

Northumbria Research Link

Citation: Du, Hu (2012) Modelling of building performance under the UK climate change projections and the prediction of future heating and cooling design loads in building spaces. Doctoral thesis, Northumbria University.

This version was downloaded from Northumbria Research Link:
<http://nrl.northumbria.ac.uk/5837/>

Northumbria University has developed Northumbria Research Link (NRL) to enable users to access the University's research output. Copyright © and moral rights for items on NRL are retained by the individual author(s) and/or other copyright owners. Single copies of full items can be reproduced, displayed or performed, and given to third parties in any format or medium for personal research or study, educational, or not-for-profit purposes without prior permission or charge, provided the authors, title and full bibliographic details are given, as well as a hyperlink and/or URL to the original metadata page. The content must not be changed in any way. Full items must not be sold commercially in any format or medium without formal permission of the copyright holder. The full policy is available online: <http://nrl.northumbria.ac.uk/policies.html>

www.northumbria.ac.uk/nrl



**MODELLING OF BUILDING
PERFORMANCE UNDER THE UK
CLIMATE CHANGE PROJECTIONS
AND THE PREDICTION OF FUTURE
HEATING AND COOLING DESIGN
LOADS IN BUILDING SPACES**

HU DU

PhD

2011

**MODELLING OF BUILDING
PERFORMANCE UNDER THE UK
CLIMATE CHANGE PROJECTIONS
AND THE PREDICTION OF FUTURE
HEATING AND COOLING DESIGN
LOADS IN BUILDING SPACES**

HU DU

A thesis submitted in partial fulfilment
of the requirements of the
University of Northumbria at Newcastle
for the degree of
Doctor of Philosophy

Research undertaken in the School of
Built and Natural Environment

November 2011

ABSTRACT

New climate change projections for the UK were published by the United Kingdom Climate Impacts Programme in 2009. They form the 5th and most comprehensive set of predictions of climate change developed for the UK to date. As one of main products of UK Climate Projections 2009 (UKCP09), the Weather Generator, can generate a set of daily and hourly future weather variables at different time periods (2020s to 2080s) and carbon emission scenarios (low, medium and high) on a 5 km grid scale. In a radical departure from previous methods, the 2009 Projections are statistical-probabilistic in nature.

A tool has been developed in Matlab to generate future Test Reference Year (TRY) and Design Reference Years (DRY) weather files from these Projections and the results were verified against results from alternative tools produced by Manchester University and Exeter University as well as with CIBSE's Future Weather Years (FWYs) which are based on earlier (4th generation) climate change scenarios and are currently used by practitioners. The Northumbria tool is computationally efficient and can extract a single Test Reference Year and 2 Design Reference Years from 3000 years of raw data in less than 6 minutes on a typical modern PC. It uses an established ISO method for generating Test Reference Year data and an alternative method of constructing future Design Reference Years data is proposed.

Fifteen different buildings have been identified according to alternative usage, thermal insulation, user activity and construction details. Besides these variants, the buildings were chosen specifically because they either exist, or have received planning consent and so represent 'real' UK building examples. Two investigations were then carried out based on the 15 case study buildings.

The first involved applying TRYs generated for London, Manchester and Edinburgh for a variety of carbon emission scenarios at time horizons of 2030, 2050 and 2080. The TRYs were developed into a weather data format readable by the EnergyPlus energy simulation program to simulate summertime internal comfort (operative) temperatures, cooling demands and winter heating demands. All results were compared with a control data set of nominally current weather data, together with the same results produced using the alternative weather data generators of Manchester University, Exeter University and the CIBSE FWYs. Results revealed a good agreement between the various methods and show that significant increases in internal summer operative temperatures in non-air-conditioned buildings can be expected as time advances through this century, as well as increased air conditioning cooling energy demands and small reductions in winter heating energy demand.

The second investigation involved generating time series of design internal peak summertime operative temperatures, design cooling demands and design winter heating demands for the same conditions as the first investigation. The results were then used to develop a simplified estimation method to predict

future design cooling loads using multiple regressions fitting to selected data from the DRY simulation inputs and outputs. The simplified estimation method forms a useful tool for estimating how future cooling design loads in buildings are likely to evolve over time. It also provides a basis for designers and practitioners to determine how buildings constructed today will need to be adapted through life to cope with climate change.

TABLE OF CONTENTS

ABSTRACT.....	1
TABLE OF CONTENTS.....	4
LIST OF FIGURES.....	6
LIST OF TABLES.....	8
ACKNOWLEDGEMENTS.....	9
AUTHOR'S DECLARATION.....	10
1 Introduction.....	11
1.1 Research background.....	12
1.2 Aims and objectives.....	17
1.3 Organisation of this thesis.....	18
1.4 Contributions of this thesis.....	20
2 Literature review.....	22
2.1 Weather data format.....	22
2.2 Climate data and its use in building performance prediction.....	29
2.3 Thermal comfort.....	36
2.4 Insulation standards.....	41
2.5 Building heat transfer and cooling load calculation method.....	45
2.6 Summary.....	56
3 Selection of case study buildings and preliminary simulation studies.....	57
3.1 Exemplar buildings.....	57
3.2 Modelling assumptions.....	63
3.3 Simulation results and analysis.....	65
3.4 Summary.....	70
4 Method 1: Development of Test Reference Years.....	71
4.1 Method of generating Northumbria Test Reference Years.....	71
4.2 Verification.....	81
5 Application of TRYs to building simulation.....	91
5.1 Building modelling.....	91
5.2 Results of freefloat simulation.....	95
5.3 Results of cooling and heating simulation.....	104
5.4 Conclusions.....	111
6 Method 2: Development of Northumbria Design Reference Years.....	113
6.1 Available DRYs/DSYs.....	113
6.2 Development of Northumbria Design Reference Years.....	116
6.3 Inter-method comparison.....	121
6.4 Conclusion.....	125
7 Application of DRYs to building design (load sizing).....	129
7.1 Results using four sets of DSYs/DRYs.....	130
7.2 Results using Northumbria DRY only.....	136
7.3 Conclusion.....	142
8 Method 3: Development of a simplified method for predicting future air conditioning loads.....	145
8.1 Development of the method of predicting design loads.....	145
8.2 Procedures of the method.....	157
9 Conclusion and future research.....	161

9.1	Conclusions	161
9.2	Future research	164
	REFERENCES	167
	APPENDICES.....	180
	Appendix A1: TRY results: cooling energy demand	181
	Appendix A2: TRY results: heating energy demand.....	189
	Appendix A3: TRY results: Summer average temperature during occupied hours	197
	Appendix A4: TRY results: Winter average temperature during occupied hours	205
	Appendix A5: TRY results: Overheat percentage of occupied hours.....	213
	Appendix B1: DRY results: Overheat percentage of occupied hours	221
	Appendix B2: DRY results: Building and zones cooling design loads	229
	Appendix B3: DRY results: Building and zones heating design loads	237
	Appendix C: Published outputs	245
	Appendix D: Matlab scripts.....	301

LIST OF FIGURES

Figure 1-1 10%, 50% and 90% probability levels of changes to the average daily mean temperature (°C) during summer by the 2080s, under the medium emissions scenario (Jenkins <i>et al.</i> , 2009)	16
Figure 2-1 Example of TMY3 data (US Department of Energy, 2011b)	24
Figure 2-2 Example of IWECC EPW file (US Department of Energy, 2011b)	26
Figure 2-3 Example of CIBSE TRY file (CIBSE, 2008)	27
Figure 2-4 Example of CIBSE DSY file (CIBSE, 2008)	29
Figure 3-1 Exemplar buildings	60
Figure 3-2 Internal overall peak operative temperature against external peak temperature change	66
Figure 3-3 Predicted operative temperature – internal averaged zone peaks against external peak temperature change	66
Figure 3-4 Comparison of predicted average dry bulb (bottom) and operative temperatures (top) against external average temperature change	67
Figure 4-1 Comparison of data sets: dry bulb temperature	86
Figure 4-2 Comparison of data sets: solar radiation	86
Figure 4-3 Deviations from Northumbria data in external air temperature	88
Figure 4-4 Deviations from Northumbria data in solar radiation	89
Figure 5-1 Overheat percentage of occupied hours (reference: 28 °C)	97
Figure 5-2 Averages of overheat percentages of occupied hours over 28 °C	99
Figure 5-3 Max and min of overheat percentages	100
Figure 5-4 Averages of summer average operative temperature during occupied hours	101
Figure 5-5 Averages of winter average operative temperature during occupied hours	102
Figure 5-6 Simulated peak of the total zone cooling loads per unit of treated floor area	107
Figure 5-7 Simulated annual building sensible cooling energy demand	108
Figure 5-8 Simulated peak of the total zone heating loads per unit of treated floor area	109
Figure 5-9 Simulated annual building heating energy demand	110
Figure 6-1 Comparison of alternative DSY/DRYs annual temperatures	126
Figure 6-2 Comparison of alternative DSY/DRYs summer temperatures	127
Figure 6-3 Comparison of alternative DSY/DRYs daily global horizontal solar radiation values	128
Figure 7-1 Overheat percentage of aged persons' accommodation	132
Figure 7-2 Overheat percentage of an office building	133
Figure 7-3 Peak cooling loads of aged persons' accommodation	134
Figure 7-4 Peak cooling loads of an office building	135
Figure 7-5 Sample of heating design load results	138
Figure 7-6 Changing trend of building heating design loads	138
Figure 7-7 Sample of summer percentage overheating results	139
Figure 7-8 Changing trend of average overheat percentage	140
Figure 7-9 Sample of cooling design load results	141
Figure 7-10 Changing trend of building cooling design loads	142

Figure 8-1 Outdoor temperature and the time peak cooling loads occur	147
Figure 8-2 Global horizontal solar radiation and the time peak cooling loads occur	148
Figure 8-3 Example estimated vs. simulated cooling loads (control and future DRY data)	156
Figure 8-4 Example estimated vs. simulated design cooling loads (all DRY data)	157
Figure 8-5 Example distribution of 3000 design cooling loads (control data) ..	159
Figure 8-6 Example distribution based on 3000 control and future design cooling loads	160

LIST OF TABLES

Table 2-1 Comparison of standard maximum permitted U-values of construction elements specified in UK Building Regulations from 1965 to 2002 and glazing type and percentage of facade glazed used in analyses (Chow & Levermore, 2010)	41
Table 2-2 U-values ($Wm^{-2}K^{-1}$) mentioned in Building Regulation 2006 and 2010	42
Table 2-3 U-values for notional building in NCM guide 2010 (DCLG, 2010b)...	44
Table 3-1 Building details.....	61
Table 4-1 Available time slices of the UKCP09 projections	72
Table 4-2 Matlab scripts and input files list	80
Table 4-3 Timelines and carbon emission scenarios of TRYs	81
Table 4-4 Key to symbols on figures in this chapter.....	87
Table 6-1 Time periods of UKCP09	117
Table 6-2 Matlab scripts list for DRY.....	121
Table 6-3 Timelines and carbon emission scenarios of DSYs/DRYs.....	123
Table 8-1 Regression using four independent variables	149
Table 8-2 Independent variables repeat times count results.....	152
Table 8-3 Results of fitted constants (Equation 8-1)	154

ACKNOWLEDGEMENTS

I must express the most grateful thanks to Prof. Chris Underwood and Dr. Jerry Edge of the School of the Built and Natural Environment, University of Northumbria at Newcastle, for their valuable suggestions, critical comments, kindly guidance and encouragement given during the course of this work. I am also grateful for their patience that drove me to complete this thesis.

I would like to thank the UK Engineering and Physical Sciences Research Council and University of Northumbria at Newcastle for the resources given.

I would like also to thank Dr Richard Watkins of University of Manchester for his help on validation of my Matlab scripts.

Finally, I would like to thank my parents Mr. Du XianYou and Mdm. Wang CongNian for supporting me throughout all my studies.

AUTHOR'S DECLARATION

I declare that the work contained in this thesis has not been submitted for any award and that it is all my own work.

Any ethical clearance for the research presented in this thesis has been approved. Approval has been sought and granted by the School Ethics Committee / University Ethics Committee / external.

Name:

Hu Du

Signature:

The image shows a handwritten signature in black ink. The characters are '杜 瓊' (Du Qiong), which corresponds to the name 'Hu Du' mentioned in the text above. The signature is written in a cursive, calligraphic style.

Date:

2nd November 2011

CHAPTER 1

1 Introduction

This chapter presents a brief background of this study, and outlines the research aims and objectives together with the structure of the thesis and the context within which the research was undertaken.

This project was funded by EPSRC (Engineering and Physical Sciences Research Council, grant reference EP/F038135/1) and is a part of a consortium project named COPSE (Coincident Probabilistic climate change weather data for a Sustainable built Environment), which was conducted by Manchester, Sheffield, Northumbria, Bath and Edinburgh Napier universities. The COPSE project (COPSE, 2011) is aimed at developing a methodology for providing the weather data that the building community needs for making decisions about new and existing buildings. The project is based on new weather data projections originating from the United Kingdom Climate Impacts Programme's 2009 Projections (UKCP09).

As the lead university responsible for COPSE, Manchester University developed new Test Reference Year (TRY) and Design Reference Year (DRY) control and future weather data from UKCP09 raw data and work on urban heat island effect. Sheffield University researched the future wind and rainfall data for design, and predicted the energy consumption of natural ventilation in the future. Bath University explored the adaptive comfort and built environment story lines and impacts arising from the new weather data. Edinburgh Napier

University researched future daylight and solar design data including shading and the impact of building facades. Northumbria University focused on modelling case studies and investigated the calculation of future heating/cooling design loads using the new weather data. The five university-based project partners were supported by a Stakeholder Group of practitioners who advised the projects partners throughout the conduct of the research. The Stakeholder Group consisted of approximately 30 industrial collaborators (mainly building design consultants) that helped steer the research and provided advice on required outcomes as well as to suggest and facilitate modelling case studies and exemplars.

1.1 Research background

Climate change, as a result of rising greenhouse gas emissions, is one of the most serious global issues faced by humankind at start of the 21st century. The Intergovernmental Panel on Climate Change (IPCC, 2007) published global future climate predictions for the 21st century. They indicate an increase in global average surface temperature in different scenario ranging from 1.1–2.9°C to 2.4–6.4°C from a 1990s baseline towards the end of the 21st century.

The growing impact of this on the built environment will be increased internal temperatures (particularly during summer), increased air conditioning demands and reduced winter heating demands. Since most buildings in the UK are either not air conditioned or partially air conditioned, the implications of this for the design of future buildings, and in the operation and refurbishment of existing buildings are profound. Many of the buildings that will be in use in the later part

of this century already exist. It is therefore of considerable interest to establish how these buildings will respond to the effects of a changing climate both from the point of view of the design of new buildings in the immediate years ahead as well as from the point of view of the development of mitigation strategies for application in the periodic refurbishment of existing buildings.

To help mitigate climate change, the Climate Change Act 2008 aims to cut UK carbon dioxide emissions by 34% by 2020 and at least 80% by 2050, against 1990 baseline (DECC, 2009). Because 27% of all UK CO₂ emissions are generated by housing and 18% from the non-domestic sector (DTI, 2007), buildings must bear a substantial burden of responsibility for achieving this target. The key objectives of the global effort to deal with climate change are to predict the trend of climate in the future accurately and to reduce the production of the greenhouse gas emissions that are causing climate change, particularly carbon dioxide emitted from the buildings sector.

The United Kingdom Climate Impacts Programme (UKCIP) is a UK-based agency established to provide support and advice to organisations concerning adaptiveness and resilience to climate change. Among other things, it has coordinated the generation and dissemination of predicted climate change scenarios to assist organisations to assess levels of risk and strategies for remediation arising from a changing climate in the UK. There have been five of these scenarios during the past 20 years, the most recent and sophisticated of which was published in 2009 and termed the UK Climate Projections (Jenkins *et al.*, 2009) (abbreviated simply to UKCP09). UKCP09 is the most

comprehensive package of climate information for the 21st century to be made available for the UK to date, and forms a globally-unique information resource. It provides users with probabilistic climate projections, marine projections and observed climate information, reflecting scientists' best current understanding of how the climate system operates and how it might change in the future (UK Climate Impacts Programme, 2008).

UKCP09 superseded the previous climate change projections (UK Climate Impacts Programme, 2002) (abbreviated simply to UKCIP02) which formed the basis of the current Future Weather Years (CIBSE, 2008) recommended by the Chartered Institution of Building Services Engineers (CIBSE) for use in the simulation modelling of buildings in the UK.

UKCP09 differs from the UKCIP02 climate change scenarios in two fundamental respects. UKCP09 provides monthly projections of climate change and absolute future climate data on a 25km grid-scale over seven 30-year time-slices starting on a baseline of 1961-1990 for three carbon emission scenarios. The data were generated by the UK's Meteorological Office Hadley Centre Climate Model 'HadCM3' (CIBSE, 2009). An accompanying Weather Generator is used to spatially downscale the 25km data to 5km and to temporally downscale the monthly data to daily or hourly data. The Weather Generator uses stochastic modelling methods to perform the downscaling.

The earlier UKCIP02 climate change scenario data were generated by downscaling an existing climate model to give, at 50km resolution, predictions of changes in the monthly average values of 15 climate variables at three time

slices and four carbon emission scenarios. Uncertainty bounds were attached based on results from other climate models. Extraction of future weather data for building simulation requires to be constructed from an existing hourly time series (described in detail later) whereas hourly time series data can be extracted directly from UKCP09 and uncertainties form an inherent part of the probabilistic method used.

UKCP09 expresses a probability that a given climate change outcome will arise. Results are usually expressed as a cumulative distribution function (CDF) which gives a plot of the probability (%) of a climate variable's change being less than a given amount. Key thresholds are the central estimate (50% probability) at which a climate change amount is as likely to be exceeded as not, and UKCP09 interprets a cumulative probability of 90% as 'very likely to be less than' (or very unlikely to be greater than) and 10% as 'very unlikely to be less than' (or very likely to be greater than).

The UK Climate Projections Briefing Report (Jenkins *et al.*, 2009) indicates that the changes in summer mean temperatures are greatest in parts of southern England (up to 4.2°C (2.2 to 6.8°C)) and least in the Scottish islands (just over 2.5°C (1.2 to 4.1°C)) from a 1990s baseline towards the 2080s. The values in brackets give the central estimates of change (those at the 50% probability level), and the changes which are very likely to be exceeded, and very likely not to be exceeded (10% and 90% probability levels, respectively). The geographical distributions of daily mean temperature changes of the summer by the 2080s are displayed in Figure 1-1. The immediate impact on the built

environment will be increased internal temperatures particularly during summer and the changes of heating and cooling energy demand.

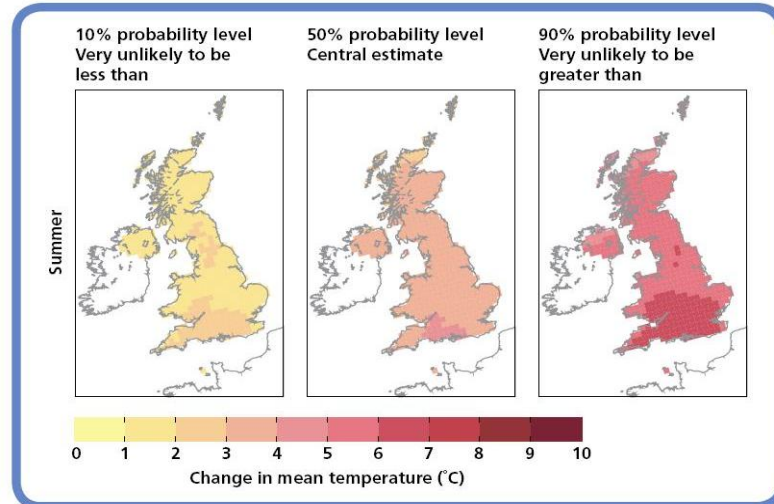


Figure 1-1 10%, 50% and 90% probability levels of changes to the average daily mean temperature (°C) during summer by the 2080s, under the medium emissions scenario (Jenkins *et al.*, 2009)

The new UKCP09 data have the potential to form a vital resource for architects, planners, engineers and surveyors involved in building design, planning and life-cycle management as well as construction companies involved in new building and refurbishment projects. However the raw data generated from UKCP09 are probabilistic and not in a form that is recognisable and usable by these practitioners. There is therefore a need for a new generation of weather data in formats suited for building design, planning and management and for the evaluation of these data in practical case studies – specifically for dynamic thermal simulation of buildings and for the assessment of design air conditioning loads.

1.2 Aims and objectives

The aim of this work is to firstly generate Test Reference Year/Design Reference Year data from UKCP09 for a variety of future time slices and carbon emission scenarios and followed by applying the data to the simulation modelling of a variety of building case studies in order to investigate probable patterns of overheating and likely changes in cooling and heating demands over time.

The research objectives are:

- To select a sample of realistic UK building exemplars and develop dynamic thermal models of them.
- To perform initial testing of the behaviour of the building models using existing files of future weather data (UK Climate Impacts Programme, 2002) applied to the investigation of building internal temperatures.
- To apply a suitable statistical method to the extraction of annual TRY data from probabilistic raw data produced by the Weather Generator in UKCP09 and to express these results using a file format suited to building thermal modelling.
- To apply the TRY data to the simulation modelling of the sample of UK building types using a dynamic thermal modelling tool for a range of carbon emissions and future time slices, and to generate and present time series results of summertime internal zone operative temperatures, heating demand and cooling demand for comparison with current (control) weather data.

- To compare the results based on the TRY files generated in the present work with the results based on TRY files generated by other research groups.
- To apply a suitable statistical method to the extraction of annual DRY data from probabilistic raw data produced by the Weather Generator in UKCP09.
- To apply the DRY data to the simulation modelling of the sample of UK building types, and to generate and present time series results of summertime overheating and heating and cooling peak (design) loads.
- To develop a simple approximate method for use by design practitioners for calculating cooling design loads for building spaces in future climates.

1.3 Organisation of this thesis

The thesis has been arranged in following order according to the objectives of this study.

Chapter one presents a brief background of the study, setting out the research aims and objectives and the contributions achieved.

Chapter two contains a literature review on the subject areas related to this study, including weather data file formats; future climate data and its use in predicting the future performance of buildings; thermal comfort standards; evolving standards of building thermal insulation and building cooling load calculation methods.

Chapter three presents a preliminary study of building performance under future weather conditions. The future weather data used in this chapter is CIBSE Future Weather Year (FWY) data (CIBSE, 2008) which is an important reference point because it is the currently-available future weather data in use by practitioners in building simulation and other branches of the industry. The performance of fourteen non-dwelling buildings were modelled in building simulation package EnergyPlus Version 4 (US Department of Energy, 2011a).

Chapter four explains the method of generating Northumbria Test Reference Year (TRY) data based on the UKCP09 Weather Generator outputs (UK Climate Projections, 2010). The Northumbria method was compared with other methods proposed by research groups at CIBSE (CIBSE, 2002), Exeter University (Coley, Kershaw & Eames, 2011) and Manchester University (Watkins, Levermore & Parkinson, 2011).

Chapter five illustrates the application of Test Reference Year data to building energy demand simulation. A sample of four buildings is simulated using the TRYs generated by the research groups mentioned above. A further study is conducted by modelling eleven further buildings using Northumbria data only.

Chapter six describes the development of Northumbria future Design Reference Years from the UKCP09 Weather Generator outputs. A comparison is made with DRYs generated using alternative methods from other research groups.

Chapter seven presents simulation results using DRY data generated in previous chapter. The impacts on overheat percentage and heating/cooling peak (design) loads are investigated.

Chapter eight proposes a simpler approximate method of calculating cooling design loads. The method is designed for preliminary studies by practitioners and avoids the need for large numbers of energy simulations.

Chapter nine draws a conclusion of this study and outlines the needs of future research in this area.

1.4 Contributions of this thesis

The contributions of this research are summarised as follows:

- A tool had been developed in Matlab to generate future Test Reference Year and Design Reference Year weather files from the UKCP09 Weather Generator raw data. The Matlab tool has the particular advantage of very efficient processing large quantity of data.
- Fifteen contrasting public buildings had been identified as case studies. The modelling of these buildings involved applying Test Reference Years and Design Reference Years data generated for London, Manchester and Edinburgh for a variety of carbon emission scenarios and at time horizons of control period, 2030s, 2050s and 2080s. The prediction of future building performance (particularly building energy consumption, overheating risks and building peak cooling load) were presented. It is believed that this is the most comprehensive range of case studies applied to the investigation of the impacts on future weather data on building performance.

- A simple calculation method of future cooling design load has been developed by regression analysis of simulation results. This tool forms a unique and simple procedure aimed at practitioners.

The contributions of this work are supported by following publications. Full copies of each paper are attached in appendix C.

Du, H., Underwood, C. P. & Edge, J. S. (2011) 'Generating design reference years from the UKCP09 projections and their application to future air conditioning loads', *Building Services Engineering Research and Technology* (accepted; to appear in Special Edition 33(1), 2012).

Du, H., Underwood, C. P. & Edge, J. S. (2011) 'Generating test reference years from the UKCP09 projections and their application in building energy simulations', *Building Services Engineering Research and Technology*, 418132 (20 pp.). DOI: 10.1177/0143624411418132.

Du, H., Edge, J. S. & Underwood, C. P. (2011) Modelling the impacts of new UK future weather data on a school building. *Building Simulation 2011*. 14-16 November 2011. Sydney, Australia: International Building Performance Simulation Association.

Du, H., Underwood, C. P. & Edge, J. S. (2010) Modelling the impact of a warming climate on commercial buildings in the UK. *Clima 2010 -10th REHVA World Congress "Sustainable Energy Use in Buildings"* 9-12 May. Antalya, Turkey: Federation of European HVAC Associations.

CHAPTER 2

2 Literature review

Based on the research aims and objectives, it is recognised that several strands of research will be brought together in this work: weather data format, future climate data and its use in predicting the future performance of buildings; thermal comfort (particularly in relation to summertime overheating); evolving standards of building thermal insulation; and sustainable methods of delivering air conditioning to mitigate summertime overheating. The following review addresses each of these strands in turn.

2.1 Weather data format

The need for appropriate meteorological data for long term prediction of the annual performance of energy systems with relatively low computational time led to the development of methodologies for generating the so-called Typical Meteorological Year (TMY) a term mainly used in the USA, or Test Reference Years (TRY) a term mainly used in Europe (Argiriou *et al.*, 1999). Typical Meteorological Year data provides designers and other users with a reasonably sized annual data set that holds hourly meteorological values that typify conditions at a specific location over a longer period of time, such as 20 or 30 years depend on the availability of historical weather data. TMY data sets are widely used by building designers and others for modelling renewable energy conversion systems. Although not designed to provide meteorological extremes, TMY data have natural diurnal and seasonal variations and represent a year of

typical climatic conditions for a location. The TMY should not be used to predict weather for a particular period of time, nor is it an appropriate basis for evaluating real-time energy production or efficiencies for building design applications or solar conversion systems (Wilcox & Marion, 2008). TMY are also not appropriate for simulations of wind energy conversion systems (Marion & Urban, 1995).

The TMY data set is composed of 12 typical meteorological months (January through December) that are concatenated essentially without modification to form a single year with a serially complete data record for primary measurements. These monthly data sets contain actual time-series meteorological measurements and modelled values, although some hourly records may contain filled or interpolated data for periods when original observations are missing from the data archive. The 12 selected typical months for each station were chosen using the Finkelstein-Schafer statistic determined by considering the following variables: global horizontal solar radiation, dry bulb temperature, direct normal solar radiation, wind speed and dew point temperature. These variables are important for building performance simulations.

For America, there are three versions of TMY data. Compared to the TMY and TMY2 data bases, TMY3 have a better model for estimating real weather conditions, and for measured data the instrument calibration methods are improved. Minor changes to the algorithm were made between the TMY2 and TMY3 production runs. TMY data sets were derived from 1952-1975 data,

TMY2 data sets were derived from the 1961-1990 American National Solar Radiation Data Base and TMY3 data sets were derived from a 1991-2005 period of records.

The format for the TMY3 data is radically different from the TMY and TMY2 data. The comma separated value (CSV) format is used for TMY3 due to its easy usage. Figure 2-1 illustrates an example TMY3 file for New York J F Kennedy International airport. TMY3 weather files consist of 8760 lines of weather data (one for each hour of 365 days) and 2 header lines indicating location and unit information. TMY, TMY2 and TMY3 are not normally interchangeable because of differences in time, formats, elements and units. However, the National Renewable Energy Laboratory (NREL) in the USA has produced an application to convert them.

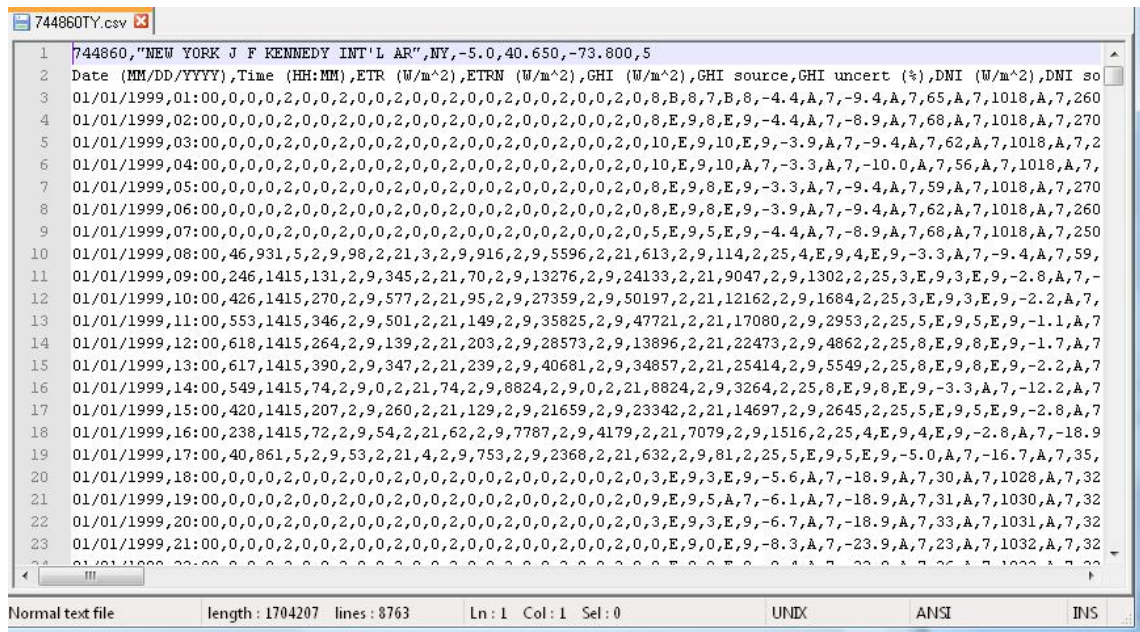


Figure 2-1 Example of TMY3 data (US Department of Energy, 2011b)

The intention of using TMY data is for computer simulation of solar energy conversion systems and building systems to facilitate performance comparisons of different system types, configurations, and locations in the United States and its territories (Wilcox & Marion, 2008).

For use with building energy simulation programs specifically, International Weather for Energy Calculation (IWECC) data sets were developed by American Society of Heating, Refrigerating and Air-Conditioning Engineers.

As the most popular weather data, International Weather for Energy Calculation (IWECC) data sets were made available for download in EPW format from the US Department of Energy (2011b) website. The EPW format is a unique file format used by the EnergyPlus dynamic thermal modelling software (US Department of Energy, 2011a) which is widely used by both practitioners and researchers in a number of countries. The IWECC data files are 'typical' weather files suitable for use with building energy simulation programs for 227 locations outside the USA and Canada. The files are derived from up to 18 years of 'DATSAV3' hourly weather data (DATSAV3 data were originally archived at the U. S. National Climatic Data Centre).

Similar to a TMY3 file, IWECC data in EPW format includes 8 header lines and 8760 lines of hourly weather data. An example of an IWECC EPW file for London Gatwick airport is illustrated in figure 2-2. The hourly weather variables include dry bulb temperature, dew point temperature, wind speed, wind direction etcetera. They were derived from the DATSAV3 database of surface observations developed by the National Climatic Data Centre, Asheville, NC;

and hourly solar radiation and illuminance data that is calculated from earth-sun geometry and cloud cover.

```

1 LOCATION,LONDON/GATWICK,-,GBR,IWEC Data,037760,51.15,-0.18,0.0,62.0
2 DESIGN CONDITIONS,1,Climate Design Data 2009 ASHRAE Handbook,,Heating,2,-4.6,-3,-7.6,2,-2.1,-6,2.3,-0.7,12.6,7.9
3 TYPICAL/EXTREME PERIODS,6,Summer - Week Nearest Max Temperature For Period,Extreme,8/17,8/23,Summer - Week Neare
4 GROUND TEMPERATURES,3,.5,,,,4.16,5.30,7.51,9.61,13.58,15.67,16.24,15.18,12.74,9.69,6.69,4.70,2,,,,5.73,6.01,7.27
5 HOLIDAYS/DAYLIGHT SAVINGS,No,0,0,0
6 COMMENTS 1,"IWEC- WHO#037760 - Europe -- Original Source Data (c) 2001 American Society of Heating, Refrigeratin
7 COMMENTS 2, -- Ground temps produced with a standard soil diffusivity of 2.3225760E-03 {m**2/day}
8 DATA PERIODS,1,1,Data,Sunday, 1/ 1,12/31
9 1991,1,1,1,60,C9C9C9C9*0?9?9?9?9?9?9?9A7A7A7A7A7*0E8*0*0,2.7,1.1,89,101000,0,1415,264,0,0,0,0,0,0,220,1.0,2,
10 1991,1,1,2,60,C9C9C9C9*0?9?9?9?9?9?9?9A7A7A7A7A7*0E8*0*0,1.2,0.2,93,101000,0,1415,258,0,0,0,0,0,0,220,2.6,1,
11 1991,1,1,3,60,C9C9C9C9*0?9?9?9?9?9?9?9A7A7A7A7A7*0E8*0*0,0.2,-0.4,95,100900,0,1415,249,0,0,0,0,0,0,220,1.5,0
12 1991,1,1,4,60,C9C9C9C9*0?9?9?9?9?9?9?9A7A7A7A7A7*0E8*0*0,-0.5,-0.8,97,100900,0,1415,246,0,0,0,0,0,0,240,2.1,
13 1991,1,1,5,60,C9C9C9C9*0?9?9?9?9?9?9?9A7A7A7A7A7*0E8*0*0,-0.8,-1.1,98,100900,0,1415,245,0,0,0,0,0,0,230,3.1,
14 1991,1,1,6,60,C9C9C9C9*0?9?9?9?9?9?9?9A7A7A7A7A7*0E8*0*0,-1.1,-1.3,98,101000,0,1415,243,0,0,0,0,0,0,230,2.6,
15 1991,1,1,7,60,A7A7E8E8*0?9?9?9?9?9?9?9A7A7A7A7A7*0E8*0*0,1.0,-0.9,86,101000,0,1415,251,0,0,0,0,0,0,140,1.0,1
16 1991,1,1,8,60,A7A7E8E8*0?9?9?9?9?9?9?9A7A7A7A7A7*0E8*0*0,0.7,-0.3,93,101000,0,1415,255,0,0,0,0,0,0,170,1.0,2
17 1991,1,1,9,60,A7A7E8E8*0G9G9G9I9I9I9I9A7A7A7A7A7*0E8*0*0,0.6,0.0,96,101100,57,1415,255,19,0,19,2100,0,2100,580
18 1991,1,1,10,60,A7A7E8E8*0G9G9G9I9I9I9I9A7A7A7A7A7*0E8*0*0,2.5,1.2,91,101000,206,1415,264,52,7,51,5700,100,5600
19 1991,1,1,11,60,A7A7E8E8*0G9G9G9I9I9I9I9A7A7A7A7A7*0E8*0*0,5.7,3.5,86,100900,316,1415,282,92,17,88,10100,700,98
20 1991,1,1,12,60,A7A7E8E8*0G9G9G9I9I9I9I9A7A7A7A7A7*0E8*0*0,7.9,4.7,80,100800,374,1415,288,115,22,109,12700,1100
21 1991,1,1,13,60,A7A7E8E8*0G9G9G9I9I9I9I9A7A7A7A7A7*0E8*0*0,8.7,5.6,81,100600,377,1415,307,116,22,110,12800,1100
22 1991,1,1,14,60,A7A7E8E8*0G9G9G9I9I9I9I9A7A7A7A7A7*0E8*0*0,8.9,5.8,81,100500,326,1415,312,95,17,91,10500,700,10
23 1991,1,1,15,60,A7A7E8E8*0G9G9G9I9I9I9I9A7A7A7A7A7*0E8*0*0,8.8,5.7,81,100400,222,1415,323,57,4,56,6300,100,6200

```

Figure 2-2 Example of IWEW EPW file (US Department of Energy, 2011b)

There are two steps in the development process of the IWEW files. First, small gaps in the DATSAV3 weather data (up to 18 years (1982-1999)) were filled, and solar radiation was computed from cloud cover and earth-sun geometry. Second, twelve Typical Meteorological Months were selected by Finkelstein-Schafer statistic method from the long-term time series and assembled into an IWEW file.

US Department of Energy summarised the main weather data sources available for building modelling tools users, such as Canadian Weather for Energy Calculations (CWEC) for Canada, City University of Hong Kong (CityUHK), Chinese Standard Weather Data (CSWD) and Chinese Typical Year Weather (CTYW) for China, Egyptian Typical Meteorological Year (ETMY) for Egypt and

many more. All the detailed information of 20 sources of weather data are available on the website of the US Department of Energy (2011b).

For the United Kingdom, the Chartered Institution of Building Services Engineers (CIBSE) developed Test Reference Year and Design Summer Year data sets for 14 cities in the UK.

```

London_Heathrow.try
1 Test Reference Year TRY for: Heathrow Heathrow
2 Start Year = 1983. End Year = 2005.
3 Latitude = 51.48N. Longitude = 0.45W. Altitude = 25m.
4
5 Selection using FS method with equal weighting for Cloud, DryT and WS.
6 Selected years for each month are:
7 January: 1988
8 February: 2004
9 March: 2004
10 April: 1992
11 May: 2000
12 June: 2001
13 July: 1991
14 August: 1996
15 September: 1987
16 October: 1988
17 November: 1992
18 December: 2003
19
20 Notation and units:
21 ID = Station Identifier
22 PWC = Present Weather Code
23 Cloud = Cloud amount 1/8
24 DryT = Dry Bulb Temperature degrees C
25 WetT = Wet Bulb Temperature degrees C
26 Press = Mean Sea Level Pressure hPa
27 WD = Wind Direction degrees
28 WS = Wind Speed knots
29 G1Rad = Global radiation Watts per sq. metre
30 DiRad = Diffuse radiation Watts per sq. metre
31
32 ID Year Month Day Hour PWC Cloud DryT WetT Press WD WS G1Rad DiRad
33 3772 1988 1 1 0 2 0 6.5 5.8 1006.0 210 8 0 0
34 3772 1988 1 1 100 3 1 6.5 5.8 1006.0 210 8 0 0
35 3772 1988 1 1 200 3 1 6.1 5.4 1006.2 200 7 0 0
36 3772 1988 1 1 300 3 1 6.3 5.6 1005.9 200 8 0 0
37 3772 1988 1 1 400 3 1 6.5 5.8 1005.6 210 8 0 0
38 3772 1988 1 1 500 3 3 6.7 5.9 1005.3 220 11 0 0
39 3772 1988 1 1 600 3 6 7.1 6.1 1004.6 210 11 0 0
40 3772 1988 1 1 700 3 7 7.8 6.8 1004.5 210 10 0 0
41 3772 1988 1 1 800 3 7 8.5 7.4 1004.1 210 10 11 11

```

Norma length: 780666 lines: 8793 Ln: 1 Col: 1 Sel: 0 Dos\Windows ANSI INS

Figure 2-3 Example of CIBSE TRY file (CIBSE, 2008)

The Test Reference Year (CIBSE, 2002) consists of hourly data for twelve typical months, selected from approximately 20-year data sets (typically 1983-2004), and smoothed to provide a composite, but continuous, 1-year sequence of data. The selection of typical months applied by CIBSE is similar to the selection procedure of TMY data, but it only applies to dry bulb temperature, global horizontal solar radiation and wind speed. Figure 2-3 illustrates an example CIBSE TRY file for London Heathrow airport. TRY weather files consist of 8760 lines of weather data (one for each hour of 365 days) and 32 header lines indicating location, unit information and selected years for each month.

The Design Summer Year (CIBSE, 2002) consists of an actual 1-year sequence of hourly data, selected from the 20-year data sets to represent a year with a hot summer. The selection is based on dry bulb temperatures during the period April–September. The year selected is the mid-year of the upper quartile. This enables designers to simulate building performance during a year with a hot, but not extreme, summer. Figure 2-4 illustrates an example CIBSE DSY file for London Heathrow airport. DSY weather files consist of 8760 lines of weather data (one for each hour of 365 days) and 20 header lines indicating location, unit information and selected year.

All above weather data are based on historical records. They cannot represent future weather conditions.

```

London_Heathrow.dsy
1 Design Summer Year DSY for: Heathrow Heathrow
2 Start Year = 1983. End Year = 2004. Selected Year = 1989.
3 Latitude = 51.48N. Longitude = 0.45W. Altitude = 25m.
4
5 Selection using third highest average temperature for the
6 summer months April-September inclusive.
7
8 Notation and units:
9 ID = Station Identifier
10 PWC = Present Weather Code
11 Cloud = Cloud amount 1/8
12 DryT = Dry Bulb Temperature degrees C
13 WetT = Wet Bulb Temperature degrees C
14 Press = Mean Sea Level Pressure hPa
15 WD = Wind Direction degrees
16 WS = Wind Speed knots
17 G1Rad = Global radiation Watts per sq. metre
18 DiRad = Diffuse radiation Watts per sq. metre
19
20 ID Year Month Day Hour PWC Cloud DryT WetT Press WD WS G1Rad DiRad
21 3772 1989 1 1 0 5 7 7.6 6.1 1039.7 0 0 0 0
22 3772 1989 1 1 100 5 7 7.6 6.1 1039.7 0 0 0 0
23 3772 1989 1 1 200 2 7 8.4 5.4 1039.5 0 0 0 0
24 3772 1989 1 1 300 2 7 7.7 6.0 1039.2 0 0 0 0
25 3772 1989 1 1 400 5 7 7.5 6.0 1039.1 0 0 0 0
26 3772 1989 1 1 500 5 7 7.0 5.8 1039.0 360 1 0 0
27 3772 1989 1 1 600 2 7 7.7 5.4 1038.8 0 0 0 0
28 3772 1989 1 1 700 2 7 7.4 5.5 1038.9 0 0 0 0
29 3772 1989 1 1 800 2 7 6.9 5.2 1039.0 150 1 11 11
30 3772 1989 1 1 900 2 7 7.0 5.0 1039.2 140 1 52 44
31 3772 1989 1 1 1000 2 7 7.1 5.0 1039.6 160 2 89 74
32 3772 1989 1 1 1100 2 7 8.0 5.0 1039.7 170 1 109 91
33 3772 1989 1 1 1200 2 7 8.2 5.1 1039.3 10 1 110 92
34 3772 1989 1 1 1300 2 8 8.2 5.4 1038.7 100 2 44 44
35 3772 1989 1 1 1400 2 8 8.0 5.4 1038.1 140 4 28 28
36 3772 1989 1 1 1500 2 8 7.9 5.4 1037.8 130 3 15 15
37 3772 1989 1 1 1600 2 7 7.5 5.2 1037.8 130 3 0 0
38 3772 1989 1 1 1700 2 8 7.6 5.1 1037.9 140 4 0 0
39 3772 1989 1 1 1800 2 8 7.0 4.6 1037.8 150 5 0 0
40 3772 1989 1 1 1900 2 8 7.1 4.5 1037.6 150 7 0 0
41 3772 1989 1 1 2000 2 8 6.9 4.4 1037.8 160 6 0 0

```

Norma length: 780478 lines: 8781 Ln: 1 Col: 1 Sel: 0 Dos\Windows ANSI INS

Figure 2-4 Example of CIBSE DSY file (CIBSE, 2008)

2.2 Climate data and its use in building performance prediction

Over the past two decades, the building simulation discipline has matured into a field that offers unique expertise, methods and tools for building performance evaluation (Hensen & Augenbroe, 2004). For example, DesignBuilder, IES and TRNSYS were successfully introduced into building consultancies because of

their friendly user interface and reliability of results compared with previous simulation programs. As essential input element for dynamic building simulation programs, various weather data files representing local climate condition are required. Those programs use the same climate representations as in the past - a simple set of hourly temperature, humidity, wind speed and direction, and atmospheric pressure and solar radiation or cloud cover data (Crawley, Hand & Lawrie, 1999). Although weather data files for those programs improved after 30 years of significant development in simulation capabilities (e.g. Typical Meteorological Year weather data is introduced and extreme conditions are replaced by typical values within 3 decades), they still cannot present building performance under future weather conditions.

