x_{l+1}) - \mathrm{y}(x_l)]}{\Delta} \tag{3-1}$$

$$\mu_i{}^* = \frac{1}{r}\sum_{j=1}^{r}\left|EE_{i,j}\right| \tag{3-2}$$

$$\sigma_i^2 = \frac{1}{r-1}\sum_{j=1}^{r}\left(EE_{i,j} - \mu\right)^2 \tag{3-3}$$

Where,

$\mu_i{}^*$, is the mean sensitivity measure

σ_i , is the standard deviation, sensitivity measure

EE_i^j, is the elementary effect relative to factor *i* along trajectory *j*

r, is the total number of trajectories

j, is the current trajectory

*i, i*s the parameter analysed

Δ*,* Sampling distance interval

For each sensitivity analysis simulation case evaluated in this thesis, the Morris EE sensitivity method was utilised. The number of input parameters to be screened was distinct, as shown in Table 3.1. The input parameter range was varied across *p* number of levels, six in the CLIMA (Zeferina, Birch, *et al.*, 2019) and CISBAT (Zeferina, Wood, *et al.*, 2019) conference papers prepared as part of this thesis research on a simplified building model and eight for the more complex archetype models. The number of trajectories was defined differently for each case, 80 for the archetype studies, 35 and 50, respectively for the preliminary studies CLIMA and CISBAT. This number of trajectories is considered a large enough number of trajectories for the number of parameters and levels selected (Sarrazin, *et al.*, 2016). Each trajectory included *k+1* samples configurations, leading to a total number of 595 samples for CLIMA study, 450 samples for CISBAT study, 1,200 samples for each location considered for the large office building archetype, 1,040 for the other two archetypes (small and medium). In the simulation case with archetype office models, the method was applied considering each of the six locations, consequently leading to 7,200 simulation runs, for large offices, and 6240 simulation runs for medium and small offices. The sensitivity metrics, μ^* and σ were calculated for each one of the output metrics considered. The importance of input parameters was ranked based on the μ^*. An assessment of the influence on each output metric was done and contrasted between the different locations and building types.

Table 3.1 – Morris EE method parameters for each office building model case

Model	k	r	p	Iterations	Climate scenarios	Output
CLIMA	16	35	6	595	5	Cooling Requirements
CISBAT	8	50	6	450	1	HVAC
Small	12	80	8	1040	6	Total, SPC, HVAC
Medium	12	80	8	1040	6	Total, SPC, HVAC
Large	14	80	8	1200	6	Total, SPC, HVAC

3.2.2 Applying the Sobol methodology to assess the sensitivity of outputs to selected input parameters

The second stage of the sensitivity approach was applied in the CISBAT study model (Zeferina, Wood, *et al.*, 2019) and the large office building archetype cases, using a more complex variance-based method, the Sobol method. Sobol is considered one of the most efficient methods to quantify the variance of the output and decompose it according to the uncertainty of input factors (Saltelli, *et al.*, 2008). The method was only applied to these models, due to the associated complexity, as it requires a larger number of simulation runs. Indeed, CISBAT study (Zeferina, Wood, *et al.*, 2019) was a development of the CLIMA study (Zeferina, Birch, *et al.*, 2019) and the large office buildings was considered the type of building more relevant to further study.

The approach considered uncertainty in all eight parameters on the CISBAT model and selected six of the initial parameters in the large office building model, based on the screening of the input parameters with the largest contribution, using the Morris Effect method described in 3.2.1. The Sobol method generates two random samples with n iterations of all input parameters using simultaneous and independent random sampling techniques for each input parameter considered. After that, i additional sample matrices (C_i) were generated, based on the replacement of values in sample A by the correspondent parameter values on sample B. Thus, it made a total number of ((i +2) times n) iterations of the building model condition, as there were two base sample iterations (A and B), and i more transformed samples (C).

Figure 0.1 and Figure 0.2 show the convergence of Sobol indices, both for the outputs of peak and annual total electricity demand for all parameters, with the sample size, which indicates the stability of the results presented.

Variance effect indices are computed, measuring the first-order (S_i) and total-effect indices (S_T) of the input model parameters. S_i is the measure of the parameter's primary effect, indicating how much the output variance could be reduced if the parameter *i* could be fixed. S_T is the total-effect Sobol index, and it is the addition of the parameter's main effect and the interaction effect with other parameters. The main effect (S_i) and the total effects (S_T) can be computed as Eq.(3-4) and Eq. (3-5) from Saltelli et al. (2008).

$$S_i = \frac{V[E(Y|X_i)]}{V(Y)} \tag{3-4}$$

$$S_T = 1 - \frac{V[E(Y|X_{\sim i})]}{V(Y)} \tag{3-5}$$

where,

Y, is the generic scalar model output equal to Y = f(X)

$X_{\sim i}$, is the matrix of all factors but Xi

X_i, is the matrix of the generic factor *i*

V(Y), is the variance of the output

3.3 Methodology to assess the effects of uncertainties associated with climate data in energy performance of buildings

In this section, the methods used to evaluate the sensitivity of peak and annual electricity demand to individual weather metrics (dry and wet bulb temperature, relative humidity, HIR, direct and diffuse solar gain and wind speed) are presented.

In the second part of the research methodology of this thesis, a method to generate future weather time-series through morphing procedures was developed to be used to explore the relationship between weather and model outputs (in this building simulation case: peak electricity demand and annual electricity demand). The approach aimed to assess the effects of the potential weather uncertainty, through morphing procedures, and the implications of different patterns of weather characteristics on the energy performance of buildings, as summarised in Figure 3.3, addressing research question number 3 of this thesis.

It did this in two parts. First, it it analysed the variability in weather parameters within the existing published weather files (Sub-section 3.3.1), both historical (Lawrie, et al., 2019) and those which have been generated to represent future climate scenarios (Prometheus (Eames, *et al.*, 2011; Exeter, 2020), WeatherShift (Dickinson, *et al.*, 2016; Troup, *et al.*, 2016; Arup, *et al.*, 2020) and Meteonorm (Meteotest, 2020)). Therefore, it identified potential uncertainties in future weather data that permitted to define/set the parameter ranges to be analysed in the weather sensitivity tests step. Secondly, linear sensitivity tests of morphing operations on the total electricity demand of office buildings were assessed (Sub-section 3.3.2). Each morphing operation modified the annual timeseries of a particular weather variable in the representative weather file of the location to be analysed. This permitted evaluating: the impact of individual variations of the weather parameters, dry and wet bulb temperature, relative humidity, HIR, direct and diffuse solar radiation and wind speed on the model output (Sub-section 3.3.3). In the building simulation case utilised in this research, the outputs analysed were annual total electricity demand and peak total electricity demand.

This approach is pioneering because it enables to assess the implication of each morphing operation on the energy performance of the building models. Creating this type of synthetic weather files, enables to decouple/isolate the modification of each weather variable from the remaining variables.

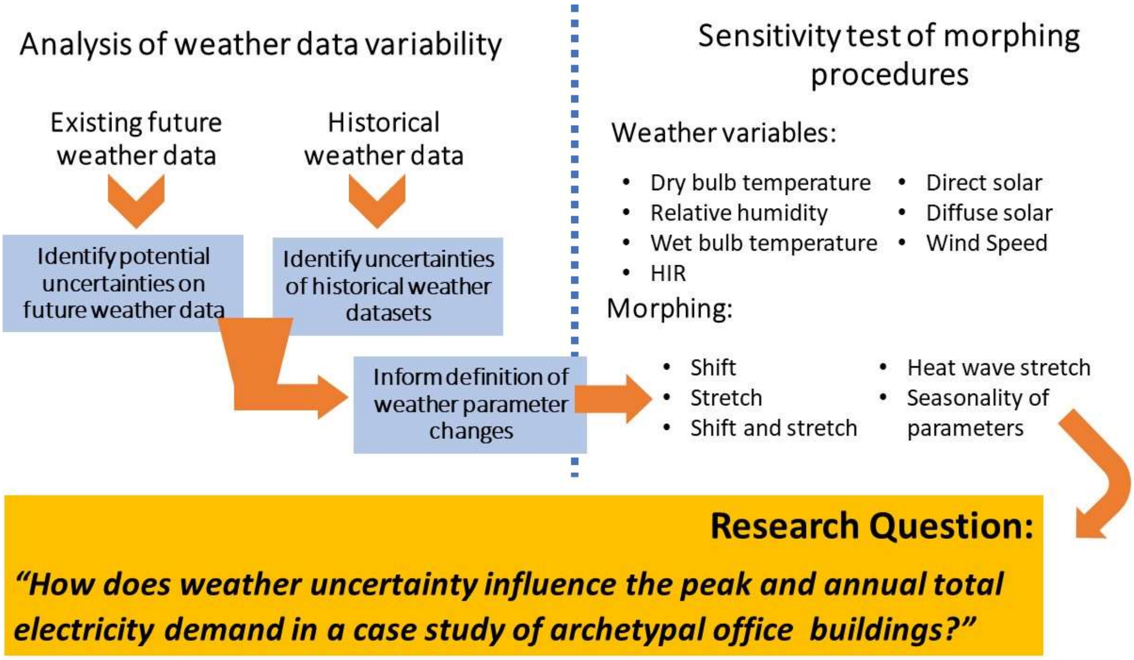

Figure 3.3 – Description of the second methodology stage

3.3.1 Analysis of the patterns in historic weather data and published projections

The analysis of the weather data examined the changes and uncertainties of several weather variables included in the annual hourly weather files used in dynamic building performance simulation . The EnergyPlus thermal engine uses 13 out of the 35 variables available in EnergyPlus Weather Format (EPW) files (see Table 0.4, it presents the list of variables in EPW files), of which three relate to temporal resolution (year, month and day). The weather variables chosen to be analysed in this research methodology are included in this list, and they have been determined to be crucial to assess space cooling demand. The analysis focussed on the effects due to changes in the dry-bulb temperature (DBT), relative humidity (RH), wind speed, and three solar radiation parameters the horizontal infrared radiation intensity (HIR), direct normal radiation (DNR) and diffuse horizontal radiation (DHR) because these are the variables used in the EnergyPlus thermal engine (EnergyPlus, 2015).

Multi-year historical sets of weather data are analysed to identify some of the possible inter-annual natural weather variability that may occur. A statistical analysis of the different weather variables was conducted, analysing the standard deviation (σ) of the annual means and maximum yearly values. Similarly, the historical data-set average deviations to the base

TMY considered (*Δ*) were presented for the different weather variables analysed. In this research, the sets of historical weather data were made available by climate.one.building.org (Lawrie, et al., 2019), which derived the data from several public data sources.

To analyse the potential changes associated with climate change projections, future weather data generated by currently available weather generators, for time-frames up to the 2080s were analysed. In this research (Section 5.2) weather patterns of EnergyPlus Weather (EPW) data files generated by WeatherShift (all case study locations (Dickinson, *et al.*, 2016; Troup, *et al.*, 2016; Arup, *et al.*, 2020)) and the Prometheus Study (for London only (Eames, *et al.*, 2011; Exeter, 2020)) were analysed. Shifts on annual average temperatures, maximum temperatures, and changes in average solar radiations were compared. The WeatherShift and Prometheus datasets used different approaches and sources of weather data; however, the Prometheus study only generated results for the UK, including London – the only location in common with the sets of locations selected for the simulation case of this research.

The results of this analysis identified potential uncertainties in future weather data, which allowed to set which morphing operations were to be tested. In addition, it permitted to define/set the ranges of the uncertainty of parameters for the morphing operations to be analysed in the weather sensitivity tests step.

3.3.2 Application of morphing methods to develop future weather files capturing the uncertainties associated with climate change.

In this sub-section, the description of the morphing operations utilised in the research methodology of this thesis is presented. The morphing methodology described by Belcher et al. (2005) is used in the research approach to producing design weather data for dynamic building simulation, combining present weather data with projections from global climate model results.

These morphing operations are utilised to modify and generate future weather data at different stages of the research methodology of this thesis. First, it is applied in the research approach to create weather files for the linear sensitivity analysis of morphing parameters (described in Sub-section 3.3.3). Respective research results are presented in Section 5.3, addressing research question 3 of this thesis. Second, morphing operations are used to generate the weather datasets samples to create climate pathway approaches, which are described in Sub-section 3.4.1. Respective research results are presented in Section 6.3, which aimed to address research question number 4 of this thesis.

The morphing procedure uses three generic operations: shift (or designated additive shift), linear stretch (also designated scaling transformation or multiplicative shift) and a combination of shift and stretch. The morphing technique uses the weather variables' monthly-mean values to morphed high resolution (hourly) present/baseline weather data-sets for the site. Equations (3-6), (3-7) and (3-8) describe the basic operation for morphing weather data-sets.

Shift operation:

$$\boldsymbol{x} = \boldsymbol{x_0} + \Delta \boldsymbol{x_m} \tag{3-6}$$

Linear stretch operation:

$$\boldsymbol{x} = \boldsymbol{\alpha_m} \cdot \boldsymbol{x_0} \tag{3-7}$$

Combination of shift and stretch operation:

$$\boldsymbol{x} = \boldsymbol{x_{0,m}} + \Delta \boldsymbol{x_m} + (\boldsymbol{1} + \boldsymbol{\alpha_m}) \cdot (\boldsymbol{x_0} - \boldsymbol{x_{0,m}}) \tag{3-8}$$

where,

$\boldsymbol{x}$	is the changed variable value;
$\boldsymbol{x_0}$	is the baseline value of the variable;
$\Delta \boldsymbol{x_m}$	is the monthly mean shift of the variable
$\boldsymbol{\alpha_m}$	is the fractional change in the monthly-mean value of the variable
$\boldsymbol{x_{0,m}}$	is the baseline mean monthly value of the variable

For this research methodology, a divergent seasonal shift of weather parameters is used, and Equation (3-10) shows the seasonal summer ratio, the relationship between the summer shift parameter (*Δx_{Summer}*) and the annual global shift parameter (*Δx_{Global}*). The approach to perform distinct seasonal shifts based on the summer ratio parameter was developed to mimic seasonal differences in weather changes. Divergent seasonal/monthly changes were used when generating dry-bulb temperature timeseries, but they were also applied to shifts on RH or stretches on solar radiation. Equation (3-9) shows the relationship between the summer change parameter ($\Delta \mathrm{x}_{\mathrm{Summer}}$) and the change parameter for the remaining of the year ($\Delta x_{Rem.}$).

Seasonal Change:

$$\Delta \mathrm{x}_{Global} = \Delta \mathrm{x}_{Summer} \cdot \frac{n_{summer}}{365} + \Delta \mathrm{x}_{Rem.} \cdot \frac{365 - n_{summer}}{365} \tag{3-9}$$

$$R_{Seas.} = \frac{\Delta \mathrm{x}_{Summer}}{\Delta \mathrm{x}_{Global}} \tag{3-10}$$

where,

$\boldsymbol{R_{Seas.}}$	**is the seasonal summer ratio of the change in variable *x;***
$\Delta \mathbf{x}_{\boldsymbol{Global}}$	is the annual value change of the variable *x;*
$\Delta \mathbf{x}_{\boldsymbol{Rem.}}$	Is the change/shift value of the variable *x* during summer period;
$\Delta \mathbf{x}_{\boldsymbol{Summer}}$	Is the change/shift of the variable *x* during the remaining period of the year;
$\boldsymbol{n_{summer}}$	number of days in summer period;

A different stretching approach was executed to alter dry-bulb temperature time-series during annual extreme hot (hottest) periods (heatwaves). This operation intends to generate an additional stretch on dry-bulb temperature series during the hottest period in the weather data, to reflect a heatwave period. Equation (3-11) presents the change made on dry-bulb temperature during the five days considered in each weather file. Daily dry-bulb amplitude for each day in this period was stretched by a factor (R -1), and corrected by a sinusoidal function that was lagged by a daily shift factor of around 8h (considering daily peak at 14 and then subtracting 6). This leads to the high and low end of the amplitude at 2 p.m. and 2 a.m., respectively, where the additional shift will be the largest (positive or negative). Thus, the daily average temperatures of the weather data series after this operation were unaltered from the initial timeseries, as the positive stretch performed during peak periods will be cancelled out by negative stretches below the average temperature periods. However, this morphing stretching operation is done after executing a shift morphing operation described by Equation (3-6), which had then previously modified the initial dry-bulb temperature time series by monthly mean shift value of $\Delta \boldsymbol{x_m}$.

The values and patterns of weather changes executed by these morphing operations described in the previous paragraphs were derived from the findings of the analysis of historical and future weather data, described in Sub-section 3.3.1 and the research results presented in Section 5.2.

Daily amplitude stretch operation during heatwaves:

$$T_{shift} = \Delta T_{Daily,Original} \times (R_{daily} - 1) \times \sin\left(\frac{t - (d - 6)}{24} \times 2\pi\right) \qquad (3\text{-}11)$$

$$R_{daily} = {}^{\Delta T_{Daily,New}}\!\big/\!{}_{\Delta T_{Daily,Original}} \qquad (3\text{-}12)$$

where,

T_{shi} , the temperature shift during the heatwave temperature sequence;

$\Delta T_{Daily,Original}$, is the daily temperature amplitude on the original daily temperature sequence;

$\Delta T_{Daily,Original}$, is the daily temperature amplitude on the updated temperature sequence;

R_{daily}, is the ratio of the daily temperature amplitudes;

t, is the hour of the day;

d, is the hourly daily shift of the peak to the standard sinusoidal wave (at 8h).

Some restrictions on the morphing operations were considered when changing the weather variables. For example, relative humidity (RH) was restricted to stay within 20% to 100%, so the final value of the variable after the operation cannot be extrapolated beyond this range. This restriction avoids the relative humidity to takes values over 100%, that is the state in which the air is super saturated with water vapor. Below 20%, relative humidity is extremely low, and humidification is recommended, which brings into consideration more factors to the building simulation assumptions. In addition, the wet-bulb temperature is re-calculated based on Equation (3-13), after changes in dry-bulb temperature or relative humidity. A threshold on the maximum values of these weather variables was identified in the future weather data from Prometheus projections, but no restrictions on stretching of solar irradiance were made in these tests.

$$T_{dew} = T_{DBT} - \left(\frac{100 - RH}{5}\right) \tag{3-13}$$

where,

T_{dew}	Dew point temperature in °C
T_{DBT}	Dry-bulb temperature in °C
RH	Relative humidity in per cent [%]

3.3.3 Sensitivity analysis tests of morphing procedures

In this sub-section, a description of the linear sensitivity analysis (LSA) for the electricity demand of office buildings, using the building simulation case of this thesis is presented. Table 3.2 lists the different LSA tests performed. For each test, the influence of different parameters associated with a morphing operation executed in the weather variables time-series is analysed in order to evaluate the effects on the electricity demand of office buildings. The results are compared to the same outputs from simulations using the baseline representative weather file for each location. The baseline weather file is the current representative typical weather dataset for the location, which are made available in EnergyPlus weather databases (U.S. Department of Energy, 2021). In Sub-section 3.5.2, a detailed description of the baseline weather conditions for the locations chosen in the simulation case of this research is made.

The shift operation of the 'morphing' procedure was used to transform dry-bulb temperature data series in tests 1 and 2, and to transform relative humidity in tests 5 and 6. For test 1 and test 5, a constant annual increase by (Δx_{Global}) was performed using a shift operation from the morphing procedure, for each hourly value in the annual weather variable time-series, following Equation (3-6), respectively for dry-bulb temperature and relative humidity. Thus, for test 1 a shift operation was executed on dry-bulb temperature, considering a constant increase on a range between 0°C (present – no change) and 5°C (maximum), and for test 5 the shift operation on relative humidity variable was executed between a -10% (drier) 0% (current values – no change). Test 2 and test 6, considered two different shift change values, one for summer months (Δx_{Summer}) and the other for the remaining months ($\Delta x_{Rem.}$). In both tests, the seasonal summer ratio is tested, varying between 1 (constant) to 1.75 (maximum). The response to changes in the seasonal summer ratio of dry-bulb temperature was studied in test 2, assuming an annual average temperature shift of 2.5°C. On test 6, the sensitivity driven by seasonal summer changes ($R_{Seas.}$) on relative humidity was studied, assuming an annual global shift ($\Delta\mathrm{RH}_{Global}$) of -5%.

Table 3.2 – Linear sensitivity analysis tests performed, the test description and weather variables operated

Test number	Weather Variable	Description of the test
1	DBT	Annual DBT shift, using an annual average shift
2	DBT	Fix average annual average DBT shift, with different seasonal shifts levels
3	DBT	Fix average annual average DBT shift, with a localised stretch during the hottest annual period
4	WS	Stretch of wind speed value series
5	RH	Test of different levels of annual shift of RH variable
6	RH	Constant annual shift of RH, with different seasonal shifts levels
7	HIR	Test of different levels of horizontal infrared radiation series stretch.
8	DNR	Test of different levels of DNR series stretch.
9	DHR	Test of different levels of DHR series stretch.

The linear stretch operation, defined by Equation (3-7) were executed in the remaining weather variables, producing a growth by a factor $\boldsymbol{\alpha_m}$ in each hourly value of the variable in the annual series. The weather variables that were modified using this approach were the wind speed (WS) – test 3, horizontal infrared radiation (HIR) – test 7, direct normal radiation (DNR) -test 8 and diffuse horizontal radiation (DHR) – test 9. For these variables, the stretching parameter was unique for the whole year, not considering any variation across different months. For test 4, the wind speed variable was stretched considering factors between 0.5 and 3, meaning that values were halved or got tripled, respectively. On test 7, 8 and 9, the sensitivity was driven by HIR, DNR and DHR, which tested the effect of multiplying different constant factors for stretch, which were between 1 (no change) to 1.25, leading to an additional 25% of the parameter value in all points in the data series.

Table 3.3 summarises each of the LSA tests performed, informing the weather variable transformed, and the operation (stretch or/and shift) undertaken and the range of values iterated in each case. The range of values considered intends to explore the influence of these parameters in the electricity demand of these buildings, based on a plausible range of alteration of the parameters. The values were identified in historical data-sets and in existing future weather data-set projections, where some limits of these ranges have been present in changes for RCP 8.5 weather data.

Table 3.3 – Details on the operations executed on weather variables in each test

	Test number								
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Variable	DBT	DBT	DBT	WS	RH	RH	HIR	DNR	DHR
Shift	0-5°C	3°C	3°C	-	-10%-0%	-5	-	-	-
Seasonal R	-	1-1.75	-	-	-	1-2	-	-	-
Stretch	-	-	1 - 1.25	0.5 - 3	-	-	1-1.25	1-1.25	1-1.25

The results of each test indicated the effect of the respective iterated weather parameter on the electricity demand of the building analysed. Therefore, it was possible to rank the contribution of each morphing operation to changes in the electricity demand, and to compare the levels of change of the same morphing operation among different locations and building types. Thus, the findings of this research stage allowed to identify which morphing operations are more relevant to be utilised in the sampling of weather data to generate the climate pathway weather data sample, utilised in the next stage of the research approach (presented in Sub-section 3.4.1).

3.4 Climate pathway and the effects of adaptation measures

The third stage of the methodology generated a climate pathway approach to evaluate a wide range of potential climate change impacts. The analysis using the climate pathway approach was applied into two distinct steps as described in Figure 3.4. The first evaluated the effects of climate change impacts on the building energy performance. After that, the second step evaluated the potential mitigation effects of adaptation measures on the energy performance of buildings studied under the climate pathway scenario. The generation of future weather files for the make-up of a climate pathway sample is presented in Sub-section 3.4.1, and also describing how the effects on the energy performance were quantified. The climate pathway sample was composed of a large number of weather data-sets (in the simulation case used, 200 iterations per location were considered), independently generated from changes of baseline weather data-set. Section 1.1.1 presents the different design adaptation measures, and Sub-section 1.1.1 presents the methods to quantify their impacts on the energy performance of the case studies.

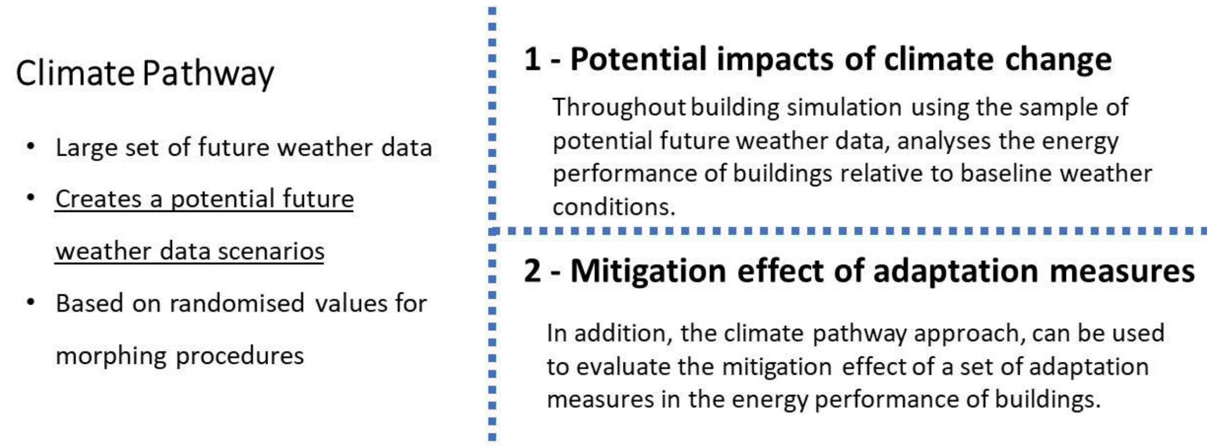

Figure 3.4 – Overview of the climate pathway strategy

3.4.1 Climate pathway sampling

The generation of synthetic future weather files was made to analyse a broad spectrum of plausible weather conditions that may represent future weather conditions. In the generation of these annual hourly weather files, the baseline weather data-set (hourly time series) were transformed, while a set of weather variables were modified. For the climate pathway created for the research analysis in this thesis, five parameters were considered to produce the synthetic changes for each weather file in the climate pathway. These parameters were annual dry-bulb temperature shift, the seasonal ratio of dry-bulb temperature shift, the stretch parameter on dry-bulb temperature for a heatwave period, relative humidity (RH) shift and the stretch parameter for solar irradiation parameters. The solar variables transformed in the weather data-sets were the horizontal infrared radiation (HIR), direct normal and diffuse horizontal irradiance.

The climate pathway utilised to analyse potential climate change impacts aimed to include a large set of independently generated weather data-sets. The climate pathway generated for this research included 200 files generated using this approach and the baseline data-set. Each weather parameter considered on the climate pathway generation was independently attributed from a uniform random number on the respective defined range. Table 3.4 presents the range and weather parameters utilised to generate the pathway in this thesis. The ranges selected for the operations to modify the baseline weather data-sets were based on the analysis of existing future weather data-sets generated based on existing climate projections (research findings in Section 5.2). For example, changes in annual mean temperatures were set to be between 0°C and 5°C. However, changes in average dry-bulb temperature for the summer season were between 1 to 1.75 times the value for the winter season, and the stretch of DBT daily amplitude in the heatwave period was between 1 to 1.75. Changes in annual mean relative humidity were from -5% to 0%, and the stretch on solar irradiance variables was between 1 to 1.25.

Output results of these simulation samples were normalised to the respective location baseline result, which were related to the respective building energy model simulation coupled to the baseline weather data-set.

Table 3.4 – Parameters used to generate synthetic weather files and the possible range of the parameter value

Operation Parameter	Range
DBT shift [°C]	0-5
DBT seasonal ratio	1-1.75
DBT stretch on heat wave	1-1.75
RH shift [%]	-5 to -0
Solar Radiation stretch	1-1.25

3.4.1.1 Comparison with other weather data-sets

For comparison, the simulations were also executed with weather files that are morphed with climate projections using available weather generator tools (WeatherShift (Dickinson, *et al.*, 2016), Meteonorm (Meteotest, 2020) and CCWorldWeatherGen (Jentsch, *et al.*, 2013)). A second series of future weather files, which was obtained from weather generators tools.. This step intended to identify how the simulation outcomes from the existing weather data-sets used for climate impact studies compared to simulation runs with the climate pathway data-sets developed here. The simulation results (Pathway + comparison weather data-sets) were presented in ascending order, and the quantile which the simulation results for weather generators data-sets fall in were indicated within the results for the pathway sample.

3.4.2 The impact of-adaptation measures on mitigating additional electricity demand due to the climate change, using climate pathway approach

The second step of this stage of the methodology intended to evaluate the mitigation effect of a set of adaptation measures, on reducing the additional demand due to potential climate change impacts. The simulation case of this thesis was utilised for this, and the simulation results using the climate pathway generated were used to estimate the potential additional demand. In this research, a total of nine adaptation measures were evaluated as presented in Table 3.5. Measures 1 to 6 considered the change of one individual design parameter. The design parameters varied by these adaptation measures were identified as some of the most used in prior studies as discussed in the literature review (Sub-section 2.2.4). Measures 7 to 9 considered the combined effect of several measures.

Adaptation measure 1 considered the change of cooling ambient set-point temperature from 24°C to 27°C. Measure 2 considered a reduction of outdoor ventilation rate of 36 % from 0.673 $lt/s.m^{-2}$ to 0.4312 $lt/s.m^{-2}$. Adaptation measures 3 and 4 analysed reducing equipment and lighting load density, respectively, from 10.76 to 7.5 $W.m^{-2}$, a 30% reduction. Measure 5 investigated improvements on the coefficient of performance of the HVAC/chillers systems of buildings, with an improvement of 20%, increasing from 5.5 to 6.5 for large office buildings, from 3.23372 to 3.9 in medium office buildings and from 3.66684 to 4.4 for small office building model cases. Measure 6 studied the change of solar heat gain coefficients of windows in these buildings to a level of 0.15. The combined measure number 7 considered the combined effect of adaptation measures 3,4 and 5, and the combined measure 8 evaluated the combined effect of measures 1,2, 5 and 6. Measure 9 investigated the combined effect of all the individual adaptation measures (1-6). The choice of the change in the values of the measures investigated was based on the expected progress of energy efficiency measures in the related technologies, using assumptions levels that have been used in previous studies (e.g. (Korolija, *et al.*, 2013))and the most recent values used in ASHRAE prototype building models (Goel, *et al.*, 2014).

Simulations were executed with all-weather data-sets from the scenario pathway sample for each iteration of the building model representing the adaptation measure. Thus, 3 618 runs for each of the adaptation measures were simulated (201 weather files in the pathway × 6 locations × 3 building type) and for all adaptation measures yielded a total of 32,562 EnergyPlus simulation runs. Simulation output results under the climate pathway sample for each adaptation measure were compared to the original office model sample (no adaptation). Overall reduction metrics were compared as discussed in the following section.

Table 3.5 – Adaptation measures

Adaptation Option		**Description**
1	Cooling set-point	Cooling set-point from 24°C to 27°C
2	Ventilation	36% reduction of ventilation rate: 0.673 $lt/s.m^{-2}$ to 0.4312 $lt/s.m^{-2}$
3	Equipment	From 10.76 to 7.5 $W.m^{-2}$ (30 % reduction)
4	Lighting	From 10.76 to 7.5 $W.m^{-2}$ (30 % reduction)
5	COP	20% improvement

		Small from 3.66684 to 4.4 Medium from 3.23372 to 3.9 Large from 5.5 to 6.5
6	Solar HGC	Small from 0.39 to 0.15 Medium from 0.3 to 0.15 Large from 0.25 to 0.15
7	3+4+5	
8	1+2+5+6	
9	All Individual measures	

3.4.3 Ranking and comparison of adaptation simulation results

A normalisation operation was executed within the simulation results for the set of simulation results for each adaptation measure analysed in this research. This was achieved by making a ratio between the output result of each iteration in the pathway sample and the original base condition (baseline) for that location and specific type of office building. Equation (3-14) presents this relationship:

$$Normalised\ Output_{Loc,Model,Var,n} = \left(\frac{Sample\ Output_{Loc,Model,Var,n}}{Baseline\ Output_{Loc,Model,Var}} - 1\right) \times 100 \quad (3\text{-}14)$$

Where:

$Sample\ Output_{Loc,Model}$	, is the simulation output, for the output variable *Var*, in location *Loc*, for the office type *Model*, in the *n* iteration of the climate pathway;
$Base\ Output_{Loc,Model}$	, is the simulation output for the variable *Var*, in location *Loc*, for the office type *Model,* for the baseline weather file;
$Normalised\ Output_{Loc,Model,Var,\mathrm{n}}$	, is the normalised simulation output for the variable *Var*, in location *Loc*, for the office type *Model,* to the baseline weather conditions.

Therefore, the simulation results of a simulation case in the research (one location and type of office building) were presented in ascending order, from 0 to the number of files generated, where position 0 is the baseline case condition. The normalised output value represented the rate of change relative to the original base condition. Therefore, a value 0 meant no relative change to the original condition (baseline value). The last position of the ordered sample was the most extreme value, so the most considerable effect change relative to the current base values. For output values considering adaptation measures, values can be below zero, meaning that demand output is reduced under the baseline condition value.

In order to analyse the effectiveness of design adaptation measures, the reduction of the demand across all sample conditions was quantified, considering the average change from the base case (building case with no adapting measures). Equation (3-15) shows the calculation of this value:

$$RD(Out., Loc., Buil.)_{Measure\ n} = \frac{\overline{Output}_{Measure,n} - \overline{Output}_{No\ Adaptation}}{\overline{Output}_{No\ Adaptation}} \quad (3\text{-}15)$$

Where:

$RD(Out., Loc., Buil.)_{Measure\ n}$	, is the reduction rate for measure n, for a specific output, location and building type;
$\overline{Output}_{Measure,n}$	, is the average value of a simulation output across the sample with adaptation measure *n*, for a location and building type;
$\overline{Output}_{No\ Adaptation}$	, is the average value of a simulation output across the sample with no adaptation measure, for a location and building type.

3.5 Description of the simulation case (building models and locations) used for the research analysis

In this section a description of the building model simulation case utilised for the research analysis of the thesis is presented. Three office buildings, based on the DOE reference building model set were selected and utilised to apply the methodology developed. Details on the description of these building models are given in Sub-section 3.5.1. Similarly, six different locations were selected for the analysis in this research, representing a broad set of base climate conditions. In Sub-section 3.5.2, further details are given about the weather conditions of these locations. A description of the building models and the input model parameters studied in the sensitivity analysis stage of the research methodology are described in further detail in Sub section 3.5.3. Finally, in Sub-section 3.5.4, a description of the software tools to prepare the building simulation case for this research are presented.

3.5.1 Archetype office buildings

In the simulation case for the research analysis, the three office buildings models from the DOE reference buildings model data-set were used, small (Figure 3.5), medium (Figure 3.6) and large (Figure 3.7). These office building models were developed based on DOE commercial reference building models of the US national building stock. The DOE commercial reference buildings are a set of reference buildings developed by the US DOE representing the whole national building stock. Deru et al. (2011) reported the development and reference characteristics of these models in detail, including model definition and sources for the parameter values. The DOE reference model data-set considers 16 different locations, exploring and representing all eight climate zones and most of the moisture regimes defined by ASHRAE (ASHRAE, American Society of Heating, 2020). Therefore, envelope and HVAC system model assumptions for each climate condition are adapted to the different requirements that climates present to building design.

The DOE reference building models provide an initial point to measure energy efficiency research progress and enable consistent and robust comparison of results. The models are a reasonably realistic representation of building characteristics and construction practices. However, these buildings are not representative of the 'buildings' characteristics and their energy use in any particular building type. They are hypothetical models, with ideal/fixed operation assumptions and following minimum requirements defined in ASHRAE building design standards (ASHRAE, American Society of Heating, 2013). For each type of buildings, the same form, area and operation assumptions are considered for all the submodels. Three types of sub-models are created for each type of building, namely new construction, post-1980 construction, and pre-1980 construction. These differences reflect a different level of values for the 'buildings' characteristics: equipment, HVAC, lighting and insulation.

In the simulation case utilised for this research work, six different locations were considered; however, the base office model assumptions were defined equally for all locations for the same office type. For example, using the same base model assumptions for different locations in different countries may neglect the different design specificities of internal spaces, envelopes, and HVAC systems for different countries and regions. On the other hand, for an accurate study of the propagation of uncertainties in a model, standard base conditions must exist to analyse the impacts of the 'parameter's changes. One can also argue that the uncertainty range study leads to design conditions that will differ significantly from all locations' initial design conditions. In this research, the building model base case was adapted considering the most recent construct vintage (new 2004) and from the climate zone 3A-Miami.

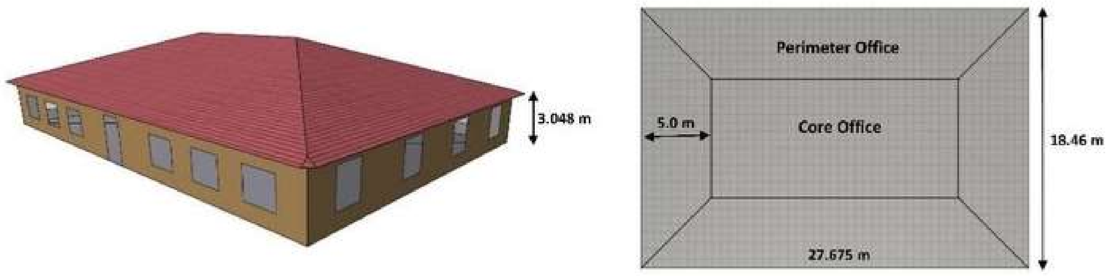

Figure 3.5 – Small office reference building model

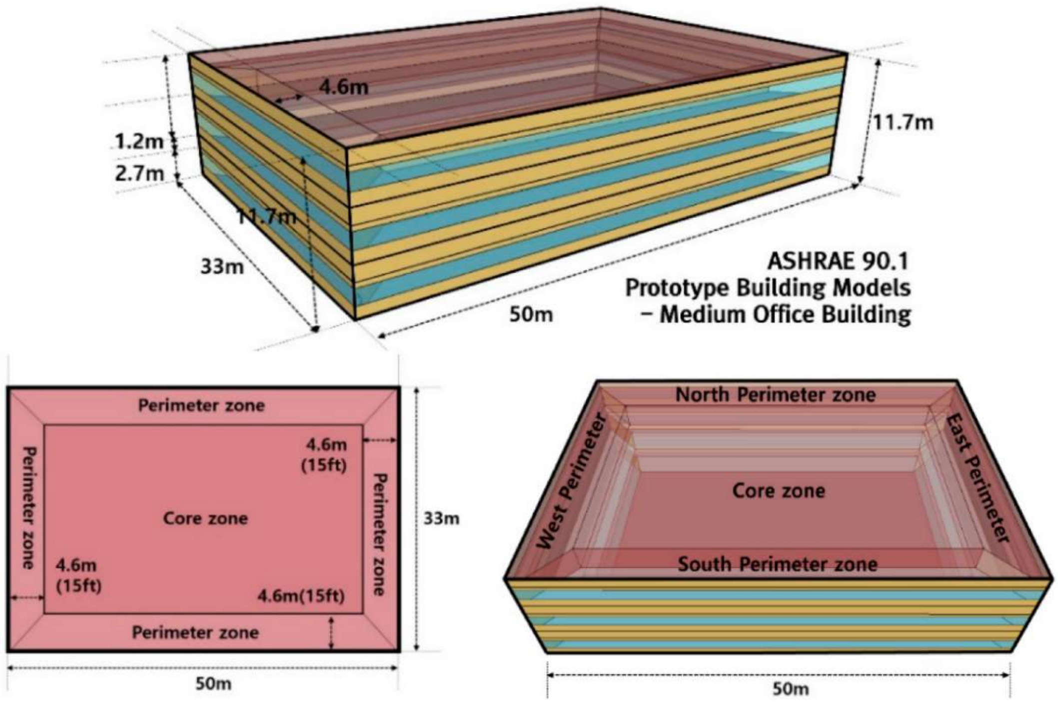

Figure 3.6 – Medium officereference building model

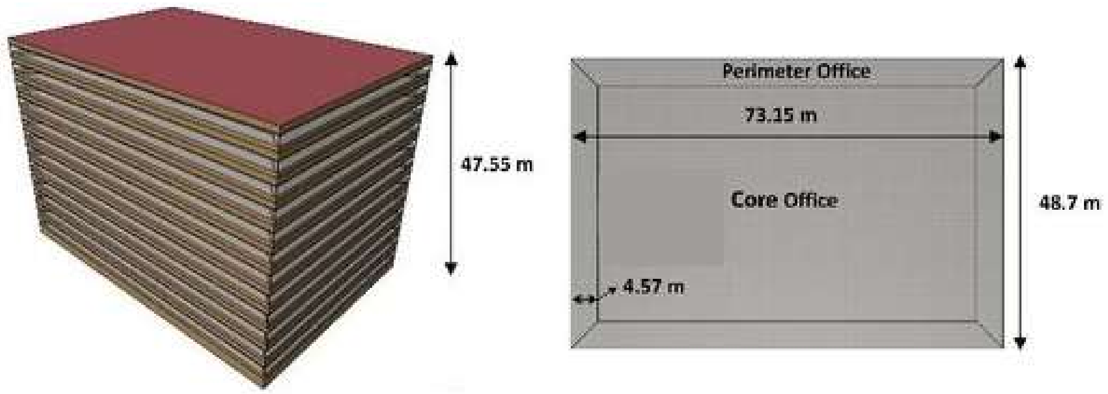

Figure 3.7 – Large office reference building model

Table 3.6 shows an overview of the building model form details for the three office types. The total floor space area of the building models was 511 m^2 (1 story), 4,982 m^2 (3 storeys) and 46,320 m^2 (12 + Basement), respectively for small (Figure 3.5), medium (Figure 3.6) and large (Figure 3.7) office building types. Each storey equally distributes the total floor space area, and the space in each office floor was divided into four perimeter zones and a central core zone. The ratio between external building surfaces (external wall area plus roof area) and floor space area was 33% for the large office, 70% for the medium and 155% for the small office. The HVAC system for the large office building type included two water-cooled chillers, used as the cooling source, and multizone variable air volume equipment, used for space air distribution. The small and medium buildings considered direct expansion systems: the small office with a single-speed and the medium office with a double speed system.

Table 3.6 – Office building model form details

	Unit	Small	Medium	Large
Total area	m^2	511	4982	46320
Floors		1	3	12
Total height	m	3.05	11.7	51
Width	m	18.5	33.3	48.7
Length	m	27.7	49.9	73.1
Aspect ratio		1.5	1.5	1.5
Perimeter zones	% of total	155%	70%	33%
Thermal zones		5 per floor	5 per floor	5 per floor

For modelling of buildings, design and construction characteristics are often taken from benchmark data. Benchmark data is defined as the representative information of building stock characteristics. Benchmark data is often collected from surveys or expert insights. Design standards and building energy codes, which set thresholds on building design parameters, may also be another source for benchmark information. For example, ASHRAE prototype building models (Goel, *et al.*, 2014) use ASHRAE standard values (ASHRAE, American Society of Heating, 2013)and DOE building energy code program to define building model archetypes. The ASHRAE prototype archetypes present multiple model editions, as for each new set of standard models values are updated. The chartered institution of building services engineers (CIBSE) and the ASHRAE have collected and made several data-sets that statistically describe the type of internal loads and schedules of building operations. These data-sets yield detailed information for office buildings (CIBSE, 2012; American Society of Heating, Refrigerating and Air-Conditioning Engineers, 2013).

The CIBSE published several technical documents in the UK, such as design guidelines, good practices booklets, technical memorandums, or application manuals. These documents are the source for multiple reference values and the data relative to the building stock information in the UK. The design details for the office models in the research have been significantly shaped by the values presented in CIBSE documents (CIBSE, 2007; Butcher, *et al.*, 2015).

3.5.2 Locations / Baseline climate conditions

The simulation case utilised for this research work considered six different locations to evaluate the effects of different climate conditions. These locations were C1-Singapore, C2-Cairo, C3-Athens, C4-Beijing, C5-Lisbon and C6-London. The weather files used to represent these climates were typical meteorological years (TMY) and were accessed from the EnergyPlus weather database(U.S. Department of Energy, 2021).

Table 3.7 – Summary of weather files (TMT) used

	C1 – Sin	C2 – Cai	C3 – Ath	C4 – Bei	C5 – Lis	C6 - Lon
ASHRAE Classification	Zone 1	Zone 2	Zone 3	Zone 4	Zone 4	Zone 4
Average DBT	27.5	21.7	17.9	12.6	16.3	10.2
Max. DBT	33.8	43	37.2	37.2	36	31.3
Min DBT	21	7	2	-14.2	4.1	-5.9

CDD 10	6374	4276	2966	2274	2328	864
CDD 18	3454	1746	1076	837	474	32
HDD 10	0	0	82	1308	20	778
HDD 18	0	390	1112	2790	1087	2866
Hot days	259	152	58	64	34	1
Tropical nights	365	123	89	61	6	0
DBT Monthly Shift [C]	2.1	14.2	18.0	30.3	11.9	13.4
Annual IHR [KWh.m^{-2}.day^{-1}]	9.80	8.61	8.21	7.75	8.04	7.60
Annual GHR [KWh.m^{-2}.day^{-1}]	4.58	5.26	4.57	3.84	4.52	2.77
Annual avg. RH[%]	83.6	58.9	61.5	55.4	74.1	79.3

The meteorological conditions in these locations are significantly different, as they aimed to represent different climates. C1-Singapore weather is defined by a typical tropical humid climate, leading to almost constant space cooling requirements. C2-Cairo is a hot desert climate. C3-Athens and C5-Lisbon present Mediterranean climates, but present different ASHRAE climate region classifications. With a dry winter and a hot and humid summer, C4-Beijing is a continental climate and presents a large temperature amplitude between seasons. On the other hand, C6-London has a humid maritime climate, which drives much lower cooling requirements. These differences are expressed in the summary of the weather data presented in Table 3.7. Figure 3.8 provides the summary statistics for several of the main weather variables: a) and d) dry-bulb temperature (DBT), b) global horizontal radiation (GHR) and c) relative humidity (RH). As shown in the figure, the number of cooling degree days (CDD) between all these locations varies between 32 in C6-London and 3454 in C1-Singapore. The maximum annual dry-bulb temperature is the highest for C2-Cairo, with 43°C, and the lowest for C6-London with a value of 31.8°C.

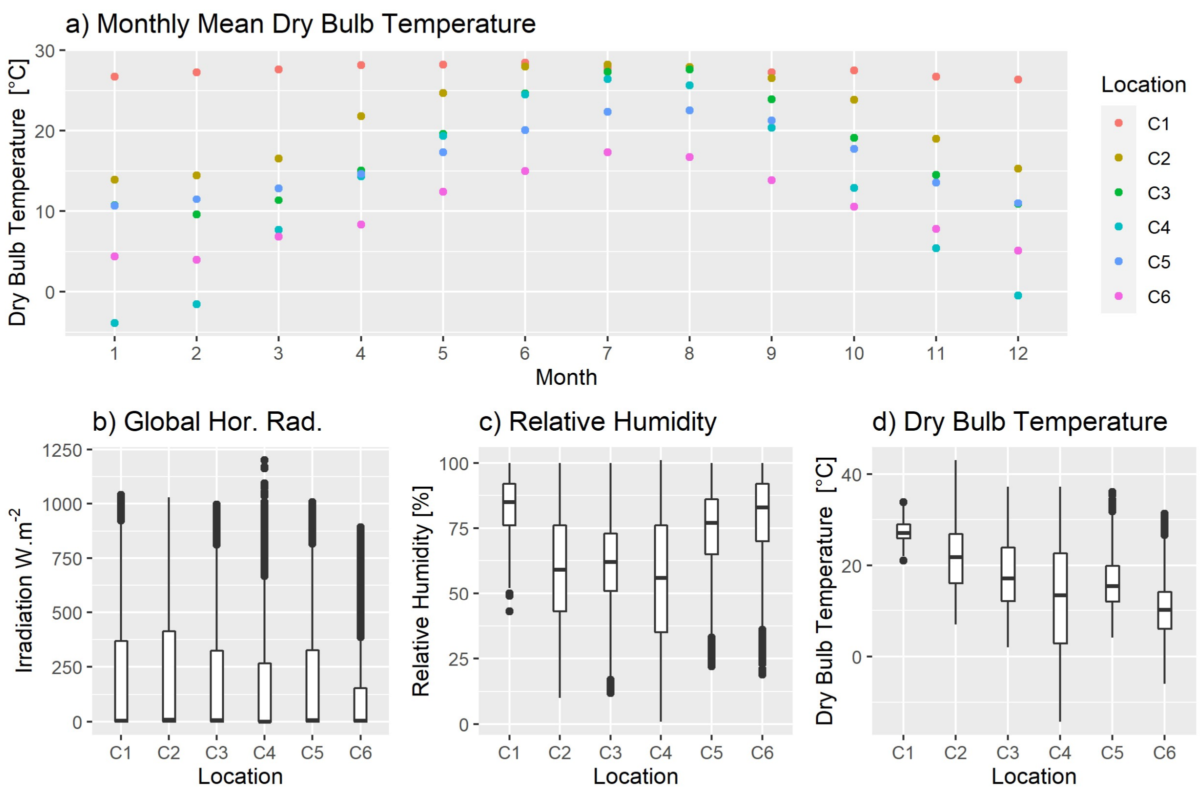

Figure 3.8 – Climate variables annual distribution: a) Monthly mean DBT, and boxplot of annual values b)GHR, c) RH and d)DBT

For the research analysis in this thesis (results presented in 5.2.3 and methodology described in 3.3.1), a set of actual meteorological year (AMY) data for the different locations were analysed, from data made available by climate.one.building.org (Lawrie, et al., 2019) deriving the data from a number of public data sources. The AMY reports data from 1975-2018 (for C1-Singapore, due to lack of data for 1975 to 1981, the analysis presented was between 1982-2018). Table 3.8 presents a summary of the information of the sources of both AMY and TMY data for the locations analysed.

Table 3.8 – Details about weather stations related to weather files analysed (TMY and AMY)

Location	TMY description	Weather station number	Lat. ; Long.	AMY source
C1 – Sin	IWEC Data	486980	1.35,103.99	Singapore Changi Airport
C2 – Cai	IWEC Data	623660	30.13,31.40	International Airport of Cairo
C3 – Ath	IWEC Data	167160	37.88,23.735	Hellinikon International airport
C4 – Bei	CSWD Data	545110	40.38,116.86 (AMY different)	Beijing Capital International Airport
C5 – Lis	INETI Data	085360	38.77,-9.13 (AMY different)	Portela Airport - Lisbon
C6 - Lon	IWEC Data	037760	51.15,-0.18	Gatwick Airport

3.5.3 Sensitivity analysis implemented with simulation cases in the thesis

In this subsection, a description of the parameters used in the building simulation cases utilised in the research analysis for the first stage of the methodology (sensitivity analysis) is presented. First, in Sub-section 3.5.3.1, a more detailed description of the simplified models and the parameters analysed in the preliminary sensitivity studies is given. Then, in Sub-section 3.5.3.2, a description of the parameters and range of values used for the sensitivity analysis in archetype models is provided. Figure 3.9 provides an overview of the parameters and building models utilised in the simulation cases for the research analysis at the sensitivity analysis stage of the research methodology.

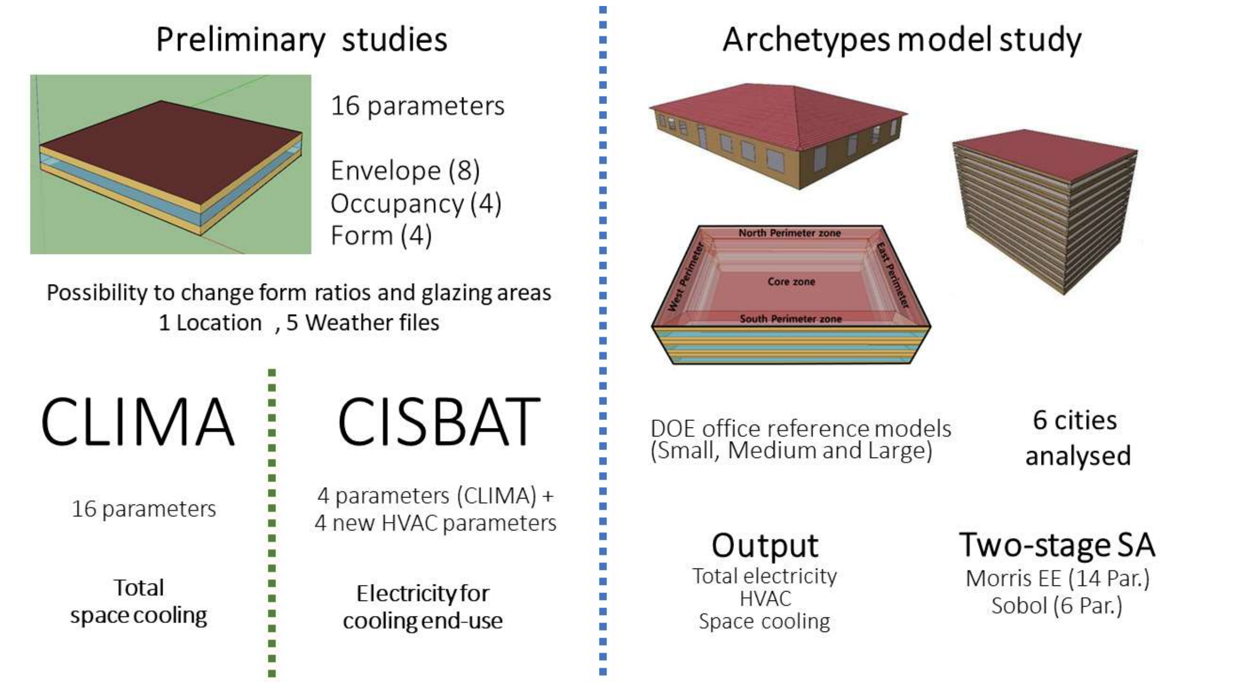

Figure 3.9 – Scheme of the methodology approach used in the different studies in the chapter

3.5.3.1 Preliminary sensitivity analysis simulation case

Two batteries of sensitivity analysis tests were performed, using a simple generic office building model, as shown in Figure 3.10. For the first batch of tests (CLIMA study (Vasco

Zeferina, Birch, Edwards, et al., 2019)), the Morris EE screening method was executed to identify the space cooling demand's sensitivity. The findings of this part of the work were presented at the CLIMA 2019 conference, and published in the conference proceedings referred to as the CLIMA study in this thesis. For the second batch of tests, both Morris EE and Sobol sensitivity analysis were performed to study electricity demand sensitivity for cooling requirements. This second study's findings were presented at the CISBAT 2019 conference (V. Zeferina, Wood, et al., 2019) and published on its proceedings and are referred to as CISBAT study. Both studies' simulations were executed using the whole annual hourly data in the test reference year (TRY) weather file for the current climate in Manchester - the UK, produced by the PROMETHEUS project (Eames, *et al.*, 2011).

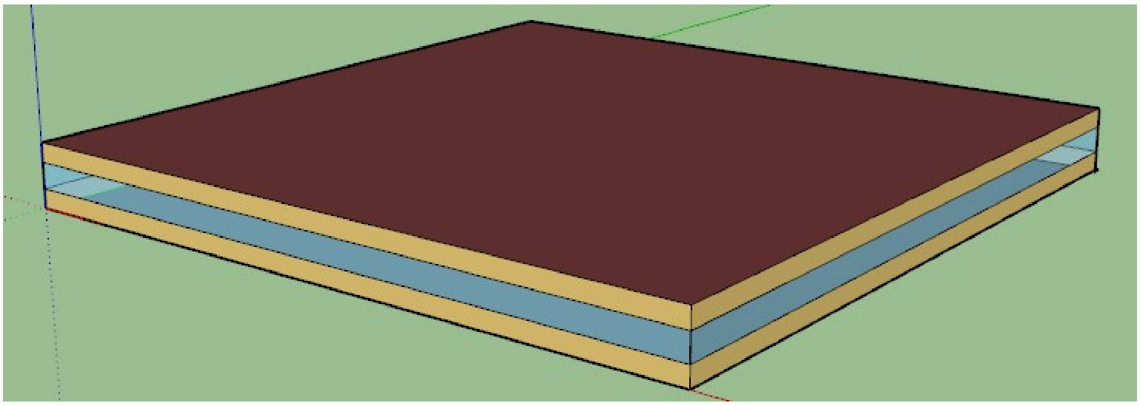

Figure 3.10 – Simplified office model used in the preliminary studies (CISBAT and CLIMA)

A generic simplified office building energy model was used for the analysis, as shown in Figure 3.10. An one-floor building model was developed in EnergyPlus, consisting of a single space zone, with a gross internal floor area of 1600 m^2, 40 m width, 40 m length, 3.5 m height, with a glazing area of 40% on its external wall. The building model's envelope characteristics were selected based on the benchmark values of ASHRAE 189.1 (ASHRAE, 2009), available in OpenStudio libraries (US DOE, 2019). A summary of the thermal properties of these construction materials is given in Table 3.9. The algorithm chosen for internal calculations of the EnergyPlus engine was the standard option. Therefore, the heat balance in the geometries used the conduction transfer function model, the zone air heat balance used the third-order backward difference model and TARP. DOE-2 was used to calculate inside and outside surface convection coefficients, respectively.

Table 3.9 – General Conditions of the Simplified generic building

Building Component	Program's Construction Object	U-Values [$W.m^{-2}.K^{-1}$]
Floor	ExtSlabCarpet 4 in Cli. Zone 1-8	0.19
External Wall	ASHRAE 189.1-2009 External Wall	0.45
Windows	ASHRAE 189.1-2009ExtWindow Cli. Zone 4-5	2.5
External Roof	ASHRAE 189.1-2009 ExtRoof IEAD Cli. Zone 2-5	0.22

For the building model in CLIMA study, the Ideal HVAC system object was used, representing a building operation where cooling or heating loads were supplied to meet the zone control specifications. Space cooling demand was reported as the output results, and different post-process was conducted to obtain analysis at different time resolutions (annual and peak demand). This output referred to the HVAC system's total cooling load, including sensible and latent cooling loads. The building model for CISBAT study used a Fan coil HVAC system to replace the idealised HVAC system in the CLIMA model. In this case, the simulation output results covered were the electricity demand for HVAC systems (cooling + fan). The simulations were then executed at six timesteps per hour for both cases, and results were reported hourly during a whole simulation year.

The operation settings of the building model for both studies were defined as being uninterrupted, so all the occupancy assumptions were fixed at a single constant value for the whole simulation period. For the analysis, the operational parameters assumptions were based on generic benchmark information for office buildings given by CIBSE (Butcher, *et al.*, 2015) and BRE (Energy, 2003). For example, total IHG was set at 40 $W.m^{-2}$, and the ventilation rate plus the building's infiltration rate was defined to be 1.6 air changes per hour. The cooling set-point of the zones in the model was set at 24°C. Table 3.10 shows the base values of the different input parameters iterated in the preliminary studies.

Korolija et al. (2013) defined similar baseline input parameters as used in this base model, for the UK office buildings archetypal models proposed IHG, infiltration and ventilation rates and cooling set-pointset-points. The latest review of UK regulation for office buildings (HM Government, 2010) defined maximum values for envelope elements U-values [$W.m^{-2}.K^{-1}$] as 0.35 for external walls and 2.2 for glazing and 0.25 for roof and ground floor. The base model in these studies presented higher U-values than these legislation limits for glazing and external wall envelopes. However, the range of parameters covered in the SA also included samples that will simulate cases with much lower values than the legislation limits. The range of values covered in these sensitivity studies covered either buildings that pre-dated or not matched the standards as builds, and buildings that specifications overcome standards. For the CISBAT study, only four input parameters from the building model in CLIMA study were considered, and four additional parameters were included related to the operation of the HVAC system (Table 3.10, column CISBAT). The value of the parameters not transposed from the model in CLIMA to the CISBAT study were kept at baseline levels of the original CLIMA study model.

The range considered in the analysis of the model input parameters conducted for both CLIMA and CISBAT studies is shown in Table 3.10. The analysis presented has tested the input variation with this range of parameters; accordingly, the distribution of conditions used, and it did not intend to represent the parameters' statistical representation in the current office building stock. Instead, the purpose was to test the model output results' sensitivity on the possible foreseeable range of the input parameter. Therefore, uniform distribution of these parameter values was considered, with ranges spanning from the minimum and maximum values assumed to be plausible to find in office buildings.

The first preliminary sensitivity study, CLIMA, analysed the sensitivity of 16 parameters on the space cooling demand. In this case, the input parameters were grouped into three functional categories of building characteristics. The first group focused only on the building envelope (P1-P8), the second focused on operational parameters (P9-P12), and the third category focused on the building form (P13-P16). For CISBAT preliminary sensitivity study, a selection of the four most important from CLIMA's analysis was carried to further analysis (P1-4 at CISBAT Model). Four more parameters were included, relative to HVAC systems operation systems (P5-P8 at the CISBAT model). In this study, the Morris EE Method and Sobol global sensitivity analysis were used to analyse the sensitivity of eight parameters, for the electricity demand for HVAC end-use.

Table 3.10 – CLIMA 2019 - Input Parameters

		Parameter description	Unit	Baseline value	Distribution range	CISBAT's model
Envelope	P1	Thermal absorptance[1,2]		0.9	0.5 ; 0.96	n/a
	P2	Solar absortance[1,2]		0.7	0.3 ; 0.96	n/a
	P3	Solar glass transmissivity[1]		0.3311	0.15 ; 0.38	n/a
	P4	CP concrete[1,3]	$J.kg^{-1}.K^{-1}$	837	200 ; 4000	n/a
	P5	Glass conductivity[1]	$W.m^{-1}.K^{-1}$	0.0133	0.005 ; 0.03	n/a
	P6	External wall insulation[1]	$W.m^{-1}.K^{-1}$	0.0432	0.01 ; 0.065	n/a
	P7	Roof insulation[1]	$W.m^{-1}.K^{-1}$	0.049	0.01 ; 0.065	n/a
	P8	External absorptance[1,2]		0.92	0.5 ; 0.97	n/a
Operation	P9	Sensible IHG [4,5]	$W.m^{-2}$	40	10 ; 80	P1
	P10	Ventilation rate[4,5]	$m^3.s^{-1}.m^{-2}$	0.0015	0.0005 ; 0.005	P2 *
	P11	Infiltration rate[4,5]	$m^3.s^{-1}.m^{-2}$	0.0002	0.0001 ; 0.001	n/a
	P12	Cooling set-point[4]	°C	24	18 , 26	P3 **
Form	P13	North rotation	°	0	0 ; 180	n/a
	P14	Glazing area	%	40	5% ; 75%	n/a
	P15	North facade / East facade ratio		1	0.4 ; 9	n/a
	P16	Area ratio relative to base model		1	0.08 ; 25	P4
HVAC	n/a	Chiller water SP.	°C	7.22	5 – 9	P5
	n/a	Nominal chiller COP		4	2.5 - 6	P6
	n/a	Chiller sizing factor		1.2	1 – 1.4	P7
	n/a	Min. unloading factor		0.25	0.1 – 0.4	P8

**For CISBAT model, Ventilation Rate range was considered to be 0.5-10.3 ACH, and at a baseline of 1.54 ACH*
*** For CISBAT model parameter range was considered to be 20-28°C*

The future weather data-sets files, produced by the PROMETHEUS project (Eames, *et al.*, 2011), were utilised in these simulation procedures, and Manchester was used as the location for the study. Five files were used, as shown in Table 3.11, one representing the baseline weather conditions (C5) and four different potential future climate impacts (C1-4). It evaluated the implications of different levels of climate change impacts, as these four files considered the different level of probabilities (10%, 50%, and 90%) for the high emission scenario (A1F1) in 2080 and 90% probability of the medium scenario (A1B) in 2080, using UKCP09 data-sets.

Table 3.11 – Weather data information on climate files utilised

Weather data description	Annual CDD*	3 Days CDH*	Max. Temp.
C1 2080 A1F1 90%	1020	813	37.2
C2 2080 A1B 90%	836	767	33.3
C3 2080 A1F1 50%	596	703	31.4
C4 2080 A1F1 10%	296	415	28
C5 Baseline period	103	337	28.3

**CDD and CDH calculated based on 15ºC baseline*

Simulations were executed using the whole annual hourly data contained in these weather files. Figure 3.11 compares the DBT hourly profile of three weather data-sets used, between the days that preceded and succeed the maximum temperature day in the annual data-set. It emphasises the possible level of change during annual extreme warmer periods. The DBT profile is significantly shifted in these scenarios compared to the current baseline weather profile (C5). The annual maximum temperature is expected to reach 37.2°C in the worst analysed case conditions (C1), almost 9°C higher than the current baseline maximum DBT. summarises the weather data in terms of annual cooling degree days (CDD) and cooling degree hours (CDH) in the five weather data-sets. A steep increase (tenfold) in the number of CDDs is predicted within the A1F1 (C1 case) climate projection. Similarly, during the three days analysed in , the CDH in scenario C1 doubled compared to the baseline period levels (C5). For the CLIMA study (Zeferina, Birch, *et al.*, 2019), the same series of simulations will be conducted with the five different weather files to assess the climate's implications in the space cooling demand of the model. For the CISBAT study (V. Zeferina, Wood, et al., 2019), only one climate condition (C5) was considered, as the analysis was focused on quantifying each parameter's implication on electricity demand for cooling demand.