To study the impact of climate change on building performance, previous studies of predicting future weather data have been done in four steps. They may be classified as: the global climate models, extrapolating statistical method, morphing method and stochastic weather model. (Guan, 2009)

In 1996, meteorologists developed a complex and fundamental method of climate change model. However, because of the complex and chaotic nature of the global climate system, detailed modelling of complete atmospheric or surface processes using this method would be extremely difficult. Thus, after simplification, the Global Climate Model (also known as General Circulation Model, both labels are abbreviated as GCM) (McGuffie & Henderson-Sellers, 2005) which coupled atmosphere and ocean models, has been developed. It is

reliable, particularly at continental scales and larger, where the influences of local geological factors may be ignored (Sturman & Tapper, 1996).

Extrapolating statistical historical weather data is used to predict future weather conditions. Examples of the application of this method include the prediction of building energy consumption trends using degree-days, so that different levels of impact can be compared between different cities. The advantage of this method is that it is simple and fast. However, the energy estimates from the degree-day calculations can be fairly coarse, because the degree-day method is appropriate only if the building use and the efficiency of the HVAC equipment are constant (ASHRAE, 2001).

To represent future weather conditions, Cullen (2001) attempted to create a file with a summertime mean of 2.0°C above the 1961-1990 dataset mean (15.3°C). In this method, only dry bulb temperatures were shifted and there is no change in other factors, such as wet bulb temperature, cloud cover, solar intensity and wind speed and direction.

To optimize the above method, Belcher *et al.* (2005) developed a method (called 'morphing') for transforming CIBSE TRY and DSY weather files to future weather data. Current hourly CIBSE weather data for present day climate was adjusted with the monthly climate change prediction values of the UKCIP02 scenario (UK Climate Impacts Programme, 2002). A 'shift' (i.e. scale), 'stretch' (i.e. project) and a combination of 'shift' and 'stretch' methods are used to modify total solar irradiance on the horizontal, diffuse solar irradiation on the horizontal, sunshine duration, cloud cover, dry bulb temperature, wet bulb

temperature, atmospheric pressure and wind speed. There is no change for rainfall duration, present weather code and solar altitude in Belcher *et al.*'s (2005) method.

Hacker and Holmes (2007) examined how serious climate change impacts may be under the UKCIP02 climate change scenarios and investigated the implications of two types of adaptive solution: passive cooling measures, as traditionally used in countries with warmer climates, and mechanical cooling. A qualitative assessment was made through consideration of building design weather years 'morphed' under the UKCIP02 scenarios. A quantitative investigation was then made through dynamic thermal modelling of three notional case study office buildings under morphed weather years for London, Manchester and Edinburgh for the UKCIP02 Medium-High emissions scenario.

Guan (2009) summarised the advantages of the morphing method:

First, the sources of constructing future weather data are available. For example, the projected temperature increases under climate change are often available from IPCC or relevant national research organizations, and the base weather data for the current climate is also normally available online or purchasable from meteorological departments. Second, the comparison between current and future weather conditions can be made on a consistent base. Because impact studies are more concerned with relative change, it is essential that all the comparisons are based on the same base.

The limitations of this method are also quite obvious (Guan, 2009), as it is based on the following series of assumptions.

First, although the possible close relationship between air temperature and air humidity are considered with different assumptions, a common approach will be needed to provide a systematic approach. Second, the daily hourly dry bulb temperature is assumed to increase 'constantly' over a day. Therefore, the future increases in daily maximum and minimum temperature are assumed to be the same as the predicted increases in average temperatures. Third, the change in solar insolation and wind speed has been ignored.

Jensch *et al.* (2008) recognised that no bespoke climate change weather files are readily available that can be loaded directly into environmental simulation software. Again, they used a morphing method to transform current CIBSE TRYs and DSYs into climate change weather years and presented a tool to convert these to a Typical Meteorological Year (TMY) and other file formats readily readable by building simulation packages. These weather data were used to perform simulations of a naturally ventilated building to assess the potential summer overheating problems caused by climate change. They found a 'significant difference' in applying current and future weather data in building simulation and compare predicted results with some observed temperature readings in a case study building. Numerous modelling studies have since been conducted using morphed weather data based on the UKCIP02 climate change scenarios applied to building comfort, energy use and ventilation performance analyses (Holmes & Hacker, 2007; Hacker *et al.*, 2008; Coley & Kershaw, 2010; de Wilde & Tian, 2010; Du, Underwood & Edge, 2010).

Van Passen and Luo (2002) and Adelard (2000) developed stochastic weather models by generating an artificial meteorological database by inputting a sample of weather variables. However, due to the stochastic nature of this method, it will be necessary to generate weather data over many years, in order to be representative of the climatic patterns during the desired time periods. Moreover, this method has difficulties in accurately modelling many climatic variables at that time (Guan, 2009).

More recent work has been carried out using the UKCP09 projections. UKCP09, UKCIP02 and historical measured data were used to analyse likely changes in temperature, sunshine duration and solar irradiation by Tham and Muneer (2010). They studied 3 locations in the UK and found that both data sets showed an increase in these three variables when compared to the measured historical data as well as concluding that data based on UKCP09 produced abnormally elongated sunshine duration for some scenarios. Eames *et al.* (2011) discussed a method for the creation of future probabilistic reference years using UKCP09 for use in simulating the thermal performance of buildings. They identify a number of parameters not produced by the UKCP09 weather generator such as wind speed and direction, air pressure and cloud cover which have to be calculated separately. Kershaw *et al.* (2010) used the UKCP09 weather generator to generate 3000 example weather years and created probabilistic future reference years using the method detailed in Eames *et al.* (2011). They found that the external data from the reference years compared very well to the 3000 years weather data. Building simulations were then carried out for all 3000 example years and the reference years to compare

the results. They found that the probabilistic reference years can be adequately used to assess the risk of building failure and risk to occupants but a number of these reference years need to be considered in order to represent the variation in possible future climates.

Watkins *et al.* (2011) present a method to construct a future weather file using UKCP09. They highlight that the UKCP09 data has no wind or cloud data and detail algorithms to produce these for their inclusion in a TRY. They use the 3000 years weather data in a method similar to Eames *et al.* (2011). Wind speed was calculated from the potential evapotranspiration (PET) values included in the UKCP09 data. Historical weather files were used to provide typical wind directional data. The UKCP09 data only includes diffuse and direct solar irradiation on the horizontal plane so they adjust the solar data so that the direct normal radiation can be correctly calculated. Day time cloud cover is generated from sunshine hours and linear interpolation is used to produce night time cloud cover data. They produce a single composite TRY to provide a common, practical weather year against which designers can compare the average performance of their buildings. In related work, Watkins and Levermore (2010) used the CIBSE calculation method (CIBSE, 2006) to examine the effect of future increasing external temperature on the peak cooling load. They found that relatively small increases in external temperature could have a significant effect on the peak load and its associated plant items. Patidar *et al.* (2011) investigate the use of a probabilistic method of analysing the overheating of buildings in the future. They used a domestic dwelling to demonstrate a technique of linear filtering and regression analysis to analyse its

thermal performance for various climate change scenarios and compared the results to results from building simulation software analysis. A linear predictor is constructed for the bedroom temperature corresponding to climate data from a preceding period of time. Least squares regression is used to fit the model. They found that results from their model were just as reliable as a detailed building simulation for many different climates however the regression relationship might not be suitable for more complex buildings.

2.3 Thermal comfort

To assess the performance of buildings in conditions of evolving climate change which is expected to feature increased warming effects, one of the important things is to identify an acceptable limit of thermal comfort. A thermal comfort standard is intended to help building designers to provide an indoor climate that building occupants will feel comfortable in. The definition of good thermal comfort is important to buildings, not only for achieving comfort, but also because of its influence in sustainability in terms of energy consumption and carbon dioxide emission.

International standards (ASHRAE, 2004; ISO, 2005a) have been established to describe comfortable internal thermal environments based on theoretical analysis of human heat exchange with the environment calibrated using the results from experiments in special climate-controlled laboratories or climate chambers. The ISO 7730 standard (ISO, 2005a) suggests the use of Fanger's Predicted Mean Vote (PMV) indices which express the mean value of the votes of a large group of people on the ISO thermal sensation scale (+3=hot;

+2=warm; +1=slightly warm; 0=neutral; -1=slightly cool; -2=cool; -3=cold). The predicted percentage dissatisfied (PPD) is the predicted percent of dissatisfied people at each PMV (Fanger, 1970). As PMV changes away from zero in either the positive or negative direction, PPD increases.

The PMV indices have been used to help setup the thermal comfort standard for cooling and heating system since the 1970s. CIBSE guide A (CIBSE, 2006) lists heating and cooling design criteria for different room types. The recommended comfort (operative) temperature ranges correspond to a PMV of ± 0.25 , and the temperature ranges may be widened by approximately 1 °C at each end if a PMV of ± 0.5 is acceptable.

Fanger (1982) indicated that people cannot adapt to preferring warmer or colder environments, and therefore the same comfort conditions can likely be applied throughout the world. However, it is thought that many people can acclimatize themselves by exposure to hot or cold surroundings. A recent study (Heidari & Sharples, 2002) shows that the people of Iran could achieve comfort at higher indoor air temperatures than would be recommended by international standards like ISO 7730, and, more importantly, the variability of acceptable conditions at different times of the year. Therefore, the Adaptive Comfort Model (ACM) has been developed as an alternative comfort limit.

The notion of ACM is that thermal comfort is related to climate and that occupants within buildings are comfortable at a greater spread of indoor temperatures than predicted by the PMV (de Dear & Brager, 2002; Nicol & Humphreys, 2002). By changing heating and cooling systems sufficiently slowly,

people will adjust their clothing to suit the weather. The indoor comfort temperature will naturally change with the seasons. This idea, called an 'adaptive algorithm' (Nicol, 1995), will significantly reduce energy use (Nicol & Humphreys, 2002).

Adaptive comfort models include some variations of outdoor climate for determining indoor thermal comfort. The adaptive comfort models commonly used by practitioners are American National Standards Institute (ANSI)/ American Society of Heating, Refrigeration and Air-Conditioning Engineers (ASHRAE) adaptive standard (ASHRAE, 2004), European adaptive standard BS EN 15251:2007 (British Standards Institution, 2007a) and the adaptive limits mentioned in CIBSE Guide A (CIBSE, 2006).

European and CIBSE adaptive comfort limits are based on a daily running mean outdoor temperature (Equation 2-1), and the ANSI/ASHRAE adaptive comfort limits are based on monthly mean outdoor air temperature (Equation 2-2). The daily running mean outdoor temperature could be calculated by Equation 2-3.

For the last term of Equation 2-1, constant 2, 3 or 4 would be used for different levels of comfort expectations. For a group with high level of comfort expectation, such as very sensitive and fragile occupants with special requirements like handicapped, sick, very young children and elderly persons, constant 2 would be used. The constant 3 would be used for new buildings with normal level of thermal expectation, and constant 4 would be used for existing buildings with an acceptable, moderate level of thermal expectation.

$$t = 0.33t_{rm} + 18.8 \pm (2\sim 4) \quad \text{Equation 2-1}$$

$$t = 0.31t_{mm} + 17.8 \pm 2.5 \quad \text{Equation 2-2}$$

$$t_{rm(d)} = (1 - \alpha)t_{0(d-1)} + \alpha t_{rm(d-1)} \quad \text{Equation 2-3}$$

Where

t_{rm} = daily running mean outdoor temperature

t_{mm} = monthly outdoor air temperature

$\alpha = 0.8$ running mean constant

$t_{0(d-1)}$ = daily mean outdoor temperature for previous day

$t_{rm(d-1)}$ = daily running mean temperature for previous day

Comfort studies on different age groups (ages 21 to 84) in Denmark and the United States were conducted by Fanger (1982), Langkilde (1979), Rohles and Johnson (1972). The studies revealed that the thermal environments preferred by older people do not differ from those preferred by younger people, because the low metabolism in older people is compensated for by a lower evaporative loss (Collins & Hoinville, 1980). However, the fact that young and old people prefer the same thermal environment does not necessarily mean that they are equally sensitive to cold or heat. In practice, the ambient temperature level in the homes of older people is often higher than that for younger people (ASHRAE, 2001). Both ASHRAE and the European standard defined different adaptive standard limits for different occupancies or building types.

McGilligan *et al.* (2011) introduced the concept of the Adaptive Comfort Degree-Day as a means of comparing energy savings from Adaptive Comfort Model standards by quantifying the extent to which the temperature limits of the thermal comfort zone of the Predicted Mean Vote Model can be broadened. They also compared the potential energy saving from the ASHRAE 55 standard and the BS EN 15251 standard.

The Heat Stress Index (HSI) (Belding & Hatch, 1955) was introduced for health and safety purposes in industrial buildings. It is based on the physical analysis of heat exchange developed by Machel and Hatch (1947) and later applied to industrial situations (Haines & Hatch, 1952). When $HSI > 0$, body heating occurs; when $HSI < 0$, body cooling occurs. For steady state conditions, when HSI is 50, workers are physically fit, but break times are required. The working conditions are unsuitable for activities requiring sustained mental effort. When HSI is over 70, very severe stress can be expected; only a small percentage of the population may be expected to qualify for work in an environment like this. They should be subjected to medical examination or tests during work and after acclimatization (Mark, 2009).

In conclusion, the PPD-PMV Index is well accepted by the industry and academics. Adaptive thermal comfort is an approach to develop sustainable thermal comfort standards, potentially widening a currently-accepted thermal comfort range. The heat stress Index can be used to predict health-related impacts.

2.4 Insulation standards

To investigate building thermal performance over an extended time horizon, it is necessary to consider the evolving standards of thermal insulation likely to be used in buildings constructed in the past and refurbished in the future.

The U-values of the exterior envelope of a building is a major factor to the thermal performance of a building. It is a measure of the rate of heat transfer by conduction between the inside and the outside via the building fabric. Chow and Levermore (2010) summarised the standard maximum permitted U-values of construction elements and glazing types and percentages of façade in UK building regulations from 1965 to 2002 for non-domestic buildings in following table.

Table 2-1 Comparison of standard maximum permitted U-values of construction elements specified in UK Building Regulations from 1965 to 2002 and glazing type and percentage of facade glazed used in analyses (Chow & Levermore, 2010)

Year of Building Regulations	U-Values ($Wm^{-2}K^{-1}$)					Glazing used	
	Wall	Window	Floor	Roof	Door	Glazing type	% façade glazed
1965	1.7	5.6	1.42	1.42	3	Single	60
1976	1	5.6	1	0.6	3	Single	60
1985	0.45	3.3	0.45	0.25	3	Double	35
1995	0.45	3	0.35	0.2	3	Double	34
2002	0.35	2.2	0.25	0.2	2.2	Double (K-coating)	36

Table 2-2 U-values ($\text{Wm}^{-2}\text{K}^{-1}$) mentioned in Building Regulation 2006 and 2010

	Document	Flat roof	External wall	Floor	Window / door	Notes
New dwellings	L 1A 2010	0.2	0.3	0.25	2	worst acceptable standard
	L 1A 2006	0.25	0.35	0.25	2.2	area weighted average value
New buildings other than dwellings	L 2A 2010	0.25	0.35	0.25	2.2	worst acceptable standard
	L 2A 2006	0.25	0.35	0.25	2.2	area weighted average value
Existing buildings	L 1B&2B 2010	0.18	0.28	0.22		standards for new thermal elements
		0.35	0.7	0.7		threshold for retained thermal elements
		0.18	0.3	0.25		improved for retained thermal elements
	L 1B&2B 2006	0.25	0.35	0.25	2.2	area weighted average value

Unlike the previous building regulations, building regulation part L 2006 (Office of the Deputy Prime Minister, 2006a; c) and 2010 (HM Government, 2010a; c) for new buildings do not specify U-values for the building elements. Instead they define a building carbon dioxide Emission Rate (BER) that must be achieved. The CO₂ emissions target in Part L1A (2010) is a reduction by 25% over the Part L1A (2006) level. This is a 40% improvement for a dwelling built to the 2002 regulations. In general, achievement of the target emission rate is likely to require better fabric performance than set out in following table which defined

'notional' values to be used in target-setting. The last column of the table notes the usage of the U-values. For existing buildings, building regulation 2010 (HM Government, 2010b; d) listed standards of U-values for new elements, thresholds for retained elements and improved values for retained elements. Building regulation 2006 (Office of the Deputy Prime Minister, 2006b; d) only gave the area weighted average U-value for a whole building.

U-values shall be calculated using the methods and conventions set out by BRE (Anderson, 2006), and should be based on the whole element or unit (including frame). In the case of windows, the U-value should be the smaller of the two standard windows defined in BS EN 14351-1 (British Standards Institution, 2006) or a calculated value based on the BRE method (Anderson, 2006) or the actual value (if known).

The target carbon dioxide emission rate (TER) is the emission rate of a notional building which has same shape as the actual building, but with thermal properties defined according to a concurrent specification. The National Calculation Method (NCM) modelling guide (for buildings other than dwellings in England and Wales) 2010 editions (DCLG, 2010b) specified the U-values for a notional building meeting the concurrent specification, and the information is listed in the following table. The calculation of target emission rate only can be done by approved software (Building Energy Calculation Software Approval Scheme, 2011). One basis is called the Simplified Building Energy Model (SBEM) (DCLG, 2010a).

Table 2-3 U-values for notional building in NCM guide 2010 (DCLG, 2010b)

Element	U-values ($Wm^{-2}K^{-1}$)
Roof	0.18
Walls	0.26
Windows, roof windows and roof lights	1.8
Vehicle access and similar large doors	1.5
Pedestrian doors	2.2

The current mandatory house standard in UK is the Code for Sustainable Homes (DCLG, 2006). The Code aims to protect the environment by providing guidance on the construction of high performance homes built with sustainability in mind. As one of the key issues, building materials are designated according to the level which future house building standards should achieve. However, the current highest level 'net-Zero Carbon' is only a target for 2016 (pending further review (DCLG, 2010c)). It is clear from the Code that UK new houses are targeted to pursue a gradual tightening of standards which will converge with the best practice in Europe (a stated aim of the Energy Performance of Buildings Directive) which is the so-called 'Passive house' standard. This standard results in net space and ventilation air heating energy usage which approaches zero for new-build houses. However, building constructed to such standards tend to exhibit a greater tendency to summertime overheating which, when coupled with creeping global warming, suggests a future emphasis on cooling rather than heating for buildings. It is also noted that refurbished buildings will frequently be unable to adopt full 'net-zero' standards of this kind

for practical reasons and so these types of buildings will exhibit different behaviour.

2.5 Building heat transfer and cooling load calculation method

A cooling load may be defined as the amount of heat that must be removed to maintain a constant room air temperature. The peak or design cooling load, which is used to determine the size of ducts and equipment, is an important parameter for building services system designers. The calculation of cooling loads usually involves the calculations of heat transfer through the opaque building envelope, heat transfer through transparent elements, internal heat gain (people, lighting and heat-producing equipment), infiltration and latent loads.

There are three modes of heat transfer: conduction, convection and radiation which occur simultaneously. Conduction heat transfer through building envelope is an important contribution to the building load and room thermal response.

The calculation of conduction heat transfer can be treated in two ways: steady-state model and transient model.

In the United States, the cooling load calculation methods were first introduced in the 1933 ASHVE (American Society of Heating and Ventilating Engineers, predecessor of ASHRAE) Guide. It was noted that a customary rule-of-thumb was to 'add 14 K to the outside dry bulb temperature in calculating the heat transmission through walls, glass and roof, which may be exposed to the sun

for some time'. This semi-empirical approach was based on measured surface temperature and conductance data. Some time later, the sol-air temperature concept was defined and used to calculate heat gain through building fabrics by Mackey and Wright (1943), and their method for homogeneous constructions was included in the 1947 ASHVE Guide. However this method was thought to be too complex for practical application at that time.

The method of calculating 'equivalent temperature differentials' for different materials and hours of the day was developed by Stewart (1948). The conduction heat gain simply equals to equivalent temperature difference multiplied by the U-value. The concept of this method formed the 'Total Equivalent Temperature Difference / Time Averaging' method and 'Cooling Load Temperature Difference / Solar Cooling Load / Cooling Load Factor' method described in the 1997 ASHRAE Handbook of Fundamentals.

All of the above methods are based on a steady-state model. As digital computers were introduced to calculate building thermal response in the US in the late 1960s (Briskin & Reque, 1958), various ways could be used to solve partial differential equations for describing transient heat conduction in conjunction with the boundary conditions at two surfaces of the fabric elements, such as the Z-transform method (Mitalas, 1978), numerical method (Underwood & Yik, 2004) and lumped parameter method (Lorenz F. & Masy G., 1982).

Methods based on Z-transform theory include response factors (Stephenson & Mitalas, 1967), conduction transfer functions (Stephenson & Mitalas, 1971) and the periodic response factors method. These methods have a high degree of

accuracy and are computationally efficient. They are used widely in building simulation today.

The response factors method was first proposed by Stephenson and Mitalas (1967). These response factors were used to define the response of a particular wall or roof construction to a unit temperature pulse. In this method, the room thermal response factors need be calculated only once for any room, and then they could be used to calculate surface temperatures, room air temperature, room heating and cooling load. It was computationally efficient at the time of development (1960s), because of limitations in computer power at that time. The time interval usually is 1 hour for long term building simulation, and the interval would be shorter if needed for plant modelling. The shorter interval led to a larger number of response factors.

Stephenson and Mitalas developed the response factors method further in 1971 to allow the heat transfer through building envelopes to be determined more efficiently. The method is called Conduction Transfer Function method (Stephenson & Mitalas, 1971). It has been successfully employed in the TARP (Walton, 1983), BLAST (1986) and EnergyPlus (US Department of Energy, 2011a) programs.

Although the usage of response factors and the conduction transfer function method are relatively straightforward, the calculation of the factors themselves is more difficult. Spitler (1996) cited a number of other methods, of which the most common are the Laplace method and the state-space method (Seem *et al.*, 1989). Recently time-domain (Davies, 1996) and frequency-domain

regression methods (Wang & Chen, 2003) have been developed making it possible to derive response factors or conduction transfer function coefficients, although they are not usually used as a precursor to simulation.

Periodic response factors (Hensen & Lamberts, 2011) are used for hourly heat gain calculations needed by the Radiant Time Series Method (RTSM) for cooling load calculation. Periodic response factors can be calculated with the same methods as conduction transfer functions.

The response factor method and conduction transfer function method are analytical methods for solving the governing partial differential equations. An alternative approach is to use a numerical method which includes finite difference and finite element methods. These methods can have a high level of accuracy if parameterised appropriately but are typically less computationally efficient than Z-transform methods. However they offer more flexibility for radiation across air gaps and phase change materials. ESP-r (Hand, 2011) and ApacheSim (Intergrated Environmental Solutions, 2010) are examples of simulation programs that use numerical methods.

Lumped parameter methods treat wall and roof elements as discrete resistances and lumped capacitances. The first-order lumped parameter method has been used since the late 1970s to model buildings when a fast and easily maintained computer code is required. Due to its poor dynamic performance for high thermal capacity spaces, a second-order model lumped parameter model was developed at the University of Liège by adding one node of building fabric mass and one air mass node (Lorenz F. & Masy G., 1982).

Although this was shown to give an improvement, it can fail badly when it is used to model a very high thermal capacity space with large temperature swings (Tindale, 1993). Therefore, a third-order model was developed by Tindale (1993). The third-order model still retains reasonable simplicity and can be solved at each time step without iteration and provides sufficient accuracy for modelling very high thermal capacity spaces. One application of the third-order model is the DBsim calculation engine which has been recently developed by DesignBuilder software Ltd.(2011).

The heat transferring through transparent surfaces, such as windows, is another key component of the cooling load. It includes reflection, absorption and transmission of direct and diffuse solar radiation, conduction and convection due to a temperature difference between the internal and external environments. To simplify the calculation, the thermal resistance of the glass is often ignored.

A validated model of calculating optical and long-wave radiation characteristics of slat-type blinds was presented in the ISO standard 15099 (ISO, 2003). A simple window model was developed later by Lawrence Berkeley National Laboratory (Arasteh, Kohler & Griffith, 2009) to match the requirement of practitioners. This model only needs the U-value and Solar Heat Gain Coefficient (SHGC) to translate these into the detailed properties for a 'representative layer'. Once the representative layer is defined, the calculation method in the ISO 15099 standard is applied to model the layer. For example,

the total solar gain from direct radiation can be calculated using the following equation:

$$TotalSolarGain = E_d * SHGC \quad \text{Equation 2-4}$$

where

E_d is incident solar spectral irradiance, W/m^2

The Solar Heat Gain Coefficient (SHGC) is the fraction of incident beam solar radiation that enters the room. It includes the transmitted solar radiation and the inward flowing heat from the solar radiation that is absorbed by the glazing. SHGC applies only to the centre of the glazed part of a window construction; it does not include the effect of beam solar radiation absorbed by a window frame or divider. Whilst glass manufacturers often describe the SHGC as calculated at standard summer condition, such as, 23.9 °C inside air temperature, 31.7 °C outside air temperature, 3.35 m/s wind speed and 783 W/m^2 incident beam solar radiation normal to glazing, the real value of SHGC is depended on the sun angle and wavelength.

For cooling load calculations, strong daily variations in solar radiation and outdoor air temperatures should not be ignored, because of the thermal storage capacities of building elements. In the most recent ASHRAE Handbook of Fundamentals (Mark, 2009), the Radiant Time Series Method (RTSM) (Spitler, Fisher & Pedersen, 1997) and Heat Balance Method were recommended to practitioners to conduct cooling load calculations (Pedersen, Fisher & Liesen, 1997).

The Radiant Time Series Method (RTSM) is a simplified method (i.e. may be used for manual calculations in principle) in which the calculation of heat storage and release in the zone is based on a set of predetermined thermal response factors, called radiant time factors. The transient conduction calculation is approximated using another set of predetermined thermal response factors, called periodic response factors. The procedure of RTSM can be summarised as follows (lu, 2002):

1. Calculate hourly internal heat gains;
2. Calculate hourly conduction heat gain for each surface using periodic response factors;
3. Calculate hourly solar heat gains through glazed surfaces;
4. Split all heat gains into convective and radiative portions;
5. Calculate hourly infiltration heat gains and add them to the convective portion of heat gain;
6. Convert radiant heat gains into hourly cooling loads using radiant time factors;
7. Sum the resulting hourly convective heat gains from step 5 with the converted hourly cooling loads from step 6.

The Heat Balance method involves the calculation of the outside face heat balance, transient heat conduction of walls, inside face heat balance and air heat balance. The wall conduction process may adopt one of the following methods: numerical finite difference, numerical finite element and Z-transform methods. All detailed equations are shown in ASHRAE Handbook Fundamentals (Mark, 2009). The advantages are that it contains no arbitrarily

set parameters, and no processes are hidden from view, and the only disadvantage of the Heat Balance method is that it requires detailed input and a computer implementation to solve the hourly simultaneous heat balance equations.

In the United Kingdom, the admittance method was originally developed to calculate maximum temperatures in natural and mechanically ventilated buildings (Danter, 1960), because air conditioned buildings were not popular in UK architectural practice at that time. This method was to deal with heat flow transmitted through the structure driven by sinusoidal external excitation (24-hour cyclical basis). In the 1970s, with the help of the digital computer, fabric admittance and related surface factors were introduced to indicate time lead/lags of temperature inside the zone (Milbank & Harrington-Lynn, 1974).

The admittance method is not suitable for buildings with a large thermal capacity or the effects of rapid changes in load (CIBSE, 2006), but it is the simplest of the dynamic methods available (Milbank & Harrington-Lynn, 1974). The method is given further justification by Davies (1994). The required input data for the admittance method are latitude of the building, internal design temperature, hourly dry bulb temperature, hourly values of direct and diffuse solar radiation, dimensions of the space, building material properties, internal heat gains, infiltration rate/ventilation rate, boundary conditions for internal surfaces and times of plant operation.

The calculation procedures of the computer based admittance method can be summarised as follows (CIBSE, 2006):

1. Calculate U-value, thermal admittance, decrement and surface factor for all fabric elements;
2. Calculate the position of sun and obtain direct and diffuse radiation normal to the sun;
3. Obtain hourly dry bulb temperatures;
4. Calculate the sol-air temperature for all external surfaces;
5. Calculate the radiation transmitted through, and absorbed within, the glazing;
6. Calculate solar, infiltration/ventilation, fabric and internal gains for environmental and air node;
7. Sum the gains and determine the cooling load for 24-hour plant operation;
8. Apply correction for intermittent plant operation.

For manual calculation of the admittance method, the thermal response, admittance, decrement factor, surface factor, and solar gain factor would be obtained from a design guide.

In the admittance method, the response of a space is the sum of two components: a daily mean value and a cyclic value (the difference between the instantaneous value and the mean value; often called the 'swing'). For example, the cooling load due to conduction is decomposed into two components: a steady component and a fluctuating component.

The steady (mean) component heat gain is calculated using following equation:

$$\phi_{mean} = F_{cu} \Sigma(AU)(T_{eo} - T_c) \quad \text{Equation 2-5}$$

Where

ϕ_{mean} is the mean fabric gain to the room

$$F_{cu} = \frac{3(C_v + 6\Sigma A)}{\Sigma(AU) + 18\Sigma A} \quad \text{Equation 2-6}$$

F_{cu} is the room conduction factor with respect to operative temperature

C_v is the ventilation loss, W/K

A is the area of the surface through which heat flow occurs, m²

U is the thermal transmittance of the surface, W/(m²•K)

T_{eo} is the mean sol-air temperature, °C

T_c is the mean operative temperature, °C

The fluctuating component which is cyclic variation about the mean is given by:

$$\phi_{var} = F_{cy} \Sigma(AU) f T_{eo(t-\phi)} \quad \text{Equation 2-7}$$

Where

ϕ_{var} is the swing in fabric gain to the room

$$F_{cy} = \frac{3(C_v + 6\Sigma A)}{\Sigma(AY) + 18\Sigma A} \quad \text{Equation 2-8}$$

F_{cy} is the room admittance factor with respect to operative temperature

Y is thermal admittances, W/K

f is decrement factor

$T_{eo(t-\phi)}$ is the swing in sol-air temperature at time $(t - \phi)$ where ϕ is the time lag associated with decrement factor

The sol-air temperature is expressed as a sinusoidal wave with a period of 24 hours. The method can be used to make a rapid assessment of peak summertime temperatures, space cooling loads and preheat requirement. However, due to the assumption of periodic excitations, the admittance method is useful for determining design cooling loads based on a fixed daily pattern of outdoor conditions, but would be cumbersome to use for predicting cooling loads of buildings based on actual weather conditions. The detailed information on the calculation of admittances and related parameters is defined in BS EN ISO 13786 (British Standards Institution, 2007b).

A series of analytical comparisons and experimental validation (Rees, Spitler & Haves, 1998; Spitler & Rees, 1998; Rees *et al.*, 2000a; Rees *et al.*, 2000b; Lu, 2002) were conducted to compare the difference between Heat Balance method, Radiant Time Series Method and Admittance method. The conclusion was made that there could be considerable convergence in these methods; the admittance method does not always give conservative results relative to the Heat Balance Method, and Radiant Time Series Method resulted in an over-prediction of cooling loads, compared to the Heat Balance method.

All the methods discussed above are theoretical models which reached a considerable degree of maturity. Another key element to achieve a good estimation of a peak cooling load is reliable input data including building characteristics, occupancy profiles and weather data. Domínguez-Muñoz *et al.*

(2010) conducted a sensitivity analysis to identify the most important uncertainties among input data, however weather data was not included in their research.

2.6 Summary

This chapter reviewed developments in weather data formats, future climate data and its use in predicting the future performance of buildings, thermal comfort (particularly in relation to summertime overheating), evolving British standards of building thermal insulation; and sustainable methods of delivering air conditioning to mitigate summertime overheating.

The review shows that it is necessary to evaluate weather data evolving from UKCP09 in a wider range of building types and to gain better understanding of climate change impacts on building performance, particularly on cooling design loads which building services designers are interested in.

CHAPTER 3

3 Selection of case study buildings and preliminary simulation studies

The main purpose of this preliminary study is to select, define and evaluate a range of case study buildings. Note that UKCP09 projections was not yet available at the time when this research was conducted, therefore CIBSE Future Design Summer Year data (CIBSE, 2008) were then used for an evaluation as a 'benchmark' method because they are in current use and there were published outputs based on their use which could be used for comparison and verification. CIBSE future weather data were generated using historical weather patterns with UKCIP02 (UK Climate Impacts Programme, 2002) projections. Fourteen non-dwelling buildings were selected as case studies to estimate how internal operative temperatures of these building are likely to change without air conditioning during the next 70 years. The simulations were conducted by using building simulation package EnergyPlus Version 4 (US Department of Energy, 2011a).

3.1 Exemplar buildings

The intention was to select 'real' buildings that either exist or have received planning consent and are therefore likely to be built, as well as to capture a range of construction styles and activity levels that would ensure contrasting

thermal comfort and energy demand results. The selected buildings were chosen with reference to the following criteria:

- Range – to ensure a contrasting spread of non-dwelling building types.
- Realism – to use only recently constructed buildings, or buildings that had recently been given planning consent (and would, therefore, most likely get built). Note that there was no intention to include alternative insulation standards because, for a consistent comparison of the results, all selected buildings were ‘standardised’ as the nominal standards of thermal insulation and leak tightness.
- Treatment – to ensure buildings that, at least in UK terms, could conceivably been designed to operate without any specific requirement for air conditioning based on current climate data.
- Usage – to ensure a range of usage patterns; some buildings in continuous use and others operated during normal business hours only.
- To include buildings occupied by comfort-vulnerable groups such as children and the elderly.

Accordingly, details of 14 buildings were obtained from stakeholders of COPSE project to form the basis of the modelling and, though most of these buildings actually exist in different towns and cities in the UK, they were all exposed to the same climate data which allows direct comparisons to be made. The COPSE stakeholder group was very helpful in choosing these buildings and the selection of buildings also reflects their interests.

The aged persons' accommodation, primary school and secondary school were selected because these buildings are used by vulnerable social groups with sensitivity to extremes in thermal comfort standards. The international airport, hotel, students' accommodation and prison are in continuous use by a wide range of social group types. The museum, archive building, theatre and library are buildings open to public with special requirements for lighting, ventilation and comfort standards dependent on internal processes as much as for human comfort. Three typical types of office buildings including multi-cellular offices, open-plan offices and hybrid (i.e. part open-plan, part cellular) offices were selected because they represent a very common group of office building types.

Note that there are atria inside the museum and prison buildings with fully-glazed roof. Fully glazed glass curtain walling is in use in the east and west façades of the top floor of the museum. High levels of glazing are also used in the reception area of the aged person's accommodation and in sight-seeing areas of the hotel.

Thumbnail summaries of the buildings are shown in figure 3-1 and further detailed information is given in table 3-1. Note that building 15 (the hospital) was not included in this preliminary study because the building model was not available at this stage in the research, but it was included in further studies in Chapter 5 and Chapter 7.

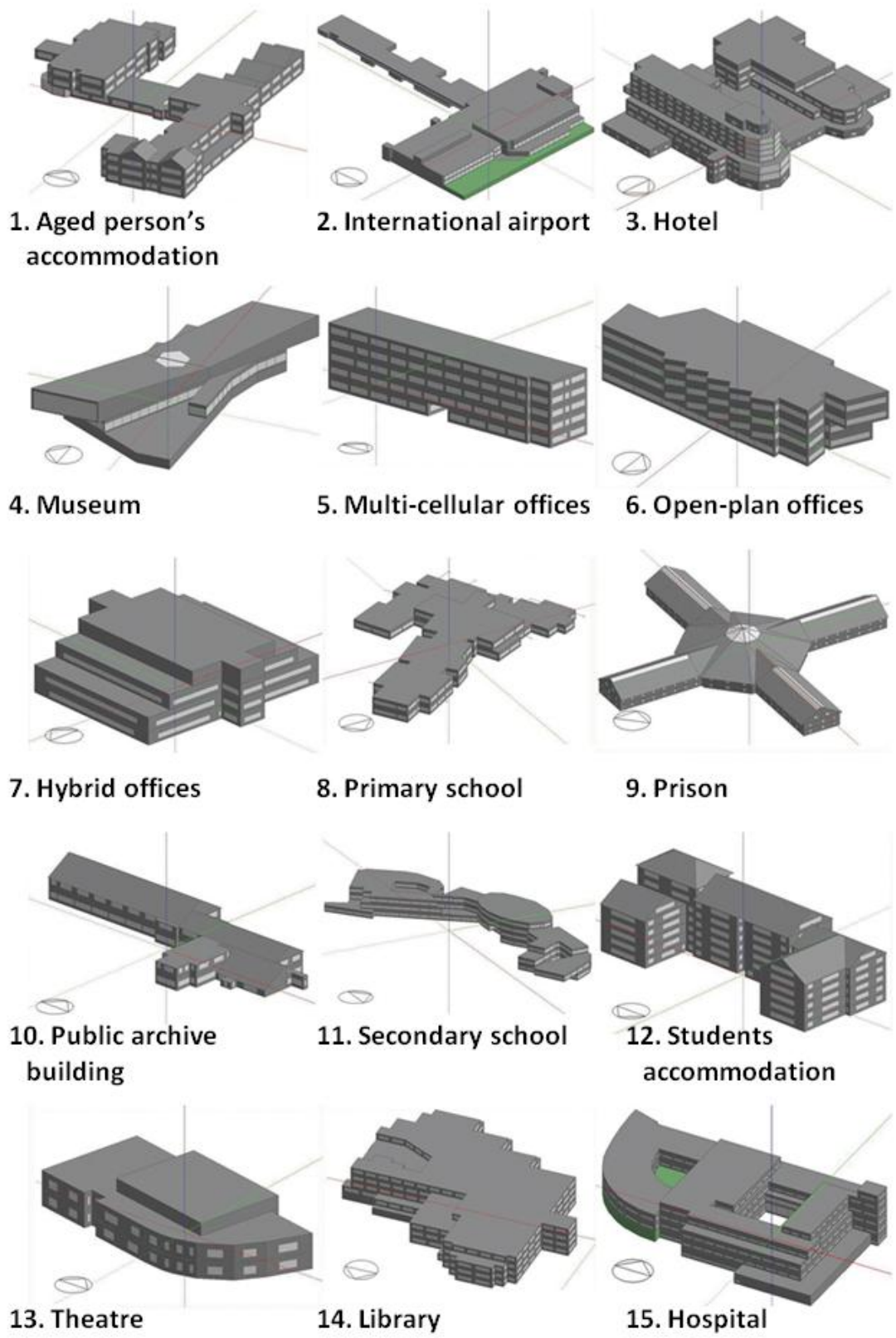


Figure 3-1 Exemplar buildings

Table 3-1 Building details

Building (Figure 3-1)	Zones	GFA (m ²)	TFA (m ²)	C _{Eff} (kJm ⁻² K ⁻¹)
1	51	5683	5345	425
2	77	49795	37445	305
3	51	21275	17910	338
4	40	12802	10518	300
5	36	4269	2977	466
6	24	3779	2632	476
7	22	8682	6172	357
8	25	4870	2844	285
9	67	10063	9411	500
10	23	2347	2201	470
11	64	13200	8259	397
12	86	9256	6053	503
13	14	1257	1010	409
14	64	20289	18530	348
15	145	21897	12786	259

KEY: GFA gross floor area TFA occupied/treated floor area C_{Eff} effective thermal capacity per unit GFA

Most of the buildings have been either newly built or refurbished to recent standards – either the 2002 edition of the UK Building regulations, Part L, or the 2006 edition. Briefly, the 2002 edition sets minimum standards of u-values for external walls and roofs of 0.35Wm⁻²K⁻¹ and 0.20 Wm⁻²K⁻¹ respectively, and external elevations glazed to a maximum of 36% of the overall envelope area using double air-cavity glazing (The Stationery Office, 2002). The maximum

building leakage to be equivalent to $10\text{m}^3\text{h}^{-1}\text{m}^{-2}$ of facade at 50Nm^{-2} . The later 2006 edition of the Regulations sets the same 'notional' standard but goes on to require a 23-28% reduction in carbon emission beyond that standard. Buildings (2) and (7) were constructed to earlier standards; the main differences of which were slightly higher u-values in external elements (i.e. external walls and roofs).

Buildings (4) – (8), (10), (11), (13) and (14) were scheduled to operate during normal business hours with, in some instances, additional weekend opening such as in the cases of the library and theatre. All other buildings were scheduled for continuous use. Allowances were made for occupancy density and casual heat gains due to electrical equipment and lighting using loadings typical for the building types involved. During summer, all buildings were excited with a scheduled natural ventilation rate of 3 air changes per hour plus a constant allowance for infiltration of 0.5 air changes per hour. This air change rate is considered to be a typical value that might be expected for mainly single-sided building spaces on still, or virtually still, warm summer days (Underwood, 2010). Thus, it might be considered as a 'worst case' ventilation scenario.

The thermal capacity of each zone was calculated using the simplified method set out in ISO 13786:2007 (British Standards Institution, 2007b) based on a maximum effective element thickness of 0.1m. Total values for each zone were added to give a building total and this value was then divided by the gross building floor area for comparative purposes. The construction element heat capacities ranged from $3.8\text{kJm}^{-2}\text{K}^{-1}$ to $312.8\text{kJm}^{-2}\text{K}^{-1}$ for all buildings.

3.2 Modelling assumptions

The completed building models were simulated in EnergyPlus version 4 (US Department of Energy, 2011a). EnergyPlus is an energy simulation program developed by the US Department of Energy and has been subjected to a series of verification tests and evaluations. A series of tests were conducted to maintain the accuracy and reliability of the software. The tests include analytical tests (such as HVAC tests based on ASHRAE research project 865 and building fabric tests based on ASHRAE research project 1052) and comparative tests, such as ASHRAE Standard 140-2007.

Another reason of choosing EnergyPlus is that the method and tool of generating weather data in EPW format (needed for EnergyPlus) is open to public access (i.e. EnergyPlus and its supported data and databases is a freeware facility), whereas the tools of generating weather file in other formats, such as FWT (used in IES) format or WEA (used in Ecotect), are commercial tools with restricted access to certain data and databases. Despite IES being able to read EPW files downloaded from the EnergyPlus website, it is not readily possible to read EPW files created by other users at this moment.

The following alternative weather files from the CIBSE future weather data set were used for simulations of summertime overheating with the essential assumption that all buildings were naturally ventilated in summer.

- Control data: London design summer year

- Future set 1: London 2020 design summer year predictions based on 'low', 'medium low', 'medium high' and 'high' carbon emission scenarios
- Future set 2: London 2050 design summer year predictions based on 'low', 'medium low', 'medium high' and 'high' carbon emission scenarios
- Future set 3: London 2080 design summer year predictions based on 'low', 'medium low', 'medium high' and 'high' carbon emission scenarios

The CIBSE future design summer years data are based on the use of the UK Meteorological Office's general circulation model results of predictions of changes in monthly average values of climate variables for the period 1962-2100 based on four future carbon emission scenarios ('low', 'medium low', 'medium high' and 'high'). These were firstly published under the United Kingdom Climate Impacts Programme in 2002 (UK Climate Impacts Programme, 2002). To obtain annual sets of hourly time series data required for energy simulations, the mean monthly predictions of changes to climate variables were used to generate time series adjustments (sometimes called 'morphing') to current time series weather data. These adjustments involved 'stretching' (i.e. scaling) and 'shifting' (i.e. time-adjusting) the current climate values of variables so that they have the same monthly average statistics as the predicted climate change variables. Full details of the method can be found in Belcher *et al.* (2005).

3.3 Simulation results and analysis

Results of simulated internal temperatures (T_{oi} , T_{ai} denoting operative and air temperatures respectively) are plotted against external (peak) temperature change, ΔT_e in figures 3-2, 3-3 and 3-4.

Figure 3-2 illustrates building internal overall peak operative temperatures in July against external peak temperature changes in July from the control period to 2080 (high carbon emission scenario). The 'overall peak' for each building is the **maximum** of peaks for all zones in that building in July.

Figure 3-3 shows internal averaged zone peak operative temperatures in July against external peak temperature changes in July from the control period to 2080 (high carbon emission scenario). The 'averaged zone peaks' is the average of peaks for all zones in one building.