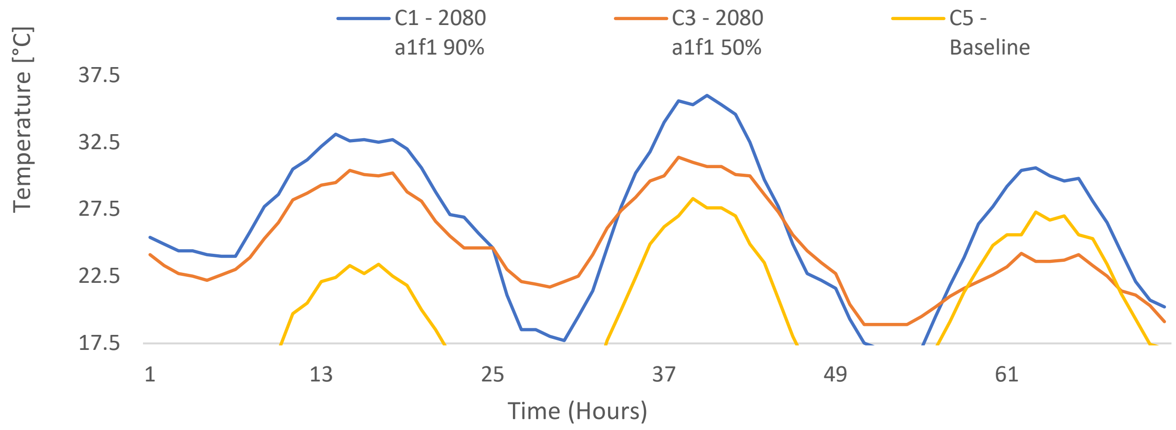

Figure 3.11 – Dry-bulb temperature in a 3-day period, between the days that precede and succeed the day of maximum temperature

3.5.3.2 Sensitivity studies with archetype office building models

In the following section, a presentation of the range of input parameters iterated for the sensitivity analysis of the archetype office buildings is given with an explanation and sources of the underlying data. The parametric range of the sensitivity analysis studies conducted in this part of the work is presented in Table 3.12. A total of 14 input parameters was considered in this analysis. For small and medium office buildings, parameter 9 (chiller's water-cooling temperature) and parameter 13 (unload chiller ratio) were not included as the HVAC system of these models did not use such parameters. The base conditions for each office model type were based on the respective DOE reference model's baseline characteristics. Whenever the impacts of a particular parameter were not to be explored in the sensitivity analysis iteration approach, this parameter in the building model was assumed as the standard base case value.

The quantification of uncertainty on the probabilistic distribution for input parameters is the most challenging aspect of uncertainty analysis (Sun, Gu, *et al.*, 2014; Tian, Heo, *et al.*, 2018). Each office type model represented several vintages and locations in this study, so model parameters concatenated different benchmark data. Uniform distributions are commonly used to represent different possible design strategies (Tian, Heo, *et al.*, 2018). In this study, the 14 design input parameters were considered as continuous variables, and the inputs ranges were assumed to be a uniform distribution. The limits of these ranges were an own research choice based on a variety of data sources collected from previous publications that were reviewed in Section 2.1.4. For example, these choices were based on data identified in (Petersen, *et al.*, 2019), the range of existing parameters on the reference model data-set (Deru, *et al.*, 2011) and on benchmark values given in standards and guidelines (American Society of Heating, Refrigerating and Air-Conditioning Engineers, 2007; CIBSE, 2012; Chartered Institution of Building Services Engineers, 2016).

Differences between base model assumptions for the different office types existed for envelope characteristics (P1-P4), infiltration rates (P11) and COP of the HVAC system (P12). For parameter P14, the number of effective annual hours of operation for equipment and lighting were controlled. Operation schedules for lighting, equipment and occupants in the model were adapted from Korolija et al. (2013). The range values went from 3,132 hours for lighting and 3,602 hours for equipment to a maximum of 4,007 and 4,285, respectively. It was achieved by stretching the operational index of schedules during weekend hours (6 a.m. - 9 p.m.) and on the standard workdays' margins (6 a.m.- 7 a.m. and 8 p.m. - 9 p.m.). Figure 3.12 shows an illustration of the changes in the schedules. The choice to have large amplitudes of input parameters ranges, and uniform distribution of these ranges, was made as this study intended to evaluate design parameter options. Therefore, the methodology was not focused on comparing the plausibility of each value within the range. Nevertheless, the input ranges were chosen based on limit values considered possible to occur as design parameters and have been reported in previous literature (Deru, *et al.*, 2011; Petersen, *et al.*, 2019). Large amplitudes of the parameter limits were considered for ventilation (P10) and infiltration (P11), as the rates can be fine controlled and assumptions can be substantially different based on the operation of the space. For example, due to the indoor air quality (IAQ) requirements needed or the number of people.

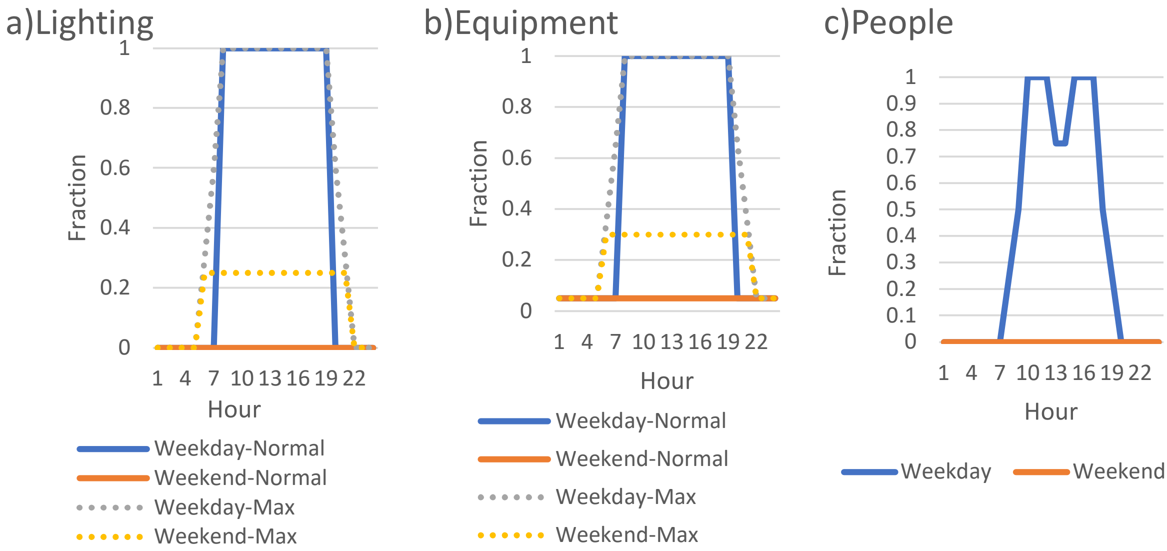

Figure 3.12 – Schedules used on simulations assumptions, a) lighting, b) equipment and c) people

Table 3.12 – Input parameters used on sensitivity analysis

	Description	Unit	Large Lower Limit	Large Upper Limit	Large Std DOE	Small Lower Limit	Small Upper Limit	Small Std DOE	Medium Lower Limit	Medium Upper Limit	Medium Std DOE
P01	Conductivity of the concrete layer on the external wall	W.m^{-1}.K^{-1}	0.1	2	1.311				0.005	0.08	0.049
P02	Roof Conductivity	W.m^{-1}.K^{-1}	0.005	0.08	0.049	0.02	0.3	0.16	=	=	=
P03	Solar heat gain coefficient (SHGC)	-	0.075	0.5	0.25	=	=	0.39	=	=	0.3
P04	Window U-value	W.m^{-2}.K^{-1}	1	7	6.92716	=	=	3.23646	=	=	2.6118
P05	Lighting	W.m^{-2}	5	20	10.76	=	=	=	=	=	=
P06	Equipment	W.m^{-2}	6	22	10.76	=	=	=	=	=	=
P07	Floor space per person	m^2.p.$^{-1}$	5	20	18.58	=	=	=	=	=	=
P08	Ambient temperature set-point	°C	21	26	24	=	=	=	=	=	=
P09	Cooling water set-point	°C	5.5	8	6.7	n/a	n/a	n/a	n/a	n/a	n/a
P10	Ventilation rate	m^3.s^{-1}.m^{-2}	0.0002	0.005	0.000625	=	=	=	=	=	=
P11	Infiltration rate	m^3.s^{-1}.m^{-2}	0.0001	0.003	0.000302	0.05	1.5	0.36	0.05	1.5	0.36
P12	Reference coefficient of performance (COP)	-	4	7	5.5	2.2	5.5	3.66684	2.2	5.5	3.23372
P13	Minimum 'chiller's unload ratio	-	0.1	0.3	0.2	n/a	n/a	n/a	n/a	n/a	n/a
P14	Schedule stretch	-	0	1	0	=	=	=	=	=	=

=, means it is equal to large office building model
P05 – 06 – 07 – 10 - per floor space area
P11 - per external envelope surface area
P13 – it is where the chiller capacity can no longer be reduced by unloading

3.5.4 Tools used

The following sub-section describes the function of different tools and the interaction between outcomes from each tool is presented. Figure 3.13 presents a diagram with the links between tools used. The office building energy models were developed in EnergyPlus (E+) and Openstudio was utilised in the research methodology approach as a reliable source for benchmark data and objects for the E+ building models. The Energyplus input text files templates (IDF) were prepared to perform changes directly and automatically in parts/objects of the building office models. To make automated changes in E+ input files, input macro files (IMF) were developed, which are imported in an auxiliary program of EnergyPlus (EP-Macro program). The EP-Macro program automatically generates E+ input files (IDF) from the IMF, updating complete changes in E+ building model objects that are ready to be imported in the program and simulated. This approach was also used by Korolija et al. (2013), in order to define and modifying EnergyPlus building models in IDF files, by iterating from a poll of different modelling objects, utilising jEplus (jEPlus, 2013).

The Python library eppy (Santosh, *et al.*, 2016) was used to analyse the E+'s objects defining existing E+'s archetype models. This tool takes advantage of the rich data structure available in Python programming to script Energyplus input and output files. It permits fast and repeatable ways to compare different models and make automated queries about input values. The jEplus software (Zhang, 2009) was used to perform the automatic parameterisation of values to be studied and execute all the simulations required. IMF files were adapted to indicate the parameters to be iterated. To execute the parametric model simulations, jEPlus requires a joblist, a *CSV* file, and a RVX file, a text file with a data structure to collect the 'simulation's output results. Joblists are *CSV* files that include all the values of the variables in the project's parameter tree, model templates, and weather files used in each iteration of the parametric study. The RVX file is a JSON language-based file that stores the output variables' positions that should be collected. For more information on jEPlus software refer to the program manual in (jeplus.org, 2014).

The R programming environment (R Core Team, 2020) was used using RStudio (RStudio Team, 2019) in several stages of this research as a statistical and visualisation tool. For example, it was used to generate the joblists, using the functions from the *sensitivity* package (Weber, 2020) , namely: *morris* and *sobolmartinez*, to sample the input values for the iterated input parameters. After that, a case name column for the respective IDF file and EPW weather file was filled to each model iteration. The simulations were executed and managed by jEPlus, which uploaded these files to the program and set the directories to store output files and the necessary IDF and EPW files to load in the iteration. The jEPlus program enabled a distribution of the model simulation jobs in parallel by the CPU processors cores. Every simulation run in EnergyPlus generated specific output files that were stored in a specific iteration case directory. At the end of the parametric simulation process, jEPlus collected the output variables defined in the RVX file from the output files in 'iterations' directory, creating summary tables of the output variables and the values for the simulations executed.

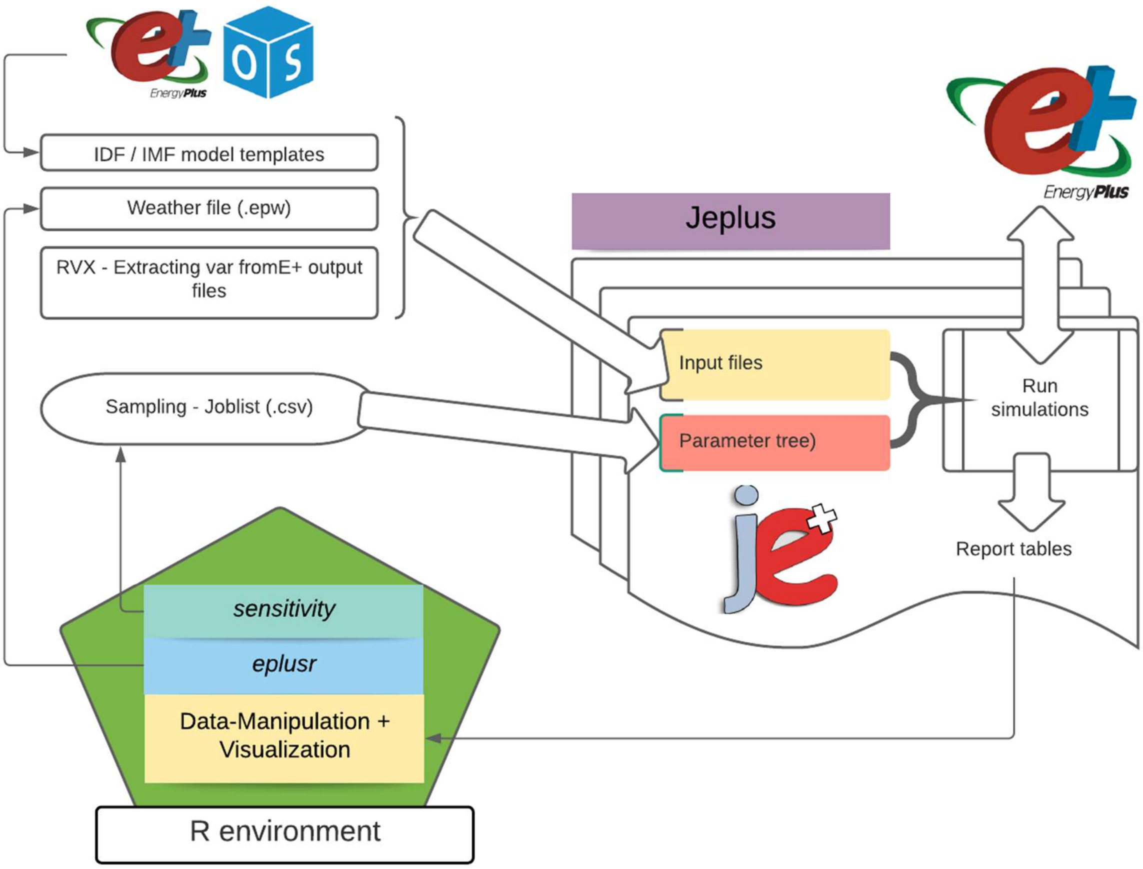

Figure 3.13 – Overview of the integration of modelling tools in the research methodology

The research data analysis was performed on these summary output files created by jEPlus. The data analysis was initiated by uploading the simulation output CSV file in the R-environment. For the research analysis conducted, the simulation output results evaluated were often aggregated to the whole building model level, and results were always normalised by the model floorspace area and frequently by the model base case result. Equation (3-16) presents the floorspace normalisation operation done to the simulation results. In addition, to compare the sensitivity and uncertainty of results among different types of buildings, results were often normalised by the original base case. After that, all parametric study results were to be divided by the respective base case scenario (i.e. standard input modelling conditions for that respective city and building model), as shown in Equation (3-17). The results were also to be analysed with no normalisation to the base, when the absolute value was significant to be retained, for example, for base case values.

$$Output_{i,NormtoArea} = \frac{Output_i}{Area} \tag{3-16}$$

$$Output_{i,NormtoBase} = \frac{Output_i}{Output_{Base}} \tag{3-17}$$

where,

$Output_{i,NormtoArea}$	, is the output result in iteration I normalised to the office floorspace area [unit.m^{-2}];
$Output_i$	is the output result for iteration i ;
$Area$	office floor space area of the model in consideration [m^2];
$Output_{i,NormtoBase}$	normalised output result for iteration i, relatively to the base case result in the city analysed;
$Output_{Base}$	is the output result for the city analysed in base conditions.

The coefficient of variation (*CV*) measures the variability of a population concerning the mean of this population and can be written as Equation (3-18). It is the ratio between the standard deviation of the population (σ) to the mean of the population (μ). For the comparison of different design options on case studies, the coefficient of variation was calculated for all output results of each site, building type and building design iteration analysed.

$$CV = \frac{\sigma}{\mu} \tag{3-18}$$

Statistical tools were utilised in the research data analysis, such as boxplot, scatterplots, and Q-plots, to identify the parametric studies' variability. Multiple R packages were used for the necessary data manipulation, processing and visualisation. The main R-packages used for this were: *dplyr* (Wickham, *et al.*, 2020), *ggplot2* (Wickham, 2016), *tidyverse* (Wickham, *et al.*, 2019) and *tidyr* (Wickham, 2020). In addition, the R-package *eplusr* (Yu, *et al.*, 2020) was used to import and manipulate EPW files. Weather data-sets were manipulated using *eplusr* functions, executing morphing operations and generating new EPW files to be utilised in parametric simulation studies.

3.5.5 Building model simulation output results

In this section, an explanation of the research simulation output variables analysed for the case study is provided. EnergyPlus provides multiple variables and meters as output results, which can be assessed for each 'simulation's timestep. EnergyPlus also aggregates results in summary tables, reporting consumption for the whole building and for critical/specific components or requirements (for example HVAC systems, lighting and indoor air quality). For the simulation cases of this research work, the study was primarily on buildings' electricity demand, and EnergyPlus reports a total of 13 electricity end-uses. The 'EnergyPlus' summary table: Annual Building Utility Summary provides the annual electricity consumption for all the energy end-uses for annual demand. Similarly, results can be extracted from the summary table *'Demand End Use Components Summary'* for peak demand. For more information on the source of the EnergyPlus 'outputs' variables, refer to 'EnergyPlus' *Input Output Reference* document (EnergyPlus, 2015), and refer to 'EnergyPlus' *Output Details and Examples* document (Berkeley, *et al.*, 2017) for a detailed description of the EnergyPlus output files.

The space cooling requirements output result was extracted from the E+ output meter: *"Cooling:EnergyTransfer"*. This meter refers to the sum of all the model 'zones' Air System

Sensible Cooling energy. This variable's annual demand is reported in the EnergyPlus summary table "Annual and Peak Values – Other" on the Energy Meters Report. The peak results presented reported to the end-use demand at the moment of total peak electricity demand. Therefore, the results were not precisely the moment of maximum demand for each end-use or the space cooling demand. The peak demand result was a snapshot of all outputs at the moment of total peak demand.

The methodology for sizing the cooling loads in the EnergyPlus models took on several assumptions. The E+ object *Sizing:Parameters* set the sizing factor as 1.33 for cooling, as given by the DOE archetype models used. The *SimulationControl* object set active the sizing calculation of zone, system and plant. The *SizingPeriod* defined for the models is the *SizingPeriod:WeatherFileConditionType,* which takes the *SummerExtreme* condition of EPW weather files to perform the office 'models' sizing calculations. Therefore, it enabled the 'model's sizing to be adapted to the weather data coupled with the simulation run. ASHRAE handbook fundamentals (American Society of Heating, Refrigerating and Air-Conditioning Engineers, 2013) presents multiple criteria for design day conditions and mentions that designers should adapt the chosen design criteria to the situation under consideration. For several simulation cases used in this research, the design criteria of the weather files utilised had led to unmet cooling hours or similar performance degradation. However, the research methodology required an unique approach for the design criteria to ensure a reliable comparison of the results.

3.6 Chapter summary

This chapter presents the research methodology used in this thesis. The three main stages composing the research methodology developed applied in this thesis are presented. First, a detailed description of the sensitivity analysis executed in this research is presented in Section 3.2. Second, the research approach to evaluate the effects uncertainty in weather datasets through morphing procedures is presented in Section 3.3. In Section 3.4, the third and final stage of the research methodology is presented, the generation of climate pathway to evaluate a wide range of potential climate change impacts, followed by the assessment of the mitigation effect of adaptation measures. Finally, a description of the building simulation cases used in the research for this thesis and the tools used for its generation is presented in Section 3.5.

The methodology presented in this chapter introduces the research approach utilised in the research studies presented in the research result chapters (Chapter 4, Chapter 5 and Chapter 6).Therefore, it provides an overview of the research approach common to the research work done in this thesis, which is further detailed in each of the following chapters.

4 Sensitivity analysis of office building energy models

4.1 Introduction

In previous chapters, the research background for the analysis of climate change impacts for building energy performance was disclosed, so the relevance and the related challenges were discussed. Before in this thesis, it has also been discussed and summarised some of the challenges related to future building energy modelling scenarios. To better understand simulation results, it is essential to explore the uncertainty and sensitivity of energy models. This chapter intends to address this requirement, exploring the sensitivity and uncertainty of office building energy modelling. Specifically, analysing the sensitivity and uncertainty of different office models, regarding the simulation results of cooling requirements.

Building performance simulation (BPS) requires detailed physical correctness of the building energy model, thus detailed characterisation of the building envelope and operational conditions. Similarly, rational and sensible development of modelling approaches and definition of their outputs is required, to keep models targeted to the simulation study's objectives (Hensen, *et al.*, 2011; Clarke, *et al.*, 2015). Furthermore, the adaptation of buildings to climate change impacts is one of the main challenges in building design (Hensen, *et al.*, 2011). Therefore, it will require detailed and dynamic simulation to estimate how building energy performance changes with meteorological conditions and due to uncertainty of design conditions.

To bridge the often-reported energy performance gap, it is necessary to define how, what, and when the comparisons are made. It is also necessary to understand that the energy performance models have limitations, and one should expect and accept differences between the model results and actual building performance. It is also essential to use the correct modelling tools, and analysts should have the ability and knowledge to apply them appropriately (de Wilde, 2014). For example, systematic and holistic design optimisation is needed to avoid unintended side effects from changes to building design standards (Hensen, *et al.*, 2011; Clarke, *et al.*, 2015). In not doing so, the credibility of models, modellers and design teams is affected, and the design solutions proposed by the industry to reduce energy consumptions and or shave peak loads on buildings operations may be rejected.

More research has been done using BPS tools as computational capacity has been increasing. Hensen et al. (2011) concluded that computational simulation is a powerful analytical tool, but it is challenging to ensure quality. Therefore, the building design community should pursue an understanding of the topic area. Uncertainty and sensitivity analysis techniques can enable further understanding of the parameters and factors that are most critical for buildings' energy performance. This enables the accuracy of the models to be improved by updating model assumptions. On the other hand, it enables the dimensional reductions of models while preserving most of the variance. Thus, the number of model input iterations can be minimised and still effectively analyse the possible range of building design choices.

The scope of uncertainty and sensitivity analysis in BPS is multifield, and the potential number of statistical methods available is considerable. For example, the uncertainty on future buildings' energy performance is the aggregation of different sources of uncertainties in model inputs and modelling scenarios (Hopfe, *et al.*, 2011; Tian, 2013). Uncertainties result from possible discrepancies in occupancy characterisation, building envelopes and HVAC systems in future building stocks, and the estimation of future weather conditions. It is important to quantify the implication of each building system model component and boundary conditions, on the energy demand and peak load of space heating and cooling demand. Previous literature has not often focused on cooling demand for office buildings and their peak loads. However, these peak loads may have a critical impact on system design capacities and power network operation, as Wood et al. (2015) suggested. Therefore, the research work presented in this chapter aims to understand and quantify the sensitivity of office buildings modelling to different inputs. The quest to pursue this research aim, was based in two main research questions, that are addressed in this chapter:

- The first research question: How sensitive is the office building energy modelling to different operational and design input parameters?
- The second research question: What is the relative impact on peak and annual HVAC and total electricity demand of office buildings as cooling requirements differ with changing building design and operational conditions?

The research contributes to understanding the implications of input parameterisation for the simulated demand of buildings' cooling requirements. More specifically, it examines the sensitivity of cooling demand related results (total electricity demand, HVAC end-use and space cooling) for different types of buildings and different locations. Moreover, this study investigates the difference between the effects of annual and peak analysis for cooling demand of office buildings, which can provide insight on cooling demand from the perspectives of total cooling energy and system capacity for building cooling systems, respectively. The study would also help identify cooling design best practices for office buildings to guide energy engineers during the retrofit and development of new buildings.

Finally, the work presented in this chapter summarises the findings on the extensive pre-analysis of the sensitivity office building models that were in the preamble of this PhD research project. This work has led to three distinct research publications. First, the work entitled: "Sensitivity analysis of peak and annual space cooling load at simplified office dynamic building model" (Zeferina, Birch, *et al.*, 2019) presented at the CLIMA 2019 conference. Second, a study of the "Sensitivity analysis of a simplified office building" (Zeferina, Wood, *et al.*, 2019) presented at CISBAT 2019. Finally, the "Sensitivity analysis of cooling demand applied to a large office building" published in the Energy and Buildings journal (Zeferina, *et al.*, 2021).

4.2 Research results

4.2.1 Preliminary sensitivity analysis studies

4.2.1.1 CLIMA study

In this section, the results for the SA in the CLIMA study are presented. In the study, sensitivity was analysed considering five different weather data files for the same location, considering different climate change projections. The results of the SA are then presented for the baseline weather data (C5) and for the future weather data with the largest impacts of climate change, 2080 A1F1 -90% probability (C1).

Figure 4.1 shows the *CV* values on the simulation sample of both annual and peak cooling demand. It is possible to conclude that the variation of results is significantly more considerable for annual than peak demand resolution. For the annual demand, the *CV* is 1.27 for annual demand in the control base file, and the peak demand is 0.44. However, the difference between annual and peak demand *CV* is significantly reduced with warmer climate projections conditions, so in C5-2080, the *CV* is 0.71 for annual demand and 0.37 for the peak. Similarly, the sensitivity $\mu*$ values of parameters are larger for the annual demand than for peak demand, as presented in Figure 4.2–.

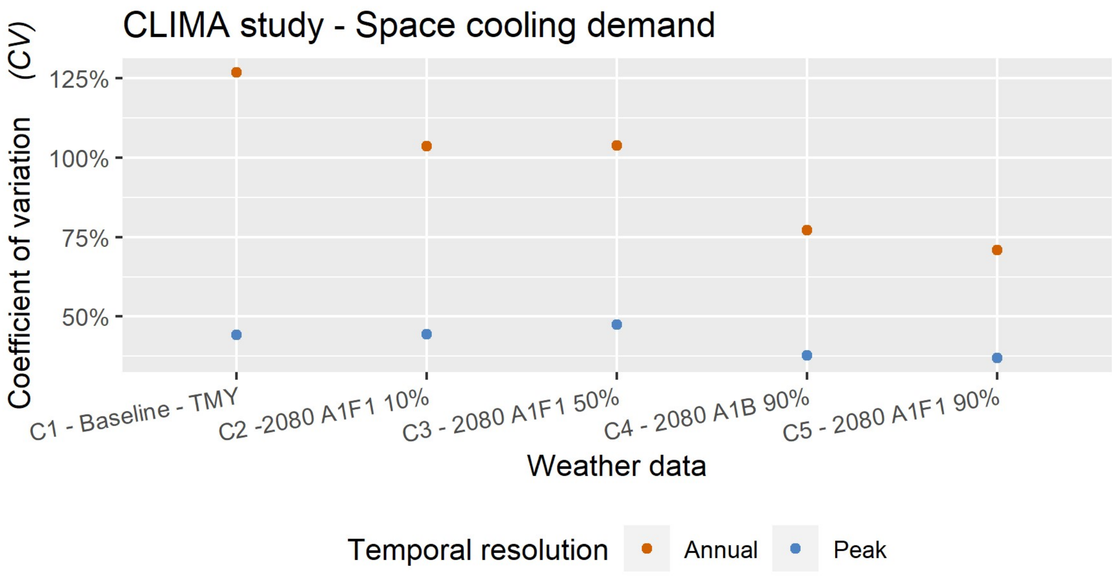

Figure 4.1 – Coefficient of variation of space cooling demand considering the temporal resolution, for the different samples of weather files simulated on CLIMA study

For the annual demand, the internal heat gains (P9) is the parameter with the largest contribution for change, followed by the cooling set-point (P12) and ventilation rate (P10), with a $\mu*$ value half of the value of the contribution of P9. Infiltration rate (P11) and area ratio (P16) follows, showing approximately a tenth of the contribution of P10 or P12 and almost 20 times lower than P9. Com paring results between the analysis for two different weather data scenarios (2080 A1F1 90% weather data versus the baseline TMY), the contribution for annual demand of P9 and P12 are larger than for the baseline weather data analysis, and the contribution of P10 is reduced. For peak demand, IHG (P9) is the parameter that contributes the most, followed by the cooling set-pointset-point (P12) and the ventilation rate (P10). The area ratio (P16) and the glazing area (P14) follows with lower contributions. For the future weather data (2080 A1F1 90%), the ventilation rate (P10) contribution significantly increases and becomes the largest, but the changes for parameters 12 and P9 are small, and the value of P16 also doubles.

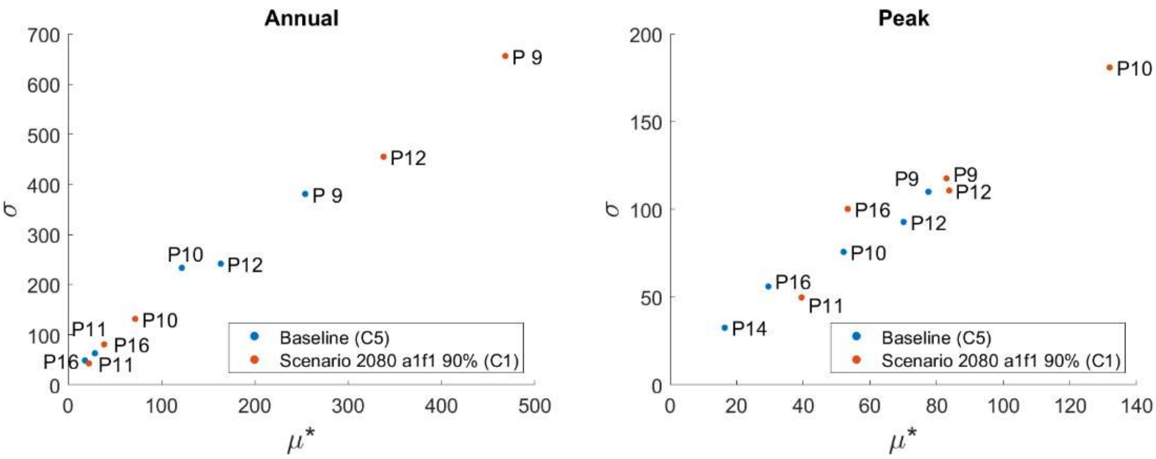

Figure 4.2— CLIMA Morris SA indexes relative to the space cooling demand

4.2.1.2 CISBAT study

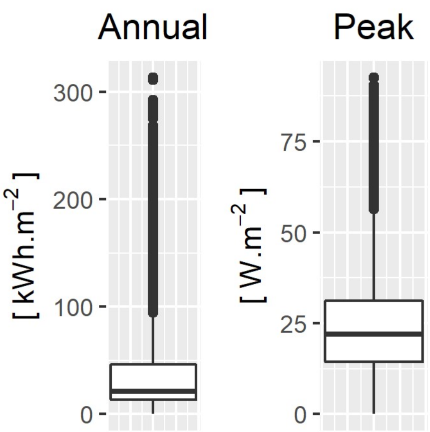

Figure 4.3 – Boxplot the electricity demand for cooling in the CISBAT study

Table 4.1 – Distribution of the electricity demand for cooling results in CISBAT study, Sobol Sample

	Annual	Peak
CV	1.0795	0.5535
Mean	38.2 kWh.m^{-2}	23.9 W.m^{-2}
Stand. dev.	41.3 kWh.m^{-2}	13.2 W.m^{-2}
Base cond.	38.9 kWh.m^{-2}	16.3 W.m^{-2}

This section presents the results for the sensitivity analysis performed on the simplified office model for the CISBAT case study. In this case, the output analysed is the electricity demand for the HVAC end-use, both for annual and peak resolution. Figure 4.3 presents the distribution of sample results and *CV* values are presented in Table 4.1. It is possible to say that the variation of annual demand is larger than for peak demand. For annual demand, the *CV* value is 1.0795, and for peak demand, it is 0.5535.

For annual demand, the parameter that contributes the most is P1, IHG, and at a lower level by ventilation rate (P2) and cooling set-point (P3). The remaining parameters present much lower contributions. The sensitivities calculated by both Morris EE (Figure 4.5 –) and Sobol (Figure 4.7 –) methods/samples show similar findings for the ranking of the input parameters contribution to the annual demand. For the peak demand, the area ratio parameters (P4), cooling water set-point (P5), sizing factor (P7) and unload factor (P8) show low contribution for the result. The ambient cooling temperature set-point (P3) is the parameter that presents the largest contribution, followed by similar levels of contribution from IHG (P1) and ventilation rates (P2), and at a smaller level by the COP (P6). For peak output, the Morris method (Figure 4.4 –) shows similar contribution levels from ventilation rate and cooling set-pointset-point; however, the Sobol method (Figure 4.6 –) shows that the contribution of P3 is significantly larger. In addition, for annual demand, the contribution of the individual parameters identified is much larger than for peak, as the IHG present almost 60% of the change in annual demand, while for peak P3 at maximum contributes 38%.

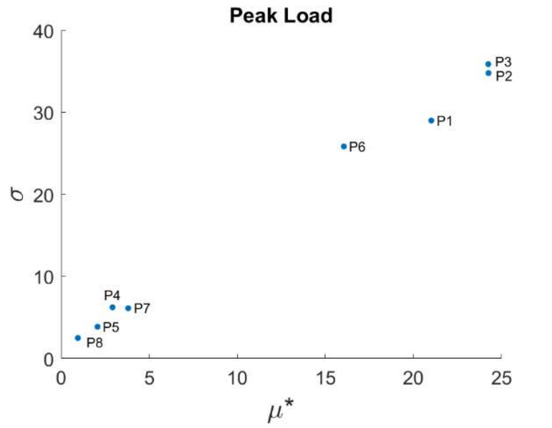

Figure 4.4 – Morris EE metrics for peak power

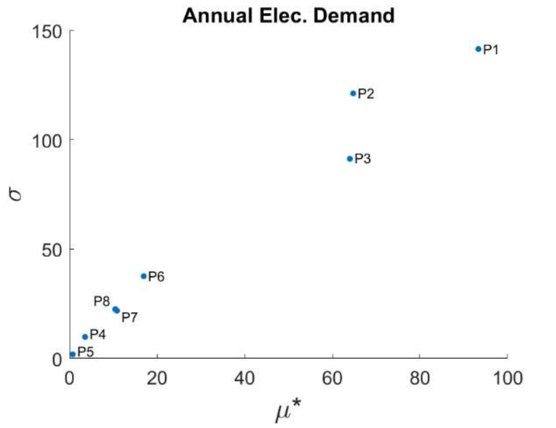

Figure 4.5 – Morris EE metrics for annual demand

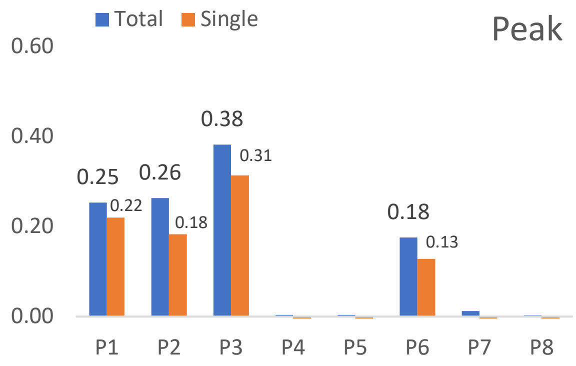

Figure 4.6 –Sobol indices for peak power cooling demand.

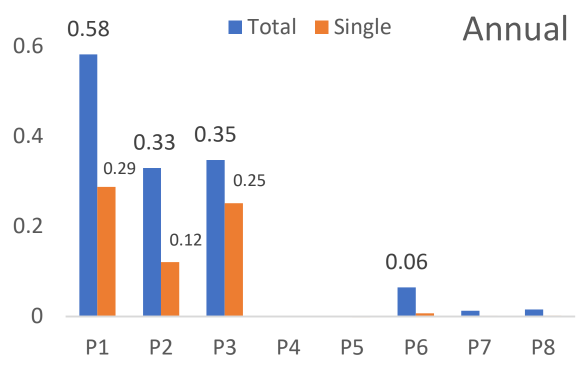

Figure 4.7 –Sobol indices for annual cooling demand

4.2.2 Archetype office model studies

4.2.2.1 Demand for base cases conditions

In this section, the results for the archetype buildings are presented. This sub-section presents annual and peak demand for the base case conditions for all models in different locations. The base case conditions of the models were presented in , as the standard DOE column in each office type. Figure 4.8 presents the total electricity demand, divided by the different end-uses, for each office type, in each location, both annually and at peak period.

First, looking at the annual demand, the demand may be up to 50% larger on location C1-Singapore than it is in location C6-London. The total annual electricity demand varies between a minimum of 97.3 kWh.m^{-2} (Large and Medium C6-London) and 151 kWh.m^{-2} (Medium – C1-Singapore). Total demand on a m^2 basis is larger for small buildings, up to 15 kWh.m^{-2} (up to 10%), for all locations except C1, where total annual electricity demand is approximately the same for all three office types. The non-HVAC demand (other total) is equal across all locations, as is not dependent on weather conditions, and is slightly larger for medium office buildings (90.4 kWh.m^{-2}) than it is for small (87.8 kWh.m^{-2}) and large (84.4 kWh.m^{-2}) offices. The total HVAC demand is heavily related to the location/climate. For the three types of office models, the annual demand in C1-Singapore is between 60.7 kWh.m^{-2} and 63.5 kWh.m^{-2}. On the other hand, for C6, the HVAC demand varies between 7 kWh.m^{-2} for medium and 19 kWh.m^{-2} for small buildings. It is related to the much larger annual demand verified for fans electricity end-use on small buildings. For this office type, the fans annual demand is between 15.4 kWh.m^{-2} to 20 kWh.m^{-2}, while for other building types, the value is no more than 4 kWh.m^{-2}.

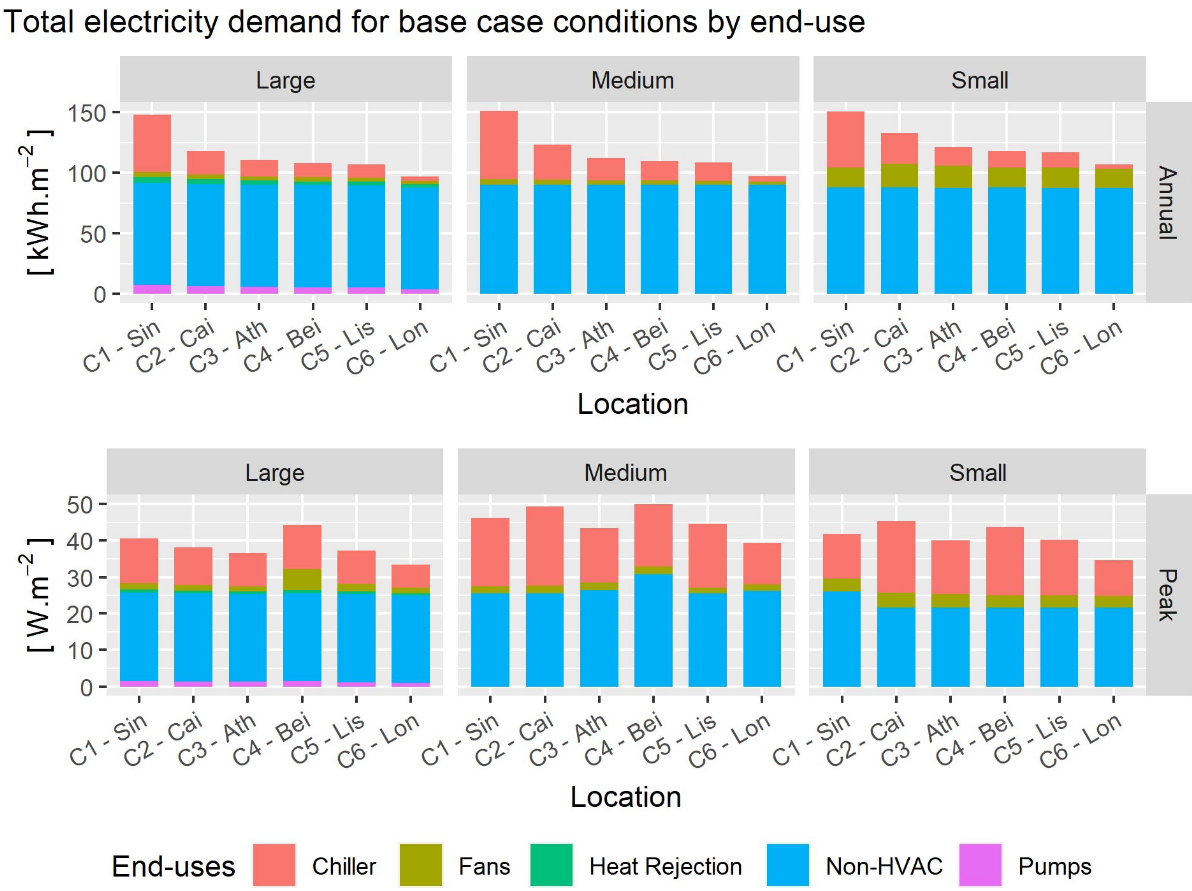

Figure 4.8 – Electricity demand by end-use for base case conditions in the archetype study

Relative to peak demand, the range of values verified for total peak demand is between 33.5 W.m^{-2} (Large – C6) and almost 50.1 W.m^{-2} (Medium – C4). Medium office building office types across all locations present the largest total peak demands, followed by the small office and the large office building types (except C4). For location C2, the difference between medium and large office building types is more than 11 W.m^{-2} (49.3 W.m^{-2} – Small vs 38.1 W.m^{-2} - Large). The proportion of total HVAC demand is significantly larger for peak demand than for annual demand, except for location C1. For example, the electricity for HVAC end-use represents 40% of total load in C2-Cairo, medium office building but only 10% in the annual demand. The Non-HVAC demand is variable relative to the location, as the peak time may occur at different periods of the day.

4.2.2.2 Distribution of results on archetype Morris samples

Figure 4.9 shows the distribution and amplitude of the several results analysed in this study. The base model conditions results are in the lower end of the spectrum of results in the sample obtained for this Morris EE analysis. For all office types, locations, output variables analysed and time resolutions, the base condition is within the first quantile. Looking at the coefficient of variation *(CV)* of different output results in Figure 4.10, the peak demand output has larger *CV* values than for annual demand. There are some exceptions, namely for the total electricity demand in C1 – Singapore, for small buildings and medium offices in C6-London. In addition, for SPC demand, the *CV* of the annual demand is for all models and all locations larger than peak demand. However, it is essential to emphasise that differences between annual and peak *CV* increases significantly from C1-Singapore to C6-London.

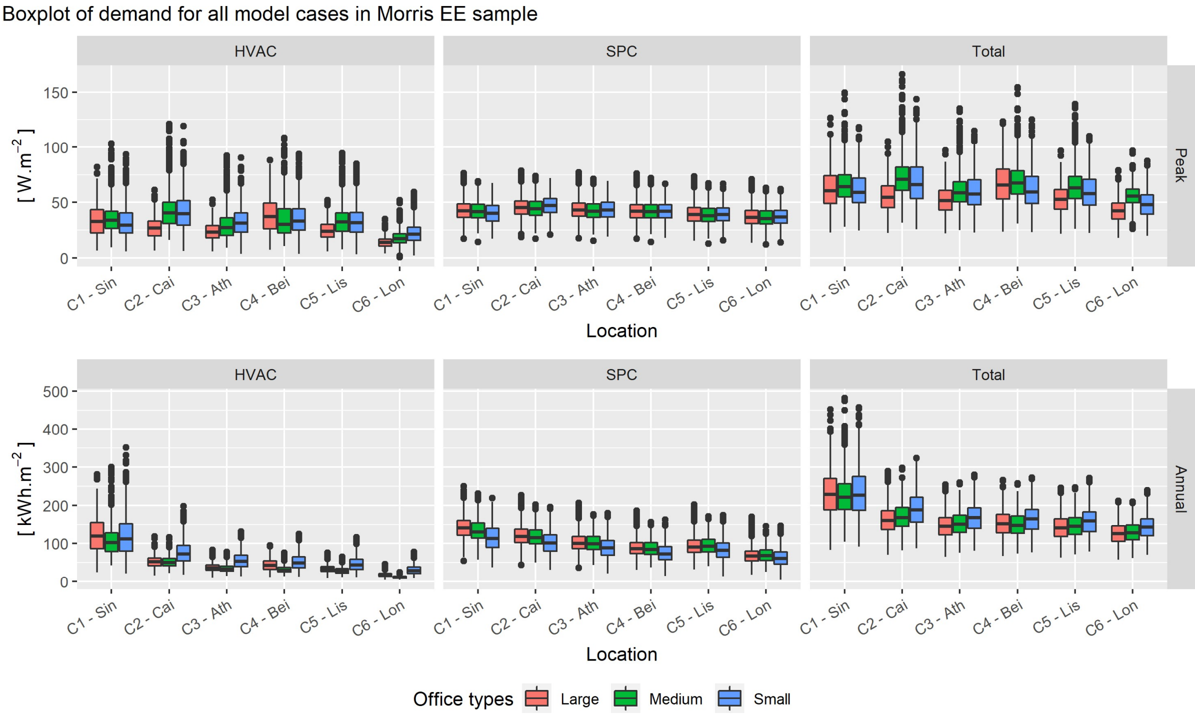

Figure 4.9 – Boxplot of results for the Morris EE method in the archetypes study

Relatively to differences among the type of office buildings, it is possible to identify that the medium office type presents lower *CV* than large and small buildings across all locations, both for SPC, Total and HVAC, for annual demand. Again for annual demand per m^2, the small office building type has a wider spread of results, larger upper-end outliers, which are also expressed by the larger *CV* than the remaining models for all locations, for HVAC and SPC. In total annual demand, large office building *CV* presents similar values with small office buildings, which are slightly higher than medium offices.

Looking at peak demand distribution in Figure 4.9, the medium office building has larger upper outliers, but the base case peak demand for this type of offices has also presented larger than the other type of offices. Looking at the *CV* values for the peak demand, the small office buildings present the largest values relative to the total demand, and medium buildings show the lowest values for total demand. For some locations, namely, C1-Singapore, C4-Beijing and C6-London, large office buildings show larger *CV* than small office types, but on the remaining locations values are similar to medium office buildings. However, for the peak HVAC demand, *CV* values the large office type are the smallest for most of the locations, and the *CV* of medium offices are the largest for most of the locations. For SPC, the *CV* of all office types is similar, with a slight lead for large office buildings followed by medium and then small offices.

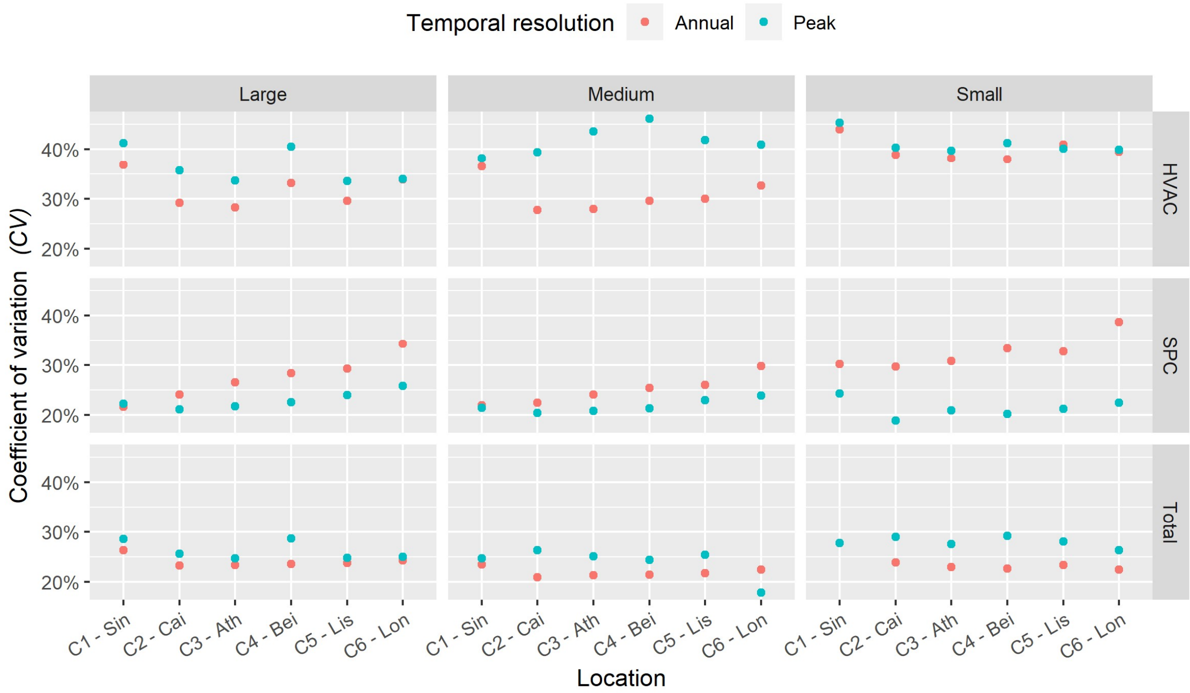

Figure 4.10 – Coefficient of variation (CV) values for the different results and modelling groups

4.2.2.3 Morris EE sensitivity analysis results

In Figure 4.11, the contribution of each input parameter analysed by the Morris EE method is shown for total electricity demand, presenting the mean sensitivity measure μ^*. Looking at annual demand, the parameter P05, lighting and P06, equipment density, present the largest contribution for all office types, in all locations, except for C1- Singapore. The value of the contribution of parameters P05 and P06, on total annual electricity demand is the largest for C6-London and the minimum for C1- Singapore. The mean sensitivity measure μ^* varies from 0.495 to 0.577 (C6-London, large), or 0.575 (C1-Singapore, large) to 0.675 (C6-London, large), respectively for P05 and P06. See figures and tables in Appendix C1 to consult all mean sensitivity measures values. The parameter P08, ambient cooling set-point, and P12, COP, also contribute significantly after P05 and P06, especially for small and medium office buildings. Parameter P10, the ventilation rate, presents significant contribution, especially in large office types, namely for location C1-Singapore. P14, occupancy schedule stretch, also has a significant contribution, similar across all locations and models, around 0.2.

Looking at the contribution of the different input parameters on total peak demand, lighting (P05), equipment (P06), ambient set-point (P08), ventilation rate (P10) and COP (P12), all present similar large contributions (μ^*), when compared to the remaining parameters. The contribution of P05 and P06 is at a similar level for all models. However, there are slight differences among locations, larger for C6-London and minimum for C4-Beijing or C2-Cairo (medium offices). For small office buildings, the contribution of P08, P10 and P12 present similar levels of contribution to total peak load as presented by parameter P05 or P06. Medium office buildings also present large contributions of these parameters, but at slightly smaller levels. For large office buildings, the contribution of P08 and P12 is lower than for the other models. On the other hand, parameter P10 shows the largest contribution for large office buildings for C1 and C4 (0.79 and 0.85 respectively). The fact that the ventilation rate contribution outstand in these specific case conditions, may be related to large relative humidity conditions existing for these locations, especially for peak conditions. Cooling latent loads are expected to have larger impacts for the electricity demand in large office building models.

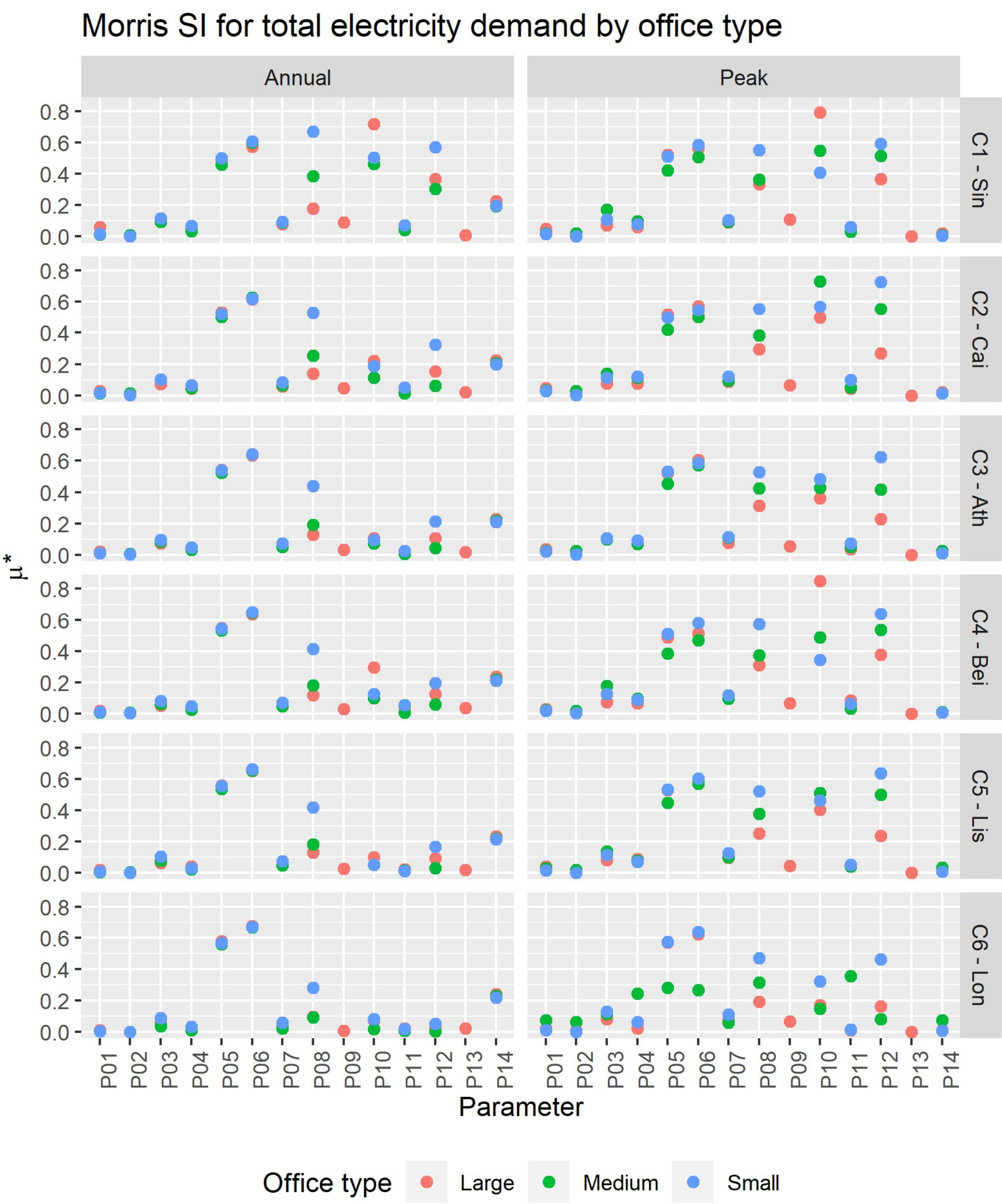

Figure 4.11 – Morris EE μ value for total electricity demand*

For HVAC electricity end-use demand, the $\mu*$ value is significantly larger than for total electricity demand, except for parameters P05, P06 and P14. For annual demand, cooling set-point temperature parameter (P08) is the one with the largest contribution, especially for small office buildings. Parameter P10, ventilation rate, follows, especially for large office buildings, with larger values for location C1 and C4. The following parameter with a larger contribution is the COP (P12), which for small offices, have significantly larger $\mu*$ values. P08, P10 and P12 show similar large levels of contribution for the variation of HVAC demand for peak demand. Parameter P12 presents the largest $\mu*$ value for most locations, especially for small and medium office types. The mean sensitivity measure (μ^*) for parameter P10 outstands the remaining parameters, for large office buildings, on-location C1-Singapore and C4-Beijing.

For space cooling, what stands out is that the different input parameters' contribution among locations is very similar for peak demand. However, for annual demand, there are apparent differences in the contribution to different locations. Especially for location C6-London, the contributions are significantly larger, even more for small office types. Lighting (P05) and equipment (P06) densities are the parameters with larger contribution both on annual and peak results. Similarly, cooling set-point, P08, also presents one of the largest levels of contributions, both on-peak and annual resolution, with more evidence for small buildings. Solar heat gain coefficient parameter (P03) presents a more significant relative contribution for SPC than it has shown for total electricity demand and HVAC electricity end-use.

Comparing the $\mu*$ values for the different types of office models, the values are similar for the different types of offices for almost all parameters. However, differences are outstanding for cooling set-point (P08), ventilation rate (P10) and COP (P12) parameters. For example, small office buildings present larger $\mu*$ values on P08 and P12 than large office buildings, for total electricity demand and HVAC demand. Comparing the $\mu*$ among the different types of output variables, it is clear and expected that HVAC results are significantly larger for HVAC than for total demand. Similarly, for some parameters (P5,06 and P10), the contrary is expected and seen, as $\mu*$ on total demand is larger than for HVAC. It is evident that C1 – Singapore outlies the remaining locations for total annual electricity demand results regarding discrepancies among locations. On the other hand, the results for C6-London stand out on the lower end for total peak demand. For space cooling demand, a clear distance of $\mu*$ results can be seen across locations, at annual demand resolution. For this, the relative contribution on C6-London location is larger than warmer location as C1-Singapore.

4.2.2.4 Sobol sensitivity analysis

In this section, the findings for the Sobol sensitivity analysis on the large office building are presented. Figure 4.12 and Figure 4.13 present the Sobol total sensitivity indices for all output variables, respectively for annual and peak demands. For the Sobol sensitivity analysis, only the large office type was utilised, due to the large number of simulation runs that are required. The quantification of sensitivity with Sobol analysis, for the different outputs and across different locations, enables to better understand and rank the importance of the different design parameters, regarding the different potential design constrains. In addition, this also enables to understand that the contribution of particular design parameters may stand out for particular locations.

For annual total electricity demand, the total contribution of lighting (P5) and equipment density (P6) may reach up to 40% and 60% of the total contribution on change, for location C6 - London, while the other parameters have little to almost no impact for annual electricity demand. However, for C1-Singapore, the contribution of cooling set-point parameter (P10) is 42%, while the contribution of P5 and P6 is around 20% for each. Parameters P08 and P12 (COP) have a maximum contribution of 8% and 10% for change in annual electricity demand respectively, in this location, the largest across all locations analysed. For the peak total electricity demand, the contribution of P10 – ventilation rate is the largest, reaching a total contribution up to 42%. The contribution of P05 and P06 is between 20% and 30%, and the contribution of P08 and P12 is around 10%. However, for location C6-London, the contribution of P05 and P06 is around 40%, while the contribution of P10 is 12% and around 5% for both P08 and P12. The contribution of occupants density (P07) is almost neglectable both on annual and peak resolution.

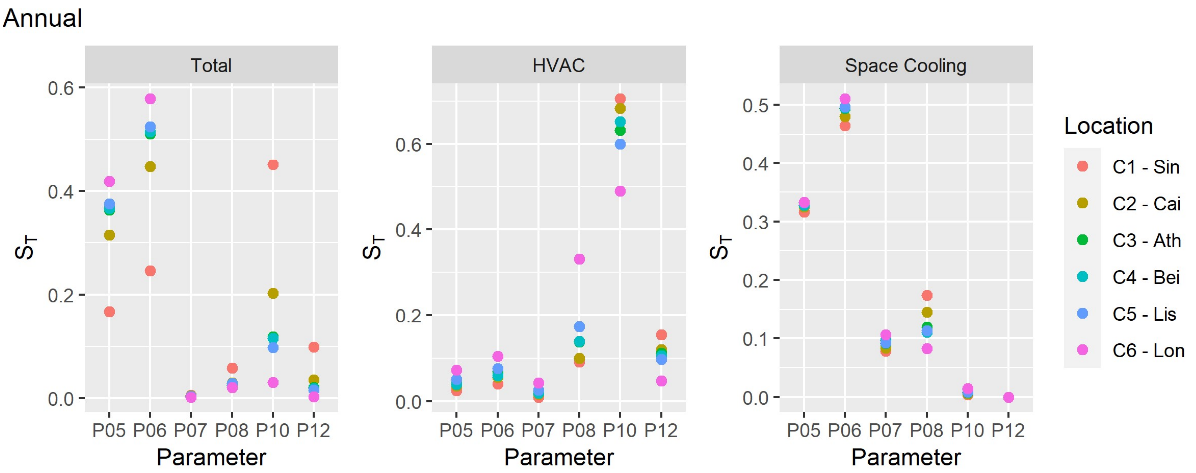

Figure 4.12 – Sobol total sensitivity indices for annual demand for the large office

The contribution of the different parameters on HVAC electricity end-use demand, both on annual and peak resolution, is significantly more alike across the different locations than for total electricity demand. P10, ventilation rate, has the largest contribution, with up to 70% of the total change in results. While the contribution of P08, cooling set-point, and P12, COP, are between 15% to 20% each. The contribution of the remaining parameters is minimal. For annual space cooling demand, the contribution of lighting (P05) and equipment (P06) densities parameters is the most significant, with contributions slightly larger than 30% and around 50%, respectively. In this case, the contribution of P08, cooling set-point, follows with a contribution of up to 20% and by P07, occupants density, with a contribution of around 10%.

Peak

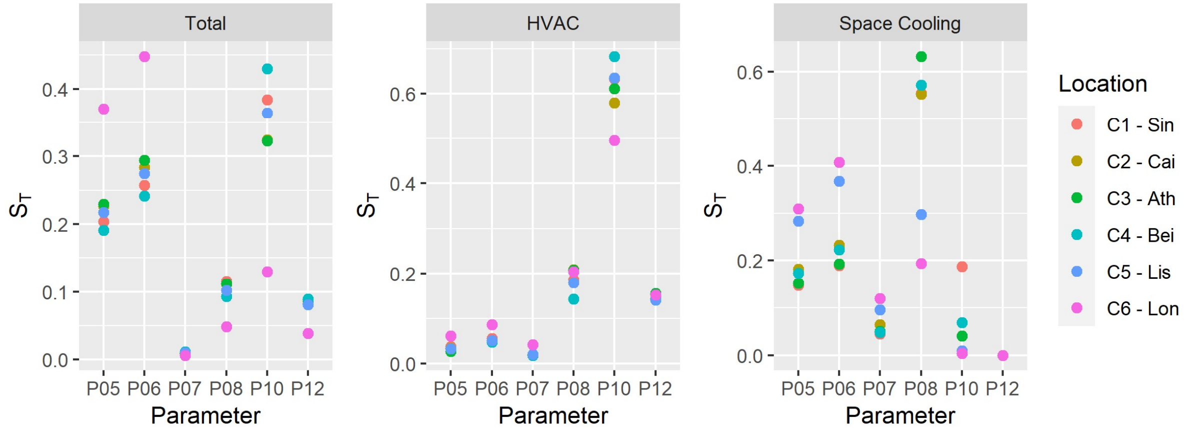

Figure 4.13 – Sobol total sensitivity indices for peak demand for the large office

4.3 Discussion

The main aim of this chapter was to evaluate and quantify the sensitivity of office building models utilised in the simulation case of the thesis. Relative to the first research question: "*How sensitive is office building energy modelling to different operational and design input parameters?*" the research shows that few parameters have major contributions for the HVAC demand of office buildings. For electricity demand for HVAC end-use, the parameters that contribute the most are the ventilation rate, cooling set-point, and COP (e.g. for large offices in the Sobol analysis was respectively around 50%, 20% and 18%). The contribution for total electricity demand may be significantly reduced, depending on the climate profiles of the location (average and extreme weather conditions) and type of building. The share of HVAC on annual total demand is smaller than for peak demand, for most of the cases analysed (for C1-Singapore the proportion is similar throughout the whole year, but for all other locations analysed the value is much larger for peak demand). The internal heat gain density parameter also makes a significant contribution, especially for HVAC end-use annual demand (up to 15% in the same analysis). On the other hand, when looking to the space cooling requirements sensitivity, internal heat gains (lighting and equipment) present the largest contribution (up to 70% for peak and 80% for annual demand).

At total electricity demand level, cooling set-point (P08), ventilation rate (P10), COP (P12), lighting (P05) and equipment (P06) densities all present a high contribution, both for peak and annual demand. However, for annual demand, the parameters lighting (P05) and equipment (P06) densities have the largest contribution for most sites analysed (up to 40% and 50% respectively, looking at the Sobol analysis case study). In general, the sensitivity indices for different parameters within the output variables and model types are relatively stable/consistent across the sites analysed. However, for specific simulation results (office type, output variables) some sites analysed clearly stand out. For total annual demand, the results for C1-Singapore stand out from the remaining sites and on the other hand, the results for C6-London stand out for total peak demand. The cooling requirements are significant throughout the whole year in C1-Singapore, and so the contribution of internal heat gains is smaller than for other locations. Conversely, for C6-London, due to the milder extreme weather conditions, the internal heat gains (lighting and equipment) present larger contributions for peak demand.

Relative to the second research question: "*What is the relative impact on peak and annual HVAC and total electricity demand of office buildings as cooling requirements differ with changing building design and operational conditions?*", the research findings show that the difference between the coefficient of variation (*CV)* for the annual and peak demand is different regarding sites, building types, and output metrics analysed. The *CV* or relative standard deviation is a measure of frequency distribution in a population, expressing the variability in relation to the mean. As it would be foreseeable, the uncertainty of total building electricity demand is usually larger for peak demand than for annual demand. For example, the *CV* was 29% for peak and 24% for annual demand in large offices in C4-Beijing. The differences in uncertainty between annual and peak demand is clearly related to the location (i.e. the weather conditions), and the type of office building analysed. For example, the difference between annual and peak demand *CV* values is larger for small offices than large. However, for C1-Singapore in the small office, the *CV* value is 28% for both, while for large offices is 29% for peak and 26% for annual demand.

At electricity demand for HVAC end-use level, the difference of *CV* values between peak and annual demand for small buildings is much smaller than for large and medium office buildings (it is respectively 41% vs 38 for small offices, and 40% vs 33% for large and 46% vs 30% for medium, in C4 - Beijing). By contrast, in the preliminary study presented at the CISBAT (Zeferina, Wood, *et al.*, 2019), the HVAC demand variation is significantly larger for annual demand than for peak demand (annual 108% and peak 55%). Similarly, for space cooling requirements, the findings show that the *CV* for annual demand is larger for all locations except C1–Singapore. The research findings also show that the difference between annual and peak *CV* is increasing from C1-Singapore to C6-London, and is larger for small office types (e.g. 39% vs 22% for C6- London, or 30% vs 24% for C1- Singapore, for small buildings). In terms of differences on sensitivity indices (μ^*) for different simulation cases, the values may be significantly different for different building types. For example, in large office buildings, the ventilation rate is clearly more important than for the other office building types. It seems possible that these results are due to differences in the HVAC system of each building type and the relationship of the cooling needs, and the electricity consumption of each building case analysed. These results therefore need to be interpreted with caution. More detailed analysis is required, in order to mutually evaluate the sensitivity of parameters for the different components of HVAC electricity demand, and analyse potential correlation effects.

The methods presented in this chapter have several limitations that restrict the scope and wider applicability of the research findings. For example, the sensitivity analysis of archetype office models conducted in this chapter did not include the building form characteristics, such as glazing area ratio, the ratio between the building's length and width, or expanding stretch the ratio between floor space and envelope area. These parameters were possible to iterate on the simplified office models used for the preliminary studies (Zeferina, Birch, *et al.*, 2019; Zeferina, Wood, *et al.*, 2019). However, due to DOE reference office models' additional modelling complexity, it is onerous to iterate such input model parameters recursively. The pre-analysis studies showed that these parameters do contribute to the response of cooling demand, but they have only a minor individual contribution. However, the analysis of some of these parameters' implications is still relevant, especially regarding the possible interactions that may exist with some of the other parameters considered. The lack of exploration/evaluation of the interaction effects and non-linearities of the sensitivity analysis in the studies presented is another limitation of the work done in this chapter. The relationship between σ and μ^* on Morris EE shows the linearity of the interaction of the parameters. Similarly, the differences between S_T and S_I in a Sobol sensitivity analysis are a measure for the interaction of a parameter on the remaining parameters' change. The analysis of such influences may lead to a better understanding of the effects of parameters in models. However, it also requires a larger number of simulations and increases the result analysis' detail and complexity.

The literature reviewed presented a focus on single-site studies, and not many studies have analysed the implications of different sites for the sensitivity of cooling related demand in buildings. It is not common to compare the sensitivity across different building archetypes, as the range of uncertainties of the inputs does not coincide. Mechri et al. (2010) identified that the value of a parameter's sensitivity index for cooling energy needs is similar across five different locations representing significantly different climates across Italy. In this study, similar findings were achieved on the sensitivity linked to space cooling demand. However, the effects on total and HVAC demand are significantly different, also found by Huang et al. (2018). The weather conditions significantly influence the optimal configuration of building chillers in studying the uncertainty of cooling loads. These different findings show that it is essential to have a more holistic approach to analysing the uncertainty and sensitivity of building models. Therefore, this study has analysed simultaneously different output variables and considering both peak and annual periods. It is not common to compare the sensitivity across different building archetypes, as the uncertainty range of the design and operational model input parameters are potentially distinct between the models.

The research results presented in this chapter utilises simulation cases that include several offices and considers up to six distinct sites/cities. Exploring a larger number of building archetypes, and extending the analysis to a broader range of climate conditions, or the same analysis for multiple sites in each climate zone, could give better insight on design solutions for different climate conditions and type of buildings. In the same way, the assumptions on the limits of the uncertainty range and especially on the distribution of these ranges may lead to bias in the results. Further work is required to establish the effect of uncertainty quantification assumptions, considering diversified archetypes that include more detailed and representative benchmark data. Finally, it may be interesting to analyse the implications between HVAC demand and space cooling needs, considering the requirements specifically for sensible and latent loads.

The Morris EE method undertakes an efficient sampling to screen many input parameters in a model. However, there are limitations for the use of this method. For example, it creates a sparse number of iterations throughout the input range, which for non-linear methods may create more discontinuities. In this chapter, the Morris EE method was used to compare the different office archetype models' sensitivity. In the future, it would be interesting to run global sensitivity analysis, for example with Sobol methods, for all these building types. For example, it would be interesting to explore the interaction effect analysis on the Sobol method and include the analysis of building form parameters. Besides the difficulties of recursively iterating these parameters in the current building model, the number of samples to be executed are also onerous.

For the design of new buildings or the retrofit of buildings, the research findings can inform that it is important to focus on the reduction of the ventilation rate, equipment and lighting densities, to reduce total electricity building peak load. It is also important for small and medium offices to look at ambient cooling set-point temperatures and COP of the HVAC systems. To reduce annual electricity demand, reduction on equipment and lighting energy use can have the largest contribution. However, for climates with constant large cooling demand throughout the whole year, such as Singapore, ventilation rates have the largest contribution to the annual electricity demand. For the sizing of the HVAC equipment (peak and annual HVAC electricity demand), the ventilation rate is the parameter that contributes the largest, and it is followed by the ambient set-point and the coefficient of performance. Nevertheless, changing anyone of these parameters there will be ramification for the occupants of the buildings and other non-energy performance indicators (for example IAQ or lighting requirements).

The results presented in this chapter are significant in at least two significant respects. First, peak demand change can be significantly larger than it is for annual demand, especially in climates with hot summers and significant seasonal patterns (C2-Cairo, C3-Athens, C4-Beijing and C5-Lisbon). Second, the input parameters' contribution to the HVAC demand is similar between locations, both annually and for peak demand. However, the total electricity demand contribution is strongly affected by the location, which is caused by the share of HVAC loads on the total demand. Finally, for both annual and peak demand, ventilation rate (P10) is the single parameter that contributes the most for HVAC demand, and consequently for total demand. Equipment (P06) and lighting (P05) densities are the contributors that follow for total demand, and together they can still contribute to more than 50% of demand.

4.4 Chapter summary

The research analysis presented in this chapter was aimed to understand and quantify the sensitivity of office buildings modelling to different inputs. The research findings presented have identified and quantified the input parameters on building performance simulation that have the largest influence on the cooling demand of office buildings and related electricity demand. The ranking and level of contribution of the parameters depends on the site, office building type and output metric analysed. Similarly, this research enabled to assess the cooling demand and related electricity consumption for different types of office building models, for different sites, comparing the uncertainty ranges for different output metrics and cases analysed. For example, the research finding showed that for total electricity, the response for peak demand is in general larger than for annual demand, for most of the sites and building types.

The findings presented in this chapter provide insights to address two research questions of this thesis, which were introduced in Section 1.3 and restated in the Introduction of this chapter (4.1). For the design of new buildings or retrofit of buildings, the research findings can inform that it is important to focus on minimising the ventilation rate, equipment and lighting densities, to reduce total electricity building peak load. It is also important for small and medium offices to look at ambient cooling set-point temperatures and COP of the HVAC systems. This chapter enabled us to screen the parameter range of the building model assumptions, identify estimations for what-if analysis scenarios and spot unexpected sensitivities of the models. Having a good understanding of the limits of models utilized is critical for the application of these models in the research approaches in the following chapters.

5 The effects of the uncertainties associated with climate data on the cooling demand of office buildings

5.1 Introduction

Chapter 4 aimed to understand and quantify the sensitivity of office buildings modelling to different inputs (design and operational). Thus, the thesis moves on, pursuing to understand and quantify the effects of weather data changes. Then, the research findings will enable to inform the range of potential weather changes considered in the application of the climate pathway framework presented in Chapter 6.

The main aim of the study presented in this chapter is to analyse the changes in electricity demand for office buildings due to weather variability. Firstly, it identifies and quantifies the natural variability and potential change due to climate change impacts by analysing existing sets of weather data (both historical weather data and future weather data based on climate projections). Thus, it explores the effects of weather variability using linear sensitivity analysis tests on different weather variables and so evaluates the effects for the electricity demand of office buildings. The analysis intends to identify the weather variables with the largest effect on the electricity demand, such as wind speed, solar irradiation, relative humidity and dry-bulb air temperature. The study also analyses how the electricity demand responds to these changes across different climates (six locations are analysed) and building types (three types of DOE reference office buildings are used. Consequently, this study addresses the following research question:

- How does the morphing of weather timeseries influence the peak and annual total electricity demand in a case study of archetype office buildings?

The study presented in this chapter has three objectives:

- Firstly, to explore, identify and quantify the natural variability of weather using historic datasets (Sub-section 5.2.3);
- Secondly, to identify the variability of weather metrics within two sets of weather files generated from global climate models for different locations; each set was developed using a different downscaling method to interpret global outputs at hourly resolution into city-scale weather files and used different climate models and emission scenarios (Sub-section 5.2.1 and 5.2.2);
- Thirdly to assess and quantify how individual weather variables influence annual and peak electricity demand (Section 5.3).

The structure of the chapter is as follows: first, in this section, it introduces the context of the research and the aim of the study. Second, Section 5.2 presents an analysis of the variability of different variables in several weather datasets. Third, it shows the results on the electricity demand of offices of the linear sensitivity analysis on weather parameters (Section 5.3). Then, the research findings are discussed (Section 5.4) and finally, a summary of the chapter is presented in Section 5.5.

5.2 Analysis of weather variability in existing weather data

The following part of this chapter moves on to describe the analysed changes in multiple weather variables, on different sets of weather data. This analysis intended to study the variability of variables in historical weather data, and the patterns of change of weather variables due to the impacts of climate change projections. First, an analysis of the changes of the weather variables in WeatherShift (Dickinson, *et al.*, 2016; Arup, *et al.*, 2020) data is presented (Sub-section 5.2.1), identifying the average shifts for the different levels of likelihoods and emission scenarios. Second, an analysis of other future weather data-sets generated from morphing global projections is presented (Sub-section 5.2.2), analysing the data available from the Prometheus project. Finally, a historical multi-annual data-set for all locations is analysed (Sub-section 5.2.3), identifying the variability and the deviation of these data-sets from the used TMY. This analysis collectively identified the natural variability and potential levels of change due to the climate change impacts, thus it allows a quantification of the limits of the uncertainty to explore when studying the effects of these on the cooling demand of office buildings.

5.2.1 Analysis of WeatherShift data

In the section that follows, the future weather data-sets (total of 36 files per location) generated by WeatherShift are analysed for each one of the six locations studied in this work. An analysis of several weather variables is made, such as dry-bulb temperature (DBT), relative humidity (RH), wind speed (WS), horizontal infrared radiation (HIR) intensity, direct normal (DNR) and diffuse horizontal radiation (DHR). As shown in Figure 5.1 b), annual mean DBT are estimated to increase across these locations between 3.1°C to 5.2°C in 2090, considering the emission scenario RCP 8.5 with 50% probability level.

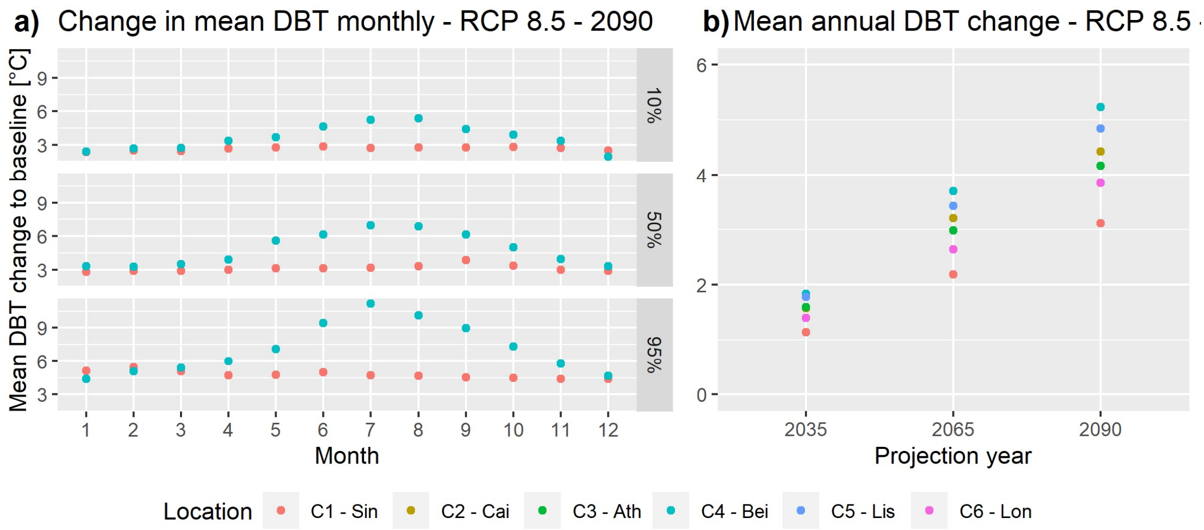

Figure 5.1 – Changes in mean dry-bulb temperature for the different location in weather data from WeatherShift a) Monthly in RCP 8.5 – 2090 and b) annually for RCP 8.5 50% probability level.

An overview of the changes in dry-bulb temperature across all locations, scenarios and timelines is presented in Figure 5.2. When analysing the DBT changes for the different projections for RCP 8.5 - 2090, it was found that these changes can go from 2.4°C (C6-10%) to 7.1°C (C5-95%). It is apparent from Figure 5.2 that the temperature change is different between locations: smaller for C1-Singapore and larger for locations such as C4-Beijing and C5-Lisbon. As can be seen from Figure 5.1 a), the difference in mean DBT for month seven, July, can be up to 57% larger for C4-Beijing than the change in the annual average value. However, the difference in DBT month average change is very small for C1 (ratio change of 15%).

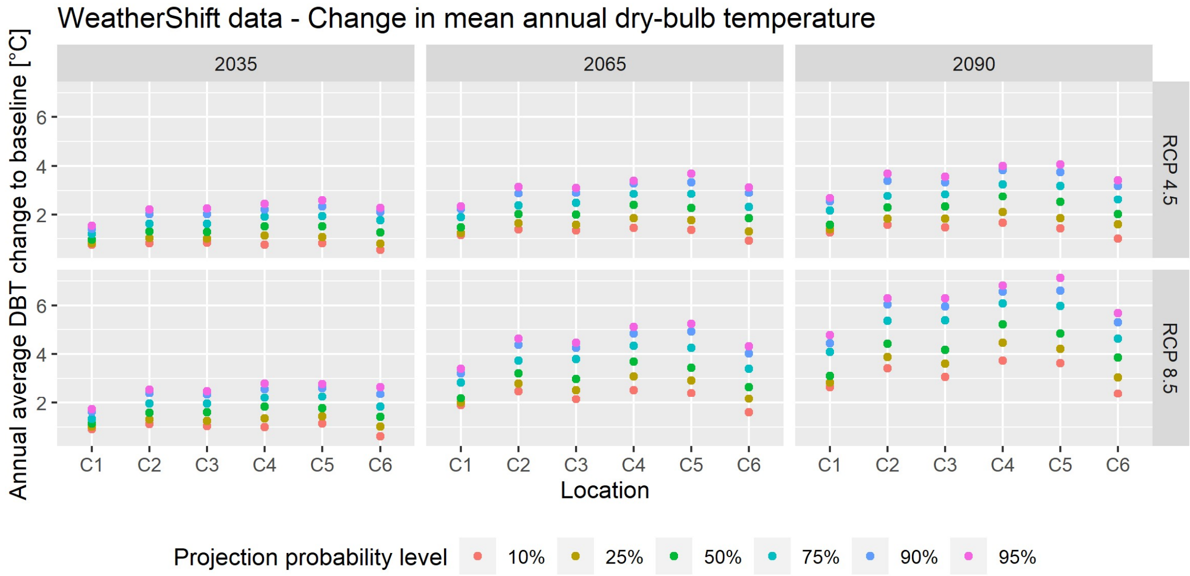

Figure 5.2 – Annual mean change in dry-bulb temperature in all future weather data from WeatherShift

Table 5.1 shows the projected change in the wind speed values for RCP 8.5 (2090 – 95%), where the largest relative change on annual mean value is 0.3% over base/original climate conditions. Monthly relative changes are at a maximum of 0.9% of the original monthly mean values. For relative humidity, as shown in

Table 5.2, the weather data-set presents drier weather conditions in the future across all locations. In C5-Lisbon, the annual relative humidity mean value can decrease up to 6.4% in absolute value. For monthly averages, the changes are larger for summer months, as shown in Figure 5.3, when RH can decrease in absolute values up to 11.4% in C5-Lisbon or 11.5% for C6-London.

Table 5.1 – Wind speed changes [$m.s^{-1}$] in RCP 8.5 – 2090 proj. prob . 95%, WeatherShift data

	C1 Sin.	C2 Cai.	C3 Ath.	C4 Bei.	C5 Lis.	C6 Lon.
Mean annual change [$m.s^{-1}$]	0.0002	0.0030	0.0018	-0.0005	-0.0007	0.0017
Growth(%)	0.02%	0.3%	0.18%	-0.05	-0.07	0.16%
Monthly max. change	0.07	0.15	0.15	0.04	0.05	0.12
Growth(%)	0.27	0.59	0.89	0.38	0.31	0.67

Table 5.2 – RCP 8.5 – 2090 – Change in relative humidity, WeatherShift data

	C1 Sin.	C2 Cai.	C3 Ath.	C4 Bei.	C5 Lis.	C6 Lon.
Mean change for proj. prob. 50% [%]	-1.1	-1.05	-2.14	-0.76	-4.40	-3.15
Mean change for proj. prob. 95% [%]	-3.2	-1.3	-3.2	-1.2	-6.4	-4.4
Monthly max. change for p.p. 95% [%]	-6.9	-2.9	-4.5	-4.7	-11.4	-11.5

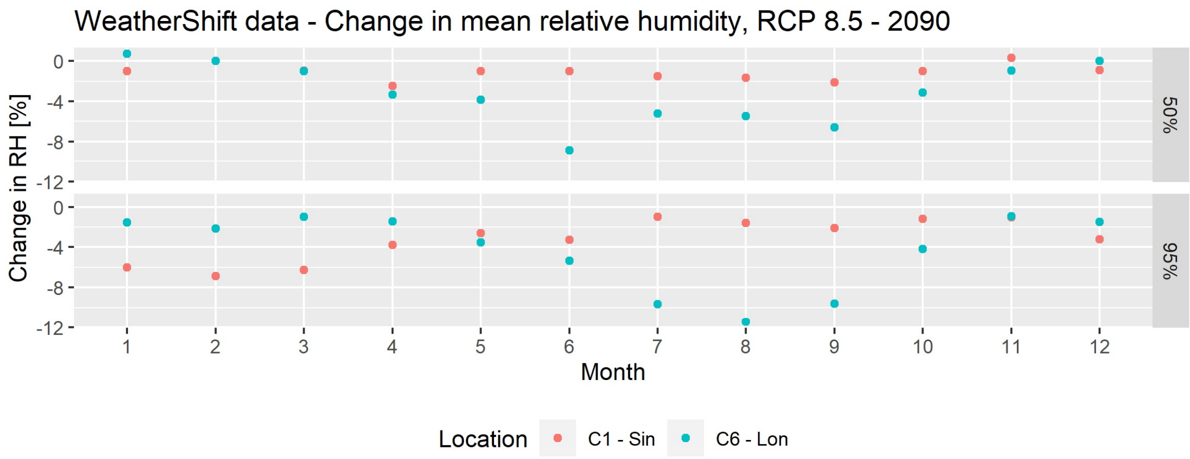

Figure 5.3 – Monthly change in relative Humidity for RCP 8.5 - 2090, location C1-Sin and C6-Lon for probability 50% and 95%

In the WeatherShift RCP 8.5 data, it was noticed that absolute changes in global horizontal (GHR), direct normal (DNR) and diffuse horizontal radiation (DHR) are precisely the same, as shown in and Table 5.3. On the other hand, there are no changes in the horizontal infrared radiation (HIR) intensity from the sky. Annual mean irradiation change (DHR, DNR and GHR) can go up to 17 W.m^{-2} (C5-Lisbon) and may represent an annual increase up to 14.2% in GHR annual mean for C6-London, with a 16.3 W.m^{-2} increase (Table 5.3). This absolute change, 16.3 W.m^{-2} in C6-London, represents a 19% and 24% annual increase, respectively for DNR and DHR.

Table 5.3 – Change on solar radiation relative to baseline, for RCP 8.5 – 2090, probability 95%

	C1 Sin.	C2 Cai.	C3 Ath.	C4 Bei.	C5 Lis.	C6 Lon.
GHR [W.m^{-2}]	7.8	3.8	15.5	6.3	17.0	16.3
Share(%)	4.1	1.7	8.1	4.0	9.2	14.2
DNR [W.m^{-2}]	7.8	3.8	15.5	6.3	17.0	16.3
Share(%)	9.9	2.0	8.9	4.2	9.7	19.3
DHR [W.m^{-2}]	7.8	3.8	15.5	6.3	17.0	16.3
Share(%)	6.0	4.5	19.9	10.4	23.0	24.1
HIR [W.m^{-2}]	0	0	0	0	0	0

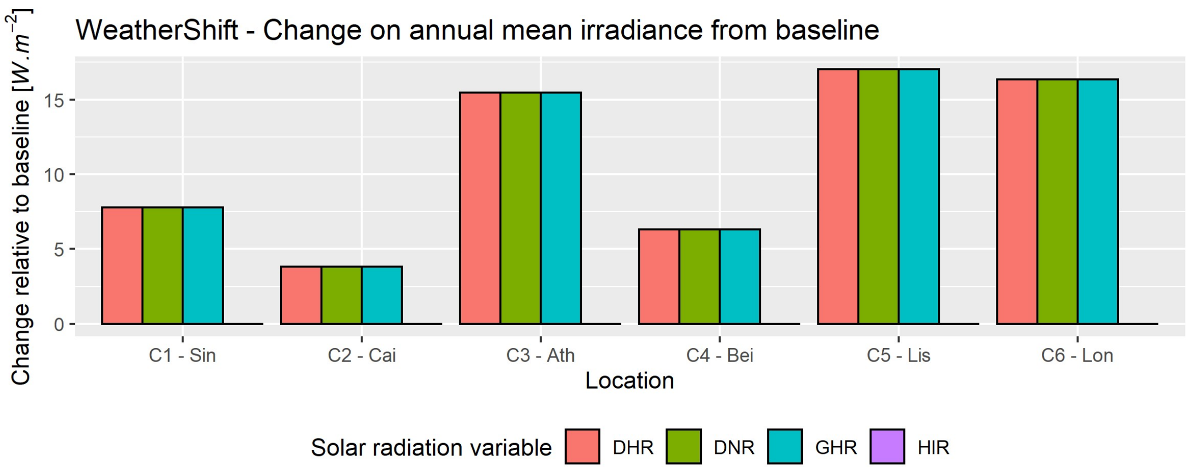

Figure 5.4— Change on solar radiation variables relative to baseline, for RCP 8.5-2090-95%, across all locations

5.2.2 Weather Analysis of the Prometheus data

Another set of future weather data downscaled from global climate projection was analysed to assess the assumptions used in the downscaling of solar radiation variables. The data analysis is focused only on solar radiation changes, as the approach used in the previous data-set (WeatherShift) was found to have discrepancies from weather changes that would be expected to occur.

The new data-set analysed is from the Prometheus project (Exeter, 2020). Table 5.4 presents the pattern of changes for the same weather variables analysed in the previous sub-section for WeatheShift data. Looking at dry-bulb temperature for London, the average change of the annual mean value is 5.8°C, but the monthly average change can go up to 8.8°C, for the A1F1 emission scenario, 2090, with 90% probability. Annual total GHR increases by 10.52%, but the yearly maximum value does not change (Figure 5.5). A similar pattern of change is identified for DNR and DHR, with changes in annual mean values of +24.32% and -0.94%, respectively. However, there are no changes in yearly maximum values. Regarding HIR, the annual mean value increase by 11.84%, and the maximum yearly increases by 27.18%.

Comparing the changes on the timeseries data for solar radiation variables for the Prometheus and WeatherShfit cases, it is possible to identify different trends in the morphing procedures. First, for the horizontal infrared radiation series, the Prometheus approach proceeds with morphing procedure, but the WeatherShift approach does not. Second, the Prometheus morphing approach shows to promote different changes for diffuse and direct radiation, and that the procedure is truncated at maximum radiation levels, making that no changes occur at maximum values. By contrast, for Weather Shift, the morphing approach for these solar variables (GHR, DHR and DNR) was precisely the same.

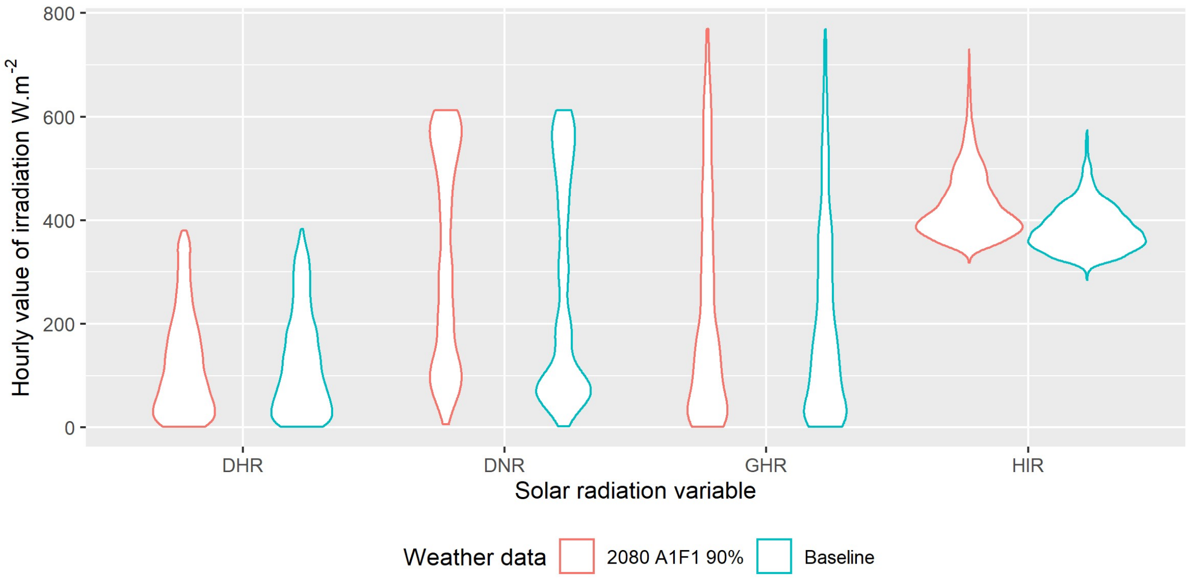

Figure 5.5 – Violin-plot of solar radiation variables (DHR, DNR,GHR and HIR) for two cases in Prometheus future weather data for London

Table 5.4 – Changes between A1F1 – 90% -2090 scenario and the baseline in Prometheus weather data for London

	DBT	HIR	GHR	DNR	DHR
Mean change	5.8°C	+11.84%	+10.52%	24.32%	-0.94%
Max. change	8.8°C	+27.18%	0.13%	0.00%	0.00%

5.2.3 Annual variability of actual meteorological year data-sets of all locations

In this subsection, actual meteorological year (AMY) data for the different locations are analysed, from data made available by climate.one.building.org (Lawrie, *et al.*, 2019) deriving the data from a number of public data sources. Therefore, an assessment and quantification of the variability of weather data across a multiple year data records is possible to be made and assess the differences to the baseline weather data in the typical weather files data records.

Table 5.5 summarises the statistical analysis made for all cities and several weather variables. For example, mean values, standard deviation across the whole data-set period, and the mean difference between AMY weather data and TMY data are presented for each city. For dry-bulb temperature, the standard deviation of the annual mean is up to 0.8°C, for C2 - Cairo and C5 - Lisbon, and the standard deviation for the annual maximum is up to 2.7°C in C6 - London. The difference between dry-bulb temperature mean for the AMY data and the respective TMY data are between +0.1°C for C4 – Beijing and +0.4°C for C2 - Cairo. The difference of the maximum annual DBT between the AMY and TMY is negative by 1.1°C and 0.8°C, for C6 and C2, respectively. However, this difference is positive for all the other cities, up to a maximum of 2.2°C for C5-Lisbon. Interestingly, annual mean dry-bulb temperature are similar between TMY data and AMY data, but maximum annual temperatures registered can be significantly different.

Looking to relative humidity, the standard deviation of the mean annual value on the AMY data is between ±1.9% for C6 and up to ±3.3% in location C4. The difference in mean values between AMY and TMY data is from -2.3% for C2 – Cairo to +1.3% in C6 - London. Looking to global horizontal radiation, it is possible to identify that standard deviation among the inter-annual mean values on the AMY data is between 2.3 $W.m^{-2}$ for C2 - Cairo and 18.5 $W.m^{-2}$ for C1 - Singapore, and the coefficient of variability (*CV*) is between ±1% for C2 - Cairo and ±10.7% for C6 - London. The deviation of the mean GHR value between the AMY to TMY data is between -3.4% for C1 - Singapore and +15.6% for C4 - Beijing. The standard deviation of GHR annual maximum is between ±4.1 $W.m^{-2}$ (C3) and ±7.8 $W.m^{-2}$(C6), while C1 – Singapore outlies with ±22.8 $W.m^{-2}$. These values correspond to CVs between ±0.4% (C3 and C4), ±0.9% (C6) and ±2.2% for C1. The difference between AMY and TMY maximum values is between -1.7% for C1 and +0.4% for C2, having an outlying value of -21.4% for C4 - Beijing.

Table 5.5 – Summary of AMY data and comparison to TMY data for the 6 locations in the simulation case

Variable	Annual	AMY Serie	C1 Sin.	C2 Cai.	C3 Ath.	C4 Bei.	C5 Lis.	C6 Lon.
DBT [°C]	Mean.	Min. year	26.7	20.9	16.6	11.1	14.9	9.0
		Mean	27.7	22.1	18.1	12.7	16.6	10.4
		Max. year	28.5	24.2	19.5	13.8	18.2	11.8
		σ AMY	0.4	0.8	0.7	0.7	0.8	0.7
		Δ AMY-TMY	0.2	0.4	0.2	0.1	0.3	0.2
	Max.	Min. year	33.0	38.0	35.0	33.0	35.0	26.9
		Mean	34.2	42.2	38.0	38.1	38.2	30.2
		Max. year	37.0	45.0	42.0	42.0	43.0	39.0
		σ AMY	0.9	1.7	1.8	2.0	2.2	2.7
		Δ AMY-TMY	0.4	-0.8	0.8	0.9	2.2	-1.1
RH [%]	Mean	Mean AMY	82.8	56.6	61.4	54.6	73.4	80.5
		σ AMY	2.0	2.2	2.2	3.3	3.0	1.9
		Δ AMY-TMY	-0.8	-2.3	-0.1	-0.8	-0.7	1.3
GHR [W.m^{-2}]	Mean	Mean AMY	184.5	240.1	205.9	189.4	194.3	126.9
		σ AMY	18.5	2.3	6.4	8.8	6.5	13.6
			10.0%	1.0%	3.1%	4.6%	3.4%	10.7%
		Δ AMY-TMY	-6.3	21.0	15.3	29.5	6.1	11.6
			-3.4%	8.7%	7.4%	15.6%	3.1%	9.2%
	Max	Mean AMY	1022.4	1033.2	999.7	988.5	993.9	883.6
		σ AMY	22.8	6.7	4.1	4.4	4.6	7.8
			2.2%	0.6%	0.4%	0.4%	0.5%	0.9%
		Δ AMY-TMY	-17.6	4.2	2.7	-211.5	-14.1	-9.4
			-1.7%	0.4%	0.3%	-21.4%	-1.4%	-1.1%
HIR [W.m^{-2}]	Mean	Mean	438.8	368.4	353.0	321.2	350.8	324.5
		σ AMY	5.9	3.7	4.3	3.8	5.7	3.1
			1.3%	1.0%	1.2%	1.2%	1.6%	1.0%
		Δ TMY	30.5	9.7	11.0	-1.5	16.0	7.8
			6.9%	2.6%	3.1%	-0.5%	4.6%	2.4%
	Max	Mean	483.0	485.0	456.1	487.1	457.1	428.6
		σ AMY	4.7	15.7	10.2	7.6	14.4	14.8
			1.0%	3.2%	2.2%	1.6%	3.1%	3.5%
		Δ TMY	22.0	8.0	21.1	0.1	-0.9	20.6
			4.6%	1.6%	4.6%	0.0%	-0.2%	4.8%

Looking to results on horizontal infrared radiation, the standard deviation of the annual mean values on the AMY data for the different locations is between 3.1 W.m^{-2} (C6) and 5.9 W.m^{-2} (C1). The coefficient of variation (*CV*) is between 1.0% (C6 and C2) and up to 1.6% (C5). The annual maximum values of the AMY data present *CV*s between 1% C1 and 3.5% for C6. The deviation of the mean of the AMY data to the respective TMY can be from -0.5% for C4 and 6.9% for C1. The deviation between the average of the annual maximums and the respective TMY data is between -0.2% for C5 and 4.8% for C6.

5.3 Analysis of the effects on total electricity demand of office buildings, due to linear sensitivity analysis of weather parameters modified through morphing procedures

In this section, the response of total electricity consumption is analysed to changes driven by linear sensitivity analysis (LSA) tests on different weather parameters, for the building energy models of three different office types. Figure 5.6 and Figure 5.7 present the maximum response of total electricity demand on the office buildings models, among the simulations iterated for each linear sensitivity analysis test, respectively for peak and annual temporal resolution. It is apparent from the results that changes in annual mean dry-bulb temperatures (test 1) drive the most significant impacts on electricity demand, both for peak and annual loads, for all office building energy models. The value of the maximum change driven for each LSA test is presented in Appendix C2, where values for peak demand are summarised in Table 0.5 and for annual demand, are summarised in Table 0.6.

For example, the shift on dry-bulb temperature annual mean (test 1) is associated with increases in total electricity peak demand between 13% (C6-London in large office) up to 27% (C1–Singapore in medium office). The screening of the summer seasonal ratio that changes the seasonal shift of dry-bulb temperature (test 2) drives changes up to 15.4% (C3–Athens in a large office), and in the minimum case by 4.9% (C6–London in a large office). The screening of the heatwave stretch parameter (test 3) imposes a change up to 9.4% for C5–Lisbon in a medium office. On the screening of the shift (negative - drier) on relative humidity (test 5), peak demand can decrease up to 5.7% (C5–Lisbon in a large office). However, in some locations (C2-Cairo and C3-Athens), reductions may only lead to peak consumptions increases of 1.3% and 3.1 %, respectively. The screening on relative humidity seasonal ratio (test 6) can lead on its own, to a reduction of 2.6%, for C5–Lisbon in a large office. The stretch on wind speed (test 4) presented the lowest implication to the peak total demand, for the three office models, up to a maximum of 1.4% (C5–Lisbon in a large office). The three LSA tests related to solar irradiations weather variables (HIR – test 7, DNR – test 8 and DHR -test 9) have shown relatively low implications on total peak load (up to +4.3%, test 7, C4 - Beijing in a small office).

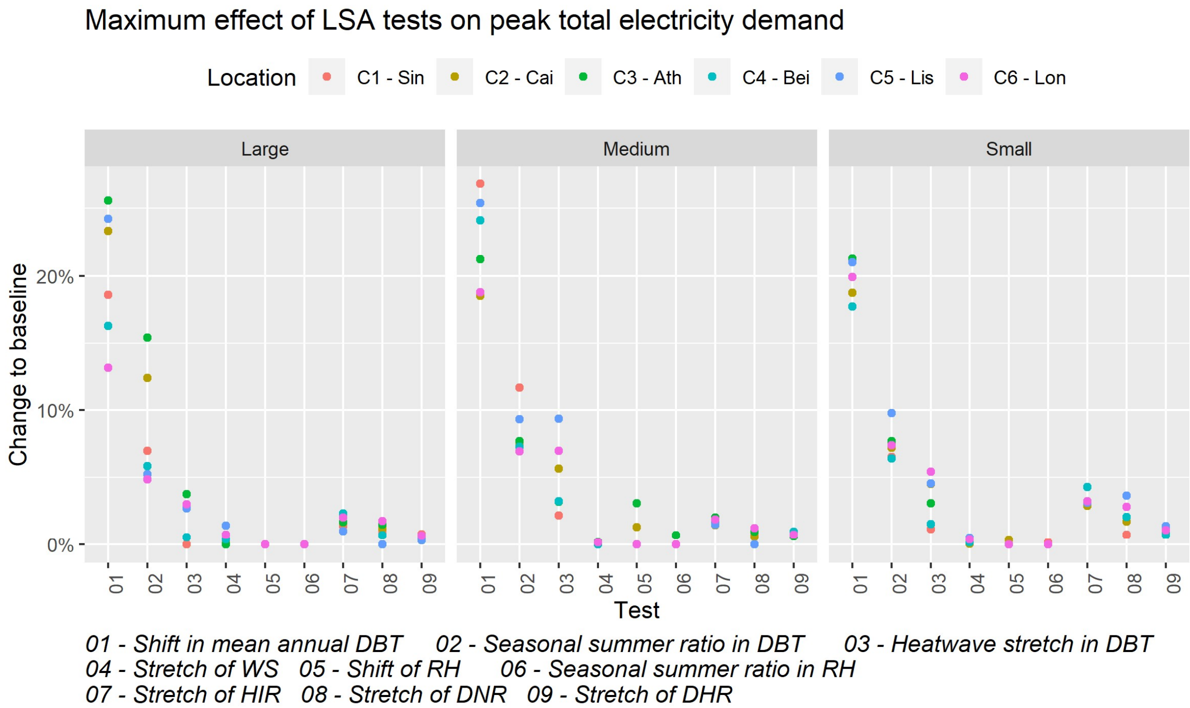

Figure 5.6 - Maximum change on peak total electricity demand for the different LSA tests executed, in the three type of offices (large, medium and small)

For the response of total annual electricity demand, the LSA ratio results are presented in Figure 5.7. The screening of the dry-bulb temperature mean annual shift (test 1) can lead to a change between 9.1% for C6–London in a small office, to up to 38% for C1–Singapore in a large office. The response to the screening of the dry-bulb temperature seasonal ratio shift (test 2) leads to a change up to a maximum of 3.1%, for the medium model, 3.4% for a small model, and 4.5% for a large office, in C4-Beijing. The response to screening the stretch of wind speed data (test 4) has shown low implications, with a maximum increase of 0.75% (C5–Lisbon in a large office). The results for the heatwave stretch parameter screening (test 3) are up to 0.5%. Shifts in the relative humidity variable (test 5) drive changes up to -5.1% for the maximum negative. The response to seasonal ratio changes (test 6) leads to changes up to -0.9%.

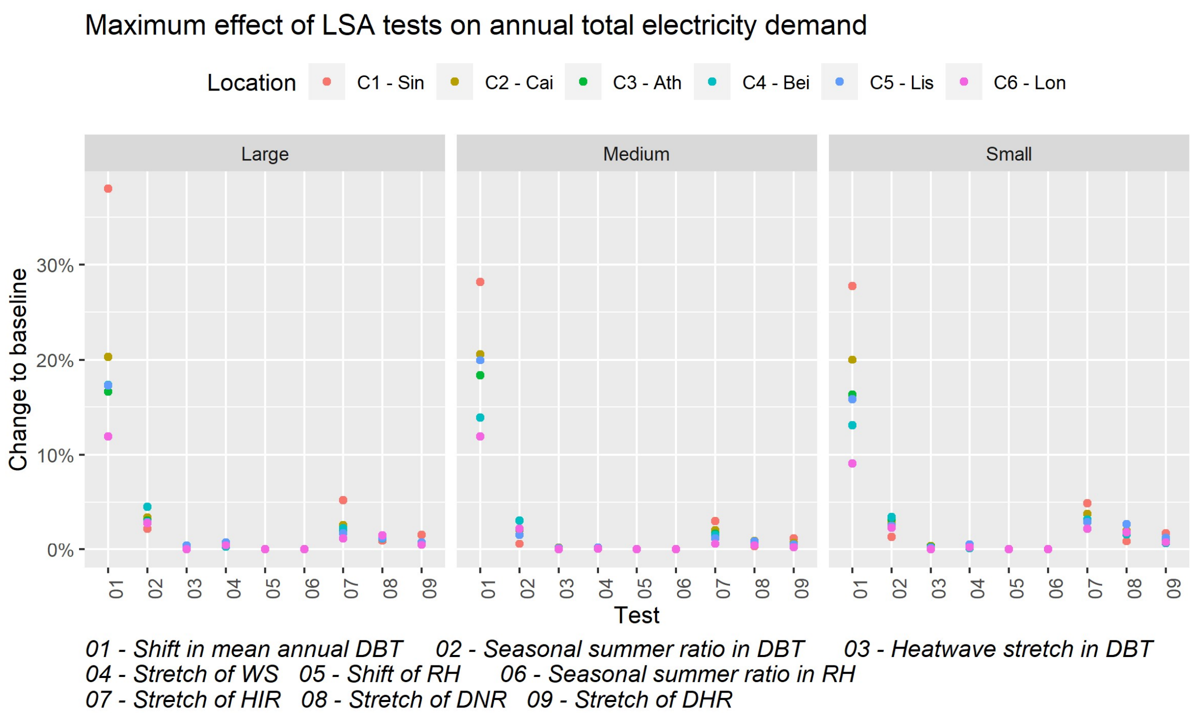

Figure 5.7 – Maximum change on annual total electricity demand for the different LSA tests executed, in the three type of offices (large, medium and small)

A more detailed percentile analysis of the result throughout the LSA series of results is provided in Appendix C2. These graphs enable to assess the relative changes to baseline in different percentiles of the annual hourly results, and it also informs on the slope of the change within the series of results in each test.

In Figure 5.8, the number of cooling hours for each simulation run in these series for test 1 is presented. For example, in C1 - Singapore cases, for test 1 – shift DBT, the change in mean hourly results is significantly higher (equivalent to annual change) than for the highest percentiles (Q95, Q99 and Peak-Q100). It is somewhat surprising that the number of annual hours requiring cooling increases significantly (from 5,503 hours to 8,021 hours, for large office type in C1-Singapore), while for other locations for the large office type, the number of hours requiring cooling tends to be steady (see: C3-Ath, C5-Lis, C6-Lon). A possible explanation for this might be that the increase in the space cooling needs during the less demanding unoccupied hours of the building does not surpass the threshold cooling value driven by the unload factor on chillers (that only exists for large office types). The same does not occur for medium and small offices, as the HVAC systems model does not include an unload factor.

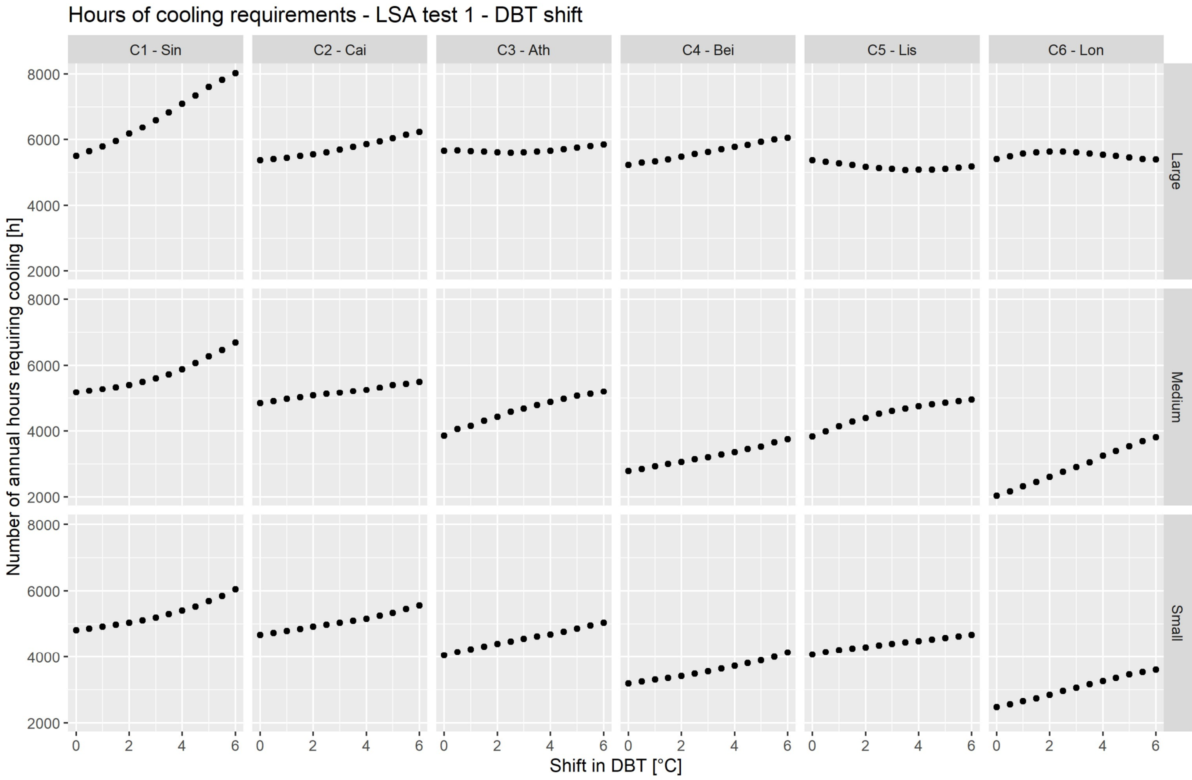

Figure 5.8 – Number of annual hours requiring cooling for the different simulation cases for LSA test 1 – DBT shift

For large office type, in C2 - Cairo and C3 - Athens, for the maximum percentile, there are sudden significant increases by the end of the Test – 1 serie (see Figure 0.3). The simulation iterations of the series where the discontinuity of the results coincide with a discontinuity/change in the time occurrence/moment of the total electricity peak demand of the simulation run. This discrepancy could be attributed to the fact that the peak demand is not only driven by the change in the DBT timeserie, but that other weather variables and building operation conditions influence the change and the occurrence of the peak demand. It is also somewhat surprising that lower wind speeds increase demand, but higher wind speeds reduce total electricity demand, when looking at the series of test 5 results (wind speed stretch, see Figure 0.6).

Figure 5.9 summarises the effect on total electricity demand in response to the LSA test on shifts in relative humidity (test 5). The most interesting aspect of this graph is that it illustrates that shifts in relative humidity can either decrease total electricity demand (if shifts are negative) or increase if shifts in relative humidity are positive. For peak load, the increase in the peak electricity load can be up to +11.5% C5-Lisbon in a large office. Interestingly, in locations C2-Cairo and C3-Athens, the screening has shown that for drier conditions (negative shift) on small and medium building models, the peak demand can increase 3.1% (C3-Athens) and 1.3% (C2-Cairo). These outlier trends may be related to the actual value of the relative humidity weather variable at the moment of peak cooling requirements of the building case analysed. For example, for C2-Cairo and C3-Athens, the relative humidity is below 20% at the timestep of the peak load, and the research approach for the morphing of relative humidity update the value for the 20% threshold assumed by the research approach (details in Sub-section 3.3.2). The linear sensitivity analysis on the shift of relative humidity (from negative to positive shift values in Figure 5.9) is less prominent for annual demand, but it can drive variations of ±5% for C1-Singapore in a large office.

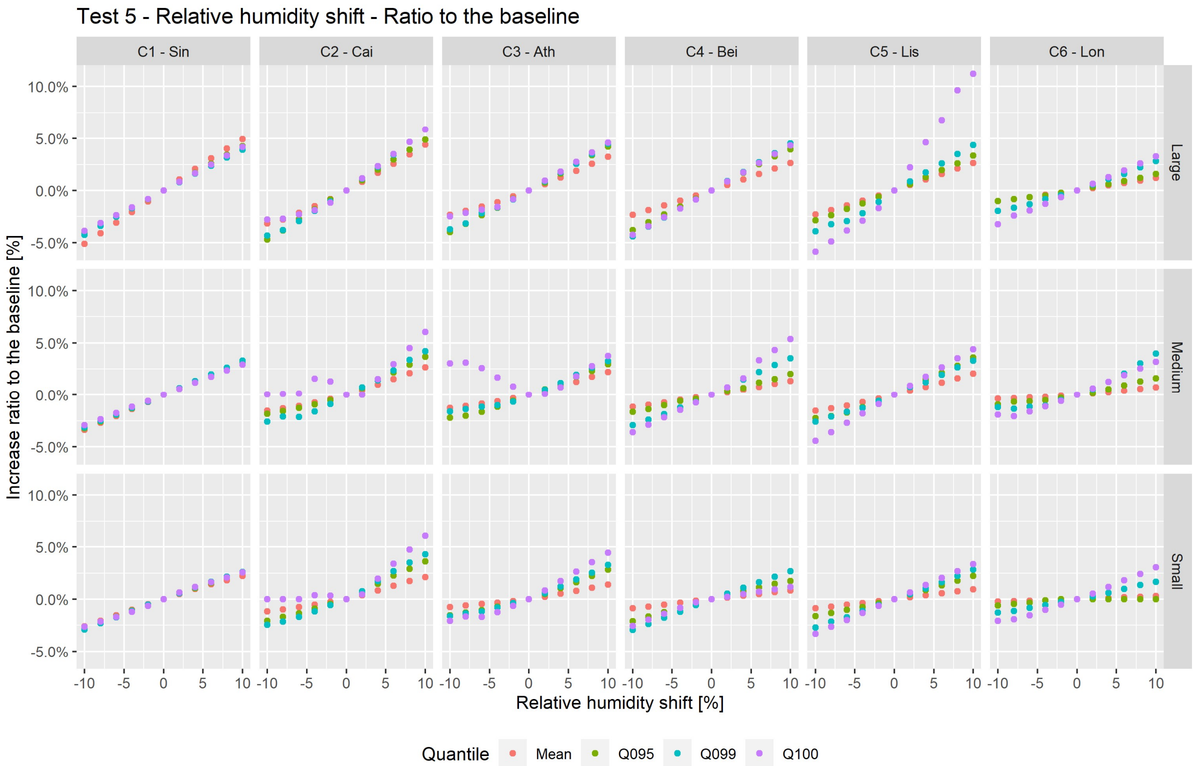

Figure 5.9 – Effect on total electricity demand in response to shifting changes in relative humidity

Figure 5.10 presents the change in total electricity demand for the LSA screening tests related to the screening of solar radiations weather variables (HIR, DNR, DHR). What stands out in this figure is that the response is consistently more significant for horizontal infrared radiation screening, both for peak and annual, across the three office models. The change can go up to +5% in annual total electricity demand for a location such as C1. In Figure 5.10, there is also a clear trend that the response is consistently larger for a small office compared to large and medium, both for annual and peak load. For peak demand, the stretch of horizontal infrared radiation (test 7) and direct normal radiation (test 8) can lead to responses up to +4.1% and +3.6%, respectively.

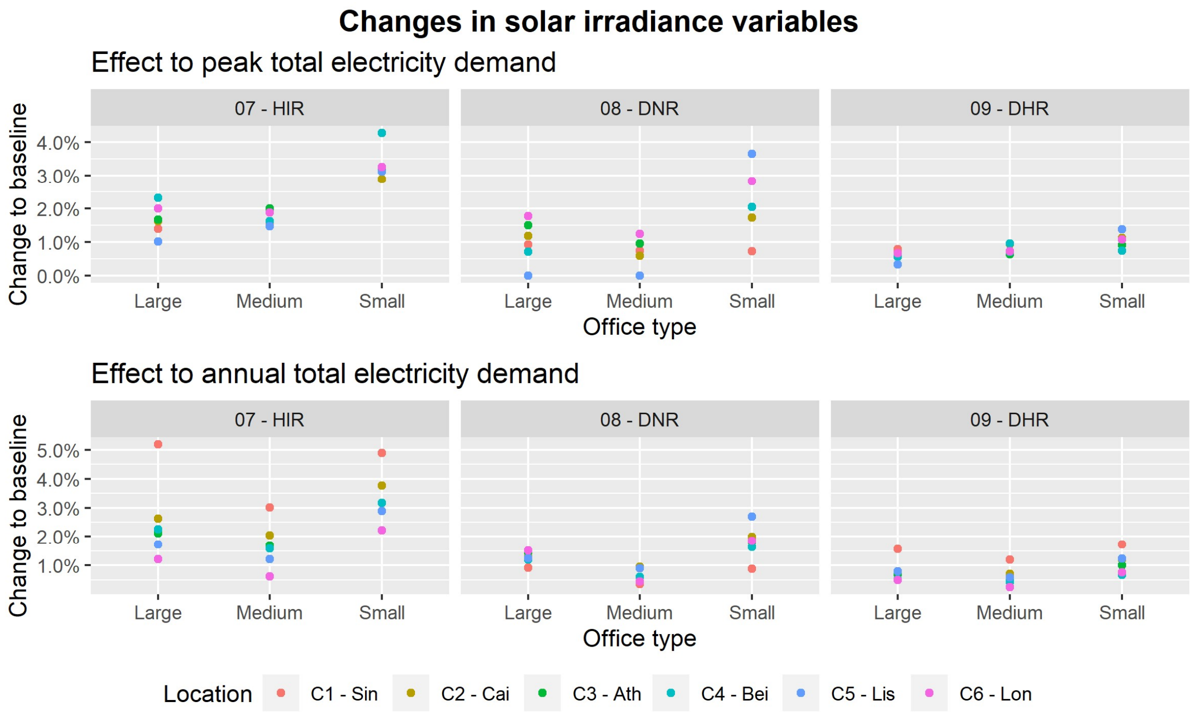

Figure 5.10 - The response of total electricity demand for LSA test on solar radiation variables (HIR, DNR and DHR)

Comparing the response of total electricity demand for the different office building types across all the screening tests, the response is slightly different for the different types of models. It is also evident that model types that are more responsive to some variables can be the least responsive to other weather variables. In addition, the significant response levels may be only evident to some of the locations analysed. For example, for solar radiation screening tests (test 7, 8 and 9), the response of small office results is larger than for large and medium office models. For the screening of relative humidity (test 5), the change in the total demand for a large office model is larger than for the other two office models, especially for the annual demand. For test 3, the stretch of dry-bulb temperature during a heatwave period, the peak demand response on medium and small buildings is consistently larger than for large office buildings. Similarly, for the other tests related to the change of dry-bulb temperature (test 1 and 2), the peak total electricity demand change seems larger for medium and small office buildings than for large models. However, this is not the case for all locations.

5.4 Discussion of the effects of the uncertainties associated with weather data on the electricity demand of office buildings

This chapter analyses the effects of morphing procedures associated with future weather data considering the impacts of climate change upon office buildings' electricity demand. This was made on a two-step approach: first, identifying the possible changes in weather data and the associated variabilities in the different variables, to have a better understanding of the factors influencing weather parameters (Section 5.2). Secondly, an analysis was made on the effects of the changing weather variables (applying morphing procedures) on office buildings' electricity demand (Section 5.3), based on a plausible range of the weather variables identified in the first step.

The analysis of the different sets of historic weather data (available in climate.one.building.org (Lawrie, et al., 2019)) and that from climate projections (from WeatherShift (Dickinson, *et al.*, 2016) and the Prometheus Project (Eames, *et al.*, 2011; Exeter, 2020)) enabled the identification of patterns of potential weather changes due to climate change as well as the natural variability of weather conditions. The analysis of future weather data-sets associated with climate change, created using morphing procedures to downscale global climate models projections, have shown that projections of future weather changes can vary substantially. The amplitude of changes varies considering different emission scenarios, timelines, and the probability of projections under each scenario.

For example, projections of annual average dry-bulb temperature changes in C5-Lisbon can go from 0.8°C (2035 – 10%) to 7.1°C (2090 – 90%) under RCP 8.5. The changes are distinct between cities analysed, as projected annual average dry-bulb temperature changes are 3.1°C (2090 – 95%) for C1 – Singapore and 5.2°C (2090 – 95%) using the same GCM outputs for RCP 8.5 for C4 – Beijing. Likewise, the impacts of climate change will lead to lower values for relative humidity, with annual average reductions of up to 6.4%. Changes in annual mean global horizontal radiation value may lead to an increase by up to 14%. In addition, the impacts of climate change will lead to lower values for relative humidity, with annual average reductions of up to 6.4%. Changes in annual mean global horizontal radiation value may lead to an increase by up to 14%.

It is also evident that the monthly changes may be significantly different from the overall annual change. For example, in some locations, the dry-bulb temperature average month shift in July is up to 58% larger than the annual average change (12°C versus 7.1°C, for C4 – Beijing). Similarly, the change on monthly mean relative humidity is much more intense in some months than it is annually. This shows that impacts of climate change may have a significant seasonal trend, being prone to have more intense warming effects during the summer season than on the remaining seasons. For maximum annual values, shifts may even be more extreme as seen for changes in maximum dry-bulb temperature.

It is important to emphasise that assumptions used in the downscaling of climate projections may lead to different trends and levels of change. For example, the WeatherShift and Prometheus weather data-sets have shown different assumptions on the morphing approaches for the temporal downscaling of solar radiation variables. The generation of weather data from WeatherShift tool does not consider changes in horizontal infrared radiation intensity (HIR), but the Prometheus approach does. On the other hand, the shift changes for direct (DNR) and diffuse (DHR) radiation on Prometheus approach is truncated, not enabling the value to exceed the current maximum values. However, these variables are shifted with no restrictions on WeatherShift approach. The variability of historical weather data (5.2.3), is in contrast with this approach, as it is reported variability of mean GHR, but low variability for maximum annual GHR. Hence, it seems that there is a potential bias due to the downscaling methods as referred in (Hall, 2014; Trzaska, *et al.*, 2014; Maraun, 2016), which may lead to entirely unreasonable trends in some weather variables, as for solar radiation.

The analysis of historic weather annual hourly data (AMY) of these locations permits to understand the level of inter-annual variability of these weather variables. The different variables' level of variance is significant, especially on DBT, where annual average temperatures were found to differup to 3.3°C (from minimum to maximum annual mean records), or the maximum annual temperatures registered in the multiple-year series were found to differ up to 12.1°C. The variance of annual mean relative humidity was found to be around 3%, and the coefficient of variance of global horizontal radiation is up to 10%. The coefficient of variation (*CV)* of the maximum annual GHR is lower than 1%. On the other hand, the *CV* of maximum HIR is above 3%. These type of variances have been reported in other weather data-sets analysis (Hong, *et al.*, 2013)

Barnaby et al. (2011) stated that it is challenging to represent all possible weather variability with a TMY data. Thus, it is possible to expect that in extreme years during their lifetime, buildings may face very different weather conditions than are represented in typical design weather data-sets used. This can lead to significant differences in model result for energy estimated demand between real (AMY) and standard typical weather files (TMY). This is often more significant for peak demand, as concluded by Hong et al. (2013). Therefore, when analysing future conditions, it is essential to consider both the natural variability of the weather and expected future changes due to the impacts of climate change.

Both the quantification of weather changes on sets of future weather data (WeatherShift in Sub-section 5.2.1 and Prometheus in Sub-section 5.2.2) and the inter-annual variability of the actual weather data (in Sub-section 5.2.3) helped to identify plausible ranges of weather conditions that may take place in the future. In summary, this allows the identification of the potential ranges in variability for the different climate parameters in the future for each location.

On the second stage of this study (Section 5.3), the implications of weather variability on the office reference buildings' electricity demand were analysed. It assessed how weather effects (through morphing procedures) the building's annual and peak total electricity demand. The linear sensitivity analysis study findings showed that dry bulb temperature leads to the largest response on both peak and annual electricity demand. However, for peak demand, changes in the seasonal ratio parameter (test 2) and the heatwave stretch parameter (test 3) present a much larger effect than for the annual demand. The change in solar radiation variables leads to an increase of up to 4%, both for peak and annual demand. The wind speed shows minimal effects on the demand, even if the changes tested are much larger than the changes estimated on climate projections. The change in relative humidity leads to a reduction of demand up to 4%.

For location C1 - Singapore, annual demand changes are larger than peak demand changes for all models. A similar finding is discussed in Chapter 4, when there is a constant high demand for cooling over the whole year, for C1-Singapore, and so changes in space cooling requirements due to building model parameter uncertainty lead to more considerable changes on annual than on peak demand. It is also possible to verify that responses differ from the building model type and the location analysed. These responses are also significantly different for the different variables tested. In the same way, for small office buildings types, demand may be strongly biased by not accounting for the potential changes in solar radiation variables, while it may be possible to neglect the implication of these variables for other types of office buildings.

Considering that dry-bulb temperature is the weather variable with the most considerable implications for building electricity demand, it is necessary to detail the downscaling of GCM projections of this variable into hourly weather data-sets. For peak demand, which is critical on the sizing of HVAC systems, it is also evident that it is necessary to account for the seasonal patterns of change and the possible trend in extreme conditions. The downscaling of dry-bulb temperature has been already identified to be critical, and that dynamic options are preferable (Hall, 2014; Trzaska, *et al.*, 2014), to account for the possible variations, seasonal and during the extremes. It is also critical for a specific type of buildings or locations to account for changes in other weather variables, such as solar radiation or relative humidity. However, there is always a compromise between the necessary effort and data requirements to generate data-sets, plus the additional simulation conditions to be computed against the building demand's accuracy requirements.

To date, little research has been paid into the analysis of the implication of weather variability on building energy demand. While research studies have analysed the singular effects of different weather variables on building performance analysis (Bhandari, *et al.*, 2012; Chen, *et al.*, 2012; Kalamees, *et al.*, 2012; Kim, *et al.*, 2017), this is the first study to investigate the sensitivity of energy demand to a range of weather modifications through morphing procedures. The approach utilised is innovative, as it isolates the effects of individual weather variables from the effects of other weather variables upon the electricity demand of office buildings.

The findings in this research have shown that the effects of the changes in weather variables may be significantly different for different locations/climates. Previous studies have only looked at a limited type of base climate condition which may infer limitations to the research findings. The research also indicates that changes in dry-bulb temperature variable presents a principal effect on the annual and peak electricity demand of the buildings analysed. Nevertheless, changes in other variables like relative humidity and solar radiation can show considerable effects on electricity demand. Previous studies have identified dry-bulb temperature as the single weather variable with more significant energy demand implications. Bhandari et al. (2012) identified that it is essential to incorporate detailed dry-bulb temperature and relative humidity data variables to analyse cooling demand in buildings. Chen et al. (2012) presented a similar finding for office buildings. In contrast to previous studies, this research has provided evidences that the pattern of change in dry-bulb temperature (seasonal ratio test 2 and heatwave stretch – test 3) present significant implications for the effect on electricity demand. On the other hand, Kalamees et al. (2012) and Kim et al. (2017) utilised the same research approach to modify weather data in the same geographies, but presented contradictory findings on the relevance of weather parameters changes for energy demand of buildings. It suggests that modelling assumptions and modelling methods may lead to considerable difference on results.