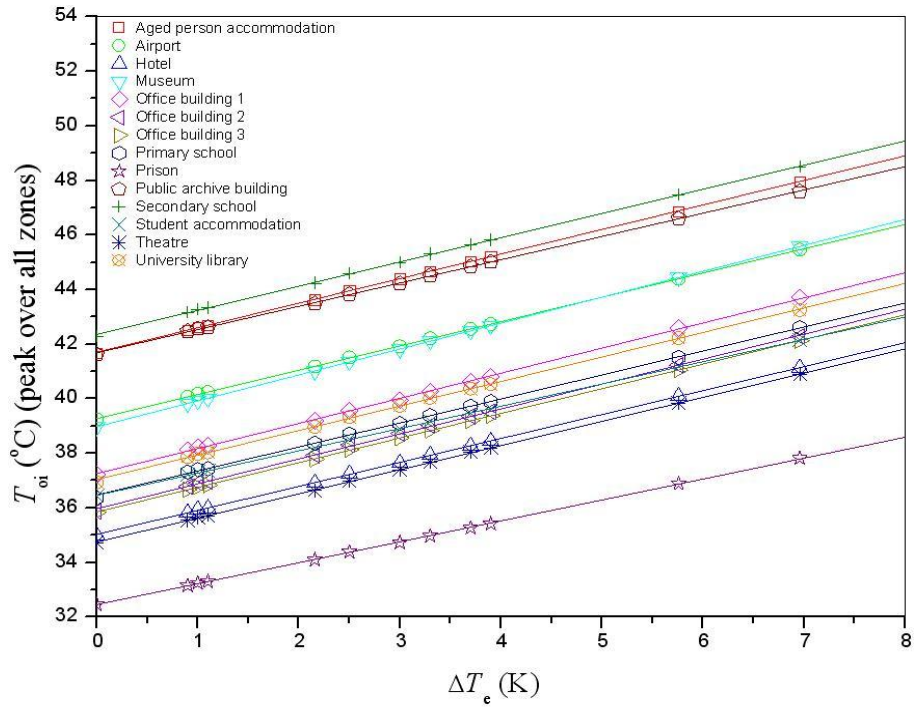


Figure 3-2 Internal overall peak operative temperature against external peak temperature change

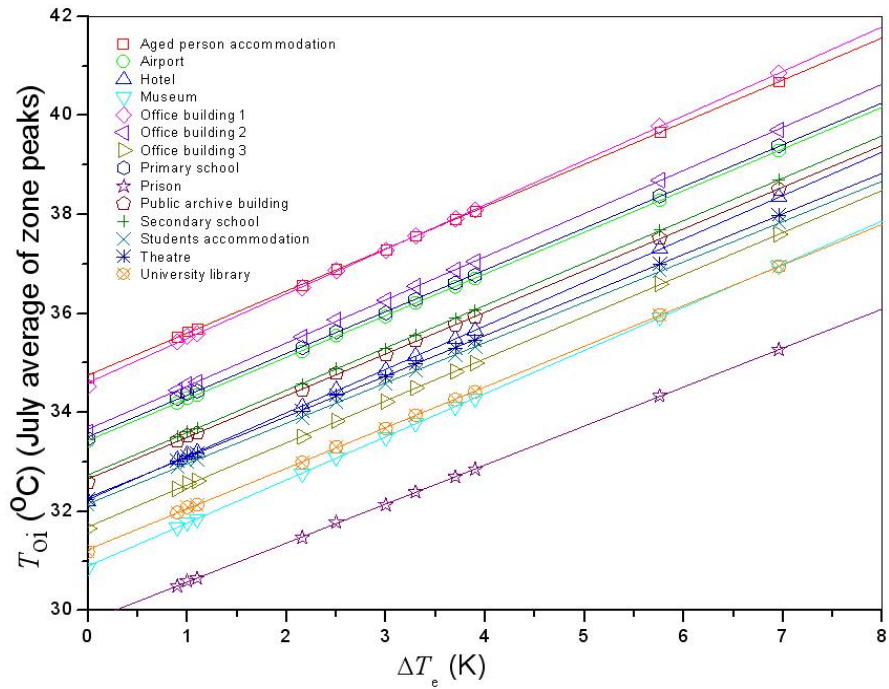


Figure 3-3 Predicted operative temperature – internal averaged zone peaks against external peak temperature change

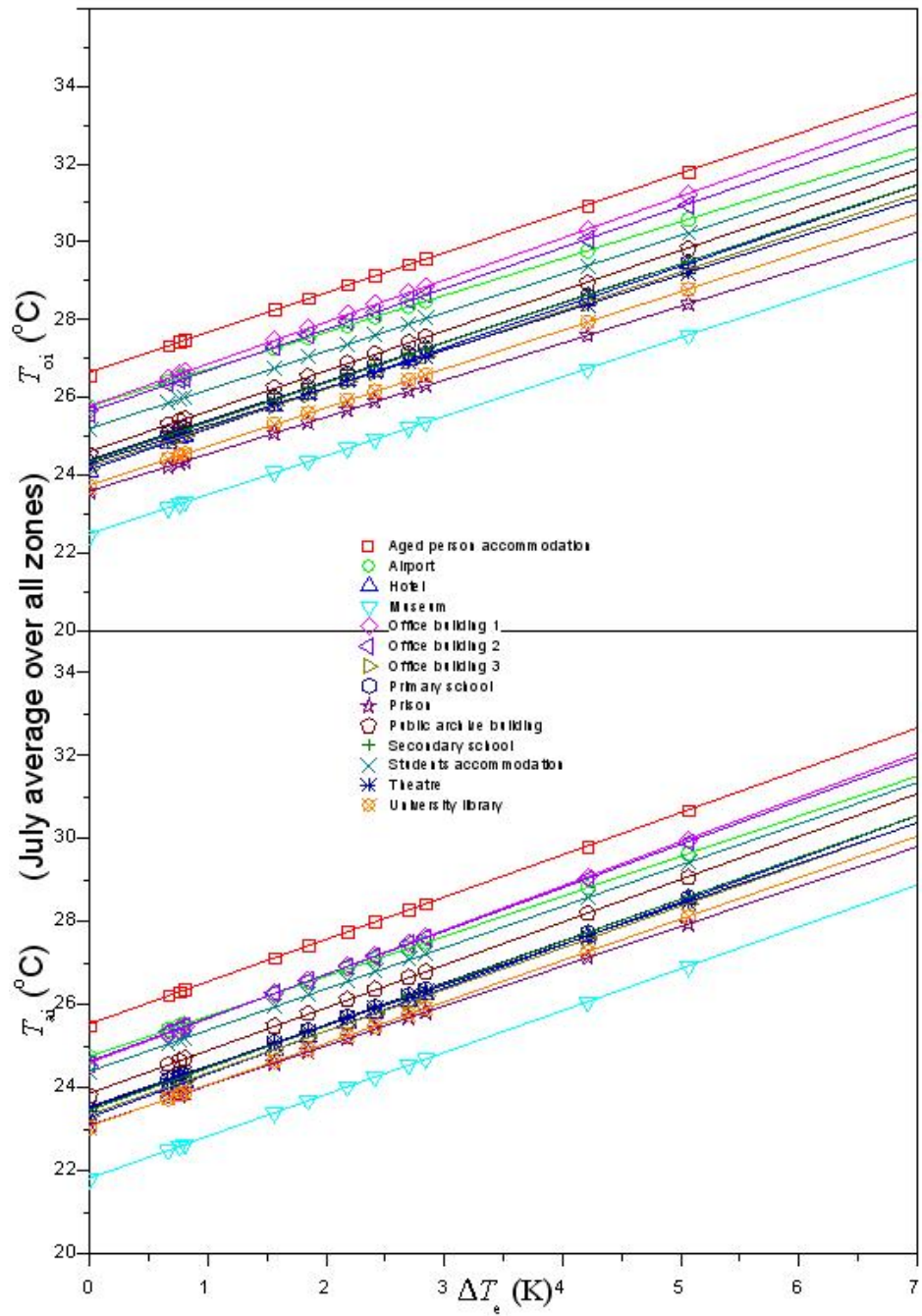


Figure 3-4 Comparison of predicted average dry bulb (bottom) and operative temperatures (top) against external average temperature change

Figure 3-4 shows average (over all zones and time period in July) internal operative temperature and air temperature changes against external average

dry bulb temperature changes from the control period to 2080 (high carbon emission scenario).

A strong linear relationship between internal operative (or air) temperature and external air temperature is evident in all results obtained (figures 3-2, 3-3 and 3-4). The reason of strong linear relationship is considered to be due to the way in which the future weather data were generated. The 'morphing' method did not change the hourly pattern of weather variables, therefore the pattern of internal operative or air temperature remain similar in future.

For short time period, such linear relationship between external and internal temperature should have vary due to the dynamic characteristics of the building materials. However for relatively long time period (from control across which these results are presented), the variation has been suppressed.

Figure 3-4 shows that the operative temperatures are generally slightly higher than the internal air temperatures as might be expected due to elevated internal surface temperatures arising from higher rates of solar radiation absorbed into these surfaces in summer.

One of the reasons for presenting these preliminary results in this format is that similar work had previously been done by Coley and Kershaw (2010) for a much smaller range of building types and it is therefore considered appropriate to use their results to verify preliminary modelling results of the present work. Coley and Kershaw (2010) define a 'global warming amplification factor' as:

$$C_{\text{mean}} = \frac{\Delta T_{i,\text{mean}}}{\Delta T_e} \quad \& \quad C_{\text{max}} = \frac{\Delta T_{i,\text{max}}}{\Delta T_e} \quad \text{Equation 3-1}$$

(where $\Delta T_{i,\text{mean}}$, $\Delta T_{i,\text{max}}$ is the difference in internal air or operative temperature at some time in the future based on mean and maximum values respectively and ΔT_e is the corresponding difference in external air temperature). Evidently, this is essentially the gradient of the slopes given in figures 3-2, 3-3 and 3-4 based on either internal air temperature or operative temperature as appropriate.

Coley and Kershaw (2010) dealt with houses, schools, apartments and offices. For their housing sample, they obtained results with the same linear characteristics as obtained in this work with warming gradients of between 0.817 and 0.958 (based on internal air dry bulb temperature only). In this work, a much wider range of commercial building types has been considered and the operative temperature was used as a better index for thermal comfort sensation (defined in this work as the average of the air dry bulb temperature and mean radiant temperature). A mean warming gradient of 0.882 (standard deviation: 0.045) has been obtained based on the peak (over all zones) operative temperature; 1.009 (standard deviation: 0.037) based on the overall average internal operative temperature for July; and 0.846 (standard deviation: 0.029) based on the average of the individual zone peak operative temperatures for July. Differences between internal overall average air dry bulb temperature and overall average operative temperature gradients were found to be very small.

3.4 Summary

The response in internal operative temperature to a warming climate by commercial buildings in the UK has been addressed in this chapter. Overall maxima, overall July averages, and the July average of zone peak temperature increases were obtained. Results indicate a strong linear relationship between internal operative temperature increase and corresponding external dry bulb temperature increase. The gradient of this increase was found to vary between 0.767 and 1.009 for a wide range of contrasting commercial building types with differing constructions and were consistent for either dry bulb or operative temperature results. The results were found to agree with similar findings of an earlier study which dealt with housing, schools and offices (Coley & Kershaw, 2010). The results of this (and the earlier) work provides valuable information to predict a timeline for the introduction of air conditioning in existing buildings as the climate warms.

The work in this chapter forms the preliminary stage of a larger study to develop design procedures and gain a better understanding of comfort and internal warming using United Kingdom Climate Projections. It also helps to verify building models created by author. The next chapter will focus on the development of Test Reference Year based on the latest climate projections (UKCP09) which represents a radically new way of assessing future climate impacts.

CHAPTER 4

4 Method 1: Development of Test Reference Years

In this chapter, the ISO 15927-4 (ISO, 2005b) method of generating Test Reference Year (TRY) data was adapted to generate TRYs from the UK climate projections 09 Weather Generator (UK Climate Projections, 2010). The method was compared with other methods proposed by research groups at Exeter University and Manchester University and also with the earlier UKCIP02 results forming the CIBSE FWYs (Chapter 3). To distinguish the methods and results proposed and described in this thesis, the method proposed here is named the Northumbria TRY method and the data generated by this method is named Northumbria TRY data. Similarly, TRY data forming the CIBSE FWYs, and the Exeter University and Manchester University data are named CIBSE TRY data (CIBSE, 2008), Exeter TRY data (Coley, Kershaw & Eames, 2011) and Manchester TRY data (Watkins, Levermore & Parkinson, 2011) respectively.

4.1 Method of generating Northumbria Test Reference Years

The method adopted to generate TRYs is broadly described in British Standard BS EN ISO 15927-4:2005 (ISO, 2005b). The standard requires a minimum of 10 years (normally, but preferably more) of measured data though, in this case, the raw data were modelled. The UKCP09 Weather Generator (UK Climate Projections, 2010) provided an opportunity to generate TRYs for the future because the Weather Generator can produce a set of raw data consisting of 30 years of hourly weather data (further details of the Weather Generator are given

in Kilsby *et al.* (2007)). The time slices available from Weather Generator are summarised in table 4-1.

Table 4-1 Available time slices of the UKCP09 projections

Nominal Time Period	Time Slice
Control (reference) data	1961-1990
2020s	2010-2039
2030s	2020-2049
2040s	2030-2059
2050s	2040-2069
2060s	2050-2079
2070s	2060-2089
2080s	2070-2099

In this work, the nominal time periods of 2030s, 2050s and 2080s were chosen together with the control period data; the former representing a sample of future time slices looking sufficiently far towards a time horizon likely to be of interest for the life span of buildings currently under development and construction. The number of probabilistic variations (or change factors) used by the UKCP09 Weather Generator for hourly data is 100. Thus, for each 30-year band of climate data, 3000 annual files of hourly and daily weather data were extracted to represent each of the 4 selected time slices (including the control data) at each of three carbon emission scenarios. The following procedure was then used:

1. The average of daily maximum and minimum dry bulb temperature, T ($^{\circ}\text{C}$), and relative humidity, H , and the total daily horizontal solar radiation, I (Whm^{-2}), were captured from the 3000 daily weather files.
2. For each calendar month in all years of data, the daily values of each variable from (1) were ranked in increasing order and the following was evaluated in order to arrive at a cumulative distribution function of the daily means for all years in the data set and for each variable $f(T_{m,i}, I_{m,i}, H_{m,i})$:

$$f(T_{m,i}, I_{m,i}, H_{m,i}) = \frac{K(i)}{N+1} \quad \text{Equation 4-1}$$

(where $K(i)$ is the rank order of the i^{th} value of the daily mean within that calendar month across the entire data set, N is the total number of days for that calendar month in the whole data set and m is the month number in the year).

3. For each month in each year the cumulative distribution function of the daily mean of each variable within each calendar month, $F(T_{y,m,i}, I_{y,m,i}, H_{y,m,i})$, was then obtained by ranking the variables in each month in increasing order and then applying the following:

$$F(T_{y,m,i}, I_{y,m,i}, H_{y,m,i}) = \frac{J(i)}{n+1} \quad \text{Equation 4-2}$$

(where $J(i)$ is the rank order of the i^{th} daily mean within a calendar month in one year, y is the year number and n is the number of days in each individual month).

4. For each month in each year of the data set, the Finkelstein-Schafer statistic, $FS(T_{y,m}, I_{y,m}, H_{y,m})$, was then obtained:

$$FS(T_{y,m}, I_{y,m}, H_{y,m}) = \sum_{i=1}^n \left| F(T_{y,m,i}, I_{y,m,i}, H_{y,m,i}) - f(T_{m,i}, I_{m,i}, H_{m,i}) \right| \quad \text{Equation 4-3}$$

5. The FS statistic of each variable in each individual month for the whole data set was then ranked in an ascending order and, for each month in each year, the individual variable rank values were added.
6. For the 3 months with the lowest total ranking, the deviation of the monthly mean wind speed from the corresponding mean value for each set of calendar months in the data set was obtained and the month with the lowest deviation in wind speed was selected to be included in the Test Reference Year.

The release of UKCP09 data excluded daily or hourly wind speed data. However, evapotranspiration rates were provided from which daily wind speed can be obtained by the Penman-Monteith equation (Allen *et al.*, 1998) which is re-arranged here for that purpose:

$$u_w = \frac{E(\delta + \gamma) + 0.408\delta(G - R)}{900\gamma \frac{(P_{vs} - P_v)}{(T + 273)} - 0.34\gamma E} \quad \text{Equation 4-4}$$

where:

- E reference evapotranspiration (mm/day)
- P_v vapour pressure (kNm⁻²)
- P_{vs} saturation vapour pressure (kNm⁻²)
- T mean daily temperature at 2m height (°C)
- G surface heat flux density (MJm⁻²day⁻¹)
- R net radiation at the surface (MJm⁻²day⁻¹)
- δ slope of the vapour pressure curve (kNm⁻²K⁻¹)
- γ psychrometric constant (kNm⁻²K⁻¹)

Watkins *et al.* (2011) evaluated the reliability of extracted wind speed data from evapotranspiration using Equation 4-4 based on a (non-UKCP09) dataset containing evapotranspiration rates and wind speed. The authors obtained a good agreement between Equation 4-4 wind speeds and the wind speeds in the measured data (coefficient of determination 0.94). They also concluded small instances of negative wind speeds (affecting less than 5% of the data). In the present work, negative wind speed results were set to zero and the very small instances of implausibly-high wind speed were cropped at 20ms⁻¹. The 20 ms⁻¹ threshold was used because historical daily winds (CIBSE, 2008) speed rarely exceeded this value.

Because each TRY consists of different statistically-representative months 'stitched' together to form one year, there were inevitable step transitions in the values of certain variables at midnight on the last day of each calendar month. These transitions were smoothed using cubic-spline fitting. The fitting interval used was a 16-hour period centred at the relevant midnight instants as recommended in BS EN ISO 15927-4:2005 standard. The variables affected were dry bulb temperature, vapour pressure and relative humidity.

In order to carry out a variety of energy simulations using in simulation package EnergyPlus (version 6) (US Department of Energy, 2011a), the weather data generated as described above were adjusted to meet the formatting and content requirements of the 'EnergyPlus Weather' ('EPW') file format. The procedures were followed:

7. Disjointed dry bulb temperature, vapour pressure and relative humidity values at midnight on the last day of each month were smoothed using a cubic-spline interpolation.
8. The EPW format requires the hourly dew point temperatures. This was calculated using hygrometric properties of humid air based on the known TRY dry bulb temperature, vapour pressure and relative humidity values. The equations (Barenbrug, 1974) are as follows:

$$Temperature_{dewpoint} = \frac{237.7 * r}{17.271 - r} \quad \text{Equation 4-5}$$

Where

$$r = \frac{17.271 * Temperature_{drybulb}}{237.7 + Temperature_{drybulb}} + \ln \left(\frac{RH}{100} \right) \quad \text{Equation 4-6}$$

$Temperature_{drybulb}$ = dry bulb temperature ($^{\circ}C$)

RH = relative humidity (%)

9. The direct-normal solar radiation (also required by the EPW format) was obtained from the known direct-horizontal radiation using standard solar geometry calculations. The equations (Szokolay, 2008) are as follows:

$$DirectNormal = \frac{DirectHorizontal}{\sin(SolarAltitude)} \quad \text{Equation 4-7}$$

Where

$DirectNormal$ = Direct normal solar radiation intensity (Whm^{-2})

$DirectHorizontal$ = Direct horizontal radiation intensity (Whm^{-2})

$SolarAltitude$

= $\arcsin(\sin(SolarDeclination))$

* $\sin(LAT) + \cos(LAT)$

* $\cos(HRA)$

* $\cos(SolarDeclination)$

Equation 4-8

$$HRA = 15 * (HourNumber - 11.5) * pi/180$$

Equation 4-9

SolarDeclination

$$\begin{aligned} &= \frac{\pi}{180} * (0.33281 - 22.984 \\ &* \cos(N) + 3.7872 * \sin(N) \quad \text{Equation} \\ &- 0.3499 * \cos(2 * N) + 0.03205 \quad \text{4-10} \\ &* \sin(2 * N) - 0.1398 * \cos(3 * N) \\ &+ 0.07187 * \sin(3 * N)) \end{aligned}$$

$$N = 2 * \pi * \left(\frac{\text{DayNumber}}{366} \right) \quad \text{Equation 4-11}$$

DayNumber = The number of the day in that year (1-365)

SolarDeclination = Solar Declination (between the earth-sun line and the equator plane), in radians

HourNumber = hour number at that day (0-23)

HRA = Hour angle from solar noon, 15 degree per hour, in radians

LAT = Latitude of the location, in radians

10. The cloud cover was converted in tenths based on the known sunshine hours. The night-time cloud cover was linear interpolated by using the cloud cover values at sunrise and sunset.
11. The EPW format requires the horizontal infrared radiation flux. This was obtained by first calculating the sky emissivity from the opaque cloud cover (in tenths) and the dew point temperature and then multiplying the sky emissivity by the Stefan-Boltzmann constant and the hourly dry bulb temperature (K) to the fourth power (US Department of Energy, 2010).

Very little information is available regarding UK *opaque* cloud cover values and this is clearly an avenue for further work. In the present work, it was assumed to be constant at 0.5 of the cloud cover value as previously used by Jentsch *et al.* (2008). The equations (US Department of Energy, 2010) are as follows:

$$Horizontal_{IR} = Sky_{emissivity} * Sigma * Temperature_{drybulb}^4$$

Equation 4-12

Where

$$Sky_{emissivity} = \left(0.787 + 0.764 * \ln \left(\frac{Temperature_{dewpoint}}{273} \right) \right) * (1 + 0.0224N + 0.0035N^2 + 0.00028N^3)$$

Equation 4-13

$Horizontal_{IR}$ = horizontal infrared radiation intensity from sky (Wh/m²)

$Sky_{emissivity}$ = sky emissivity

$Sigma$ = Stefan-Boltzmann constant = 5.6697e-8 (W/m²K⁴)

$Temperature_{drybulb}$ = dry bulb temperature (K)

$Temperature_{dewpoint}$ = dew point temperature (K)

N = opaque sky cover (tenths)

The above procedure was coded into Matlab scripts. Processing times for 3000 years of input files to a single TRY were typically less than 5 minutes on a conventional personal computer. By using Matlab scripts, one hundred daily

files were read into Matlab using the ‘dlmread’ function, and the data were treated as a pre-allocated array resulting in a significant reduction of computation time. Two user-defined functions were created to calculate the ranks and cumulative distributions of a series of numbers according to the definitions in ISO 15927-4:2005 standard. The user-defined functions can significantly reduce the computation time because Matlab creates a local workspace for a function’s local variables every time the M-file is called. All intermediate results were saved as MAT-files resulting in a significant increase of reading/writing speed. Programming technologies such as array pre-allocation and vector-based calculations also help reduce the computational time. Batch processing was also used. The names and descriptions of all scripts developed in this work are listed in table 4-2 and the full script listings are given in appendix D.

Table 4-2 Matlab scripts and input files list

File name	File description
runcontrol.m	used for batch processing
TRYDRY_Hu.m	main script generating TRY data for future time line
TRYDRY_Hu_control.m	main script generating TRY data for control period
rankt.m	user-defined ranking function
CDFiso.m	user-defined function for calculating CDF
GenDef.m	generating DEF file for converting data into EPW format
filename.mat	input file names
fileslist.xlsx	input file folders
list.lst	used for batch converting CSV to EPW

Users need to setup the locations of their UKCP09 raw data by editing the files highlighted in bold font in above list. A CSV file (TRY.csv) and a DEF file

(TRY.def) will be generated as outputs of these Matlab scripts. The EPW format of weather data can be produced by inputting the CSV and DEF files into the EnergyPlus Conversions tool which comes with the EnergyPlus simulation package. The 'list.lst' file can be used as input for batch converting CSV files into EPW files.

4.2 Verification

Verification of the results of Northumbria TRY data sets generated in the present work was carried out with reference to two alternative sets of methods:

1. The CIBSE Future Test Reference Year data (CIBSE, 2008).
2. Alternative generations of TRY data based on UKCP09 carried out by Exeter University (Eames, Kershaw & Coley, 2010a) and Manchester University (Watkins, Levermore & Parkinson, 2011).

Table 4-3 Timelines and carbon emission scenarios of TRYs

	C	2020s				2030s			2050s				2080s			
CIBSE TRY	C	L	ML	MH	H	/			L	ML	MH	H	L	ML	MH	H
Exeter TRY	C	/				/	M	H	/	M		H	/	M		H
Manchester TRY	C	L	/		H	/			L	/		H	L	/		H
Northumbria TRY	C	/				L	M	H	L	M		H	L	M		H

CIBSE, Exeter University, Manchester University and Northumbria University produced weather data for different timelines and carbon emission scenarios. Table 4-3 illustrates distribution details. 'C' indicates control or current period. 'L', 'M', 'H', 'ML' and 'MH' indicate low, medium, high, medium low and medium

high carbon emission scenarios respectively. The '/' indicates that weather data is unavailable for that timeline and carbon emission scenario.

The CIBSE Future Weather data forms an important reference point because it is the currently-available data in use by practitioners. These data were generated using the climate change scenario data forming the earlier UKCIP02. Because these scenarios were presented in the form of monthly data, it was necessary to decompose the data into hourly time series suitable for building simulation such that the hourly data preserves the same statistical distribution as the original monthly data. This was done using a technique called morphing full details of which can be found in Belcher *et al.* (2005). Briefly, files of existing CIBSE TRY climate data each consisting of 'typical' months derived from 1983-2004 records of actual weather data were used. These files were used to generate projected future weather data by either 'shifting', 'stretching' or shifting and stretching each existing climate variable. A shift involves adding the absolute mean change (from the UKCIP02 scenario data) to each existing hourly value for the relevant month and is applied when the climate change scenario is in the form of an absolute change to the monthly mean. A stretch involves a multiplicative adjustment of the existing variable based on the fractional change in the monthly mean value for the relevant month and is used when the scenario data is defined as a fractional or percentage change. A combination of shift and stretch is applied when both the mean and variance are required (e.g. a daily mean and its maximum and minimum values).

In the selection procedure applied by Exeter University (Eames, Kershaw & Coley, 2010a), 100 'typical' years from 100 samples of each year in each 30 year band were captured using the Finklestein-Schafer (*FS*) statistic (using a procedure similar to that described above but involving different variables). Each set of 100 months was then ranked based on ascending values of the mean monthly temperatures. They then select each month based on the same chosen percentile value (e.g. 10th, 33rd, 50th, 66th, and 90th). Thus, the 50th percentile January is joined by the 50th percentile February and so on to form a complete year. This two-stage process places a strong emphasis on dry bulb temperature which, it is argued, will form greater coherence between variables in each month. However, there is virtually no concurrency between months with this method (i.e. there is a negligible chance that a January from the original set of 100 Januarys will be joined by the corresponding February in the February set). Step changes in variables occurring at midnight on the last day of each month were smoothed by taking the average of the 5 hours of data either side of midnight. In following work, the 50th percentile weather files from Exeter were used as Test Reference Years with the assumption that they would be most 'typical'.

The method used by Manchester University (Watkins, Levermore & Parkinson, 2011) is very similar to that used in the present work. Both Manchester University and Northumbria University used the method recommended in BS EN ISO 15927-4:2005, but applied the method directly to 3000 years of weather data (100 probabilistic sets of 30 years data). There are two significant differences between this method and the method used by Exeter University.

First, Exeter University applied the *FS* statistic equally to dry bulb temperature, global horizontal solar irradiation and wind speed, whereas this method applied the *FS* statistic to dry bulb temperature, global horizontal solar irradiation and relative humidity (step 4 above) to select three candidate months, and then one month out of the three with lowest wind speed deviation was selected as the 'best' month to be included in the Test Reference Year. The second difference was the method of ranking. The method reported here added the separate ranks of the *FS* statistic values of the three climate variables together then chose three months with lowest total rank, while Exeter added absolute values of *FS* statistic of their three climate variables together, then chose the month with lowest total *FS* statistic value. In terms of interpretation, users may choose an Exeter file with a high percentile (e.g. 90th) to factor in risk. In the present work, design and risk are dealt with by using an alternative Design Reference Year (DRY) file of climate data which involves selections of candidate months using probabilistic percentiles. The detailed information of DRY will be reported in Chapter 6 and 7.

As to the relatively minor differences between the Manchester and Northumbria approaches, Manchester University implemented the ISO method in Turbo Pascal using conventional programming based on element-wise calculations, while Northumbria University applied the same method in Matlab to take advantage of superior array-handling, resulting in a significant reduction of computation time. The results of both methods were cross checked and there are two minor differences in calculation procedures. First, Manchester included weather data of the 29th February in leap years whereas Northumbria did not

include these days in order to compare the annual energy consumption among 365-day years only. Second, Manchester used 15ms^{-1} as an upper limit when generating daily wind speed from Equation 4-4, whereas Northumbria used 20ms^{-1} after examining the typical distribution ranges of wind speeds in historical UK weather data. The two differences will occasionally cause different selections of 'typical' months when precisely the same raw data are used, so they are not expected to give exactly the same climate data, but both will result in reasonably comparable 'typical' climate data files.

Results of two key weather variables are compared in figures 4-1 and 4-2 for three UK cities (Edinburgh (55.95N, 3.34W), Manchester (53.36N, 2.28W) and London (51.48N, 0.45W)), a variety of future time slices and carbon emission scenarios. Figure 4-1 shows air dry bulb temperatures and Figure 4-2 shows global horizontal solar radiation. The definitions of symbols used in following figures are listed in table 4-3.

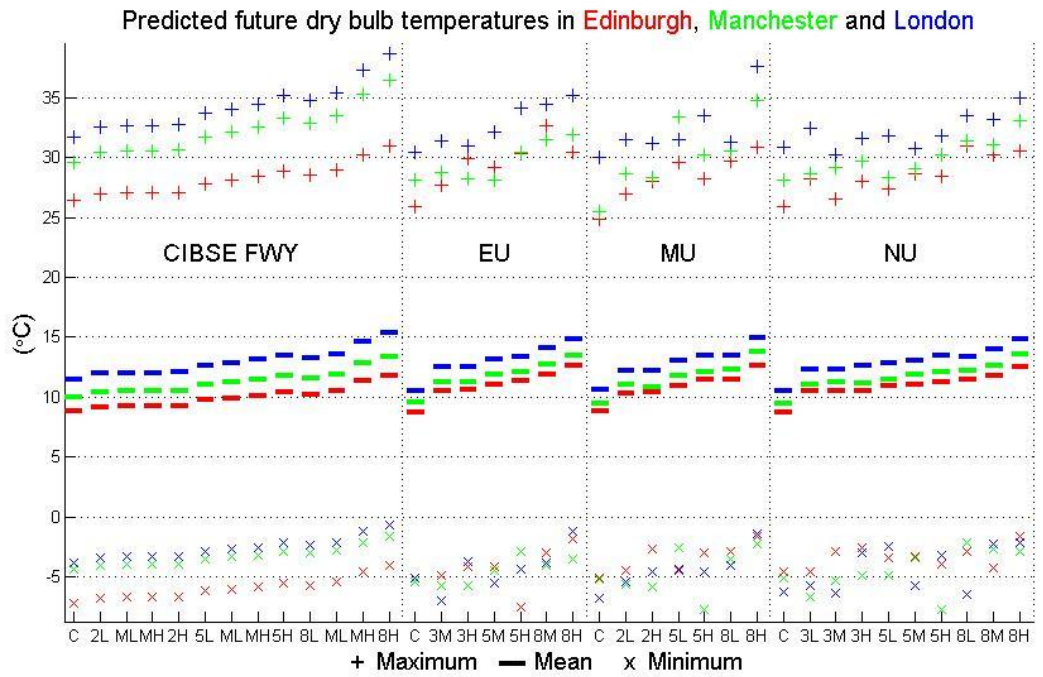


Figure 4-1 Comparison of data sets: dry bulb temperature

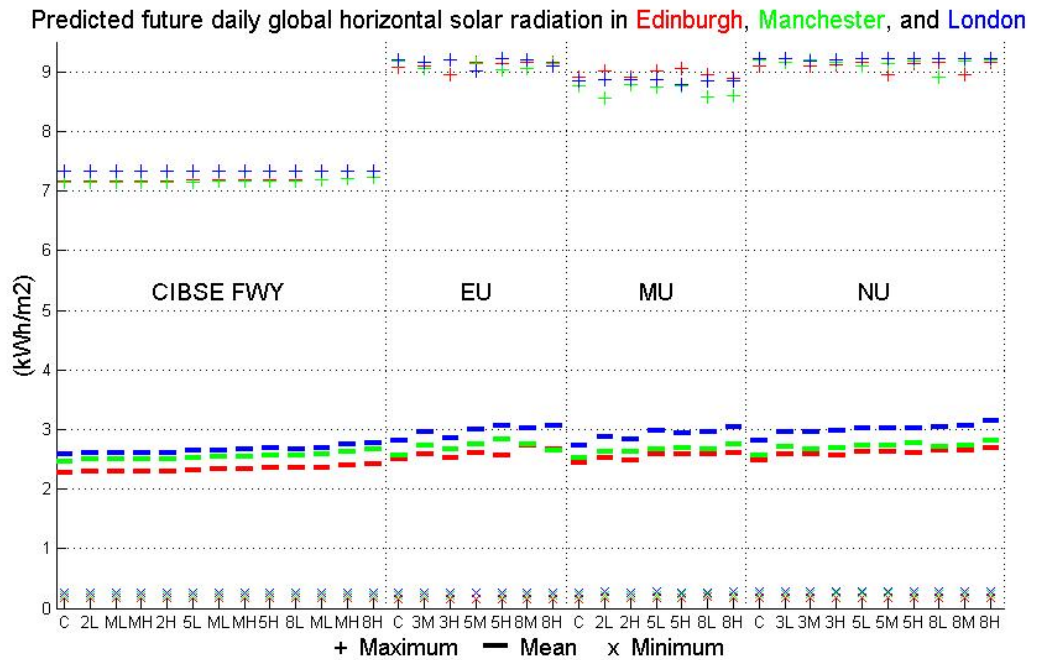


Figure 4-2 Comparison of data sets: solar radiation

Table 4-4 Key to symbols on figures in this chapter

CIBSE FWY Future CIBSE TRY or DSY	C	Control data (1983-2004)
	2L	2020s low carbon emission scenario
	ML	2020s medium low carbon emission scenario
	MH	2020s medium high carbon emission scenario
	2H	2020s high carbon emission scenario
	5L	2050s low carbon emission scenario
	ML	2050s medium low carbon emission scenario
	MH	2050s medium high carbon emission scenario
	5H	2050s high carbon emission scenario
	8L	2080s low carbon emission scenario
	ML	2080s medium low carbon emission scenario
	HL	2080s medium high carbon emission scenario
	8H	2080s high carbon emission scenario
EU Exeter Uni	C	Control data (1961-1990)
	3M	2030s medium carbon emission scenario
	3H	2030s high carbon emission scenario
	5M	2050s medium carbon emission scenario
	5H	2050s high carbon emission scenario
	8M	2080s medium carbon emission scenario
	8H	2080s high carbon emission scenario
MU Manchester Uni	C	Control data (1961-1990)
	2L	2020s low carbon emission scenario
	2H	2020s high carbon emission scenario
	5L	2050s low carbon emission scenario
	5H	2050s high carbon emission scenario
	8L	2080s low carbon emission scenario
	8H	2080s high carbon emission scenario
NU Northumbria Uni	C	Control data (1961-1990)
	3L	2030s low carbon emission scenario
	3M	2030s medium carbon emission scenario
	3H	2030s high carbon emission scenario
	5L	2050s low carbon emission scenario
	5M	2050s medium carbon emission scenario
	5H	2050s high carbon emission scenario
	8L	2080s low carbon emission scenario
	8M	2080s medium carbon emission scenario
	8H	2080s high carbon emission scenario

Additionally, the deviations from Northumbria data arising from the CIBSE TRY, Exeter and Manchester climate data are given in figures 4-3 and 4-4.

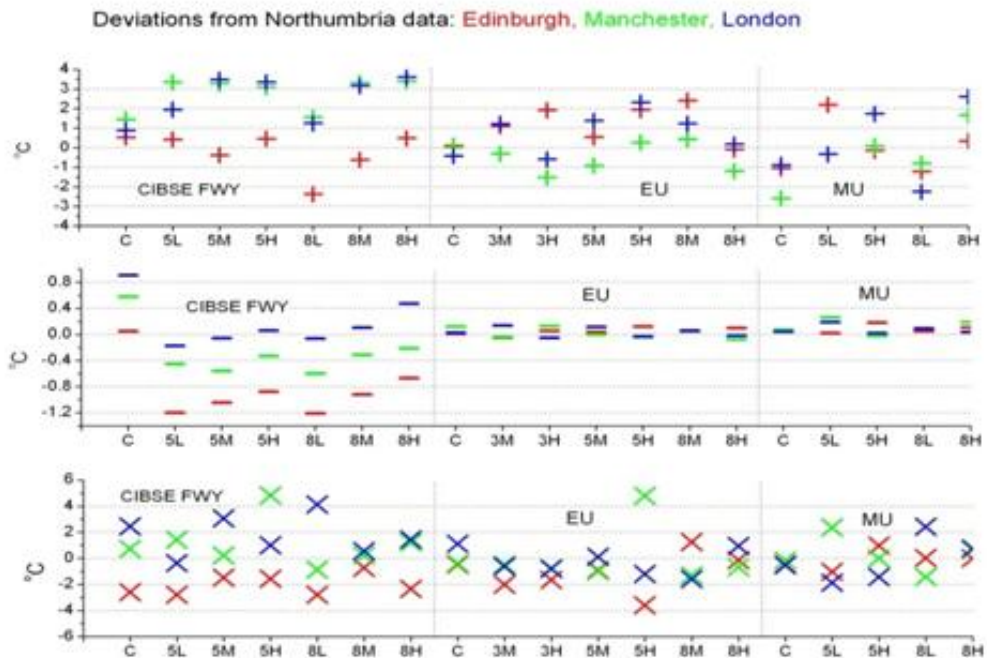


Figure 4-3 Deviations from Northumbria data in external air temperature (Top: max, Middle: mean, Bottom: min)

For dry bulb temperature, there is good agreement between the various data sets all of which support an increasing trend in temperature throughout this century the precise extent of which depends on the carbon emission scenario. The mean dry bulb temperatures of control period are notably higher for the CIBSE FWY data set than for all of the UKCP09-based results. This is considered to be due to different definitions of time period. Control data for the CIBSE FWY data is based on original data from the period 1983-2004 whereas all UKCP09-based methods use a control period from 1961-1990. Whilst there is some inevitable scatter in predictions of absolute maximum and minimum

external dry bulb temperatures due to the differences in the methods described above. The deviations in mean external air temperature between those methods using UKCP09 are negligible (Figure 4-3).

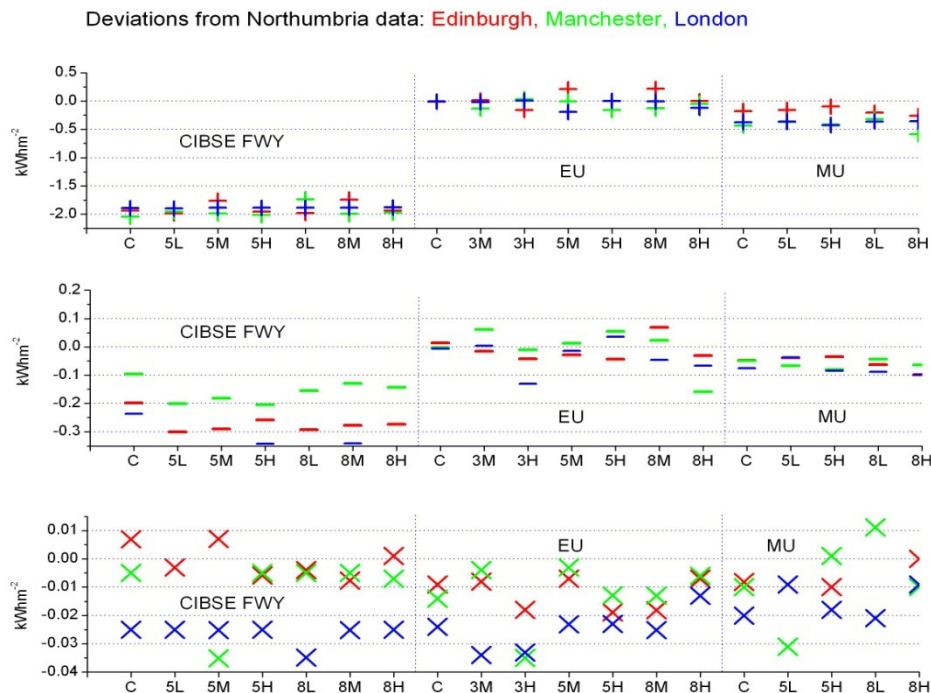


Figure 4-4 Deviations from Northumbria data in solar radiation

(Top: max, Middle:mean, Bottom:min)

For global horizontal solar radiation, there is again good agreement between the various data sets though the UKCP09-derived data all suggest higher peak radiation intensities than those predicted using the morphed UKCIP02-based data of the CIBSE FWYs (figure 4-2). An inspection of the data suggests that UKCP09 tends to predict higher periods of bright clear sunshine than existing data would suggest as first reported by Tham and Muneer (2010). Deviations between methods for those cases using UKCP09 are, however, very small (Figure 4-4).

In this chapter, the method of generating Test Reference Year data from UKCP09 Weather Generator was described, the data generated by this method was compared with data from other sources. The next chapter will focus on the application of these TRYs.

CHAPTER 5

5 Application of TRYs to building simulation

The aim of this chapter is to test the TRY data generated in previous chapter and investigate the impacts of the UK Climate Projections 09 (UKCP09) on internal building comfort (operative) temperatures, and heating and cooling energy demands.

Fifteen sample buildings have been simulated using a dynamic thermal modelling program (EnergyPlus Version 6) together with 4 sets of future Test Reference Year data which were produced by the UK Chartered Institution of Building Services Engineers (CIBSE, 2008), Exeter University (Coley, Kershaw & Eames, 2011), Manchester University (Watkins, Levermore & Parkinson, 2011) and the present work. Heating and cooling energy demand of the sample buildings, overheat percentage, summer and winter average indoor operative temperatures, at three locations (Edinburgh, Manchester and London) under control and future climate conditions (time slices: 2020s/2030s, 2050s and 2080s; carbon emission scenarios: low, medium and high) were simulated in order to compare the impacts of future weather data on building performance. The results for each individual building are given in appendices A1-A5.

5.1 Building modelling

The case study buildings used in this chapter are those described in chapter 3 with one further addition – that of a hospital building. The hospital building is a

recently-constructed oncology department which was selected due to extensive deep space planning and high internal heat gains due to scanning equipment, etc. The detailed information of the fifteen buildings was reported in chapter 3 section 1. Thumbnails of the buildings modelled are in figure 3-1 and key physical attributes of each building are given in table 3-1.

The models of fifteen sample buildings used for EnergyPlus simulation were built up in DesignBuilder software (DesignBuilder Software Ltd, 2011) and then the models were exported as IDF files which can be fed into EnergyPlus to conduct simulation. The reason of doing it in this way is that EnergyPlus (version 6) supports multi-core computer and batch simulation applications. This can significantly reduce the time of simulation and the amount of work. The version 6 is the most up-to-date version and its calculation speed has up to 25-40% execution time reduction in most simulations comparing with previous version.

Three simulations were then carried out on all buildings using the TRY weather files from the present work and from the three other comparative sources described previously. Simulations were conducted for Edinburgh (55.95N, 3.34W), Manchester (53.36N, 2.28W) and London (51.48N, 0.45W) from the control period to the 2080 high carbon emission scenario. The three simulations were:

- A 'freefloat' simulation to generate hourly operative temperatures for each building under conditions of natural ventilation. In all cases, a natural ventilation rate of 4 air changes per hour was used and this was

switched to become active in any zone when the internal operative temperature reached 25°C. Results from these simulations were extracted during the warmest summer months (June through August) and coldest winter months (December through February). In practice, the summer results would be used to help inform design decisions regarding the need for zone air conditioning, and the winter results could indicate how building performance without heating system.

- A cooling simulation in which it was now assumed that all treated zones would be air conditioned to a nominal set point temperature (range from 21-25°C dry bulb depending on type of room). Results from these simulations include both hourly time series cooling demands as well as annually-integrated total cooling energy demands.
- A heating simulation with all treated zones heated to set points of between 19°C and 21°C (depending on the nature of usage). Again, results from these simulations include both hourly time series heating demands as well as annually-integrated total heating energy demands.

The occupancy densities, occupied period profiles, equipment and lighting gain, heating and cooling setting points of all zones were configured according to the UK National Calculation Method database (DCLG, 2008).

The computer running time for a single simulation varies from 1 minute to 2 hours depending on the complexity of building models (mainly the number of zones), and the input and output settings. The total simulation time of all 4995

cases (15 buildings x 3 operation modes x 37 sets of weather data x 3 locations) lasted 4-6 days on an 8-core Windows workstation.

In the cooling simulation cases, the winter heating was not activated which had the advantage of reducing simulation running times slightly. In practice the heating would in any case be inactive outside the normal heating season periods (typically from May through to October). Therefore, at least one month will elapse from the end of the heating cycle and the start of cooling or peak summertime temperature cycle such that the heating cycle is unlikely to influence the cooling cycle significantly.

A constant effective mean allowance for infiltration of 0.5 air changes per hour was applied to all buildings and, additionally an allowance for natural/mechanical fresh air ventilation during occupied hours only of 10Ls^{-1} per person was applied. There are few zones having special requirements of ventilation, such as laboratories and treatment rooms in the hospital. The setting of these zones was configured according to the UK National Calculation Method database.