The independent transformation of weather variables values used in this study enables the identification of the impact of each weather variable change on the electricity demand. Therefore, the analysis enables the critical weather parameters to be identified for different building performance simulation outputs (sizing, annual energy demand or peak energy demand). Having identified the critical weather parameters for different types of simulation studies here, it may be possible to know when simplifying the downscaling operation for some weather variables such as wind speed or related solar radiation variables is appropriate, for example when looking at annual demand. Whereas for peak load analysis, it may be necessary to apply approaches that capture the more extreme shifts on dry-bulb temperature, with different time resolution for shift and stretch parameters used to generate downscaled weather data.

Real weather data-sets contain climate variability, and it is not possible to isolate the changes on one variable from the remaining (Guan, *et al.*, 2007). Therefore, the independent and individual screening of weather variables studied in these tests is not expected to occur in real weather data and is an explicit limitation of this study. However, the approach aims not to deliver precise results but to understand the propagation of weather uncertainty in building performance simulation outcomes. To pursue a reliable understanding of the variability of individual weather parameters on the response of cooling demand in office buildings, it is necessary to decouple analysed weather variables from the potential response noise effects from other weather variable changes. Rastogi (2016) has also discussed that synthetic weather data may contribute to a more robust assessment of building design solutions.

The synthetic weather data-sets created to perform these analyses are not representative of real weather conditions. The creation of these specific synthetic files enabled the exploration of the effects of designed weather variables changes. For example, it allows the exclusion of the possible contribution of other weather variables and focuses exclusively on the effect of the changes in one particular weather variable. This approach enables the further understanding of the effects of weather changes on building energy performance, but there are limitations on the scope of the findings, as it was done only for a limited range of locations and type of buildings. The complexity of the building systems and the interaction of multiple variables may lead to different trends. Similarly, these findings were considered using EnergyPlus, and specific algorithms for the internal thermal calculations. It would also be interesting to understand the implication of similar tests on different main thermal engines (IES or TRNSYS). Even different internal EnergyPlus processing algorithms may have different implications for results.

This study allowed the quantification of the implications of the variability of several weather variables on the annual and peak total electricity demand for office buildings. In addition, this study identified and ranked the weather variables that have larger implications for the electricity demand for office buildings. These findings enable trends across locations and type of office buildings to be identified, and make it possible to adapt the morphing procedure of each weather variable differently, in the generation of future weather datasets. The approach taken to generate the weather data-set may differ depending on the target output variable for different locations, or building types analysed.

5.5 Chapter summary

The main aim of the work presented in this chapter was to analyse how does weather uncertainty influence the peak and annual electricity demand in office buildings. However, it was necessary two divide the approach in two distinctive stages: first, analysing weather variability in existing weather datasets and; second, analysing the sensitivity of electricity demand of office buildings to changes in the different weather parameters. A summary of the main findings:

- Changes may be significantly larger during summer than annual changes;
- Differences on morphing approaches of solar radiation create significant differences on changes of these variables;
- Dry-bulb temperature is the variable that clearly contribute the most for change in electricity demand, both for peak and annual demand;
- Sensitivity for seasonal changes and stretches in heatwave periods show significant contribution for electricity demand for peak demand.

The research findings in this chapter are important to understand the effect of different climate change projections for the electricity demand of buildings. Having quantified these effects on the models and mapping the range of potential changes due to the impacts of climate change for the different weather variables, it is possible to develop alternative approaches to generate synthetic future weather files. These type of files, can be used to map a pathway of potential climate change states, that can robustly and continuously assess the effects of climate change to building energy performance

6 The impacts of climate change under a climate pathway and the effects of adaptation measures

6.1 Introduction

The previous chapters presented the results of sensitivity analysis on cooling demand of office buildings regarding uncertainty in design and operational energy modelling parameters and the effects of weather morphing procedures. Thus, those findings provide a detailed understanding of the implications of the energy modelling assumptions and give an insight on the potential impacts of climate change on sample reference office buildings electricity demand for cooling.

To date, most of the studies looking to the impacts of climate change in buildings have only been carried out in limited deterministic future conditions; hence, there has been few solid analyses of the effects on the electricity demand for cooling in a broad range of buildings and conditions. In addition, the generation of future hourly weather data-sets, that is required for dynamic building simulation, requires complex efforts, weather data and climate projections to produce. Therefore, heuristic approaches are often used to assess the impacts of climate change on building energy performance. Instead, deterministic approaches are made by discrete examinations of future scenarios using an ensemble set of future weather scenarios. Existing analyses are also limited in the number of building technologies/designs scenarios used and the locations considered. Regarding research on the effect of adaptation measures to mitigate the effects of climate change, it is concluded that combined sets of different adaptation measures are utilized to reduce the complexity and number of simulations required. Therefore, this study has prepared a methodology and applied it in a case-study to address some of these research gaps.

In the study presented in this chapter, a climate change pathway, reflecting climate change projection scenarios, is created to provide a range of possible weather conditions, and the effect of these on the electricity demand of office buildings for cooling are analysed. More specifically, the effects of extreme weather conditions in the climate pathway for the peak and annual electricity demand of the office buildings are quantified, at a total and HVAC end-use level. After quantifying these potential impacts, the study uses the climate pathway approach to evaluate the potential reduction effects of a set of adaptation measures, comparing to the base case impact scenario.

Nik et al. (2020) emphasised the need to develop methods that consider climate uncertainties, as well as to account for high stochasticity and multi-dimensional impacts of weather uncertainty, for assessing climate resilience of energy systems. To fully assess climate risks for building operations, it is necessary to screen a much wider range of potential climate scenarios, and including a large range of design assumptions. A number of researchers have utilised an ensemble of future weather files from WeatherShift to reflect a broad range of climate change scenarios and have elevated building energy performance (Moazami, *et al.*, 2019; Troup, *et al.*, 2019; Berardi, *et al.*, 2020).What remains unclear, however, is precisely how the effects of global warming for building performance occur throughout the potential path of progressive impacts climate change, for any given location in the world.

Specifically, the study will address the fourth research question of this thesis, presented in Section 1.3: “To what extent could the electricity demand of office buildings be affected by changes in cooling demand due to the impacts of climate change, given a wide range of future weather scenarios?”. Thus, the climate pathway method is applied in the proposed case study of this thesis, to study the effects on electricity demand for cooling, on three different types of office buildings, for six different locations in the world. The effects for the peak and annual electricity demand, both on total and HVAC end-use are studied (Section 6.3). In addition, it is quantified and compared the effect of different adaptation measures in reducing additional cooling demand during this pathway. The specific question which drives the research in this second part of the chapter (Section 6.4) is the fifth and final research question of this thesis: “To what extent and magnitude could a potential increase in electrical peak load due to cooling provision be limited in future scenarios by adaptation measures?”.

6.2 Analysis of weather variables in the climate pathway

In this section, an analysis of the weather changes throughout the climate scenario pathway and across the weather variables is made. Figure 6.1 presents the spectrum of values for the different weather metrics for the different locations across the pathway, namely presenting the annual values for mean DBT, maximum DBT, CDD, mean DNR, and mean HR. Looking at the distribution of values on the climate pathway for the different location, in Figure 6.1 b), relative to mean HR and mean DBT, it is possible to identify the same distribution pattern for all locations. This is due to the fact that the changes made to each location base weather file are the same for all locations.

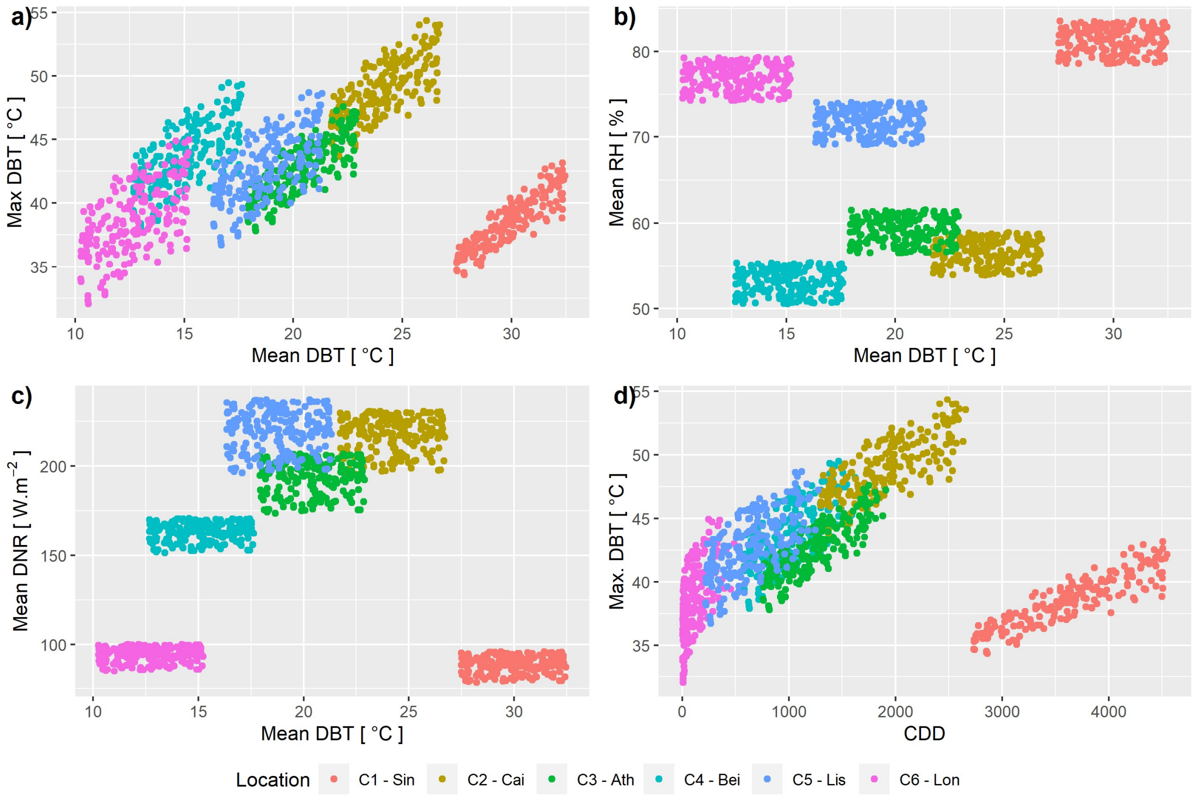

Figure 6.1 – Distribution of different weather metrics in the whole pathway sample for each location: (a) CDD, (b) maximum DBT, (c) annual mean DBT and (d) Mean DBT/Max. DBT

On the other hand, the changes for maximum DBT or DNR are different among the locations, as can be observed in Figure 6-1 (a) and (c), respectively. In Figure 6-1 (b) or (c), it is also possible to observe that the distribution of samples in the space is not entirely uniform, which is explained by the method and the number of iterations used to generate the sample. However, the space range is widely covered, and this approach may be sufficient to explore the effects of conditions represented in the scenario pathway.

Figure 6-1(d) shows the changes in maximum DBT and CDD across the scenario climate pathway for each location. It can be seen that maximum DBT within each location increases in different scales, and the amount of change in CDD is also distinct. This is because each location presents different weather patterns, that are captured in the base weather file. Therefore, for each location, when stretching DBT in extreme periods of these datasets, changes are more extensive for baseline datasets that show larger DBT amplitudes. In Table 6.1, the delta between maximum DBT observed in the scenario sample and original weather datasets maximum DBT is also presented. For location C6-London or C5-Lisbon, changes can go up to 13.7°C and 12.7°C, respectively, and only 9.3°C for location C1-Singapore.

Similarly, CDD will increase in larger amounts for climates with larger original average temperatures; however, relative changes are more extensive for climates with lower CDD. For example, in location C1, CDD is increased by 1821 degree days (67%). In contrast, for C6-London, there is an increase of 481 CDD (7117%). The range of change in average DNR is also slightly different among locations. For C5-Lisbon it goes from 195 to 241 W.m^{-2} (+24%), and for C1-Singapore it goes from 76 to 96 W.m^{-2} (+26%). Observed weather changes in the weather pathway created for each location are similar and, on average present similar levels of changes. However, the level of change for extreme and for CDD requirements is not the same which is expected. Weather changes will be unique for different conditions, therefore, attempting to uniformise methods and levels of change across different locations may lead to additional discrepancies.

Table 6.1 – Analysis of weather metrics in the pathway sample for each location

Location	Max. DBT [°C]	Original Max. DBT [°C]	Δ Max. DBT [°C]	Max CDD	Original CDD	CDD ratio [%]
C1–Singapore	43.1	33.8	9.3	4545	2724	67
C2–Cairo	54.3	43.0	11.3	2657	1291	106
C3–Athens	47.6	37.2	10.4	1910	754	153
C4–Beijing	49.5	37.2	12.3	1623	577	181
C5–Lisbon	48.7	36.0	12.7	1278	218	485
C6–London	45.0	31.3	13.7	488	7	7117

6.3 Impacts of climate change for electricity demand of office buildings applying the climate pathway

In this section, the effects of the possible impacts of a synthetic climate pathway on office building electricity demand are evaluated. First, in Sub-section 6.3.1, the effects on total electricity demand on both annual and peak conditions are analysed. Next, in Sub-section 6.3.2, the effect on HVAC electricity end-use is analysed for annual and peak resolutions. Finally, in Sub-section 6.3.3, the effects on demand due to the impacts of climate change represented in already existing future weather files for building simulation are compared to the results obtained for the climate scenario pathway generated, for each location.

6.3.1 The effect on total electricity demand under the climate pathway

In Figure 6.2, the total peak demand results for all model runs included in the climate pathway is presented. Results are presented for each location and grouped by the type of office building. Peak demand results are presented in ascending order for each building type and each location. Looking at the whole climate pathway, it can be seen that the total electricity peak demand can increase up to a maximum of 62.3%, for the medium office model in C5-Lisbon. For other extreme case conditions, the rate of change is below 40% for the same building type (medium office building) in other locations. For example, in locations C2–Cairo, C3–Athens or C4-Beijing, the changes are 38.6% or 39.5% and +36.5%, respectively. For large office buildings, changes in peak demand are smaller, and the lowest rate of change on the most extreme condition of the pathway is 25.6% for C4-Beijing, followed by 26.3% for C2-Cairo. From the results presented, it can be seen that changes in peak demand are significantly larger for medium office building types, and the lowest for large office types, generically across all locations.

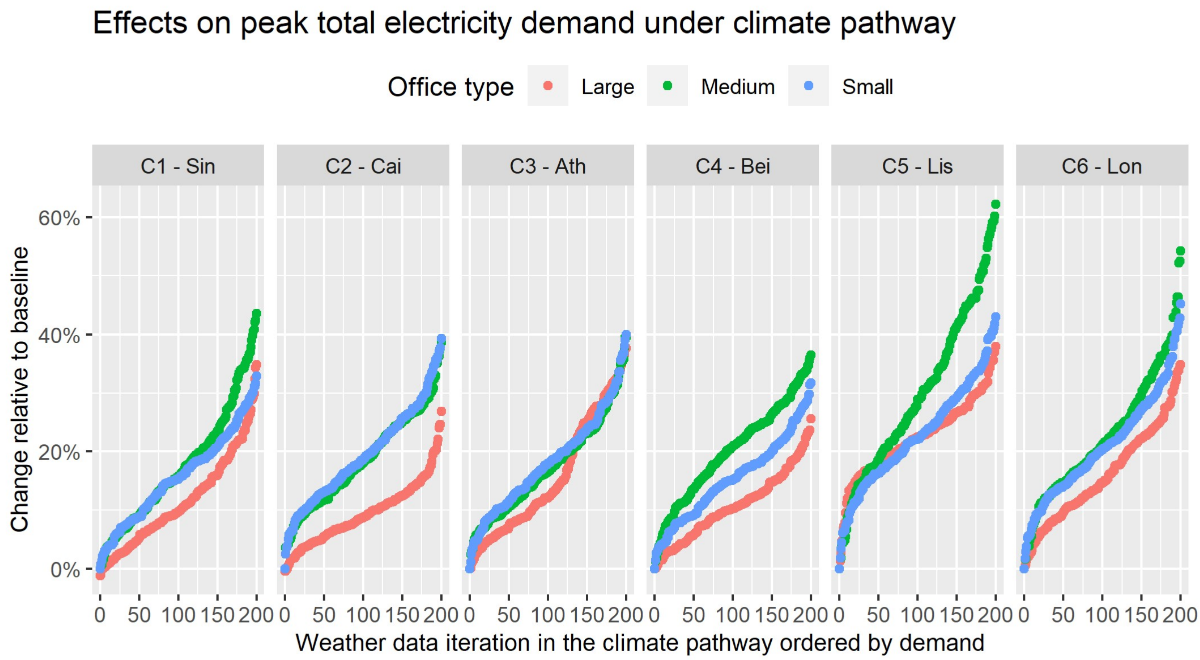

Figure 6.2 – Normalised rate of peak demand change for total electricity along the weather pathway, for all locations and grouped by office building type

In Figure 6.3, the effects on annual total electricity demand are presented. For large office buildings in location C1-Singapore, the increase in demand at the end of the scenario pathway is up to 37.7%. On the other hand, for location C6-London, the change in annual demand for the most extreme weather condition in the scenario pathway is up to 15.4%, 13.1% and 13.4%, respectively for large, medium and small office buildings. Changes in annual demand are generally larger for locations with larger CDD, as can be seen by the decreasing rate of change from location C1-Singapore to C6-London. The mean annual demand rate change for the pathway is 16.8%, for large buildings in C1-Singapore and only 5.3% for medium office buildings in C6-London, more than a three-fold difference. The trend of the progression of the total annual demand across the pathway approximately presents a linear trend for the first three quantiles (75% of the sample), when it shows an inflexion point, and then it observed a larger linear relationship in the last quantile. This points to a tendency for a larger additional total electricity consumption at the extreme end of the pathway.

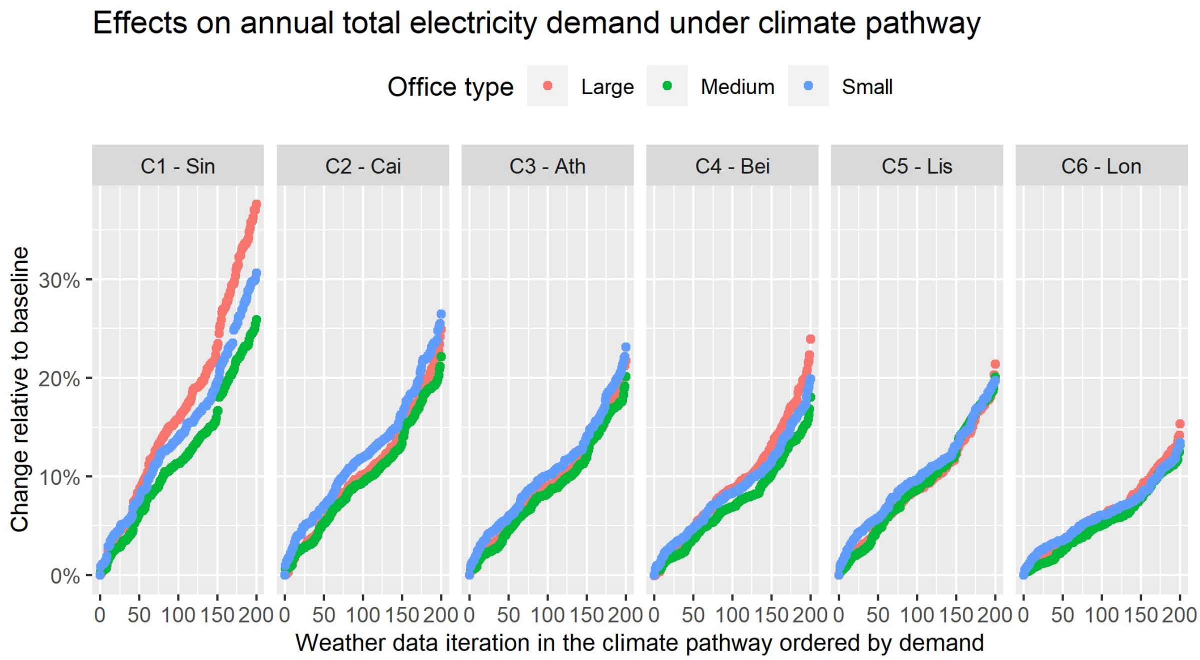

Figure 6.3 – Normalised rate of annual demand change for total electricity along the weather pathway, for all locations and grouped by office building type

Comparing the increase in total electricity peak demand to the increase in annual demand, the rate of change on the peak demand is substantially larger than for the annual demand, for most buildings and locations. For example, the mean rate change of the peak demand across the scenario pathway differs 20% in absolute terms from the respective annual demand change for medium office buildings for location C5-Lisbon or 17% for C6-London. However, this difference is substantially smaller for location C1-Singapore, which for medium buildings is 1% larger. For large buildings, annual demand is even larger than average peak change, for location C1-Singapore and C2-Cairo. Across all locations, the difference between peak and annual demand change rates is much smaller for large buildings. In Appendix C3, Table 0.7 and Table 0.8 present a summary of the changes in total electricity throughout the results under the climate pathway, respectively, for peak and annual temporal resolutions.

6.3.2 The effect on electricity demand for HVAC end-use under the climate pathway

In this sub-section, the changes in electricity demand for HVAC end-use are presented. First results for peak demand (Figure 6.4) are presented and then the results for annual demand resolution (Figure 6.5) are given. Changes for peak demand can go up to 158% in location C6-London or 145% in C5-Lisbon, for the medium office building. The change on the end of the scenario pathway is significantly smaller in other locations, as low as 56.4% for large office buildings in C4-Beijing, or approximately 62% for medium office buildings (C4-Beijing). The average change of HVAC peak demand on the pathway can be as high as 70.3% for C5-Lisbon location (Medium) or 65.7% for C6-London (Medium). However, for the large office building, the mean average change is approximately 25% for locations such as C1-Singapore, C2-Cairo or C4-Beijing.

Table 0.9 and Table 0.10 presented, in Appendix C3, present a more detailed summary of the changes in demand throughout the pathway, respectively, for peak and annual demand.

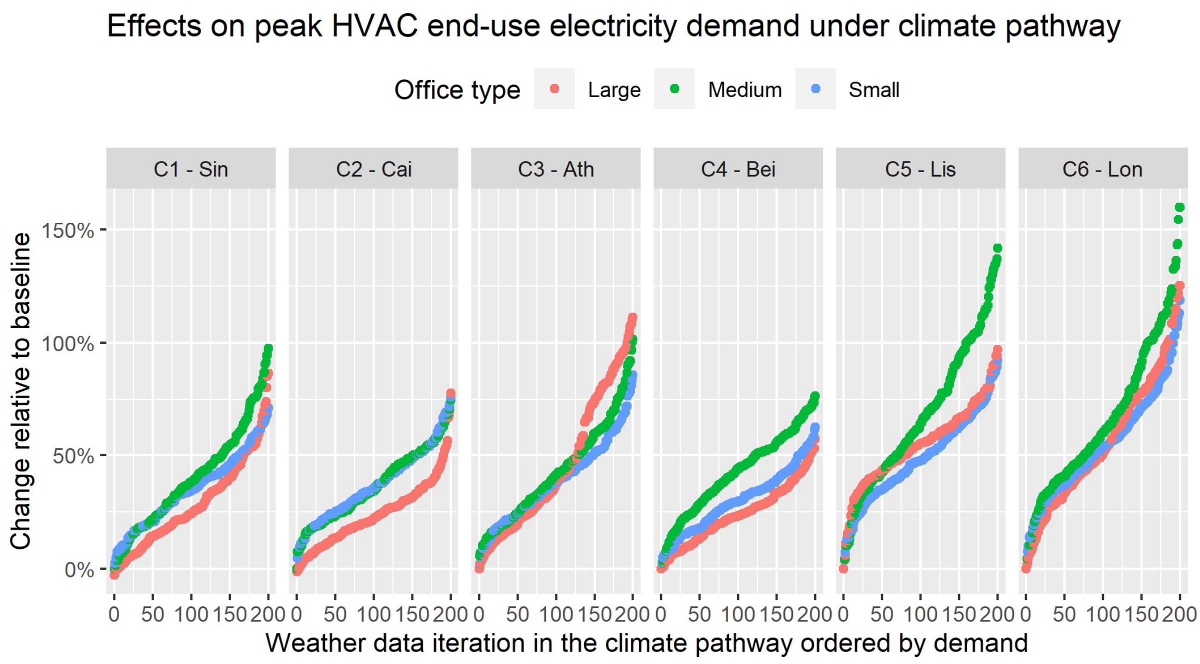

Figure 6.4 – The implication of the climate pathway for HVAC electricity end-use peak demand

Changes in annual electricity demand for HVAC end-use are presented in Figure 6.5. The change in annual HVAC demand on the extreme end of the climate scenario pathway is up to 182% in location C6-London, for the medium office building. For small office buildings, the trend of the rate of change on the scenario pathway sample is similar across all locations. At the extreme warmest end of the sample, the rate of change is approximately 75% of the original level, and the mean rate of change across the pathway is 35%. The lowest rate of change at the end of the samples is in C1-Singapore and for the medium office buildings, where it is 64%. The mean average rate of change is the largest in the location C6-London, for the medium office building, with a value of 75%, and followed by C5-Lisbon with 53%.

On the other hand, for medium office buildings, the mean rate of change is only 29% in location C1. Among different locations, changes tend to be more significant for location C6-London, and then for location C5-Lisbon. For location C6-London, medium office buildings present the larger rate of change across the scenario pathway, followed by large office types and the last are small office buildings. This trend is also evident for location C5-Lisbon, but differences are relatively smaller between building types. For example, in location C1, medium office buildings have the smallest degree of change, and large buildings present the most considerable change.

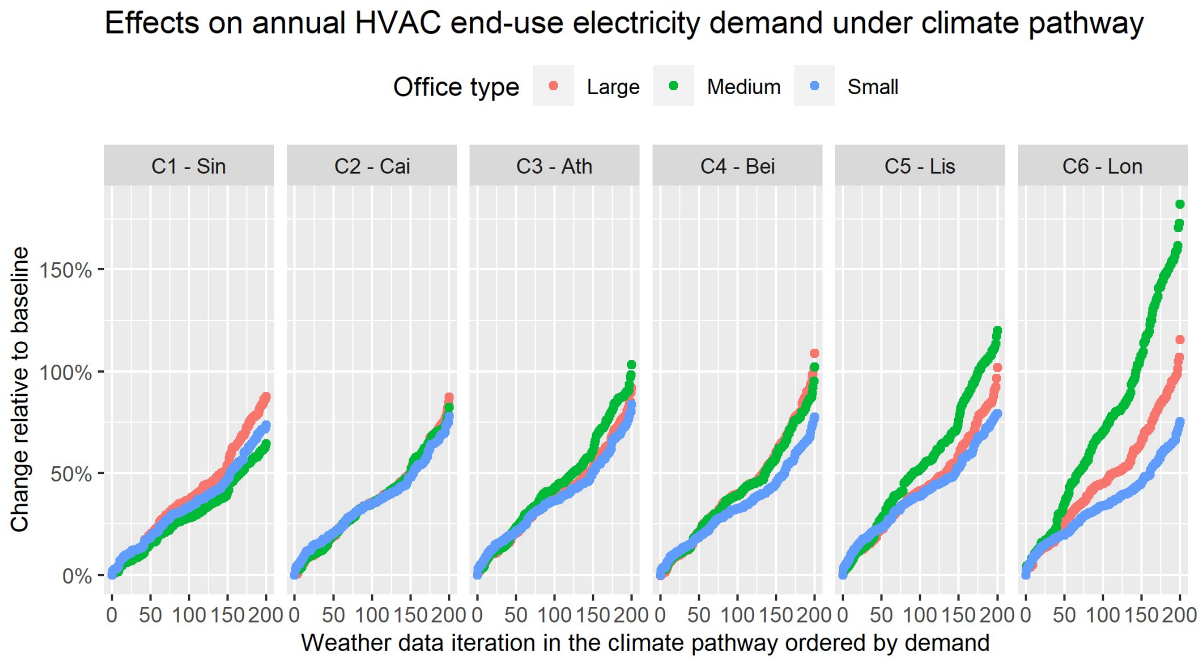

Figure 6.5 – The implication of the climate pathway for HVAC electricity end-use annual demand

Closer inspection of the evolution of annual HVAC demand throughout the climate pathway sample, categorised by end-uses as presented in Figure 6.6, the distinct responses across different locations and office types can be observed. Looking at results for C6-London, it becomes evident that changes are the most significant for medium offices, as the change in cooling end-use is much higher in relative terms of the whole HVAC load. Thus, even if the cooling category increase is similar, from 0.5 $W.m^{-2}$ to 1.5 $W.m^{-2}$ for the different offices, the change in the whole HVAC demand is much sharper for medium building (from around 0.75 $W.m^{-2}$ to 2.25 $W.m^{-2}$ for medium offices, versus around 1.5 $W.m^{-2}$ to 3.2 $W.m^{-2}$ for large offices). In addition, changes are larger for C6-London than for C1-Singapore, as the non-cooling components (fan, heat rejection and pumps) present a large share of the whole HVAC annual load.

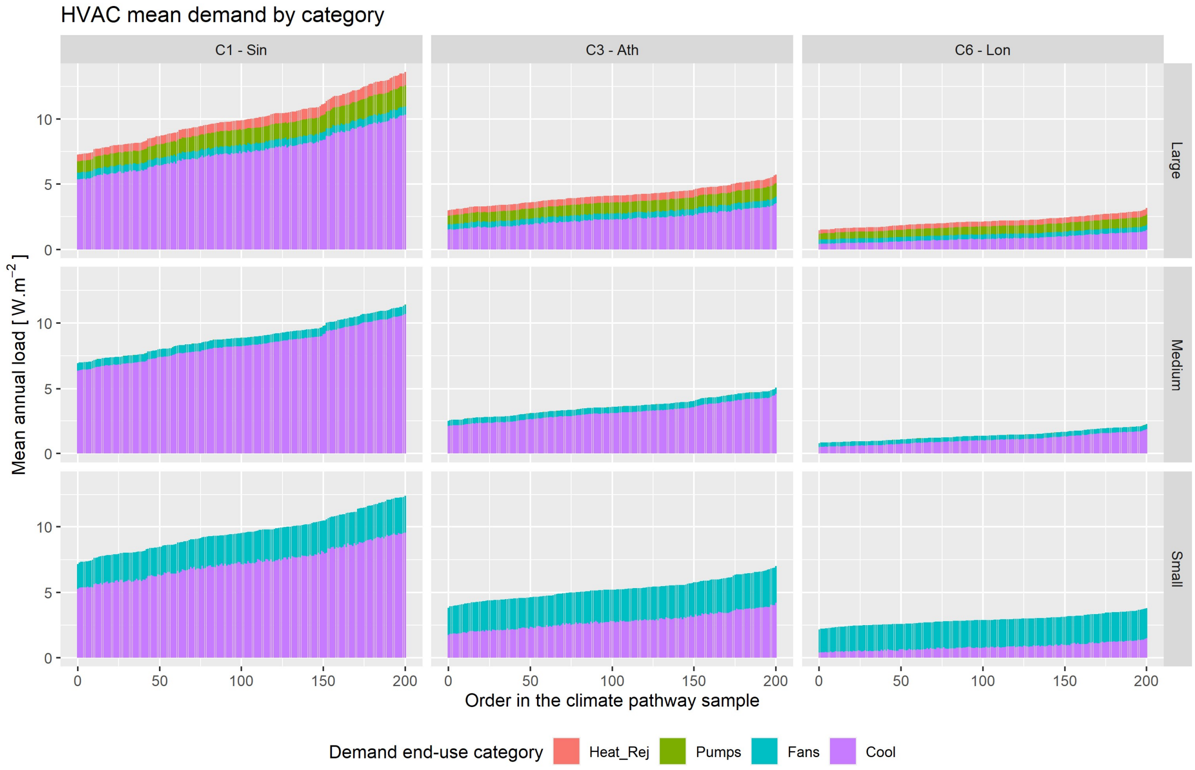

Figure 6.6 –Annual HVAC demand stacked by different end-use categories, for locations C1-Sin., C3-Ath. and C6 – Lon.

Turning to the peak demand on HVAC demand, detailed by different end-uses in Figure 6.7, it is striking that the increase in cooling component is much larger for medium offices than for large offices. It is also apparent that there is a sudden rapid increase for large buildings, for some locations (C3- Athens and C5-Lisbon), throughout the climate pathway sample. The detailed analysis by end-use reveals that these changes are due to increases in the fans end-use (e.g. C3-Athens around position #150, C5-Lisbon around position #25). Similar trends are also present, for medium offices, for location C5-Lisbon or C6-London, by the end of the climate pathway sample. A possible explanation for this might be that the ventilation rate due to additional cooling requirements is increased. These hypotheses are related to the research finding in Chapter 4, where it is indicated that ventilation rate is indicated to be one of the parameters with the main contribution to the sensitivity of peak electricity demand, and it is even more evident for large offices.

Similar trends were observed for total peak demand (see figure Figure 6.2); though, the ratios of changes are significantly smaller. That is the case once the non-HVAC end-use (other) load is included in the total demand, diluting the relative rate of change. Looking at total annual demand, demand increases for C-Singapore much more than for the other locations, and that can be explained as the HVAC share represents 43% of the total in C1-Singapore and only 13% in C6-London, for the baseline condition for large offices cases. In addition, what stands out is that annual demand for large offices increases at a larger rate, mainly for location C1. Like what was observed in the LSA tests analysis, comparing the change in the different hourly quantiles, the increase for this building is only larger at lower percentiles (see Figure 0-18).

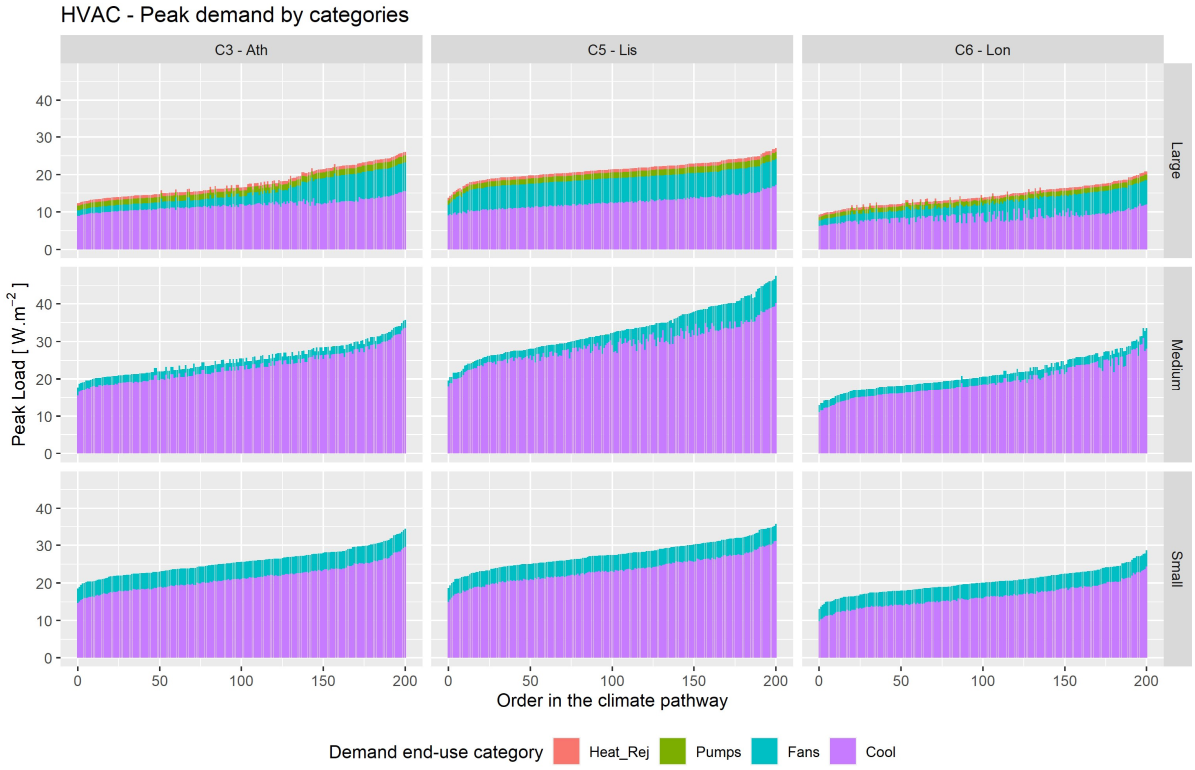

Figure 6.7-Peak HVAC demand stacked by different end-use categories, for locations C3-Ath., C5-Lon. and C6 – Lon.

6.3.3 Comparison of pathway results with weather data from existing weather generators

In this sub-section, the distribution of the results for weather data from existing weather generators into the results from the pathway is analysed. Figure 6.9 and Figure 6.8 show the comparison of the results relative to the baseline between the existing weather data and the weather data from the pathway sample, respectively, for peak and annual demand. It can be seen that these existing weather data cover a broad range of the results from pathway data both annual and peak demand. This means that the climate scenarios represented in the existing future weather files are included in the space covered by the climate pathway prepared here. For example, looking at the annual demand of medium office type (Figure 6.8), the largest result weather data from existing weather generators (RCP 8.5, 2090, 95%) file fits in the upper end of the pathway sample for most locations. Likewise, for location C5-Lisbon, the results from some weather data by weather generators are slightly larger than the limit conditions on the climate pathway sample. Looking at the peak demand (Figure 6.9), it can be noticed that the most critical existing files at maximum, fit the 85% and 54% percentile of the pathway, respectively for locations C4 - Beijing and C6 - London. As a result, this indicates that the scenario pathway sample suits the range of results represented in existing files better for annual demand than for peak demand. In addition, it is possible to report differences between locations, as weather generators results covered most of the pathway sample for location C5-Lisbon, especially for peak demand. However, for C1-Singapore or C6-London, the weather generator results cover a much smaller portion of the results under the climate pathway. When looking for similar emission scenarios for the same climate projections, the fit on the pathway for C5-Lisbon is ranked at larger positions than for C6-London.

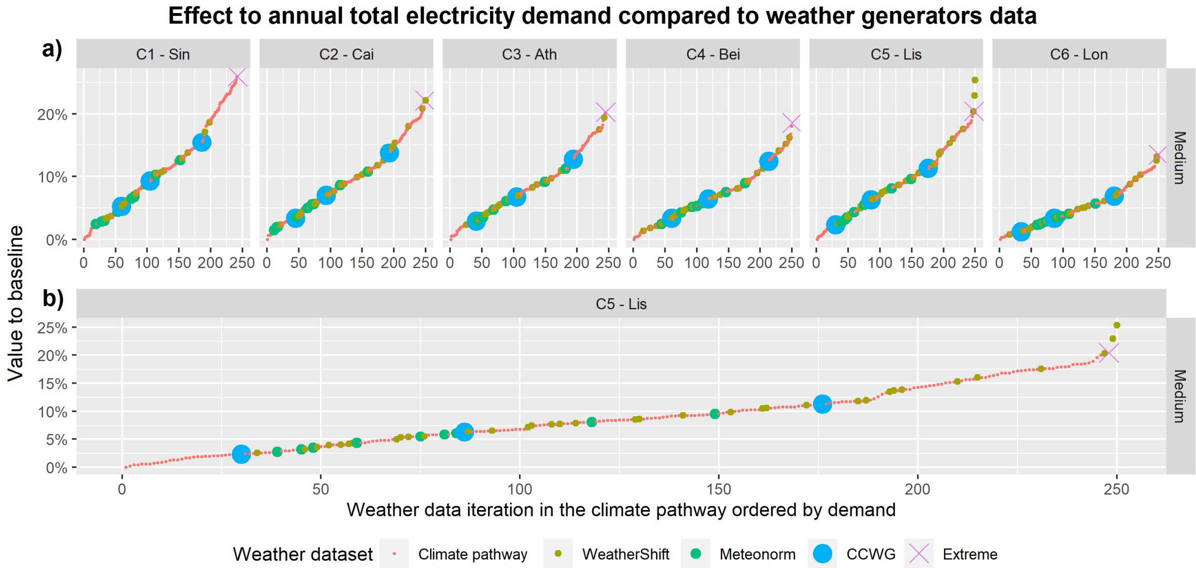

Figure 6.8 – The implication of the climate pathway for total electricity annual demand, compared to weather data from existing weather generators

Looking in detail for results for a single location and one type of building as presented in Figure 6.10 (a) and Figure 6.10 (b), it is possible to distinguish the differences of the effects of weather data reporting to different emission scenarios, timelines, and probability levels. For example, weather data relative to the scenario RCP 8.5, and data relative to the end of century timelines (2090) and relative to the largest probability levels present larger implication to the demand. It is evident that weather data from lower emission scenarios like RCP 4.5 present a relative fit to the pathway sample region with lower effects (below 50% of the sample). In general, only a minority of the existing future weather data from weather generators fit results in the upper half of the pathway, for peak. While for annual demand, most of RCP 8.5 projections for 2090 are included in the upper half of the pathway. Figure 6.10 clearly indicates that the pathway presents larger changes on peak conditions than annual, when compared to data from WeatherShift.

Finally, it is important to note that the world seems to be heading to global warming of about 3°C by 2100, which is significantly lower than RCP 8.5 projections and closer to RCP 4.5.

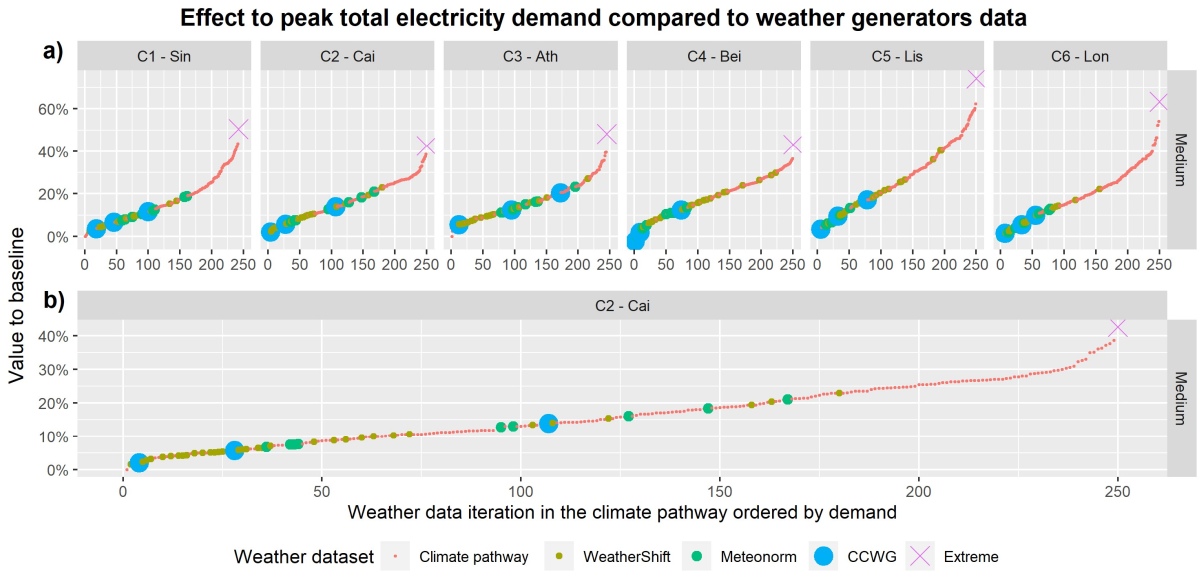

Figure 6.9 – The implication of the climate pathway for total electricity peak demand, compared to weather data from existing weather generators

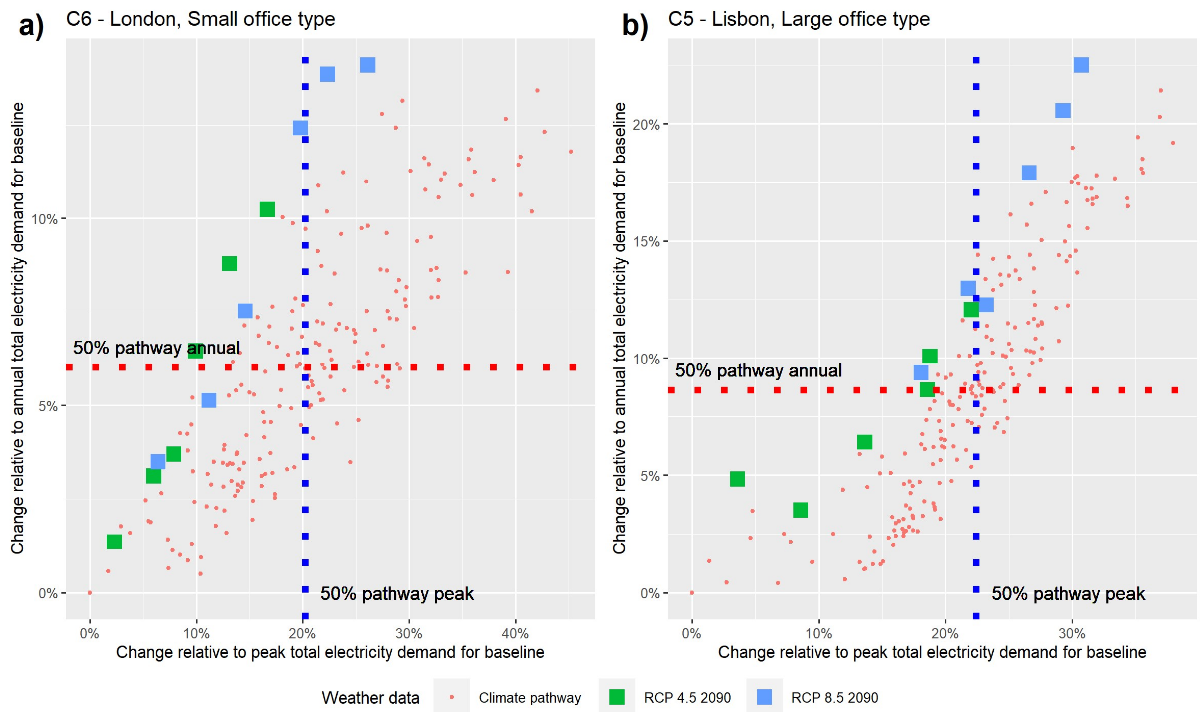

Figure 6.10 – The effects of weather data from WeatherShift compared to the climate pathway a) for a small office in C6-London and (b) for a large office in C5-Lisbon

6.4 Effects of adaptation measures on mitigating additional electricity demand

6.4.1 Reduction on the whole pathway

The reduction levels achieved by adaptation options can be significantly different from the baseline value (start of the pathway, 0 in the x-axis) to the end extremity result under the climate pathway (200 in the x-axis). In general, the pattern of the change across the pathway sample is substantially different across the measures and varies for each location, building type, and simulation output. The complete set of results for the climate pathway and the reduction effect due to adaptation measures is given in Appendix C3. In Figure 6.11, the reduction of different adaptation scenario options is shown, relative to baseline, for total annual demand, for a small office in C2-Cairo. For total electricity annual demand, the difference in demand reduction for the baseline result (0 on x-axis) and the result for the end limit extremity of the climate pathway (200 on x-axis) is noticeable on measure 1 (17.6% vs 31.2%), measure 2 (3.9% vs 8%) and 5 (7.2% vs 13.4%).

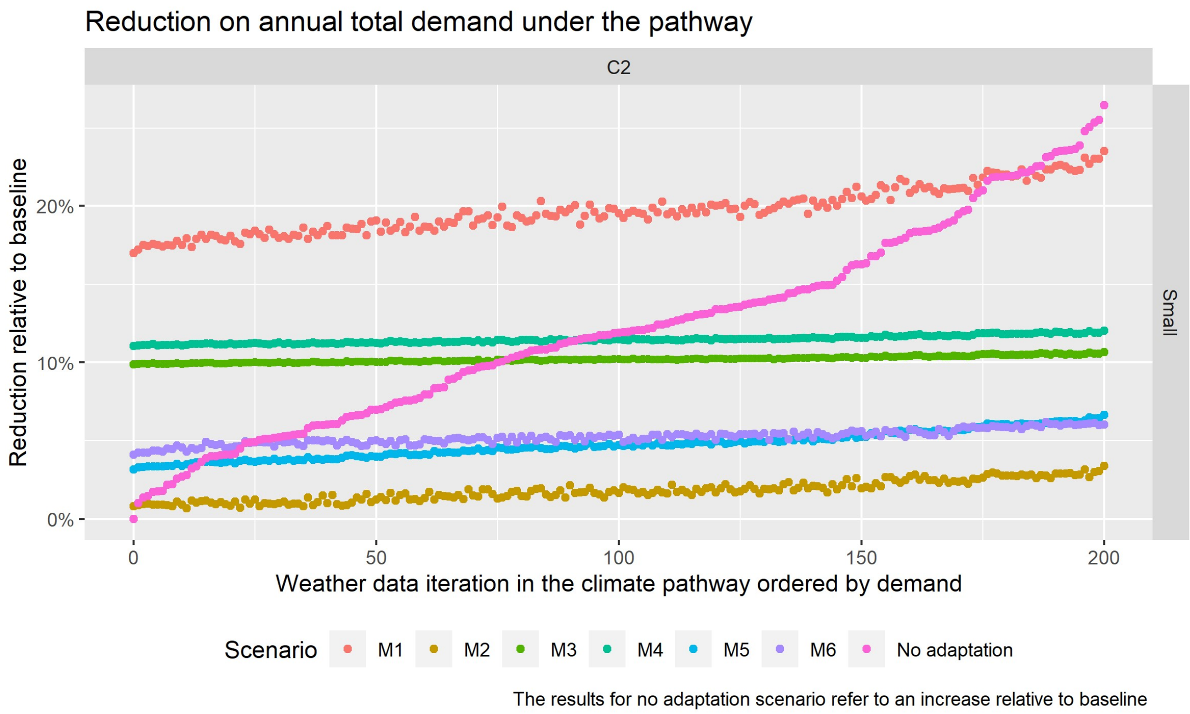

Figure 6.11 – Reduction effect of different adaptation measures for annual total electricity demand under the climate pathway, for a small office in C2-Cairo.

It is necessary to acknowledge that throughout the pathway, the annual total electricity demand for the no adaptation scenario increases substantially over the baseline (+27%). It is also important to acknowledge that the original change under the climate pathway reported by the *'No adaptation'* scenario, is significantly different depending on the location, office type, and output analysed (peak vs annual, HVAC vs total). Therefore, in the following sub-sections results are evaluated separately for total electricity demand and electricity demand for HVAC end-use. Results are analysed utilizing a reduction metric (RD) that measures the reduction effect of the adaptation options for the whole pathway, for each office type and location, as expressed in equation .

6.4.2 The effect of adaptation measures in total electricity demand

The effects of all single adaptation measures (M1 – M6) on total electricity demand are presented in Figure 6.12. The effect of adaptation measures on total peak demand tends to be more extensive for small buildings, than for medium and last for large office building types. This trend is apparent on measure 1, 5 and 6 (for example, the average RD among the six locations for measure 1 is 20.9% for small, 12.9% for medium and 8.6% for large office). However, for measure 3 and 4, the effects are similar across all models (average RD of all location for measure 3: 9.5% – large, 8.3% - medium and 10% - small). For measure 2, reduction of ventilation rate, the effect on small offices show smaller reductions than the other types (small 4.2%, medium 6.4% and large 5.4%). These trends occur both for annual and peak total demand. But, for annual demand, the large building has more considerable reductions than medium buildings for measure 2 (2% vs 1.9%), measure 5 (3.1% vs 1.1%) and measure 6 (2.4% vs 1.9%). Looking among different locations, reduction levels on annual demand are generally larger on locations with larger CDD (C1 - Singapore) for measures 1, measure 2 and measure 5. In contrast, the trend is opposite for measure 3 – lighting and measure 4 – equipment, being the largest in locations with smaller CDD (C6-London). For peak electricity demand, locations C4-Beijing and C5-Lisbon, have the largest reductions from measure 1 – relaxing cooling set-point.

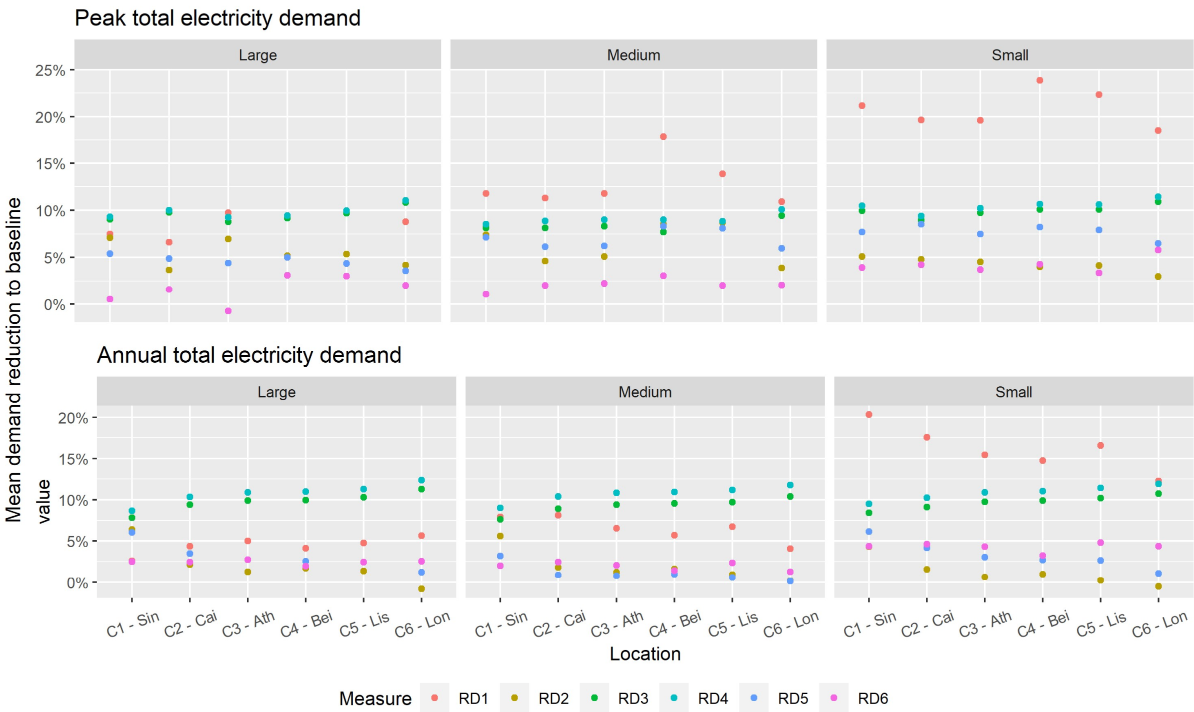

Figure 6.12 – Average reduction (RD) in total electricity on the pathway sample, for all single adaptation measures

The single measure with the largest effect in reducing the peak demand is adaptation measure 1, the relaxation of the cooling set-point temperature. For small buildings, this is especially evident, where reductions of 18.5% (C6) and up to 23.8% (C4) can be seen. For medium buildings, reductions of 10.9% and 17.9% can be seen for C6 and C4, respectively. For large building type, the reduction is between 6.6% (C2) and 9.8% (C4); however, there are other measures with larger individual effects. For example, measures 3 (M3) and 4 (M4) have average demand reduction of 10% across all locations, for both peak and annual temporal resolution. The reduction is marginally larger for M4 than for M3, especially on the annual demand. For the annual demand, the effect of M1 is dominant for small buildings, with reductions between 12.4% (C6) and 20.4% (C1), but for other building types the reduction is substantially lower (4.1%-8.1% for medium offices, 2.6%-5.0% - for large offices), being surpassed by measure 3 and 4. For peak demand, measure 5 leads to declines around 8% for small buildings, making the 4th measure most effective for all office types followed by measure 2, being more effective in medium and large offices, where reductions are between 3.5% and 8.5%.

6.4.3 The effect of adaptation measures in HVAC demand

The following section presents the effects of adaptation measures in reducing the HVAC electricity demand end-use, for both annual and peak resolution. Figure 6.13 presents the reduction effect on peak and annual HVAC electricity demand for the different adaptation measures. Adaptation measure 1 has the largest individual reduction effect for all building types, both at annual and peak demand scale/resolution. Adaptation measure 5 (increase in COP) is the second most effective on reducing peak HVAC demand, followed marginally by measure 2 (reducing ventilation rate), namely for large and medium office building types. On the other hand, measure 6 (reducing SGHC) tends to be the second most effective in reducing annual HVAC demand. Likewise, the remaining measures present almost similar reduction levels.

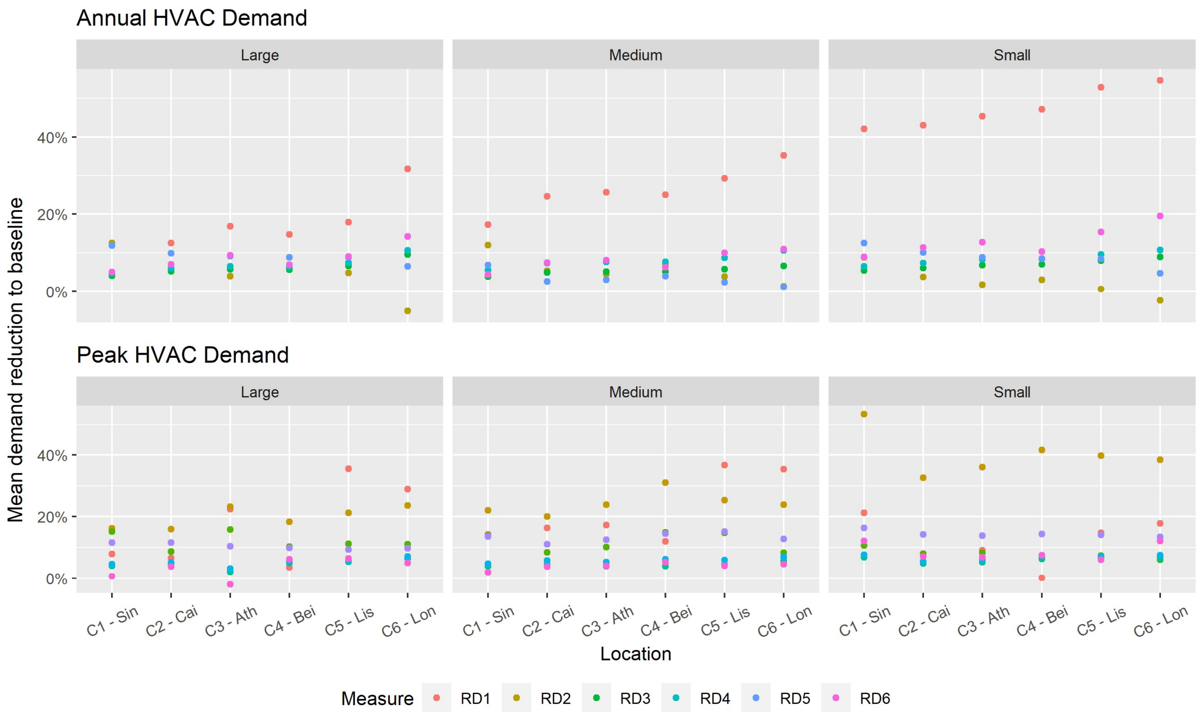

Figure 6.13 - Average reduction (RD) in HVAC electricity end-us on the pathway sample, for all single adaptation measures

Reductions on peak HVAC demand are significantly larger than for annual demand for measure 2 and measure 5, and for measure 1 for large buildings. By contrast, the remaining measures present more considerable reductions in annual demand than for peak demand. Reduction on HVAC demand, both for annual and peak demand is the largest for small office building types for most measures (all except for measure 2). Likewise, the reductions on medium office buildings types tend to be larger than for large office buildings, namely for measure 1, 5 and 6, for peak demand. However, annually, the reduction on large buildings becomes larger for measure 5 and 6. Relative to differences between locations, reductions for annual HVAC demand due to measure 1, 3, 4 and 6 seem to be larger in locations with lower CDD. On the other hand, for measure 2 and measure 5, reductions seem to be larger for locations with larger CDD.

6.4.4 Combined measures

In this section, the effect of combined adaptation measures (M7, M8 and M9) on electricity demand is presented. The combined adaptation measures are the coupling of several single adaptation measures, which effects are presented in the previous sections. Regarding the peak total electricity demand, it is apparent that results for M9 are consistently below baseline consumption levels, for all locations and building types, as shown in Figure 6.14 for large office buildings. Even for the end extremity results under the climate pathway, reductions are seen to be at a minimum of 30%, 13.3% and 11.5%, for small, large and medium office building types, respectively, below the baseline consumption levels. Similarly, across the whole climate pathway, results for adaptation measure 8 in small office buildings for all locations are lower than the baseline peak demand results. At the extremity of the pathway results, reduction levels are around below 3% the baseline. In Appendix C3, a summary of the reduction levels from the baseline value, across the pathway is given, for example in Table 0.11 for the peak total electricity demand level in comparison of the baseline in the extremity of the pathway. In Table 0.12, it is done the same for annual total electricity demand.

Turning now to the effects on annual total electricity demand, adaptation measure 9 consistently permits consumption to stay below baseline levels, for the whole climate pathway. Likewise, adaptation measure 7 is effective on restraining annual consumption below baseline levels, with the exception for location C1-Singapore, where results show to be higher for 3% 4.5% and 19.4% of the iterations in the scenario sample, for the small, medium and large office cases respectively. Measure 8 is effective in restraining annual demand for small office buildings, but for large office buildings at all locations, at least 25% of the pathway will present larger consumption than original values. For medium buildings, for location C6, almost 38% of the pathway will still present greater demand than current levels.

Looking at these effects on HVAC end-use demand, even all combined measures (measure 9) cannot guarantee restraining demand below current base levels, for all building types in all locations analysed. For example, for peak demand, in location C3-Athens, C4-Beijing and C5-Lisbon, and for large and medium office buildings in some iterations (up to 8% of the sample) of the pathway scenario, the demand will be higher compared to original levels. For medium office buildings, the values may be 16% larger than original levels at the extreme point of the pathway. For annual demand, measure 8 and 9 permit consumption to be restrained below current levels, for small office types. In contrast, for large and medium building types, demand may be superior to current levels, for up to 18% and 17% of pathway conditions, when looking at results for measure 9. Similarly, for measure 9, at the extreme pathway point, demand can increase up to 31% for medium buildings and between 10%-20% for large buildings.

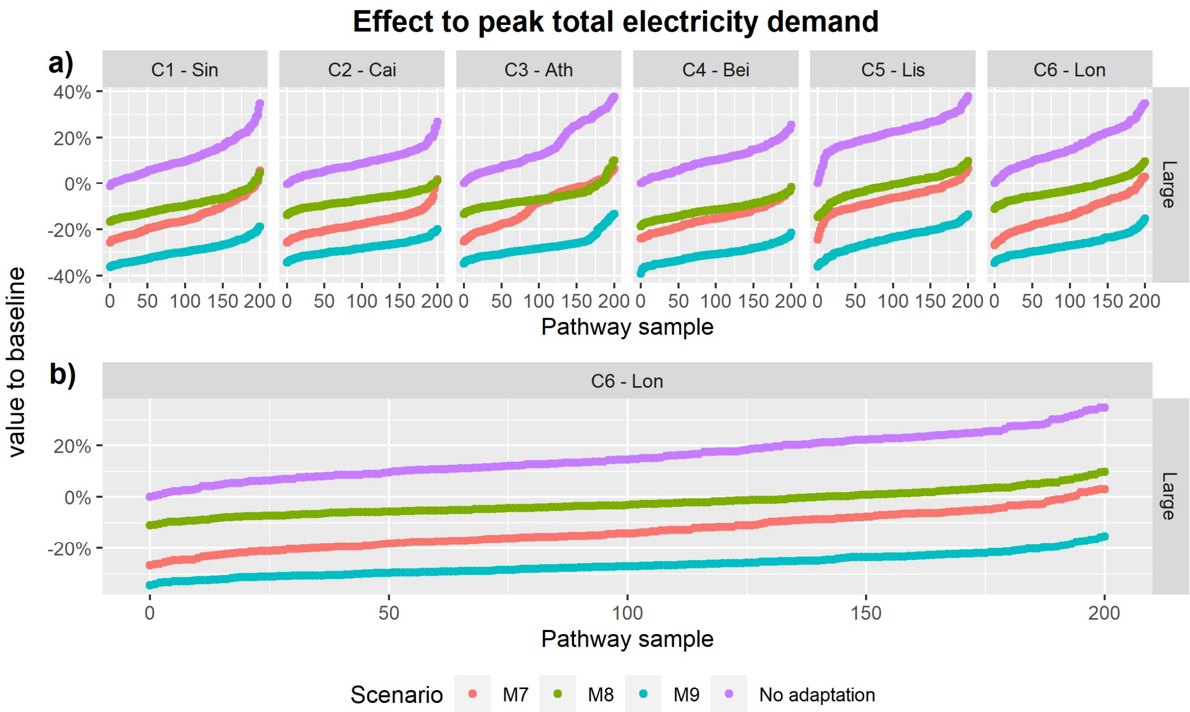

Figure 6.14 – The effect of combined adaptation measures (M7,8 and 9) on the climate pathway for the peak total demand

6.5 Discussion

The research results presented in this chapter evaluate the implications of changing climates on building electricity consumption, using an innovative climate pathway approach. The thesis simulation case study is utilised, three office building archetypes for the six locations selected, and assessed using 200 distinct future weather datasets for each location generated using a climate pathway approach. Across the pool of datasets created for the case study locations, by the climate pathway approach, annual maximum dry-bulb temperature reached a maximum between 54.3°C for C2-Cairo and 43.1°C for C1-Singapore. These changes in maximum annual dry-bulb temperature represent an increase from original values of between 13.7°C (C6 - London) and 9.3°C (C1 - Singapore). The respective value for Weather data from WeatherShift is respectively, 8°C for London and 4°C for Singapore. Likewise, the CDD can reach a maximum between 488 in C6 - London and 4 545 in C1 - Singapore. The respective increase in CDD from the original value is 481 (+7117%) for C6 - London and 1 821 (+67%), for C1 - Singapore. The change in CDD from WeatherShift data is 426 (+6 071%) for C6-London and 1 568(+58%) for C1-Singapore.

The effects of the climate change impacts on the total electricity demand are significant, especially for peak demand,throughout the case study for which the climate pathway was applied and results analysed. The magnitudes of the effects on electricity demand are notably distinct, considering the different model types, the locations, and between annual and peak temporal resolution. For example, in medium office buildings, an increase in total electricity peak demand may be driven up to 62.3% for C1-Singapore, whereas for the large office building, in C4-Beijing, it is only 25.3%. Regarding annual demand, the maximum increase under the climate pathway may be up to 37.7%, in C1 - Singapore, for large office buildings, or in contrast 13.1 %, for medium office buildings, in C6 - London. For HVAC electricity end-use, the growth of peak demand on the high end of the climate pathway may be between 158%, for medium offices, in C6-London, and 56% for large offices, in C4 - Beijing. Annual HVAC demand may increase up to 160%, for C1 - London, or 150% in C5-Lisbon. The mean values of change under the climate pathway are between 5% and 15% for annual demand, and 7% and 20% for peak demand. It is clear that medium office buildings present more sensitivity under the climate pathway, and that distinct locations have different levels of changes.

The comparison of the effects of the climate change impact on the electricity demand of office buildings, under the climate pathway developed and the weather data from weather generators showed that the approach developed includes the impacts from existing weather data. For the total annual energy demand, the simulation results from the set of existing future weather data (WeatherShift, CCWeatherGen or Meteonorm) cover most of the extension of the results under the climate pathway. For some locations in the case study, the results regarding weather scenarios with largest impacts are above the maximum result from the pathway sample. By contrast, for the total electricity peak demand, the simulation results for these weather scenarios correspond to only a value below the 75% percentile of the climate pathway simulation results, which for some locations is even below 50% (C1-Singapore or C6-London). Consequently, the climate pathway approach may overestimate the effects on peak conditions (extreme warm-weather events), especially when comparing to the highest climate impact projections considering RCP 8.5 emission scenario. However, the climate pathway indicates to be a good proxy of the range of effects on an annual demand basis. Considering that current carbon emission trajectories are likely to avoid RCP 8.5 scenario, a significant part of the impacts created by the climate pathway are more severe than the likely weather futures.

Regarding the effectiveness of adaptation measures, it can be concluded that no single individual measure can robustly reduce the electricity demand levels, throughout the whole climate scenario pathway, in all locations and for all models. The results varied depending on the building case and location under the case study. Results showed that the adaptation measure 1 is the most effective measure on reducing annual and peak demand, especially for small and large office building types. It is also possible to indicate that adaptation measure 3 and 4 (reduction on lighting and equipment density), produce significant levels of demand reduction, especially for total electricity demand. However, the same was not seen for HVAC electricity end-use, as these measures (M3 and M4) only have an indirect effect over the requirements and performance of HVAC systems.

For most of the locations, building types and type of demand end-uses selected for the case study, the analysis of the effectiveness of the combined adaptation measures (M7, M8 and M9) indicates that it is possible to restrain demand levels below baseline results. Interestingly, all the three combined measures show robust capacity to restrain demand levels below original baseline demand, for all modelling conditions (office types and locations), both for peak and annual demand. In contrast, for HVAC end-use, demand is not restrained below original base values, for some pathway conditions, when up to 18% of the iterations included in the pathway exceed the baseline results, while for peak HVAC demand it is 8%. However, the maximum increase rate over the original levels for all the models analysed is up to 15% for peak or 31% for annual demand, for medium offices in C6 – London.

Previous studies showed similar findings when, assessing whether adaptation measures can offset the effects of climate change, - showing that adaptation can consistently reduce energy demand to levels below current conditions. For example, Wan et al. (2012) evaluated the mitigation of the impacts of climate change on annual demand, by analysing several measures: lighting densities, improving COP levels, or changing building envelopes. All these measures were sufficient to mitigate the additional demand due to impacts of climate change on an office building in China. Jenkins et al. (2013) showed that improving COP can reduce the annual demand substantially, but that the reduction of the peak load is not considerable, in an office building in London. In contrast, some studies (Patidar, *et al.*, 2012; Dodoo, *et al.*, 2016; Pagliano, *et al.*, 2016) showed that different adaptation measures may not be sufficient to avoid the use of active cooling systems, in the long-term and for high emission scenarios. However, in those analyses, the focus is on naturally ventilated buildings, which present a different type of design and operational constraints.

One of the main limitations of the study performed in this chapter is that it analyses a limited number and type of standard adaptation measures. Likewise, the analysis is aimed only on peak and annual demand time resolution, and only for electricity demand end-use. For a more insightful understanding of the impacts of climate change in the energy performance of these type of buildings, it would be interesting to analyse other metrics related to cooling requirements and indoor environment. For example, it would be relevant to analyse both the sensible and latent space cooling requirements of the building, or the number of hours that the cooling set-point is unmet, and the overheating limits verified.

Another limitation of the study, is that it does not explore alternative HVAC systems or passive cooling solutions in the analysis. For example, it would be interesting to analyse the effects considering mixed-mode ventilation solutions, hydronic cooling systems, absorbent chillers and other passive solutions. Similarly, it is necessary to analyse further adaptation measures, namely more flexible operative conditions and demand responses mechanisms utilizing thermal storage potential in buildings and potential load shifting associated with HVAC end-uses. However, including such type of measures on building energy models, leads to changes on building operations assumptions that increase the complexity and requirements of the simulation runs.

6.6 Chapter summary

In this chapter, the effects climate change impacts on the electricity demand of buildings were assessed, using an innovative climate pathway approach on the thesis case-study. The climate change pathway was developed to provide a range of potential future weather conditions, reflecting climate change projection scenarios. The set of office building models and locations of the simulation case study of this thesis was utilised to evaluate the effect of these climate pathways on the electricity demand of office buildings for cooling. Section 6.2 presented an analysis of the changes in the different variables of the weather data in the climate pathway sample. The effects for the peak and annual electricity demand, both on total and HVAC end-use were presented in Section 6.3. In addition, it was quantified and compared the effect of different adaptation measures in reducing additional cooling demand under the climate pathway, in Section 6.4.

Previous result chapters (Chapter 4 and Chapter 5) and the findings from research questions addressed in those chapters (research question 1 and 2 in Chapter 4, research question 3 in Chapter 5) were fundamental to developing the climate pathway framework and set of adaptation options analysed in the results presented in this chapter. However, the research findings presented in this chapter are the ones that directly permit to address the primary aim of this thesis:

"to study the implications of climate change upon the space cooling requirement for office buildings in different regions of the world, operating in different representative future climates over this century (up to 2100)."

In the following chapter, an overall discussion of the findings in this thesis is done, leading to putting the findings presented in this chapter in perspective with remaining findings and the wider research area.

7 Discussion

This chapter discusses the broad implications of the research findings presented in the previous chapters of this thesis. Chapter 1, the introduction chapter of this thesis, provides the context and rationale for each research question addressed. In Chapter 4, the sensitivity and uncertainty of the cooling demand of office buildings to different building design and operational parameters are quantified. In Chapter 5, the implications of morphing procedures used to develop time series of weather variables from historical and climate projections are analysed and the impacts of individual weather parameters on total electricity demand were assessed. In Chapter 6, the analysis of the impacts of climate change was conducted, using a climate pathway for each of the study locations. In addition, the effect of different adaptation measures on reducing cooling demand is also evaluated. This chapter discusses how the research findings answer each research question (Section 7.1), the significance of the research findings (Section 7.2), and some of the study's limitations and future research work in this area (Section 7.3).

7.1 Addressing the research questions

7.1.1 The first research question: *"How sensitive is the office building energy modelling to different operational and design input parameters?"*

The results presented show that ventilation rate (P10) made the most significant contribution to electricity HVAC end-use both for peak and annual demand (around 60% for both according to the Sobol analysis (4.2.2.4)), with cooling set-point (P08, around 20%) and coefficient of performance (P12, around 18%) following as the most influential. The contribution of lighting (P05) and equipment (P06) densities (internal heat gains) were the most significant for annual total electricity demand changes (around 35% and 50%, respectively). While lighting and equipment densities have a small indirect contribution to electricity demand for HVAC end-use (below 5%), they have a significant impact on total electricity demand, by the direct contribution on lighting and equipment end-use. For peak total electricity demand, not only lighting (20%) and equipment (25%) densities but also ventilation rate (35%), cooling set-point (10%) and COP (8%) present significant contributions. For example, for large office buildings, in the Sobol analysis, the contribution of lighting and equipment densities are around 40% and 50%, respectively, for the annual total electricity demand, while it is around 20% for each of these, for peak total electricity demand.

The preliminary sensitivity model studies research findings (Zeferina, Birch, *et al.*, 2019; Zeferina, Wood, *et al.*, 2019), presented in Sub-section 4.2.1, showed that internal heat gains, ventilation rate and cooling set-point parameters have large implications for space cooling requirements. The space cooling requirement is the rate at which sensible and latent heat must be removed from the space to maintain a constant space air temperature and humidity. At the same time, the electricity demand for HVAC end use is the electricity supplied to the HVAC system to follow set-point controls. For electricity consumption on HVAC end-use, the contribution of internal heat gains is much larger (up to 58%) than the other two parameters for annual demand, but only 25% for peak. Preliminary studies (Sub section 4.2.1) also identified the relatively minor contribution of envelope and building form parameters in influencing cooling demand; however, the floor space area stretching parameter was found to present some contribution.

The analysis presented in Chapter 4 set out to better understand the sensitivity and uncertainty of peak demand. Only a handful of studies have analysed the sensitivity, both for total electricity and HVAC end-uses, and looked at peak loads. The research methodology developed is set out to extract peak demand results from building model simulations, to normalise results among the different modelling conditions (locations, type of buildings) and outputs (annual vs peak, electricity demand for HVAC end-use vs Total). Thus, it is possible to assess and compare sensitivities (S_T of parameters) and the uncertainty levels (*CV*). In this thesis, an analysis of a simulation case study is made that includes three office types and six locations, focused on electricity demand at total and HVAC end-use. However, the methodology can be applied and adapted for any building model, parameters, and energy performance simulation outputs, determined for the specific research aims. Therefore, more than the research findings reported relative to the case presented, the research provides an approach to assess sensitivities and uncertainties in building simulation systematically and thoroughly. The results presented quantify the difference in the level of contribution of each of the parameters and their ranked order, to total and HVAC demand at a temporal resolution of both peak and annual demand. Differences in the sensitivities were also identified among the three different office buildings and the different cities considered. For example, the contribution of cooling set-point (P12), both for total electricity demand and for HVAC end-use, is much larger for small than medium and large office building types. However, lighting or equipment density parameters present a similar level of implications for the total electricity demand among all locations and office types.

The research work elucidated that just a few parameters drive most of the change in electricity end-use for HVAC and the total annual demand. However, the ranking of these design and operational parameters and the level of contribution of each one may be significantly different for different cities or types of offices. For example, for Singapore, where there are high cooling requirements throughout the year (CDD at 18°C is 3454), HVAC control parameters such as cooling set-point, ventilation rate and COP, present a significantly larger contribution for the annual total electricity demand than for the other cities. On the other hand, for London, with typical mild summers (CDD at 18°C is 32), the contribution of these parameters is much smaller on total electricity demand, both annually and for the peak.

For the large office building type, looking at the Sobol sensitivity analysis, the contribution on annual total electricity demand is 0%, 7% and 3%, in London and 8%, 45% and 10% for Singapore, respectively for cooling set-point, ventilation rate and COP. The contribution of these parameters in total electricity demand and HVAC end-use demand is directly correlated; however, the share of HVAC consumption in the total electricity demand follow different trends. For example, the HVAC end-use share in total electricity demand is larger for peak consumption than annually. Hence the cooling set-point, COP and ventilation rate are the parameters with the largest contribution for HVAC demand. Nevertheless, if looking solely at total electricity demand, the lighting and equipment densities are also as critical, especially at the annual scale for all locations and building types.

Previous studies on sensitivity analysis applied to building energy model simulation do not generally assess the sensitivity of peak electricity demand to different parameters. For example, Sun, Gu, et al. (2014) concluded that occupancy has the largest contribution on peak cooling demand, while Eisenhower, et al. (2012) found that a set of parameters related to the cooling source (chiller) has the largest contribution on peak total electricity demand. Similarly, very few studies have compared sensitivity across different building types (Huang, *et al.*, 2018) and among different cities (Mechri, *et al.*, 2010; Wang, *et al.*, 2012). One example, Mechri et al. (2010) identified that the sensitivity index values for cooling energy needs of the model input parameters are similar across five different locations across Italy. The findings in this thesis provide additional evidence that for space cooling demand, the location does not vary the sensitivity towards different parameters. However, the effects on sensitivities for the total and HVAC electricity demand are significantly different among different locations, which is also concluded by Huang et al. (2018). Space cooling and electricity demand for HVAC end-use may correlate significantly differently between locations, and/or based on HVAC technologies, so further investigation on this is required. Wang et al. (2012) concluded that weather uncertainty created by a weather time series of 15 years created low uncertainty on total annual demand compared to the uncertainty created by other parameters. On the other hand, the uncertainty range driven by other parameters is significantly different among the different cities analysed.

Multiple previous research studies have identified that internal heat gains have one of the most considerable contributions to annual electricity demand (Lam, *et al.*, 2008; Heiselberg, *et al.*, 2009; Wang, *et al.*, 2012) or electricity for cooling demand (de Wilde, *et al.*, 2009; Tian, *et al.*, 2014), which is aligned with the finding of this research. Tian et al. (2014) have also identified the COP and ambient cooling set-point to have significant implications for annual space cooling requirements. Tian, de Wilde (2018) and Sun, Gu, et al. (2014) concluded that occupant density is the largest contributor for sensitivity for cooling demand, which differs from the finding in this work. This inconsistency is likely to be related to modelling assumptions associated with ventilation rate, as in this work, it is completely decoupled from occupancy, which is often not the case. In contrast, ventilation rate was found to be the most or one of the most important factors for demand in buildings as concluded in (Heiselberg, *et al.*, 2009; Wang, *et al.*, 2012; Østergård, *et al.*, 2017; Huang, *et al.*, 2018). Infiltration rate was also found to have a minor contribution to sensitivity in demand as in this research, in studies such as (Mansur, *et al.*, 2008; Tian, *et al.*, 2014) but paramount relevance in studies like (Tian, *et al.*, 2012; Sun, Gu, *et al.*, 2014). Heiselberg et al. (2009) and Lam et al. (2008) have found that annual operation hours contribute to the sensitivity of total electricity annual demand, as found for the total annual electricity demand of office archetype models in this work.

Clarke et al. (2015) discussed that building performance simulation should screen the variability of input ranges to seek more robust design solutions and look for vulnerabilities in the model assumptions. In the same way, Tian (2013) identified that more uncertainty and sensitivity analysis studies are required to improve the credibility of results from building model simulations. The research presented in this thesis about the sensitivity of office building models, and making the methodology openly available, clearly contribute to addressing this major challenge in the building simulation research domain. A particular focus was put on developing a methodology for sensitivity studies that enables multiple variables and time resolutions, cities and buildings types to be assessed simultaneously. Simplified modelling geometries were utilised to first screen ranges (pre-analysis studies) in a broad scope of parameters, including investigating the physical form parameters. Then, more complex geometries were investigated, using archetype models and more circumscribed range of uncertainties.

Rather than high absolute accuracy, i.e. aiming to be close to a known actual value, building performance simulation should seek to analyse the effects of change and uncertainty in design parameters as discussed by Augenbroe (2011). Unfortunately, current approaches in building design decision making do not introduce enough uncertainty consideration in the simulation process, which is imprudent, as concluded by Hopfe, et al. (2013). The sensitivity analysis of the research simulation case presented in Chapter 4 has extended our knowledge on the contribution of key design parameters to the electricity demand of office buildings. The possibilities for parametric evaluation in building performance simulation are endless, as models can have thousands of input parameters. Therefore, an exhaustive investigation of the uncertainty in the main modelling assumptions can be executed with the research framework developed in this thesis. This is possible to achieve by following a holistic approach in understanding the implications of the different parameters, looking for the impacts over multiple variables, time resolutions and different cities.

The findings summarised in the last paragraphs are relevant to both designers and practitioners on building design, providing insights for the preparation of models, and the parameters that require more detailed assessment. This also provides some ideas on which energy-saving measures may most significantly reduce cooling and total energy demand on office buildings. In these sensitivity analyses, the influence of external weather is only taken into account, by replicating the simulation case analysis among six different locations, using TMY weather data for each. A more detailed analysis of the effects of weather uncertainty on the total electricity demand of the office buildings was done in Chapter 5, when addressing research question number three.

7.1.2 The second research question: *"What is the relative impact on peak and annual HVAC and total electricity demand of office buildings as cooling requirements differ with changing building design and operational conditions?"*

The research findings showed that the uncertainty of the demand of office buildings differs for different types of office buildings and when looking at different cities. In addition, the level of response was significantly different for the different energy performance variables analysed, namely when looking at peak or annual demand levels. The uncertainty range of the total electricity demand for reference office models may go from 53% to 337%, or from 57% to 319%, for peak and annual demand respectively, from baseline demand. The maximum coefficient of variation (*CV)* values among office types and locations were 29.1%

and 27.7%, respectively, for peak and annual demand respectively. The level of response of HVAC electricity demand end-use is significantly larger than it is for total electricity demand; hence the range of results for HVAC was shown to go from 5% to 588%, and 35% to 560% and the *CV* can be as high as 46.9% or 43.9%, respectively for peak or annual. This indicates that HVAC end-use demand is far more variable than total electricity demand.

Differences in the level of variability among different climate conditions (cities) are also significant, showing different profiles for hot climates such as C1-Singapore. For example, *CV* on annual total electricity demand for small offices is around 28% in C1-Singapore, while around 22% for the other cities. For climates with relatively mild summers, such as C6-London, the *CV* on peak total electricity demand for medium offices is around 18% while around 24% for the remaining cities. For example, *CV* values are consistently larger in C1-Singapore for the total and HVAC annual demand (for small offices is respectively 28% and 44% in C1-Singapore and around 23% and 38% for the other locations). In contrast, for large office buildings in C4-Beijing, the *CV* for HVAC peak demand is 41% and 34% for annual demand, while for total electricity, *CV* is 29% and 24% respectively for peak and annual demand. For annual space cooling demand, the *CV* is significantly larger for C6-London (39% for small and 34% for large offices) than for the other cities (C1-Singapore is 30% and 22% respectively for small and large). While for space cooling peak demand, results for C6-London are larger than other cities, when for small buildings, it is C1-Singapore that presents the largest *CV* value (24% for C1-Singapore, followed by 22% for C6-London and minimum 19% for C2-Cairo).

In general, it is expected that cooling requirements differ between different office building types, especially looking at the building form characteristics, volume and aspect ratio differences existing between the office types analysed in simulation cases of this research, as concluded in (Hong, *et al.*, 2013; Huang, *et al.*, 2018). Similarly, the different climate severities presented among the cities considered are expected to drive different cooling requirements levels and substantially different total electricity demand levels, as concluded in (Guan, 2012; Huang, *et al.*, 2018). The findings in this research work contribute to existing knowledge, by quantifying the differences in uncertainty among locations and different types of offices. The share of HVAC, and non-HVAC loads in the total electricity demand, is distinct for each modelling condition considered (cities and building type), both for annual and peak demand levels. The electricity demand density per floor space area is also distinct. Therefore, when screening the input ranges at normalised levels, these differences identified at the initial base modelling condition results are perpetuated through the models' response during the parameter screening.

DOE reference buildings have been utilized for multiple research studies, namely to explore demand and/or performance of for the building stock level (Hong, *et al.*, 2013; Wang, *et al.*, 2014), or sensitivity studies (Wang, *et al.*, 2012; Huang, *et al.*, 2018). Some studies have compared the energy performance of the different types of buildings. For example, Hong et al. (2013) investigated the influence of the different climate zones on the heating and cooling demand of buildings. However, it focused on understanding the response of annual and peak demand due to the effect of varying weather datasets from actual meteorological years data. In this research case study, different locations were utilised to evaluate the potential response differences on electricity demand of office buildings for different climate severities represented by the different locations. Korolija et al. (2013) have developed UK office models, but have focused on annual demand levels, with no insight into the sizing of HVAC systems. In the simulation case utilised in this research, only three types of office buildings and six cities were investigated. However, the thesis has developed a novel framework for systematic comparison of electricity demand both for peak and annual demand for a broad scope of different conditions. Analysing the variability of the sample of results analysed, studying *CV* values and the boxplot of results, and comparing these between simulation case conditions (buildings, sites and time resolution) allows insights rarely presented in the literature.

The research findings found that the three office types investigated presented different responses when exposed to similar input uncertainty levels. However, it is essential to remember that the buildings' HVAC systems and building form characteristics were substantially different in this set of simulation cases. For example, a large office building has a smaller ratio of envelope area by floor space (0.40 for large office versus 1.05 and 2.55 for medium and small respectively), and a much more complex HVAC system. Therefore, it is reasonable that large office buildings differ from medium and small buildings on the ranking of their sensitivity to parameters and the different response variability they showed to peak versus annual demand. These findings are consistent with Hong et al. (2013), who have highlighted that HVAC and envelope differences led to a different response to the weather impacts among office archetype results.

This research has demonstrated and quantified the difference in the sensitivity to different parameters between simulation cases of different office types and locations. For example, the results for some cities in this research work were outliers trends for some but did not for other office types. Singapore and Beijing presented the largest *CV* values for total peak demand for large office buildings (29% vs around 25% for others), while Cairo presented the largest for small (29%) and medium offices (26%). This may be related to the different responses of different HVAC systems coupled with different building forms and differences in climates for different systems. For example, C2-Cairo and C4-Beijing have larger solar irradiance during peaks, and C4-Beijing and C1-Singapore have larger relative humidity.

A note of caution is due here since the research approach was not focused on understanding the implications of the parametric analysis at more granular levels of cooling requirements (e.g. sensible or latent loads, percentile analysis of hourly demand) and assessing potential correlation effects of input parameters and output performance metrics. Nevertheless, the developed research framework is an essential tool to provide/increase confidence in building simulation research methods and results, as it enables a very systematic and broad analysis of design and operational input parameter sensitivities; however, the development of building models structures is required to allow automatic iteration of building form parameters such as glazing area, aspect ratios, volume/envelope ratio, or HVAC definition.

7.1.3 The third research question: "*How does the morphing of weather timeseries influence the peak and annual HVAC and total electricity demand?*"

Research results showed that changes in dry-bulb temperature (DBT) have the largest impact on the total electricity demand of office buildings. A uniform increase (shift) of 5°C in DBT hourly data led to the largest contribution to the change in total electricity demand, both for peak (up to 26.8% more than baseline) and annual level (up to 38% more than baseline). For annual demand, the ratio between summer and winter mean DBT shift changes, the uniform reduction of 10% (negative shift) in relative humidity and the growth by a factor of 1.25 (stretch) in horizontal infrared radiation (HIR) present a similar level of implication (4.5%, -5.1% and 5.2% of the baseline, respectively). For peak demand, changes in the DBT seasonal ratio (up to 1.75 ratios between mean shift change in DBT during summer and the remaining seasons) and heatwave stretch parameter (growth/stretch of up to 1.25 in the daily DBT amplitude in the hottest period of the year) are the parameters that followed, with an increase of up to 15.4% and 9.4%, respectively.

The research findings showed that uniformly reducing relative humidity (RH) by 10% (in absolute terms) tended to reduce the total electricity demand of office buildings (-5.7% for peak and -5.1% annually). Even at significant growth levels (200%), the impact of an increase in wind speed has low implications for changes in total electricity demand (up to 1.4% for peak and 0.7% annually). Growth of up to a factor of 1.25 (stretch) in solar radiation timeseries (horizontal infrared radiation (HIR), direct normal (DNR) and diffuse horizontal irradiation (DHR)), drove larger changes for HIR (peak:4.3% and annual:5.2%), than for direct (peak:3.6% and annual:2.7%) and than for the diffuse (peak:1.4% and annual:1.7%) variable. Though the demand change effect was smaller than for changes in DBT, together, simultaneous composite growth/stretch of 1.25 (of the three radiation weather variables) could potentially drive a change in demand up to 10%. The response of total electricity demand for growth in solar radiation is especially acute for the small office case. The research findings have also shown that sensitivity is different among different cities and slightly different for different building types.

These research results showed that the main driver for additional electricity demand is the changes in DBT , although there are differences in the implications among different office buildings and locations. Uniform increase (shift changes – test 1) in DBT is critical for changes in electricity demand; however, the seasonal pattern of the DBT increase (test 2) and the growth of DBT in extreme periods (test 3) presents a significant contribution to electricity demand changes for peak periods. The findings related to the variability of relative humidity (uniform reductions up to 10% - test 5) showed that this is the only weather parameter range test that could give a consistent reduction in total electricity demand due to the expected impacts of climate change. On the other hand, the implication of wind speed might be neglected. The implication of a 1.25 growth factor (stretch) in solar radiation variables can be quite significant in total electricity demand increase (up to 5%), but they present a much lower impact than changes in DBT.

This is the first study to investigate the effect of different 'morphing' operations in weather variable timeseries on the total electricity demand of building models. The method to process changes in weather data is based on the seminal ‘morphing’ method by Belcher et al. (2005). In this research study, the different morphing procedures applied on the different weather variable time-series were decoupled to assess their isolated effect on demand. Only a few studies have attempted to isolate the effect of particular weather variables on building energy demand. For example, (Bhandari, *et al.*, 2012; Kalamees, *et al.*, 2012; Kim, *et al.*, 2017) also concluded that DBT has the largest contribution to the cooling demand of buildings. However, Kalamees et al. (2012) and Kim et al. (2017) had contradictory findings on the importance of air humidity and solar radiation for cooling demand, while utilizing the same approach to generate weather data. For example, Kim et al. (2017) utilised a basic building model program on residential buildings cases, disregarding internal heat gains and moisture loads, to focus only on the influence of different climate parameters on building energy consumption. While Kalamees et al. (2012) used a dynamic simulation tool (IDA-ICE) on office and residential cases to show the influence on heating and cooling energy demand. These inconsistencies in the simulation cases selected may explain the contradictory findings presented. Therefore, the framework developed in this thesis and the selected simulation case was intended to address a consistent and systematic analysis of these effects.

The findings in this research work described and quantified the implication of each weather parameter, for the total electricity demand of office buildings. Although the changes produced in weather data, by the research method, are theoretical, the present study has offered a framework for the exploration of the effects of the different weather parameters on the electricity demand of buildings. For example, Rastogi (2016) developed an innovative emulator to generate weather time-series that enable explicit calculation of the uncertainty in building simulation due to weather inputs. However, it is unable to evaluate the implication of each weather parameter in the uncertainty of building simulation. This is the first study the author is aware of to have quantified the impacts of the different ‘morphing’ operations in weather data on the electricity demand of buildings.

It is important to bear in mind the possible bias of the building simulation results from the implication of some weather parameters (primarily wind and irradiation). These results are often very reliant on how the integration of these weather parameters is made in the calculations within the building energy model. For example, the building simulation program used by Kim et al. (2017) is based on hygrothermal component models that weigh weather parameters significantly on the outputs analysed, while EnergyPlus use integrated building simulation techniques that often dilute the effect of individual weather parameters on the whole building energy performance. The research findings indicated that the effects from wind speed modifications could be neglected and individual modification in solar radiation variables present modest implications. Interestingly, the effect was significantly larger for small office buildings than the other types. Hong et al. (2013) concluded that the weather has the most significant impact on medium office archetypes; there are greater effects on peak electricity demand than annual demand and better quality of solar radiation data is required for robust assessment of HVAC end-use demand.

These research findings identified and stated some of the main differences in response to weather data changes, between building types and simulation results (annual vs peak, total and HVAC). It can thus be suggested that to assess the effects of changing climates in building electricity demand, a special focus should be put on how the dry-bulb temperature data serie is modified, and changes in solar radiation are significantly more important than wind speed changes in building cases more driven by external heat gains (as small or medium office buildings). However, further analysis and focus on different energy performance factors (e.g. space cooling requirements, not meet cooling hours) are required to analyse the root causes of the different sensitivities across different simulation cases.

The research approach to operating changes in weather data-sets to study weather variables' uncertainty to the demand for buildings is simple and decoupled from the known relationships among climate variables. Therefore, the weather datasets used are unrealistic, as they neglect the intrinsic correlation between weather variables. However, as Huang et al. (2019) concluded, weather uncertainty must be further included in building performance analysis, as currently it is sparsely used, and when included, it is done using variability within AMY datasets or the use of weather generators. In the same way, it may be possible to hypothesise that linear sensitivity analysis restricts the scope of the analysis, as it is a simple approach to execute sensitivity analysis, as discussed in Sub-section 2.1.6. However, as Tian (2013) concluded, even with its shortcomings, the simplest approach can still be a very useful tool to analyse the sensitivity of parameters in building performance analysis.

7.1.4 The fourth research question: *"To what extent could the electricity load of office buildings be affected by changes in cooling demand due to the impacts of climate change?"*

The research results show that HVAC end-use demand and total electricity demand for office buildings might increase significantly, considering the climate pathways developed. The increase in total electricity demand in the pathway analysed can be as high as 37.7% annually (C1-Singapore with an increase in CDD of 67%) and 62.3% for peak demand (C5-Lisbon with maximum dry-bulb temperature increasing 12.7°C). For HVAC demand, the increase can be as high as 182.3% annually and 158.4% for peak demand. For most future climate iterations points in the pathways, changes in total peak demand are larger than annually, except for large office buildings in Singapore and Cairo. However, changes in annual HVAC demand are often larger than for peak. Relative changes in electricity for HVAC end-use, both for peak and annual demand, are larger for the cities which currently have lower annual cooling needs (lower CDD18 – London, 32 and then Lisbon, 474). For changes in total peak demand, the level of changes is also more significant for these cities, which can be attributed to larger increase in maximum temperatures, which is likely to be related to the existence of larger daily temperature amplitudes in these locations. However, for annual total electricity demand, the increase in demand is significantly larger for the cities with larger CDD (Singapore and then Cairo), even considering that they show lower potential relative increases in CDD (C1-Singapore 67% versus 488% in C5-Lisbon).

These findings provide important insights into the response of the electricity demand for different office buildings in different locations under climate pathway scenarios. The research presented a progression of results across the climate pathway and quantified the differences among the building simulation conditions analysed. Thus, it rendered the difference in shape and proportion of the results, depending on each analysed variable, demand temporal resolution, city and office type. Though the electricity demand change might be significant for HVAC end-use (could increase more than 100%), the increase in total electricity demand is significantly lower (no more than 62.3%, for peak). Once the share of HVAC end-use on total electricity demand for peak periods was larger than annually, the implication of a similar rate of changes on HVAC demand always led to higher total electricity changes for peak periods.

The use of weather data provided by weather generators related to the climate projections from RCM, has been one distinct approach to incorporate uncertainty into the analysis of the impacts of climate change, as concluded by Huang et al. (2019). Weather datasets generated by weather tools like WeatherShift or CCWeatherGen utilise ensemble climate model projections to generate a probabilistic sample of future weather files. However, downscaling methods ignore some aspects of future climate change, which lead to some inaccuracies, especially for extreme conditions, as concluded by Herrera et al. (2017). Herrera et al. (2017) also reviewed that an increase in frequency and intensity of extreme events is expected, and so there is a growing urgency to simulate buildings in such conditions.

The climate pathway research method developed in this research work provides a framework that enables a more profound insight into the effect of the uncertainty of future weather datasets on the building energy performance of buildings. The review of the literature has identified that including uncertainty on future weather data is central to the assessment of climate change impacts on building energy performance. Rastogi (2016) discussed that the building community has faced a “deterministic paradigm”, so uncertainty based approaches (including weather) may not be integrated into current building design workflows. In the same way, Huang et al. (2019) concluded that there have been very few attempts to examine the effect of weather uncertainty in building performance simulation and advocated that it is necessary to develop tools to generate uncertainty in weather datasets that enable to incorporate the analysis of this type of uncertainty in BPA. Nik, Perera, et al (2020) stated that to assess the climate resilience of built environment infrastructure, assessments must incorporate a broader scope of weather and technological conditions, including much more significant and broad uncertainties in modelling.

In this research, it was possible to incorporate the similar uncertainty approach found in (Moazami, *et al.*, 2019) or (Jenkins, *et al.*, 2013), whilst comparing the implications at multiple locations as conducted by (Dirks, *et al.*, 2015) and (Wang, *et al.*, 2014). However, the research did not present the effects for aggregated stock levels of demand that (Moazami, *et al.*, 2019) and (Dirks, *et al.*, 2015) had. Moazami et al. (2019) and Jenkins et al. (2013) used a large sample of future weather datasets to more robustly evaluate building designs under the impacts of climate change. However, this type of approach to generate weather datasets is onerous to replicate into other locations worldwide, as it requires the detailed outcomes of regional climate model projections, as discussed in Sub-section 2.2.3.

Thus, the application of the climate pathway framework developed in the simulation case study, enabled multiple locations to be assessed using the same approach in a time-efficient manner. In addition, the simulation case focused on the effects upon total and HVAC end-use electricity demand of office buildings, both annually and for peak level, central to the challenges to systematic and broad analyses of the impacts of climate change in building performance.

The research results on the effects of climate change under the climate pathway scenarios presented, provide an understanding of the extent to which buildings are or can be climate-proofed. The screening of building models for different future weather has a pivotal role in assessing the climate resilience of buildings designs. However, it is necessary to analyse the implications for both annual and for peak energy demand, not only for cooling purposes but also for the changes it represents at the total demand level (while also bearing in mind that future heating systems for buildings may also become electrified). Changes in the electricity demand for HVAC end-use are essential to evaluate the implication for the sizing and operation of HVAC systems. On the other hand, the total electricity demand effect highlights the overall implications for the power network. Therefore, this research distinctively showed that in the future, weather scenarios represented under the pathway scenario would lead to a significant increase in the design capacity of HVAC systems. However, the implication to the electricity demand of buildings is up to 62%, but the peak increase is smaller for most of the climate pathway points included in the simulation case conditions utilised in this research.

7.1.5 The fifth research question: *"To what extent could a potential increase in electricity demand due to cooling provision be limited in future scenarios by adaptation measures?"*

The research results indicated that a set of elementary adaptation/energy-saving measures could robustly maintain an office building electricity demand levels, below baseline results, in a climate pathway scenario that incorporates extreme impacts of climate change. Throughout the climate pathway simulation sample, it is easier to restrain electricity demand below the current baseline values for the total level, than it is to reduce electricity HVAC end-use. For example, for the total electricity demand, the largest value in the whole climate pathway sample is 11.5% and 8% below the baseline values, for peak and annual resolution respectively. While for HVAC end-use, the largest values in the whole pathway can reach up to 16% and 31% more than the baseline values, for peak and annual demand respectively.

In any case, even for HVAC electricity demand, for both peak and annual levels, it is often possible to keep demand below baseline conditions for most of the pathway scenario sample. The individual measures that have the largest effect on reducing total electricity demand are: reducing either lighting or equipment densities (measure 3 and 4, which reduce around 10% both for peak and annual resolution) and relaxing cooling set-point temperatures (measure 1, up to 24% reduction and especially for small buildings). The adaptation measure options that combine a number of individual measures (measure 7, 8 and 9) reduce all types of existing electricity loads under baseline levels (HVAC and total;

peak and annual), for the large majority of the climate pathway scenarios evaluated. For almost all buildings and locations, it is possible to restrain demand below baseline values, for all the pathway sample points, if all individual measures are applied (measure 9). Finally, the effect on demand reduction of the measures and their effectiveness significantly differs among the different office types and cities analysed. The research results elucidated that demand loads can be substantially and consistently reduced below baseline demand levels, even considering the implications of the future climate pathways scenarios. However, the research analysis had only considered standard, and elementary types of adaptation measures. It is possible to hypothesise that novel and more sophisticated adaptation measures could save even more electricity demand.

From previous literature, very limited studies have systematically analysed and compared the effects of different individual and combined adaptation/energy-saving measures in mitigating the additional demand from the impacts of climate change. In the review of the literature for this thesis, no studies were found looking at the effects on aggregated building stock level, using dynamic building simulation that also assesses the effects of adaptation measures (some examples that do not consider adaptation (Wang, *et al.*, 2014; Dirks, *et al.*, 2015; Moazami, *et al.*, 2019)). The present study makes noteworthy contributions to the assessment of adaptation measures in mitigating the impacts of climate change in buildings. For example, Jenkins et al. (2013) has concluded that the effect of adaptation scenarios considered is not significant on peak loads. The present study has presented pieces evidence showing that a set of measures can substantially reduce demand, even for peak electricity demand for HVAC demand. Mata et al. (2019) have presented a new methodology to robustly assess multiple retrofit measures to reduce heating demand in the future with climate change, for four Swedish cities. This Thesis = has taken a similar framework to evaluate multiple adaptation/energy-saving options, into the analysis for electricity demand for cooling. This study is one of the first studies that has evaluated multiple adaptation options, considering a climate pathway, and for several distinct locations. Some studies have analysed the effects of adaptation measures, but often they have taken approaches, that only provide a snapshot and static assessments of future scenarios, evaluating for single or a couple of climate scenario conditions. In the approach taken in this study, the focus is to understand the feasibility of attenuating additional electricity demand for cooling due to the impacts of climate change.

The research results described that the impacts of climate change on cooling demand are significant, but the effect of adaptation measures might balance out the impact of climate change on the total electricity demand of buildings. Therefore, overall total electricity demand annually and at peak periods might not increase unrestrainedly as it might be intuitively assumed. The research approach used models that automatically resized the HVAC equipment to every iteration of weather data on climate pathways. In practice, HVAC systems have spare capacity, which may accommodate additional requirements from warming climates. However, the ordinary rate of replacement of HVAC systems may not occur sufficiently regularly to keep up with the impacts of climate change, creating unmet cooling demand and the potential for more energy inefficient cooling measures to be implemented by occupants.

The research also identified and quantified the single measures that are the most effective in reducing cooling demand, both annually and for peak periods. Reducing both lighting or equipment power densities by 30% on its own, was sufficient to reduce total electricity demand by around 10%, both annually and for peak. For HVAC demand, increasing cooling set-point temperatures from 24°C to 27°C, is clearly the most effective individual measure. The combination of some of these measures (relaxing cooling set-point, increase COP, reducing lighting and equipment densities) may often be sufficient to reduce demand bellow baseline levels, for the HVAC demand. However, for some model case conditions, especially for annual HVAC demand, it is more challenging to reduce demand below current baseline levels. The results showed that for large and medium office buildings, the reduction effect of measures were not enough to keep annual HVAC demand restrained below current baseline levels, for the most challenging scenario iterations in the climate pathway. While for small office buildings the levels were kept well below current levels considering combining all individual measures.

Anyway, this type of analysis shows that there is potential on currently known and available adaptation measures to robustly reduce electricity demand below current baseline levels, even considering for the most extreme likely future climate scenarios. The comparison of the weather data from current weather generators have shown that only the future weather data with the largest probability levels (90% and 95%) and relative to the highest emission scenario (RCP 8.5) will compare to the highest percentile at the end of the climate pathways scenario sample. Most of the future weather data generated by existing weather generators (WeatherShift (Dickinson, *et al.*, 2016), Meteonorm (Meteotest, 2020) and CCWorldWeatherGen (Jentsch, *et al.*, 2013)), is comparable to iterations on the first half of the climate pathway, for all locations analysed.

7.2 Significance of the research work

Clarke et al. (2015), Hopfe et al. (2013) and Tian (2013), have all advocated that it is necessary to introduce uncertainty into the inputs to building models, even for the most accurate models. Building models are only approximations of actual performances, and it is impossible to validate models of unbuilt buildings or hypothetical operations of existing buildings, but only to increase the robustness of their results. It is necessary to increase the robustness of building simulation results, and sensitivity and uncertainty can play essential roles in this, supporting better design decisions. The research framework presented in this thesis has a systematic approach to evaluate the implications of input uncertainty and explore a broad scope of design and operational parameters. The research framework developed provides a deep understanding of the sensitivity and uncertainty of the office building model utilized. These sensitivity studies explored the limits and understood the difference between building models, which disclosed the various responses of office cooling demands. Therefore, more confidence in applying these models was gained, shaping and preparing the research conditions explored in the following stages.

The deep exploration and screening of the model's assumptions revealed the different responses of their electricity demand, for different time resolutions (peak and annual), locations and different simulation output metrics (total electricity, HVAC end-use or space cooling). The approach has methodically compared the effects of different building design and operational parameters uncertainties, for different cities and types of office buildings. The research focused on the implications on the peak loads, not only for cooling needs but also for total electricity demand, which the majority of previous studies using BPS tools have not included (few examples: Dirks, *et al.*, 2015; Tarroja, *et al.*, 2018)). In the future, with the supplementary effects of the impacts of climate change on building peak loads, these may become very challenging constraints for the design and planning of infrastructures. The additional demand for cooling is not only critical for the sizing of HVAC systems of buildings, but also for the operation of power networks, the sizing of grid infrastructure or potentially for the sizing of cooling district networks.

Previous studies such as Wang et al. (2014) or Hong et al. (2013) have identified that energy demand of buildings is significantly different for different cities and building types. This thesis has disclosed and quantified the different effects of these options. In the same way, in this work, the effects of the uncertainty of different weather variables = on the total electricity demand of buildings were investigated, addressing one of the research gaps identified by Huang et al. (2019), in the study of uncertainty in building simulation results.

In this thesis, the screening of model design parameters along with weather parameters in the weather datasets used in building simulation were studied. Up to now, previous research studies have not generally analysed the sensitivity of 'morphed' future weather time-series in building simulation results. Therefore, this study is innovative for enabling the quantification of the implication of each weather variable and weather characteristics on the electricity demand of office buildings. The type of weather data generated for the research did not represent any actual weather record; however, this approach gave valuable insights, as it made it possible to explore the response of the models.

The research framework has developed systematic methods to automatically analyse sensitivity and uncertainty in archetype models, which are made openly available, and guided by open science principles. Tian (2013) and Clarke et al. (2015) have advocated for the automatic generation of sensitivity analyses, collecting simulation data and automatic statistical analyses of simulation results, which was addressed with some of the tools developed in this work.

The research in this thesis contributed to the existing knowledge by providing a clear numerical understanding of the potential impacts of climate change for the total and HVAC electricity demand of office buildings, both for peak and annual levels. Andrić et al. (2019), de Wilde and Coley (2012), and Yassaghi et al. (2019) have concluded that studies on the effects of the impacts of climate change in buildings present significant differences. The identified differences in results could have been due to differences in the origins of weather datasets, building modelling assumptions, or climate modelling assumptions. The effects of climate change seem to be higher for hot climates than for cold (Andrić, *et al.*, 2019). This study confirms that the relative increase in total electricity annual demand is larger for hot climates(the largest simulation case was for large offices in C1-Singapore with 37.7% increase) than for colder climates (large office, C6-London, 15.4% or 13.1% for medium); However, the opposite is verified for total electricity peak demand (62.3% for medium office in C5-Lisbon versus 32.9% for small offices in C1-Singapore). The review of the literature in Chapter 2, and more specifically in Section 2.2, identified that effects for the peak demand were often overlooked; whilst, the impacts of climate change have been identified to potentially lead to further strain on the power grid due to significant growth on peak demand driven by additional cooling end users.

The research approach utilized in this work was innovative by developing a climate pathway scenario to recreate a path of uncertain future climate conditions (Chapter 6) that enables exploring and screening multiple levels of climate warming and quantifying its implications on building energy performance. In addition, in this thesis, a set of simulation cases was analysed to explore and compare the implications for different locations, for different types of buildings and at different degrees of end-use of the electricity demand. Moazami et al. (2019) concluded that the impacts of climate change studies have been focused on cold climates, where accessible future weather datasets are made available and have led to most of the existing research studies. However, it is not easy to apply similar approaches to any other location without the detailed climate projections datasets underpinning the generation of these future weather datasets. De Wilde and Coley (2012) have also concluded that there is a lack of uncertainty studies on the climate projections used for impact studies. Similarly, Nik, Perera, et al. (2020) concluded that it is necessary to account for the uncertainties and variations on climate projections and future technological scenarios to effectively develop climate-resilient designs – which is addressed by this Thesis.

De Wilde and Coley (2012) advocated the development of approaches to rank different adaptation measures in impact studies analysis. The research also adds to the knowledge by quantifying the effect of a broad number of simple and well-established adaptation/energy-saving measures in reducing demand levels. Some of these adaptation measures scenarios considered are already happening driven by mitigation efforts in reducing demand. For example, there are trends in the reduction of the power density of lighting and IT equipment in buildings, and efficiency improvements in HVAC equipment, substantially raising the system COP.

Therefore, the research findings gave a clear view of the impacts of climate change on the electricity demand of office buildings and the effect of adaptation measures to attenuate the potential growth of electricity demand

7.3 Research limitations and further work

All the analyses included in this thesis include only the three primary types of DOE reference office buildings, which incorporate generic HVAC systems and enable only a limited analysis of the building envelope characteristics. However, there may exist shares of the building stock that shall differ substantially from the characteristics represented by these archetypes, namely in the form characteristics, glazing areas, and the type of ventilation and cooling mechanisms. In the same way, the office building stock may be substantially different across the different cities/countries utilised in the simulation case. Therefore, the reference office models may not be representative of the building stock. Therefore, it would be interesting to analyse additional types of office building archetypes, that could represent a more extensive set of building sizes, different shapes and especially and different types of

HVAC systems. Energy demand is highly correlated to the HVAC option considered, as Korolija et al. (2013) explored, in investigating UK office archetypes. Finally, the study is conducted only for six different locations, and this choice may not cover all types of climates.

The research work presented in this thesis is limited in the scope of the building design and operational parameters analysed and the conditions included when analysing the office models' electricity demand for cooling requirements. For example, there is limited understanding of the implication of form envelope parameters for the demand and/or the analysis of the effects for more complex components of the cooling requirements, namely latent and sensible loads. The number of options for HVAC systems considered in these studies is limited, limiting the analysis to single systems, and the findings can be considerably changed with the other HVAC options. Future research should look to similar building performance comparisons considering a wider variety of HVAC systems for each office type. Similarly, it may be relevant to analyse the differences in more detail for different cities and representative climates and other buildings.

In this thesis, a static approach was used to model several operational parameters in the research analysis, namely for lighting, occupancy and equipment densities, ventilation rates and HVAC system settings. A more dynamic and sparse modelling approach will enable to analyse the implication of intelligent control of detrimental operational parameters during peak periods. Such a type of modelling may mimic real practices on building systems management and upgrade the impacts of the analysis.

A more dynamic setting of the building models could allow analysing the interaction effect between some energy-saving measures and the response of the thermal zone status and HVAC systems. For example, it could be analysed automatic management of heat gain loads in response to weather conditions or more flexible and stochastic behaviour of internal heat gains. Samuelson et al. (2020) concluded that it is imperative to take advantage of the synergies of multiple energy-saving measures on different performance indicators. Performing a similar analysis of the mitigation effect of other types of adaptation options and more complex simulation settings, are important to be undertaken. Further energy-saving opportunities may be provided by these, and could be more easily incorporated in future building designs and operations than the measures studied here.

It is also limiting that only one HVAC system option is analysed for each building in these simulation case studies. It is difficult to compare the performance of different types of building models without bringing in a lack of consistency to the analysis. Trying to compare systematically and screen model conditions and assumptions may easily result in inconsistencies. One of the future steps should be looking at similar sensitivity/uncertainty comparisons considering a wider variety of HVAC systems for each office type. This approach will enable the screening of the technology options in office models and highlight any vulnerabilities of the different technology options. However, it is still relevant to understand and quantify the different responses of each model, to check potential vulnerabilities on modelling assumptions/approaches that are taken when using these models.

7.3.1 Limitation on sensitivity and uncertainty analysis

In this thesis, a systematic and broadly methodical analysis of the sensitivity and uncertainty of office buildings is presented. While broadly and systematically screening 14 input model parameters, many other parameters were still not accounted into the analysis. For example, the implications of physical envelope/form parameters are poorly investigated. As discussed above in this section, a more insightful investigation of these parameters and understanding of the implications on space cooling requirements and electricity demand for this end-use is required to drive wider-reaching and generalisable findings. One other limitation of this study is that it might incur inconsistencies when setting the same uncertainty levels for all modelling conditions investigated (cities and office types). For example, Tian et al. (2018) concluded that uncertainty databases should cluster information by model types, climate, and the vintage of buildings.

For a more insightful sensitivity analysis for building performance analysis, it is important to quantify and relate probability functions that better represent the input parameters' uncertainty ranges to better evaluate the uncertainty of results. An improved ability to integrate building models is necessary for this to occur, permitting more standard changes of archetypes. More repositories of building models could be made available to understand and reproduce previous research studies. Another limitation of exploring the uncertainty of results as done in the present investigation is the cluttered and communication/presentation of key results. In the future, it is necessary to develop new tools that facilitate the generation of building models, collect simulation results, execute statistical analysis and better visualization methods to conduct and present this analysis as discussed in (Tian, 2013; Tian, Heo, *et al.*, 2018; Huang, *et al.*, 2019).

A limitation of the research approach assessing the sensitivity of weather parameters was focusing mainly upon the total electricity demand, and so it was unattainable to explore in detail the implications of these weather changes for specific HVAC end-uses and space cooling requirements. The effects of weather variability in the total electricity demand were critical to evaluate, and so identify the different responses for the different types of buildings, locations and temporal resolutions of the demand. The analysis only looks at the implication for office models using the EnergyPlus thermal engine. It would be very relevant to quantify and compare the effects of these weather changes for different thermal engines, as it is likely to exist different intricacy of weather variables on thermal engines, Another limitation of the study is not to explore more complex sensitivity and uncertainty analysis techniques to quantify the combined uncertainty of multiple variables and so to analyse the potential interaction effect between climate parameters and other modelling parameters (namely: form and envelope characteristics).

The sensitivity/uncertainty studies performed in this thesis, looked separately at the uncertainty of input model parameters (Chapter 4) and the uncertainty of weather variables (Chapter 5). Thus, the approach is limited in its ability to identify the potential interaction effects between building modelling parameters and weather parameters. Nevertheless, the research approach presented in this thesis provides a framework that addresses the need for flexible and systematic analysis of sensitivity. In future investigations, there is abundant room for further progress in extending the approach to different simulation case conditions to focus on different output metrics and consider more complex model parameters to iterate.

7.3.2 Limitations on the assessment of the impacts of climate change and the effects of adaptation/energy-saving measures

Regarding the impacts of climate change using a synthetic climate pathway, some limitations are identified and discussed. The generation of the weather datasets in the climate pathway for the different locations presents limitations, as the same approach led to different levels of the sprawl of the weather variables time series across different locations (presented in Sub-section 6.2). The climate pathway approach ignores the known fact that climate change impacts are geographically distinct and all the microclimate phenomena that may affect the performance of buildings. In the same way, only six locations were analysed, limiting the understanding of the effects of such pathways scenarios to other climates and even other cities with similar climates. It would also be interesting to introduce correlation patterns between weather variables when operating changes on future weather datasets for a climate pathway. It would also be helpful to create climate pathways adapted to the time span of the climate change projection results at the source of the analysis.

The approach was also focused on the effects on the electricity demand, and did not evaluate the implications for multiple other metrics that could also be detrimental to the operation of buildings (overheating, heating demand and space cooling). In addition, the research findings reported the effects at the individual building level and did not quantify the effects at the aggregated stock level, which is the level that stresses energy networks. In any case, the use of weather datasets from the climate pathway scenario enabled a more robust evaluation of building design climate resilience. Climate pathways allowed climate-proof building designs in a faster and straightforward approach, which can be systematically replicated. As Nik, Perera, et al (2020) discussed, this is fundamental to assessing the climate resilience of built infrastructure designs. Finally, with the increasing number of simulation iterations and the number of output variables analysed, it becomes incredibly challenging to communicate uncertainty in this type of research work. Tian et al. (2018) advocated that new visualization tools should be developed, and new statistical metrics should be used to communicate the outcomes of uncertainty studies in building performance analysis. Whilst this research intended to evidence straightforward comparison of sensitivities and uncertainties, part of this challenge remains to be solved.

The research findings reveal the direction and magnitude of the overall change associated with well-known adaptation measures. In the future, it would be interesting to evaluate a range of integrated adaptation solutions, which consider more flexible building operational conditions. It is also important and relevant that other types of solutions, and how they relate to other occupancy factors (lighting, thermal comfort, well-being, productivity) are assessed. It will also be important to understand the cost-effectiveness of the solutions analysed. The individual building level scope of the analysis limited the extrapolation of findings to a larger building stock level. However, it is valuable to understand the fundamental level effect of different type of measures, when trying to design adaptation solutions for the whole stock. It will also be essential to analyse the effects of urban morphology adaptation measures at individual levels, and develop simplified ways to integrate into building performance simulation runs, the effects of such measures. In addition, it would also be interesting to analyse the effect of stock level solutions, such as demand response, thermal storage, district cooling networks, on shaving peak demand, and reducing cooling demand of the building stock.

7.4 Chapter summary

This chapter discussed how the research findings in this thesis addressed the research questions defined for the project, and described in the introduction (Chapter 1). Each of the five research questions is explored (Section 7.1), scrutinising the research findings that address those. Following, a reflection on the significance of these research findings (Section 7.2) is provided, and the research limitations and recommendations for further analysis are discussed (Section 7.3). The discussion made in this chapter puts in a larger perspective on research findings presented throughout the thesis. The remarks made establish and support the research conclusions presented in the next chapter and propose ideas for future research.

8 Conclusions and recommendations

In this investigation, the aim was to explore the potential effects of future climate change impacts on the cooling HVAC demand of office buildings, and quantified the implications for electricity demand in different regions of the world. This thesis set out to examine the impacts of climate change upon the cooling requirement and total electricity demand for three type of office buildings (small, medium and large office reference models) in six different cities (Singapore, Cairo, Athens, Beijing, Lisbon and London). A climate pathway framework was developed to capture the uncertainty in the future weather datasets, and used to quantify the impacts of climate change for cooling demand of office buildings.

First, in Chapter 4, the sensitivity of different input parameters on office buildings was assessed together with the uncertainty of different building energy modelling outputs. In these studies, the two first research questions are addressed. In Chapter 5, an assessment of the effects of isolated morphing procedures is made, addressing the third research question. Finally, in Chapter 6, the last result chapter, the effect of a synthetic future climate pathway on the space cooling requirements and electricity demand of the office buildings were analysed (Section 6.3) and assessed the effectiveness of several adaptation measures in controlling additional demand due to the effects of climate change (Section 6.4). Thus, it addressed the fourth and fith research questions of this thesis. The following section summarises the responses to these research questions.

8.1 Answering research questions

8.1.1 The first research question: *"How sensitive is the office building energy modelling to different operational and design input parameters?"*

The research question was addressed by conducting a systematic sensitivity analysis of office building design and operational parameters on total electricity, HVAC end-use and space cooling requirements for both peak and annual demand levels. A systematic framework to perform parametric building simulation studies was developed, utilising a dual-stage sensitivity analysis (Morris EE and Sobol analysis), first in simplified office building models and then on archetype DOE office models.

The research findings showed that lighting and equipment densities, cooling set-point temperature, coefficient of performance and ventilation rate, make a significant contribution to the total electricity demand in office buildings. For HVAC electricity end-use and space cooling, cooling set-point temperature, coefficient of performance and ventilation rate, were the key parameters for both annual and peak demand. However, it was clear that both the ranking and the relative contribution of the parameters differed, when looking at different output and temporal resolutions. Similarly, the relative contribution of parameters varied for each office building type and city analysed.

8.1.2 The second research question: *"What is the relative impact on peak and annual HVAC and total electricity demand of office buildings as cooling requirements differ with changing building design and operational conditions?"*

The systematic framework developed in this thesis for sensitivity studies on building performance analysis was prepared to assess and compare the simulation results across different locations, different types of office buildings, for different simulation output metrics and for different demand levels (peak and annual). The framework normalises results among different simulation case conditions to compare results systematically. Similarly, results are compared across the different locations looking at *CV* of simulation result samples, and boxplots are presented to compare results across the different simulation case conditions.

The research findings in this work have shown that, in general, the response of peak demand is larger than for annual demand for all office buildings across most of the locations analysed within the simulation cases evaluated. In addition, the response was more significant on electricity demand for HVAC end-use and more limited on total electricity demand. Besides the exhaustive and comprehensive analysis among demand levels, type of buildings and locations, it is challenging to make a general conclusion for the whole building sector/building stock based on these findings for a limited set of simulation cases. Nevertheless, the research framework developed and applied to investigate the sensitivity of building design and operational parameters, and the uncertainty of electricity demand for cooling requirements is innovative and pertinent for the building design and building simulation research.

The research approach was developed to contribute to a breakthrough on the systematic and broad dissemination of uncertainty and sensitivity analysis in building simulation studies. Finally, the work presented in Chapter 4 has led to three distinct research publications (Zeferina, Birch, *et al.*, 2019), (Zeferina, Wood, *et al.*, 2019) and (Zeferina, *et al.*, 2021).

8.1.3 The third research question: *"How does the morphing of weather timeseries influence the peak and annual HVAC and total electricity demand?"*

In Chapter 5, the research explored the implications of climate variability for the total electricity demand of archetype office buildings. The research study applied an innovative methodology developed approach to assess the sensitivity of morphing operations at weather timeseries in building performance simulation.

The research findings, regarding the simulation results for the simulation cases where the approach was applied, have shown that the dry bulb temperature is the weather variable that drives total electricity demand the largest, due to additional demand from the HVAC end-use. For example, an uniform 5°C increase (shift) in dry-bulb temperature variable values lead to a rise up to 26.8% and 38%, respectively, for peak and annual total electricity. The temperature change operation for summer season prevalence (larger shifts in summer than in the remaining of the year) or additional growth on the daily dry-bulb temperature amplitude (stretch) during heatwave periods were also relevant for peak total electricity demand of buildings (the first leads to rise up to 15.4% and the other up to 9.4%). The implication of relative humidity for the electricity demand is likely to reduce total electricity demand (a uniform reduction of 10%, may decrease up to 5.7% peak demand and 5.1%

annual demand). The effect due to a growth factor (stretch) of 1.25, individually in solar radiation variables lead to increases up to 5.2% (annually). Wind speed has shown low implications for the demand (no more than 0.7% annually or 1.4% for peak).

The research provides pieces of evidence that the implications of the choices on how morphing operations are executed on dry-bulb temperature may create significant changes in electricity demand. In addition, it indicates that solar radiance is important in assessing demand in future weather scenarios, while wind speed shows lower effects than the changes in the other weather variables. In addition, it also shows that the effects are related to the building types utilised and the original weather data considered (locations).

8.1.4 The fourth research question: *"To what extent could the electricity load of office buildings be affected by changes in cooling demand due to the impacts of climate change?"*

A climate pathway framework was developed to evaluate a wide range of potential climate change impacts, in a systematic and time-efficient approach for different locations. In the simulation case conditions utilised, 200 synthetic future weather sample conditions were iterated for each location, and building simulations were run for the three distinct archetype office buildings. The comparison of the energy performance results among the sample of simulations was based on the additional electricity demand over the baseline values, for HVAC end-use and total demand, for both peak and annual levels.

The weather changes represented by the climate pathway framework is driven by morphing procedures that are inferior to annual mean temperature shifts of 5°C (which can be up to 7°C shifts on summer periods while only 4°C for winter). Thus, in the climate pathway sample, maximum dry-bulb temperatures increased up to 13.7°C for C6- London and 12.7°C for C5-Lisbon; while the maximum change in cooling degree days was for C6-London from 7 to 488 and from 218 to 1278 for C5-London. Some of these weather changes are equivalent to the most extreme future scenarios within WeatherShift file sample (RCP 8.5 – 2085 – 95 probability).

The research results showed that the potential impacts of climate change are significant, both for the HVAC demand end-use and the total electricity demand end-use. For the simulation case selected to apply the climate pathway approach developed, increase relative to the baseline in total annual electricity demand, when considering the whole climate pathway, can reach up to 38%, and for peak total demand can go up to 62%. For HVAC demand, the level of change relative to the baseline was found that could be much larger (182% for annual and 158% for peak). The relative level of change is different across all cities analysed and for the different office types. From the results, for HVAC demand, it is evident that the pathway developed drove larger changes for colder climates, so a marked rise in C6-London (e.g. up to 182% - annual and 156% - peak, medium office), than for hotter climates, so a slower increase in C1-Singapore (e.g. up to 64% - annual or 97%,- peak for medium office). However, for total annual electricity demand, the implications of the climate pathway are larger for cities with hotter climates cities than for colder cities. In comparison, the opposite occurs for peak total electricity demand.

More than the quantification of the impacts of climate change on annual and peak electricity demand for the set of conditions covered in the simulation cases (office types and six locations), this research presents a method that guarantees a broad set of weather scenarios. The approach delivers a sample with a large range of weather iterations, including extreme peak conditions, that is possible to apply for any weather dataset in the world and adapt the uncertainty ranges that may apply for the likely time-span. Therefore, the research is able to provide a tool to assess the reliability of the building performance and so assess the climate resilience of a building design in future conditions/scenarios.

8.1.5 The fifth research question: *"To what extent and magnitude could a potential increase in electrical peak load due to cooling provision be limited in future scenarios, by adaptation measures?"*

To pursue this, a set of adaptation/saving measures (six simple/single and three sets of combined measures) were selected, to evaluate the potential to mitigate additional demand due to potential climate change impacts, using the simulation sample generated by the climate pathway framework created. A systematic framework to normalise and compare the simulation output results was developed to evaluate the mitigation potential throughout the climate pathway sample.

The research findings have shown that even in the worst point of the synthetic climate pathway, total electricity demand can be maintained below current baseline demand levels, both for annual (option measure 9 lead to reduction at least of 8% - large, 16% - medium or 27% - small offices) and peak demand (13% - large, 11% medium or 29% - small), in all cities and building type analysed. For HVAC demand, reduction levels achieved robustly reduce levels under current base conditions, but for the same cases, at extreme weather datasets for some modelling options (city and building type), demand will grow relative to baseline levels (. 15% or 16% above peak baseline demand, and 10% and 31% for annual, in London, respectively for large and medium offices). Research results also showed that the relaxation of the cooling set-point, reduction of lighting and equipment power densities are the individual measures that can have the largest reductions in the total electricity demand (mean reduction effect for the first can reach 20% and the for the other two is around 10% each).

The findings showed that total electricity consumption levels could be maintained below current baseline levels, both for peak and annual resolution, for all office types and cities analysed, using a range of known and straightforward measures. However, for HVAC electricity end-use, the effect of these measures might not be sufficient to reduce the potentially large increase for some points under the whole pathway scenario and for all modelling options (cities and building types).

Having summarised the conclusions of this thesis, it will now move on to identifying the contribution of these research findings for the research community and building modelling practitioners.