The simulation results of hourly indoor operative temperatures, cooling and heating loads were saved as a CSV format by EnergyPlus. A Matlab script was written to read the results and capture the essential results (i.e. building cooling and heating annual energy demands and freefloat operative temperatures). The operative temperature was chosen instead of air temperature because it forms the normal basis for assessing thermal comfort. The operative temperature was

calculated as the average of the air dry bulb temperature and of the mean radiant temperature in each room or zone.

Five figures were generated for each building: summer indoor average operative temperature during occupied hours; the percentage of occupied hours over an operative temperature of 28°C; the winter indoor average operative temperature during occupied hours (no heating and cooling present for three sets of results above); the annual cooling energy demand and the annual heating energy demand. All figures are presented in appendices A1-A5. A summary of a key sample of the results is given in the following sections. This summary deals with a sample of 4 of the 15 buildings; the aged person's accommodation, the multi-cellar offices, the secondary school and the hospital.

5.2 Results of freefloat simulation

Hourly operative temperatures for all occupied zones in conditions of natural ventilation condition were produced by an EnergyPlus 'freefloat' simulation. These results were generated by assuming natural ventilation at a constant rate of 4 air changes per hour would be introduced to each zone when the zone internal operative temperature exceeds 25°C and the external dry bulb temperature is less than the zone dry bulb temperature.

In order to assess the overheating risk, the percentage of annual occupied hours over an operative temperature of 28 °C was chosen as the criterion. The CIBSE Guide A (CIBSE, 2006) currently recommends that if this percentage exceeds 1%, air conditioning should be considered.

Figure 5-1 demonstrates the potential overheating situation for multi-cellar offices. The top, middle and bottom rows show simulation results of the building at the Edinburgh, Manchester and London locations respectively. The figure was broken into 4 columns to represent results based on all 4 weather data sources including the present work (CIBSE FWY, Exeter University, Manchester University and Northumbria University, ordered from left to right in the figure). Labels under the X axis indicate timelines and carbon emission scenarios listed in table 4-3.

The symbol 'x' in the figure indicates the percentage of annual occupied hours over an operative temperature of 28 °C for each zone, and the bar in the figure indicates the average of percentages of all occupied zones in the building. The pink, green and red bars in the figure highlight control, 2050 high emission scenario and 2080 high emission scenario results respectively.

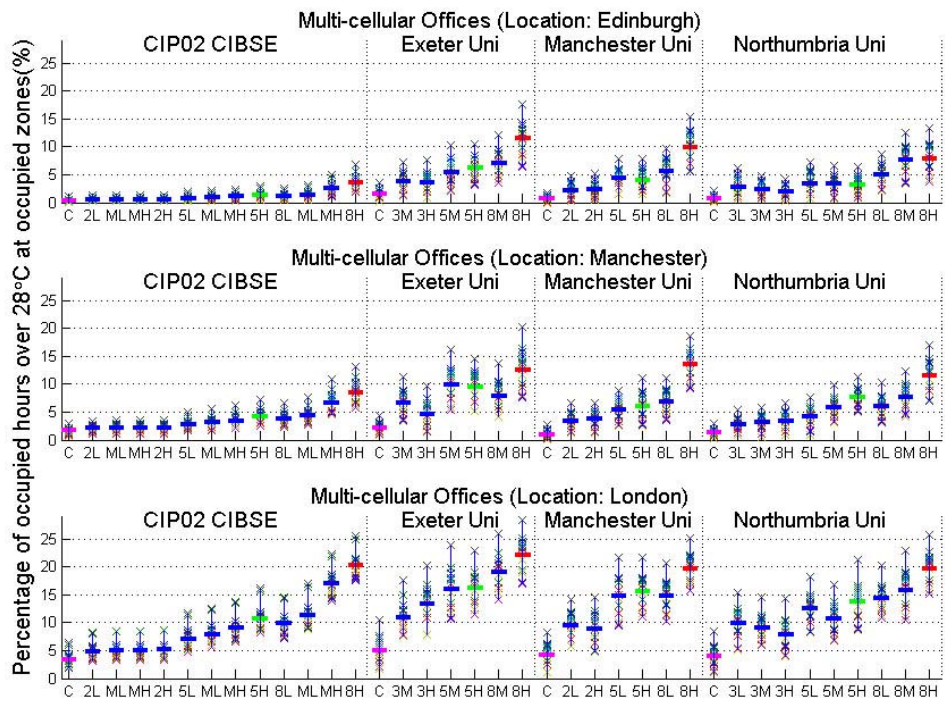


Figure 5-1 Overheat percentage of occupied hours (reference: 28 °C)

This pattern of visualising the results was also used in all figures in appendix A3, A4 and A5. The only difference is that symbol 'x' indicates different values. For example, it means zone summer average temperature during occupied hours at natural ventilation conditions in appendix A3.

Figure 5-1 shows that the duration of overheating by the end of this century will, typically, involve a fourfold increase. It is also shown that UKCP09 (for Exeter, Manchester and the present work weather file samples) and UKCIP02 Projections (CIBSE FWY data) in London indicate similar overheat percentages, but for the northern city Edinburgh, UKCP09 indicates a higher overheat risk in the late part of this century than UKCIP02. The overheat percentage from

Exeter data is significantly higher than the percentages predicted by the present work and the Manchester University data sample.

In order to view the performance of more buildings, figure 5-2 plots the average of overheat percentages for four case study buildings (i.e. individual zone values are excluded in this case). In general the trend lines for advancing time (and carbon emission intensity assumption) suggest a smoother growth in values due to the scaled and stretched CIBSE TRY data than is the case with the probabilistic data from UKCP09.

The Manchester and Northumbria results are generally in reasonably close agreement but there are minor anomalies due mainly to the different maximum wind speed assumptions used as detailed in Section 4.2. The more pronounced differences between the Exeter results and those from both Manchester and Northumbria are due differences in the methods used to select climate data as discussed in detail in Section 4.2.

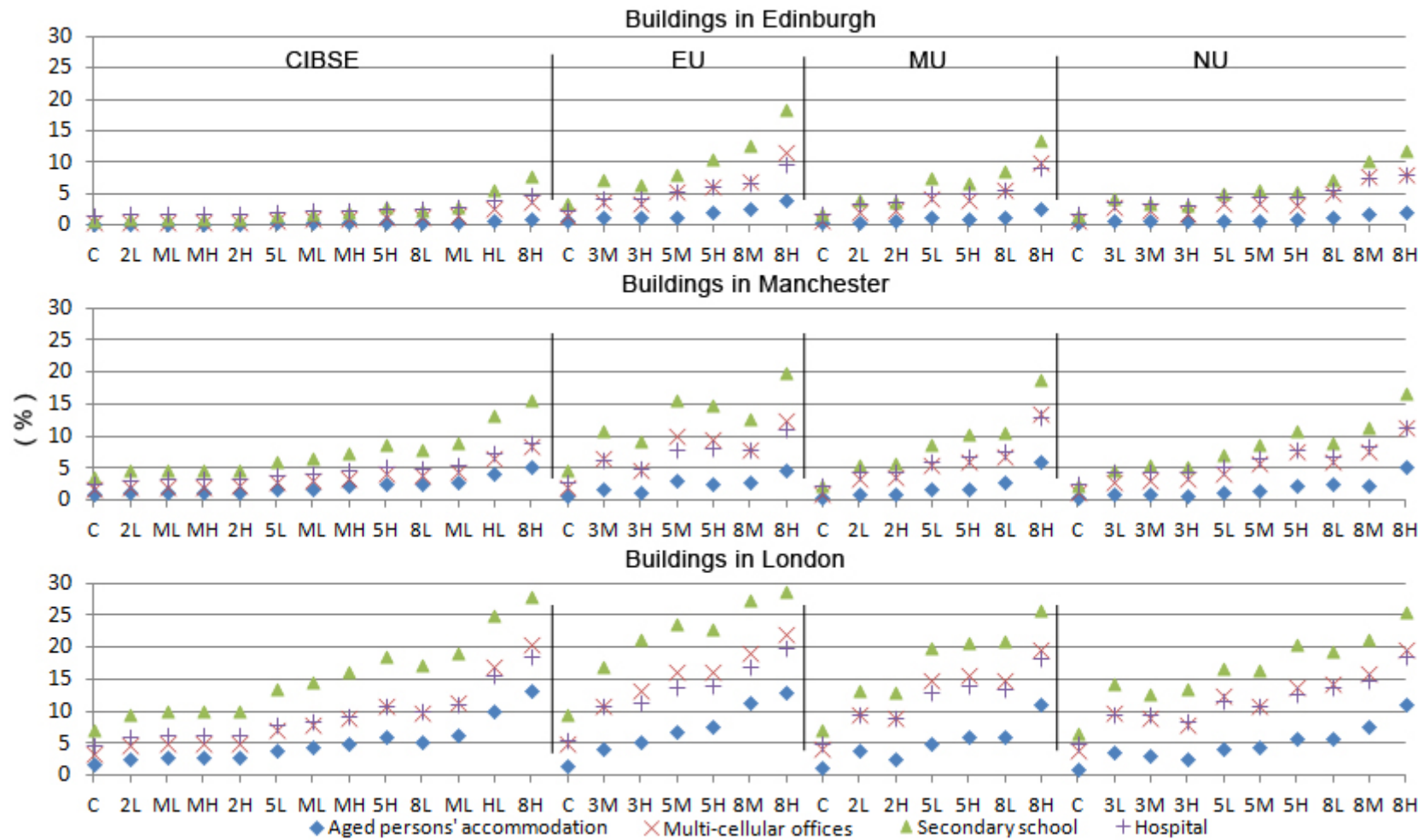


Figure 5-2 Averages of overheat percentages of occupied hours over 28 °C

%	Aged persons accommodation		Multi-cellular offices		Secondary school		Hospital	
	Max	Min	Max	Min	Max	Min	Max	Min
Control (1983-2004)	6.6	0.2	2.9	0.8	7.6	0.7	31.4	0.0
2020s low	7.7	0.5	3.4	1.2	9.0	1.0	34.3	0.1
2020s medium low	8.1	0.5	3.6	1.2	9.3	1.1	34.7	0.1
2020s medium high	8.1	0.5	3.6	1.2	9.3	1.1	34.7	0.1
2020s high	8.2	0.5	3.6	1.2	9.3	1.2	34.9	0.1
2050s low	9.9	0.8	5.0	1.8	12.1	1.9	38.0	0.1
2050s medium low	10.8	0.9	5.7	1.8	12.9	2.3	39.1	0.2
2050s medium high	11.2	1.1	6.1	2.0	14.1	2.4	39.6	0.2
2050s high	11.8	1.3	7.3	2.6	15.5	3.0	41.1	0.3
2080s low	11.3	1.2	6.6	2.3	14.7	2.7	40.6	0.2
2080s medium low	12.7	1.3	7.7	2.8	16.0	3.1	41.9	0.3
2080s medium high	16.6	2.5	10.8	4.5	22.2	5.2	45.8	0.8
2080s high	18.9	3.2	13.2	5.7	25.3	7.2	48.4	1.2
Control (1961-1990)	8.5	0.1	4.3	1.0	11.2	0.4	34.8	0.0
2030s medium	13.3	0.3	11.2	3.3	20.1	2.6	41.6	0.1
2030s high	13.1	0.1	9.7	1.5	18.4	1.1	43.2	0.0
2050s medium	18.4	0.7	16.1	5.3	25.8	5.7	45.4	0.3
2050s high	18.0	0.4	14.7	5.2	26.1	4.1	46.6	0.5
2080s medium	16.5	0.8	13.8	4.1	24.7	3.7	50.4	0.6
2080s high	21.7	1.4	20.3	7.6	32.7	8.3	52.3	1.0
Control (1961-1990)	6.5	0.0	2.7	0.1	7.0	0.1	33.6	0.0
2020s low	11.5	0.0	6.7	1.2	13.0	0.5	42.2	0.0
2020s high	9.7	0.2	6.6	1.3	14.0	0.9	40.0	0.0
2050s low	13.0	0.5	8.8	2.5	17.0	2.5	44.9	0.2
2050s high	14.4	0.3	11.1	2.6	23.2	1.6	46.8	0.1
2080s low	15.6	0.9	11.1	3.6	20.5	3.0	46.7	0.6
2080s high	20.3	3.2	18.7	9.2	29.8	8.6	54.1	1.6
Control (1961-1990)	6.4	0.0	2.9	0.3	6.7	0.0	33.2	0.0
2030s low	9.8	0.2	5.5	1.0	10.9	0.7	41.8	0.0
2030s medium	10.3	0.1	5.8	0.6	11.5	0.6	42.5	0.0
2030s high	10.9	0.1	6.7	0.8	14.2	0.1	41.5	0.0
2050s low	11.0	0.2	7.6	1.0	15.2	0.9	42.3	0.0
2050s medium	13.4	0.3	10.0	3.3	16.1	2.3	44.4	0.2
2050s high	14.3	0.6	11.4	5.0	19.4	2.9	46.0	0.3
2080s low	15.4	0.9	10.3	3.2	17.8	2.3	46.6	0.4
2080s medium	15.1	0.6	12.3	4.3	20.4	3.1	48.6	0.3
2080s high	19.2	2.6	17.0	7.1	27.2	6.6	52.4	1.2

Figure 5-3 Max and min of overheat percentages

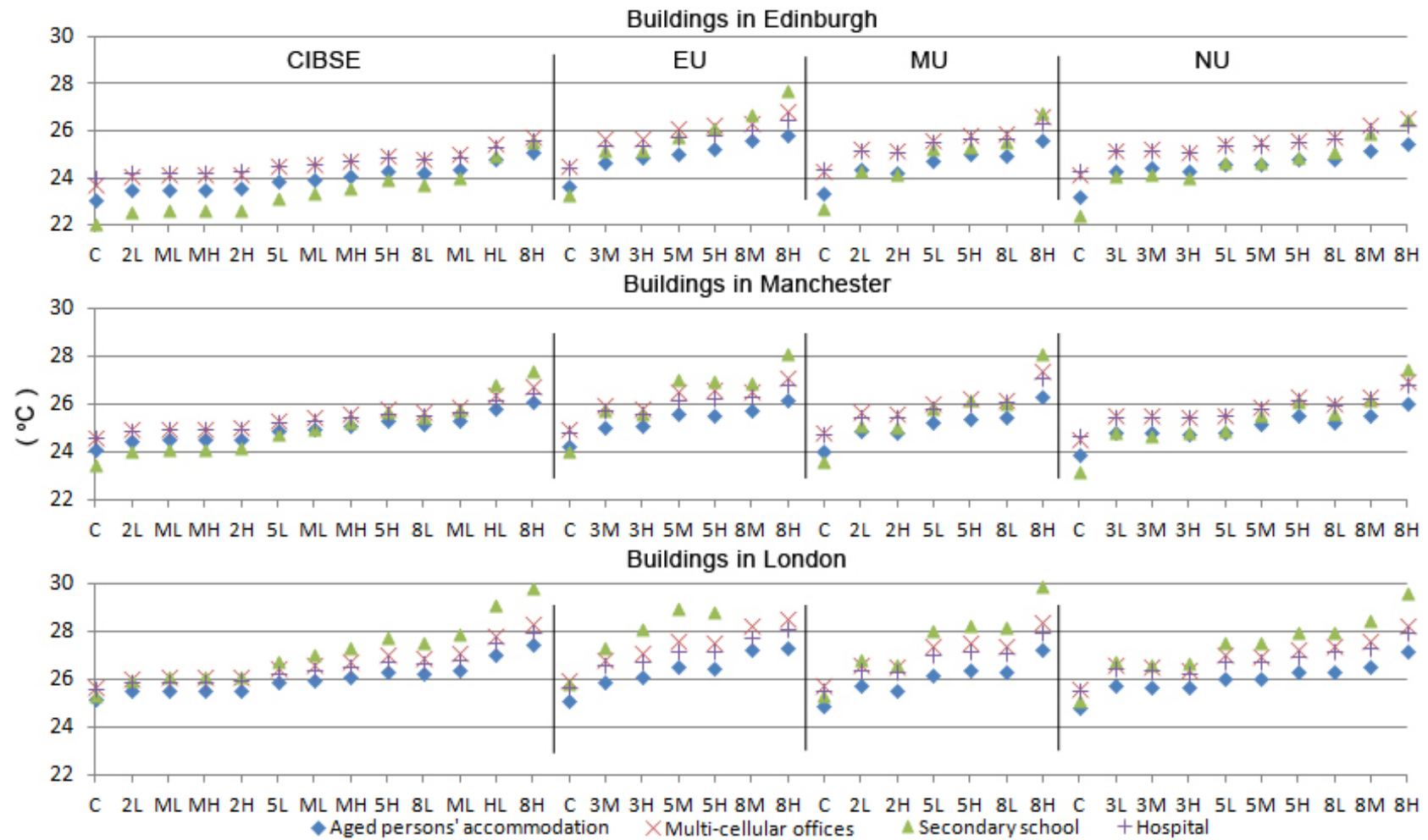


Figure 5-4 Averages of summer average operative temperature during occupied hours

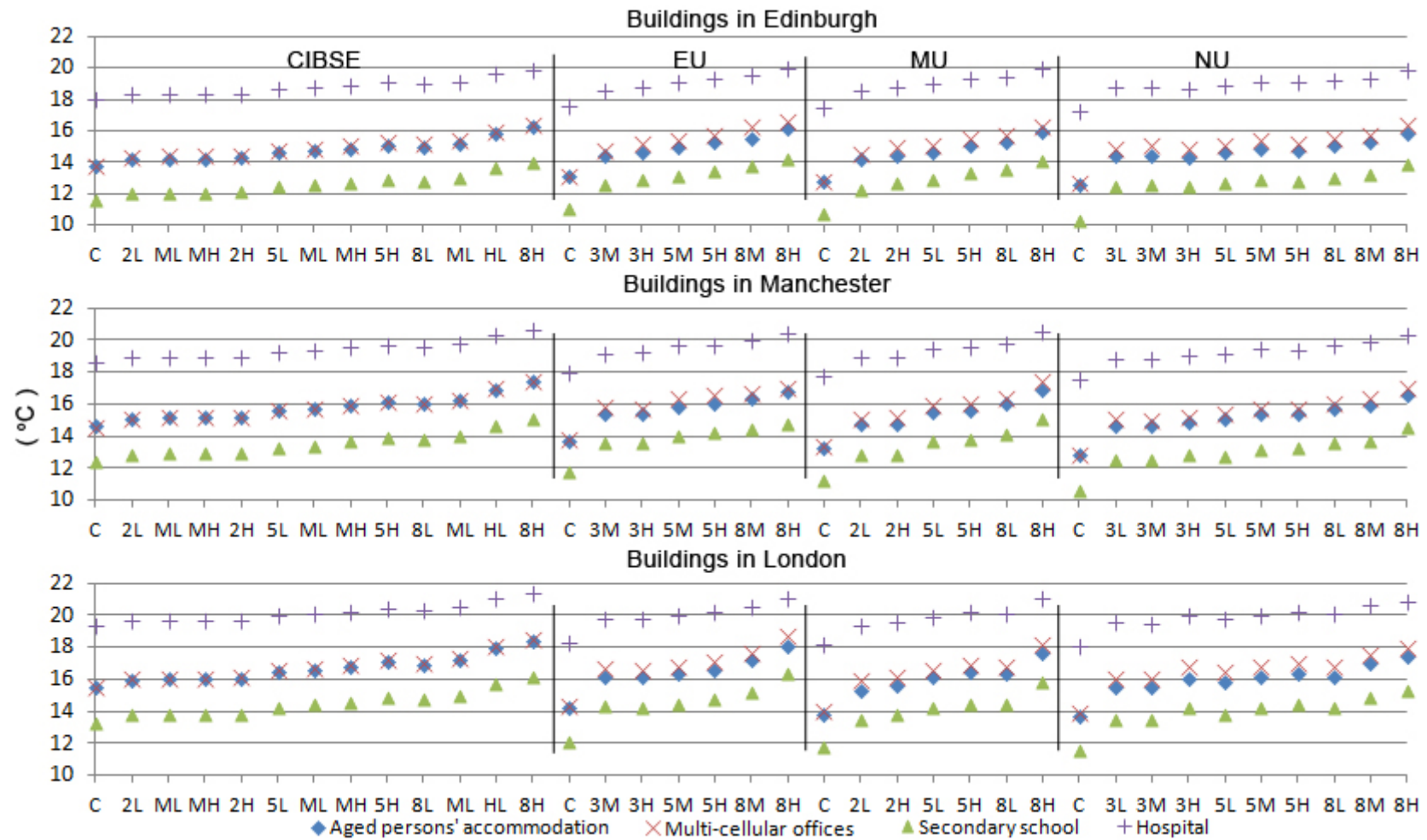


Figure 5-5 Averages of winter average operative temperature during occupied hours

Figure 5-2 also shows that the difference between UKCP09 and UKCIP02 in Edinburgh is in evidence in other building types.

The spreads of overheat percentages of different zones in each building are listed in figure 5-3. This shows the zone with biggest overheat percentage and the zone with smallest overheat percentage. The percentages are scale-coloured. As shown in the figure, the percentages of zones in the hospital are distributed more widely than in other building types due to the unusual features of this building – most particularly high internal process gains. The hospital is a deep-plan building with 145 zones for a high variety of usages.

Figure 5-4 shows averages of summer average zone operative temperatures during the warmest summer months (June, July and August) for four buildings in all selected UK cities, all TRY data sets, time slices and carbon emission scenario assumptions. All data sets for all city locations chosen are suggesting internal comfort temperature growth of around 4K through to the end of the present century from typical control data values of 22-25°C. In particular, the secondary school in London is exhibiting average operative temperatures in excess of 28°C from the middle of this century which has major implications for a trend towards at least partial air conditioning. All data tend to point to a higher degree of warming in London towards the end of the century than is the case in the two northern cities chosen.

The increase rate of temperature for the aged persons' accommodation appears to be lower than other buildings due to smaller spaces, traditional construction, and low internal heat gains.

Figure 5-5 shows averages of winter average zone operative temperatures during the winter months (December, January and February) for the four sampled buildings in all selected UK cities, all TRY data sets, time slices and carbon emission scenario assumptions. Note that heating systems do not present in this case. The temperatures here indicate how building performance in winter without heating system. It is evident that there is a warming trend in winter as well, but the increase in winter is less than the increase in summer.

This figure also indicates the spread of the average winter temperature of the buildings is wider than the spread in summer. The school example suggests a slower growth trend due to the operational assumption of it being unoccupied during Christmas and the New Year holiday. The higher average internal temperatures evident in the hospital example reflect high internal heat gains in this case due to the deep plan nature of this building and the high process heat gains.

5.3 Results of cooling and heating simulation

Figure 5-6 shows results of simulated building (sensible) cooling loads. The building cooling load expressed as the peak of the sum of simultaneous zone cooling loads divided by the treated floor area of the building. The much higher peak cooling loads evident in the hospital example reflects high internal heat gains in this case due to scanning, diagnostic and radio therapy equipment. The trend lines for advancing time (and carbon emission intensity assumption) suggest a smoother growth in values due to the scaled and stretched CIBSE

TRY data than is the case with the probabilistic data from UKCP09. (Further studies are presented in chapters 7 and 8 using Design Reference Year data).

Figure 5-7 gives the simulated annual zone sensible cooling energy demand (whole building) expressed in kWh per unit of treated floor area. Sensible room (zone) cooling demands can be expected to increase throughout this century towards 100Wm^{-2} from control values of around 50Wm^{-2} for conventional narrow-plan buildings and from 100Wm^{-2} towards 150Wm^{-2} for the high intensity deep plan hospital building used in this work. However, the impact on annual cooling energy demand is, if anything, even more pronounced with most results suggesting a near doubling in annual energy use for room cooling in air conditioned buildings with reference to control data.

Figure 5-8 shows results of the spread of simulated zone heating design loads, again expressed as the peak of the sum of simultaneous zone heating loads divided by the treated floor area of the building. Note that the high heating design loads evident in the hospital example do not conflict with the high average temperature in winter evidenced in figure 5-5, because the thermal performances of 145 zones in the building varies and the averages could not reflect all information for individual zones. Also note that the heating design loads simulated using all of the weather data samples do not have a clear decreasing trend.

Figure 5-9 gives the simulated annual zone heating energy demand (whole building) expressed in kWh per unit of treated floor area. Heating demand simulations tend to reduce by end of this century due to warmer winters if trends

in insulation and air tightness were to remain unchanged. However, there are likely to be significant improvements in the latter over the course of the next few years if the UK is to meet its various carbon reduction targets and sharp reductions unrelated to climate change might be expected as existing buildings receive refurbishment and future new buildings roll through. Though the peak heating loads (figure 5-8) are barely affected by the climate change features captured in results, the annual energy demand due to heating shows a marked reduction (figure 5-9) of, typically, 50% of the control values. This would seem to suggest that a need towards radical improvement in thermal insulation standards in the UK as mentioned above may require to be considered in a measured and incremental manner.

In summary, all of the results point to a generally good predictive agreement between simulation results obtained using the former (UKCIP02) climate change scenario data which forms the CIBSE TRY set, and methods that draw from UKCP09.

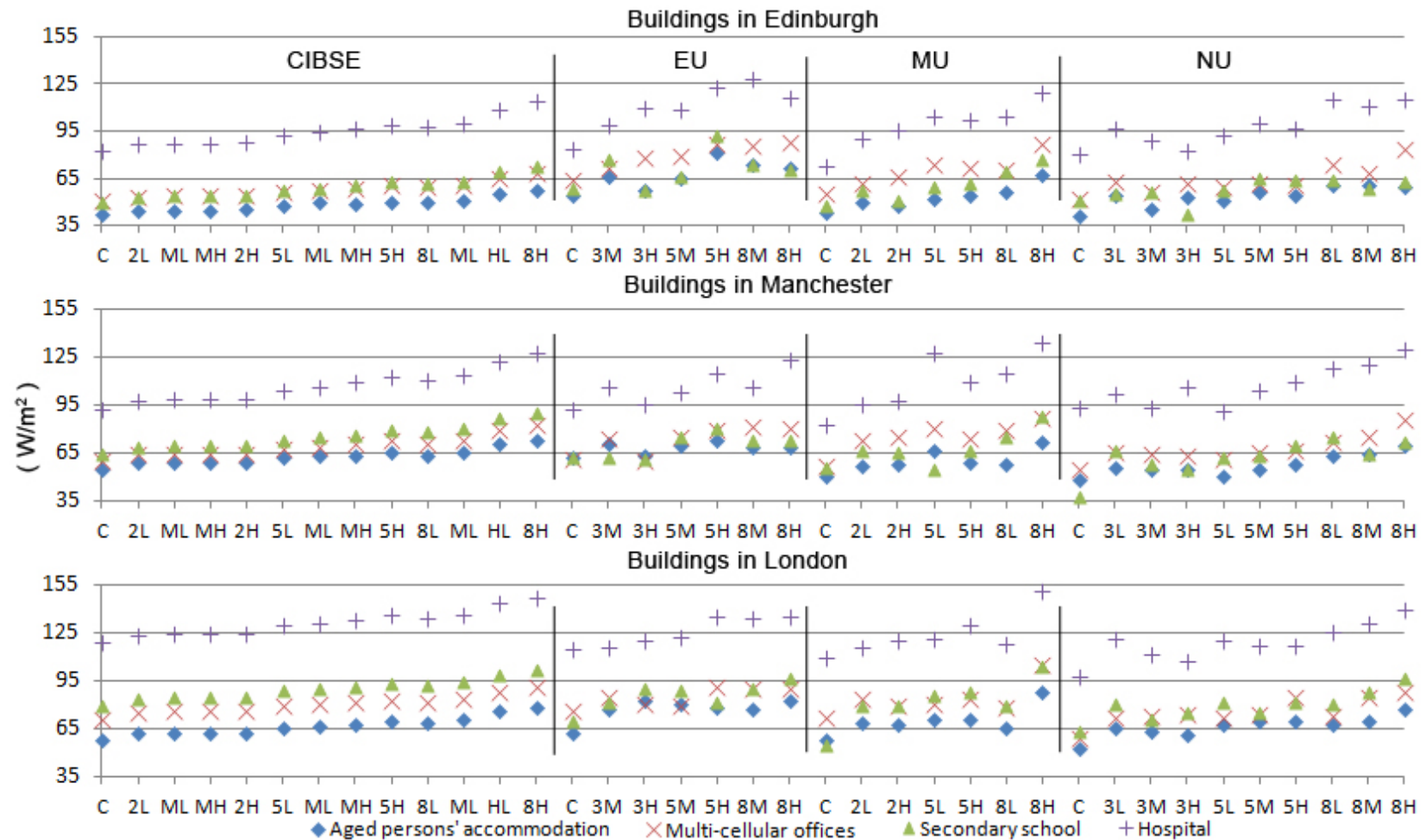


Figure 5-6 Simulated peak of the total zone cooling loads per unit of treated floor area

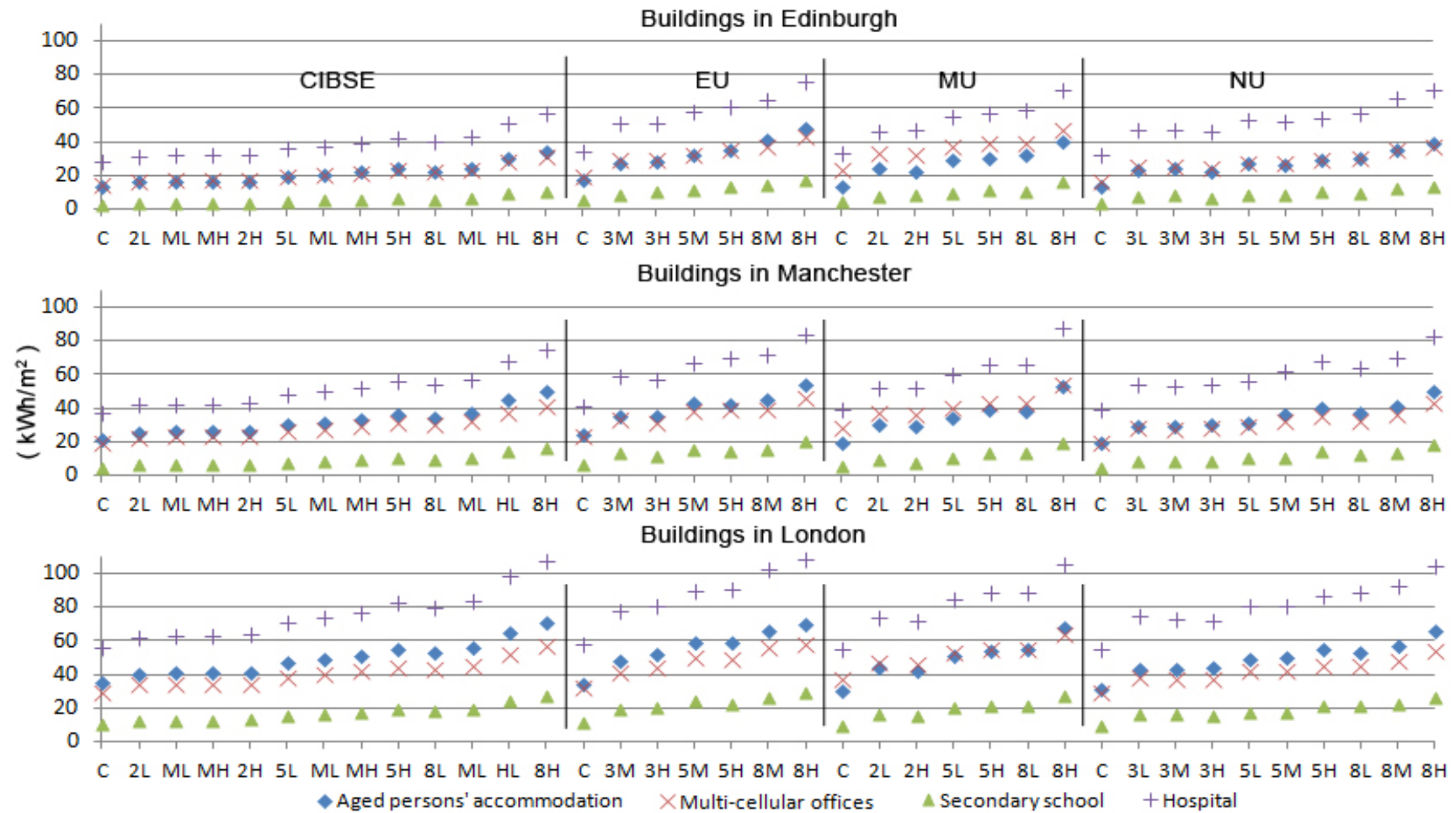


Figure 5-7 Simulated annual building sensible cooling energy demand

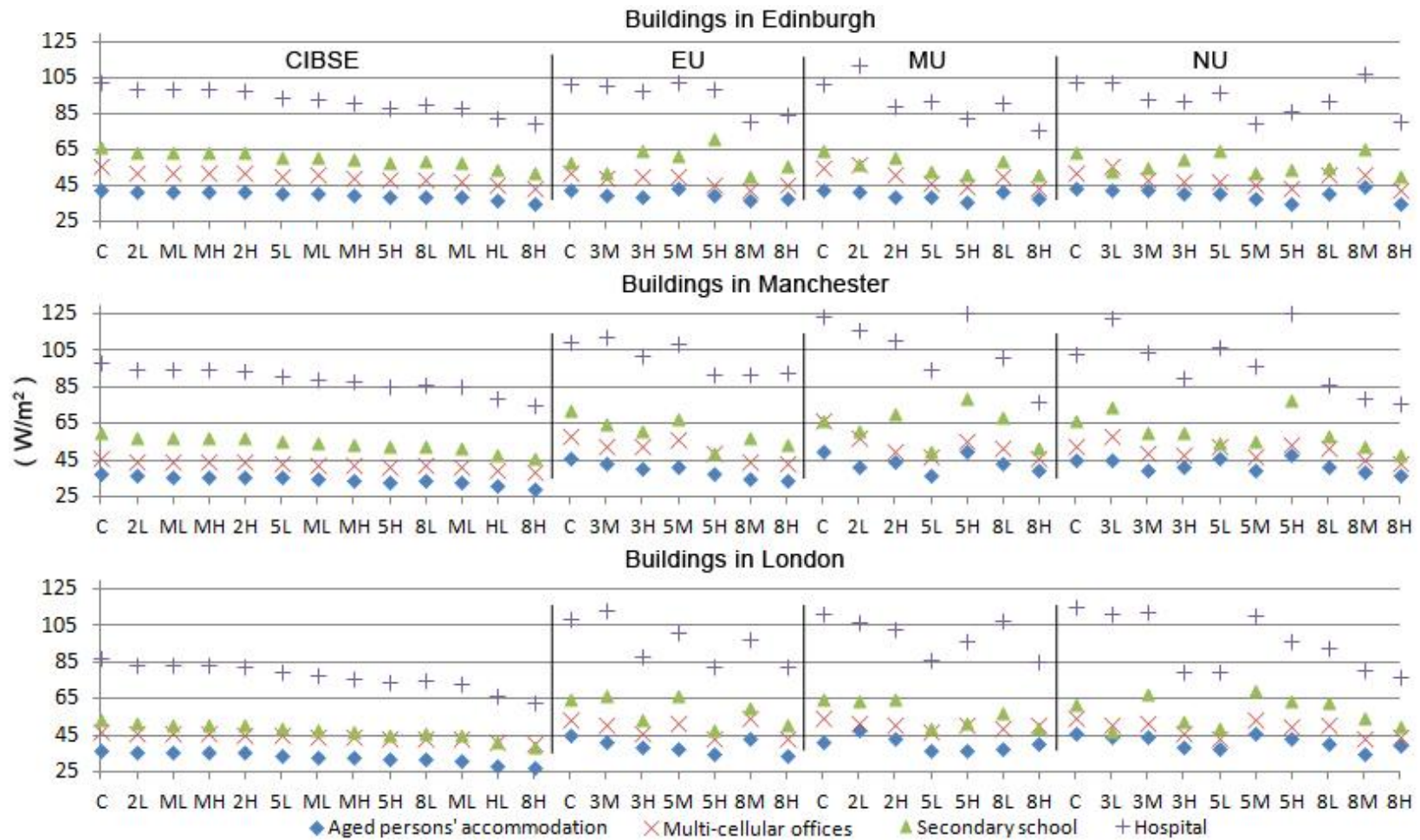


Figure 5-8 Simulated peak of the total zone heating loads per unit of treated floor area

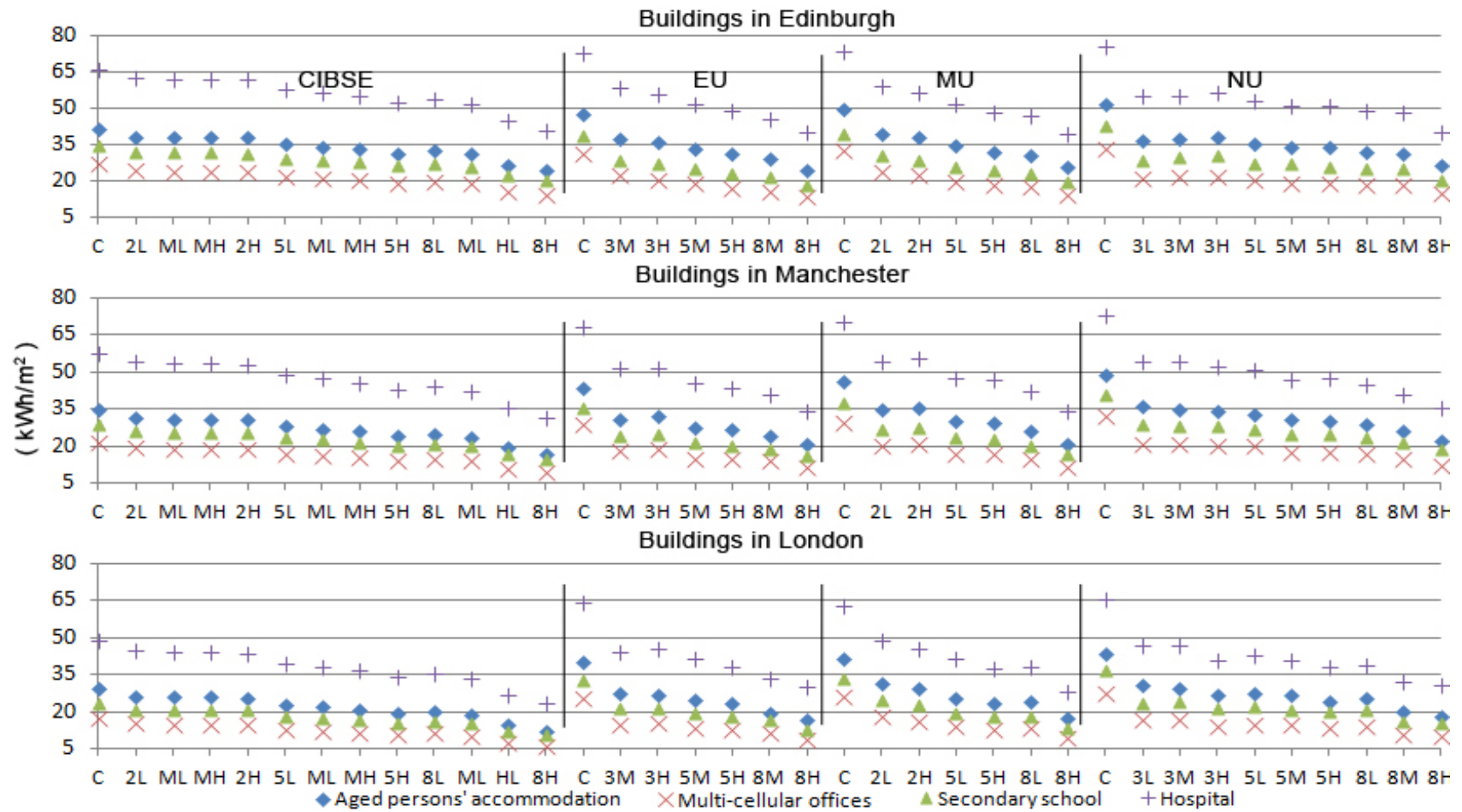


Figure 5-9 Simulated annual building heating energy demand

5.4 Conclusions

Data from the new UKCP09 climate change projections can be more easily and directly translated into future test reference years suitable for building energy simulation than was the case with previous data sets of this kind. In this work, test reference year data have been generated for a range of future time slices based on UKCP09 and used to simulate the future response of 15 contrasting building types from which a sample of 4 has been presented and described in detail in this chapter. The results have been compared with future weather data produced by other research groups including the CIBSE Future Test Reference Years which forms the basis of current practice as far as the simulation of future building behaviour is concerned. The results of this work show that UKCP09 produces simulated building performances that give a good agreement with those obtained from the CIBSE Future Test Reference Years in spite of radically different methods being used to generate the two data sets. Results also confirm the findings of a growing number of studies which point to steady increases in comfort temperature throughout this century for buildings without air conditioning and increased cooling peak load and annual cooling energy demand for buildings with air conditioning. Though the results also point to negligible reductions in peak winter heating load through this century due to climate change alone, they do suggest a significant reduction in overall seasonal heating energy demand. In overall summary, the results of 15 buildings show that there will be a 51% decrease in heating energy demand by 2080 under the high carbon emission scenario (based on control value of 44.6kWh/m²). However there will be an increase in cooling sensible energy

demand of 116% by 2080 under the high carbon emission scenario assumption from a control value of 18.8kWh/m².

In this chapter, a clear insight of building performance under future TRY data was obtained by modelling 15 buildings. However the simulation results using future TRY data are not able to reflect future plant and equipment design capacity. There is a need to construct alternative file types containing weather data that can be used for future plant and equipment sizing together with simplified methods for practitioners to use to help arrive at these design decisions which are addressed in Chapter 6 and 7.

CHAPTER 6

6 Method 2: Development of Northumbria Design Reference Years

The previous chapter discussed the application of Test Reference Years to building performance and energy simulations. This chapter describes the development of future Design Reference Years which can be used to deal with design and risk analysis for buildings services systems. The method proposed in this chapter generates future Design Reference Year (DRY) data from the UKCP09 Weather Generator outputs for a variety of future time horizons and carbon emission assumptions. The method selects three near-extreme summer months and three near-extreme winter months and weaves them into an existing Northumbria Test Reference Year. A comparison is made with DRYs generated using alternative methods from other research groups.

6.1 Available DRYs/DSYs

CIBSE produced Design Summer Years data to enable designers to simulate building performance during a year with a hot, but not extreme, summer. The Design Summer Year consists of an actual 1-year sequence of hourly data, selected from the 21-year recorded data sets (typically 1983-2004) to represent a year with a third hottest summer (CIBSE, 2002). The selection is based on average dry bulb temperatures during the period April–September. Practitioners

predominantly use Design Summer Years to calculate the risk of overheating in a building in terms of percentage of occupied hours. This is used as a basis for deciding whether a building should implement air conditioning. It is therefore an important tool for building services engineering designers.

Belcher *et al* (2005) and Jentsch *et al* (2008) both used the 'morphing' method with UKCIP02 climate change projection data to generate future Design Summer Years. However the use of this method does require some specialist expertise. The 'ready-made' data sets offered by CIBSE (2008) then became 'standard' data for the industry, thereby providing a common platform for climate change impact assessments. CIBSE offers Design Summer Years for current, 2020s, 2050s and 2080s timelines. For each future timeline, weather data based on four (low, medium low, medium high and high) carbon emission scenarios were made available.

As the outcome of the PROMETHEUS (The Use of Probabilistic Climate Change Data to Future-proof Design Decisions in the Building Sector) project, Eames *et al* (2010b) at Exeter University developed a method for generating probabilistic Design Summer Years from UKCP09 climate change projections.

In the selection procedure applied by Exeter University, for a specific location, timeline and carbon emission scenario, 100 Design Summer Years were captured from 3000 years data (100 samples of 30-year data) in a similar manner to the one used to deal with CIBSE observed data. The only difference was that Exeter chose the fourth warmest April to September period in the 30-year band, while CIBSE chose the third warmest period in the 21-year recorded

data set. For each calendar month, the 100 months were then ranked based on the ascending order of the mean monthly temperatures. Then different calendar months at the same percentile (e.g. 10th, 33rd, 50th, 66th and 90th) were joined together to form the Exeter probabilistic Design Summer Years. For example, the 10th percentile January month was joined to the 10th percentile February month et cetera.

Exeter University offers five Design Summer Years (at 10th, 33rd, 50th, 66th and 90th percentiles respectively) for the control, 2030s, 2050s and 2080s timelines. For each timeline and percentile, weather data based on low and high carbon emission scenarios were made available. In this study, the 50th percentile and 90th percentile DSYs weather files from Exeter were used as they are the middle and upper limit of their DSYs.

As part of the COPSE (Co-incident probabilistic climate change weather data for a sustainable environment) project, Watkins *et al* (2011) at Manchester University also developed a method of generating future Design Reference Years (DRYs) from UKCP09 climate change projections.

In the selection procedure applied by Manchester University, each calendar month of the DRY is derived separately from any other calendar month. 3000 Januaries, 3000 Februaries... 3000 Junes, etc., are all assessed separately. The mean temperatures (or solar, or RH) for each calendar month of the 3000 months are calculated, and the 3000 months are ranked by these monthly means. A 20-month band is taken centred at certain percentile (e.g. 87.5%, 97.5% in their study) of 3000 months. Then a 'typical' month is chosen (via the

FS-stat method) taking into account all three parameters (Temperature, Solar, Relative Humidity – and wind) regardless of which primary selection parameter has been used (Temperature, Solar or Relative Humidity). This month then becomes one of the 12 contributing months to the DRY. The process is repeated for the other 11 months.

The whole process is then repeated for the other primary selection parameters (Solar and Relative Humidity). In its application, the RH-selected DRY is more likely to be used if there is going to be air conditioning, but of course it also affects comfort as well as plant load. It could be possibly less relevant in the UK climate.

The Temperature-selected DRY and Solar-selected DRY would usually be required, with the worse case result being used. If solar gain were known not to be an issue (minimal or no glazing), the Temperature-selected DRY alone could be used.

Manchester University offers three sets of DRYs (temperature, solar radiation and relative humidity) for the control, 2020s, 2050s and 2080s timelines. For each timeline and percentile (87.5% or 97.5%), weather data based on medium and high carbon emission scenarios were made available.

6.2 Development of Northumbria Design Reference Years

The following method was developed to generate Northumbria Design Reference Years from UK Climate Projections 2009. Raw data consisting of a

30-year period of hourly weather data was obtained from UKCP09 Weather Generator. The time period available are summarised in the table below:

Table 6-1 Time periods of UKCP09

Time Period	Time Slice
Control(reference) data	1961-1990
2020s	2010-2039
2030s	2020-2049
2040s	2030-2059
2050s	2040-2069
2060s	2050-2079
2070s	2060-2089
2080s	2070-2099

In this work, the nominal time periods of 2030s, 2050s and 2080s (bold in table above) were chosen together with the control period data; the former represents a sample of future time slices looking sufficiently far towards a time horizon likely to be of interest for the life span of buildings currently under development and construction. The number of probabilistic variations used in the UKCP09 Weather Generator for hourly data output is 100. Thus, for each 30-year band of climate data, there are 3000 annual files. Hourly and daily weather data were extracted from 3000 files to represent each of the 4 selected time periods (including the control data) at each of three (low, medium and high) carbon emission scenarios. The following procedure was used:

1. A Test Reference Year for each time period (including control) was generated using the method previously presented in Chapter 4 (also described in the journal paper (Du, Underwood & Edge, 2011)).
2. Daily maximum dry bulb temperatures (T_{\max}) and daily minimum dry bulb temperatures (T_{\min}) were captured from the UKCP09 Weather Generator daily data for each complete time period, and daily mean dry bulb temperatures were then calculated from these by averaging.
3. For the two three-month sets only: December-February and June-August, the monthly mean dry bulb temperatures were calculated by averaging the daily mean dry bulb temperatures, and then for each of these calendar month sets, 3000 monthly mean temperatures were ranked in ascending order.
4. For the June-August set, 30 of each of these months with the 31st – 60th highest monthly mean temperatures (i.e. 99th percentile) were selected, from which one of each was selected by applying the Finklestein-Schafer (FS) statistic to temperature, solar radiation and relative humidity as described by Du *et al.* (2011) and chapter 4.1 (steps 1-6). This resulted in the summer DRY month selections.
5. Step 4 was repeated for the December-February set to obtain the lowest mean monthly mean temperature (1st percentile) and, again, one of each of these months was selected by applying the FS-statistic to obtain the winter DRY month selections.

6. The 3 summer and 3 winter months selections from steps 4 and 5 above were merged with 6 other months from the Test Reference Year (Step 1) to form the 99th percentile Design Reference Year.
7. Steps 4-6 were repeated using the 451st – 480th highest monthly mean temperatures among the summer months and the 451st – 480th lowest monthly mean temperatures among the winter months to form the 85th and 15th percentile summer and winter DRYs respectively.
8. To deal with spikes in the data at midnight (arising from non-chronological months being joined), the last eight hours of each month and the first eight hours of the next month were smoothed by cubic-spline interpolation. This adjustment included the December-January connections so that the Design Reference Year could be used repeatedly in simulations.

In the procedure reported above, weather data are selected at the 85th and 99th percentiles, because CIBSE design summer data has historically selected the third warmest period from 20 individual weather files (i.e. $3/20 = 0.15$ or 15%) the 85th was chosen for consistency with this. For comparison, for a much lower design risk of overheating, the 99th percentile was also used because it forms the medium-risk value of the three percentiles (98%, 99% and 99.6%) recommended for use in current practice for UK design cooling loads.

Completion of each DRY file of data require further trivial completion steps before conversion to the relevant file format for use in a dynamic energy simulation program. The precise nature of these would depend on what data fields were needed for the particular simulation program intended. In this work,

the simulation program EnergyPlus (US Department of Energy, 2011a) has been used. Completing steps for EnergyPlus EPW weather format required the following:

9. Calculation of the hourly dew point temperature based on the existing hourly dry bulb temperature and relative humidity from the DRY file, using hygrometric properties of air. The equation 4-5 (in page 76) and equation 4-6 (in page 77) were used for the calculation.
10. Calculation of the hourly direct-normal solar radiation based on the existing direct horizontal solar radiation from the DRY file using conventional sun-earth geometry procedures. The equations 4-7 to 4-11 (pages 77 and 78) were used for the calculation.
11. Translation of cloud cover into tenths using the sunshine hours data in the existing DRY file, and the addition of night-time cloud cover data which was assumed in this work to be based on a linear interpolation of sunset and subsequent sunrise values.
12. Calculation of the hourly horizontal infrared radiation flux (US Department of Energy, 2010) in which the opaque cloud cover was assumed constant at 0.5 as previously used by Jentsch *et al.*(2008). The equations 4-12 and equation 4-13 (page 79) were used for the calculation.

The entire procedure described above was carried out using bespoke Matlab scripts. Processing times to completion based on 3000 years of initial input files resulting in one TRY file and two DRY files (85th and 99th percentiles) were typically 6 minutes on a conventional personal computer. The names and

descriptions of all scripts for generating DRY were listed in the table 6-2 and full scripts were attached in appendix D. Two CSV files (DRY85.csv and DRY99.csv) and two DEF files (DRY85.def and DRY99.def) will be generated as outputs of these Matlab scripts. The EPW format of weather data can be produced by inputting the CSV and DEF files into the EnergyPlus Weather Statistics and Conversions tool which comes with the EnergyPlus simulation package.

Table 6-2 Matlab scripts list for DRY

File name	File description
DRY85_Hu_Part.m	generating DRY data at 85 percentile for future time line
DRY99_Hu_Part.m	generating DRY data at 99 percentile for future time line
DRY85_Hu_Part_control.m	generating DRY data at 85 percentile for control period
DRY99_Hu_Part_control.m	generating DRY data at 99 percentile for control period

6.3 Inter-method comparison

A sample of control and future external dry bulb temperatures for the June-August period are compared with results from other sources for DRY files at Manchester Ringway airport (53.36N, 2.28W). The other sources are from the CIBSE future design summer year (CIBSE, 2008) (these data are based on the earlier UKCIP02 climate change scenarios), a sample of results from Manchester University (Watkins, 2011), and a sample of results from Exeter University (Eames, Kershaw & Coley, 2011).

As described in section 6.1, the CIBSE data were generated using ‘morphing’ applied to existing Design Summer Year data, the latter consisting of the third

warmest April-September period based on average dry bulb temperature from a sample of 21 historical data sets. Manchester University calculated monthly average temperatures for each calendar month (3000 Januaries, 3000 Februaries, etc) and ranked them separately in ascending order. For each calendar month, one month was then selected from 20-year bands at the 87.5th percentile using the FS-statistic. Besides these dry-bulb temperature based files, Manchester also used a similar approach to select alternative DRY files based on relative humidity and solar radiation. Exeter University captured 100 design summer years from 3000 years of UKCP09 data (100 samples of 30-year data) by choosing the fourth warmest April-September periods in each 30-year band based on 6-monthly mean dry bulb temperatures. They then ranked each 100 year month set based on ascending order of mean monthly temperatures and picked off each month in each set at the same percentile (10th, 33rd, etc through to 90th) and joined them together to form a complete year of data.

Table 6-3 lists availability of Design Summer Year or Design Reference Year produced by CIBSE, Exeter University, Manchester University and Northumbria University. 'C' indicates control or current period. 'L', 'M', 'H', 'ML' and 'MH' indicate low, medium, high, medium low and medium high carbon emission scenarios respectively. The number in last column gives the total number of DSYs/DRYs for a specific location, timeline and carbon emission scenario. For example, Exeter produced 5 DSYs at 10%, 33%, 50%, 66% and 90% for a specific location, timeline and carbon emission scenario. Manchester generated 3 DRYs for temperature, solar radiation and relative humidity respectively for a

specific location, timeline and carbon emission scenario. Northumbria produced 2 DRYs at 99% and 85% for a specific location, timeline and carbon emission scenario.

Table 6-3 Timelines and carbon emission scenarios of DSYs/DRYs

	C	2020s				2030s			2050s				2080s				N
CIBSE DSY	C	L	ML	MH	H	/			L	ML	MH	H	L	ML	MH	H	1
Exeter DSY	C	/				/	M	H	/	M		H	/	M		H	5
Manchester DRY	C	L	/		H	/			L	/		H	L	/		H	3
Northumbria DRY	C	/				L	M	H	L	M		H	L	M		H	2

Note also that CIBSE and Manchester University data are not available for the 2030s period but instead the 2020s period is included. Also note that the control period of CIBSE DSYs is 1983-2004, whereas the control period of three universities' DSYs/DRYs is 1961-1990.

The results of dry bulb temperatures from the DRY file of Manchester Ringway (55.36N, 2.28W) created in this work (at the 85th and 99th percentiles) are compared with the DRYs from Manchester University (87.5th percentile) and DSYs from CIBSE and Exeter University (50th and 90th percentile) in Figure 6-1. The symbols used along the horizontal axis of following figures are as detailed in table 4-3 (page 86).

Figure 6-1 illustrates the distribution of annual hourly dry bulb temperature of DSYs/DRYs from four organisations for Manchester Ringway airport. The X-

axis shows timelines of DSYs/DRYs from four organizations, and the y-axis is hourly temperature. The '+' signs indicate maximum hourly dry bulb temperatures during the whole year; the '-' signs indicate annual average dry bulb temperatures; the 'x' signs give minimum dry bulb temperatures during the whole year; and the blue bars show standard deviations of annual hourly dry bulb temperatures. As shown in the figure, the standard deviations from Northumbria are higher than others because the DRYs from Northumbria were also designed for heating system sizing and winter risks analysis. For the same reason, the minimum temperatures from Northumbria are lower than others.

It also shows that the maximum temperature increases significantly along with time moving forward. The maximum temperatures from the Northumbria 99th percentile are significantly higher than the one from 85th percentile at the later part of this century. The results confirm a broad agreement among the four sets of data in the trends of the growth in dry bulb temperatures with advancing time and carbon emission scenarios.

In similar ways, the distributions of hourly dry bulb temperature of June-August were plotted in the figure 6-2. The value of average dry bulb, minimum temperature and standard deviations are different with Figure 6-1 as this figure only shows summer conditions. Both summer's average dry bulb temperatures and maximum temperature from the Northumbria 99th percentile are higher than the temperatures at the 85th percentile, therefore the 99th percentile weather data indicates higher risks of overheating.

The maximum, mean and minimum of the daily global horizontal solar radiation in June, July and August from four organisations were plotted in Figure 6-3. The distribution of average summer daily global horizontal solar radiation from UKCP09 is wider than the UKCIP02 projections.

6.4 Conclusion

In this chapter, the method of generating Northumbria Design Reference Year data from UKCP09 Weather Generator outputs has been described. The method selects three near-extreme summer months and three near-extreme winter months and weaves them into an existing Northumbria Test Reference Year. Two risk levels (85% and 99%) were used to select Design Reference Years. The advantage of the Northumbria DRY is that it provides an opportunity for evaluating heating design load and it adopts longer design periods in order to accommodate a wide spread in building thermal response. The data generated by this method was compared with DRYs/DSYs from CIBSE, Exeter University and Manchester University. The next chapter focuses on the application of these DRYs.

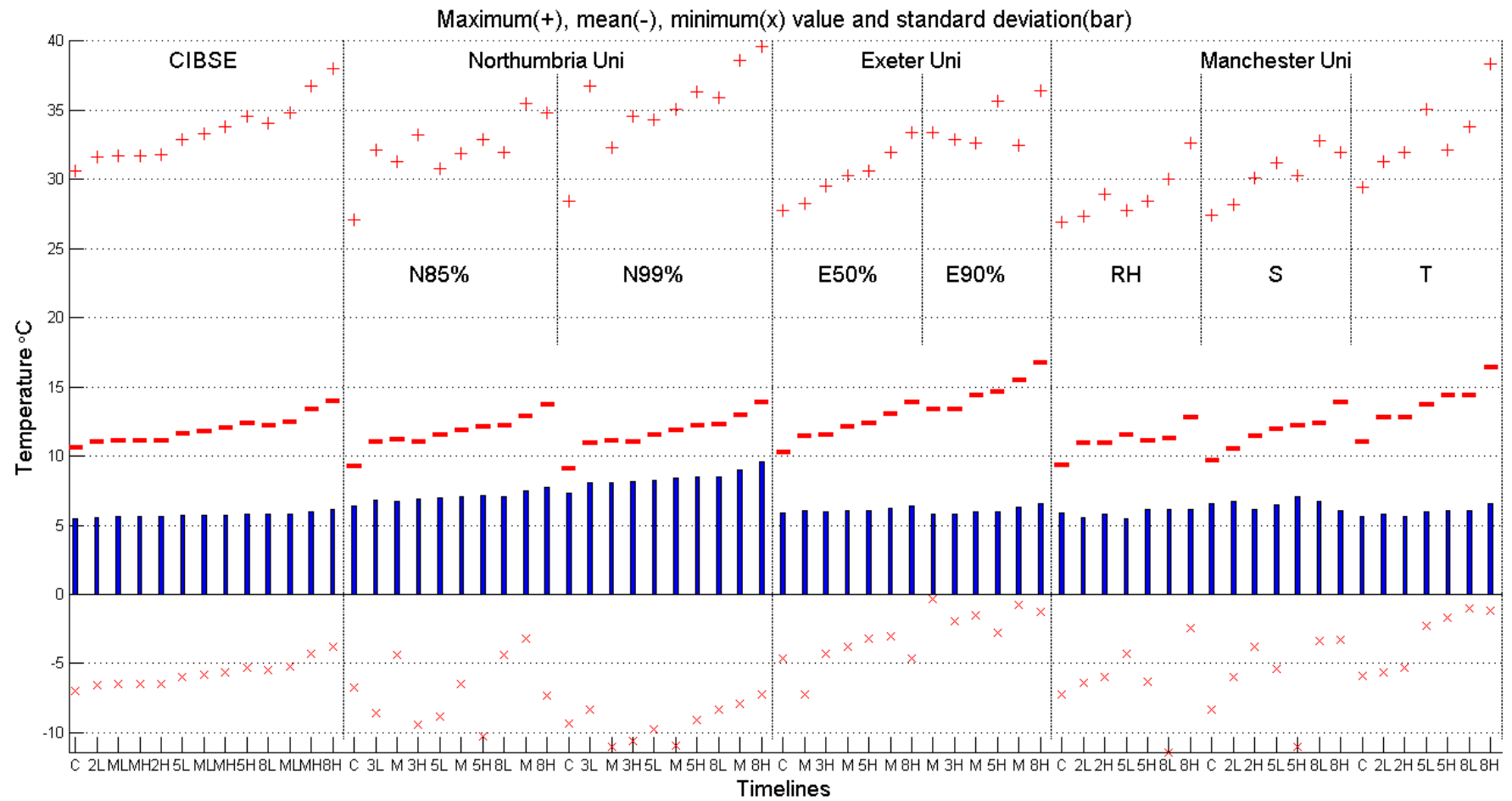


Figure 6-1 Comparison of alternative DSY/DRYs annual temperatures

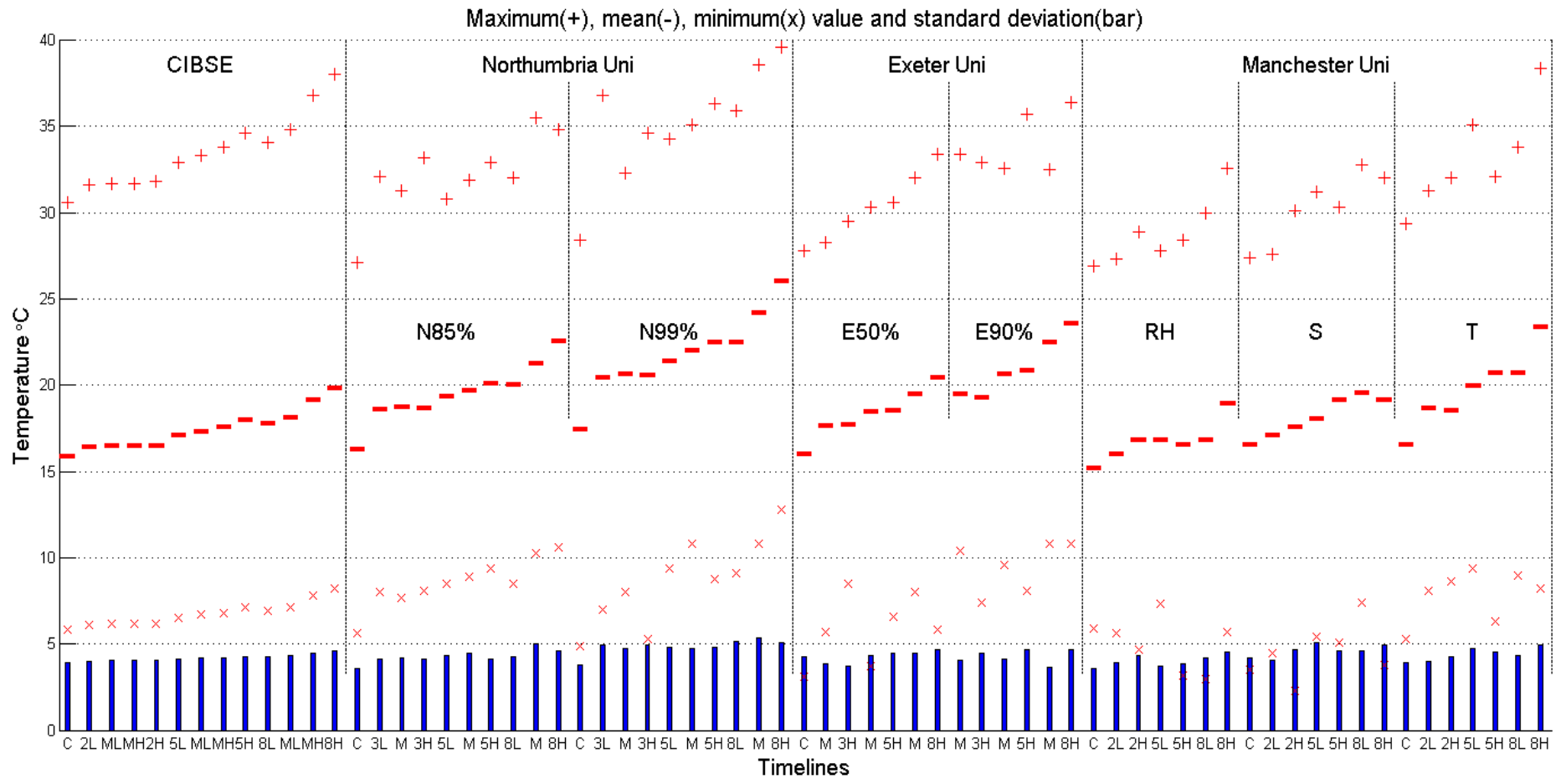


Figure 6-2 Comparison of alternative DSY/DRYs summer temperatures

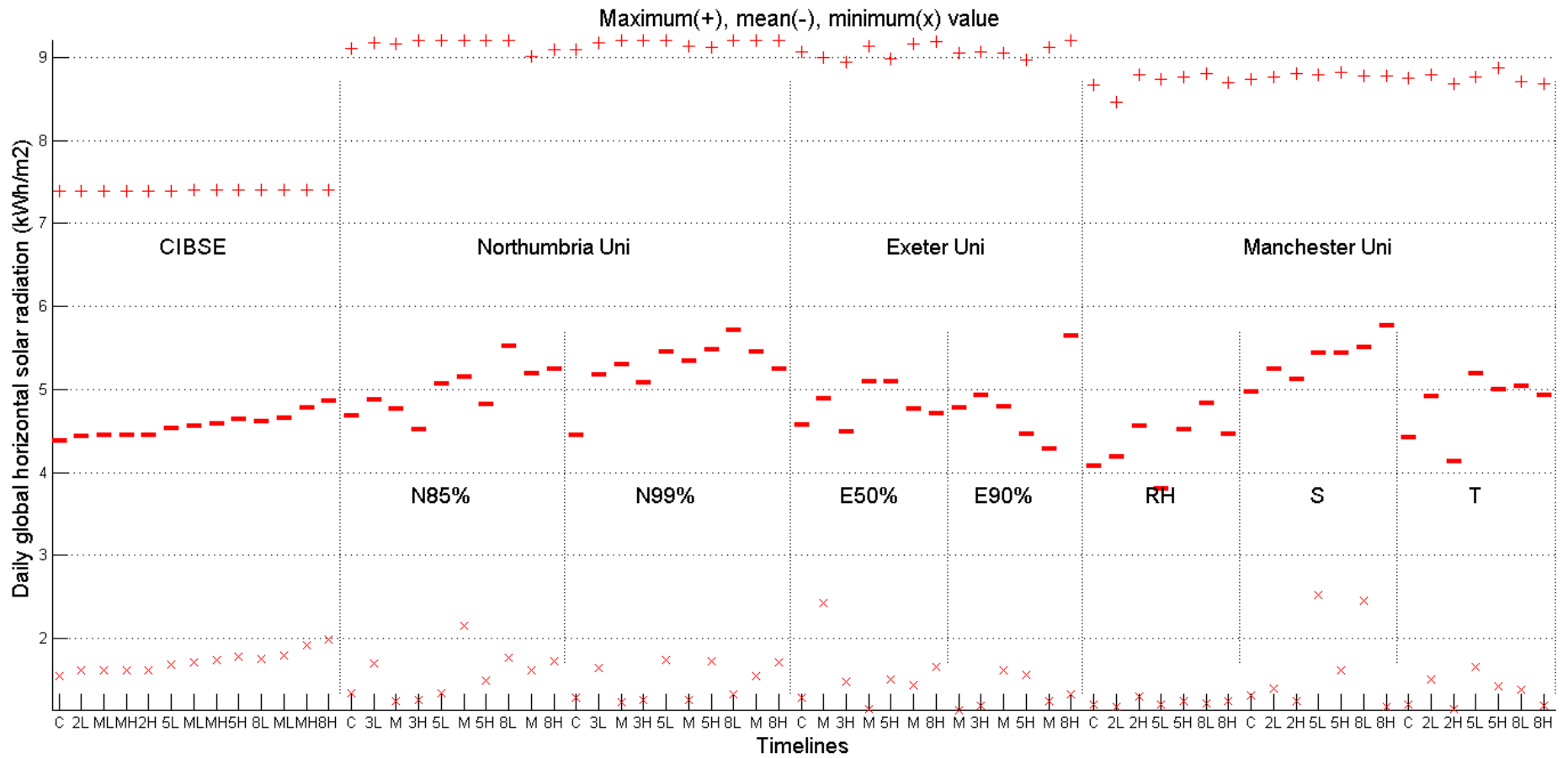


Figure 6-3 Comparison of alternative DSY/DRYs daily global horizontal solar radiation values

7 Application of DRYs to building design (load sizing)

The aim of this chapter is to test the DRY data generated in the previous chapter and investigate the impacts of UK Climate Projections 09 on overheating risk and building heating/cooling design loads.

Fifteen sample buildings have been simulated in a dynamic building performance simulation package (EnergyPlus Version 6) using Northumbria Design Reference Year data (produced in chapter 6). In order to investigate how Northumbria data differs from the alternative data sets, two of these buildings were also simulated using the future DRYs/DSYs produced by the UK Chartered Institution of Building Services Engineers (CIBSE, 2008), Exeter University (Coley, Kershaw & Eames, 2011) and Manchester University (Watkins, 2011). It is assumed that all buildings studied in this chapter were based at the location of Manchester (53.36N, 2.28W).

Two sets of Northumbria DRY data based on the 85th percentile and 99th percentile, two sets of Exeter DSY data based on the 50th percentile and 90th percentile, three sets of Manchester DRY data based on temperature-selection, solar-selection and relative humidity-selection and the widely used CIBSE DSY data were included in the comparison.

The detailed information for the buildings has been presented in section 3.1. The examples cover a range of non-domestic building case studies selected from a widely varying mix of building types with some in continuous use and others in intermittent use. The occupancy densities, occupied period profiles

and internal heat gain allowances for all zone types in all buildings were selected according to standard data presented in the UK National Calculation Method database (Shearer, 2008).

The modelling assumptions were described in section 5.1. In brief, three modes of simulation were conducted in EnergyPlus for each building, including freefloat mode, heating mode and cooling mode. The percentage of occupied hours over an operative temperature of 28 °C and the cooling and heating design loads were captured by a Matlab script from the results of the three simulation modes respectively.

The comparisons among four sets of DRYs/DSYs are presented in section 7.1. Results of the other buildings using the Northumbria data only are reported in section 7.2 and appendix B1, B2 and B3.

7.1 Results using four sets of DSYs/DRYs

Figures 7-1 and 7-2 demonstrate potential overheating situations for the aged persons' accommodation and multi-cellar offices located in Manchester respectively. The figures were broken into 8 columns to represent results from 4 organisations' datasets (CIBSE, Northumbria University, Exeter University and Manchester University ordered from left to right in the figures). Labels under the x axis indicate timelines and carbon emission scenarios listed in table 4-3 (page 60). The 'X' signs indicate the percentages of occupied hours over operative temperature 28 °C for occupied zones in the building. The bars indicate averages of all percentages in the building. Green, pink and red bars

highlight results of the control period, the 2050s high emission scenarios and the 2080s high emission scenarios which commonly exist in all the data sets. The figures also highlight 1% of occupied hours over 28 °C (CIBSE, 2006) which is the threshold indicating the need for cooling.

Both figures indicate that all occupied zones in the two buildings need air conditioning in the later part of this century. The rate of increase in percentage of overheating in the later part of this century is more rapid than in the earlier part of the century. Note that the results from the three universities' DRYs/DSYs data (primary temperature based selection) are higher than the results from the CIBSE DSYs. The distribution of overheating percentages slightly increases against advancing timeline and emission scenarios.

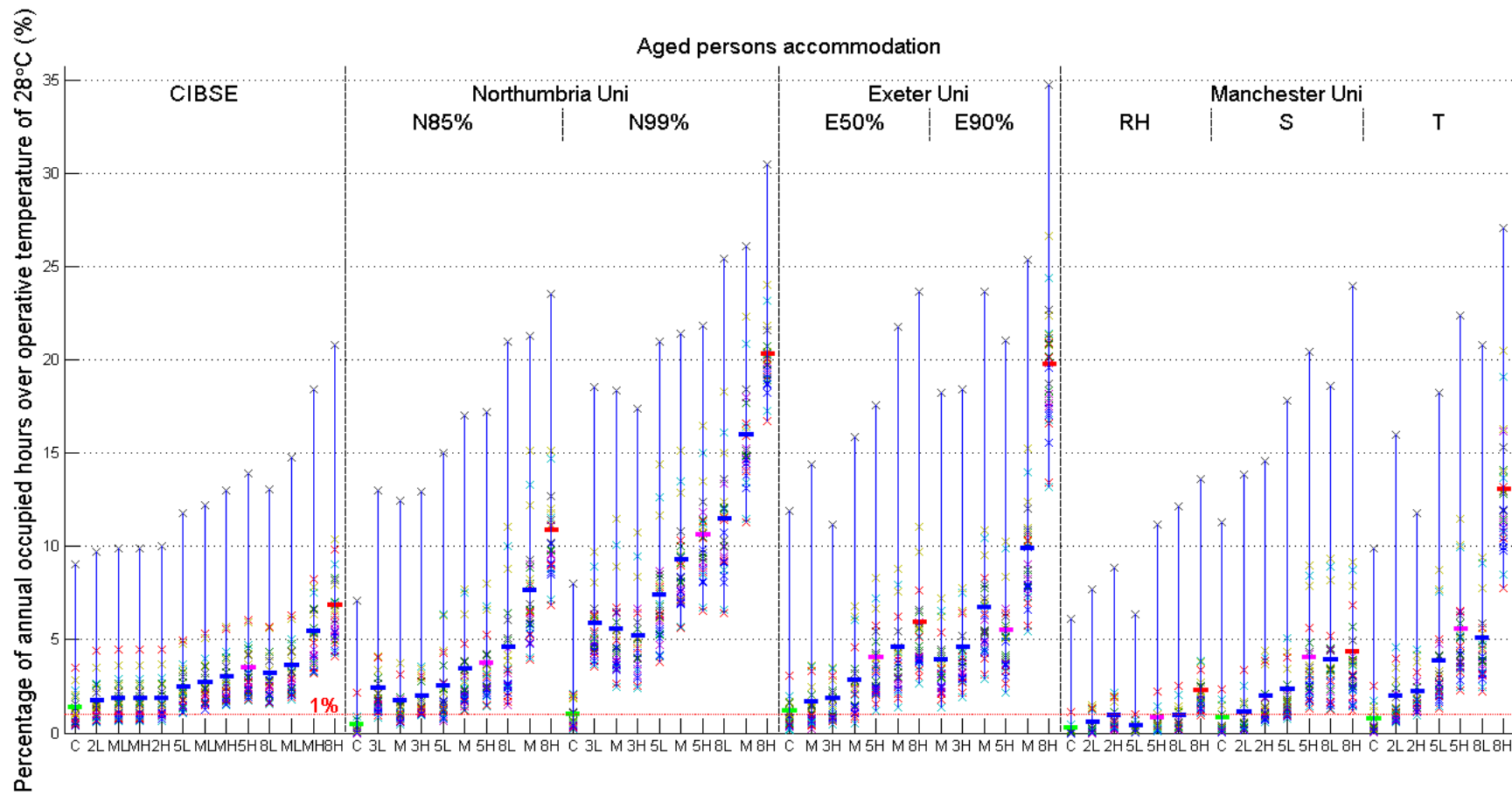


Figure 7-1 Overheat percentage of aged persons' accommodation

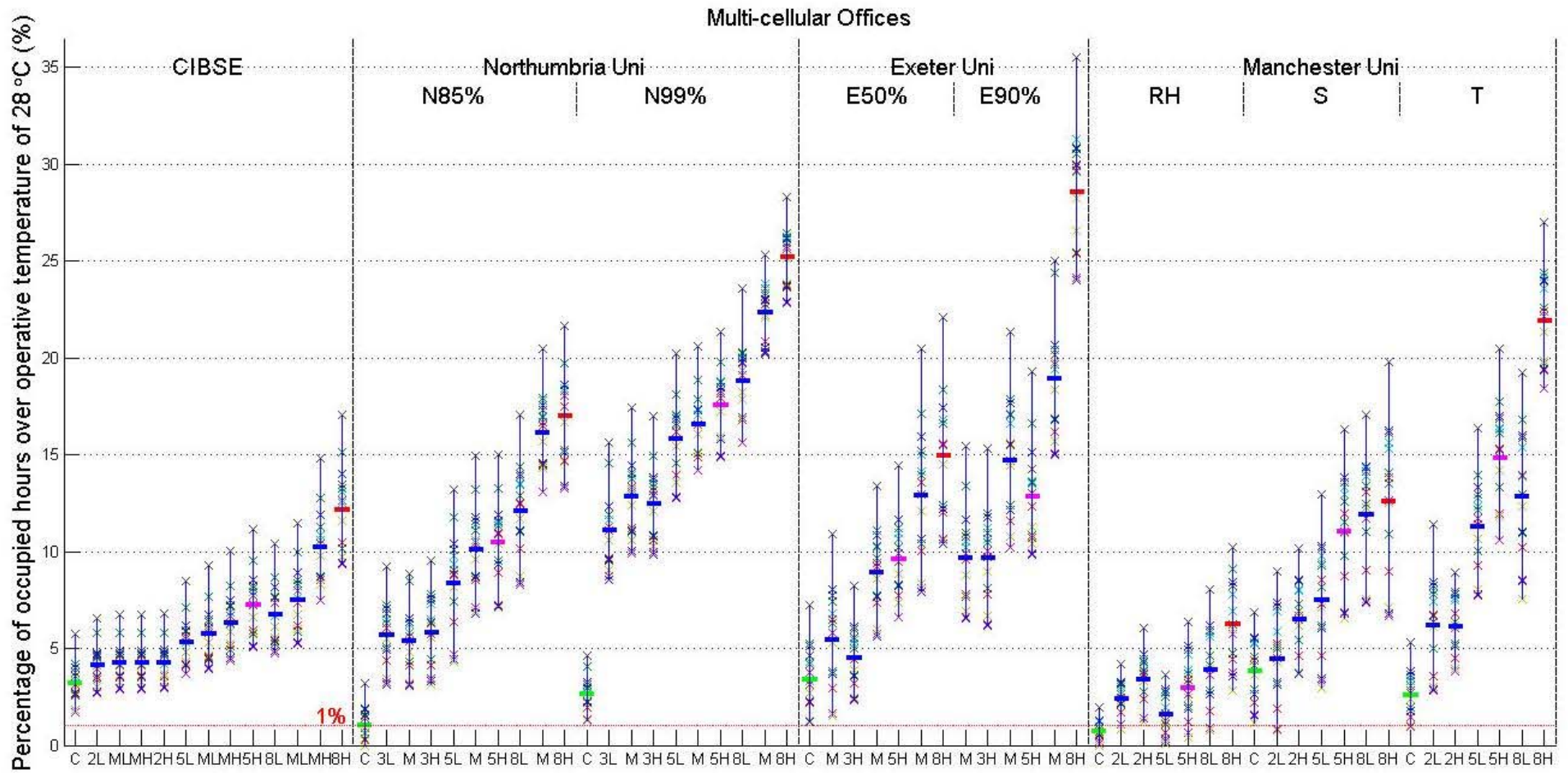


Figure 7-2 Overheat percentage of an office building

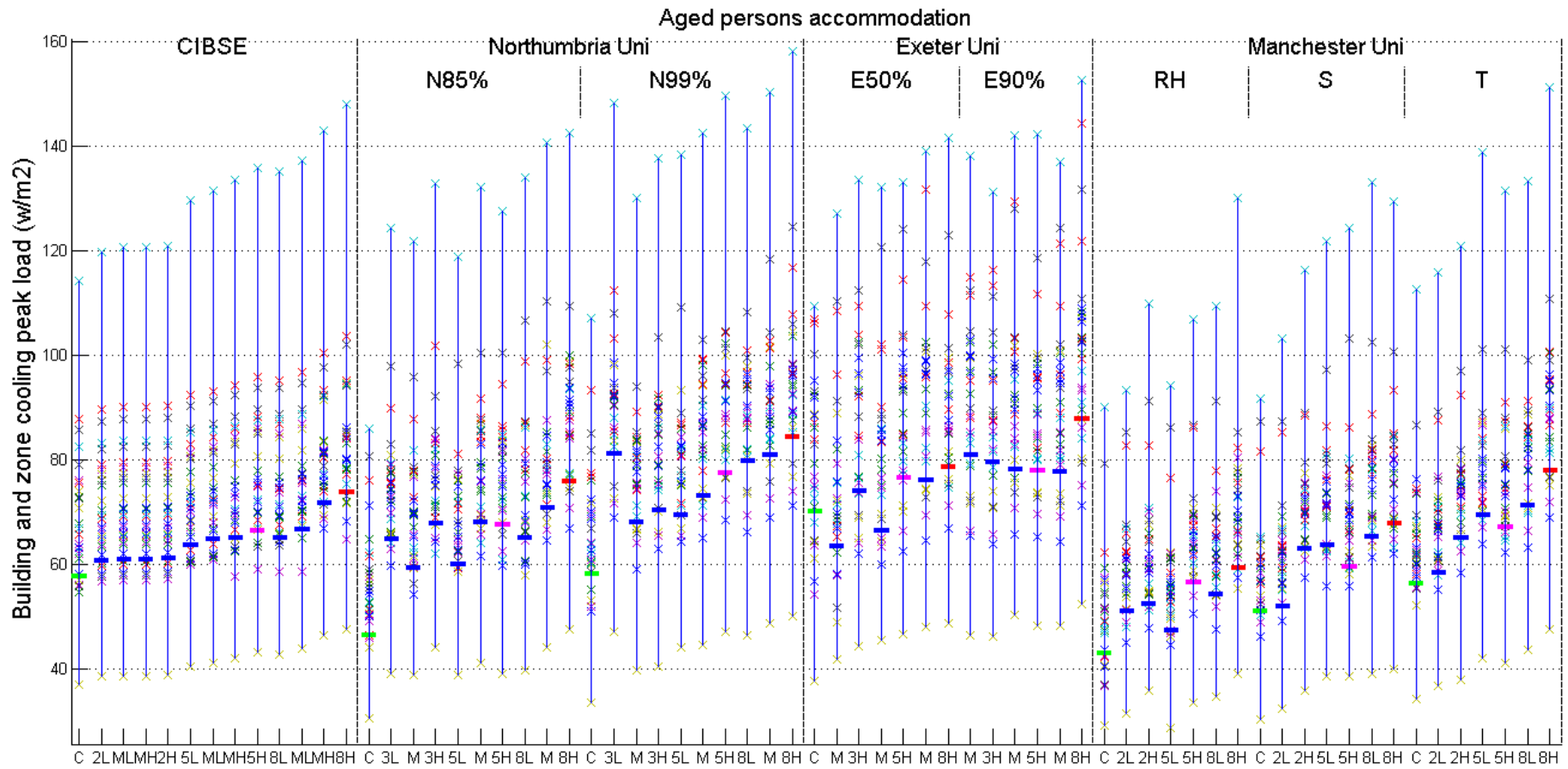


Figure 7-3 Peak cooling loads of aged persons' accommodation

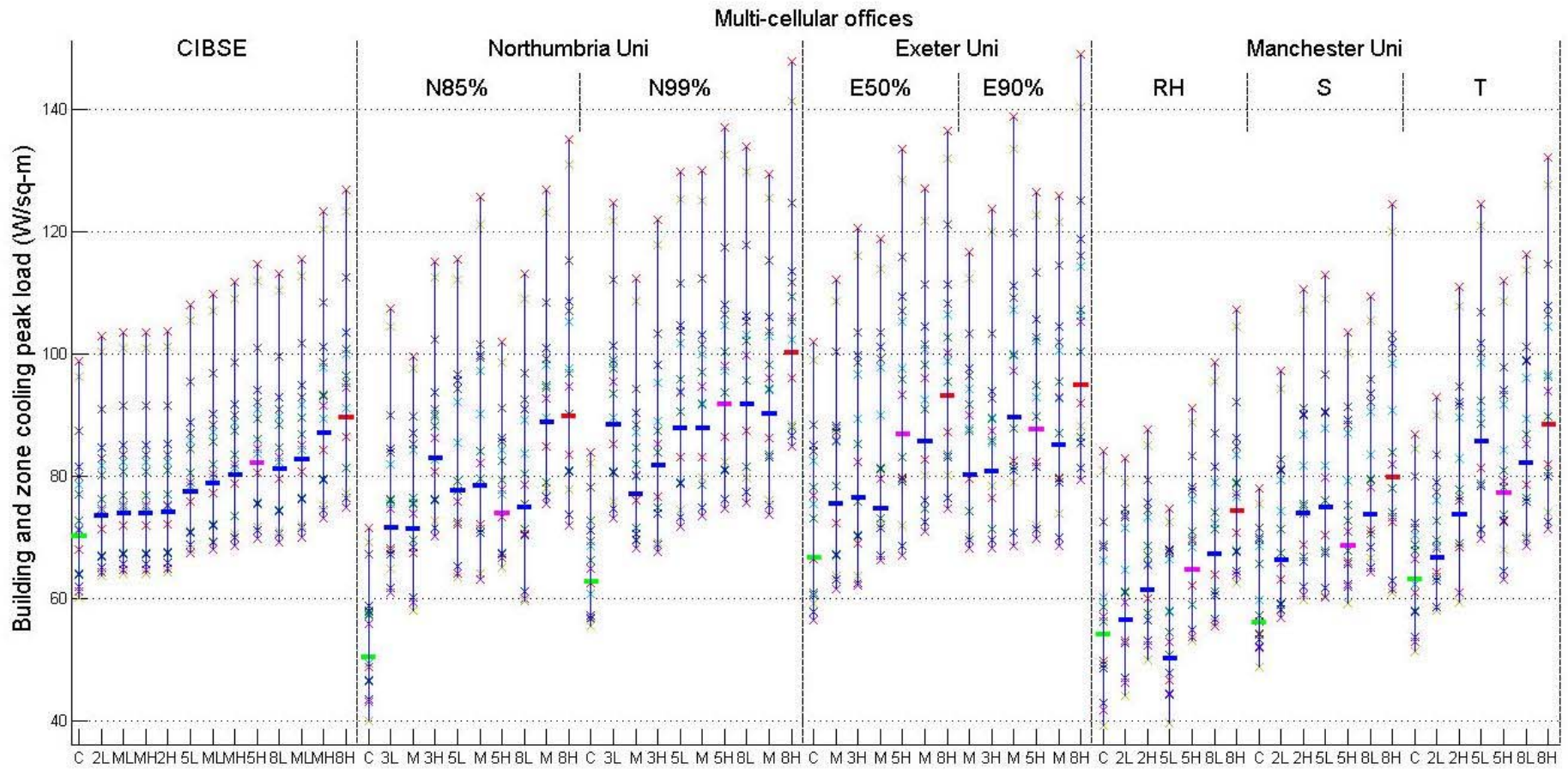


Figure 7-4 Peak cooling loads of an office building

In general the trend lines for advancing time (and carbon emission intensity assumption) suggest a smoother growth in values due to the scaled and stretched CIBSE TRY data than is the case with the probabilistic data from UKCP09.

Figures 7-3 and 7-4 show building and zone cooling (sensible) design loads. The building (sensible) design cooling load expressed here are the peak of the sum of the simultaneous zone cooling loads divided by the treated floor area of the building. Note that the solar-selection based DRY and relative humidity-selection based DRY from Manchester University give significantly lower results. This indicates that temperature is the main factor influencing cooling sensible design load for the two buildings. Although the overheat percentage at the end of this century could reach five times of the current value (shown in figures 7-1 and 7-2), the cooling design loads only increase by up to 1.5 times of the current values until the end of this century (depending on the weather source and percentile).

In general, the higher percentile used for simulation, the higher cooling design load occurs. Northumbria's 85th and 99th percentile data could cover a reasonable range of design risks.

7.2 Results using Northumbria DRY only

In addition to aged persons' accommodation and multi-cellular offices, thirteen more buildings (described in section 3.1) were simulated using Northumbria DRY only (generated in chapter 6) to test their performance under UKCP09

projections. The results of overheat percentages of occupied hours over 28 °C, cooling design loads and heating design loads for each building are attached in appendix B1, B2 and B3 respectively.

A unique feature of the Northumbria Design Reference Year weather file is that it includes three months of winter data for assessing design heating loads. As an example, results for the multi-cellular offices are illustrated here. Figure 7-5 shows simulated maximum heating demands for the building, thus forming design heating loads when using a Northumbria Design Reference Year weather file. The vertical bars on this figure (and figures 7-6 and 7-7) represent the spread of individual zone heating demands with crosses along this line representing individual zone loads. The short horizontal bars represent the overall design loads for the whole building. The green, blue, pink and red bars in the figure highlight control, low, medium and high emission scenarios at different time periods. Note that the zone design loads and overall building design loads occur at different times which is why, in some cases, the horizontal bar appears outside the range of the zone spread. For example, for a building consisting of 2 zones with identical floor areas but with different heat transfer characteristics, during 2 consecutive hours, the first zone has a load of 50Wm^{-2} and 10Wm^{-2} respectively whilst the second zone has loads of 10Wm^{-2} and 40Wm^{-2} respectively. Zone design loads of 50Wm^{-2} (zone 1) and 40Wm^{-2} (zone 2) would be returned for the two zones whilst the overall design load for the building would be the higher of the two combined and coincident values (i.e. 30Wm^{-2}).