8.2 Research contribution

In this thesis, a comprehensive and systematic analysis of the sensitivity of the model assumptions was conducted, either by analysing the sensitivity of building design and operational model parameters', or the effect of the uncertainty of weather variables. Thus, the research has enabled the quantification and a better understanding of the dynamics of the systems underlying the cooling demand of office buildings. The research done in this thesis adds to the growing body of work that understands the sensitivity of building energy modelling (Tian, 2013; Tian, Heo, *et al.*, 2018; Huang, *et al.*, 2019). This work has both deeply analysed the sensitivity of the building design and operational input parameterisation of different buildings, climates and the effects on peak load both for HVAC end -uses, space cooling, and total electricity. As far as the author is aware, this is the first study to investigate, quantify and compare the sensitivity of electricity demand model outputs, for different locations and building types. The research findings raise questions on whether looking at the findings from case studies (single building type and location) can misjudge the design decision making of building design practitioners. This research suggests that input sensitivities may be divergent among all the modelling conditions analysed (time resolution, locations and building types).

The research combined modelling approaches for the analysis of sensitivity and uncertainty in building energy modelling using the three office DOE reference models. The research done is one of the few studies systematically looking at DOE archetype models sensitivity and uncertainty. The study revealed that annual and peak demand uncertainty is significantly different, quantifying the different outputs across the iteration sample in the sensitivity studies (with *CV* values, boxplot figures and quantile value figures). One strength of these sensitivity studies is that it quantifies and compares the uncertainty for the different output metrics, temporal resolutions, building types and locations. The results revealed that the uncertainty of models is significantly different among the locations analysed and different types of buildings. The distinctions are especially highlighted when looking at total electricity and HVAC end-use.

In addition, the research takes sensitivity analysis into the screening of weather datasets through the application of morphing procedures. This is the first study the author is aware of that has explicitly examined the sensitivity of morphed weather data on the energy performance of buildings. Despite its exploratory nature, these findings offer some innovative insights into the impacts of weather variability in building simulation, as they quantify the isolated implications of 'morphing' operations in weather variables time series to the total electricity demand of office buildings. The 'morphing' operations are central to the methodologies applied in standard weather tools for the generation of weather data with generic geographical scope (e.g. WeatherShift (Dickinson, *et al.*, 2016), Meteonorm (Meteotest, 2020) and CCWorldWeatherGen (Jentsch, *et al.*, 2013)) and which are frequently utilised in research analysing the impacts of climate change in building performance. Therefore, the research approach to analyse the sensitivity of the morphing of weather timeseries provides a relevant framework to analyse the uncertainty in building performance simulation related to the generation of future weather data.

Once the analysis of the effects is made across multiple locations and types of offices, the effects on total electricity demand enable to better understand the potential effects to overall electricity demand for the power network. The findings suggested that different weather time series operations led to substantially different outcomes in the total demand and informed the demand ranking of these weather parameters. The research findings clearly state that changes in dry-bulb temperature led to more significant responses to total electricity demand than changes in other weather variables. These findings raise questions on the necessary detail of generating some of the variables for building performance simulation, as it suggests that some of these changes (for example, changes in wind speed) have a limited implication on the total demand of office buildings.

In this thesis, a research tool was developed, which generated a sample of weather datasets to simulate a pathway of future weather conditions. The climate pathway framework aims to simulate an uncertain scenario of future climate conditions, which can be applied to any geographical location, adapting the uncertainty levels and weather variables morphed to assess the potential impacts of climate change. The methodology developed has offered a framework for a robust assessment of building energy performance, on a range of different future climate conditions, and evaluating and ranking the implications of progressive levels of climate change impacts. The research simulation case, used in the application of the climate pathway framework in the thesis, replicated a research approach of evaluating the impacts of climate change using dynamic building simulation with existing archetype models (previous examples are (Drury Browne Crawley, 2008; Wang, *et al.*, 2014; Dirks, *et al.*, 2015; Tarroja, *et al.*, 2018; Moazami, *et al.*, 2019; Berardi, *et al.*, 2020)); however, focusing on observing the implications for cooling demand end-uses and total electricity demand. The literature review has identified that previous research has overlooked the analysis on peak demand, which changes might create stress on energy systems sizing, which changes on annual demand do not inform.

In addition, the research contributed to the quantification of the potential of adaptation/energy-saving measures in reducing the additional demand for cooling due to the warming effects of the impacts of climate change. The research utilised the climate pathway method to quantify a range of potential effects in the future and also assessed the effects of a set of known adaptation/energy-saving measures to attenuate the additional demand due to cooling requirements in the climate pathway. The set of adaptation/energy-saving measures included the relaxation of the cooling set point (measure 1), reduction of the ventilation rate (measure 2), reduction of lighting (measure 3) and equipment (measure 4) densities, increasing the COP (measure 5) and reducing the SHGC of windows (measure 6). The analysis replicated previous analysis that assessed the effectiveness of different adaptation/energy-saving measures on attenuating additional demand (Mata, *et al.*, 2019), extending the analysis for a range of conditions prepared throughout the pathway.

This is the first study the author is aware of that has evaluated the effectiveness of adaptation/energy-saving measures in a broad range of climate scenarios, as provided by the climate pathway framework. Therefore, the study makes several noteworthy contributions to the research assessing the effects of adaptation/energy-saving measures to mitigate additional demand due to the impacts of climate change. For example, the simulations case selected for the research in the thesis, enable to analyse the effect for demand both annually and for peak loads, both for total and HVAC electricity end-uses, for different locations and type of office buildings.

Overall, the research in this thesis contributes with an innovative and original approach to assess the potential impacts of climate change. The frameworks developed permit to generate weather data samples that mimic a range of future weather conditions that included mild to extreme changing effects. This type of tool enables the investigation of climate-resilient designs and evaluates the effects of possible and expectable adaptation measures in attenuating the effects of climate change. Having summarised the contributions of the research findings of this thesis, It will now move on to identifying the implications of these for the research community and building modelling practitioners.

8.3 Reflections

The research findings have implications for different stakeholders and on multiple research aims/topics. For example, the research findings brought out from the research analyses of the simulation cases produced, provide a better understanding of the overall energy demand implications of modelling uncertainty for offices buildings (space cooling, HVAC end-use, and total electricity demand). The research findings, relative to the simulation cases analysed, also intend to propel building energy modellers and building designers to further interrogate the implication of these uncertainties across different climates and different types of buildings with different building characteristics. The research approach and framework developed in this thesis was set up to pursue a more holistic understanding of the implications of these factors in the energy performance of buildings and in their cooling systems. This type of research study suggests the importance of moving the research field into this direction, reporting results on a broader range of output metrics and assessing the implications for a span of metrics rather than focus on single ones. Thus, the research findings and the research framework developed contribute to moving away from the deterministic paradigm that the research field has set, towards a holistic sight that is necessary for credible assessments of building performance using BPS as highlighted by Rastogi (2016).

The research work in the thesis has also brought a broader understanding of the implications of climate change using a pathway framework rather than deterministic method that are the usual approach in the building research area. Besides all limitations discussed, this type of approach provides different insights into climate change implications to buildings energy performance and designs. Policymakers, urban planners and entities responsible for building energy standards benefit from these findings, as these inform and explicitly quantifies the trend of effects of general measures, and effects of climate change in a broad range of conditions. These findings may provide important insights to tailor and adapt different type of measures for different buildings, locations, and understand their impact for different metrics.

The climate impact modelling framework developed permits to reveal the tendencies and to show a continuous progression of the changing climate effects upon the building energy performance. For the set of simulation cases produced in this research, the focus of the output performance is for cooling demand and related energy demand. This approach decouples the analysis from climate projection vectors like the temporal resolution of projections and the emission scenarios. The analysis enabled by the framework focuses on the driving factor of the implications of climate change for buildings, the uncertainty in the weather conditions, and the progressive effect that weather changes will have on buildings' energy performance. The research findings show that it is important to get the level of internal heat gains (especially lighting and equipment densities) in the analysis of buildings designs, as accurate as it is possible, once they have a major contribution to total electricity demand. Similarly, it is important to consider adapting design parameters as the COP, ventilation rate and cooling set-point temperature to minimize HVAC electricity demand and its sizing. In addition, the findings show that uncertainty in weather conditions must be considered in the evaluation of future building performance, primarily due to changes in dry-bulb temperature, but also solar irradiance and relative humidity. These findings are not only relevant for building designers and building modellers, but also for building operators and district and energy network planners. The findings have shown that there is a large uncertainty of the energy demand due to design and weather assumptions, and that these volatilities must be considered. Similarly, the research findings indicate that there are multiple opportunities in the operation of buildings that can be further explored when synchronised with energy networks operation.

In addition, the research framework introduces a systematic procedure to assess the effects of adaptation measures. Therefore, coupling these assessments with a pathway, it is possible to analyse such measures' effectiveness for a span of conditions. As highlighted by Nik et al. (2020), future research should move toward the analysis of reliability and robustness of designs solutions, developing frameworks that explore the potential uncertainties of assumptions and the effect of different scenarios, instead of seeking authoritative estimations of long-term futures.

8.4 Recommendations

- **Drive for open science principles**

The research work has pursued open science principles, opting to openly share building models, simulation outputs, research algorithm methods and data analysis. Having access to previous methods and openly available models have enabled the research to move from the time-consuming tasks of constructing and validating models to the curious exploration of different assumptions and uncertainties. Opting for open availability of methods, sources, data, models, and algorithms, the research limitations and modelling incongruences will be easily detected and challenged. Nevertheless, the open accessibility may drive researchers to build upon the work (models and frameworks), and so giving continuation to the research and the unfolded future research work ideas. In the future, it is essential that the community focus progressing to further challenges, explore different assumptions and extend frameworks.

- **Research community joint efforts**

It is necessary to invest more effort and funds in developing archetype models, tools and frameworks that enable and promote the investigation of uncertainty in building models. The research findings in this work may show the importance of investing in the development of these tools, which may lead to a better understanding of buildings' system dynamics. In addition, it is essential that efforts on validating and creating uniform frameworks to compare different simulation tools evolve to comparison on a much larger scope of conditions. Therefore, these research findings may also show the relevance of investigating and comparing the different sensitivities of building performance simulation tools on equivalent output metrics. Also, this research may show that it is necessary to generate future climate data and tools/frameworks to climate-proof building, stock and energy systems design in a more resilient way.

- **Building design guidelines**

The research findings and the further application of the research frameworks may also help to build designers to develop rules of thumb for different design choices in their projects. This type of findings may also help some building designers take existing archetype models for exploratory analysis of their assumptions and scenarios and test different hypotheses. Simultaneously, it is necessary that energy efficiency policies keep pushing the limits of building technologies and that the most outstanding efforts are made on technologies that may have the largest effects on the building stock and the design and operational challenges that they face. Therefore, it is essential to investigate the potential effects of different energy-saving measures further and compare their effectiveness. It is relevant to further expand this analysis and evaluate their effectiveness on a broader lens scope.

8.5 Future research work

To address some of the most immediate limitations of the research in this thesis identified in Section 7.3, a list of additional key analysis is proposed:

- Expand the application of the frameworks developed into simulation case studies that explore different DOE reference model types, locations, alternative HVAC systems, and use other building energy simulation tools;
- Adapt the research frameworks proposed for different building performance simulation tools and explore the implications for other building performance indicators;
- Execute sensitivity analysis looking at different types of input model parameters, associated with changes on weather parameters, and exploring possible interaction effects.

In the following paragraphs, some pivotal research options to further extend the research work beyond the current limitations of the thesis are discussed.

Considerably more work will need to be done to develop and make available archetype building models that are idealized and prepared for exploring many uncertainties in their design parameters, including the physical characteristics. Such efforts would trigger important research avenues in the building performance simulation area. For example, it could pursue sensitivity and uncertainty analysis on a broader scope of modelling parameters, leading to further understanding of the implications of modelling assumptions and the uncertainty of the building energy models. More broadly, it is pivotal to make this type of systematic analysis readily available, not only models but also simulation outputs and data manipulation procedures, following open science principles. Such an approach may enable future research efforts to extend the coverage of model uses and research analysis rather than build up and validate models repeatedly. For example, DOE reference models should be prepared and made available for parametric iterations of a larger set of parameters, different types of HVAC systems and form characteristics (glazing areas, envelope ratio areas and width-length ratios).

Further work on the research methodology on the generation/modification of weather data will have to be done, namely on the morphing operations. For example, on the stretching of extreme events, on imposing some correlation factors between solar and temperature changes, and by including considerations about cloud cover, when generating weather timeseries. In the same way, further research is required to further develop the climate pathway framework. Further development of the pathway framework could make it possible to select weather variables, the range of changes and the morphing operations made in the weather variables. Further work is also required to develop and incorporate a more quantitative analysis of risks throughout the climate pathway. In addition, another avenue for research can be to incorporate into the climate pathway framework, a similar stochastic approach used to generate weather data to define design and operational building modelling parameters, in order to analyse in wider scopes the performance uncertainty in future scenarios.

Finally, a natural progression of this work is to develop aggregate weight models based on archetype simulation results that can analyse implications at building stock levels, so helping to drive building design policies, infrastructure and energy systems planning. Another avenue for research is to understand the effects on district scale demand level, based on aggregating weight model methods, considering the uncertainty of building occupancy assumptions and/or weather uncertainty. For example, district cooling systems may become technological solutions that will be much more common in the future. However, the design of this type of solution may be affected more significantly by the implications of climate change than power grid infrastructure or buildings at individual levels.

8.6 Chapter summary

The chapter presented the concluding remarks of the thesis. Firstly, it stated the answers to the research questions addressed throughout the thesis (Section 8.1). Then, it presented the thesis's contribution (Section 8.2), some research reflections (Section 8.3) and research recommendations (Section 8.4). Finally, ideas for future research work were presented (Section 8.5).

The thesis manuscript's body is concluded here, after presenting the conclusive remarks that summarise this work's research findings. In the appendixes, supplementary results from the result chapter are presented, and summary tables of the studies covered in the literature review are given. A description is made of the materials available in the repository made available with this work. This repository is made available to allow further replication of the research and advancements in the research methods used.

References list

Abbasabadi, N. and Mehdi Ashayeri, J. K. (2019) ‘Urban energy use modeling methods and tools: A review and an outlook’, *Building and Environment*. Elsevier, 161(July), p. 106270. doi: 10.1016/j.buildenv.2019.106270.

Abela, A. *et al.* (2016) *Study on Energy Use by Air- Conditioning*, *BRE*. Available at: https://www.bre.co.uk/filelibrary/pdf/projects/aircon-energy-use/StudyOnEnergyUseByAirConditioningFinalReport.pdf.

Aijazi, A. N. and Brager, G. S. (2018) ‘Understanding climate change impacts on building energy use’, *ASHRAE Journal*, 60(10), pp. 24–32.

Allen, S. K. *et al.* (2013) ‘Technical Summary’, in Intergovernmental Panel on Climate Change (ed.) *Climate Change 2013 - The Physical Science Basis*. Cambridge: Cambridge University Press, pp. 31–116. doi: 10.1017/CBO9781107415324.005.

American Society of Heating, Refrigerating and Air-Conditioning Engineers, A. (2007) *62.1 User’s Manual: ANSI/ASHRAE Standard 62.1-2007 : Ventilation for Acceptable Indoor Air Quality*. American Society of Heating, Refrigerating and Air-Conditioning Engineers, 2007. Available at: https://www.ashrae.org/technical-resources/bookstore/standards-62-1-62-2.

American Society of Heating, Refrigerating and Air-Conditioning Engineers, A. (2013) *2013 ASHRAE Handbook - Fundamentals*. 7th edn. Atlanta: ASHRAE, 2013.

Andrić, I., Koc, M. and Al-Ghamdi, S. G. (2019) ‘A review of climate change implications for built environment: Impacts, mitigation measures and associated challenges in developed and developing countries’, *Journal of Cleaner Production*, 211, pp. 83–102. doi: 10.1016/j.jclepro.2018.11.128.

Arup and Argos Analytics LLC (2020) *Weather Shift tm*. Available at: https://www.weathershift.com (Accessed: 15 March 2020).

ASHRAE, American Society of Heating, R. and A. E. (2003) ‘ASHARE Standard 55. Thermal Environmental Conditions for Human Occupancy’, pp. 1–52.

ASHRAE, American Society of Heating, R. and A. E. (2013) *Standard 90.1-2013, Energy standard for buildings except low rise residential buildings*.

ASHRAE, American Society of Heating, R. and A. E. (2020) *Standard 169-2020 -- Climatic Data for Building Design Standards*.

ASHRAE (2009) *Standard 189.1-2009: Standard for the Design of High-Performance Green Buildings (Except Low-Rise Residential Buildings)*, *American Standards Institute*.

ASHRAE (2013a) ‘18 - Nonresidential Cooling and Heating Load Calculations’, in *ASHREA Handbook Fundamentals*.

ASHRAE (2013b) ‘19 - Energy Estimating and Modeling Methods’, in *ASHREA Handbook. Fundamentals*, pp. 19.1-38.

ASHRAE (2013c) ‘Heat Transfer’, in *ASHREA Handbook Fundamentals*, pp. 3–264. doi: 10.1016/B978-0-08-102550-5.00001-8.

Asimakopoulos, D. A. *et al.* (2012) 'Modelling the energy demand projection of the building sector in Greece in the 21st century', *Energy and Buildings*, 49, pp. 488–498. doi: 10.1016/j.enbuild.2012.02.043.

Assembly, U. G. (2015) 'Transforming our world : the 2030 Agenda for Sustainable Development'. UN General Assembly, pp. 12–14. doi: 10.1201/b20466-7.

Attia, S., Evrard, A. and Gratia, E. (2015) 'Development of benchmark models for the Egyptian residential buildings sector', *Applied Energy*. Elsevier Ltd, 94(2012), pp. 270–284. doi: 10.1016/j.apenergy.2012.01.065.

Auffhammer, M., Baylis, P. and Hausman, C. H. (2017) 'Climate change is projected to have severe impacts on the frequency and intensity of peak electricity demand across the United States', *Proceedings of the National Academy of Sciences*, 114, p. 201613193. doi: 10.1073/pnas.1613193114.

Auffhammer, M. and Mansur, E. T. (2014) 'Measuring climatic impacts on energy consumption: A review of the empirical literature', *Energy Economics*. Elsevier B.V., 46, pp. 522–530. doi: 10.1016/j.eneco.2014.04.017.

Augenbroe, G. (2011) 'The role of simulation in performance based building', in *Building performance simulation for design and operation*, pp. 15–36.

Aughenbaugh, J. M. (2006) 'Managing Uncertainty in Engineering Design Using Imprecise Probabilities and Principles of Information Economics', p. 350.

Ballarini, I., Corgnati, S. P. and Corrado, V. (2014) 'Use of reference buildings to assess the energy saving potentials of the residential building stock: The experience of TABULA project', *Energy Policy*, 68, pp. 273–284. doi: 10.1016/j.enpol.2014.01.027.

Bank, A. D. and Global Center on Adaptation (2021) *A System-Wide Approach For Infrastructure Resilience*. Manila, Philippines. doi: 10.22617/TCS210017-2.

Bank, T. W. (2021) *GDP (current US$) | Data*. Available at: https://data.worldbank.org/indicator/NY.GDP.MKTP.CD (Accessed: 21 December 2021).

Barnaby, C. S. and Crawley, D. B. (2011) 'Weather data for building performance simulation', in Hensen, J. L. M. and Lamberts, R. (eds) *Building Performance Simulation for Design and Operation*, pp. 37–55.

BCA Green Mark (2010) *BCA Green Mark for New Non-Residential Buildings*.

Beausoleil-Morrison, I. *et al.* (2014) 'Co-simulation between ESP-r and TRNSYS', *Journal of Building Performance Simulation*, 7(2), pp. 133--151. doi: 10.1080/19401493.2013.794864.

Beddoe, N. (2012) 'Design for Future Climate – Developing an Adaptation Strategy', (August), p. 59.

Beizaee, A., Lomas, K. J. and Firth, S. K. (2013) 'National survey of summertime temperatures and overheating risk in English homes', *Building and Environment*, 65, pp. 1–17. doi: 10.1016/j.buildenv.2013.03.011.

Belcher, S. E., Hacker, J. N. and Powell, D. S. (2005) 'Constructing design weather data for future climates', *Building Services Engineering Research and Technology*, 1(February 2005), pp. 49–61. doi: 10.1191/0143624405bt112oa.

Berardi, U. and Jafarpur, P. (2020) 'Assessing the impact of climate change on building heating and cooling energy demand in Canada', *Renewable and Sustainable Energy Reviews*. Elsevier Ltd, 121(October 2019), p. 109681. doi: 10.1016/j.rser.2019.109681.

Berger, T. *et al.* (2014) 'Impacts of climate change upon cooling and heating energy demand of office buildings in Vienna, Austria', *Energy and Buildings*, 80, pp. 517–530. doi: 10.1016/j.enbuild.2014.03.084.

Berkeley, L. *et al.* (2017) 'Output Details and Examples'.

Bhandari, M., Shrestha, S. and New, J. (2012) 'Evaluation of weather datasets for building energy simulation', *Energy and Buildings*, pp. 109–118. doi: 10.1016/j.enbuild.2012.01.033.

Bravo Dias, J., Carrilho da Graça, G. and Soares, P. M. M. (2020) 'Comparison of methodologies for generation of future weather data for building thermal energy simulation', *Energy and Buildings*. Elsevier B.V., 206. doi: 10.1016/j.enbuild.2019.109556.

Brøgger, M. and Wittchen, K. B. (2018) 'Estimating the energy-saving potential in national building stocks – A methodology review', *Renewable and Sustainable Energy Reviews*. Pergamon, 82, pp. 1489–1496. doi: 10.1016/J.RSER.2017.05.239.

Building and Construction Authority (2008) *Code on Envelope Thermal Performance for Buildings*.

Burillo, D. *et al.* (2017) 'Electricity demand planning forecasts should consider climate non-stationarity to maintain reserve margins during heat waves', *Applied Energy*. Elsevier, 206(March), pp. 267–277. doi: 10.1016/j.apenergy.2017.08.141.

Burillo, D., Chester, M. V., Pincetl, S. and Fournier, E. (2019) 'Electricity infrastructure vulnerabilities due to long-term growth and extreme heat from climate change in Los Angeles County', *Energy Policy*. Elsevier Ltd, 128(February), pp. 943–953. doi: 10.1016/j.enpol.2018.12.053.

Burillo, D., Chester, M. V., Pincetl, S., Fournier, E. D., *et al.* (2019) 'Forecasting peak electricity demand for Los Angeles considering higher air temperatures due to climate change', *Applied Energy*. Elsevier, 236(July 2018), pp. 1–9. doi: 10.1016/j.apenergy.2018.11.039.

Butcher, K. ; and Craig, B. (2015) *Environmental Design*. London, *CIBSE Guide A*. London. Chartered Institution of Building Services Engineers. Available at: https://books.google.co.uk/books?id=IxXKAAAACAAJ.

Campbell, I., Kalanki, A. and Sachar, S. (2018) 'Solving the Global Cooling Challenge, GCP', p. 42. Available at: www.rmi.org/insight/solving_the_global_cooling_challenge.

Campolongo, F., Cariboni, J. and Saltelli, A. (2007) 'An effective screening design for sensitivity analysis of large models', *Environmental Modelling & Software*, 22(10), pp. 1509–1518. doi: https://doi.org/10.1016/j.envsoft.2006.10.004.

Caputo, P., Costa, G. and Ferrari, S. (2013) 'A supporting method for defining energy strategies in the building sector at urban scale', *Energy Policy*, 55, pp. 261–270. doi:

10.1016/j.enpol.2012.12.006.

Cellura, M. *et al.* (2018) ‘Climate change and the building sector: Modelling and energy implications to an office building in southern Europe’, *Energy for Sustainable Development*. Elsevier, 45, pp. 46–65. doi: 10.1016/j.esd.2018.05.001.

Chai, J., Huang, P. and Sun, Y. (2019) ‘Investigations of climate change impacts on net-zero energy building lifecycle performance in typical Chinese climate regions’, *Energy*, 185, pp. 176–189. doi: 10.1016/j.energy.2019.07.055.

Chai, J., Huang, P. and Sun, Y. (2020) ‘Differential evolution - based system design optimization for net zero energy buildings under climate change’, *Sustainable Cities and Society*. Elsevier, 55(October 2019), p. 102037. doi: 10.1016/j.scs.2020.102037.

Chandramowli, S. N. and Felder, F. A. (2014) ‘Impact of climate change on electricity systems and markets - A review of models and forecasts’, *Sustainable Energy Technologies and Assessments*. Elsevier Ltd, 5, pp. 62–74. doi: 10.1016/j.seta.2013.11.003.

Chartered Institution of Building Services Engineers (2016) *CIBSE Guide B2 - Ventilation and ductwork*. 2016th edn. Edited by Chartered Institution of Building Services Engineers. London: Chartered Institution of Building Services Engineers. Available at: https://www.cibse.org/knowledge/knowledge-items/detail?id=a0q20000008JuB7AAK.

Chen, D., Wang, X. and Ren, Z. (2012) ‘Selection of climatic variables and time scales for future weather preparation in building heating and cooling energy predictions’, *Energy and Buildings*, 51, pp. 223–233. doi: 10.1016/j.enbuild.2012.05.017.

Chen, S. *et al.* (2020) ‘A review of internal and external influencing factors on energy efficiency design of buildings’, *Energy and Buildings*. Elsevier B.V., 216. doi: 10.1016/j.enbuild.2020.109944.

Chen, Y., Hong, T. and Piette, M. A. (2017) ‘Automatic generation and simulation of urban building energy models based on city datasets for city-scale building retrofit analysis’, *Applied Energy*. Elsevier, 205(April), pp. 323–335. doi: 10.1016/j.apenergy.2017.07.128.

China Standards (2012) ‘GB 50736 - 2012 - Design code for heating ventilation and air conditioning of civil buildings’.

China Standards (2015) ‘GB 50189 - Design standard for energy efficiency of public buildings’.

China Standards (2016) ‘GB 50176 - 2016 - Code for thermal design of civil buildings’, p. 43.

Chinazzo, G., Rastogi, P. and Andersen, M. (2015) ‘Robustness Assessment Methodology for The Evaluation of Building Performance With a View to Climate Uncertainties’, in *Building Simulation Conference*.

Chow, D. H. C. and Levermore, G. J. (2010) ‘The effects of future climate change on heating and cooling demands in office buildings in the UK.’, *Building Services Engineering Research & Technology*. SAGE PublicationsSage UK: London, England, 31, pp. 307–323. doi: 10.1177/0143624410371284.

Ciancio, V. *et al.* (2019) ‘Resilience of a building to future climate conditions in three

European cities', *Energies*, 12(23). doi: 10.3390/en12234506.

Ciancio, V. *et al.* (2020) 'Energy demands of buildings in the framework of climate change: An investigation across Europe', *Sustainable Cities and Society*. Elsevier, 60(March), p. 102213. doi: 10.1016/j.scs.2020.102213.

CIBSE (2007) *CIBSE Guide C: Reference Data*. doi: 10.1787/itcs-v2014-1-9-en.

CIBSE (2009) *CIBSE TM48 - Use of climate change scenarios for building simulation : the CIBSE future weather years Use of climate change scenarios for building simulation : the CIBSE future weather years*, *Tm48*. CIBSE.

CIBSE (2012) *CIBSE Guide F - Energy efficiency in buildings*. 2012th edn. Edited by K. Butcher. London: CIBSE. Available at: https://www.cibse.org/Knowledge/knowledge-items/detail?id=a0q20000008I7oTAAS.

CIBSE (2013) 'CIBSE TM52 - The limits of thermal comfort : avoiding overheating in European buildings', *CIBSE Tm52*. CIBSE, pp. 1–25. doi: 10.1017/CBO9781107415324.004.

Clarke, J. A. (2001) '2-Integrative modelling methods', in *Energy Simulation in Building Design*. Elsevier, pp. 22–63. doi: 10.1016/B978-075065082-3/50002-4.

Clarke, J. A. and Hensen, J. L. M. (2015) 'Integrated building performance simulation: Progress, prospects and requirements', *Building and Environment*, 91, pp. 294–306. doi: 10.1016/j.buildenv.2015.04.002.

Coakley, D., Raftery, P. and Keane, M. (2014) 'A review of methods to match building energy simulation models to measured data', *Renewable and Sustainable Energy Reviews*, 37, pp. 123–141. doi: 10.1016/j.rser.2014.05.007.

Communities & Local Government (2008) 'National Calculation Methodology (NCM) modelling guide (for buildings other than dwellings in England and Wales)', *Communities and local government*, (November), pp. 1–34.

Constable, S., Hamilton, J. and Pfaff, T. J. (2013) 'A case study on regional impacts of climate change: peak loads on the power grid in Rochester, New York', *Journal of Environmental Studies and Sciences*. Springer Science+Business Media, Van Godewijckstraat 30 Dordrecht 3311 GX Netherlands, 3(1), pp. 15–20. doi: http://dx.doi.org/10.1007/s13412-012-0097-5.

Costa, G. *et al.* (2020) 'A catalogue of energy conservation measures (ECM) and a tool for their application in energy simulation models', *Journal of Building Engineering*, 29(July 2019). doi: 10.1016/j.jobe.2019.101102.

Council, S. S. (2018) *SS 530 - Code of practice for energy efficiency standard for building services and equipment*.

Council, S. S. (2019) *SS 531 - Code of practice for lighting of work places – Part 1 : Indoor*.

Council, S. S. (2021a) *SS 553 - Code of practice for air-conditioning and mechanical ventilation in buildings*.

Council, S. S. (2021b) *SS 554 - Code of practice for indoor air quality for air- conditioned buildings*.

Crawley, D. B. *et al.* (2001) ‘EnergyPlus: creating a new-generation building energy simulation program’, *Energy and Buildings*, 33(4), pp. 319–331. doi: 10.1016/S0378-7788(00)00114-6.

Crawley, D. B. *et al.* (2005) ‘Contrasting the capabilities of building energy performance simulation programs’, *Building and Environment*, 43(4), pp. 661–673. doi: 10.1016/j.buildenv.2006.10.027.

Crawley, Drury Browne (2008) *Building Performance Simulation : a Tool for Policymaking*. University of Strathclyde. Available at: https://www.strath.ac.uk/media/departments/mechanicalengineering/esru/research/phdmphilprojects/crawley_thesis.pdf.

Crawley, Drury B. (2008) ‘Estimating the impacts of climate change and urbanization on building performance’, *Journal of Building Performance Simulation*, 1(2), pp. 91–115. doi: 10.1080/19401490802182079.

Davis, L. W. . b L. W. and Gertler, P. J. . b P. J. (2015) ‘Contribution of air conditioning adoption to future energy use under global warming’, *Proceedings of the National Academy of Sciences of the United States of America*, 112, pp. 5962–5967. doi: 10.1073/pnas.1423558112.

Department for Business, E. and I. S. (2020) *Energy Consumption in the UK (ECUK)*. Available at: https://www.gov.uk/government/statistics/energy-consumption-in-the-uk.

Department for Business Energy & Industrial Strategy (2016) *Energy Consumption in the UK (ECUK)*, *Department for Business, Energy and Industrial Strategy*. Available at: www.gov.uk/beis (Accessed: 10 December 2016).

Deru, M. *et al.* (2011) ‘U.S. Department of Energy commercial reference building models of the national building stock’, *Publications (E)*, (February 2011), pp. 1–118. doi: NREL Report No. TP-5500-46861.

Deru, M., Griffith, B. and Torcellini, P. (2006) ‘Establishing Benchmarks for DOE Commercial Building R & D and Program Evaluation Preprint’, *ACEEE Summer Study on Energy Efficiency in Buildings*, (June), p. 12.

Dickinson, R. and Brannon, B. (2016) ‘Generating Future Weather Files for Resilience’, *PLEA 2016 - 36th International Conference on Passive and Low Energy Architecture; Cities, Buildings, People: Towards Regenerative Environment*.

Dino, I. G. and Meral Akgül, C. (2019) ‘Impact of climate change on the existing residential building stock in Turkey: An analysis on energy use, greenhouse gas emissions and occupant comfort’, *Renewable Energy*. Elsevier Ltd, 141, pp. 828–846. doi: 10.1016/j.renene.2019.03.150.

Dirks, J. A. *et al.* (2015) ‘Impacts of climate change on energy consumption and peak demand in buildings: A detailed regional approach’, *Energy*. Elsevier Ltd, 79, pp. 20–32. doi: 10.1016/j.energy.2014.08.081.

Dodoo, A. and Gustavsson, L. (2016) ‘Energy use and overheating risk of Swedish multi-storey residential buildings under different climate scenarios’, *Energy*, 97, pp. 534–548. doi: 10.1016/j.energy.2015.12.086.

DOE and US Department of Energy (2019) *Commercial Reference Buildings | Department of Energy*. Available at: https://www.energy.gov/eere/buildings/commercial-reference-buildings (Accessed: 16 March 2018).

Domínguez-Muñoz, F., Cejudo-López, J. M. and Carrillo-Andrés, A. (2010) 'Uncertainty in peak cooling load calculations', *Energy and Buildings*, 42(7), pp. 1010–1018. doi: 10.1016/j.enbuild.2010.01.013.

Du, H., Underwood, C. and Edge, J. (2012a) 'Generating design reference years from the UKCP09 projections and their application to future air-conditioning loads', *Building Services Engineering Research and Technology*. SAGE PublicationsSage UK: London, England, 33(1), pp. 63–79. doi: 10.1177/0143624411431775.

Du, H., Underwood, C. and Edge, J. (2012b) 'Generating test reference years from the UKCP09 projections and their application in building energy simulations', *Building Services Engineering Research and Technology*. SAGE PublicationsSage UK: London, England, 33(2012), pp. 387–406. doi: 10.1177/0143624411418132.

Duarte, C., Raftery, P. and Schiavon, S. (2018) 'Development of Whole-Building Energy Models for Detailed Energy Insights of a Large Office Building with Green Certification Rating in Singapore', pp. 84–93. doi: 10.1002/ente.201700564.

Eames, M., Kershaw, T. and Coley, D. (2011) 'On the creation of future probabilistic design weather years from UKCP09', *Building Services Engineering Research and Technology*. SAGE PublicationsSage UK: London, England, 32(2), pp. 127–142. doi: 10.1177/0143624410379934.

Eisenhower, B. *et al.* (2012) 'Uncertainty and sensitivity decomposition of building energy models', *Journal of Building Performance Simulation*, 5, pp. 171–184. doi: 10.1080/19401493.2010.549964.

EMSD (2007) *Guidelines on Performance-based Building Energy Code (Guidelines)*.

Energy, A. (2003) *Energy Consumption Guide 019: Energy Use in Office*. Edited by C. Trust. doi: 10.1108/EUM0000000002226.

EnergyPlus (2010) 'Engineering Reference', *US Department of Energy*, (c), pp. 1–847. doi: citeulike-article-id:10579266.

EnergyPlus (2015) 'Input Output Reference', *Bigladder Software*, (c), p. 2109. Available at: http://bigladdersoftware.com/epx/docs/8-3/input-output-reference/index.html.

European Environment Agency (EEA) (2019) *Adaptation challenges and opportunities for the European energy system: Building a climate-resilient low-carbon energy system*. Available at: https://www.eea.europa.eu/publications/adaptation-in-energy-system.

Exeter, U. of (2020) *PROMETHEUS*. Available at: https://emps.exeter.ac.uk/engineering/research/cee/research/prometheus/.

Eyring, V. *et al.* (2016) 'Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization', *Geoscientific Model Development*, 9(5), pp. 1937–1958. doi: 10.5194/gmd-9-1937-2016.

Ezzedine Khalfallah, Rafik Missaoui, Samira El Khamlichi, H. B. H. (2016) *Energy-Efficient Air Conditioning : A Case Study of the Maghreb Energy-Efficient Air Conditioning : A Case Study of the Maghreb Opportunities for a more*.

Fabrizio, E. and Monetti, V. (2015) 'Methodologies and advancements in the calibration of building energy models', *Energies*, 8(4), pp. 2548–2574. doi: 10.3390/en8042548.

Fan, J. L., Hu, J. W. and Zhang, X. (2019) 'Impacts of climate change on electricity demand in China: An empirical estimation based on panel data', *Energy*, pp. 880–888. doi: 10.1016/j.energy.2018.12.044.

Farah, S. *et al.* (2019) 'Integrating climate change into meteorological weather data for building energy simulation', *Energy and Buildings*. Elsevier B.V., 183, pp. 749–760. doi: 10.1016/j.enbuild.2018.11.045.

Farrou, I., Kolokotroni, M. and Santamouris, M. (2016) 'Building envelope design for climate change mitigation: a case study of hotels in Greece', *International Journal of Sustainable Energy*, 35(10), pp. 944–967. doi: 10.1080/14786451.2014.966711.

Ferrando, M. *et al.* (2020) 'Urban building energy modeling (UBEM) tools: A state-of-the-art review of bottom-up physics-based approaches', *Sustainable Cities and Society*. Elsevier, 62(July), p. 102408. doi: 10.1016/j.scs.2020.102408.

Ferreira, M., Coelho, M. J. P. and Alves, R. V. L. (2006) 'Regulamento das Características de Comportamento Térmico de Edifícios (RCCTE)', *Diario da Republica*, 67(4 de Abril), pp. 67–75.

Finkelstein, J. M. and Schafer, R. E. (1971) 'Improved Goodness-Of-Fit Tests', *Biometrika*, 58(3), p. 641. doi: 10.2307/2334400.

Fonseca, J. A. and Schlueter, A. (2015) 'Integrated model for characterization of spatiotemporal building energy consumption patterns in neighborhoods and city districts', *Applied Energy*. Elsevier Ltd, 142(citation(26)), pp. 247–265. doi: 10.1016/j.apenergy.2014.12.068.

Foucquier, A. *et al.* (2013) 'State of the art in building modelling and energy performances prediction: A review', *Renewable and Sustainable Energy Reviews*, 23, pp. 272–288. doi: 10.1016/j.rser.2013.03.004.

Frank, T. (2005) 'Climate change impacts on building heating and cooling energy demand in Switzerland', *Energy and Buildings*, 37, pp. 1175–1185. doi: 10.1016/j.enbuild.2005.06.019.

Fumo, N. (2014) 'A review on the basics of building energy estimation', *Renewable and Sustainable Energy Reviews*, pp. 53–60. doi: 10.1016/j.rser.2013.11.040.

Gercek, M. and Durmuş Arsan, Z. (2019) 'Energy and environmental performance based decision support process for early design stages of residential buildings under climate change', *Sustainable Cities and Society*, 48(September 2018). doi: 10.1016/j.scs.2019.101580.

Goel, S. *et al.* (2014) 'Enhancements to ASHRAE Standard 90.1 Prototype Building Models', *Pacific Northwest National Laboratory*, (April). Available at: http://www.energycodes.gov/sites/default/files/documents/PrototypeModelEnhancements

_2014_0.pdf.

Griffith, B. *et al.* (2008) ‘Methodology for Modeling Building Energy Performance across the Commercial Sector’, *Technical Report NREL/TP-550-41956*, (March), pp. 1–161. Available at: http://www.nrel.gov/docs/fy08osti/41956.pdf.

Grudzińska, M. and Jakusik, E. (2015) ‘The efficiency of a typical meteorological year and actual climatic data in the analysis of energy demand in buildings’, *Building Services Engineering Research and Technology*, 36(6), pp. 658–669. doi: 10.1177/0143624415573454.

Guan, L. (2009) ‘Implication of global warming on air-conditioned office buildings in Australia’, *Building Research & Information*. Routledge, 37(1), pp. 43–54. doi: 10.1080/09613210802611025.

Guan, L. (2012) ‘Energy use, indoor temperature and possible adaptation strategies for air-conditioned office buildings in face of global warming’, *Building and Environment*, 55, pp. 8–19. doi: 10.1016/j.buildenv.2011.11.013.

Guan, L., Yang, J. and Bell, J. M. (2007) ‘Cross-correlations between weather variables in Australia’, *Building and Environment*, 42(3), pp. 1054–1070. doi: 10.1016/j.buildenv.2006.01.010.

Gupta, R. and Gregg, M. (2012) ‘Using UK climate change projections to adapt existing English homes for a warming climate’, *Building and Environment*, 55, pp. 20–42. doi: 10.1016/j.buildenv.2012.01.014.

Gupta, R., Gregg, M. and Williams, K. (2015) ‘Cooling the UK housing stock post-2050s’, *BUILDING SERVICES ENGINEERING RESEARCH & TECHNOLOGY*, 36, pp. 196–220. doi: 10.1177/0143624414566242.

Hall, A. (2014) ‘Projecting regional change’, *Science*, 346(6216), pp. 1461–1462. doi: 10.1126/science.aaa0629.

Hall, J. W. *et al.* (2019) ‘Adaptation of Infrastructure Systems’. Available at: https://gca.org/reports/adaptation-of-infrastructure-systems/.

Heiselberg, P. *et al.* (2009) ‘Application of sensitivity analysis in design of sustainable buildings’, *Renewable Energy*, 34(9), pp. 2030–2036. doi: 10.1016/j.renene.2009.02.016.

Hekkenberg, M., Moll, H. C. and Uiterkamp, A. J. M. S. (2009) ‘Dynamic temperature dependence patterns in future energy demand models in the context of climate change’, *Energy*, 34, pp. 1797–1806. doi: 10.1016/j.energy.2009.07.037.

Helton, J. C. (2009) ‘Conceptual and computational basis for the quantification of margins and uncertainty.’, *Sandia Report, SAND2009-3005*, (June), pp. 1–153. Available at: http://www.osti.gov/bridge/product.biblio.jsp?osti_id=958189%5Cnpapers3://publication/uuid/5263A57F-1F06-4CBE-9510-E1B2242A43CB.

Henderson, M. I., Novosel, D. and Crow, M. L. (2017) ‘Electric Power Grid Modernization Trends, Challenges, and Opportunities’, *IEEE Technology Trend Paper*, (November), p. 17.

Hensen, J. L. M. . and Lamberts, R. (2011) ‘Introduction to building performance simulation’, in Hensen, J. L. M. . and Lamberts, Robert (eds) *Building Performance Simulation for Design and Operation*. First. London: Routledge. doi: 10.4324/9780203891612.

Herrera, M. *et al.* (2017) 'A review of current and future weather data for building simulation', *Building Services Engineering Research and Technology*. SAGE PublicationsSage UK: London, England, 38, p. 014362441770593. doi: 10.1177/0143624417705937.

Hewitson, B. C. *et al.* (2014) 'Interrogating empirical-statistical downscaling', *Climatic Change*, 122(4), pp. 539–554. doi: 10.1007/s10584-013-1021-z.

HM Government (2010a) '2050 Pathways Analysis', *Analysis*, (July), pp. 1–252. doi: Ref: 10D/764.

HM Government (2010b) *Approved Document L2A Conservation of fuel and power*, *Conservation of fuel and power*. Available at: http://www.planningportal.gov.uk/uploads/br/BR_PDF_ADL2A_2010.pdf.

Hoes, P. and Hensen, J. L. M. (2016) 'The potential of lightweight low-energy houses with hybrid adaptable thermal storage: Comparing the performance of promising concepts', *Energy and Buildings*, 110, pp. 79–93. doi: 10.1016/j.enbuild.2015.10.036.

Hong, T., Chang, W.-K. and Lin, H.-W. (2013) 'A fresh look at weather impact on peak electricity demand and energy use of buildings using 30-year actual weather data', *Applied Energy*, 111, pp. 333–350. doi: 10.1016/j.apenergy.2013.05.019.

Hong, T., Langevin, J. and Sun, K. (2018) 'Building simulation: Ten challenges', *Building Simulation*, 11(5), pp. 871–898. doi: 10.1007/s12273-018-0444-x.

Hooyberghs, H. *et al.* (2017) 'Influence of climate change on summer cooling costs and heat stress in urban office buildings', *Climatic Change*. Climatic Change, 144(4), pp. 721–735. doi: 10.1007/s10584-017-2058-1.

Hopfe, C. J., Augenbroe, G. L. M. and Hensen, J. L. M. (2013) 'Multi-criteria decision making under uncertainty in building performance assessment', *Building and Environment*. Elsevier Ltd, 69, pp. 81–90. doi: 10.1016/j.buildenv.2013.07.019.

Hopfe, C. J. and Hensen, J. L. M. (2011) 'Uncertainty analysis in building performance simulation for design support', *Energy and Buildings*, 43(10), pp. 2798–2805. doi: 10.1016/j.enbuild.2011.06.034.

Huang, J. and Gurney, K. R. (2016a) 'Impact of climate change on U.S. building energy demand: sensitivity to spatiotemporal scales, balance point temperature, and population distribution', *Climatic Change*. Climatic Change, 137(1–2), pp. 171–185. doi: 10.1007/s10584-016-1681-6.

Huang, J. and Gurney, K. R. (2016b) 'The variation of climate change impact on building energy consumption to building type and spatiotemporal scale', *Energy*. Elsevier Ltd, 111, pp. 137–153. doi: 10.1016/j.energy.2016.05.118.

Huang, K.-T. and Hwang, R.-L. (2016) 'Future trends of residential building cooling energy and passive adaptation measures to counteract climate change: The case of Taiwan', *Applied Energy*, 184, pp. 1230–1240. doi: 10.1016/j.apenergy.2015.11.008.

Huang, P. *et al.* (2018) 'Optimal configuration of multiple-chiller plants under cooling load uncertainty for different climate effects and building types', *Energy and Buildings*. Elsevier B.V., 158, pp. 684–697. doi: 10.1016/j.enbuild.2017.10.040.

Huang, P. *et al.* (2019) 'Review of uncertainty-based design methods of central air-conditioning systems and future research trends', *Science and Technology for the Built Environment*. Taylor & Francis, 0(0), pp. 1–22. doi: 10.1080/23744731.2019.1570783.

Huang, Y. and Niu, J. L. (2016) 'Optimal building envelope design based on simulated performance: History, current status and new potentials', *Energy and Buildings*. Elsevier B.V., 117, pp. 387–398. doi: 10.1016/j.enbuild.2015.09.025.

Hulme, M. *et al.* (2002) 'Climate Change Scenarios for the United Kingdom: The UKCIP02 Scientific Report', *The UKCIP02 Scientific Report*, (April), p. 120. Available at: http://www.ukcip.org.uk/wordpress/wp-content/PDFs/UKCIP02_tech.pdf.

Ibraheem, O. and Ford, B. (2012) 'The feasibility of passive downdraught evaporative cooling for high-rise office buildings in Cairo', 8628. doi: 10.1080/00038628.2012.722071.

Intergovernmental Panel on Climate Change (IPCC) (2018) 'Annex I: Glossary', in Matthews, J. B. R. (ed.) *Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change,*.

International Energy Agency (IEA) (2018) *The Future of Cooling: Opportunities for energy-efficient air conditioning*, *The Future of Cooling: Opportunities for energy-efficient air conditioning*.

International Energy Agency (IEA) (2019) 'Perspectives for a Clean Energy Transition. The Critical Role of Buildings.', *Energy Transition Progress and Outlook to 2020.*, p. 117.

International Renewable Energy Agency (IRENA), International Energy Agency (IEA) and REN21 (2018) *Renewable energy policies in a time of transition: Heating and Cooling*.

Iooss, B. *et al.* (2020) 'sensitivity: Global Sensitivity Analysis of Model Outputs'. Available at: https://cran.r-project.org/package=sensitivity.

Iooss, B. and Lemaître, P. (2015) 'A Review on Global Sensitivity Analysis Methods', in Dellino G., M. C. (ed.) *Operations Research/Computer Science Interfaces Series book series (ORCS, volume 59)*. Springer, Boston, MA, pp. 101–122. doi: 10.1007/978-1-4899-7547-8_5.

IPCC (2013) *Climate Change 2013: The Physical Science Basis*, *Climate Change 2013: The Physical Science Basis*. Edited by D. Stocker, T F; Qin. Available at: https://www.researchgate.net/profile/Abha_Chhabra2/publication/271702872_Carbon_and_Other_Biogeochemical_Cycles/links/54cf9ce80cf24601c094a45e/Carbon-and-Other-Biogeochemical-Cycles.pdf.

IPCC (2020a) *CMIP6 - Coupled Model Intercomparison Project Phase 6*. Available at: https://pcmdi.llnl.gov/CMIP6/ (Accessed: 24 September 2020).

IPCC (2020b) *IPCC - AR6*. Available at: https://www.ipcc.ch/assessment-report/ar6/ (Accessed: 22 October 2020).

IPCC (2021) *CMIP5 - Coupled Model Intercomparison Project Phase 5 - Overview*. Available at: https://pcmdi.llnl.gov/mips/cmip5/.

Isaac, M. and van Vuuren, D. P. (2009) 'Modeling global residential sector energy demand for heating and air conditioning in the context of climate change', *Energy Policy*, 37, pp. 507–521. doi: 10.1016/j.enpol.2008.09.051.

Jenkins, D. P. *et al.* (2011) 'Probabilistic climate projections with dynamic building simulation: Predicting overheating in dwellings', *Energy and Buildings*, 43(7), pp. 1723–1731. doi: 10.1016/j.enbuild.2011.03.016.

Jenkins, D. P. *et al.* (2014) 'Developing a probabilistic tool for assessing the risk of overheating in buildings for future climates', *Renewable Energy*, 61, pp. 7–11. doi: 10.1016/j.renene.2012.04.035.

Jenkins, D. P., Gul, M. and Patidar, S. (2013) 'Probabilistic future cooling loads for mechanically cooled offices', *Energy and Buildings*, 66, pp. 57–65. doi: 10.1016/j.enbuild.2013.07.040.

Jenkins, D. P., Patidar, S. and Simpson, S. (2015) 'Quantifying Change in Buildings in a Future Climate and Their Effect on Energy Systems', *Buildings*. Multidisciplinary Digital Publishing Institute, 5, pp. 985–1002. doi: 10.3390/buildings5030985.

Jenkins, G. J. *et al.* (2009) *UK Climate Projections: UKCP09*, *Met Office Hadley Center*. doi: ISBN 978-1-906360-04-7.

Jentsch, M. F. (2009) *Viability of naturally ventilated buildings in the UK under predicted future summer climates*. Available at: http://eprints.soton.ac.uk/79441/.

Jentsch, M. F. *et al.* (2013) 'Transforming existing weather data for worldwide locations to enable energy and building performance simulation under future climates', *Renewable Energy*. doi: 10.1016/j.renene.2012.12.049.

jeplus.org (2014) *jEPlus User's Manual*. Available at: http://www.jeplus.org/wiki/doku.php?id=docs:manual_1_5#table_of_contents (Accessed: 1 June 2018).

jEPlus (2013) *UK Office Building Archetypal Models*. Available at: http://www.jeplus.org/wiki/doku.php?id=examples:projects:benchmark (Accessed: 1 June 2018).

Jiang, A. and O'Meara, A. (2018) 'Accommodating thermal features of commercial building systems to mitigate energy consumption in Florida due to global climate change', *Energy and Buildings*. Elsevier B.V., 179(2018), pp. 86–98. doi: 10.1016/j.enbuild.2018.08.046.

Johari, F. *et al.* (2020) 'Urban building energy modeling: State of the art and future prospects', *Renewable and Sustainable Energy Reviews*, 128(April). doi: 10.1016/j.rser.2020.109902.

Jones, P. *et al.* (2009) *UK Climate Projections science report: Projections of future daily climate for the UK from the Weather Generator*, *UK Climate Projections science report*. Available at: http://ukclimateprojections.defra.gov.uk.

Jost, R. (2012) *Developing a Run-Time Coupling Between ESP-r and TRNSYS*. Available at: http://publications.polymtl.ca/978/.

Judkoff, R. and Neymark, J. (2006) 'Model validation and testing: The methodological foundation of ASHRAE Standard 140', *ASHRAE Transactions*, 112 PART 2, pp. 367–376.

Kalamees, T. *et al.* (2012) 'Development of weighting factors for climate variables for selecting the energy reference year according to the en ISO 15927-4 standard', *Energy and Buildings*. Elsevier B.V., 47, pp. 53–60. doi: 10.1016/j.enbuild.2011.11.031.

Kampf, H. and Robinson, D. (2007) 'A simplified thermal model to support analysis of urban resource flows', *Energy and Buildings*, 39(4), pp. 445–453. doi: 10.1016/j.enbuild.2006.09.002.

Kavgic, M. *et al.* (2010) 'A review of bottom-up building stock models for energy consumption in the residential sector', *Building and Environment*, 45(7), pp. 1683–1697. doi: 10.1016/j.buildenv.2010.01.021.

Kavgic, M., Hilliard, T. and Swan, L. (2015) 'Opportunities for implementation of MPC in commercial buildings', *Energy Procedia*. Elsevier B.V., 78, pp. 2148–2153. doi: 10.1016/j.egypro.2015.11.300.

Kim, S. *et al.* (2017) 'Development of test reference year using ISO 15927-4 and the influence of climatic parameters on building energy performance', *Building and Environment*. Elsevier Ltd, 114, pp. 374–386. doi: 10.1016/j.buildenv.2016.12.037.

Kim, S. H. and Augenbroe, G. (2013) 'Uncertainty in developing supervisory demand-side controls in buildings: A framework and guidance', *Automation in Construction*. Elsevier B.V., 35, pp. 28–43. doi: 10.1016/j.autcon.2013.02.001.

Kolokotroni, M. *et al.* (2012) 'London's urban heat island: Impact on current and future energy consumption in office buildings', *Energy and Buildings*, 47, pp. 302–311. doi: 10.1016/j.enbuild.2011.12.019.

Korolija, I. *et al.* (2013) 'UK office buildings archetypal model as methodological approach in development of regression models for predicting building energy consumption from heating and cooling demands', *Energy and Buildings*, 60, pp. 152–162. doi: 10.1016/j.enbuild.2012.12.032.

Kotireddy, R., Hoes, P.-J. and Hensen, J. L. M. (2018) 'A methodology for performance robustness assessment of low-energy buildings using scenario analysis', *Applied Energy*. Elsevier, 212, pp. 428–442. doi: 10.1016/J.APENERGY.2017.12.066.

Labat, M. and Attonaty, K. (2018) 'Numerical estimation and sensitivity analysis of the energy demand for six industrial buildings in France', *Journal of Building Performance Simulation*. Taylor & Francis, 11(2), pp. 223–240. doi: 10.1080/19401493.2017.1322637.

Lam, J. C. *et al.* (2008) 'Principal component analysis of electricity use in office buildings', *Energy and Buildings*, 40, pp. 828–836. doi: 10.1016/j.enbuild.2007.06.001.

Lawrie, L. K. and Crawley, D. B. (2019) *Development of Global Typical Meteorological Years (TMYx)*. Available at: http://climate.onebuilding.org.

Li, D. H. W., Yang, L. and Lam, J. C. (2012) ‘Impact of climate change on energy use in the built environment in different climate zones – A review’, *Energy*, 42(1), pp. 103–112. doi: 10.1016/j.energy.2012.03.044.

Li, M. *et al.* (2014) ‘Future climate change and building energy demand in Tianjin, China’, *Building Services Engineering Research & Technology*, 35(4), pp. 362–375. doi: 10.1177/0143624413498245.

Lipson, M. J. *et al.* (2019) ‘Climate change impact on energy demand in building-urban-atmosphere simulations through the 21st century’, *Environmental Research Letters*. IOP Publishing, 14(12). doi: 10.1088/1748-9326/ab5aa5.

Liu, S. *et al.* (2020) ‘Development and application of future design weather data for evaluating the building thermal-energy performance in subtropical Hong Kong’, *Energy and Buildings*. Elsevier B.V., 209, p. 109696. doi: 10.1016/j.enbuild.2019.109696.

Liu, Y. (2016) ‘Seasonal relationship of peak demand and energy impacts of energy efficiency measures--a review of evidence in the electric energy efficiency programmes’, *Energy Efficiency*. Dordrecht: Springer Science & Business Media, 9, pp. 1015–1035. doi: http://dx.doi.org/10.1007/s12053-015-9407-6.

Loga, T., Stein, B. and Diefenbach, N. (2016) ‘TABULA building typologies in 20 European countries—Making energy-related features of residential building stocks comparable’, *Energy and Buildings*. Elsevier B.V., 132, pp. 4–12. doi: 10.1016/j.enbuild.2016.06.094.

Lowe, J. A. *et al.* (2018) *UKCP18 Science Overview report*. Available at: www.metoffice.gov.ukwww.metoffice.gov.uk.

M. Baudin, K. Boumhaout, T. Delage, B. I. and J.-M. M. (2016) ‘Numerical stabilit3 of Sobol’ indices estimation formula’, in *8th International Conference on Sensitivity Analysis of Model Output*, pp. 50–51. Available at: https://samo2016.sciencesconf.org/data/pages/Proceedings_Samo_2016.pdf.

Mahmoud, S. *et al.* (2020) ‘Comparative energy performance simulation for passive and conventional design: A case study in Cairo, Egypt’, in *Energy Reports*. Elsevier Ltd, pp. 699–704. doi: 10.1016/j.egyr.2019.09.052.

Mansur, E. T., Mendelsohn, R. and Morrison, W. (2008) ‘Climate change adaptation: A study of fuel choice and consumption in the US energy sector’, *Journal of Environmental Economics and Management*, 55(2), pp. 175–193. doi: 10.1016/j.jeem.2007.10.001.

Maraun, D. (2016) ‘Bias Correcting Climate Change Simulations - a Critical Review’, *Current Climate Change Reports*. Current Climate Change Reports, 2(4), pp. 211–220. doi: 10.1007/s40641-016-0050-x.

Masson-Delmotte, V. *et al.* (2018) *Summary for Policymakers. In: Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to*, *Ipcc - Sr15*. Available at: https://report.ipcc.ch/sr15/pdf/sr15_spm_final.pdf%0Ahttp://www.ipcc.ch/report/sr15/.

Mata, É. *et al.* (2019) ‘Economic feasibility of building retrofitting mitigation potentials: Climate change uncertainties for Swedish cities’, *Applied Energy*. Elsevier, 242(February), pp.

1022–1035. doi: 10.1016/j.apenergy.2019.03.042.

Mata, É., Sasic Kalagasidis, A. and Johnsson, F. (2014) ‘Building-stock aggregation through archetype buildings: France, Germany, Spain and the UK’, *Building and Environment*, 81, pp. 270–282. doi: 10.1016/j.buildenv.2014.06.013.

Mechri, H. E., Capozzoli, A. and Corrado, V. (2010) ‘USE of the ANOVA approach for sensitive building energy design’, *Applied Energy*. Elsevier Ltd, 87(10), pp. 3073–3083. doi: 10.1016/j.apenergy.2010.04.001.

Meehl, G. a (2004) ‘More Intense, More Frequent, and Longer Lasting Heat Waves in the 21st Century’, *Science*, 305(5686), pp. 994–997. doi: 10.1126/science.1098704.

Met Office (2014) *Glossary - Urban Heat Island (UHI)*. Available at: http://ukclimateprojections.metoffice.gov.uk/23193 (Accessed: 12 February 2018).

Meteotest (2020) *Meteonorm Software*. Available at: https://meteonorm.com/en/ (Accessed: 21 October 2020).

Miller, N. L. N. L. *et al.* (2008) ‘Climate, extreme heat, and electricity demand in California’, *Journal of Applied Meteorology and Climatology*, 47(6), pp. 1834–1844. doi: 10.1175/2007JAMC1480.1.

Moazami, A. *et al.* (2016) ‘Energy Retrofit of a Day Care Center for Current and Future Weather Scenarios’, *Procedia Engineering*. Elsevier B.V., 145(1877), pp. 1330–1337. doi: 10.1016/j.proeng.2016.04.171.

Moazami, A. *et al.* (2019) ‘Impacts of future weather data typology on building energy performance – Investigating long-term patterns of climate change and extreme weather conditions’, *Applied Energy*, pp. 696–720. doi: 10.1016/j.apenergy.2019.01.085.

Moffatt, S. (2004) *Methods for Evaluating the Environmental Performance of Building Stocks*, *Buildings*. Available at: http://www.iisbe.org/annex31/index.html.

Mora, C. *et al.* (2017) ‘Global risk of deadly heat’, *Nature Climate Change*, 7(7), pp. 501–506. doi: 10.1038/nclimate3322.

Morris, M. D. (1991) ‘Factorial Sampling Plans for Preliminary Computational Experiments’, *Technometrics*. [Taylor & Francis, Ltd., American Statistical Association, American Society for Quality], 33(2), pp. 161–174. doi: 10.2307/1269043.

Mulville, M. and Stravoravdis, S. (2016) ‘The impact of regulations on overheating risk in dwellings’, *Building Research & Information*. Taylor & Francis, 3218(April), pp. 1–15. doi: 10.1080/09613218.2016.1153355.

National Renewable Energy Laboratory (NREL) (2021) *OpenStudio-Standards*. Available at: https://github.com/NREL/openstudio-standards (Accessed: 21 March 2021).

Nemtzow, D. (2017) *Buildings and the Grid 101: Why Does it Matter for Energy Efficiency?*, *Office of Energy Efficiency & Renewable Energy*. Available at: https://energy.gov/eere/buildings/articles/buildings-and-grid-101-why-does-it-matter-energy-efficiency (Accessed: 15 February 2018).

Ng, P. K., Mithraratne, N. and Kua, H. W. (2013) ‘Energy analysis of semi-transparent BIPV in

Singapore buildings', *Energy and Buildings*. Elsevier B.V., 66, pp. 274–281. doi: 10.1016/j.enbuild.2013.07.029.

Nicol, J. F. and Humphreys, M. A. (2002) 'Adaptive thermal comfort and sustainable thermal standards for buildings', in *Energy and Buildings*, pp. 563–572. doi: 10.1016/S0378-7788(02)00006-3.

Nik, V. M. *et al.* (2016) 'Effective and robust energy retrofitting measures for future climatic conditions - Reduced heating demand of Swedish households', *Energy and Buildings*. Elsevier B.V., 121, pp. 176–187. doi: 10.1016/j.enbuild.2016.03.044.

Nik, V. M. (2016) 'Making energy simulation easier for future climate – Synthesizing typical and extreme weather data sets out of regional climate models (RCMs)', *Applied Energy*, 177, pp. 204–226. doi: 10.1016/j.apenergy.2016.05.107.

Nik, V. M., Mata, É. and Sasic Kalagasidis, A. (2015) 'A statistical method for assessing retrofitting measures of buildings and ranking their robustness against climate change', *Energy and Buildings*. Elsevier B.V., 88, pp. 262–275. doi: 10.1016/j.enbuild.2014.11.015.

Nik, V. M. and Moazami, A. (2021) 'Using collective intelligence to enhance demand flexibility and climate resilience in urban areas', *Applied Energy*. Elsevier Ltd, 281, p. 116106. doi: 10.1016/j.apenergy.2020.116106.

Nik, V. M. and Perera, A. T. D. (2020) 'The Importance of Developing Climate-Resilient Pathways for Energy Transition and Climate Change Adaptation', *One Earth*. Elsevier Inc., 3(4), pp. 423–424. doi: 10.1016/j.oneear.2020.09.013.

Nik, V. M., Perera, A. T. D. and Chen, D. (2020) 'Towards climate resilient urban energy systems: a review', *National Science Review*, pp. 1–18. doi: 10.1093/nsr/nwaa134.

Nik, V. M. and Sasic Kalagasidis, A. (2013) 'Impact study of the climate change on the energy performance of the building stock in Stockholm considering four climate uncertainties', *Building and Environment*, 60, pp. 291–304. doi: 10.1016/j.buildenv.2012.11.005.

Orehounig, K. *et al.* (2014) 'Projections of design implications on energy performance of future cities: A case study from Vienna', *Sustainable Cities and Society*, 12, pp. 92–101. doi: 10.1016/j.scs.2014.03.001.

Østergård, T., Jensen, R. L. and Maagaard, S. E. (2017) 'Early Building Design: Informed decision-making by exploring multidimensional design space using sensitivity analysis', *Energy and Buildings*. Elsevier B.V., 142, pp. 8–22. doi: 10.1016/j.enbuild.2017.02.059.

Ouedraogo, B. I., Levermore, G. J. and Parkinson, J. B. (2012) 'Future energy demand for public buildings in the context of climate change for Burkina Faso', *Building and Environment*, 49, pp. 270–282. doi: 10.1016/j.buildenv.2011.10.003.

Pachauri, R. K. *et al.* (2014) *Climate Change 2014: Synthesis Report. Contribution*, *Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*.

Pagliano, L. *et al.* (2016) 'Energy retrofit for a climate resilient child care centre', *Energy and Buildings*. Elsevier B.V., 127, pp. 1117–1132. doi: 10.1016/j.enbuild.2016.05.092.

Parkpoom, S. (Jake) and Harrison, G. P. (2008) ‘Analyzing the impact of climate change on future electricity demand in Thailand’, *IEEE Transactions on Power Systems*, 23(3), pp. 1441–1448. doi: 10.1109/TPWRS.2008.922254.