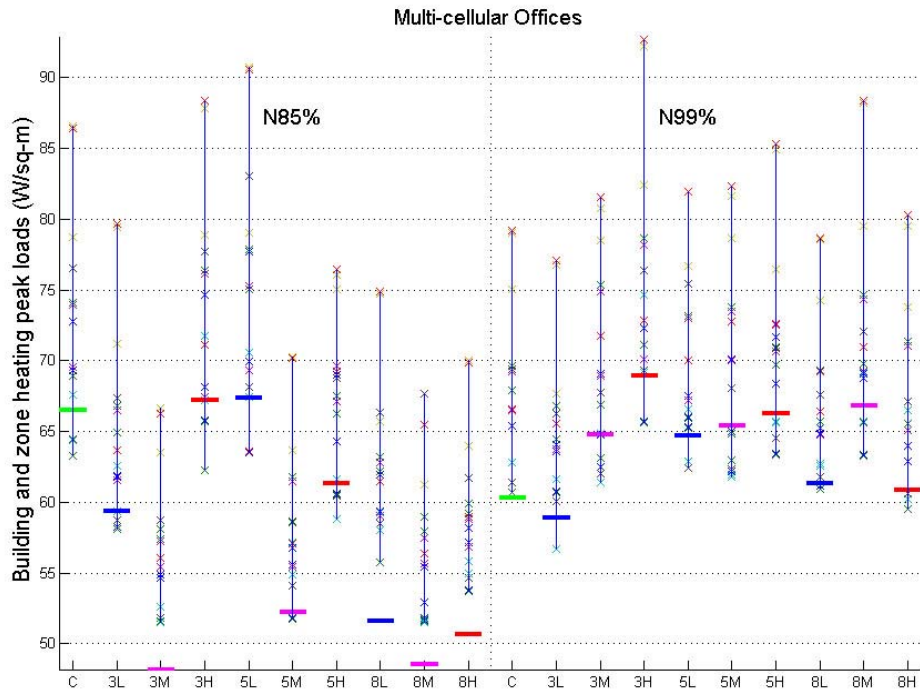


Figure 7-5 Sample of heating design load results

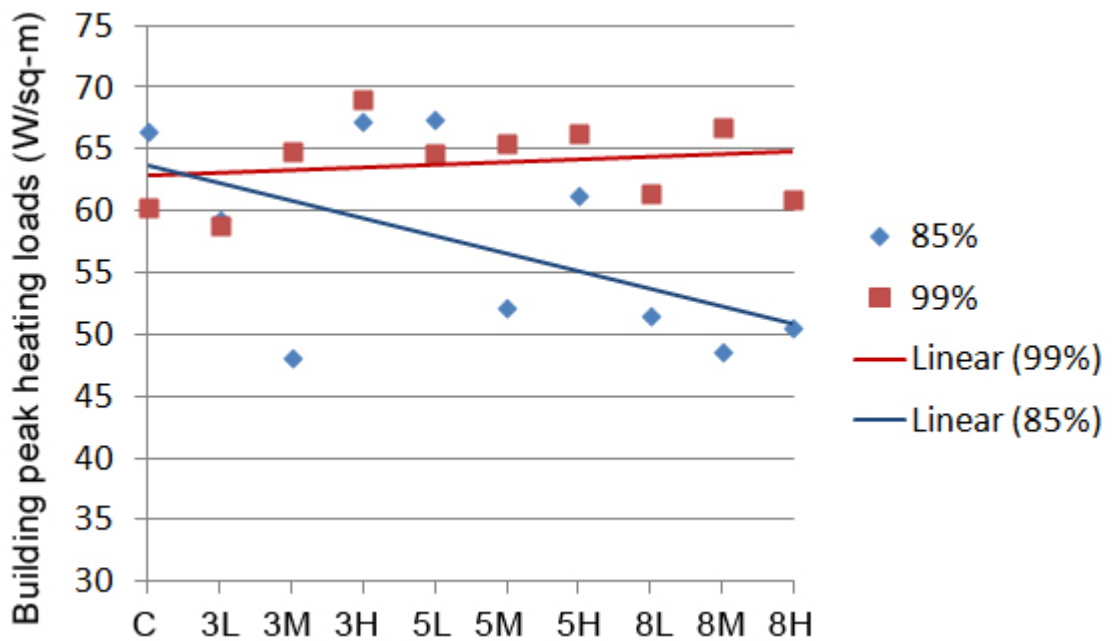


Figure 7-6 Changing trend of building heating design loads

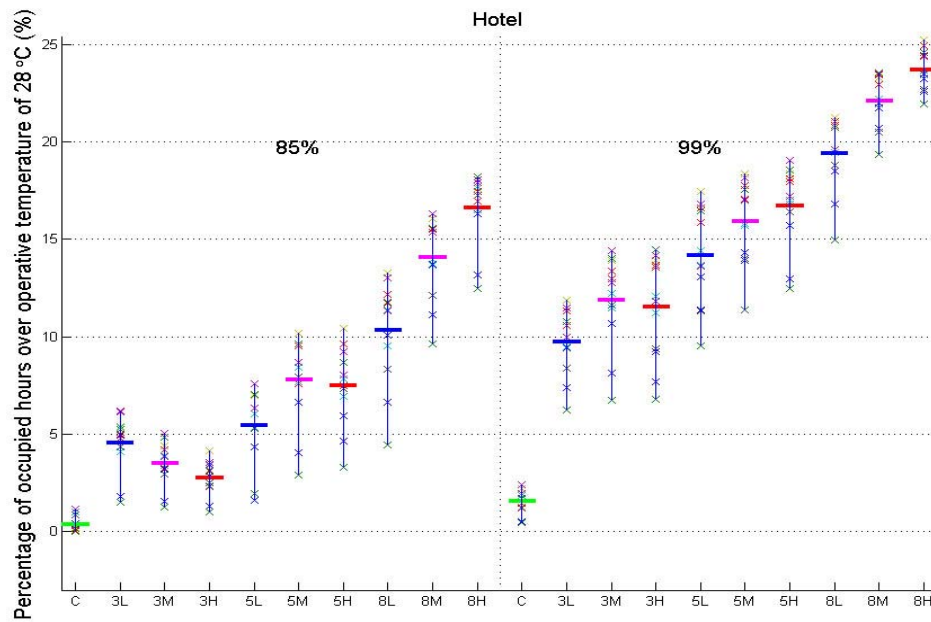


Figure 7-7 Sample of summer percentage overheating results

An interesting feature in the results given in figure 7-5 (and all figures in appendix B3) concerns the trend in heating design loads over time. The trend lines of building heating design load with time and carbon emission scenario are plotted in figure 7-6. The 99 percentile trend line (red line) shows that, with increasing carbon emission scenarios, the heating design loads do not reduce as might at first be expected but stay broadly the same. This was found in earlier work (Du, Underwood & Edge, 2011) when using three universities' TRY data for simulating heating design loads (figure 9 of the paper 2 attached in appendix C). The earlier work found that annual heating energy demands did indeed decline with time and emissions scenario whereas peak instantaneous values did not. This suggests that short instances of cold winter weather might be expected to continue to occur more or less as they do now. Correspondingly,

the 85 percentile trend (in which fewer and less-severe extreme winter conditions will be captured) shows a reducing trend in design heating load.

Figure 7-7 presents the percentage of occupied hours for the hotel during which internal zone operative temperatures exceed a notional threshold of 28°C (the typical value currently used to assess summer overheating). These results were generated by assuming that natural ventilation at a constant rate of 4 air changes per hour to be introduced to each zone when the zone internal operative temperature exceeds 25°C and the external dry bulb temperature is less than the zone dry bulb temperature.

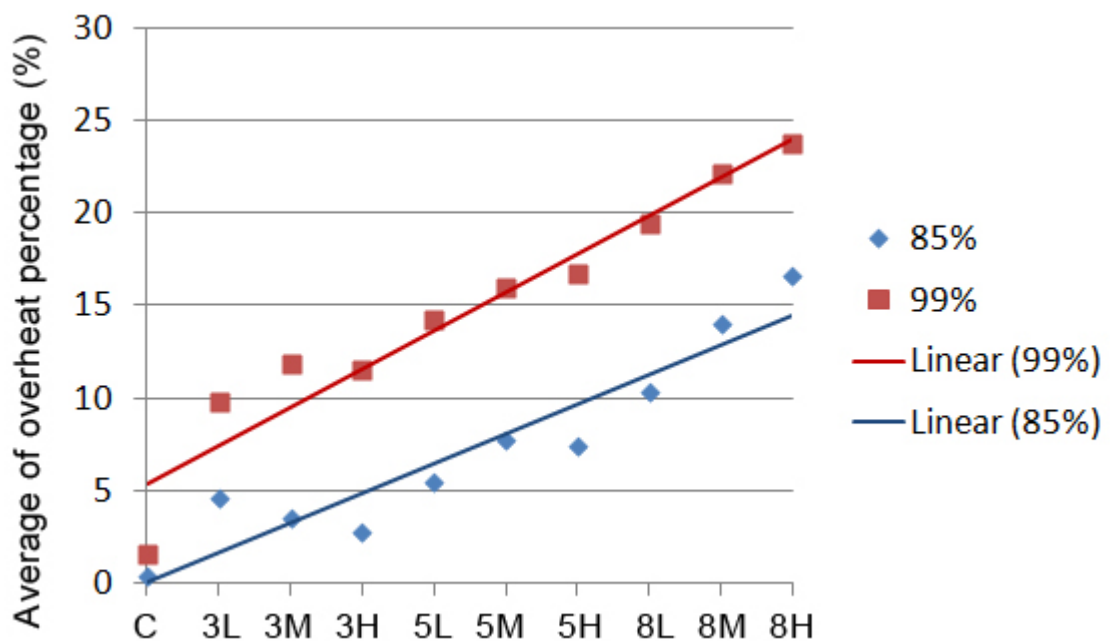


Figure 7-8 Changing trend of average overheated percentage

Trend lines of the averages of percentages of occupied hours over 28 °C operative temperature plotted against time period and carbon emission scenario are shown in figure 7-8. From the control period, a steady rise in this comfort

violation is evident with time and carbon emission. This has significant implications for the introduction of remediation measures, such as shading, night cooling and increased thermal mass, or for the uptake of air conditioning.

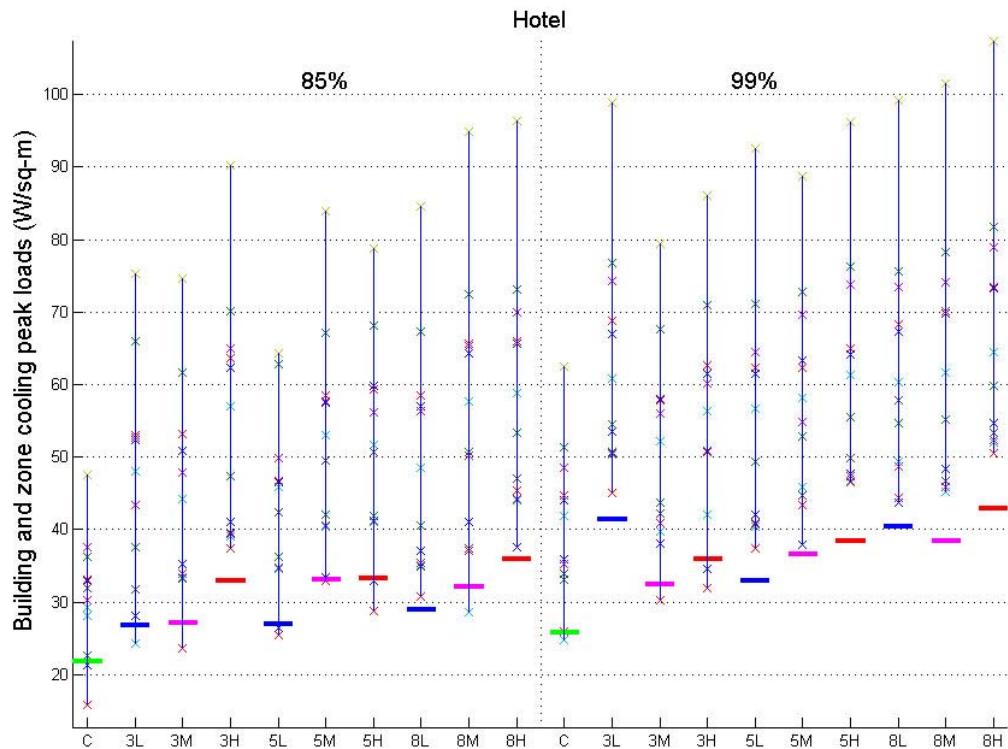


Figure 7-9 Sample of cooling design load results

Figure 7-9 shows simulated maximum hourly cooling demands for all occupied zones of the building, thus forming design cooling loads when using a Design Reference Year. Note that, again, the horizontal bar represents the overall building design loads and that all values will occur at different times. The trend lines of overall building cooling design loads are plotted in figure 7-10. A steady increase in design cooling demand is evident with time and carbon emission. The implication of this is that for buildings constructed today in which it is

adjudged unnecessary to provide air conditioning or special measures to reduce solar heat gain (etc) in current conditions, designers would be well-advised to incorporate features that would allow retro-fitting of such services in the future easy. Such features might include contingency space allowances for future plant and duct work/pipe work services distribution.

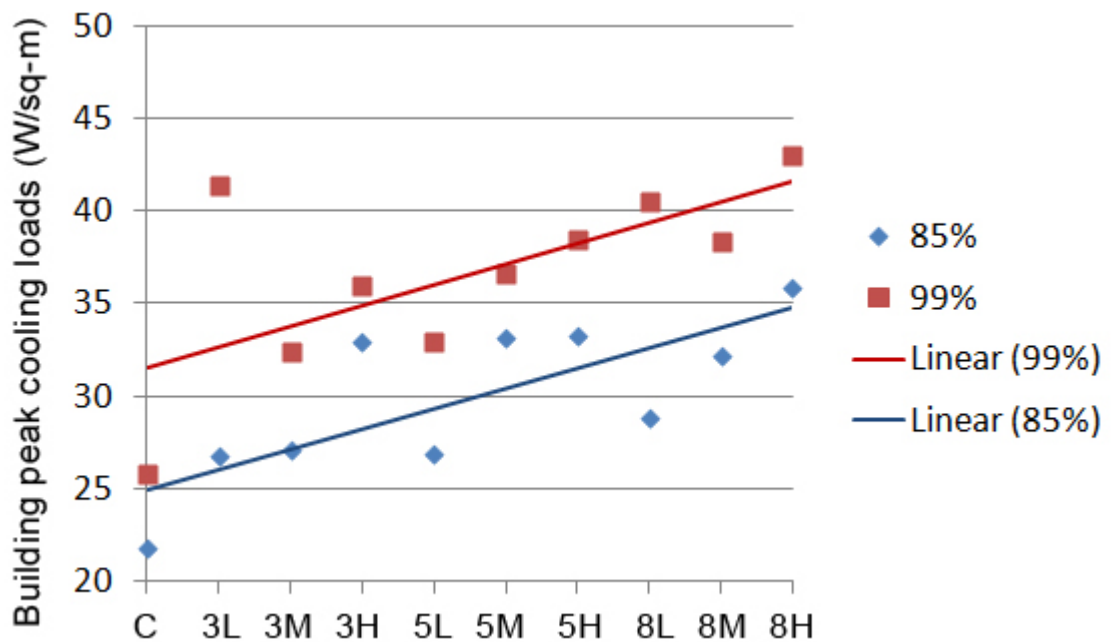


Figure 7-10 Changing trend of building cooling design loads

7.3 Conclusion

In this chapter, two buildings were used to test DSY/DRY weather files from CIBSE, Northumbria University, Exeter University and Manchester University. Further tests were conducted by simulating thirteen more buildings using Northumbria DRY files only (results are listed in appendix B). They are all 'real' buildings existing in the UK, and they capture a range of construction styles and

activities that would ensure contrasting thermal comfort and energy demand results.

The results in this chapter and appendix B show that there is a significant increase of overheat hours over the timelines and emission scenarios. The average of overheat percentages of all occupied zones in the 15 case study buildings at the 85 percentile risk level was found to increase from a control value of 2.16% to 18.45% by the 2080s based on the high carbon emission scenario. For the 99 percentile risk level, the increase is from 3.55% to 25.12%.

Results also indicate that sensible cooling design load would rise with time and there is no strong evidence showing increase or decrease of heating design loads due to climate change. The average of the sensible design cooling loads of the 15 buildings at the control period (85 percentile risk level) is 36.6W/m^2 and this is predicted to increase by 76% by the 2080s at the high carbon emission scenario. For 99 percentile risk level, the value at the control period is 46.3W/m^2 and is predicted to increase by 59% by the 2080s at the high carbon emission scenario (i.e. a smaller percentage increase than for the 85 percentile case but from a higher control value). The average of the design heating loads for the different time periods and carbon emission scenarios was 67.9 W/m^2 with deviation of 7.18W/m^2 (85 percentile) and 73.4 W/m^2 with a deviation of 3.44 W/m^2 (99 percentile).

In conclusion, a clear insight of building performance under future DRY data has been obtained by modelling 15 buildings in EnergyPlus. However the simulation results using single future DRY data are not able to fully reflect future

plant and equipment design capacity at a certain period due to the stochastic nature of UKCP09 projections. There is a need to develop a method for quickly predicting future air conditioning loads for a large number of probabilities of future weather conditions.

CHAPTER 8

8 Method 3: Development of a simplified method for predicting future air conditioning loads

In the previous chapter, results based on energy simulations using DRY weather data for example buildings were illustrated. It is recommended that dynamic energy modelling tools such as EnergyPlus (as used here) or one of the numerous other simulation tools could be adopted for future design and design-risk analysis for new and refurbished building proposals. It is however acknowledged that the resources of time and effort to conduct such design studies are not trivial particularly when applied during the early design and planning processes. At this stage, the availability of a simpler approximate method would be invaluable to practitioners. In this chapter, the development of such a method is considered and applied to the calculation of future room design cooling loads.

8.1 Development of the method of predicting design loads

A total of 43 occupied zones from the 15 buildings detailed in figure 3-1 and table 3-1 were arbitrarily selected as cases to analyse the relationship between cooling design load and possible independent variables. In theory, the room maximum (design) sensible cooling load for a given building is dependent on current and historical weather conditions (solar radiation, external dry bulb temperature) and internal casual heat gains due to lighting, equipment and

occupancy. The extent of historical data among these key independent variables will depend on the thermal capacity of the room. The objective was to ascertain the extent to which room design cooling loads could be fitted to sets of these variables through regression analysis.

In figure 8-1, hourly outdoor air temperatures during summer were scale-coloured. The black arrows indicate the time when peak cooling loads occur (43 arrows in total, there are overlaps). The polyline plots the average temperature between 10:00h – 22:00h for each day (The y-axis for the polyline is at the right side of the figure). Note that most of the peak cooling loads occur on the day with higher temperature during 10:00h – 22:00h (highlighted in the red circle).

Figure 8-2 is plotted in similar way to figure 8-1, but the colours indicate global horizontal solar radiation. Note that peak cooling loads also occur at or soon after a period of strong global horizontal solar radiation. Therefore, outdoor air temperature and global horizontal solar radiation definitely are the two independent variables for regression analysis. To include influences from the past, all independent weather data variables (and internal casual heat gain values) were arranged to consist of the current time-row values; past hour to 96 hours ago' instant values; the average of the current and previous hour values; the average of the current, and previous two hours' values, and so on to a maximum of 96 (4-days worth) instantaneous and historical values for each variable.

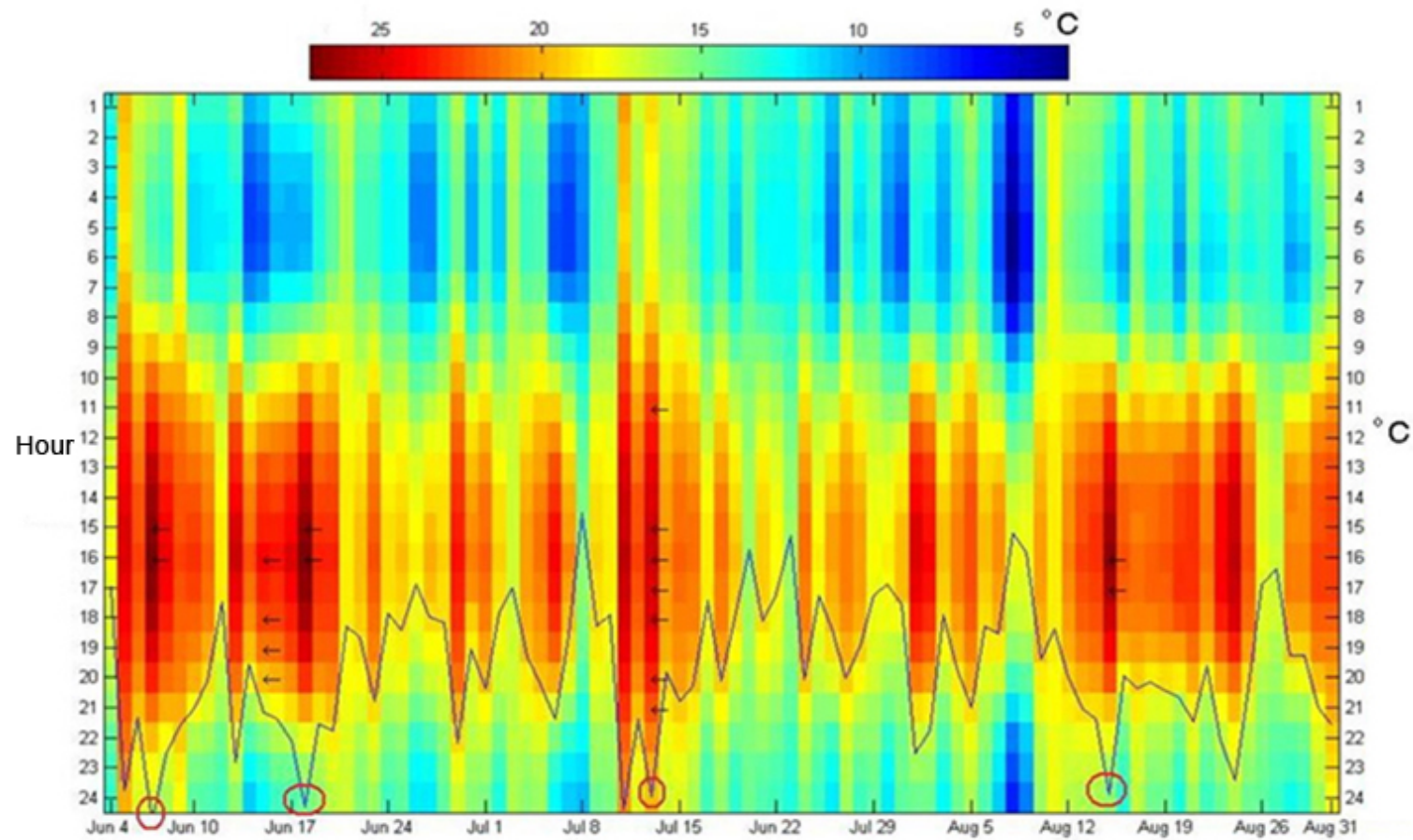


Figure 8-1 Outdoor temperature and the time peak cooling loads occur

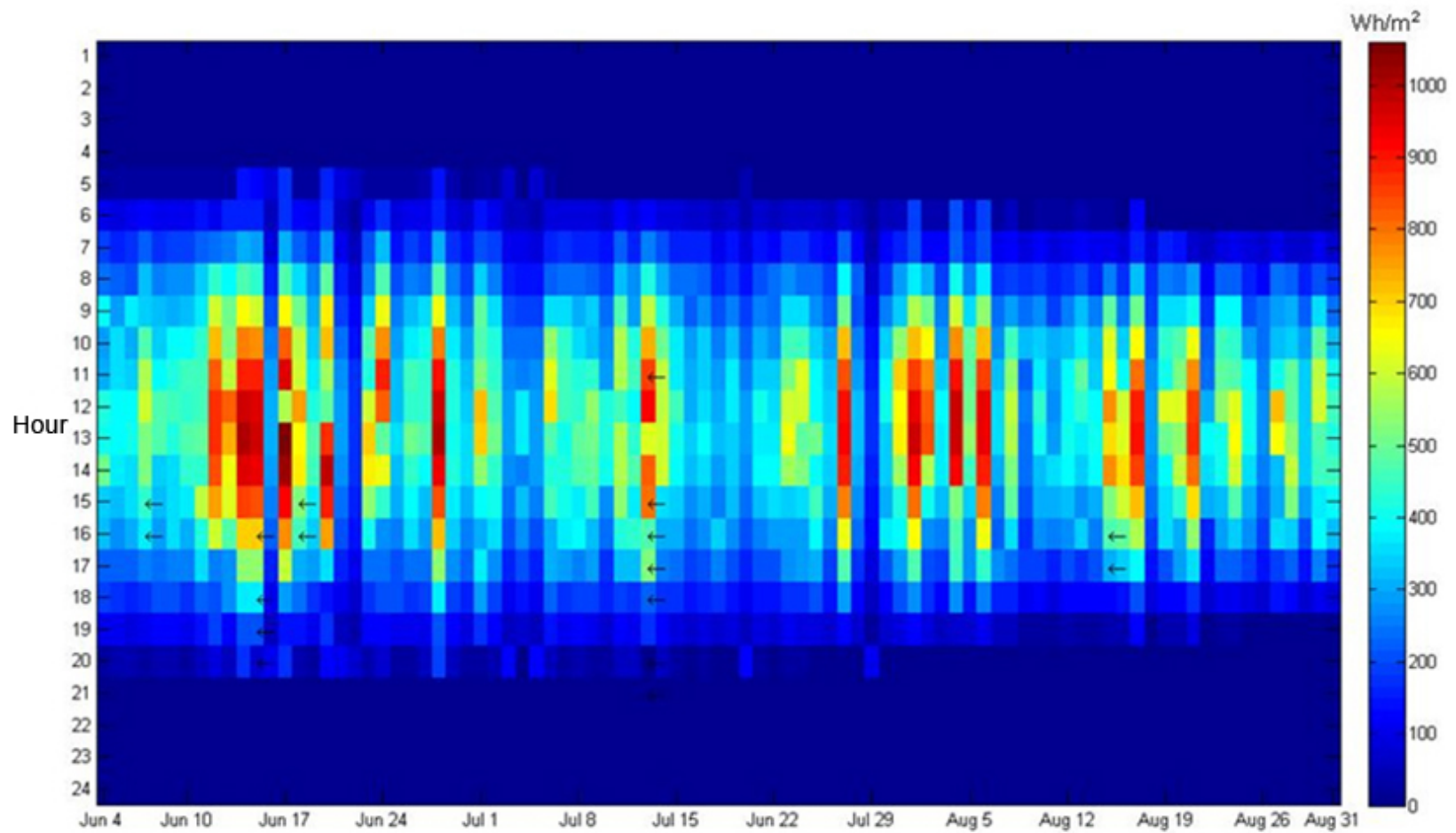


Figure 8-2 Global horizontal solar radiation and the time peak cooling loads occur

Table 8-1 Regression using four independent variables

Building name	Zone name	Constant	ID1	K1	ID2	K2	ID3	K3	ID4	K4	R Square
Aged	Ground floor – Flat	-17.11	<i>I0-7</i>	0.04	<i>T0-2</i>	1.31	<i>I0</i>	0.03	<i>q0</i>	0.39	0.89
Aged	1st floor west facing – Flat	-5.87	<i>q0-7</i>	-0.42	<i>T0-2</i>	1.48	<i>q0</i>	0.43	<i>I0</i>	0.03	0.85
Aged	1st floor east facing– Flat	-21.23	<i>T0-7</i>	1.27	<i>T0-7</i>	0.04	<i>q0</i>	0.37	<i>T0</i>	0.62	0.92
Aged	2nd floor east facing – Flat	-23.39	<i>T0-5</i>	1.92	<i>I0</i>	0.04	<i>q0</i>	0.37	<i>T0-7</i>	0.02	0.85
Aged	2nd floor west facing - Flat	-18.55	<i>T0-7</i>	1.00	<i>T0-7</i>	0.04	<i>q0</i>	0.39	<i>T0</i>	0.66	0.92
Airport	1st floor – Circulation Public	-21.17	<i>T0-2</i>	0.29	<i>T0-7</i>	0.02	<i>I0</i>	-0.01	<i>T0</i>	1.27	0.90
Airport	2nd floor - Circulation Public	5.00	<i>T0</i>	1.10	<i>T0-7</i>	0.00	<i>T0-3</i>	0.53	<i>T0-5</i>	0.01	0.89
Airport	2nd floor - Sale	-20.57	<i>T0</i>	0.11	<i>q0</i>	0.38	<i>T0-2</i>	1.60	<i>I-3</i>	0.00	0.97
Airport	2nd floor - Eat and drink	-25.49	<i>T0</i>	1.89	<i>T0-2</i>	0.01	<i>T-7</i>	0.62	<i>I0</i>	0.01	0.96
Hospital	Ground floor – Office	-33.23	<i>T0</i>	3.35	<i>I0</i>	0.01	<i>q0</i>	0.31	<i>q0-4</i>	-0.29	0.87
Hospital	1st floor - Lab	-47.74	<i>T-1</i>	2.91	<i>T0-4</i>	0.03			<i>T-3</i>	1.22	0.87
Hospital	1st floor – Waiting zone	-14.14	<i>T0</i>	0.69	<i>T0-3</i>	0.02			<i>T-1</i>	1.79	0.84
Hospital	2nd floor - Ward Patients	-64.29	<i>T0</i>	3.30	<i>T0-7</i>	0.02	<i>q0-4</i>	0.48	<i>q0</i>	0.26	0.97
Hospital	3rd floor - Counselling room	-31.62	<i>T0</i>	3.33	<i>T0-3</i>	0.03	<i>q0</i>	0.28	<i>q0-2</i>	-0.26	0.95
Hotel	Ground floor - Conference zone	-51.13	<i>q-5</i>	0.30	<i>q0-7</i>	-0.34	<i>T0</i>	2.69	<i>q0</i>	0.18	0.84
Hotel	3rd floor E - Meeting room	-43.14	<i>q-5</i>	0.33	<i>T0</i>	2.25	<i>T0-2</i>	0.01	<i>q-3</i>	-0.14	0.82
Library	1st floor - Bookshelves	-9.74	<i>T0</i>	0.91	<i>T0-2</i>	0.01			<i>q-4</i>	0.10	0.77
Library	2nd floor - Office	-3.04	<i>I-6</i>	0.02	<i>q0-7</i>	0.03	<i>T-2</i>	0.65	<i>q0</i>	0.19	0.83
Library	3nd floor - Bookshelves	-26.75	<i>T0</i>	1.72	<i>T-7</i>	-1.22	<i>q0</i>	0.10	<i>T-6</i>	1.02	0.80
Museum	Ground floor - Gallery	-21.41	<i>I0</i>	0.01	<i>T-7</i>	1.38	<i>q-5</i>	-27.06	<i>T0-3</i>	0.01	0.70
Open plan Office	Ground floor - Office	-10.11	<i>T0-7</i>	0.04	<i>q0</i>	0.38	<i>T-4</i>	0.85	<i>q-3</i>	-0.20	0.83
Open plan Office	1st floor - Office	-11.22	<i>T0-2</i>	0.03	<i>q0</i>	0.42	<i>T0-7</i>	1.10	<i>q0-7</i>	-0.28	0.77

Open plan Office	2nd floor - Office	-8.88	<i>T0-6</i>	0.03	<i>q0</i>	0.34	<i>T-3</i>	1.01	<i>q-3</i>	-0.20	0.82
Multi-cell Office	2nd floor - Office	-0.41	<i>T0-4</i>	0.03	<i>T0</i>	1.76	<i>T-7</i>	-0.71	<i>q-6</i>	0.12	0.92
Multi-cell Office	4th floor - Office	-22.47	<i>T0</i>	2.74	<i>T0-3</i>	0.01	<i>q0</i>	0.26	<i>q0-3</i>	-0.25	0.88
Hybrid Office	Ground floor - Office	-9.70	<i>T-1</i>	1.56	<i>T0-5</i>	0.02	<i>q0</i>	0.08			0.94
Hybrid Office	Ground floor - Office	-13.76	<i>T-1</i>	1.75	<i>I0</i>	0.01	<i>q0</i>	0.11			0.89
Hybrid Office	2nd floor - Office	-9.88	<i>T-1</i>	1.78	<i>q0</i>	0.27	<i>T0-5</i>	0.02	<i>q0-4</i>	-0.12	0.88
Primary School	Ground floor - Classroom	-35.67	<i>T-1</i>	3.64	<i>I0</i>	0.02	<i>T-7</i>	-1.05	<i>q-7</i>	-0.14	0.81
Primary School	1st floor - Classroom	-29.25	<i>T0-3</i>	0.03	<i>q-7</i>	-0.24	<i>T-1</i>	2.29	<i>I0</i>	0.03	0.90
Prison	Ground floor - Cells	1.70	<i>q0</i>	0.50	<i>T-1</i>	0.32	<i>q0-2</i>	-0.20			0.82
Prison	Ground floor - Cells	-20.63	<i>q0</i>	0.43	<i>T0-2</i>	1.12	<i>T0-7</i>	0.01			0.83
Prison	1st floor - Cells	-10.22	<i>q0</i>	0.41	<i>T-1</i>	0.48	<i>q0-2</i>	-0.17	<i>T-7</i>	0.36	0.80
Prison	1st floor - Cells	-13.89	<i>q0</i>	0.47	<i>T-1</i>	0.73	<i>q-1</i>	-0.14	<i>T-7</i>	0.24	0.83
SecondarySchool	1st floor - Classroom	-15.04	<i>T0-2</i>	0.03	<i>q0</i>	0.21	<i>q-2</i>	-0.21	<i>T-1</i>	1.24	0.69
SecondarySchool	2nd floor - Classroom	-19.35	<i>T0-3</i>	0.05	<i>q-7</i>	-0.63	<i>T-1</i>	1.84	<i>q-6</i>	0.26	0.89
StudentsAcc	1st floor - Bedroom	-36.04	<i>T0-7</i>	0.86	<i>q0</i>	0.23	<i>T0</i>	1.22	<i>T0-2</i>	-0.01	0.76
StudentsAcc	2nd floor - Bedroom	-24.38	<i>T0-5</i>	0.84	<i>q0</i>	0.32	<i>T0-2</i>	0.02	<i>T0</i>	0.61	0.79
Building name	Zone name	Constant	<i>ID1</i>	K1	<i>ID2</i>	K2	<i>ID3</i>	K3	<i>ID4</i>	K4	R Square

An extensive step-wise multiple regression analysis was carried out using SPSS software. The automatic procedure of choosing 'important' variables found that 38 (out of 43) zone cooling loads could be expressed reasonably well ($R^2 > 0.7$ with respect to simulated values) using only four independent variables. The four independent variables and their coefficients are listed in table 8-1. In the table, T_0 indicates current air dry bulb temperature; $T-1$ indicates previous hours' temperature, T_0-1 indicates the average of current and previous hours' temperatures. I and q represent global horizontal solar radiation and internal casual heat gain. Note that the four independent variables are not the same for each zone.

A repeat times count of the 4 independent variables for each zone was carried out. In this context, a repeat times count is the number of occasions in which a particular variable was selected across all zones by the regression analysis. The repeat times were ranked in ascending order from which it was evident that 9 different variables would be able to give good results for the 38 selected zones. These are summarised in table 8-2 (together with the repeat times count values). It was found that the peak cooling load always occurs on a day with a high average external air dry bulb temperature between 10:00h – 22:00h following a period of strong global horizontal solar radiation which confirmed the selection of the 9 independent variables used. The first 9 variables were chosen because the repeat times counts of the other variables are relatively small. The

increase of numbers of independent variables would raise the complexity of following model.

Table 8-2 Independent variables repeat times count results

Variable	Symbol used	Repeat times count
Current air dry bulb temperature	T_0 (°C)	21
Dry bulb temperature at the previous hour	T_{-1} (°C)	12
Average of current and previous 2h dry bulb temperatures	T_{0-2} (°C)	7
Dry bulb temperature 7h ago	T_{-7} (°C)	7
Current global horizontal solar radiation	I_0 (Whm ⁻²)	12
Average of current and previous 2h solar radiation	I_{0-2} (Whm ⁻²)	8
Average of current and past 7 hours solar radiation	I_{0-7} (Whm ⁻²)	13
Current internal casual heat gain	q_0 (Wm ⁻²)	29
Average of current, previous hour and previous 2h casual heat gain	q_{0-2} (Wm ⁻²)	5

The simplified zone sensible cooling load model can therefore be expressed to give the current time-row zone sensible cooling load, $Q_{0,plant}$, as follows (Equation 8-1),

$$Q_{0,plant} = k_1 + k_2T_0 + k_3T_{-1} + k_4T_{0-2} + k_5T_{-7} + k_6I_0 + k_7I_{0-2} + k_8I_{0-7} + k_9q_0 + k_{10}q_{0-2} \quad 8-1$$

in which k_1, \dots, k_{10} are constants fitted by multiple-regression. Typical fitted values for these constants for 43 selected zones are summarised in table 8-3. Note that the value in last column indicates the R-square of the regression model. This confirms that the compromises concerning the reduced number of independent variables used for model fitting has not impaired the predictive quality of the simple model greatly.

All of the fitted constants illustrated in table 8-3 were generated using simulated cooling load results for the control period. As an illustration, cooling loads based on the control Design Reference Year data for the period June-August were calculated using the regression model for the 4th floor office zone example of multi-cellular offices and plotted against the corresponding simulated results in figure 8-3 (up-right corner). To test the application of the model using data other than that used to generate it, the same model was also used on the 2030s DRY data (medium carbon), 2050s (medium carbon) and 2080s (medium carbon) and these results are plotted in Figure 8-3. The results showed that the performance of the fitted model remains good regardless of the future weather data used.

Table 8-3 Results of fitted constants (Equation 8-1)

	Building	Zone	Constant	q_0	q_{0-2}	T_0	T_{-1}	T_{-7}	T_{0-2}	l_0	l_{0-2}	l_{0-7}	R Square
1	Aged	Ground floor – Flat	-35.266	.265	.246	1.092	1.177	.697	-.956	.046	-.010	.046	.821
2	Aged	1st floor west facing – Flat	-36.244	.302	.120	1.089	1.205	1.004	-.918	.046	-.017	.032	.777
3	Aged	1st floor east facing – Flat	-36.755	.180	.198	1.405	1.462	1.337	-1.629	.018	-.022	.054	.820
4	Aged	2nd floor east facing - Flat	-35.317	.207	.127	1.145	1.124	1.141	-.872	.041	-.018	.030	.752
5	Aged	2nd floor west facing - Flat	-37.412	.183	.256	1.330	1.753	1.321	-1.950	.019	-.014	.054	.793
6	Airport	1st floor – Circulation Public	-35.459	.005	.066	1.640	-.075	.345	.181	.000	-.006	.018	.826
7	Airport	2nd floor - Circulation Pubic	-33.752	-.018	.054	1.392	1.790	.388	-1.372	.003	.000	.003	.829
8	Airport	2nd floor - Sale	-19.690	.155	-.083	1.735	-.017	.217	.350	-.002	.000	.006	.945
9	Airport	2nd floor – Eat and drink	-19.125	-.309	-.116	1.936	1.215	.687	-.936	.025	-.004	.007	.922
10	Archive	Ground floor - Archive	-24.899			-.542	10.829	.825	-9.794	.007	-.002	.010	.842
11	Hospital	Ground floor - Office	-33.695	.310	-.096	3.975	-3.179	.517	1.745	.012	-.006	.009	.895
12	Hospital	1st floor – Lab	-107.703	.171	-.428	6.691	-5.962	-.062	6.714	-.001	.000	.012	.893
13	Hospital	1st floor – Waiting zone	-36.435	.086	-.262	1.860	1.956	.281	-.135	-.006	.022	-.007	.849
14	Hospital	2nd floor – Ward patients	-70.645	.374	-.054	2.638	-.782	.312	2.133	.008	.000	.016	.953
15	Hospital	3rd floor - Counselling room	-37.842	.158	-.158	5.271	-6.084	.310	4.291	.003	.017	.010	.933
16	Hotel	Ground floor - Conference room	-65.909	.474	.017	1.423	.893	.160	.293	.002	-.002	.004	.855
17	Hotel	3rd floor E - Bedrooms	-13.190	.284	.305	.592	.101	.304	-.152	.005	.007	.016	.535
18	Hotel	3rd floor E - Meeting room	-48.937	.379	.019	1.524	-.564	.135	1.231	.005	-.001	.008	.761
19	Library	1st floor - Bookshelves	-34.133	.252	-.025	2.587	-.854	.271	-.097	.005	-.004	.007	.725
20	Library	2nd floor - Office	-12.806	.096	-.226	2.724	-.755	.495	-1.131	-.001	-.009	.025	.642
21	Library	3rd floor - Bookshelves	-31.368	.275	.029	1.293	-1.452	-.037	1.825	.001	-.001	.001	.816
22	Museum	Ground floor – Gallery	-53.383	-34.111	46.439	13.794		2.713	-14.248	.007	-.005	.030	.906
23	Museum	Ground floor - Gallery	-27.858			-.873	-23.543	-.497	26.480	.019	-.007	.014	.547

24	Openplan Office	Ground floor - Office	-28.838	.374	-.273	4.814	-2.810	.630	-.711	-.002	-.012	.048	.683
25	Openplan Office	1st floor – Office	-29.252	.271	-.260	3.525	-1.411	.727	-.754	.017	.002	.010	.661
26	Openplan Office	2nd floor - Office	-26.277	.331	-.297	4.606	-3.589	.407	.583	-.002	-.006	.031	.657
27	Multi-cell Office	2nd floor - Office	-20.520	.078	-.366	3.983	-3.015	.009	1.461	.003	.017	.013	.846
28	Multi-cell Office	4th floor - Office	-26.798	.268	-.101	3.557	-2.816	.379	1.646	.003	.001	.010	.867
29	Hybrid Office	Ground floor - Office	-20.083	.059	-.071	2.726	-1.790	.120	1.160	-.001	.000	.017	.921
30	Hybrid Office	Ground floor - Office	-15.809	-.078	-.056	3.047	-2.731	.210	1.769	.010	-.001	.005	.891
31	Hybrid Office	2nd floor - Office	-23.032	.192	-.132	3.497	-2.828	.342	1.593	.003	-.003	.016	.828
32	Primary School	Ground floor - Classroom	-64.687	.314	-.076	8.669	-18.121	.009	13.215	.007	-.004	.009	.855
33	Primary School	1st floor - Classroom	-69.537	.260	-.099	14.078	-31.767	.364	21.395	.022	.016	-.002	.840
34	Prison	Ground floor - Cells	-37.308	.434	-.115	.779	7.020	1.411	-7.136	.007	-.006	.006	.790
35	Prison	Ground floor - Cells	-36.321	.396	-.062	1.968	1.339	1.085	-2.427	.000	.000	.009	.762
36	Prison	1st floor - Cells	-33.399	.358	-.124	.503	8.529	1.625	-8.668	.003	-.006	.007	.751
37	Prison	1st floor - Cells	-38.971	.425	-.100	1.334	4.863	1.323	-5.364	.004	-.007	.007	.788
38	SecondarySchool	1st floor - Classroom	-49.731	.322	-.032	4.159	-6.266	.119	4.816	.008	-.009	.013	.789
39	SecondarySchool	2nd floor - Classroom	-66.576	.317	-.094	13.082	-33.184	-.054	23.954	.017	.013	.003	.840
40	StudentsAcc	1st floor - Bedroom	-28.264	.224	.012	1.380	.343	.516	-.555	-.012	-.008	.009	.709
41	StudentsAcc	2nd floor - Bedroom	-31.036	.280	.073	1.409	.074	.494	-.240	.010	.002	.012	.662
42	Theatre	G floor - Theatre	-48.173	.291	.230	2.063	.357	.710	-1.058	.001	.001	.002	.800
43	Theatre	G floor - Backstage	-34.075	.213	.275	1.565	-1.999	.220	1.781	.006	.008	.006	.603
	Building	Zone	Constant	q_0	q_{0-2}	T_0	T_{-1}	T_{-7}	T_{0-2}	I_0	I_{0-2}	I_{0-7}	R Square

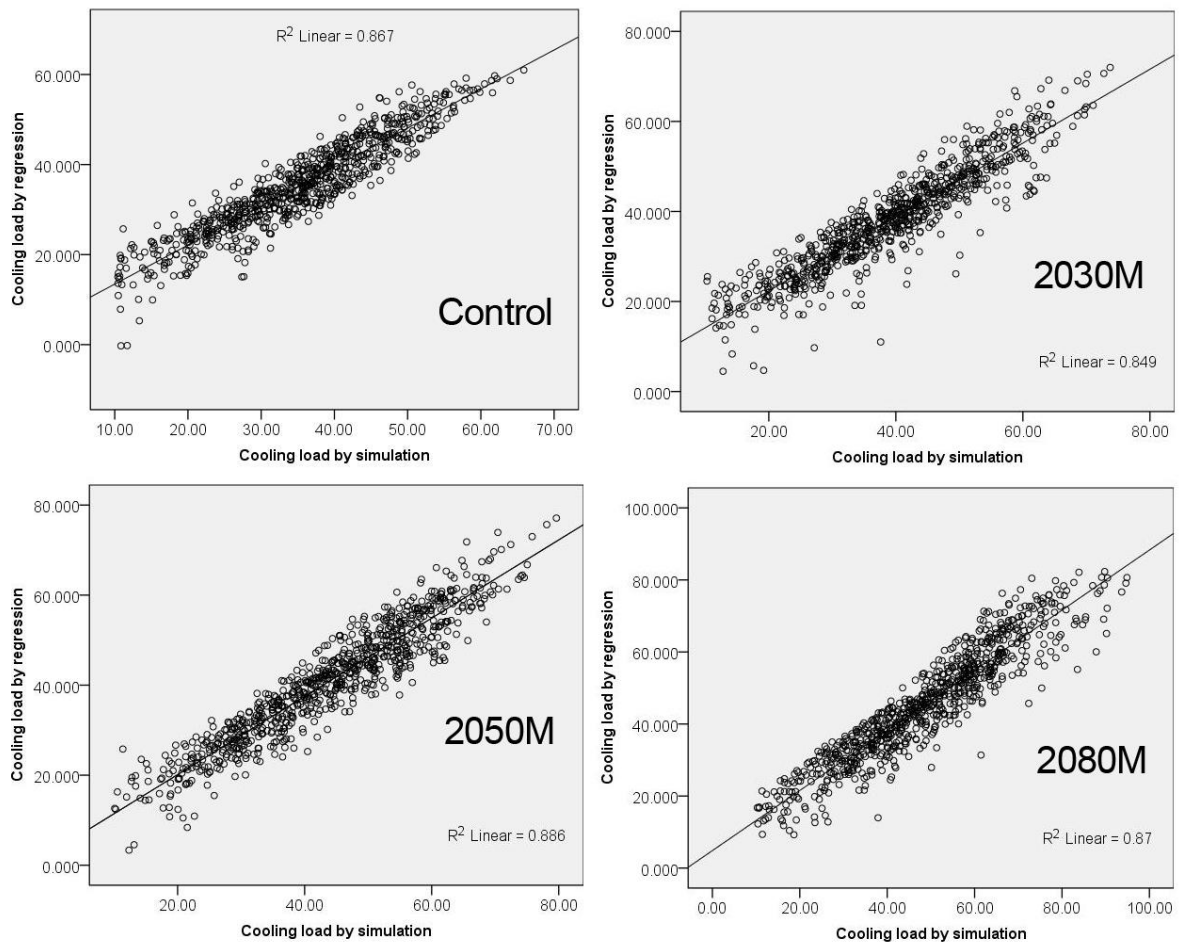


Figure 8-3 Example estimated vs. simulated cooling loads (control and future DRY data)

To obtain the design cooling load, the highest hourly load during the June-August period is selected. A comparison between the simulated design cooling loads with the corresponding loads predicted by the simple model for this example case is given in figure 8-4 for all of the DRY files generated in this work. Note that there is a good agreement between estimated peak loads and simulated peak loads, although the former give slightly lower values.

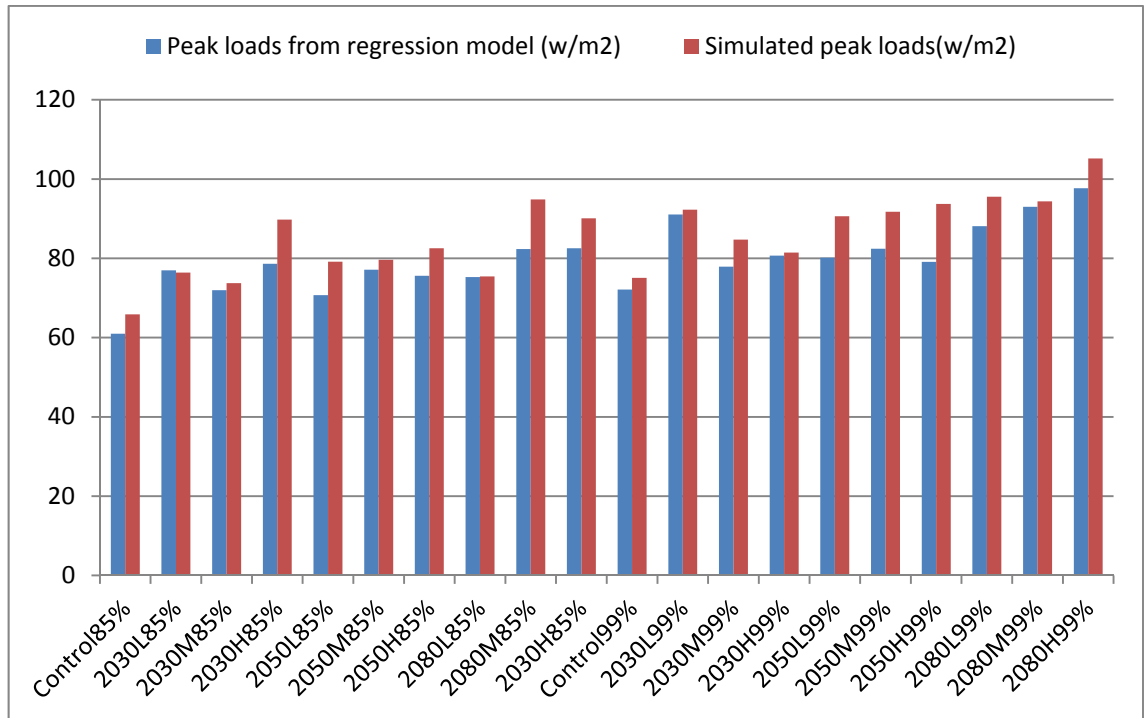


Figure 8-4 Example estimated vs. simulated design cooling loads (all DRY data)

8.2 Procedures of the method

The simplified zone cooling load model can be used through the application of the following procedure avoiding the need to engage in repeated iterations of complicated energy simulation modelling.

1. Using a reference Design Reference Year (e.g. based on existing data or some other control set), conduct a single energy simulation of the building of interest and fit regression constants according to Equation 8-1 for all building zones of interest. It is suggested that a lower threshold be applied below which cooling is deemed unnecessary (e.g. 10Wm^{-2}).

Regression constants may be fitted routinely using most statistical packages or spreadsheets.

2. Prepare files of future weather data consisting of summer (June-August) dry bulb temperatures and global horizontal solar radiation data and prepare the independent variable set as summarised in table 8-1. Using the UKCIP09, 3000 such files will be available.
3. Calculate the time series cooling loads for each summer period using the fitted model and the synoptic files of input data and select the highest cooling load result for each summer as the design cooling load for that year. This can be carried out using a spreadsheet.
4. Rank the 3000 design cooling loads in ascending order and select the design cooling load results at the desired risk percentile.

As an illustration, the distribution of the 3000 design cooling loads predicted by the simple model for the example building zone are shown in figure 8-5 for the control period. The mean value of the distribution is 62.56 W/m^2 which indicates the most likely design load to occur for that period.

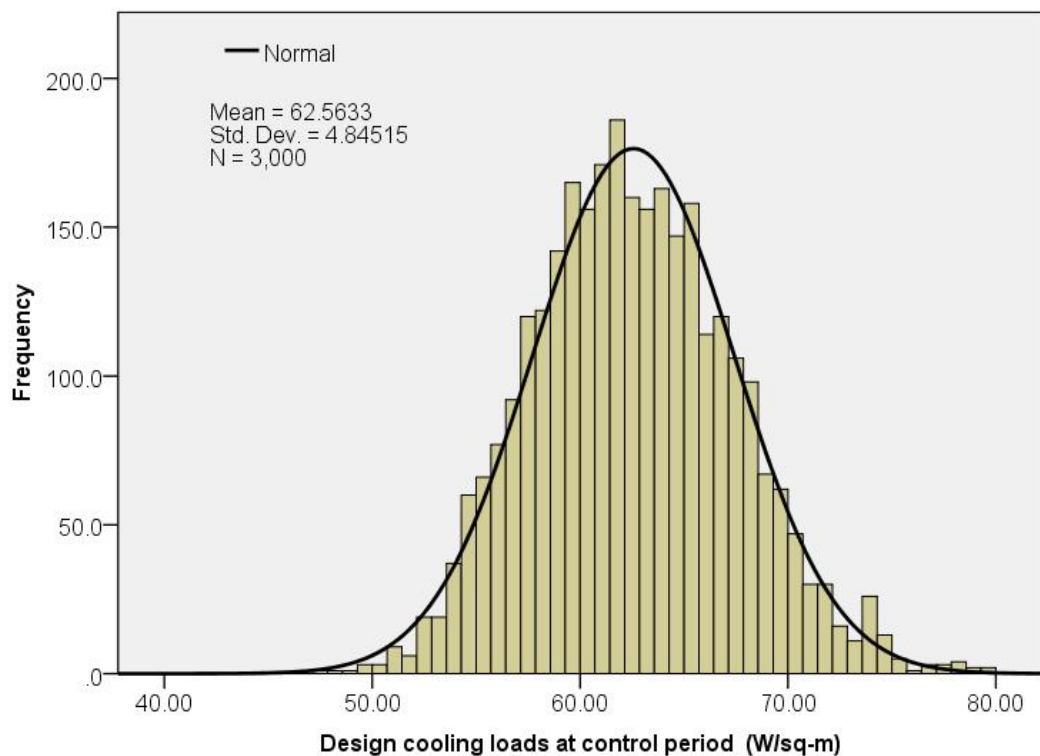


Figure 8-5 Example distribution of 3000 design cooling loads (control data)

Figure 8-6 shows the range of distribution of design loads for all the time periods. The mean values (shown as small circles) are at the 50th percentile (i.e. design cooling loads as likely to occur as not) whereas the bars represent the extents of the design cooling loads at +/- two standard deviations from the central values (i.e. 2.2 percentile and 97.8 percentile). The figure shows that the most likely design load increases smoothly with increasing timeline and emission scenarios. The range of cooling design loads at certain bands (from 2.2 to 97.8 percentile in this case) also increases with increasing timeline and emission scenarios.

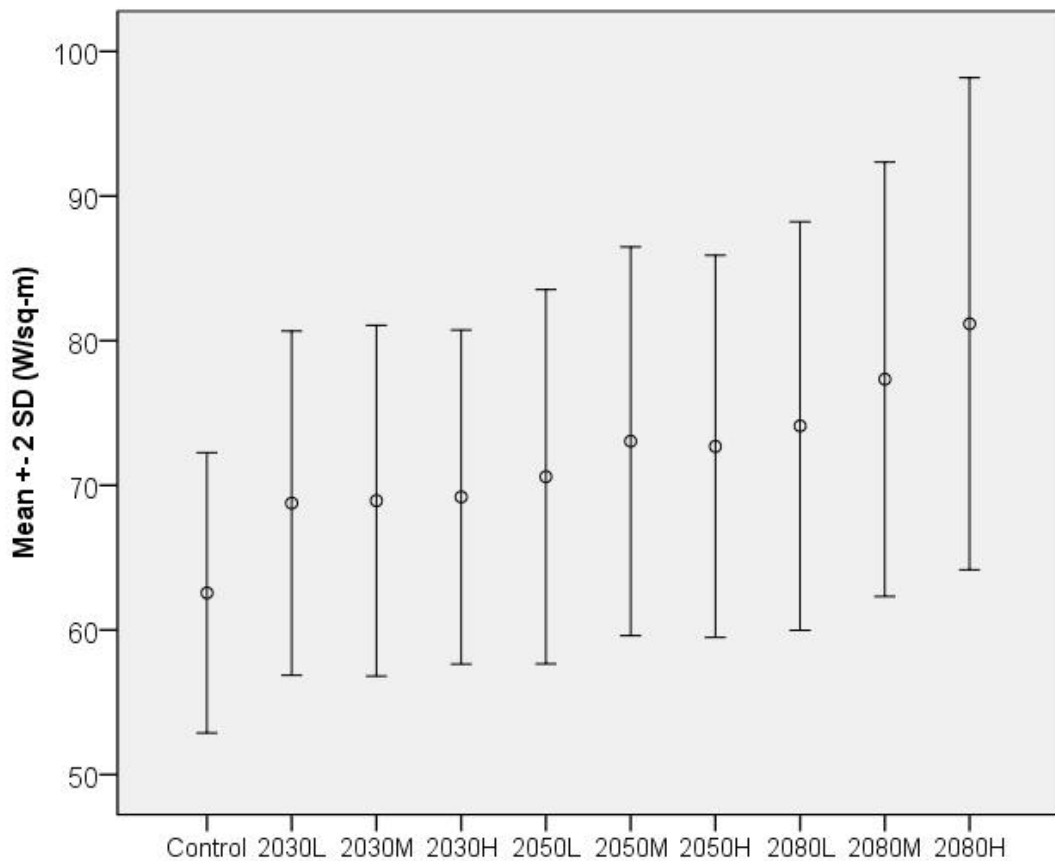


Figure 8-6 Example distribution based on 3000 control and future design cooling loads

In conclusion, to avoid the need for a large number of energy simulations to predict a number of possible cooling load changes as a result of climate change, a simple load estimating procedure is proposed which enables a zone cooling load model to be fitted to results from a single reference simulation using existing weather data. The simple model may then be used repeatedly to generate a large number of future probabilistic design cooling load results from which results can be obtained at any chosen risk percentile.

CHAPTER 9

9 Conclusion and future research

9.1 Conclusions

The aim of this work is to generate Test Reference Year/Design Reference Year data from UKCP09 for a variety of future time slices and carbon emission scenarios and to apply the data to the simulation modelling of a variety of building case studies in order to investigate probable patterns of overheating and likely changes in cooling and heating demands over time. The aim is achieved by accomplishing the objectives stated in chapter 1.

A preliminary study was conducted in chapter 3 using CIBSE future weather data ('morphing' data according to UKCIP02 projections) to represent the linear relationships between outdoor air temperatures and indoor operative or air temperatures for non-domestic buildings. Results indicate a strong linear relationship between internal operative temperature increase and corresponding external dry bulb temperature increase. The gradient of this increase was found to vary between 0.767 and 1.009 for a wide range of contrasting commercial building types with differing constructions and is consistent for either dry bulb or operative temperature results. The results were found to agree with similar findings of an earlier study (Coley & Kershaw, 2010) which dealt with housing,

schools and offices. This work also helps verify the building models created by author.

Thirdly, a tool has been developed in Matlab to generate future Test Reference Year (described in chapter 4) and Design Reference Year (described in chapter 6) weather files from UKCP09 Weather Generator outputs. The results were verified using data from alternative tools produced by Manchester University and Exeter University as well as with CIBSE's future weather data which are based on earlier (UKCIP02) climate change scenarios and are currently used by practitioners. The Northumbria tool is computationally efficient and can extract a Test Reference Year and two Design Reference Years at different risk levels from 3000 years of raw data in less than 6 minutes on a typical modern PC. Data from the new UKCP09 Weather Generator can be more easily and directly translated into ready for use files suitable for building energy simulation compared to previous data sets of this kind. The tool uses an established ISO method for generating Test Reference Year data, and an alternative method of constructing future Design Reference Years data has been proposed. Northumbria's method for generating future Design Reference Years consisting of near extreme summer months and near extreme winter months woven into an existing Test Reference Year is described. Three near extreme months are selected for each season in order to provide results that are suitable for buildings with high thermal mass. Data are selected from 3000 years of raw data from UKCP09 based on the 85th and 99th percentile risk thresholds.

Fifteen 'real' UK buildings have been identified with varying occupancy, thermal insulation, user activity and construction details. Two investigations were carried out using the 15 case study buildings.

The first involved applying TRYs generated for London, Manchester and Edinburgh for a variety of carbon emission scenarios and at time horizons of 2030, 2050 and 2080. The TRYs were developed into a weather data format readable by the EnergyPlus energy simulation program and results were generated for simulated summer average internal operative temperatures, overheat percentage of occupied hours over 28 °C, winter average internal operative temperatures, cooling demands and heating demands. All results were compared with a control data set of nominally current weather data, together with the same results produced using the alternative weather data generators of Manchester University, Exeter University and the CIBSE data.

Results revealed a good agreement in both cooling and heating energy demands, and average temperatures between the various methods. They showed that significant increases in internal summer operative temperatures in non-air-conditioned buildings can be expected throughout this century, as well as increased air conditioning cooling demands and small reductions in winter heating demand.

The second investigation involved simulating two buildings using DRYs/DSYs data produced by Northumbria University, Manchester University, Exeter University and the CIBSE data. The remaining (thirteen) buildings were simulated using Northumbria data only. Results of DRY simulations indicate that

there are significant increases in overheated hours with advancing timeline and carbon emission scenarios. Increases in design cooling loads are also shown in the results, and there is no evidence of a change in heating design loads with advancing timeline and carbon emission scenarios.

The cooling design loads from the simulations using single DRY files are not able to reflect the whole picture of all the probabilities of future weather data which might occur. The resources of time and effort to conduct simulations and to analyse the results for all probabilities (3000 in UKCP09 for example) are not trivial particularly when applied during the early design and planning processes that most new building proposals undergo. Therefore the availability of a simpler approximate method would be invaluable to practitioners. In chapter 8, the development of such a method is considered and applied to the calculation of future room design cooling loads. The method is based on regression analysis of dependent variables (hourly cooling loads) and independent variables, such as temperature, solar radiation and so on. A simple linear equation with nine coefficients to be fixed was proposed to calculate building cooling loads. The design cooling load at any design risk required could be calculated by this method.

9.2 Future research

Further work for research can be categorised into five areas. Firstly, there is a need to develop robust methods for obtaining values of variables and climate modelling parameters that are currently either not defined or badly defined by the UKCP09 data. In particular, hourly wind speed (and direction) data need to

be developed as well as data leading to the opaque cloud cover parameter which is needed for surface-to-sky radiation heat transfer modelling.

Secondly, work is needed to develop mechanisms for adjusting the test reference year and design reference year data in inner-city areas to reflect the urban heat island effect in local canyons. Localised weather data could make the calculation of cooling design loads more accurate.

Thirdly, there is a need to explore alternative future insulation, massing, shading and air tightness standards as future buildings inherit these standards and existing buildings undergo refurbishment cycles, and to harmonise the results of this with changing energy use due to climate change. This is particularly important both from the viewpoint of increasing insulation standards (reduced winter heating) and improved shading and massing (reduced summertime overheating).

Fourthly, a better understanding of how occupancy patterns (including patterns of use) in buildings might be expected to evolve in future will help in the development of mitigation strategies such as adaptive comfort algorithms and exposure limits in buildings inclined to overheating. This would involve the study of the influence of social and political impact on user behaviour and building design.

Finally, this work has dealt with sensible zone cooling loads only applied to non-domestic buildings. Further work is needed to consider simplified procedures for analysing future overheating risk and future design space heating loads in both domestic and non-domestic buildings as well as the impact of other

variables such as those influencing humidity loads. There is also a need to investigate alternative air conditioning methods in order to identify plant, control and thermal storage options that operate best in conditions of a changing climate.

REFERENCES

- Adelard, L., Boyer, H., Garde, F. & Gatina, J. C. (2000) 'A detailed weather data generator for building simulations', *Energy and Buildings*, 31 (1), pp. 75-88.
- Allen, R. G., Pereira, L. S., Raes, D. & Smith, M. (1998) *Crop evapotranspiration - Guidelines for computing crop water requirements - FAO Irrigation and drainage paper 56*. Food and Agricultural Organization of the United Nations.
- Anderson, B. (2006) *Conventions for U-value calculations 2006 edition*. Garston: BRE Press.
- Arasteh, D., Kohler, C. & Griffith, B. (2009) *Modeling Windows in Energy Plus with Simple Performance Indices* Lawrence Berkeley National Laboratory.
- Argiriou, A., Lykoudis, S., Kontoyiannidis, S., Balaras, C. A., Asimakopoulos, D., Petrakis, M. & Kassomenos, P. (1999) 'Comparison of methodologies for tmy generation using 20 years data for Athens, Greece', *Solar Energy*, 66 (1), pp. 33-45.
- ASHRAE (2001) 'ASHRAE Handbook: Fundamentals, Ventilating and Air-Conditioning Engineers', *American Society of Heating, Refrigerating and Air Conditioning Engineers, Atlanta*.
- ASHRAE (2004). *ASHRAE Standard 55-2004: Thermal environmental Conditions for Human Occupancy*. Atlanta, ASHRAE.
- Barenbrug, A. W. T. (1974) *Psychrometry and psychrometric charts*. Johannesburg: Chamber of Mines of South Africa.
- Belcher, S., Hacker, J. & Powell, D. (2005) 'Constructing design weather data for future climates', *Building Service Engineering Research and Technology*, 26 (1), pp. 49-61.

- Belding, H. & Hatch, T. (1955) 'Index for evaluating heat stress in terms of resulting physiological strains', *Heating, Piping and Air Conditioning*, 27 (8), p. 129.
- BLAST Support Office (1986) *BLAST (Building Loads and System Thermodynamics)*. [Computer Program]. Distributor: Urbana-Champaign:University of Illinois.
- Brisken, W. R. & Reque, S. G. (1958) 'Heat Load Calculations by Thermal Response', *Transactions American Society of Heating & Air-Conditioning Engineers*, 62, pp. 391-424.
- British Standards Institution (2006). BS EN 14351-1:2006 Windows and doors. Product standard, performance characteristics. Windows and external pedestrian doorsets without resistance to fire and/or smoke leakage characteristics. London, British Standards Institute.
- British Standards Institution (2007a). BS EN 15251:2007 Indoor environmental input parameters for design and assessment of energy performance of buildings addressing indoor air quality, thermal environment, lighting and acoustics. London, British Standards Institute.
- British Standards Institution (2007b). BS EN ISO 13786:2007 Thermal performance of building components. Dynamic thermal characteristics. Calculation methods. London, BSI.
- Building Energy Calculation Software Approval Scheme (2011) *Approved Software Listing*. [Online]. Available at: <http://www.ukreg-accreditation.org/ND-ApprovedSoftware.php>.
- Chow, D. H. & 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 and Technology*, 31 (4), pp. 307-323.
- CIBSE. (2002) *Guide J Weather, solar and illuminance data*. London: Chartered Institution of Building Services Engineers.
- CIBSE. (2006) *Environmental Design: CIBSE Guide A*. London: Chartered Institution of Building Services Engineers.

- CIBSE (2008) 'Current and Future CIBSE Weather Data', [Online]. Available at: <http://www.cibse.org/index.cfm?go=publications.view&item=332>.
- CIBSE. (2009) *TM48: The use of Climate Change Scenarios for Building Simulation: the CIBSE Future Weather Years*. London: Chartered Institution of Building Services Engineers.
- Coley, D. & Kershaw, T. (2010) 'Changes in internal temperatures within the built environment as a response to a changing climate', *Building and Environment*, 45 (1), pp. 89-93.
- Coley, D., Kershaw, T. & Eames, M. (2011) 'PROMETHEUS The Use of Probabilistic Climate Change Data to Future-proof Design Decisions in the Building Sector', [Online]. Available at: <http://centres.exeter.ac.uk/cee/prometheus/downloads.html>.
- Collins, K. & Hoinville, E. (1980) 'Temperature requirements in old age', *Building Services Engineering Research and Technology*, 1 (4), pp. 165-172.
- COPSE (2011) *Co-incident probabilistic climate change weather data for a sustainable environment*. [Online]. Available at: <http://www.copse.manchester.ac.uk/Design/aboutproject.htm>.
- Crawley, D., Hand, J. & Lawrie, L. (1999) *Improving the Weather Information Available to Simulation Programs: Building Simulation '99'*.
- Cullen, N. J. (2001) 'Climate Change –designing buildings with a future', *CIBSE National Conference 2001*. CIBSE.
- Danter, E. (1960) 'Periodic Heat Flow Characteristics of Simple Walls and Roof', *Journal of the Institution of Heating and Ventilating Engineers*, 28, pp. 136-146.
- Davies, M. G. (1994) 'The thermal response of an enclosure to periodic excitation: the CIBSE approach', *Building and Environment*, 29 (2), pp. 217-235.

- Davies, M. G. (1996) 'Time-domain estimation of wall conduction transfer function coefficients', *ASHRAE Transactions*, 102 (1), pp. 328-343.
- DCLG. (2006) *Code for Sustainable Homes A step-change in sustainable home building practice*. London.
- DCLG (2008) *National Calculation Methodology (NCM) modelling guide (for buildings other than dwellings in England and Wales)*. London: Department for Communities and Local Government.
- DCLG (2010a) *National Calculation Method SBEM software*. [Online]. Available at: <http://www.ncm.bre.co.uk/> (Accessed: 10th May 2010).
- DCLG (2010b) *National Calculation Methodology (NCM) modelling guide (for buildings other than dwellings in England and Wales)*. London: Department for Communities and Local Government.
- DCLG. (2010c) *Summary of changes to the Code for Sustainable Homes technical guidance*. London: Department for Communities and Local Government.
- de Dear, R. J. & Brager, G. S. (2002) 'Thermal comfort in naturally ventilated buildings: revisions to ASHRAE Standard 55', *Energy and Buildings*, 34 (6), pp. 549-561.
- de Wilde, P. & Tian, W. (2010) 'The role of adaptive thermal comfort in the prediction of the thermal performance of a modern mixed-mode office building in the UK under climate change', *Journal of Building Performance Simulation*, 3 (2), pp. 87 - 101.
- DECC. (2009) *The UK Low Carbon Transition Plan National strategy for climate and energy*. The Stationery Office.
- DesignBuilder Software Ltd (2011) *DesignBuilder* [Computer Program]. Stroud[Online]. Available at: <http://www.designbuilder.co.uk/> (Accessed:13 Oct 2011).

- Domínguez-Muñoz, F., Cejudo-López, J. M. & Carrillo-Andrés, A. (2010) 'Uncertainty in peak cooling load calculations', *Energy and Buildings*, 42 (7), pp. 1010-1018.
- DTI. (2007) *Meeting The Energy Challenge A WHITE PAPER ON ENERGY*. Norwich: The Stationery Office.
- Du, H., Underwood, C. & Edge, J. (2010) *Modelling the impact of a warming climate on commercial buildings in the UK Clima 2010 -10th REHVA World Congress "Sustainable Energy Use in Buildings"* 9-12 May. Antalya, Turkey: Federation of European HVAC Associations.
- Du, H., Underwood, C. P. & Edge, J. S. (2011) 'Generating test reference years from the UKCP09 projections and their application in building energy simulations', *Building Services Engineering Research and Technology* (accepted) DOI: 10.1177/0143624411418132.
- Eames, M., Kershaw, T. & Coley, D. (2010a) 'The creation of wind speed and direction data for the use in probabilistic future weather files', *Building Services Engineering Research and Technology*.
- Eames, M., Kershaw, T. & Coley, D. (2010b) 'On the creation of future probabilistic design weather years from UKCP09', *Building Services Engineering Research and Technology*.
- Eames, M., Kershaw, T. & Coley, D. (2011) 'On the creation of future probabilistic design weather years from UKCP09', *Building Services Engineering Research and Technology*, 32 (2), pp. 127-142.
- Fanger, P. O. (1970) *Thermal comfort*. Copenhagen: Danish Technical Press.
- Fanger, P. O. (1982) *Thermal comfort*. Malabar: Krieger RE Publishing Company.
- Guan, L. (2009) 'Preparation of future weather data to study the impact of climate change on buildings', *Building and Environment*, 44 (4), pp. 793-800.

- Hacker, J. & Holmes, M. (2007) 'Thermal Comfort: Climate Change and the Environmental Design of Buildings in the United Kingdom', *Built Environment*, 33 (1), pp. 97-114.
- Hacker, J. N., De Saulles, T. P., Minson, A. J. & Holmes, M. J. (2008) 'Embodied and operational carbon dioxide emissions from housing: A case study on the effects of thermal mass and climate change', *Energy and Buildings*, 40 (3), pp. 375-384.
- Haines, G. & Hatch, T. (1952) 'Industrial heat exposures - valuation and control', *Heating and Ventilating*, 9, pp. 93-104.
- Hand, J. W. (2011) *ESP-r* [Computer Program]. Distributor: Energy Systems Research Unit, University of Strathclyde, Glasgow[Online]. Available at: <http://www.esru.strath.ac.uk/Programs/ESP-r.htm> (Accessed:25 Oct 2011).
- Heidari, S. & Sharples, S. (2002) 'A comparative analysis of short-term and long-term thermal comfort surveys in Iran', *Energy and Buildings*, 34 (6), pp. 607-614.
- Hensen, J. & Augenbroe, G. (2004) 'Performance simulation for better building design', *Energy and Buildings*, 36 (8), pp. 735-736.
- Hensen, J. & Lamberts, R. (eds.) (2011) *Building performance simulation for design and operation*. Abingdon, Oxon; New York, NY: Spon Press.
- HM Government. (2010a) *Approved Document L1A: Conservation of fuel and power (New dwellings) (2010 edition)*. London: NBS.
- HM Government. (2010b) *Approved Document L1B: Conservation of fuel and power (Existing dwellings) (2010 edition)*. London: NBS.
- HM Government. (2010c) *Approved Document L2A: Conservation of fuel and power (New buildings other than dwellings) (2010 edition)*. London: NBS.
- HM Government. (2010d) *Approved Document L2B: Conservation of fuel and power (Existing buildings other than dwellings) (2010 edition)*. London: NBS.

Holmes, M. & Hacker, J. (2007) 'Climate change, thermal comfort and energy: Meeting the design challenges of the 21st century', *Energy & Buildings*, 39 (7), pp. 802-814.

Intergrated Environmental Solutions (2010) *IES VE* [Computer Program]. [Online]. Available at: <http://www.iesve.com/> (Accessed:20 May 2010).

IPCC (2007) *Climate change 2007: the physical science basis:Contribution of Working Group I*. Cambridge, UK and New York: Cambridge University Press.

ISO (2003). ISO 15099 Thermal Performance of Windows, Doors and Shading Devices — Detailed Calculations.

ISO (2005a). EN ISO 7730:2005 Ergonomics of the thermal environment - Analytical determination and interpretation of thermal comfort using calculation of the PMV and PPD indices and local thermal comfort criteria. Geneva, International Standards Organization.

ISO (2005b). ISO 15927-4: Hourly data for assessing the annual energy use for heating and cooling.

Iu, I. S. (2002) *Experimental validation of the radiant time series method for cooling load calculations*. Oklahoma State University.

Jenkins, G. J., Murphy, J. M., Sexton, D. S., Lowe, J. A., Jones, P. & Kilsby, C. G. (2009) *UK Climate Projections: Briefing report*. Exeter: Met Office Hadley Centre.

Jentsch, M. F., Bahaj, A. S. & James, P. A. B. (2008) 'Climate change future proofing of buildings--Generation and assessment of building simulation weather files', *Energy and Buildings*, 40 (12), pp. 2148-2168.

Kershaw, T., Eames, M. & Coley, D. (2010) 'Assessing the risk of climate change for buildings: A comparison between multi-year and probabilistic reference year simulations', *Building and Environment*.

- Kilsby, C. G., Jones, P. D., Burton, A., Ford, A. C., Fowler, H. J., Harpham, C., James, P., Smith, A. & Wilby, R. L. (2007) 'A daily weather generator for use in climate change studies', *Environmental Modelling & Software*, 22 (12), pp. 1705-1719.
- Langkilde, G. (1979) 'Thermal comfort for people of high age', *Comfort thermique: Aspects physiologiques et psychologiques*, pp. 187-193.
- Lorenz F. & Masy G. (1982) *Methode d'evaluation de l'economie d'energie apportee par l'intermittence de chauffage dans les batiments. Traitement par differences finies d'un model a deux constantes de temps, Report No. GM820130-01. (in French)*. Liege: Faculte des Sciences Appliquees, University de Liege.
- Machle, W. & Hatch, T. (1947) 'Heat : man's exchanges and physiological responses', *Physiological Reviews*, 27 (2), pp. 200-227.
- Mackey, C. O. & Wright., L. T. (1943) 'Periodic Heat Flow—Homogeneous Walls or Roofs', *Transactions American Society of Heating & Ventilating Engineers*, 50, pp. 293-312.
- Marion, W. & Urban, K. (1995) *User`s manual for TMY2s: Derived from the 1961--1990 National Solar Radiation Data Base*. [Online]. Available at: <http://rredc.nrel.gov/solar/pubs/tmy2/PDFs/tmy2man.pdf> (Accessed: 26 November 2008).
- Mark, S. O. (ed.) (2009) *ASHRAE Handbook Fundamentals*. SI Edition edn. Atlanta, USA: American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc.
- McGilligan, C., Natarajan, S. & Nikolopoulou, M. (2011) 'Adaptive Comfort Degree-Days: A metric to compare adaptive comfort standards and estimate changes in energy consumption for future UK climates', *Energy and Buildings*.
- McGuffie, K. & Henderson-Sellers, A. (2005) *A climate modelling primer*. Chichester [u.a.]: Wiley.
- Milbank, N. O. & Harrington-Lynn, J. (1974) *Thermal response and the admittance procedure*. Building Research Establishment.

- Mitalas, G. P. (1978) 'Comments on the Z-transfer function method for calculating heat transfer in buildings', *ASHRAE Transactions*, 84 (1), pp. 667-674.
- Nicol, F. (1995) *Standards for Thermal Comfort: Indoor Air Temperature Standards for the 21st Century*. London: Spon Press.
- Nicol, J. F. & Humphreys, M. A. (2002) 'Adaptive thermal comfort and sustainable thermal standards for buildings', *Energy and Buildings*, 34 (6), pp. 563-572.
- Office of the Deputy Prime Minister. (2006a) *Approved Document L1A: Conservation of fuel and power (New dwellings) (2006 edition)*. London: NBS.
- Office of the Deputy Prime Minister. (2006b) *Approved Document L1B: Conservation of fuel and power (Existing dwellings) (2006 edition)*. London: NBS.
- Office of the Deputy Prime Minister. (2006c) *Approved Document L2A: Conservation of fuel and power (New buildings other than dwellings) (2006 edition)*. London: NBS.
- Office of the Deputy Prime Minister. (2006d) *Approved Document L2B: Conservation of fuel and power (Existing buildings other than dwellings) (2006 edition)* London: NBS.
- Patidar, S., Jenkins, D. P., Gibson, G. J. & Banfill, P. F. G. (2011) 'Statistical techniques to emulate dynamic building simulations for overheating analyses in future probabilistic climates', *Journal of Building Performance Simulation*, 4 (3), pp. 271-284.
- Pedersen, C. O., Fisher, D. E. & Liesen, R. J. (1997) 'Development of a Heat Balance Procedure for Calculating Cooling Loads', *ASHRAE Transactions*, 103 (2), pp. 459-468.
- Rees, S. J., Spittler, J. D., Davies, M. G. & Haves, P. (2000a) 'Qualitative Comparison of North American and U.K. Cooling Load Calculation

Methods', *International Journal of Heating, Ventilating, Air-Conditioning and Refrigeration Research*, 6 (1), pp. 75-99.

Rees, S. J., Spitler, J. D. & Haves, P. (1998) 'Quantitative Comparison of North American and U.K. Cooling Load Calculation Procedures—Results', *ASHRAE Transactions*, 104 (2), pp. 47-61.

Rees, S. J., Spitler, J. D., Holmes, M. J. & Haves, P. (2000b) 'Comparison of peak load predictions and treatment of solar gains in the admittance and heat balance load calculation procedures', *Building Services Engineering Research and Technology*, 21 (2), pp. 125-138.

Rohles, F. & Johnson, M. (1972) 'Thermal comfort in the elderly', *ASHRAE Transactions*, 78 (1), p. 131.

Seem, J. E., Klein, S. A., Beckman, W. A. & Mitchell, J. W. (1989) 'Transfer Functions for Efficient Calculation of Multidimensional Transient Heat Transfer', *Journal of Heat Transfer*, 111 (1), pp. 5-12.

Shearer, D. (2008) *SBEM - the National Calculation Methodology for Non Domestic Buildings*. BRE Scotland [Online]. Available at: http://www.sesg.strath.ac.uk/Presentations/DShearer_SBEM_NCM_081_105.pdf (Accessed: 27 Aug 2009).

Spitler, J. D. (1996) *Annotated guide to load calculation models and algorithms*. Atlanta: American Society of Heating, Refrigeration and Air-Conditioning Engineers, Inc.

Spitler, J. D., Fisher, D. E. & Pedersen, C. O. (1997) 'The Radiant Time Series Cooling Load Calculation Procedure', *ASHRAE Transactions*, 103 (2), pp. 503-515.

Spitler, J. D. & Rees, S. J. (1998) 'Quantitative Comparison of North American and U.K. Cooling Load Calculation Procedures—Methodology', *ASHRAE Transactions*, 104 (2), pp. 36-46.

Stephenson, D. G. & Mitalas, G. P. (1967) 'Room thermal response factors', *ASHRAE Transactions*, 73 (1), p. 342.

- Stephenson, D. G. & Mitalas, G. P. (1971) 'Calculation of heat conduction transfer functions for multi-layer slabs', *ASHRAE Transactions*, 77 (2), pp. 117-126.
- Stewart, J. P. (1948) 'Solar Heat Gain through Walls and Roofs for Cooling Load Calculations', *Transactions American Society of Heating & Ventilating Engineers*, 54, pp. 361-388.
- Sturman, A. & Tapper, N. (1996) *The Weather and Climate of Australia and New Zealand*. Oxford University Press.
- Szokolay, S. V. (2008) *Introduction to architectural science: the basis of sustainable design*. Elsevier/Architectural Press.
- Tham, Y. & Muneer, T. (2010) 'Sol-air temperature and daylight illuminance profiles for the UKCP09 data sets', *Building and Environment*.
- The Stationery Office. (2002) *Approved Document L2: Conservation of fuel and power in buildings other than dwellings 2002 Edition*. London: NBS.
- Tindale, A. (1993) 'Third-order lumped-parameter simulation method', *Building Service Engineering*, 14 (3), pp. 87-97.
- UK Climate Impacts Programme (2002) *Climate Change Scenarios for the United Kingdom: The UKCIP02 Scientific Report*.
- UK Climate Impacts Programme (2008) *UKCIP08 What to expect from UKCIP08*. UKCIP.
- UK Climate Projections (2010) *UK Climate Projections 2009 Weather Generator User Interface (Version 1)*. [Online]. Available at: <http://ukclimateprojections-ui.defra.gov.uk/ui/admin/login.php> (Accessed: 27th August 2010).
- Underwood, C. (2010) Private communication, 12 Feb.
- Underwood, C. P. & Yik, F. W. H. (2004) *Modelling methods for energy in buildings*. Oxford [u.a.]: Blackwell Science.

US Department of Energy (2010) *Auxiliary EnergyPlus Programs - Extra programs for EnergyPlus*.

US Department of Energy (2011a) *EnergPlus Energy Simulation Software* [Computer Program]. [Online]. Available at: <http://apps1.eere.energy.gov/buildings/energyplus/> (Accessed:20 May 2010).

US Department of Energy (2011b) *EnergyPlus Energy Simulation Software Weather Data*. [Online]. Available at: http://apps1.eere.energy.gov/buildings/energyplus/weatherdata_about.cfm.

van Paassen, A. H. & Luo, Q. X. (2002) 'Weather data generator to study climate change on buildings', *Building Services Engineering Research and Technology*, 23 (4), pp. 251-258.

Walton, G. (1983) *Thermal Analysis Research Program Reference Manual* [Computer Program]. Distributor: National Bureau of Standards.

Wang, S. & Chen, Y. (2003) 'Transient heat flow calculation for multilayer constructions using a frequency-domain regression method', *Building and Environment*, 38 (1), pp. 45-61.

Watkins, R. (2011) 'COPSE Designing with future weather data', *Adapting our built environment ARCC contributions and Challenges*. 6-7 April 2011. University of Oxford.

Watkins, R. & Levermore, G. (2010) 'Quantifying the effects of climate change and risk level on peak load design in buildings', *Building Services Engineering Research and Technology*, 32 (1), pp. 9-19.

Watkins, R., Levermore, G. & Parkinson, J. (2011) 'Constructing a future weather file for use in building simulation using UKCP09 projections', *Building Services Engineering Research and Technology*, 32 (3), pp. 293-299.

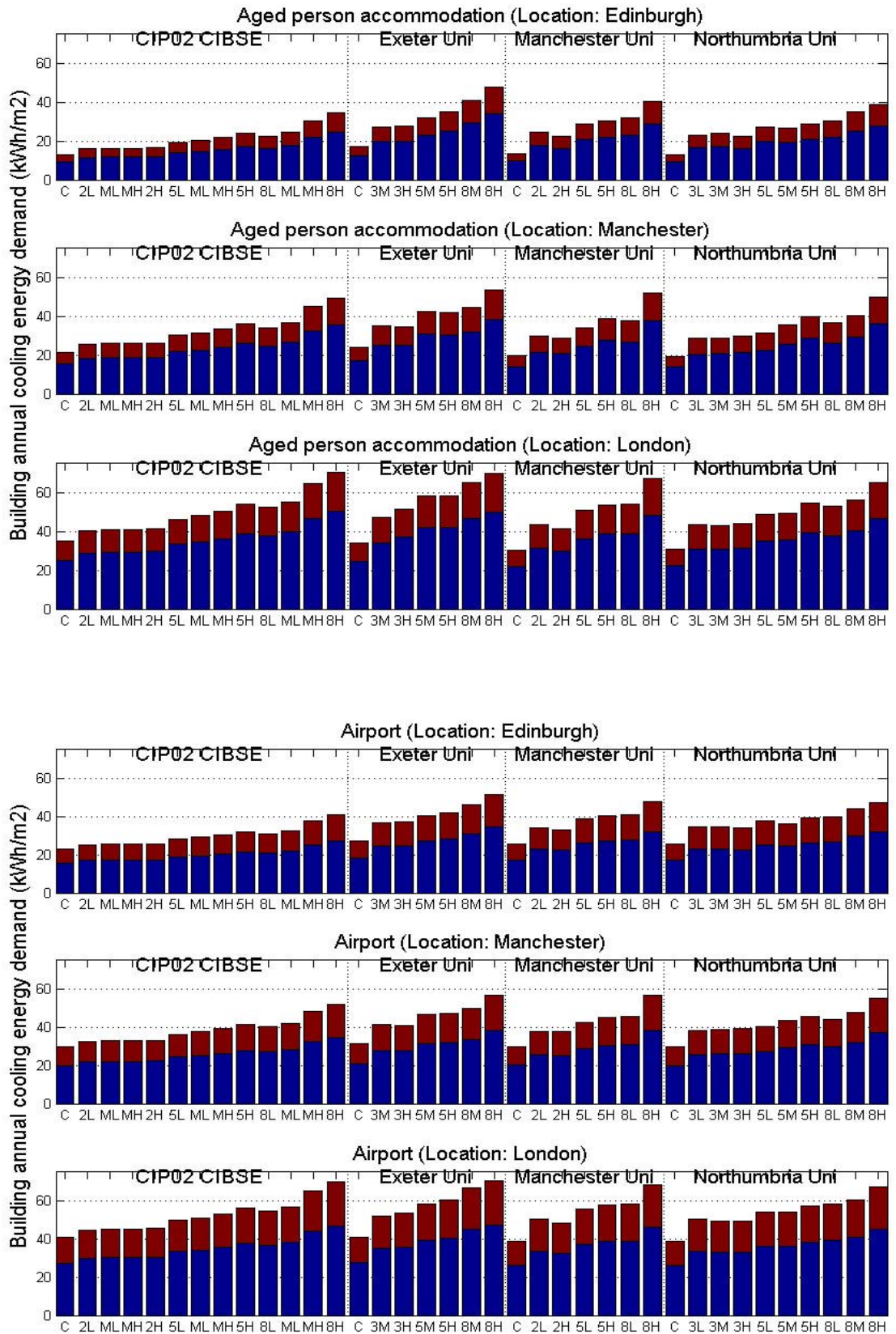
Wilcox, S. & Marion, W. (2008) *Users Manual for TMY3 Data Sets (Revised)*.
NREL/TP-581-43156, National Renewable Energy Laboratory (NREL),
Golden, CO.