Parliament, T. E. (2003) ‘DIRECTIVE 2002/91/EC on the energy performance of buildings’, *Official Journal of the European Union*, pp. 65–71.

Patidar, S. *et al.* (2011) ‘Statistical techniques to emulate dynamic building simulations for overheating analyses in future probabilistic climates’, *Journal of Building Performance Simulation*. Taylor & Francis, 4, pp. 271–284. doi: 10.1080/19401493.2010.531144.

Patidar, S. *et al.* (2012) ‘Analysis of probabilistic climate projections: Heat wave, overheating and adaptation’, *Journal of Building Performance Simulation*, 6(1), pp. 65–77. doi: 10.1080/19401493.2012.684447.

Patidar, S. *et al.* (2014) ‘Simple statistical model for complex probabilistic climate projections: Overheating risk and extreme events’, *Renewable Energy*, 61(citation(11)), pp. 23–28. doi: 10.1016/j.renene.2012.04.027.

Pérez-Andreu, V. *et al.* (2018) ‘Impact of climate change on heating and cooling energy demand in a residential building in a Mediterranean climate’, *Energy*. Pergamon, 165, pp. 63–74. doi: 10.1016/j.energy.2018.09.015.

Pérez-Lombard, L. *et al.* (2009) ‘A review of benchmarking, rating and labelling concepts within the framework of building energy certification schemes’, *Energy and Buildings*, 41(3), pp. 272–278. doi: 10.1016/j.enbuild.2008.10.004.

Petersen, S., Kristensen, M. H. and Knudsen, M. D. (2019) ‘Prerequisites for reliable sensitivity analysis of a high fidelity building energy model’, *Energy and Buildings*. Elsevier B.V., 183, pp. 1–16. doi: 10.1016/j.enbuild.2018.10.035.

Pout, C., MacKenzie, F. and Olloqui, E. (2008) *The impact of changing energy use patterns in buildings on peak electricity demand in the UK*, *Building Research Establishment*.

PSERC (2016) *Reengineering the Electric Grid*.

Pujol, G. (2009) ‘Simplex-based screening designs for estimating metamodels’, *Reliability Engineering & System Safety*, 94(7), pp. 1156–1160. doi: 10.1016/j.ress.2008.08.002.

Pyrgou, A. *et al.* (2017) ‘Differentiating responses of weather files and local climate change to explain variations in building thermal-energy performance simulations’, *Solar Energy*. Elsevier Ltd, 153, pp. 224–237. doi: 10.1016/j.solener.2017.05.040.

R Core Team (2020) ‘R: A Language and Environment for Statistical Computing’. Available at: https://www.r-project.org/.

Race, G. L. (2006) *CIBSE KS06: Comfort*, *Construction Research and Innovation*.

Race, G. L. (2012) *CIBSE KS16 - How to manage overheating in buildings: A practical guide to improving summertime comfort in buildings*, *Construction*. Available at: http//:www.cibse.org (Accessed: 29 November 2016).

Rastogi, P. (2016) *On the sensitivity of buildings to climate: the interaction of weather and building envelopes in determining future building energy consumption*.

Reinhart, C. F. and Cerezo Davila, C. (2016) 'Urban building energy modeling - A review of a nascent field', *Building and Environment*. The Authors, 97, pp. 196–202. doi: 10.1016/j.buildenv.2015.12.001.

Robert, A. and Kummert, M. (2012) 'Designing net-zero energy buildings for the future climate, not for the past', *Building and Environment*. Elsevier Ltd, 55, pp. 150–158. doi: 10.1016/j.buildenv.2011.12.014.

Robine, J. M. *et al.* (2008) 'Death toll exceeded 70,000 in Europe during the summer of 2003', *Comptes Rendus - Biologies*. Elsevier Masson, 331(2), pp. 171–178. doi: 10.1016/j.crvi.2007.12.001.

RStudio Team (2019) 'R Studio'. Available at: http://www.rstudio.com/.

Sahlin, P. *et al.* (2004) 'Whole-building simulation with symbolic DAE equations and general purpose solvers', *Building and Environment*, 39(8), pp. 949–958. doi: 10.1016/j.buildenv.2004.01.019.

Saltelli, A. *et al.* (2008) *Global Sensitivity Analysis . The Primer*. doi: 10.1002/9780470725184.ch6.

Samuelson, H. W., Baniassadi, A. and Gonzalez, P. I. (2020) 'Beyond energy savings: Investigating the co-benefits of heat resilient architecture', *Energy*. Elsevier Ltd, 204, p. 117886. doi: 10.1016/j.energy.2020.117886.

Sánchez-García, D. *et al.* (2019) 'Towards the quantification of energy demand and consumption through the adaptive comfort approach in mixed mode office buildings considering climate change', *Energy and Buildings*, 187, pp. 173–185. doi: 10.1016/j.enbuild.2019.02.002.

Santosh, P. and Tanjuatco, L. (2016) *eppy*. Available at: https://eppy.readthedocs.io/en/latest/Main_Tutorial.html (Accessed: 1 June 2018).

Sarrazin, F., Pianosi, F. and Wagener, T. (2016) 'Global Sensitivity Analysis of environmental models: Convergence and validation', *Environmental Modelling and Software*. Elsevier Ltd, 79, pp. 135–152. doi: 10.1016/j.envsoft.2016.02.005.

Shahrestani, M., Yao, R. and Cook, G. K. (2014) 'A review of existing building benchmarks and the development of a set of reference office buildings for England and Wales', *Intelligent Buildings International*. Taylor & Francis, 6(1), pp. 41–64. doi: 10.1080/17508975.2013.828586.

Shamash, M., Metcalf, G. and Mylona, A. (2014) *Probabilistic climate profiles*.

Shen, P., Braham, W. and Yi, Y. (2019) 'The feasibility and importance of considering climate change impacts in building retrofit analysis', *Applied Energy*, 233–234, pp. 254–270. doi: 10.1016/j.apenergy.2018.10.041.

Shibuya, T. and Croxford, B. (2016) 'The effect of climate change on office building energy consumption in Japan', *Energy and Buildings*, 117, pp. 1–11. doi: 10.1016/j.enbuild.2016.02.023.

Short, C. A. *et al.* (2012) 'Building resilience to overheating into 1960's UK hospital buildings within the constraint of the national carbon reduction target: Adaptive strategies', *Building and Environment*, 55, pp. 73–95. doi: 10.1016/j.buildenv.2012.02.031.

Shrubsole, C. *et al.* (2018) 'Bridging the gap: The need for a systems thinking approach in understanding and addressing energy and environmental performance in buildings', *Indoor and Built Environment*, 28(1), pp. 100–117. doi: 10.1177/1420326X17753513.

Siu, C. Y. and Liao, Z. (2020) 'Is building energy simulation based on TMY representative: A comparative simulation study on doe reference buildings in Toronto with typical year and historical year type weather files', *Energy and Buildings*. Elsevier B.V., 211. doi: 10.1016/j.enbuild.2020.109760.

Smith, K. R. *et al.* (2015) 'Human Health: Impacts, Adaptation, and Co-Benefits', in Field, C. B. et al. (eds) *Climate Change 2014 Impacts, Adaptation, and Vulnerability*. Cambridge: Cambridge University Press, pp. 709–754. doi: 10.1017/CBO9781107415379.016.

Sokol, J., Cerezo Davila, C. and Reinhart, C. F. (2017) 'Validation of a Bayesian-based method for defining residential archetypes in urban building energy models', *Energy and Buildings*. Elsevier B.V., 134, pp. 11–24. doi: 10.1016/j.enbuild.2016.10.050.

Spitler, J. D. (2011) 'Thermal load and energy performance prediction', in *Building Performance Simulation for Design and Operation*.

Standards, C. (2012) 'GBT 50378-2014 Green Building Standard in China', p. 103.

Standards, C. (2016) 'GB/T 51161- 2016 - Standard for energy consumption of building'.

Strachan, P. A., Kokogiannakis, G. and Macdonald, I. A. (2008) 'History and development of validation with the ESP-r simulation program', *Building and Environment*, 43(4), pp. 601–609. doi: 10.1016/j.buildenv.2006.06.025.

Sun, Y., Gu, L., *et al.* (2014) 'Exploring HVAC system sizing under uncertainty', *Energy and Buildings*, 81, pp. 243–252. doi: 10.1016/j.enbuild.2014.06.026.

Sun, Y. and Augenbroe, G. (2014) 'Urban heat island effect on energy application studies of office buildings', *Energy and Buildings*. Elsevier, 77, pp. 171–179. doi: 10.1016/j.enbuild.2014.03.055.

Swan, L. G. and Ugursal, V. I. (2009) 'Modeling of end-use energy consumption in the residential sector: A review of modeling techniques', *Renewable and Sustainable Energy Reviews*, 13(8), pp. 1819–1835. doi: 10.1016/j.rser.2008.09.033.

T.O.T.E.E. (2014) '20701-1/2010 - Regulation on Energy Performance in the Building Sector—KENAK', 2014.

Tarroja, B. *et al.* (2018) 'Translating climate change and heating system electrification impacts on building energy use to future greenhouse gas emissions and electric grid capacity requirements in California', *Applied Energy*. Elsevier, 225(January), pp. 522–534. doi: 10.1016/j.apenergy.2018.05.003.

Taylor, K. E., Stouffer, R. J. and Meehl, G. A. (2012) 'An overview of CMIP5 and the experiment design', *Bulletin of the American Meteorological Society*, 93(4), pp. 485–498. doi: 10.1175/BAMS-D-11-00094.1.

TESS – Thermal Energy System Specialists. LLC (2021) 'TRNSYS'. Available at: http://www.trnsys.com.

The Climate Emergency Declaration and Mobilisation (2021) *The Climate Emergency Declaration and Mobilisation*. Available at: https://climateemergencydeclaration.org/about/ (Accessed: 24 February 2021).

The European Parliament (2010) 'DIRECTIVE 2010/31/EU on the energy performance of buildings', *Official Journal of the European Union*, 63(30), p. 619.

The European Parliament (2018) 'DIRECTIVE (EU) 2018/844', *Official Journal of the European Union*, 2018(April), pp. 75–91.

Tian, W. (2013) 'A review of sensitivity analysis methods in building energy analysis', *Renewable and Sustainable Energy Reviews*, 20, pp. 411–419. doi: 10.1016/j.rser.2012.12.014.

Tian, W. *et al.* (2014) 'Bootstrap techniques for sensitivity analysis and model selection in building thermal performance analysis', *Applied Energy*, 135, pp. 320–328. doi: 10.1016/j.apenergy.2014.08.110.

Tian, W., Heo, Y., *et al.* (2018) 'A review of uncertainty analysis in building energy assessment', *Renewable and Sustainable Energy Reviews*. Elsevier Ltd, 93(May), pp. 285–301. doi: 10.1016/j.rser.2018.05.029.

Tian, W., de Wilde, P., *et al.* (2018) 'Uncertainty and sensitivity analysis of energy assessment for office buildings based on Dempster-Shafer theory', *Energy Conversion and Management*. Elsevier, 174(August), pp. 705–718. doi: 10.1016/j.enconman.2018.08.086.

Tian, W. and Choudhary, R. (2012) 'A probabilistic energy model for non-domestic building sectors applied to analysis of school buildings in greater London', *Energy and Buildings*, 54, pp. 1–11. doi: 10.1016/j.enbuild.2012.06.031.

Tian, W. and De Wilde, P. (2011a) 'Thermal building simulation using the UKCP09 probabilistic climate projections', *Journal of Building Performance Simulation*, 4(2), pp. 105–124. doi: 10.1080/19401493.2010.502246.

Tian, W. and De Wilde, P. (2011b) 'Uncertainty and sensitivity analysis of building performance using probabilistic climate projections: A UK case study', *Automation in Construction*, 20(8), pp. 1096–1109. doi: 10.1016/j.autcon.2011.04.011.

Torcellini, P. *et al.* (2008) 'DOE Commercial Building Benchmark Models; Preprint'. Available at: http://www.osti.gov/bridge (Accessed: 14 September 2017).

Trcka, M. *et al.* (2010) 'Overview of HVAC system simulation', *Automation in Construction*, 19(2), pp. 93–99. doi: 10.1016/j.autcon.2009.11.019.

Troup, L., Eckelman, M. J. and Fannon, D. (2019) 'Simulating future energy consumption in office buildings using an ensemble of morphed climate data', *Applied Energy*. Elsevier Ltd, 255, p. 113821. doi: 10.1016/j.apenergy.2019.113821.

Troup, L. and Fannon, D. (2016) 'Morphing Climate Data to Simulate Building Energy Consumption', *Building Performance Modeling Conference*, pp. 439–446.

Trzaska, S. and Schnarr, E. (2014) ‘A review of downscaling methods for climate change projections’, *United States Agency for International Development by Tetra Tech ARD*, (September), pp. 1–42.

U.S. Department of Energy (2017) *Engineering Reference of EnergyPlus 8.8.0.*

U.S. Department of Energy (2019a) *Commercial Prototype Building Models*. Available at: https://www.energycodes.gov/development/commercial/prototype_models.

U.S. Department of Energy (2019b) *OpenStudio*. Available at: https://www.openstudio.net/ (Accessed: 28 January 2019).

U.S. Department of Energy (2020) *Building Energy Codes Program - Glossary*. Available at: https://www.energycodes.gov/resource-center/glossary/s (Accessed: 17 February 2020).

U.S. Department of Energy (2021) *EnergyPlus: Weather Data Sources*. Available at: https://energyplus.net/weather/sources (Accessed: 15 January 2021).

U.S. Energy Information Administration (EIA) (2021) ‘Commercial buildings energy consumption survey (CBECS)’. Available at: https://www.eia.gov/consumption/commercial/.

Underwood, C. P. and Yik, F. (2004) ‘Chapter 1: Heat Transfer in Building Elements’, in *Modelling Methods for Energy in Buildings*, pp. 1–46.

United Nations (2020) *Emissions Gap Emissions Gap Report 2020*. Available at: https://www.unenvironment.org/interactive/emissions-gap-report/2019/.

United Nations Development Programme (UNDP) (2021) *Goal 13: Climate Action*. Available at: https://www.sdfinance.undp.org/content/sdfinance/en/home/sdg/goal-13--climate-action.html (Accessed: 24 February 2021).

University of Southampton (2014) *Climate Change World Weather File Generator for World-Wide Weather Data – CCWorldWeatherGen*. Available at: https://energy.soton.ac.uk/ccworldweathergen/ (Accessed: 21 October 2020).

Vasaturo, R. *et al.* (2018) ‘Impact of passive climate adaptation measures and building orientation on the energy demand of a detached lightweight semi-portable building’, *Building Simulation*, 2010, pp. 1163–1177.

Vine, E. (2012) ‘Adaptation of California’s electricity sector to climate change’, *Climatic Change*. Dordrecht: Springer Science & Business Media, 111(1), pp. 75–99. doi: http://dx.doi.org/10.1007/s10584-011-0242-2.

Wan, K. K. W., Li, D. H. W. and Lam, J. C. (2011) ‘Assessment of climate change impact on building energy use and mitigation measures in subtropical climates’, *Energy*, 36(3), pp. 1404–1414. doi: 10.1016/j.energy.2011.01.033.

Wan, K. K. W. W. *et al.* (2012) ‘Impact of climate change on building energy use in different climate zones and mitigation and adaptation implications’, *Applied Energy*, 97, pp. 274–282. doi: 10.1016/j.apenergy.2011.11.048.

Wang, H. and Chen, Q. (2014) ‘Impact of climate change heating and cooling energy use in buildings in the United States’, *Energy and Buildings*, 82, pp. 428–436. doi: 10.1016/j.enbuild.2014.07.034.

Wang, L., Liu, X. and Brown, H. (2017) 'Prediction of the impacts of climate change on energy consumption for a medium-size office building with two climate models', *Energy and Buildings*. Elsevier, 157, pp. 218–226. doi: 10.1016/J.ENBUILD.2017.01.007.

Wang, L., Mathew, P. and Pang, X. (2012) 'Uncertainties in energy consumption introduced by building operations and weather for a medium-size office building', *Energy and Buildings*. Elsevier, 53, pp. 152–158. doi: 10.1016/J.ENBUILD.2012.06.017.

Watkins, R., Palmer, J. A. and Kolokotroni, M. (2007) 'Increased temperature and intensification of the urban heat island: Impications for human comfort and urban design', *Built Environment*, 33(1), pp. 85–96.

Weber, B. I. and S. D. V. and A. J. and G. P. and with contributions from B. B. and K. B. and T. D. and R. E. A. and J. F. and L. G. and J. G. and L. {Le G. a (2020) 'sensitivity: Global Sensitivity Analysis of Model Outputs'. Available at: https://cran.r-project.org/package=sensitivit.

Wetter, M. (2011) 'A view on future building system modeling and simulation', in *Building Performance Simulation for Design and Operation*.

Wetter, M. *et al.* (2015) 'IEA EBC Annex 60 Modelica Library – An International Collaboration to Develop a Free Open-Source Model Library for Buildings and Community Energy Systems', in *Building Simulation Conference*, pp. 395–402.

Wetter, M., Bonvini, M. and Nouidui, T. S. (2016) 'Equation-based languages - A new paradigm for building energy modeling, simulation and optimization', *Energy and Buildings*. Elsevier B.V., 117, pp. 290–300. doi: 10.1016/j.enbuild.2015.10.017.

Wickham, H. (2016) *ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York. Available at: https://ggplot2.tidyverse.org.

Wickham, H. *et al.* (2019) 'Welcome to the {tidyverse}', *Journal of Open Source Software*, 4(43), p. 1686. doi: 10.21105/joss.01686.

Wickham, H. *et al.* (2020) 'dplyr: A Grammar of Data Manipulation'. Available at: https://cran.r-project.org/package=dplyr.

Wickham, H. (2020) 'tidyr: Tidy Messy Data'. Available at: https://cran.r-project.org/package=tidyr.

de Wilde, P. (2014) 'The gap between predicted and measured energy performance of buildings: A framework for investigation', *Automation in Construction*. Elsevier B.V., 41, pp. 40–49. doi: 10.1016/j.autcon.2014.02.009.

de Wilde, P. (2018) *Building Performance Analysis*, *Building Performance Analysis*. doi: 10.1002/9781119341901.

de Wilde, P. and Coley, D. (2012) 'The implications of a changing climate for buildings', *Building and Environment*, September, pp. 1–7. doi: 10.1016/j.buildenv.2012.03.014.

de Wilde, P. and Tian, W. (2009) 'Identification of key factors for uncertainty in the prediction of the thermal performance of an office building under climate change', *Building Simulation*. Tsinghua Press, 2(3), pp. 157–174. doi: 10.1007/s12273-009-9116-1.

de Wilde, P. and Tian, W. (2012) 'Management of thermal performance risks in buildings subject to climate change', *Building and Environment*, 55, pp. 167–177. doi: 10.1016/j.buildenv.2012.01.018.

Wilkinson (2004) *A national demand Australia*.

Wong, S. L. L. *et al.* (2010) 'Impact of climate change on residential building envelope cooling loads in subtropical climates', *Energy and Buildings*, 42(11), pp. 2098–2103. doi: 10.1016/j.enbuild.2010.06.021.

Wood, F. R. *et al.* (2015) 'The impacts of climate change on UK energy demand', *Infrastructure Asset Management*, 2(3), pp. 107–119. doi: 10.1680/iasma.14.00039.

Xu, P. *et al.* (2012) 'Impacts of climate change on building heating and cooling energy patterns in California', *Energy*. Elsevier B.V., The Boulevard Kidlington Oxford OX5 1GB United Kingdom, 44(1), pp. 792–804. doi: 10.1016/j.energy.2012.05.013.

Yassaghi, H. and Hoque, S. (2019) 'An Overview of Climate Change and Building Energy: Performance , Responses and Uncertainties', *Buildings*.

Yau, Y. H. H. and Hasbi, S. (2013) 'A review of climate change impacts on commercial buildings and their technical services in the tropics', *Renewable and Sustainable Energy Reviews*, 18, pp. 430–441. doi: 10.1016/j.rser.2012.10.035.

Ye, Y., Zuo, W. and Wang, G. (2019) 'A comprehensive review of energy-related data for U.S. commercial buildings', *Energy and Buildings*. Elsevier B.V., 186, pp. 126–137. doi: 10.1016/j.enbuild.2019.01.020.

Yoshino, H., Hong, T. and Nord, N. (2017) 'IEA EBC annex 53: Total energy use in buildings—Analysis and evaluation methods', *Energy and Buildings*. Elsevier B.V., 152, pp. 124–136. doi: 10.1016/j.enbuild.2017.07.038.

Yu, H. and Chong, A. (2020) 'eplusr: A framework for integrating building energy simulation and data-driven analytics', **In Review**. doi: 10.13140/RG.2.2.34326.16966.

Zeferina, V., Wood, R., *et al.* (2019) 'Sensitivity analysis of a simplified office building', in *Journal of Physics: Conference Series*. doi: 10.1088/1742-6596/1343/1/012129.

Zeferina, V., Birch, C., *et al.* (2019) 'Sensitivity analysis of peak and annual space cooling load at simplified office dynamic building model', *E3S Web of Conferences*, 111, p. 04038. doi: 10.1051/e3sconf/201911104038.

Zeferina, V. *et al.* (2021) 'Sensitivity analysis of cooling demand applied to a large office building', *Energy and Buildings*, 235, p. 110703. doi: 10.1016/j.enbuild.2020.110703.

Zhai, Z. J. and Helman, J. M. (2019) 'Implications of climate changes to building energy and design', *Sustainable Cities and Society*. Elsevier, 44, pp. 511–519. doi: 10.1016/j.scs.2018.10.043.

Zhang, Y. (2009) '"Parallel" EnergyPlus and the Development of a Parametric Analysis Tool', in *Eleventh International IBPSA Conference*, pp. 1382–1388. Available at: http://www.ibpsa.org/proceedings/BS2009/BS09_1382_1388.pdf.

Zheng, S. *et al.* (2020) 'Climate-change impacts on electricity demands at a metropolitan scale: A case study of Guangzhou, China', *Applied Energy*. Elsevier, 261(December 2019), p.

114295. doi: 10.1016/j.apenergy.2019.114295.

Zheng, Y. and Weng, Q. (2019) 'Modeling the effect of climate change on building energy demand in Los Angeles county by using a GIS-based high spatial- and temporal-resolution approach', *Energy*. Elsevier Ltd, 176, pp. 641–655. doi: 10.1016/j.energy.2019.04.052.

Zhou, Y. *et al.* (2014) 'Modeling the effect of climate change on U.S. state-level buildings energy demands in an integrated assessment framework', *Applied Energy*. Elsevier Ltd, 113, pp. 1077–1088. doi: 10.1016/j.apenergy.2013.08.034.

Zhou, Y., Eom, J. and Clarke, L. (2013) 'The effect of global climate change, population distribution, and climate mitigation on building energy use in the U.S. and China', *Climatic Change*, 119(3), pp. 979–992. doi: 10.1007/s10584-013-0772-x.

Appendix A - Heat transfer mechanisms

A1 - Conduction

The law of heat conduction, also known as Fourier's Law, states the heat conduction mechanism as the following (Spitler, 2011):

$$\dot{Q}_k = -k \cdot A \cdot \frac{\Delta T}{x} = U \cdot A \cdot (-\Delta T) \tag{0-1}$$

where

$\dot{Q}_k$	is the conduction heat rate between the extremities of the material [W]
k	is the material conductivity [W.K^{-1}.m^{-1}]
A	is the cross-section surface area of the material [m^2]
Δ_T	is the temperature difference between the extremities of the material [K]
x	is the distance between the extremities of the material [m]
U	is the conductance of the material [W.m^{-2}]

This is a one-dimensional simplification of more complex two and three-dimensional heat conduction patterns that occur in the envelope of a building. Thus, the heat transfer in the other directions is ignored, as it is assumed that the only temperature gradient is on the direction of the envelope's heat flow. Whenever these assumptions are not valid, as for example in a not isotropic envelope, the governing heat transfer expression has to be adapted. For example, the CIBSE guide A (2015, pp. 3–13) proposes an alternative formula to express the thermal transmittance (U_{eff}) of the floor surface to the ground and surrounding perimeter soil surface, as the heat flow pattern is more complex than a one-dimensional heat conduction case. The governing equation in such a case is proposed to be as the following:

$$\dot{Q}_k = A \cdot U_{eff} \cdot \Delta T_{air} \tag{0-2}$$

where

A	is the cross-section surface area of the material [m^2]
U_{eff}	is the effective heat transfer coefficient, considering the combination of all thermal resistance from the interior to the exterior air films [W.m^{-2}.K^{-1}]
ΔT_{air}	is the air temperature difference between the internal zone and outdoor [K]

A2 - Convection

The convective heat transfer occurs due to the flow of fluids, and in the building envelope surfaces, this phenomena occurs mainly through air flows. The convection heat transfer rate can be stated as the following (Spitler, 2011; ASHRAE, 2013c):

$$\dot{Q}_h = h \cdot A \cdot \Delta_T \tag{0-3}$$

where

A	is the surface area of the material exposed to the flow [m^2]

h	is the convection heat transfer coefficient [W.m^{-2}.K^{-1}]
Δ_T	is the temperature difference between the surface and the air [K]

The convection of heat can be driven by two distinct type of flow mechanisms such as natural and forced convection. The natural convection is driven by temperature differences in the fluid that lead to buoyancy movement of the fluid (Spitler, 2011; ASHRAE, 2013c). On the other hand, forced convection is driven by the movement of a fluid resulting from external forces, such as a fan. The heat transfer coefficient (*h*) of the flow is estimated accordingly the respective type of flow, as stated in the following expressions:

Forced:
(ASHRAE, 2013c, pp. 4–17)

$$h = \frac{k}{L_c} \cdot Nu(Re, Pr) \quad (0\text{-}4)$$

Natural:
(ASHRAE, 2013c, pp. 4–19)

$$h = \frac{k}{L_c} \cdot Nu(Ra, Pr) \quad (0\text{-}5)$$

where

Nu	Nusselt number
Re	Reynolds number
Pr	Prandtl number
Ra	Rayleigh number
k	is the conductivity of the fluid [W.K^{-1}.m^{-1}]
L_c	is the characteristic length [m]

These characteristics are quantified based on the flow properties and the development of their laminar and turbulent layers, and on the dimension of the body in contact with the flow.

A3 - Radiation

The emissive power of a perfect black-body is described by the Stefan-Boltzmann law:

$$W_b = \sigma \cdot T_S^4 \quad (0\text{-}6)$$

It relates the emissive power to the product of the 4th order of the temperature and Stefan-Boltzmann's constant (σ). The thermal radiant energy emitted by a non-perfect body assumes that the body emits a fraction, body emissivity (ε), of the equivalent perfect black body, as the body does not absorb all incident radiation. The emitted radiation heat rate is then expressed as the following:

$$\dot{Q}_{rad} = A_S \cdot \varepsilon \cdot W_b = A_S \cdot \varepsilon \cdot \sigma \cdot T_S^4 \quad (0\text{-}7)$$

where

$\dot{Q}_{rad}$	is the heat radiation rate of a body [W]
A_S	is the area of the body surface [m^2]
ε	is the emissivity of the body/surface
W_b	is the blackbody emissive power [W.m^{-2}]
σ	is the Stefan-Boltzmann constant, 5.67 x 10^{-8} [W.m^{-2}.K^{-4}]
T_S	is the absolute surface temperature [K]

Similarly, the radiation between two surfaces separated by a non-participating medium is given by:

$$\dot{Q}_{1-2} = \frac{\sigma \cdot (T_1^4 - T_2^4)}{\frac{1-\varepsilon_1}{A_1\varepsilon_1} + \frac{1}{A_1 F_{1-2}} + \frac{1-\varepsilon_2}{A_2\varepsilon_2}} \tag{0-8}$$

where

T_1, T_2	are the temperature of surfaces
$\varepsilon_1, \varepsilon_2$	are the emissivity of surfaces 1 and 2
F_{1-2}	is the view factor from surface 1 to surface 2

The thermal radiant energy that reaches a surface can be absorbed (α), reflected (ρ) or transmitted (τ) (ASHRAE, 2013c, p. 4.13). Considering the first law of thermodynamics, the following expression is applicable to any point in the surface:

$$\alpha + \rho + \tau = 1 \tag{0-9}$$

and the absorbed radiation of an object is:

$$\dot{Q}_{absorbed} = \alpha \cdot A_S \cdot G \tag{0-10}$$

where

α	is the absorptivity, the fraction of incident radiation absorbed
ρ	is the reflectivity, the fraction of radiation reflected by the surface
τ	is the transmissivity, the fraction of radiation transmitted by a non-opaque surface
A_S	is the area of the surface [m^2]
G	is the rate of radiant energy incident on a surface [$W.m^{-2}$]

Generally, the thermal radiation in building models is treated in two different procedures, distinguishing the phenomena for opaque envelopes and windows (Spitler, 2011). Furthermore, the thermal radiation reaching building's opaque surfaces is distinguished in two categories: short wavelength radiation or the visible-solar spectrum, and long wavelength radiation, the radiation emitted by bodies at relatively much lower temperatures than the sun. Finally, for windows, the radiation is divided in direct and diffuse.

External radiation

The thermal radiation in building's external surfaces is expressed in the following equations.

For short wavelength:

$$\dot{Q}_{SW,ext} = \alpha \cdot A_S \cdot G_t \tag{0-11}$$

where

G_t	is the total solar shortwave irradiation (direct and diffuse) on the surface [$W.m^{-2}$]

Long wavelength

The long wavelength radiation in external surfaces to the surrounding of buildings is a very complex phenomenon, and assumptions have to be made to simplify and make model calculations feasible. Therefore, these calculations assume opaque, diffuse and isothermal characteristics in the model surfaces, as well as uniform radiosity, which is the radiation leaving the surface (emitted plus reflected radiation) and on the incident radiation in surfaces (irradiation). The surface is assumed to be a grey body ($\varepsilon = \alpha$) and there is a single absorptivity value for the wavelength (long) spectrum analysed. The emitted radiation to an imaginary sky surface, assumes the surrounding body's atmosphere is a participating medium and it is modelled as the radiation transferred to a surface at an effective sky temperature (Spitler, 2011). The governing expression is described as the following:

$$\dot{Q}_{LW,ext} = \varepsilon \cdot \sigma\left[F_{s-gr} \cdot \left(T_{gr}^4 - T_S^4\right) + F_{s-sky} \cdot \left(T_{sky}^4 - T_S^4\right)\right] \qquad (0\text{-}12)$$

where

F_{s-gr}	is the surface to the ground view factor
F_{s-gr}	is the surface to the sky view factor
T_{gr}	is the ground temperature [K]
T_{sky}	is the effective sky temperature [K]

Internal radiation

The thermal radiation inside buildings is also distinguished between the long and short wavelength. This formulation assumes that all direct radiation transmitted by glazing is incident in the floor and the radiation reflected by the floor is uniformly absorbed by all wall surfaces. Moreover, the diffuse radiation transmitted in the glazing is uniformly absorbed by the internal envelope surfaces.

Short wavelength

The equation (0-13) and (0-14) express respectively the total short wavelength radiation in the internal walls and in the floor of the zone:

$$\dot{Q}_{SW,i,walls} = \sum \dot{Q}_{SW,diff} + \left(1 - \alpha_{floor}\right) \cdot \sum \dot{Q}_{SW,dir} \qquad (0\text{-}13)$$

$$\dot{Q}_{SW,i,floor} = \sum \dot{Q}_{SW,diff} + \alpha_{floor} \cdot \sum \dot{Q}_{SW,dir} \qquad (0\text{-}14)$$

where

$\dot{Q}_{SW,i,walls}$	is the short wavelength radiation absorbed in the zone wall surfaces [W]
$\dot{Q}_{SW,i,floor}$	is the short wavelength radiation absorbed in the zone floor [W]
$\sum \dot{Q}_{SW,diff}$	is the total diffuse short wavelength radiation transmitted from the glazing [W]
$\sum \dot{Q}_{SW,dir}$	is the total direct short wavelength radiation transmitted from the glazing [W]
α_{floor}	is the absorptivity, the fraction of incident direct SW radiation absorbed by the floor [W]

Long wavelength

The net long wavelength exchange radiation in an internal surface of a building is expressed as the following:

$$\dot{Q}_{LW,i} = \dot{Q}_{LW,surf-surf} - \dot{Q}_{LW,ihg} \tag{0-15}$$

where

$\dot{Q}_{LW,i}$	is the net exchange of long wavelength radiation in the zone wall surface [W]
$\dot{Q}_{LW,s-s}$	is the net exchange radiation between the surface and other zone's envelope surfaces [W]
$\dot{Q}_{LW,ihg}$	is the net exchange radiation from internal heat gains of the building zone [W]

Glazing

The cooling load resulting from the total heat transfer through a window can be calculated as proposed in equation (0-16) (Underwood, *et al.*, 2004, p. 45). This method assumes that the energy conducted in a window is negligible, and so only considers the incident radiation in the glazing and the convective heat transfer between the outdoor and the interior. The implication of the incident energy is divided in the effect of the transmitted energy through the surface and the absorbed energy by the glazing and then transferred through convection in the internal surface to the interior zone. The heat flux in the glazing surface is expressed as:

$$q''_G = \left(\tau + \frac{U}{h_O}\alpha\right) I_T + U \cdot (T_O - T_i) \tag{0-16}$$

where

q''_G	is the total heat flux in the glazing [$W.m^{-2}$]
τ	is the transmissivity of the window
α	is the absorptivity of the window
I_T	is the Incident total radiation [$W.m^{-2}$]
U	is the overall convective heat transfer coefficient for the window [$W.K^{-1}.m^{-2}$]
T_O	Is the outdoor temperature [K]
T_i	Is the ambient temperature [K]

Considering that absorbed and transmitted solar radiation are expressed as:

Absorptivity
$$\tau \cdot I_T = \tau_\theta \cdot I_D + \tau_d \cdot I_d \tag{0-17}$$

Transmissivity
$$\tau \cdot I_T = \tau_\theta \cdot I_D + \tau_d \cdot I_d \tag{0-18}$$

where

α	is the total absorptivity of the glazing material
α_θ	is the direct radiation absorptivity of the glazing material
α_d	is the diffuse radiation absorptivity of the glazing material
τ	is the total transmissivity of the glazing material
τ_θ	is the direct radiation transmissivity of the glazing material
τ_d	is the diffuse radiation transmissivity of the glazing material
I_T	is the incident total radiation [$W.m^{-2}$]

I_D is the total direct incident radiation [$W.m^{-2}$]
I_d is the total diffuse incident radiation [$W.m^{-2}$]

Appendix B - Literature review summarty tables

B1 - Summary table of the literature review on the impacts of climate change in buildings

Table A. 1 – Summary table of the literature review on the impacts of climate change in buildings

Key	Year	Country	BPS Dynamic	RC-Method	Hybrid	Data-Driven	Top-Down	Simplified	UBEM	National Scale	Urban scale	District scale	Single Building	Multiple Single	Commercial	Office	Residential	All	Other	DOE Prototype	DOE Reference	Cooling	Total Load	Heating	Primary Energy	Carbon Emissions	Overheat	Hourly	Annual	Peak	Monthly	Adaptation
Yassaghi2019	2019																															
Auffhammer2014	2014																															
Chandramowli2014	2014																															
Li2012	2012															Review papers																
Yau2013	2013																															
Andric2019	2019																															
Auffhammer2017	2017	USA				x				x												x			x					x		
Berardi2020	2020	Canada - Toronto	x											x				x			x	x		x		x			x			
Berger2014	2014	Austria	x										x			x						x		x					x			
Burillo2019	2019	USA - Los Angels	x								x											x								x		
Cellura2018	2018	15 Mediterranean cities	x										x			x						x						x	x	x		
Chai2019	2019	China											x			x						x	x	x								x
Chow2010	2010	UK		x									x			x						x	x	x		x			x			x
Ciancio2019	2019	Europe											x				x					x		x				x	x	x	x	

Key	Year	Country	BPS Dynamic	RC-Method	Hybrid	Data-Driven	Top-Down	Simplified	UBEM	National Scale	Urban scale	District scale	Single Building	Multiple Single	Commercial	Office	Residential	All	Other	DOE Prototype	DOE Reference	Cooling	Total Load	Heating	Primary Energy	Carbon Emissions	Overheat	Hourly	Annual	Peak	Monthly	Adaptation
Collins2010	2010	UK	x							x			x									x		x		x			x			
Constable2013	2013	USA				x					x														x					x		
Crawley2008thesis	2008	World	x										x							x												
Dias2020	2020	Iberia											x			x	x					x		x			x	x		x		
Dirks2015	2015	USA	x							x					x		x			x		x	x						x	x		
Dodoo2016	2016	Sweden	x											x			x					x		x			x	x				x
Du2012	2012	UK	x											x	x	x	x													x		
Du2012a	2012	UK												x		x						x	x				x		x	x		
Farah2019	2019	Australia	x										x				x					x		x					x	x		
Farrou2016	2016	Greece											x									x		x					x			x
Fonseca2015	2015	Switzerland		x																												
Frank2005	2005	Switzerland		x									x			x	x					x		x					x			x
GarciaKerdan2016	2016	UK																														
GarciaKerdan2016a	2016	UK																														
Guan2009	2009	Australia	x										x			x						x							x			
Guan2012	2012	Australia	x										x			x						x	x			x			x			x
Gupta2012	2012	UK - Oxford	x										x				x										x		x			x
Gupta2015	2015	UK	x											x			x					x					x		x			
HMGovernment2010	2010	UK								x									x													

Key	Year	Country	BPS Dynamic	RC-Method	Hybrid	Data-Driven	Top-Down	Simplified	UBEM	National Scale	Urban scale	District scale	Single Building	Multiple Single	Commercial	Office	Residential	All	Other	DOE Prototype	DOE Reference	Cooling	Total Load	Heating	Primary Energy	Carbon Emissions	Overheat	Hourly	Annual	Peak	Monthly	Adaptation
Hong2013	2013	USA - Worldwide	x											x		x				x		x							x	x		
Huang2016	2016	USA	x							x					x		x			x			x						x	x	x	
Huang2016a	2016	Taiwan	x										x				x					x							x			x
Isaac2009	2009	World					x	x		x																			x			
Jenkins2011	2011	UK															x										x					
Jenkins2013	2013	UK	x		x	x							x			x			x			x						x	x			x
Jenkins2015	2015	UK - Edinburgh	x								x	x					x					x		x					x	x	x	x
Lam2010	2010	HK																														
Li2018	2018	China														x																
Lu2010	2010	USA - Canada	x									x																				
Miller2008	2008	USA - California				x												x							x							
Moazami2019	2019	Switzerland										x			x						x	x		x	x				x	x		
Mulville2016	2016	UK	x										x				x										x					
Nik2013	2013	Sweden										x					x		x			x		x					x			
Nik2015	2015	Sweden																														x
Nik2016	2016	Switzerland and Sweden	x									x	x			x	x		IDA -ICE													
Pagliano2016	2016	Italy - Milan											x		x							x		x			x		x			x
Parkpoom2008	2008	Thailand				x				x																				x		
Patidar2012	2012	UK	x		x	x							x				x										x					x

Key	Year	Country	BPS Dynamic	RC-Method	Hybrid	Data-Driven	Top-Down	Simplified	UBEM	National Scale	Urban scale	District scale	Single Building	Multiple Single	Commercial	Office	Residential	All	Other	DOE Prototype	DOE Reference	Cooling	Total Load	Heating	Primary Energy	Carbon Emissions	Overheat	Hourly	Annual	Peak	Monthly	Adaptation
Patidar2014	2014	UK	x		x	x											x										x	x				
Shibuya2016	2016	Japan	x										x			x						x			x				x			x
Tarroja2018	2018	California - USA									x					x	x			x		x	x						x	x		
Tian2011	2011	UK											x									x							x			
Tian2011a	2011	UK	x											x		x						x							x			
Wan2011	2011	China	x										x	x	x	x													x			
Wan2012	2012	China	x		x	x							x			x									x	x			x			x
Wang2014	2014	USA	x											x	x	x	x				x	x			x			x	x	x		
Wright2013	2013	UK	x											x			x										x					
Xu2012	2012	USA - California								x										x		x										
Yassaghi2019a	2019	USA - Philadelphia																														
zheng2019	2019	USA - Los Angels										x			x	x	x			x		x	x	x				x	x		x	
Zhou2013	2013	China, USA					x			x												x			x	x			x			
Zhou2014	2014	USA					x			x								x				x	x						x			

Table A. 2

Appendix C - Supplementary results

C1 - Chapter 4 – Sensitivity analysis studies results

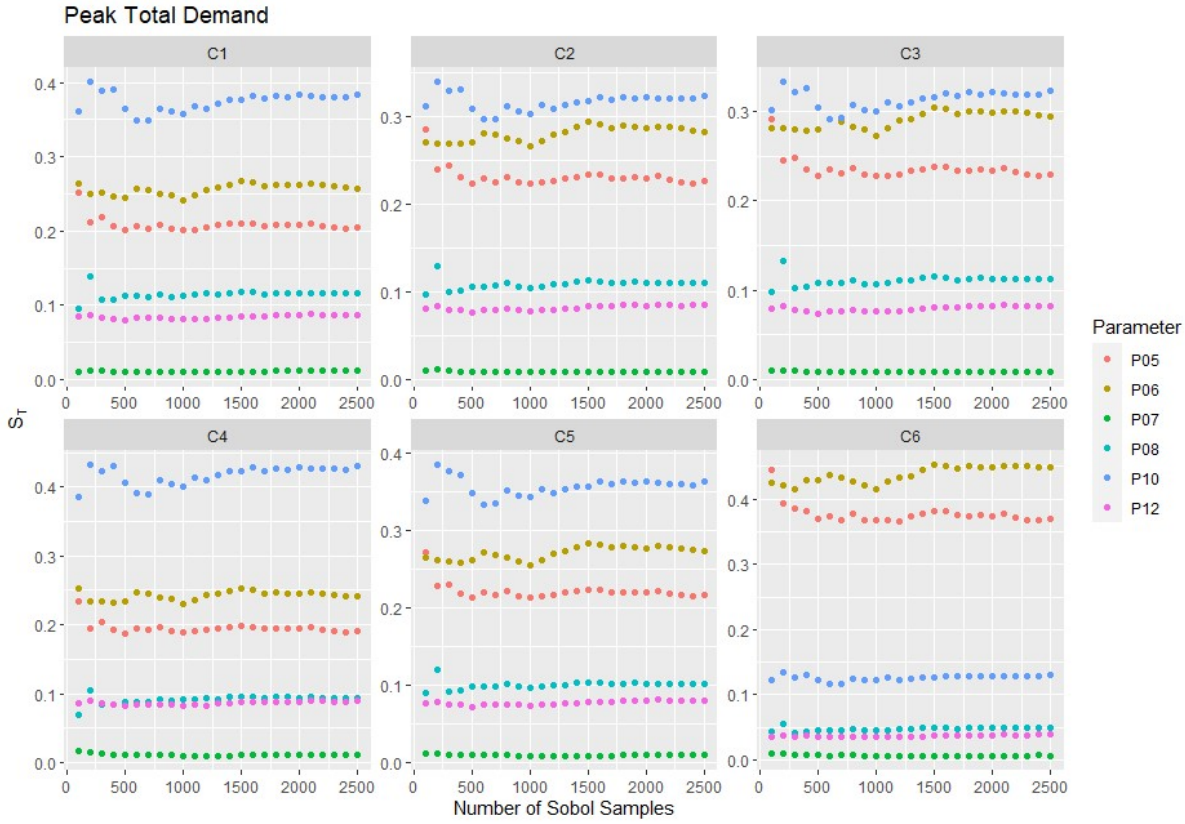

Figure 0.1 – Sobol stability -Peak total electricity demand

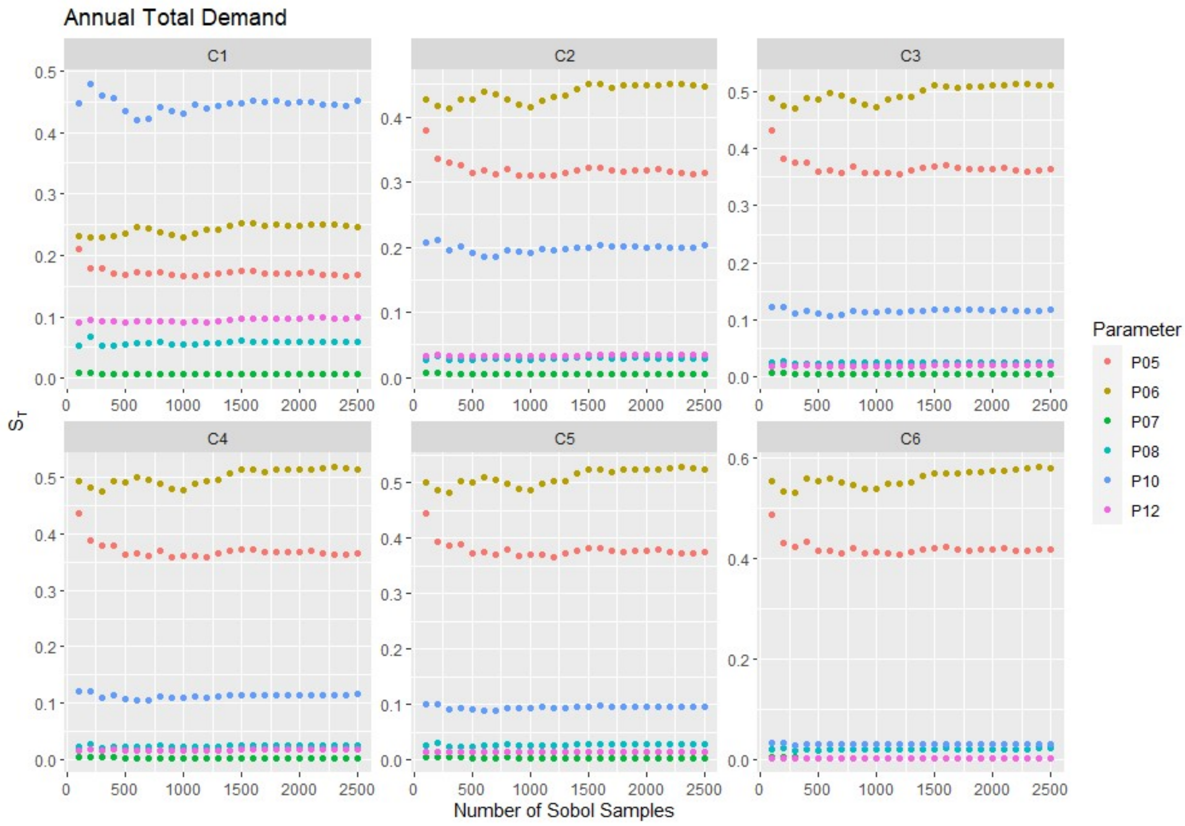

Figure 0.2 – Sobol stability for annual total electricity demand

Table 0.1 – Coefficient of variation of total electricity demand in the archetype Morris SA study

Temporal Resolution	Model	C1 – Sin	C2 – Cai	C3 – Ath	C4 – Bei	C5 – Lis	C6 - Lon
	Large	26%	23%	23%	24%	24%	24%
Annual	Medium	23%	21%	21%	21%	22%	22%
	Small	28%	24%	23%	23%	23%	22%
	Large	29%	26%	25%	29%	25%	25%
Peak	Medium	25%	26%	25%	24%	25%	18%
	Small	28%	29%	28%	29%	28%	26%

Table 0.2 – Coefficient of variation of electricity demand for HVAC end-use, in the archetype Morris SA study

Temporal Resolution	Model	C1 – Sin	C2 – Cai	C3 – Ath	C4 – Bei	C5 – Lis	C6 - Lon
	Large	37%	29%	28%	33%	30%	34%
Annual	Medium	36%	28%	28%	30%	30%	33%
	Small	44%	39%	38%	38%	41%	39%
	Large	41%	36%	34%	40%	34%	34%
Peak	Medium	38%	39%	44%	46%	42%	41%
	Small	45%	40%	40%	41%	40%	40%

Table 0.3 – Coefficient of variation of space cooling requirements in the archetype Morris SA study

Temporal Resolution	Model	C1 – Sin	C2 – Cai	C3 – Ath	C4 – Bei	C5 – Lis	C6 – Lon
	Large	22%	24%	27%	28%	29%	34%
Annual	Medium	22%	23%	24%	25%	26%	30%
	Small	30%	30%	31%	33%	33%	39%
	Large	22%	21%	22%	23%	24%	26%
Peak	Medium	21%	20%	21%	21%	23%	24%
	Small	24%	19%	21%	20%	21%	22%

C2 – Chapter 5 – Uncertainties associated with weather data

Table 0.4 – EPW file description of variables

Num.	E+ (Used)	Variable Description
1		Year
2	y	Month
3	y	Day
4	y	Hour
5		Minute
6		Datasource
7	y	Dry-Bulb Temperature {C}
8	y	Dew Point Temperature {C}
9	y	Relative Humidity {%}
10	y	Atmospheric Pressure {Pa}
11		Extraterrestrial Horizontal Radiation {Wh/m2}
12		Extraterrestrial Direct Normal Radiation {Wh/m2}
13	y	Horizontal Infrared Radiation Intensity from Sky {Wh/m2}
14		Global Horizontal Radiation {Wh/m2}
15	y	Direct Normal Radiation {Wh/m2}
16	y	Diffuse Horizontal Radiation {Wh/m2}
17		Global Horizontal Illuminance {lux}
18		Direct Normal Illuminance {lux}
19		Diffuse Horizontal Illuminance {lux}
20		Zenith Luminance {Cd/m2}
21	y	Wind Direction {deg}
22	y	Wind Speed {m/s}
23		Total Sky Cover {.1}
24		Opaque Sky Cover {.1}
25		Visibility {km}
26		Ceiling Height {m}
27	y	Present Weather Observation
28	y	Present Weather Codes

29		Precipitable Water {mm}
30		Aerosol Optical Depth {.001}
31	y	Snow Depth {cm}
32		Days Since Last Snow
33		Albedo {.01}
34	y	Liquid Precipitation Depth {mm}
35		Liquid Precipitation Quantity {hr}

Table 0.5 – Maximum peak electricity demand variation response for all LSA tests, model and locations

Model	Location	01	02	03	04	05	06	07	08	09
Large	C1 – Sin	18.6%	7.0%	0.0%	0.3%	-3.9%	-1.2%	1.4%	0.9%	0.8%
	C2 – Cai	23.3%	12.4%	0.6%	0.1%	-2.8%	-0.6%	1.6%	1.2%	0.6%
	C3 – Ath	25.6%	15.4%	3.8%	0.0%	-2.4%	-0.7%	1.7%	1.5%	0.6%
	C4 – Bei	16.3%	5.9%	0.5%	0.4%	-4.2%	-2.2%	2.3%	0.7%	0.6%
	C5 – Lis	24.2%	5.3%	2.7%	1.4%	-5.7%	-2.6%	1.0%	0.0%	0.3%
	C6 – Lon	13.1%	4.9%	3.0%	0.7%	-3.2%	-1.6%	2.0%	1.8%	0.7%
Medium	C1 – Sin	26.8%	11.7%	2.2%	0.1%	-2.9%	-1.5%	1.6%	0.7%	0.7%
	C2 – Cai	18.5%	7.4%	5.6%	0.1%	0.0%	-1.1%	1.5%	0.6%	0.9%
	C3 – Ath	21.2%	7.7%	3.2%	0.2%	0.0%	0.0%	2.0%	1.0%	0.6%
	C4 – Bei	24.1%	7.3%	3.2%	0.0%	-3.6%	-1.8%	1.6%	0.0%	0.9%
	C5 – Lis	25.4%	9.3%	9.4%	0.2%	-4.2%	-2.2%	1.5%	0.0%	0.7%
	C6 – Lon	18.8%	6.9%	7.0%	0.2%	-2.4%	-1.1%	1.9%	1.2%	0.7%
Small	C1 – Sin	19.9%	6.5%	1.1%	0.1%	-2.2%	0.0%	3.2%	0.7%	1.1%
	C2 – Cai	18.7%	7.2%	4.5%	0.0%	0.0%	-0.3%	2.9%	1.7%	1.1%
	C3 – Ath	21.3%	7.7%	3.1%	0.2%	-1.8%	-0.3%	3.1%	2.1%	0.9%
	C4 – Bei	17.7%	6.4%	1.5%	0.2%	-2.5%	-1.5%	4.3%	2.1%	0.7%
	C5 – Lis	21.0%	9.8%	4.6%	0.5%	-3.3%	-1.7%	3.1%	3.6%	1.4%
	C6 – Lon	19.9%	7.4%	5.4%	0.4%	-1.9%	-0.6%	3.2%	2.8%	1.1%

Table 0.6 - Maximum annual electricity demand variation response for all LSA tests, model and locations

Model	Location	01	02	03	04	05	06	07	08	09
		Shif DBT								
Large	C1	38.0%	2.2%	0.0%	0.6%	-5.1%	-0.6%	5.2%	0.9%	1.6%
	C2	20.3%	3.4%	0.4%	0.4%	-3.2%	-0.7%	2.6%	1.3%	0.8%
	C3	16.6%	3.1%	0.4%	0.4%	-2.3%	-0.6%	2.1%	1.4%	0.7%
	C4	17.3%	4.5%	0.0%	0.3%	-2.3%	-0.9%	2.3%	1.2%	0.5%
	C5	17.3%	2.9%	0.5%	0.7%	-2.3%	-0.7%	1.7%	1.2%	0.8%
	C6	11.9%	2.8%	0.0%	0.5%	-1.0%	-0.4%	1.2%	1.5%	0.5%
Medium	C1	28.2%	0.6%	0.0%	0.1%	-3.4%	-0.2%	3.0%	0.4%	1.2%
	C2	20.6%	2.1%	0.2%	0.1%	-1.5%	-0.4%	2.0%	1.0%	0.7%
	C3	18.3%	2.1%	0.2%	0.1%	-1.3%	-0.3%	1.7%	0.9%	0.5%
	C4	13.9%	3.1%	0.1%	0.1%	-1.1%	-0.5%	1.6%	0.6%	0.4%
	C5	19.9%	1.6%	0.1%	0.2%	-1.5%	-0.3%	1.2%	0.9%	0.6%
	C6	11.9%	2.2%	0.0%	0.1%	-0.4%	-0.1%	0.6%	0.4%	0.3%
Small	C1	27.7%	1.4%	0.0%	0.2%	-2.6%	-0.3%	4.9%	0.9%	1.7%
	C2	20.0%	3.0%	0.4%	0.3%	-1.2%	-0.3%	3.8%	2.0%	1.2%
	C3	16.3%	3.2%	0.3%	0.3%	-0.7%	-0.2%	3.2%	1.8%	1.0%
	C4	13.1%	3.4%	0.0%	0.1%	-0.9%	-0.4%	3.2%	1.6%	0.7%
	C5	15.8%	2.5%	0.2%	0.5%	-0.9%	-0.3%	2.9%	2.7%	1.2%
	C6	9.1%	2.3%	0.0%	0.2%	-0.2%	-0.1%	2.2%	1.8%	0.8%

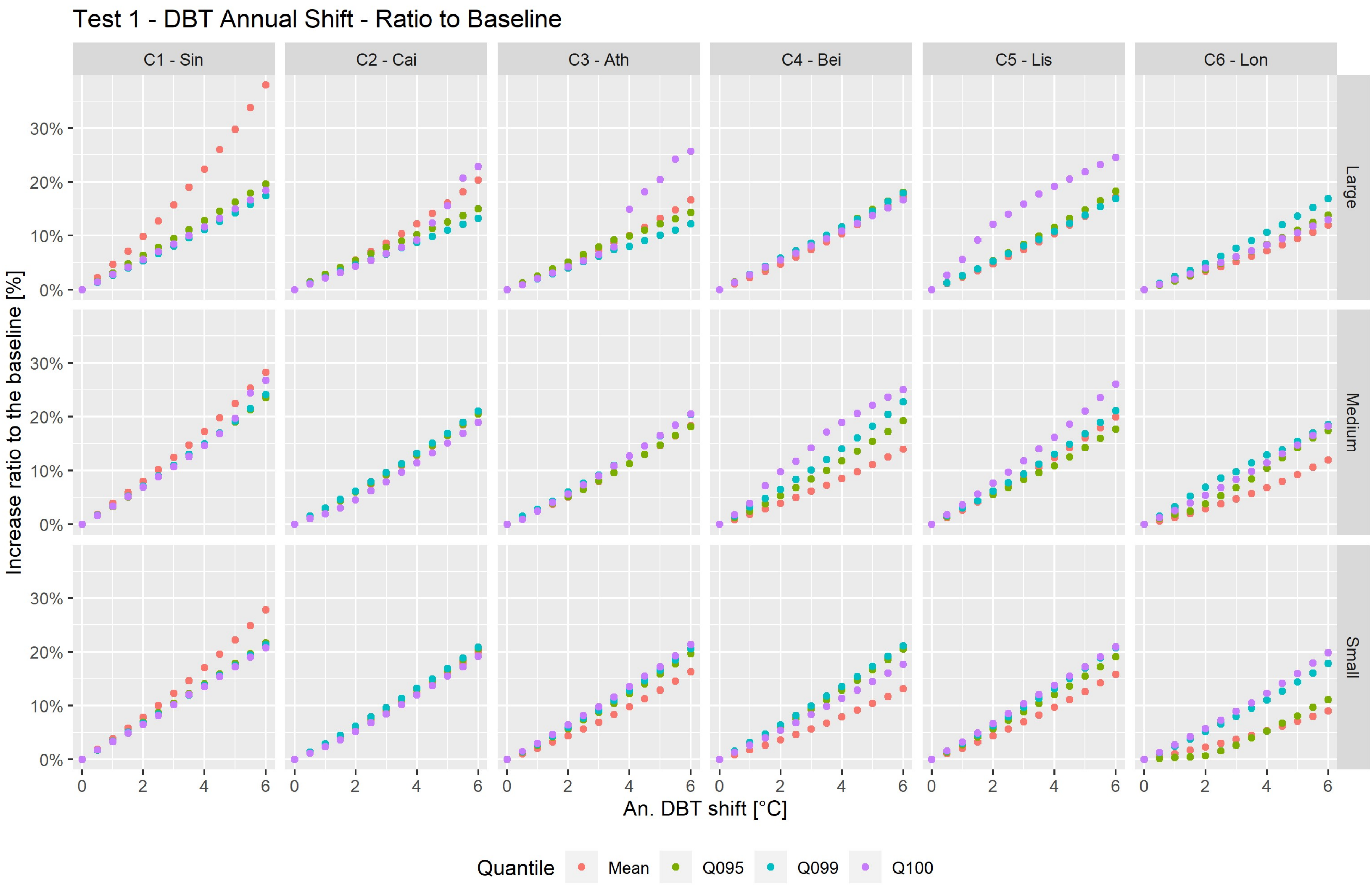

Figure 0.3 – Percentile analysis of annual hourly demand through Test 1 iterations, DBT shift

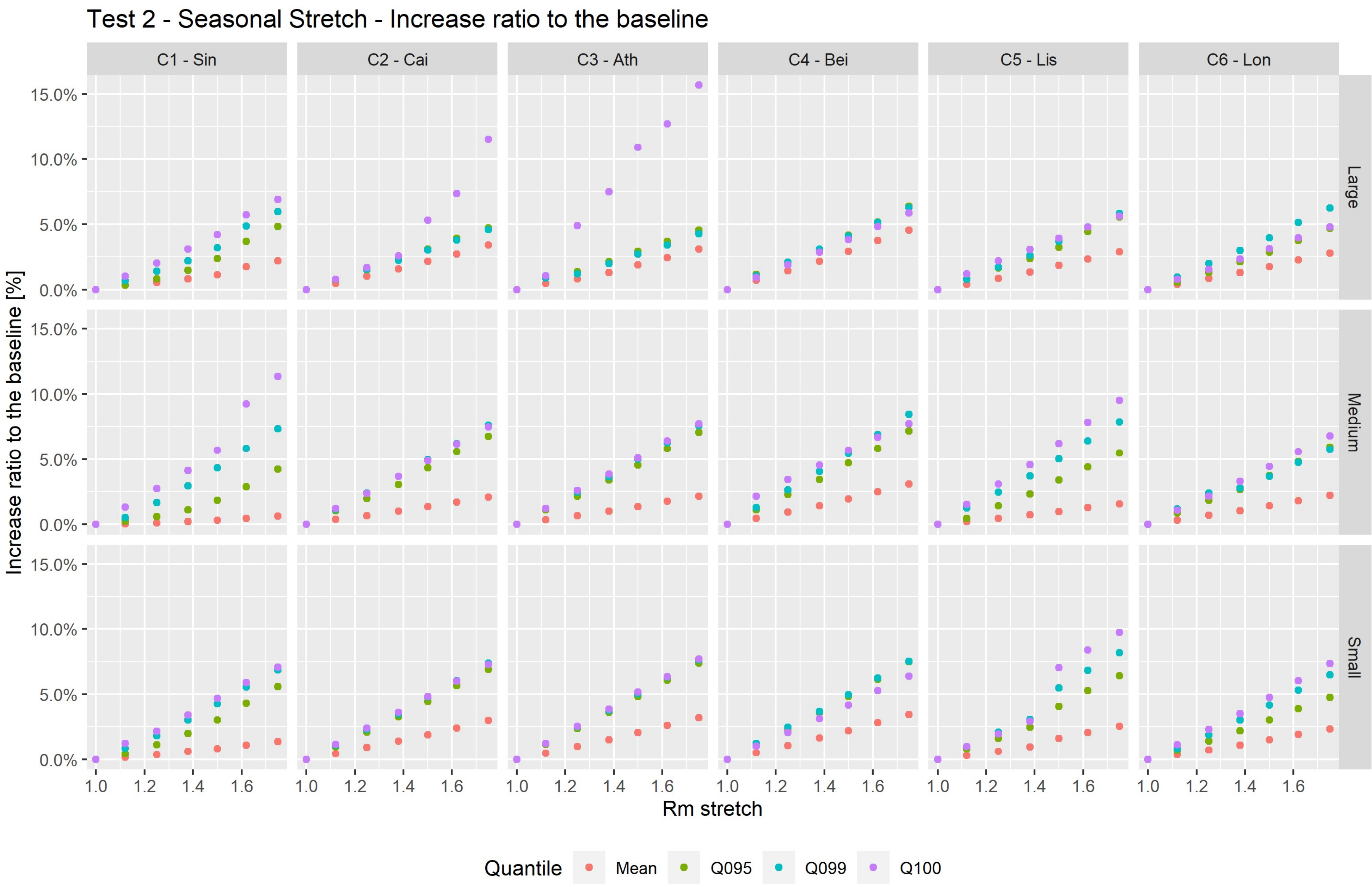

Figure 0.4 – Percentile analysis of annual hourly demand through Test 2 iterations, DBT seasonal stretch

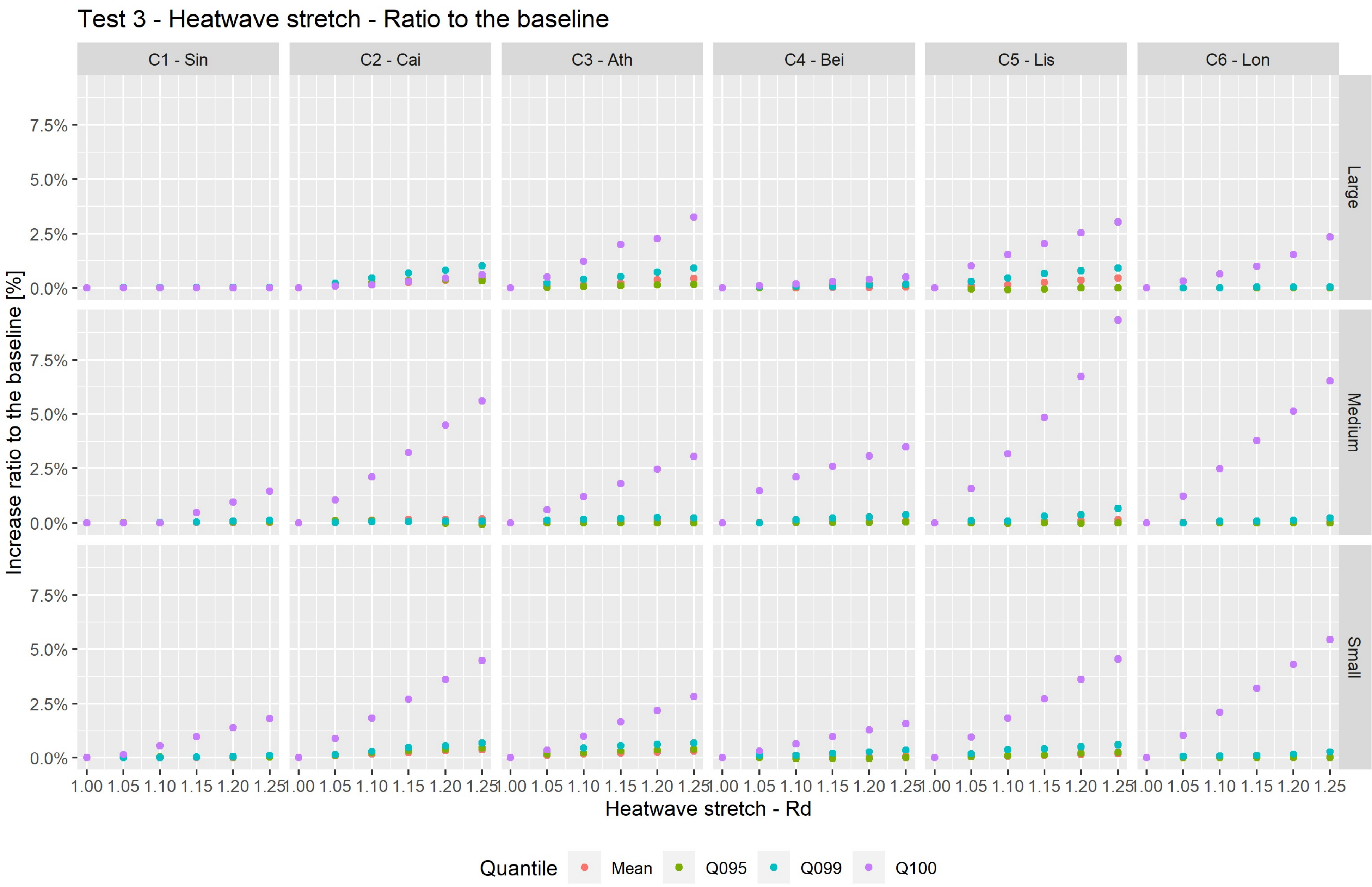

Figure 0.5 – Percentile analysis of annual hourly demand through Test 3 iterations, DBT heatwave stretch

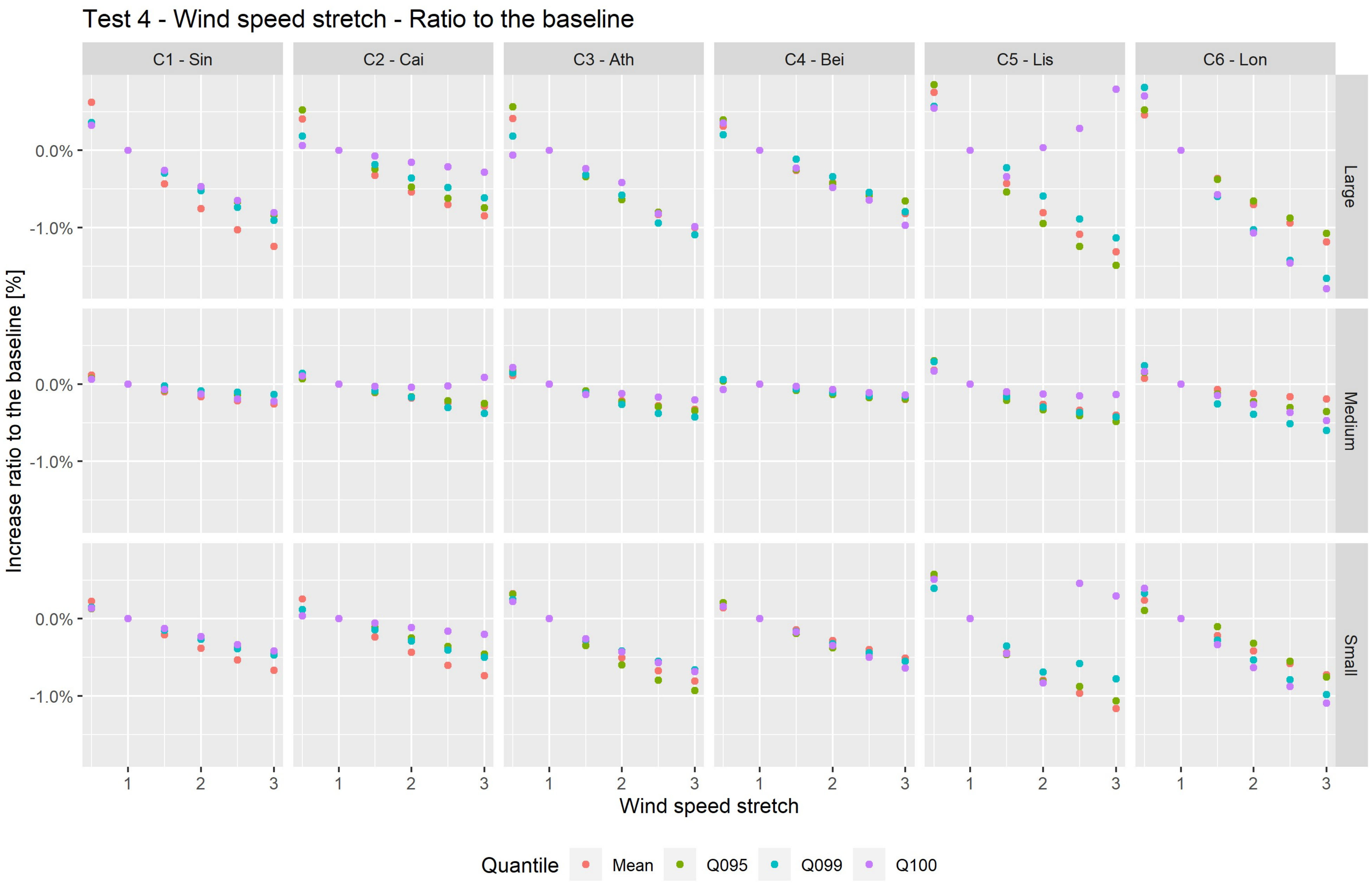

Figure 0.6 – Percentile analysis of annual hourly demand through test 4 iterations, wind speed stretch

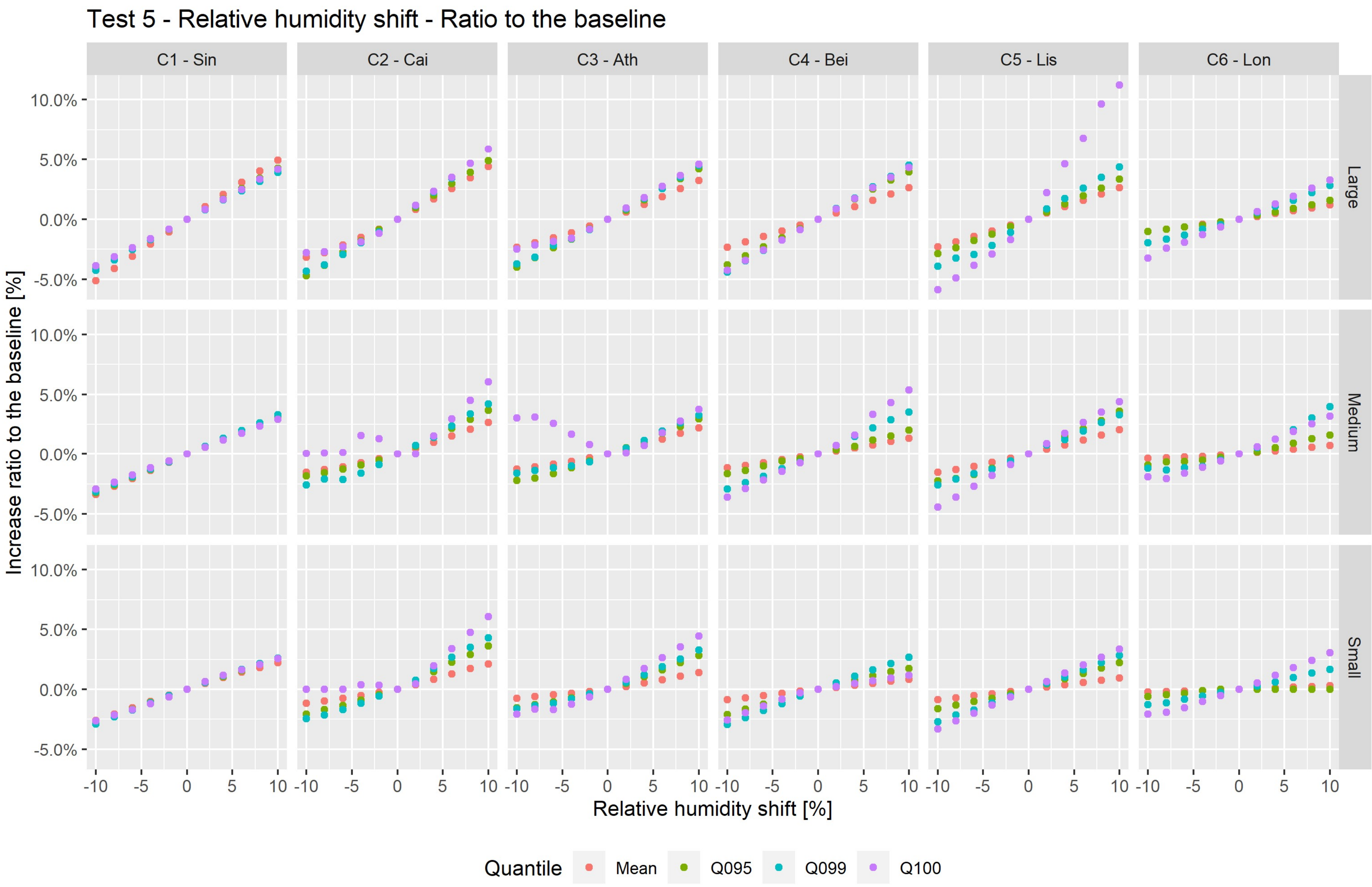

Figure 0.7 – Percentile analysis of annual hourly demand through test 5 iterations, relative humidity shift

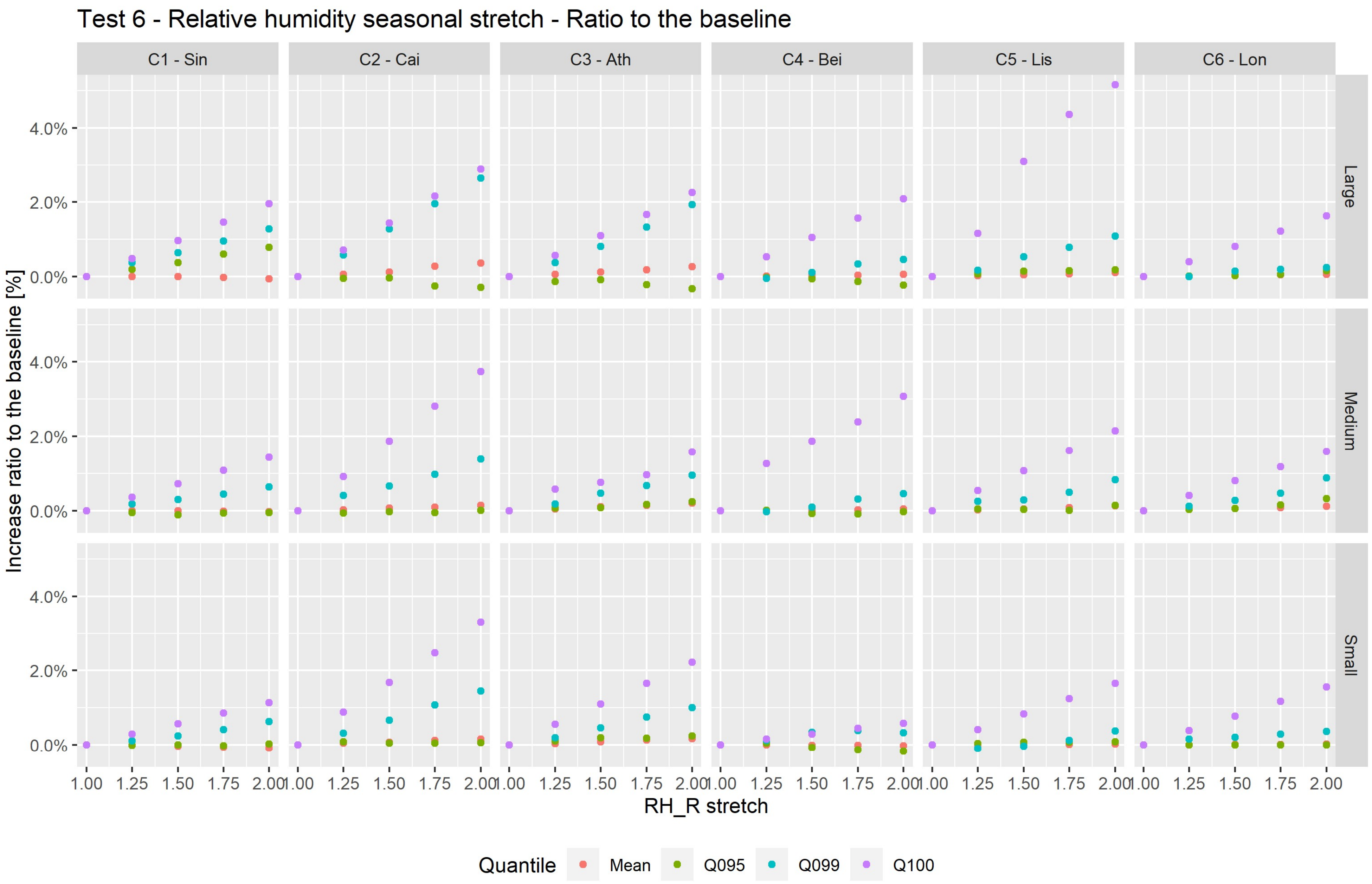

Figure 0.8 – Percentile analysis of annual hourly demand through test 6 iterations, relative humidity seasonal stretch

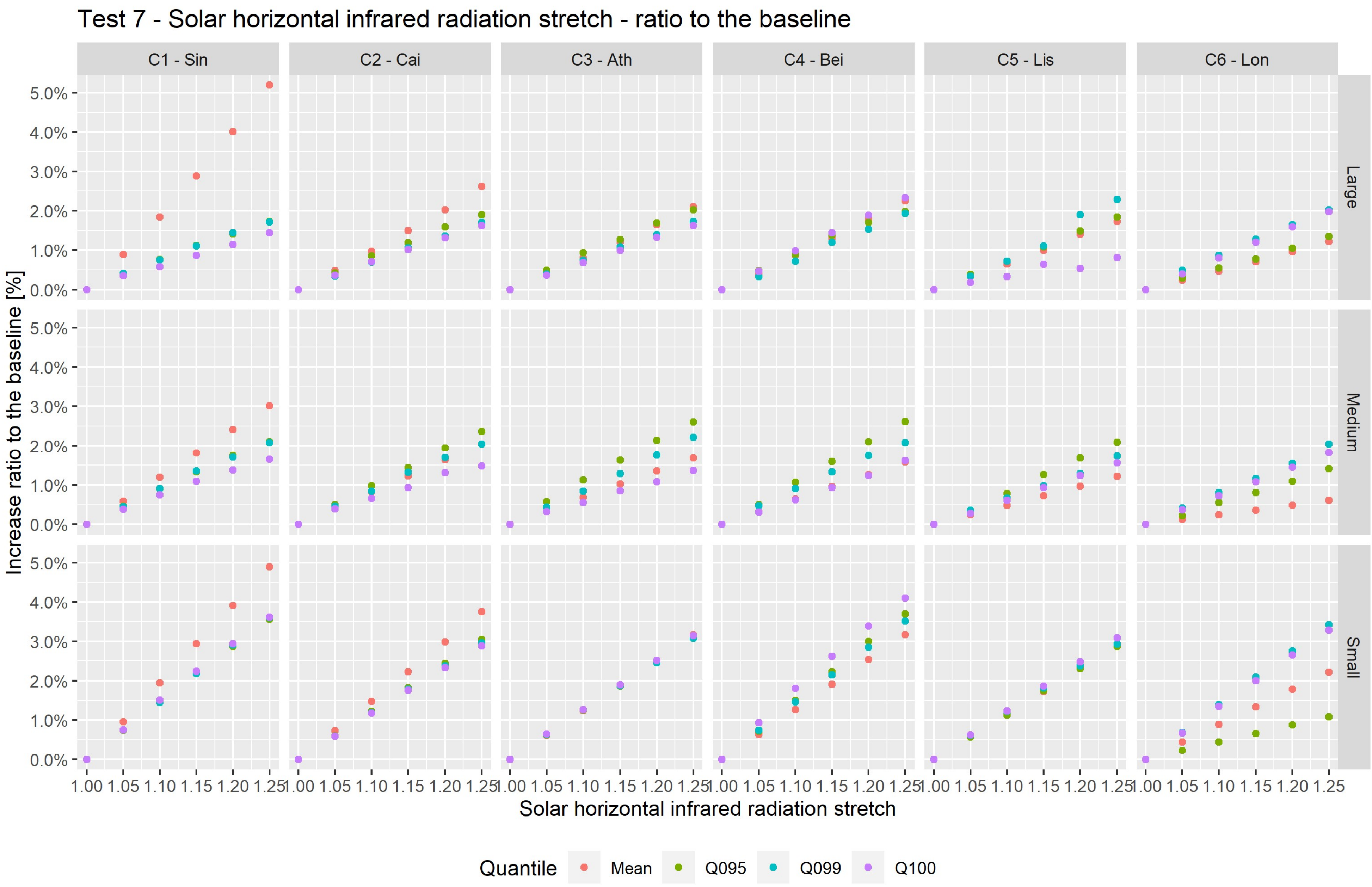

Figure 0.9 – Percentile analysis of annual hourly demand through test 7 iterations, solar HIR

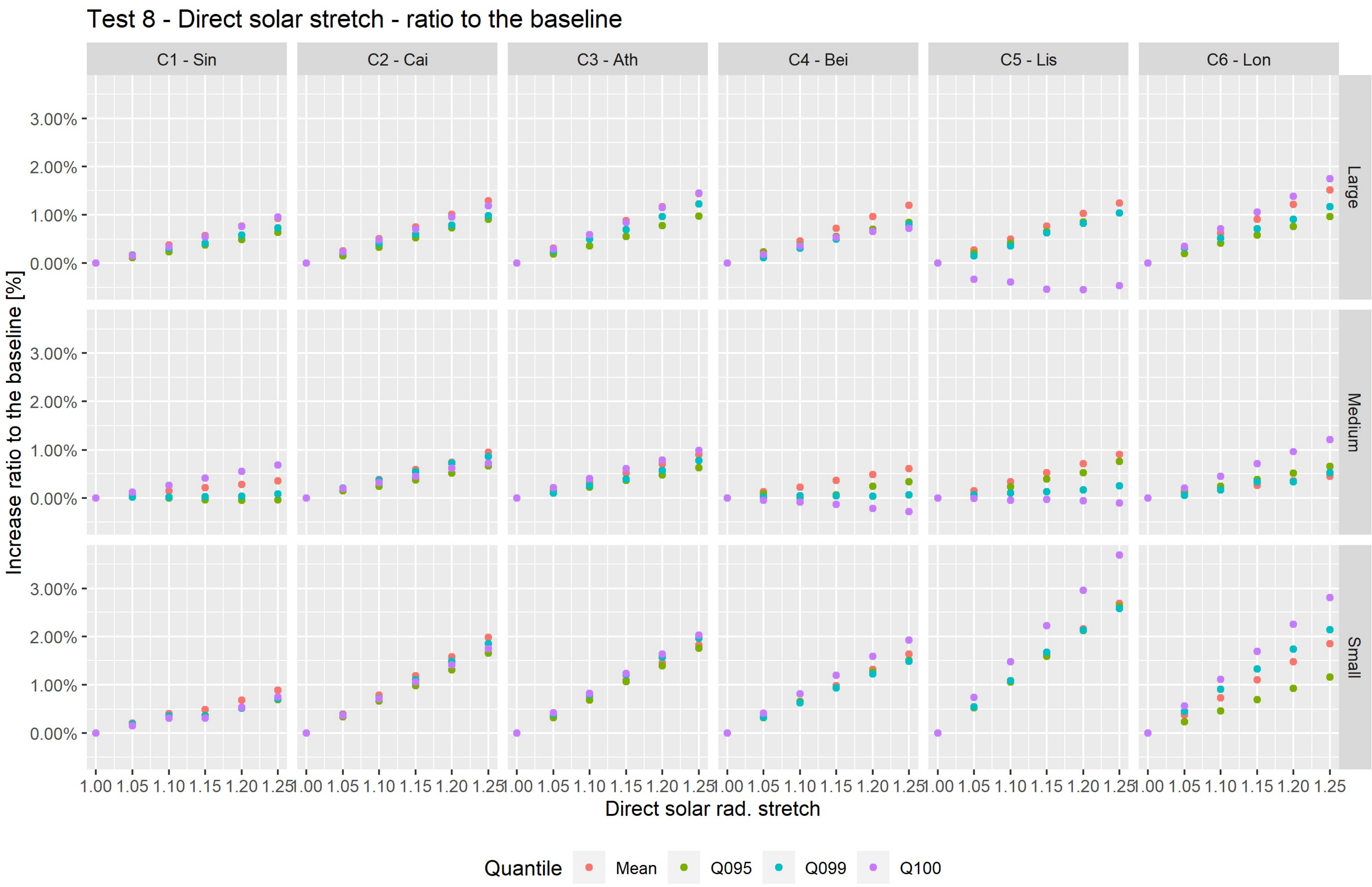

Figure 0.10 – Percentile analysis of annual hourly demand through test 8 iterations, direct solar radiation

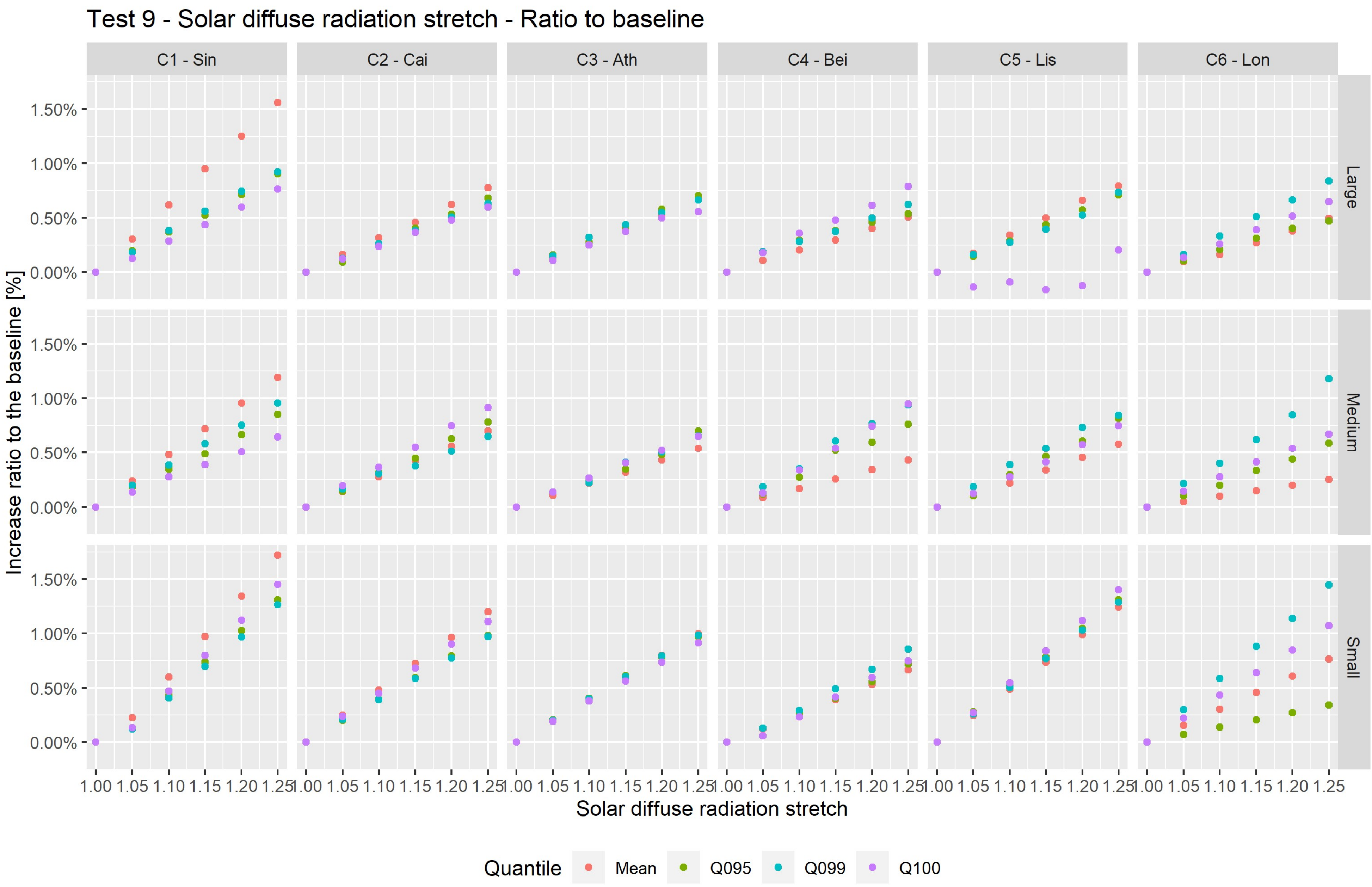

Figure 0.11 – Percentile analysis of annual hourly demand through test 9 iterations,diffuse solar

Table 0.7 – Statistical summary of change [%] under the pathway relative to baseline for peak total electricity demand

STAT.	MODEL	C1 – Sin	C2 – Cai	C3 - Ath	C4 - Bei	C5 – Lis	C6 - Lon
MAX.	Large	34.8	26.9	37.6	25.6	37.9	34.8
	Medium	43.5	38.6	39.5	36.5	62.3	54.2
	Small	32.9	39.2	40.0	31.7	43.0	45.2
MEDIAN	Large	9.7	8.7	12.0	10.3	22.5	14.6
	Medium	15.7	18.0	16.5	20.8	28.9	21.1
	Small	15.3	18.5	17.9	15.2	22.1	20.2
MEAN	Large	11.3	9.3	15.6	10.5	22.2	15.8
	Medium	17.4	18.5	17.4	20.0	29.7	22.5
	Small	15.6	19.3	18.1	15.3	22.7	20.8
MIN.	Large	-1.2	-0.4	0.0	0.0	0.0	0.0
	Medium	0.0	0.0	0.0	0.0	0.0	0.0
	Small	0.0	0.0	0.0	0.0	0.0	0.0
IQR	Large	10.7	6.9	18.0	9.0	8.6	12.7
	Medium	14.5	13.3	12.5	12.8	22.9	15.0
	Small	11.9	12.6	12.4	10.9	12.9	13.3
STD DEV.	Large	7.9	5.3	10.2	5.9	6.7	8.2
	Medium	10.2	8.1	8.4	8.5	14.3	10.7
	Small	7.7	8.2	8.5	7.0	9.0	9.0

Table 0.8 – Statistical summary of change [%] under the pathway relative to baseline for annual total electricity demand

STAT.	MODEL	C1 – Sin	C2 – Cai	C3 - Ath	C4 - Bei	C5 – Lis	C6 - Lon
MAX.	Large	37.7	24.9	21.7	23.9	21.4	15.4
	Medium	25.9	22.1	20.1	18.0	20.1	13.1
	Small	30.6	26.4	23.1	19.9	19.7	13.4
MEDIAN	Large	15.8	10.1	8.9	8.7	8.7	5.9
	Medium	11.3	9.4	8.3	6.9	8.6	5.0
	Small	13.9	11.9	10.1	8.3	9.6	6.0
MEAN	Large	16.8	10.4	9.2	9.2	8.9	6.2
	Medium	11.8	9.7	8.6	7.2	9.0	5.3
	Small	14.4	12.2	10.4	8.6	9.8	6.1
MIN.	Large	0.0	0.0	0.0	-0.1	0.0	0.0
	Medium	0.0	0.0	0.0	0.0	0.0	0.0
	Small	0.0	0.0	0.0	0.0	0.0	0.0
IQR	Large	14.7	8.9	7.7	8.7	7.6	5.4
	Medium	10.3	8.1	7.3	6.5	8.0	5.3
	Small	11.9	9.3	8.1	6.7	7.3	4.6
STD DEV.	Large	10.2	6.1	5.2	5.7	5.1	3.6
	Medium	7.0	5.6	5.1	4.4	5.4	3.4
	Small	8.0	6.3	5.4	4.7	4.8	3.1

Table 0.9 – Summary of the effects on peak electricity for HVAC end-use throughout the pathway [%]

STAT.	MODEL	C1 – Sin	C2 – Cai	C3 - Ath	C4 - Bei	C5 – Lis	C6 - Lon
MAX.	Large	85.9	79.1	111.0	56.4	108.0	124.9
	Medium	97.1	80.0	101.7	74.3	145.4	158.4
	Small	115.2	74.6	86.3	62.2	92.5	119.4
MEDIAN	Large	24.2	23.7	37.2	22.6	64.0	52.9
	Medium	35.0	37.5	40.0	42.4	67.7	61.7
	Small	68.7	35.1	38.7	29.8	47.7	53.4
MEAN	Large	28.3	25.7	46.8	23.2	63.2	57.1
	Medium	38.9	38.8	42.2	40.7	70.3	65.7
	Small	68.7	36.8	39.1	30.0	48.8	54.9
MIN.	Large	-2.9	-1.2	0.0	0.0	0.0	0.0
	Medium	0.0	0.0	0.0	0.0	0.0	0.0
	Small	0.0	0.0	0.0	0.0	0.0	0.0
IQR	Large	26.5	19.1	54.7	19.9	24.4	44.8
	Medium	32.4	28.5	30.3	26.1	50.8	43.8
	Small	31.6	23.9	26.8	21.4	27.8	35.0
STD DEV.	Large	19.7	15.0	30.4	12.9	18.8	29.4
	Medium	22.9	17.1	20.6	17.3	33.0	31.4
	Small	22.1	15.7	18.2	13.8	19.3	23.8

Table 0.10 – Summary of the effects on annual electricity for HVAC end-use throughout the pathway [%]

Stat.	Model	C1 – Sin	C2 – Cai	C3 - Ath	C4 - Bei	C5 – Lis	C6 - Lon
MAX.	Large	87.7	87.2	91.7	108.9	101.9	115.6
	Medium	64.4	82.4	103.2	102.1	120.1	182.3
	Small	73.6	77.8	83.6	77.7	79.3	75.4
MEDIAN	Large	36.7	35.4	37.7	39.6	41.2	44.8
	Medium	28.1	35.0	42.6	38.8	51.8	70.1
	Small	33.5	35.0	36.5	32.5	38.8	33.9
MEAN	Large	39.0	36.5	38.7	41.7	42.3	46.9
	Medium	29.3	36.2	44.2	40.8	53.7	74.1
	Small	34.5	35.8	37.5	33.6	39.7	34.5
MIN.	Large	0.0	0.0	0.0	-0.3	0.0	0.0
	Medium	0.0	0.0	0.0	0.0	0.0	0.0
	Small	0.0	0.0	0.0	0.0	0.0	0.0
IQR	Large	34.3	31.0	32.4	39.6	35.9	40.5
	Medium	25.7	30.1	37.6	36.7	48.0	73.0
	Small	28.6	27.4	29.4	26.2	29.5	25.6
STD DEV.	Large	23.7	21.4	22.1	26.1	24.2	27.2
	Medium	17.5	20.9	26.2	24.7	32.1	46.9
	Small	19.3	18.5	19.6	18.4	19.5	17.4

Table 0.11 – The effect on the extremity of the pathway relative to baseline for peak total demand [%]

Model	Scenario	C1 – Sin	C2 – Cai	C3 - Ath	C4 - Bei	C5 – Lis	C6 - Lon
Large	No adaptation	34.8	26.9	37.6	25.6	37.9	34.8
	M1 – Cool. Set Point	20.1	15.1	24.4	14.7	25.1	22.0
	M2 – Ventilation Rate	17.3	15.1	27.1	16.8	31.2	31.2
	M3 – Equipment	23.6	17.6	25.6	15.3	25.9	21.6
	M4 - Lighting	23.5	16.2	25.2	15.0	25.5	21.2
	M5 – COP	27.0	20.7	30.9	18.0	30.6	29.1
	M6 – Solar HGC	33.9	29.9	31.4	22.2	33.3	30.4
	M7 – 3+4+5	5.6	2.0	6.5	-1.6	6.8	2.9
	M8 – 1+2+5+6	4.8	1.3	10.0	-1.8	9.8	9.7
	M9 – 1+2+3+4+5+6	-18.9	-20.0	-13.3	-21.5	-13.5	-15.4
Medium	No adaptation	43.5	38.6	39.5	36.5	62.3	54.2
	M1 – Cool. Set Point	13.6	20.8	22.9	8.9	28.1	31.7
	M2 – Ventilation Rate	27.0	28.8	28.5	32.6	52.4	41.1
	M3 – Equipment	33.0	28.7	30.1	26.5	50.9	41.6
	M4 - Lighting	29.9	27.8	29.4	25.6	47.9	40.2
	M5 – COP	31.0	26.2	27.6	23.8	47.1	41.6
	M6 – Solar HGC	36.0	34.7	40.4	32.1	49.6	51.3
	M7 – 3+4+5	8.3	6.2	9.3	4.0	22.8	16.2
	M8 – 1+2+5+6	-0.8	1.9	4.7	-5.2	7.4	13.6
	M9 – 1+2+3+4+5+6	-21.5	-17.3	-14.9	-25.1	-14.8	-11.2
Small	No adaptation	32.9	39.2	40.0	31.7	43.0	45.2
	M1 – Cool. Set Point	1.0	8.1	6.8	-1.5	9.4	14.8
	M2 – Ventilation Rate	27.2	31.2	30.9	26.9	37.4	37.5
	M3 – Equipment	20.3	27.7	27.6	19.3	29.6	31.3
	M4 - Lighting	19.6	27.0	26.9	18.5	28.8	30.5
	M5 – COP	21.0	25.8	27.6	19.6	30.0	33.4
	M6 – Solar HGC	26.2	33.2	34.7	26.1	38.3	37.0
	M7 – 3+4+5	-2.4	3.4	3.1	-4.4	4.0	5.8
	M8 – 1+2+5+6	-9.1	-7.6	-7.1	-14.9	-7.1	-2.7
	M9 – 1+2+3+4+5+6	-30.3	-29.3	-30.5	-36.3	-31.8	-29.3

Table 0.12 – The effect on the extremity of the pathway relative to baseline for annul total demand [%]

Model	Scenario	C1 – Sin	C2 – Cai	C3 - Ath	C4 - Bei	C5 – Lis	C6 - Lon
Large	No adaptation	37.7	24.9	21.7	23.9	21.4	15.4
	M1 – Cool. Set Point	34.4	18.8	15.6	18.2	16.3	8.9
	M2 – Ventilation Rate	26.3	20.3	18.4	19.3	17.6	14.6
	M3 – Equipment	28.3	14.3	10.7	12.8	10.1	3.2
	M4 - Lighting	27.3	13.3	9.6	11.7	8.9	2.0
	M5 – COP	27.9	19.2	17.2	19.4	17.2	13.1
	M6 – Solar HGC	34.4	21.7	18.4	21.6	18.3	12.4
	M7 – 3+4+5	9.2	-2.6	-5.6	-3.3	-6.2	-11.9
	M8 – 1+2+5+6	10.9	7.3	6.1	8.1	7.1	4.8
	M9 – 1+2+3+4+5+6	-8.1	-14.6	-16.4	-14.8	-16.2	-19.9
Medium	No adaptation	25.9	22.1	20.1	18.0	20.1	13.1
	M1 – Cool. Set Point	16.6	11.7	11.2	10.8	11.0	7.1
	M2 – Ventilation Rate	16.6	18.3	17.3	14.4	17.4	12.2
	M3 – Equipment	17.3	12.2	9.7	7.6	9.2	1.8
	M4 - Lighting	15.9	10.4	8.0	6.1	7.4	0.3
	M5 – COP	20.2	20.1	18.5	15.7	18.7	12.7
	M6 – Solar HGC	24.0	19.0	17.4	16.4	16.9	11.3
	M7 – 3+4+5	1.7	-1.5	-4.0	-6.6	-4.5	-11.3
	M8 – 1+2+5+6	2.0	4.3	5.3	4.6	5.2	4.6
	M9 – 1+2+3+4+5+6	-16.4	-16.6	-16.6	-17.3	-17.4	-19.0
Small	No adaptation	30.6	26.4	23.1	19.9	19.7	13.4
	M1 – Cool. Set Point	5.6	2.9	2.4	0.8	-0.8	-2.7
	M2 – Ventilation Rate	24.0	23.1	20.9	17.7	18.5	13.2
	M3 – Equipment	20.6	15.8	12.0	8.8	8.2	1.8
	M4 - Lighting	19.2	14.4	10.5	7.5	6.8	0.4
	M5 – COP	21.4	19.8	18.0	15.4	15.4	11.3
	M6 – Solar HGC	24.5	20.4	17.5	15.7	14.4	8.3
	M7 – 3+4+5	0.7	-2.1	-5.0	-7.6	-8.2	-12.8
	M8 – 1+2+5+6	-8.0	-6.6	-5.2	-5.5	-7.6	-6.9
	M9 – 1+2+3+4+5+6	-28.1	-27.2	-26.6	-26.9	-29.5	-29.3

Table 0.13 – The effect on the extremity of the pathway relative to baseline for peak HVAC demand

Model	Scenario	C1 – Sin	C2 – Cai	C3 - Ath	C4 - Bei	C5 – Lis	C6 - Lon
Large	No adaptation	85.9	79.1	111.0	56.4	108.0	124.9
	M1 – Cool. Set Point	49.5	45.5	72.0	32.4	71.4	78.9
	M2 – Ventilation Rate	47.4	41.2	80.0	37.0	88.8	112.0
	M3 – Equipment	78.0	77.1	101.7	50.1	98.5	112.4
	M4 - Lighting	77.8	73.4	100.7	49.4	97.6	111.1
	M5 – COP	66.6	62.2	91.1	39.8	87.2	104.4
	M6 – Solar HGC	83.6	81.6	92.7	48.9	94.9	109.0
	M7 – 3+4+5	53.3	57.8	71.8	29.1	69.0	80.5
	M8 – 1+2+5+6	11.9	3.5	29.5	-4.0	27.8	34.8
	M9 – 1+2+3+4+5+6	-6.9	-8.0	13.4	-15.0	11.4	14.5
Medium	No adaptation	97.1	80.0	101.7	74.3	145.4	158.4
	M1 – Cool. Set Point	30.4	43.1	55.5	18.1	65.5	92.6
	M2 – Ventilation Rate	60.4	59.8	69.2	66.5	122.3	120.3
	M3 – Equipment	89.4	73.3	91.3	67.1	135.8	146.1
	M4 - Lighting	82.6	71.5	89.6	65.3	128.8	142.2
	M5 – COP	69.1	54.3	67.0	48.4	109.9	121.6
	M6 – Solar HGC	80.4	72.0	98.1	65.3	115.8	150.1
	M7 – 3+4+5	50.0	40.3	58.9	34.7	87.4	96.4
	M8 – 1+2+5+6	-1.9	4.0	11.4	-10.6	17.3	39.8
	M9 – 1+2+3+4+5+6	-16.6	-8.4	0.3	-24.6	-0.5	16.5
Small	No adaptation	115.2	74.6	86.3	62.2	92.5	119.4
	M1 – Cool. Set Point	20.3	15.4	14.6	-2.9	20.2	39.0
	M2 – Ventilation Rate	100.2	59.4	66.7	52.8	80.4	99.0
	M3 – Equipment	102.6	66.3	77.1	52.5	81.1	107.3
	M4 - Lighting	100.7	65.0	75.6	51.0	79.4	105.3
	M5 – COP	83.9	49.1	59.5	38.4	64.5	88.2
	M6 – Solar HGC	93.6	63.2	74.9	51.3	82.4	97.5
	M7 – 3+4+5	58.0	33.7	41.9	20.5	43.5	65.0
	M8 – 1+2+5+6	-24.0	-14.5	-15.3	-29.2	-15.3	-7.0
	M9 – 1+2+3+4+5+6	-38.8	-28.5	-30.8	-42.1	-33.5	-27.6

Table 0.14 – The effect on the extremity of the pathway relative to baseline for annual HVAC demand

Model	Scenario	C1 – Sin	C2 – Cai	C3 - Ath	C4 - Bei	C5 – Lis	C6 - Lon
Large	No adaptation	87.7	87.2	91.7	108.9	101.9	115.6
	M1 – Cool. Set Point	80.1	65.6	65.9	82.8	77.7	67.1
	M2 – Ventilation Rate	61.2	70.9	77.6	87.9	83.7	109.6
	M3 – Equipment	81.4	79.1	83.0	100.0	91.8	100.6
	M4 - Lighting	80.5	78.3	81.8	98.9	90.6	98.8
	M5 – COP	64.9	67.3	72.5	88.4	82.0	98.4
	M6 – Solar HGC	80.0	76.1	77.9	98.3	87.0	93.0
	M7 – 3+4+5	54.0	52.1	55.1	72.0	62.6	69.9
	M8 – 1+2+5+6	25.3	25.6	25.9	36.9	33.8	36.4
	M9 – 1+2+3+4+5+6	13.7	10.1	9.7	19.7	14.8	10.0
Medium	No adaptation	64.4	82.4	103.2	102.1	120.1	182.3
	M1 – Cool. Set Point	41.2	43.7	57.4	61.1	65.8	98.2
	M2 – Ventilation Rate	41.3	68.2	88.6	81.5	104.5	169.8
	M3 – Equipment	59.2	75.0	94.6	93.9	109.6	166.1
	M4 - Lighting	57.3	71.2	90.2	90.0	104.2	157.6
	M5 – COP	50.3	74.8	94.8	89.1	112.2	176.9
	M6 – Solar HGC	59.8	70.7	89.1	92.6	101.2	156.9
	M7 – 3+4+5	38.3	56.7	73.9	69.4	87.0	137.8
	M8 – 1+2+5+6	5.0	16.2	27.2	26.2	31.3	64.5
	M9 – 1+2+3+4+5+6	-6.8	0.5	9.2	8.8	9.9	31.3
Small	No adaptation	73.6	77.8	83.6	77.7	79.3	75.4
	M1 – Cool. Set Point	13.5	8.6	8.9	3.3	-3.4	-15.0
	M2 – Ventilation Rate	57.7	67.9	75.7	69.0	74.5	74.1
	M3 – Equipment	65.2	68.2	72.7	66.8	67.0	61.8
	M4 - Lighting	63.4	66.3	70.4	64.8	64.5	59.2
	M5 – COP	51.3	58.3	65.2	60.2	62.0	63.7
	M6 – Solar HGC	58.8	60.1	63.6	61.3	58.0	46.8
	M7 – 3+4+5	34.7	39.4	43.7	38.8	38.1	36.9
	M8 – 1+2+5+6	-19.1	-19.5	-18.9	-21.4	-30.5	-38.6
	M9 – 1+2+3+4+5+6	-34.6	-34.4	-34.8	-36.8	-47.5	-56.1

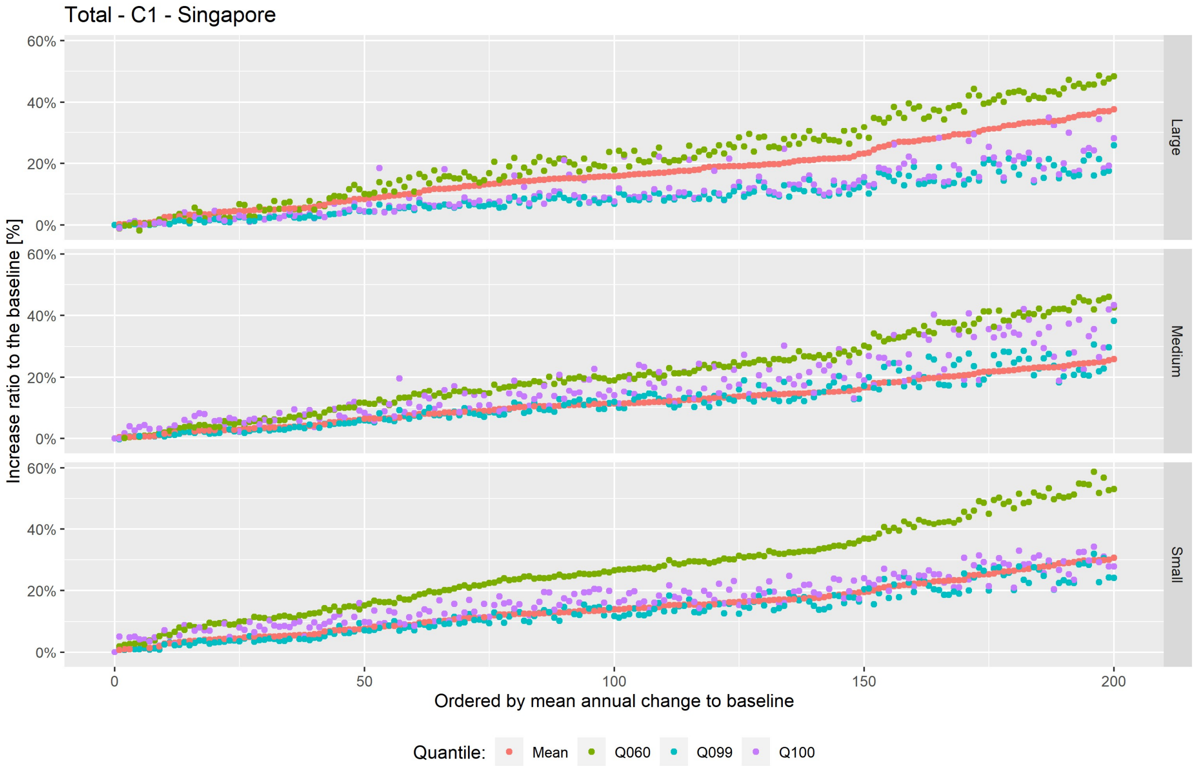

Figure 0.12 – Percentile analysis of the hourly total electricity load for C1 Singapore

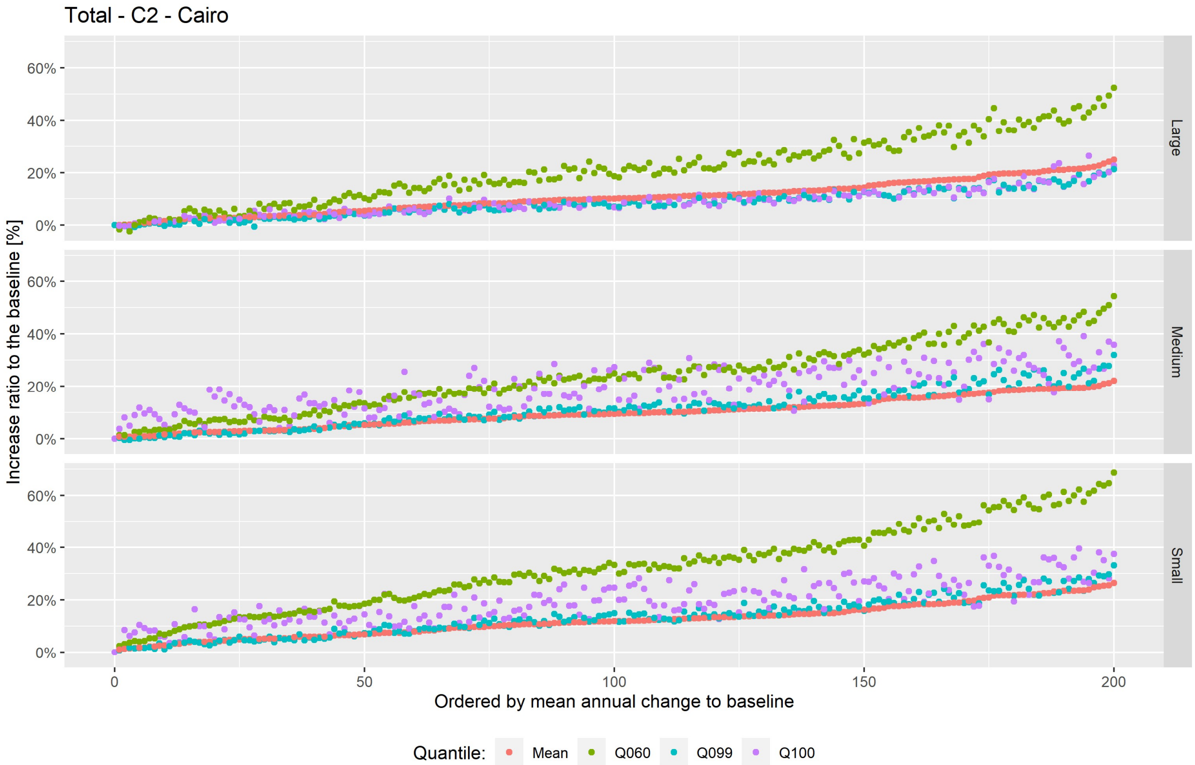

Figure 0-13 – Percentile analysis of the hourly total electricity load for C2 - Cairo

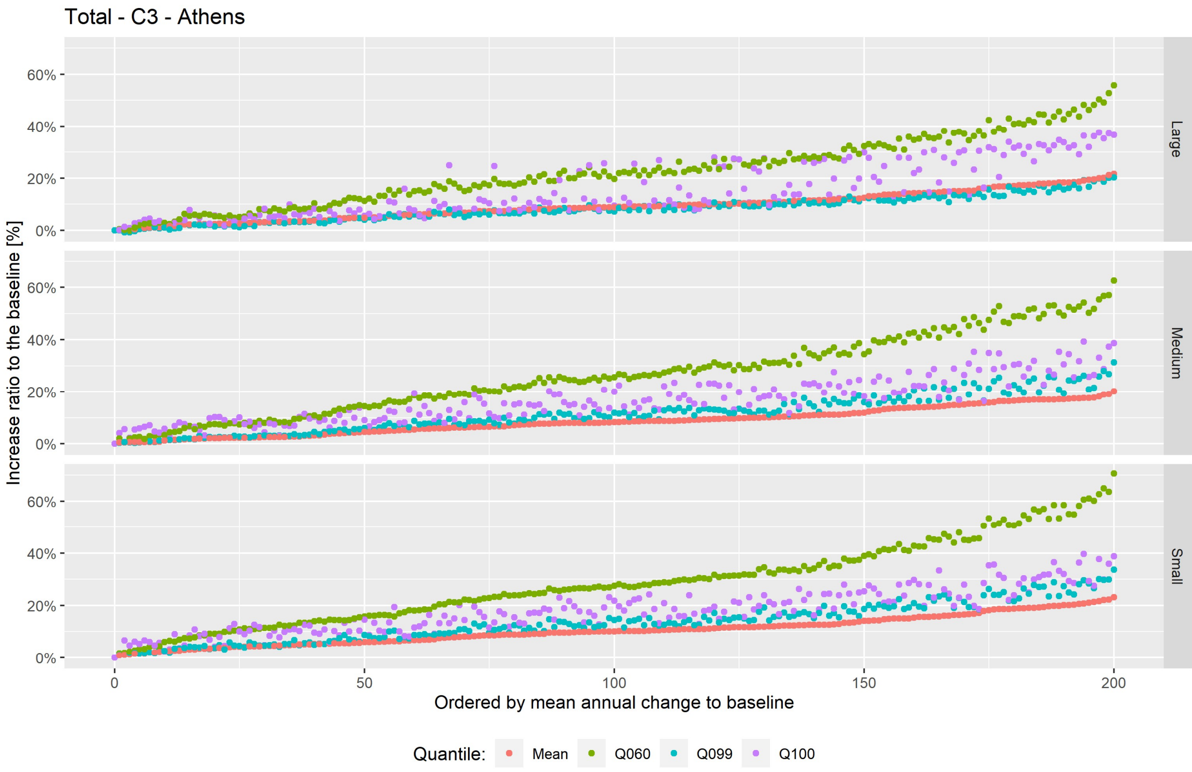

Figure 0-14 – Percentile analysis of the hourly total electricity load for C3 - Athens

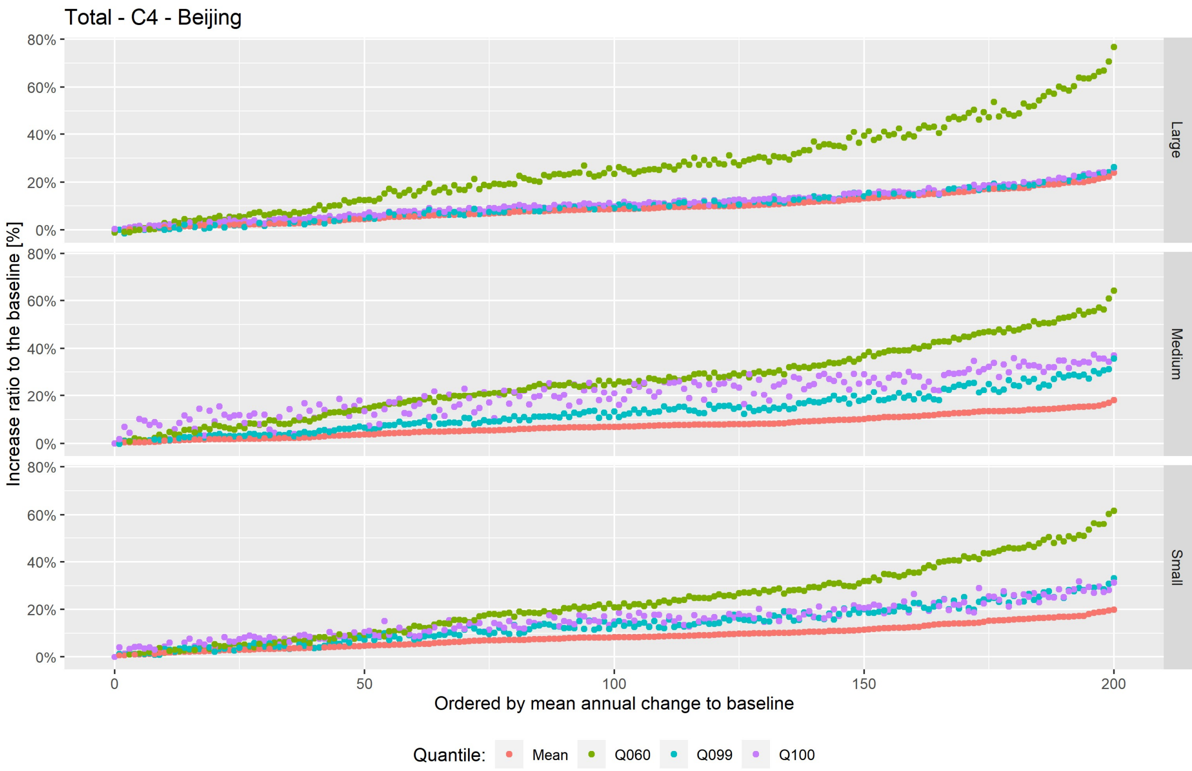

Figure 0-15 – Percentile analysis of the hourly total electricity load for C4 - Beijing

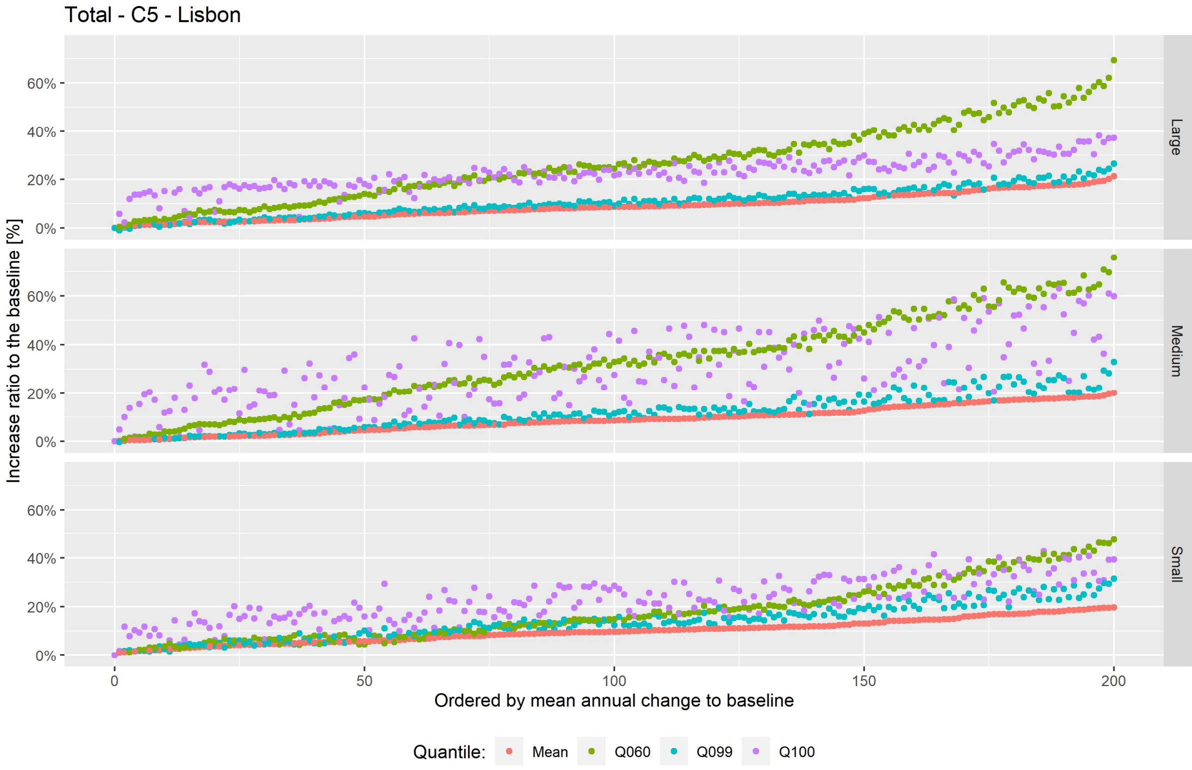

Figure 0-16 – Percentile analysis of the hourly total electricity load for C5 - Lisbon

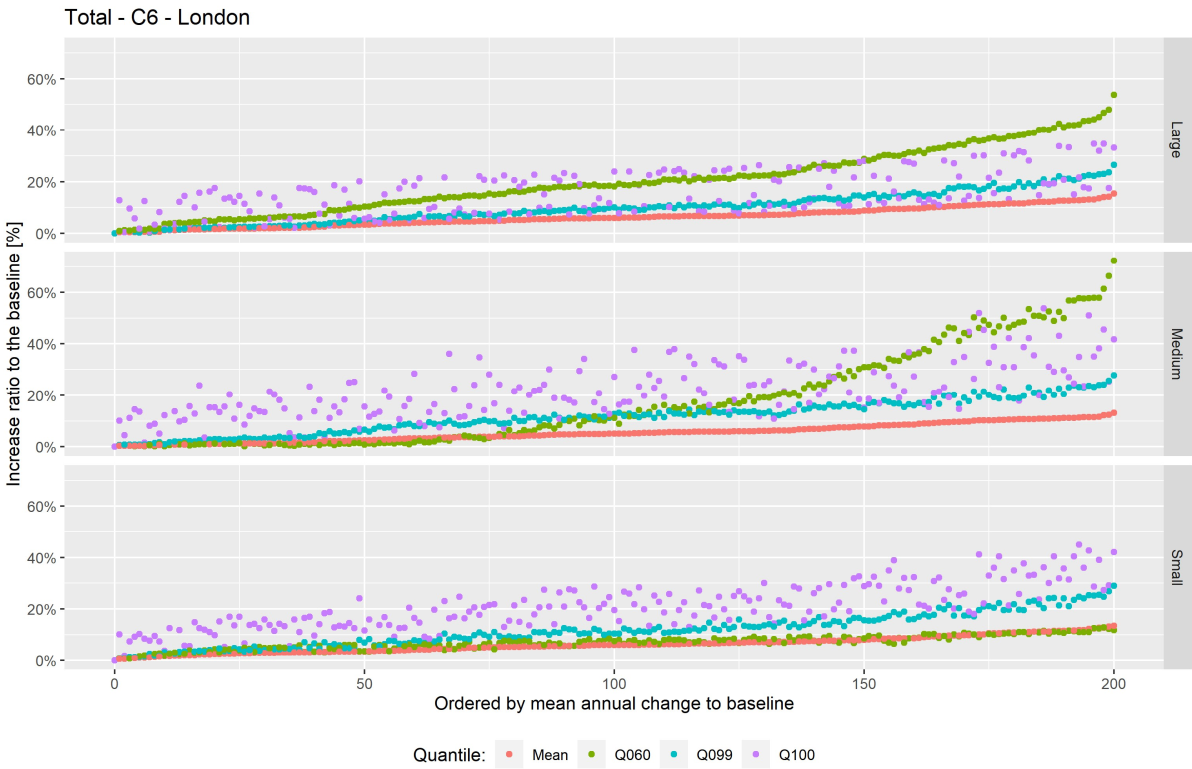

Figure 0-17 – Percentile analysis of the hourly total electricity load for C6 - London

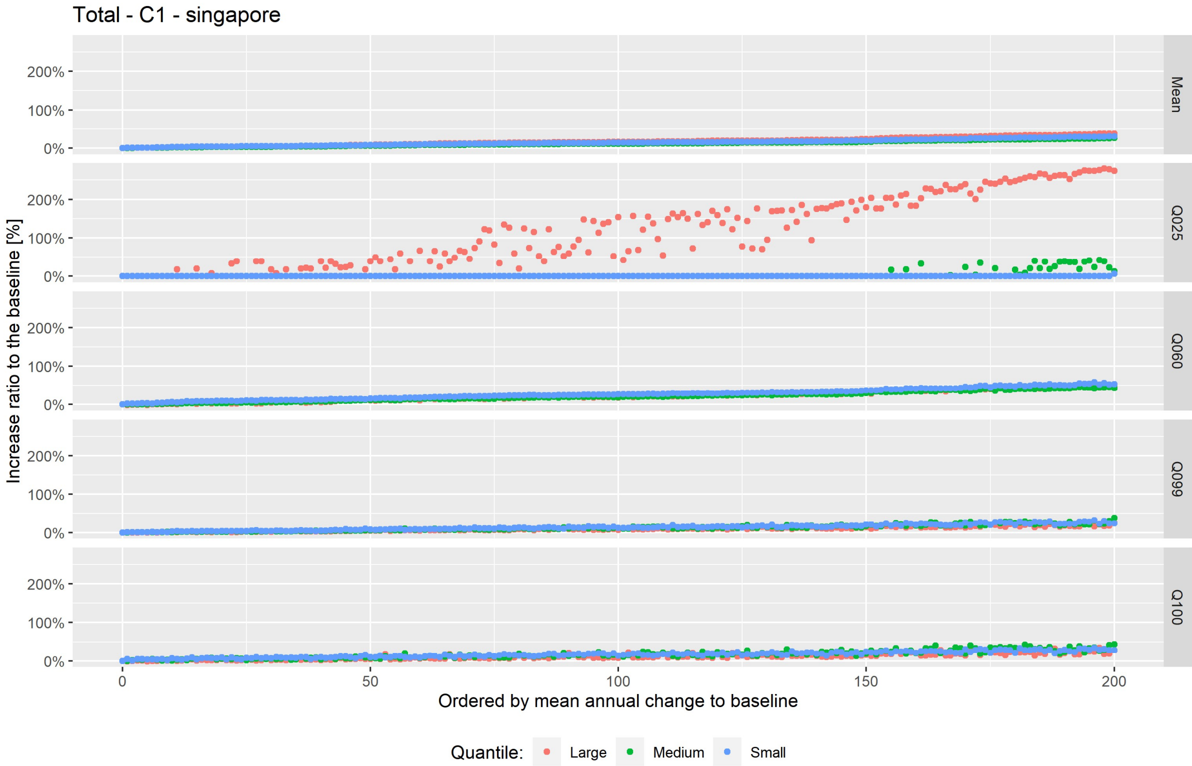

Figure 0-18 –Percentile analysis of the hourly total electricity load for C1 Singapore, for the three type of buildings

Appendix D – Repository

Mendeley Dataset

Cite the dataset:

Zeferina, Vasco (2022), “The impacts of climate change on the electricity demand of archetypal office buildings”, Mendeley Data, V1, doi: 10.17632/pw3rrtnctc.1

http://dx.doi.org/10.17632/pw3rrtnctc.1

Github:

https://github.com/vascozeferina/The-Impacts-of-climate-change-on-the-electricity-demand-of-archetypal-office-buildings