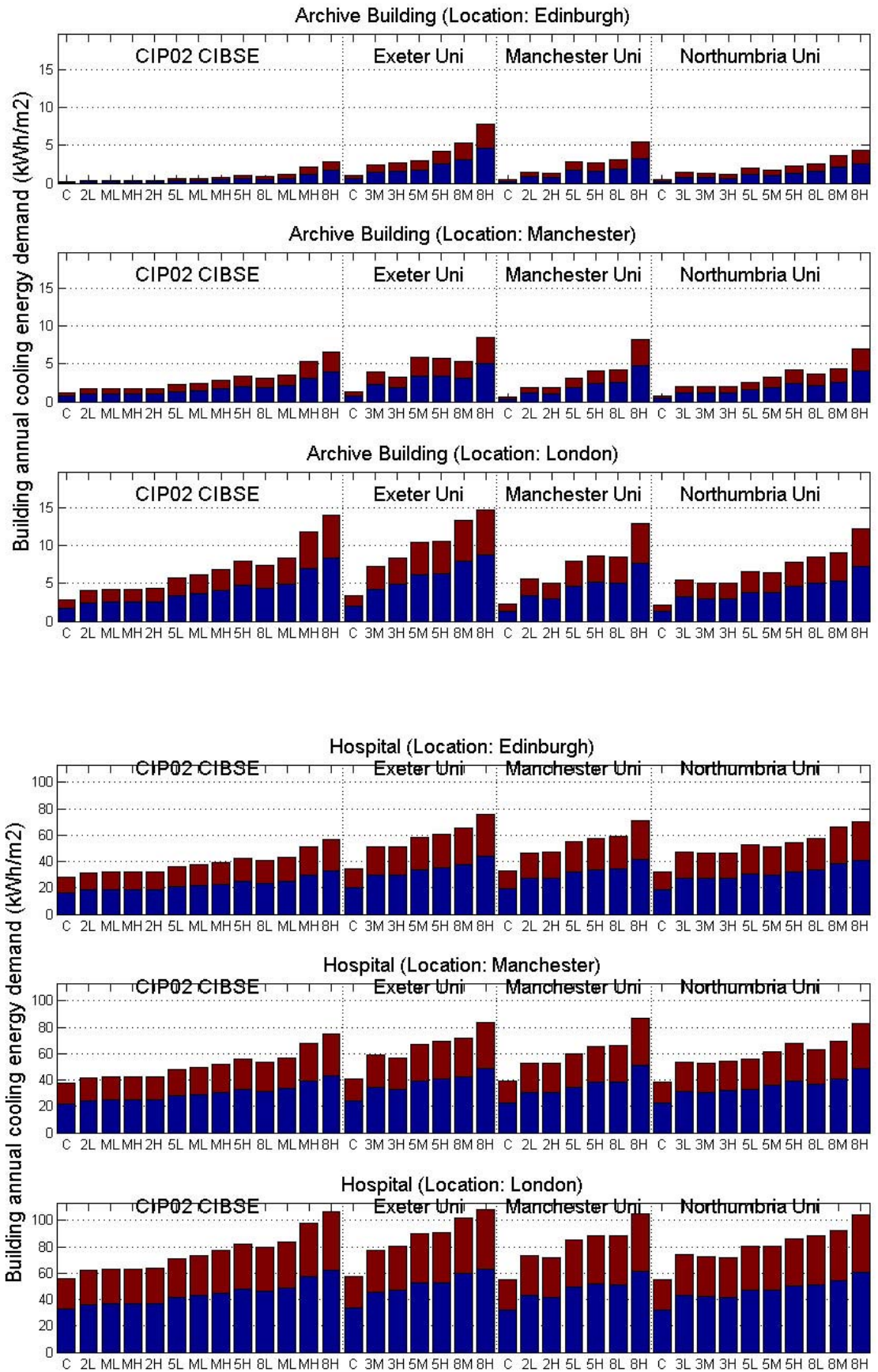
APPENDICES

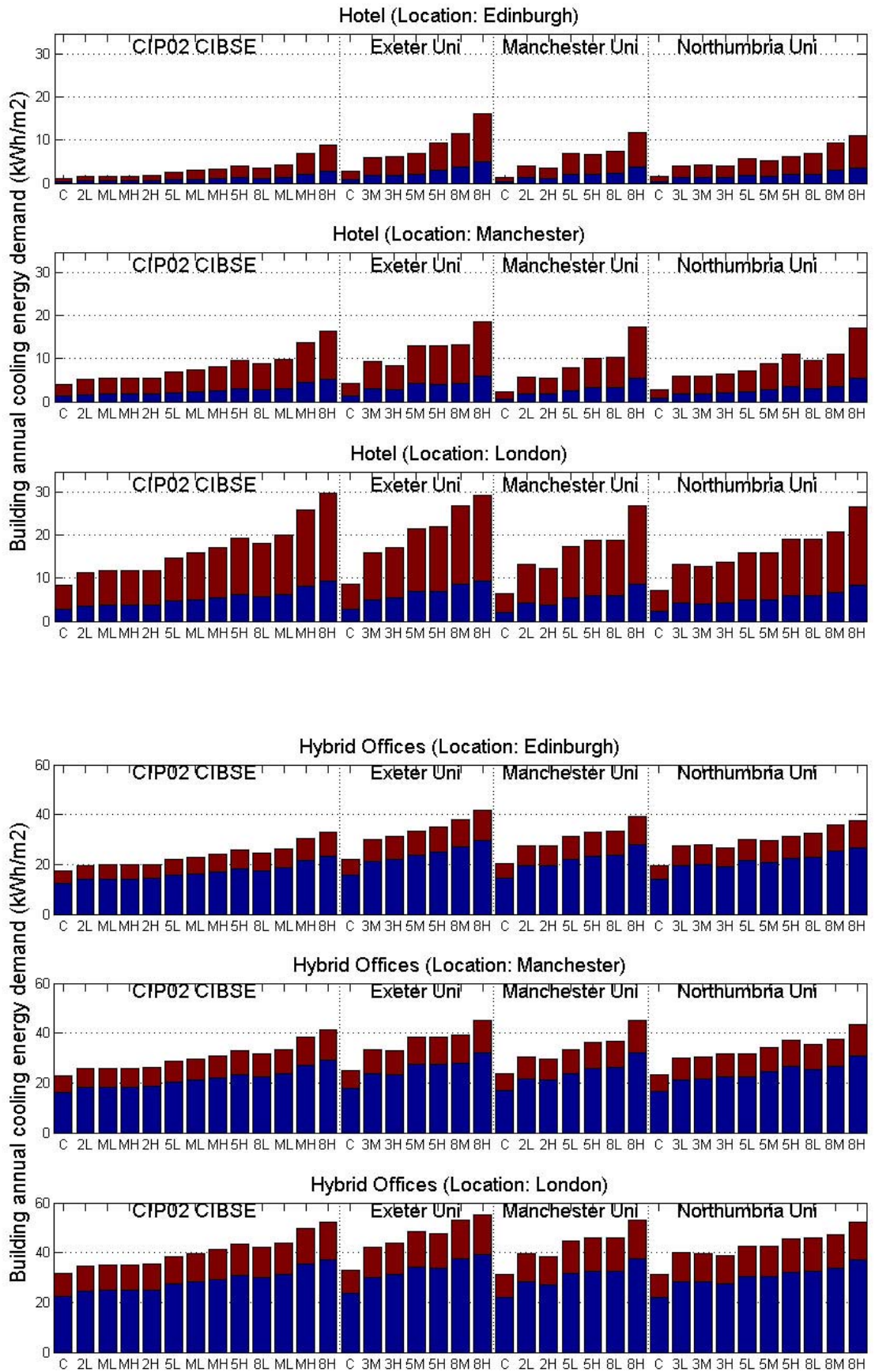
Key to symbols on figures in appendices

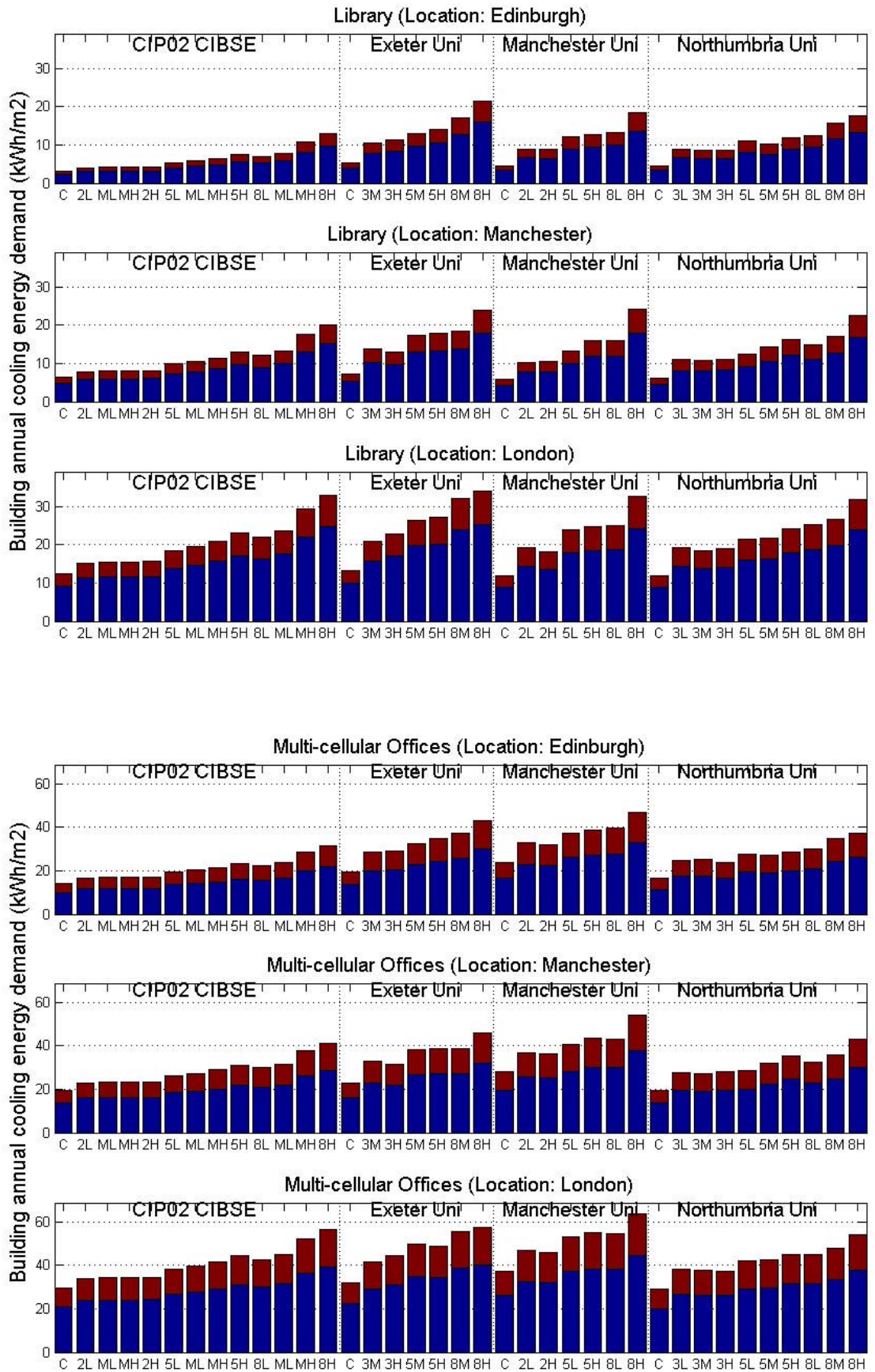
CIBSE FWY Future CIBSE TRY or DSY	C	Control data (1983-2004)
	2L	2020s low carbon emission scenario
	ML	2020s medium low carbon emission scenario
	MH	2020s medium high carbon emission scenario
	2H	2020s high carbon emission scenario
	5L	2050s low carbon emission scenario
	ML	2050s medium low carbon emission scenario
	MH	2050s medium high carbon emission scenario
	5H	2050s high carbon emission scenario
	8L	2080s low carbon emission scenario
	ML	2080s medium low carbon emission scenario
	HL	2080s medium high carbon emission scenario
	8H	2080s high carbon emission scenario
EU Exeter Uni	C	Control data (1961-1990)
	3M	2030s medium carbon emission scenario
	3H	2030s high carbon emission scenario
	5M	2050s medium carbon emission scenario
	5H	2050s high carbon emission scenario
	8M	2080s medium carbon emission scenario
	8H	2080s high carbon emission scenario
MU Manchester Uni	C	Control data (1961-1990)
	2L	2020s low carbon emission scenario
	2H	2020s high carbon emission scenario
	5L	2050s low carbon emission scenario
	5H	2050s high carbon emission scenario
	8L	2080s low carbon emission scenario
	8H	2080s high carbon emission scenario
NU Northumbria Uni	C	Control data (1961-1990)
	3L	2030s low carbon emission scenario
	3M	2030s medium carbon emission scenario
	3H	2030s high carbon emission scenario
	5L	2050s low carbon emission scenario
	5M	2050s medium carbon emission scenario
	5H	2050s high carbon emission scenario
	8L	2080s low carbon emission scenario
	8M	2080s medium carbon emission scenario
	8H	2080s high carbon emission scenario

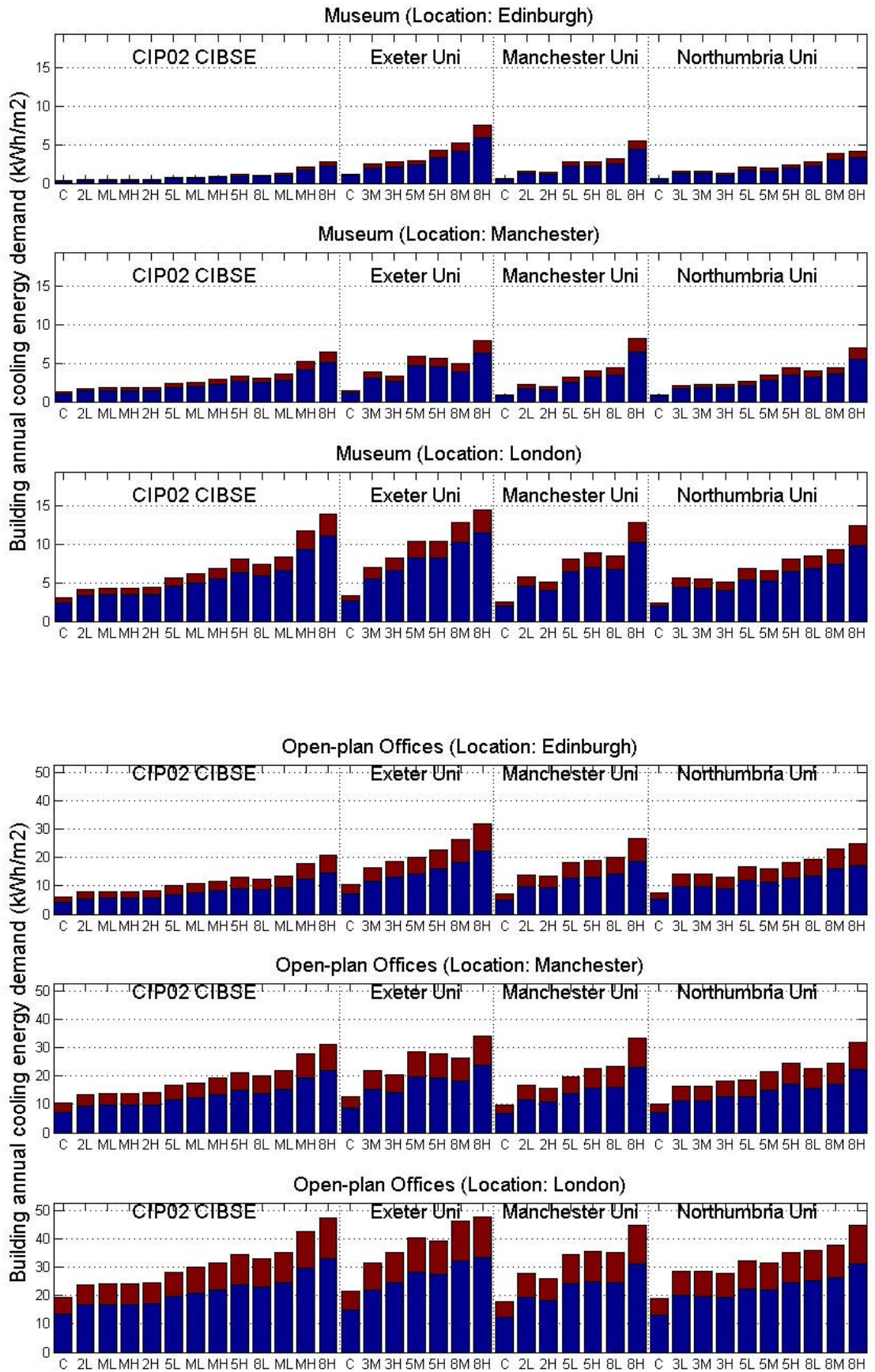
Appendix A1: TRY results: cooling energy demand

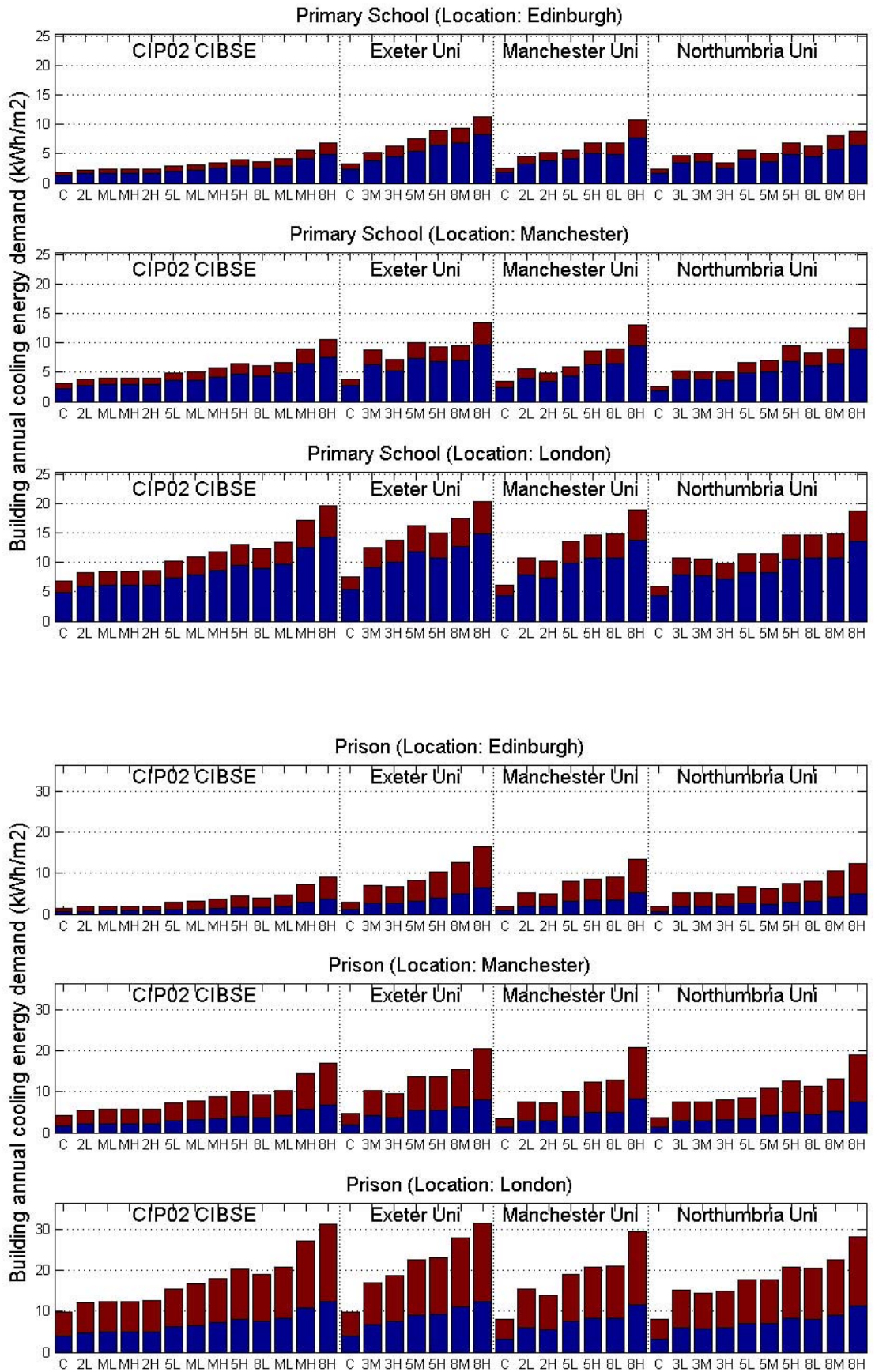


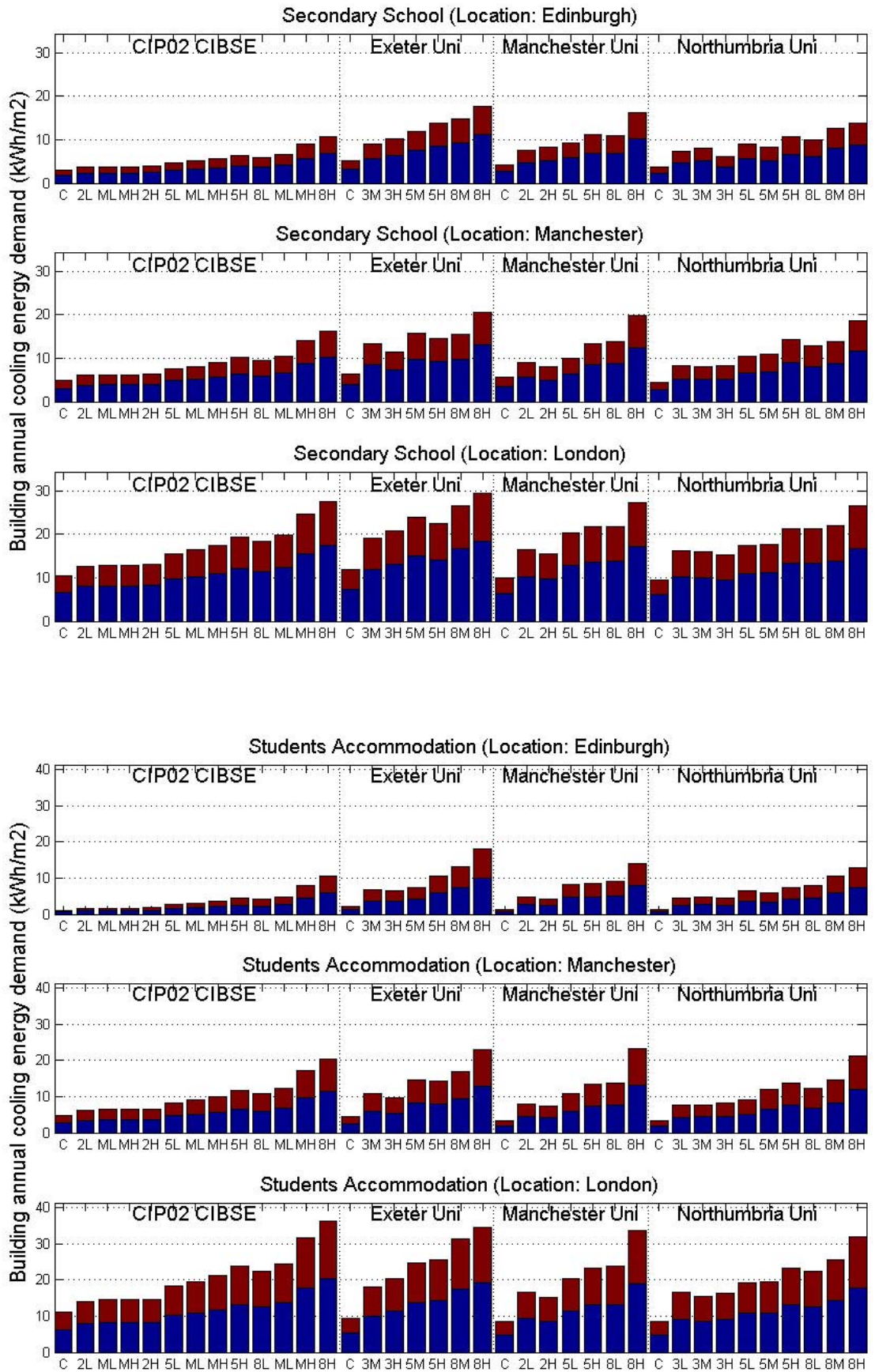


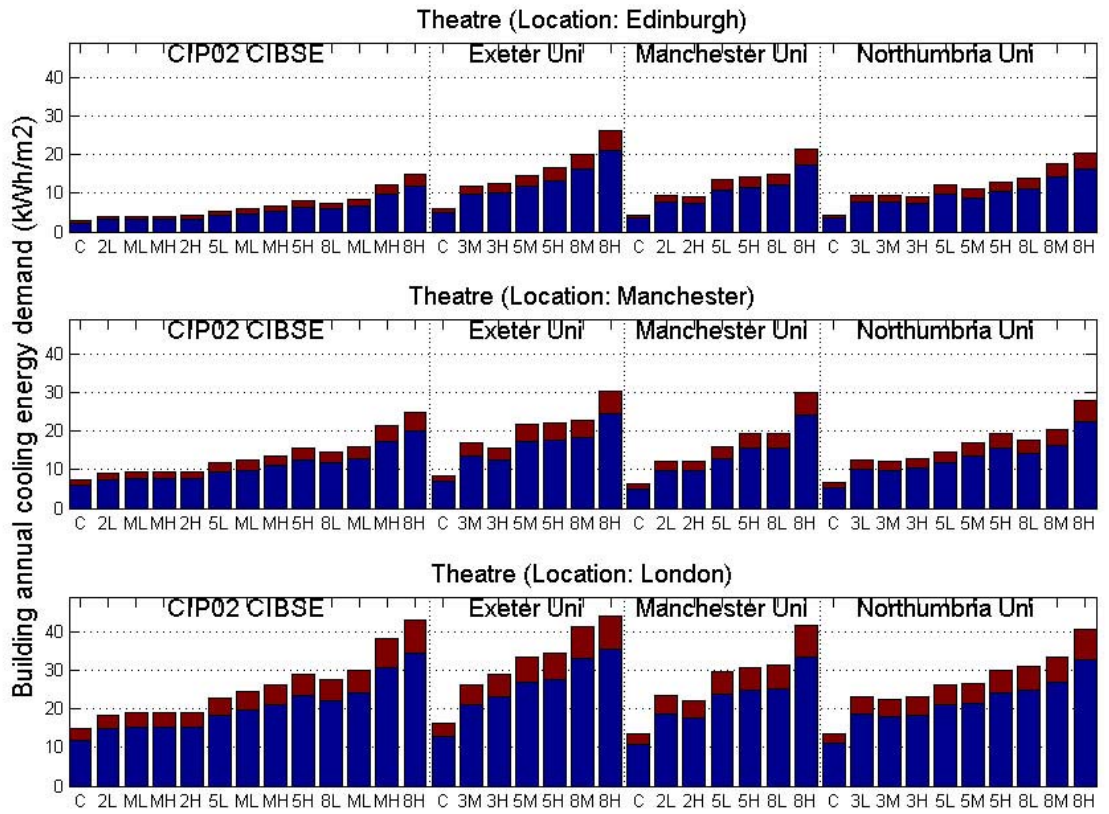




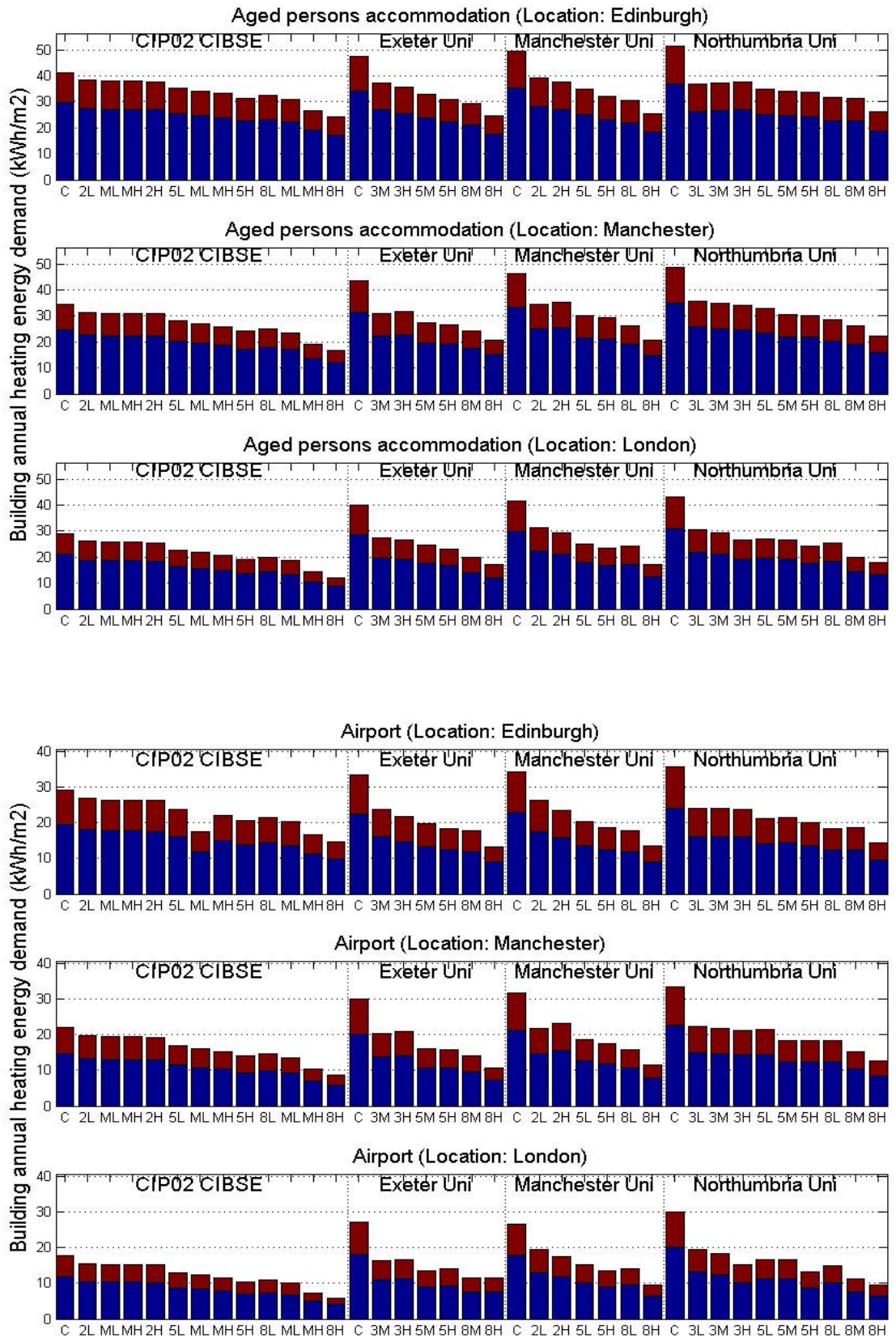


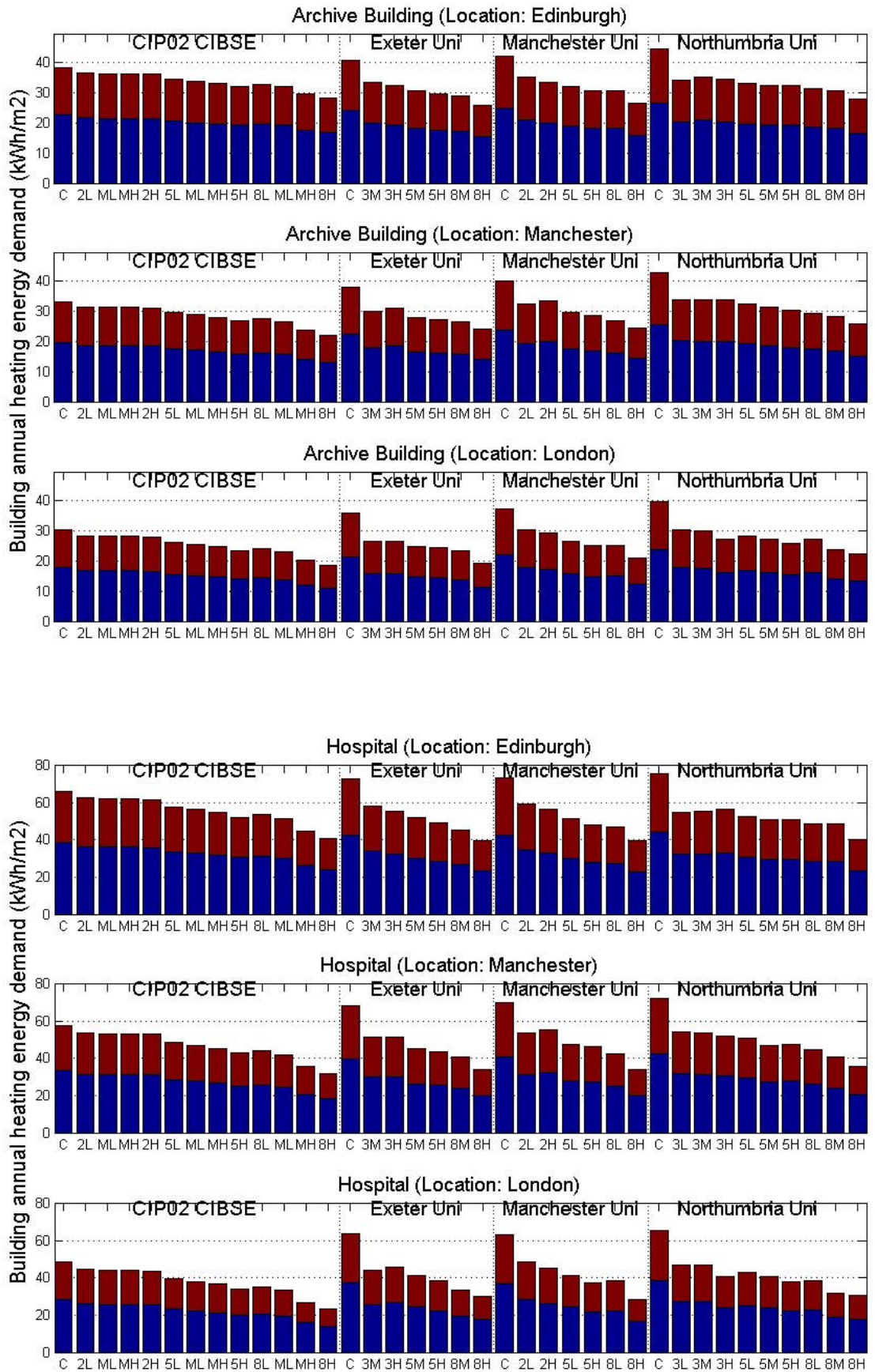


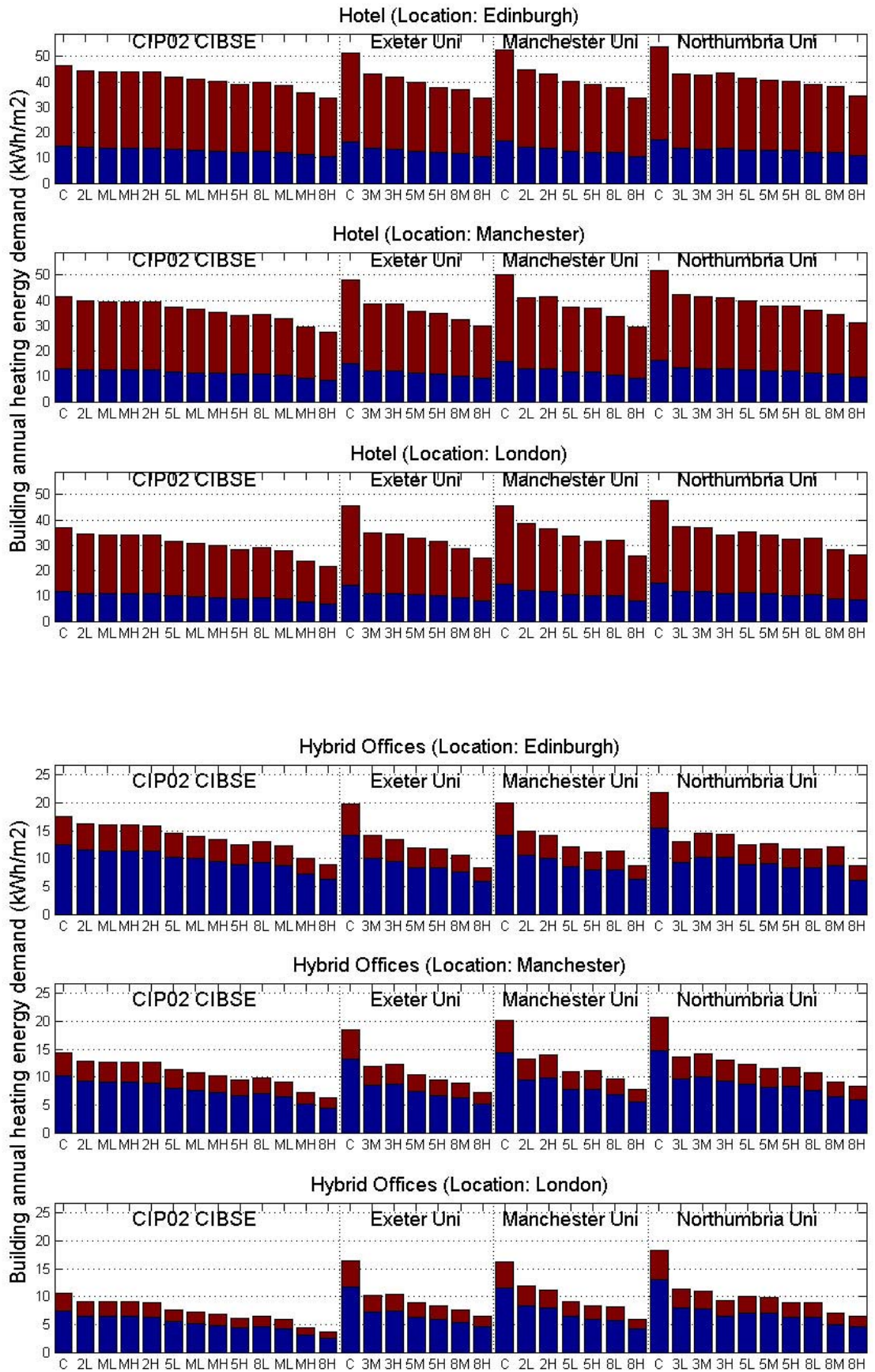


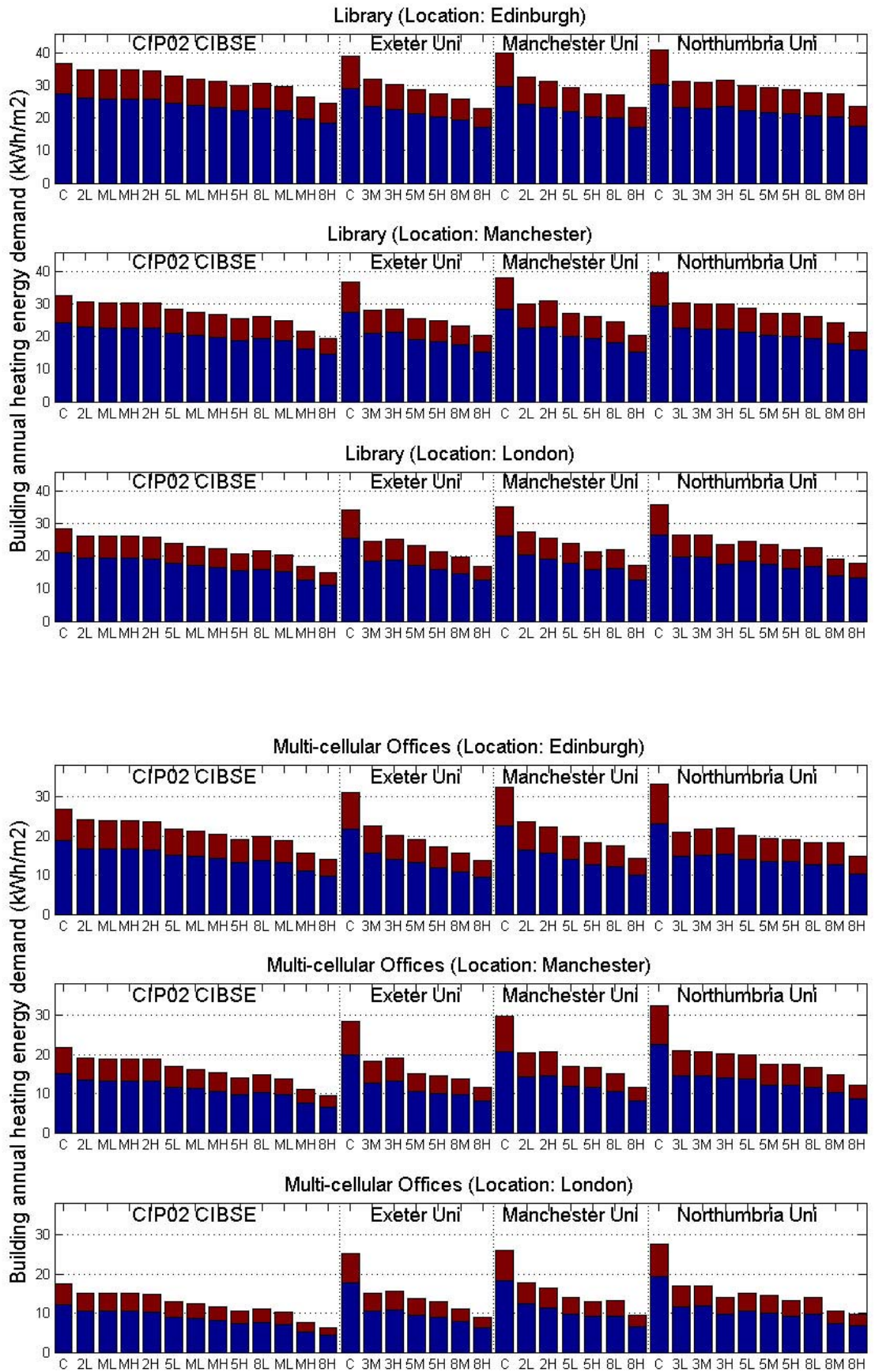


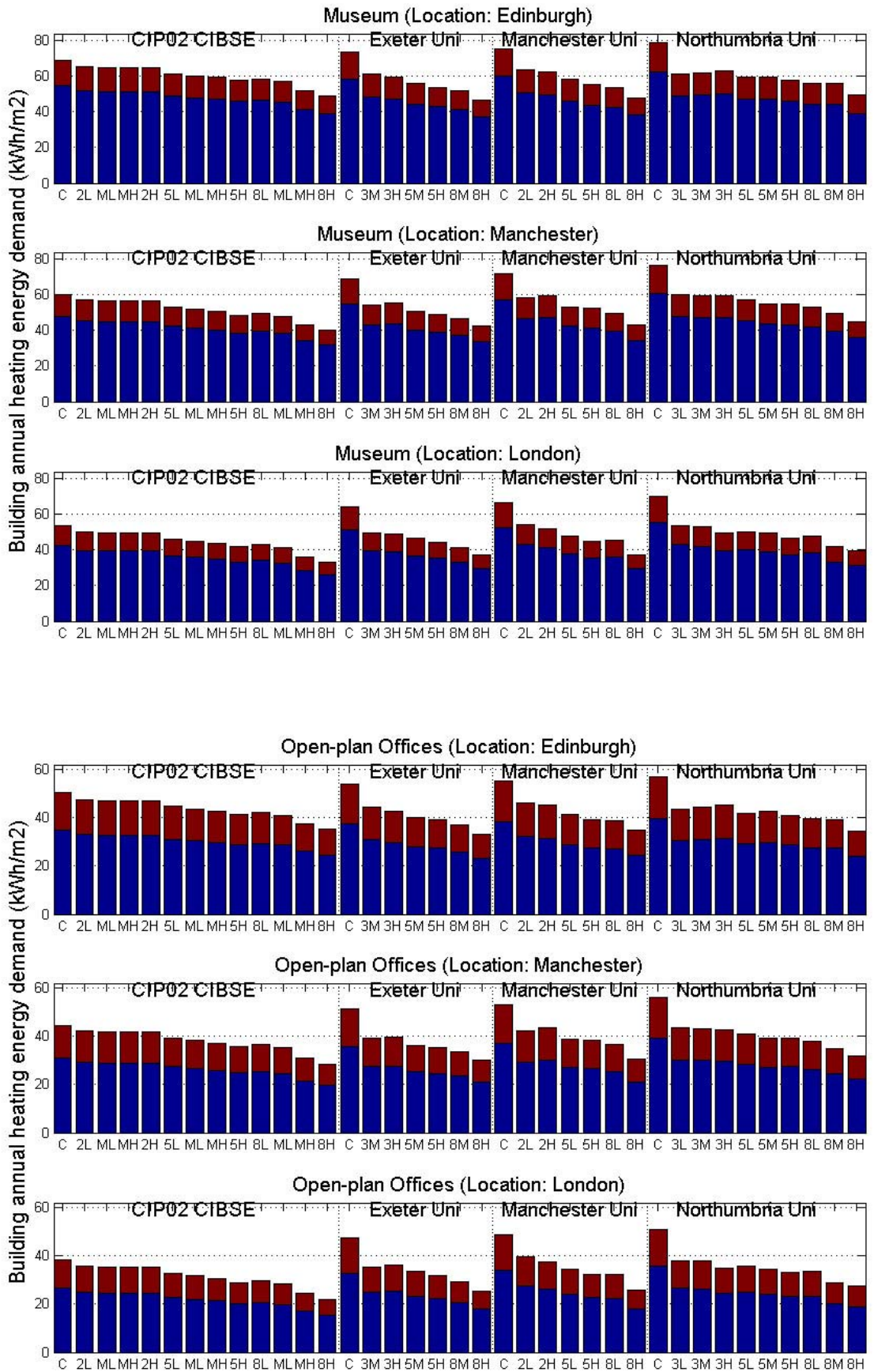
Appendix A2: TRY results: heating energy demand

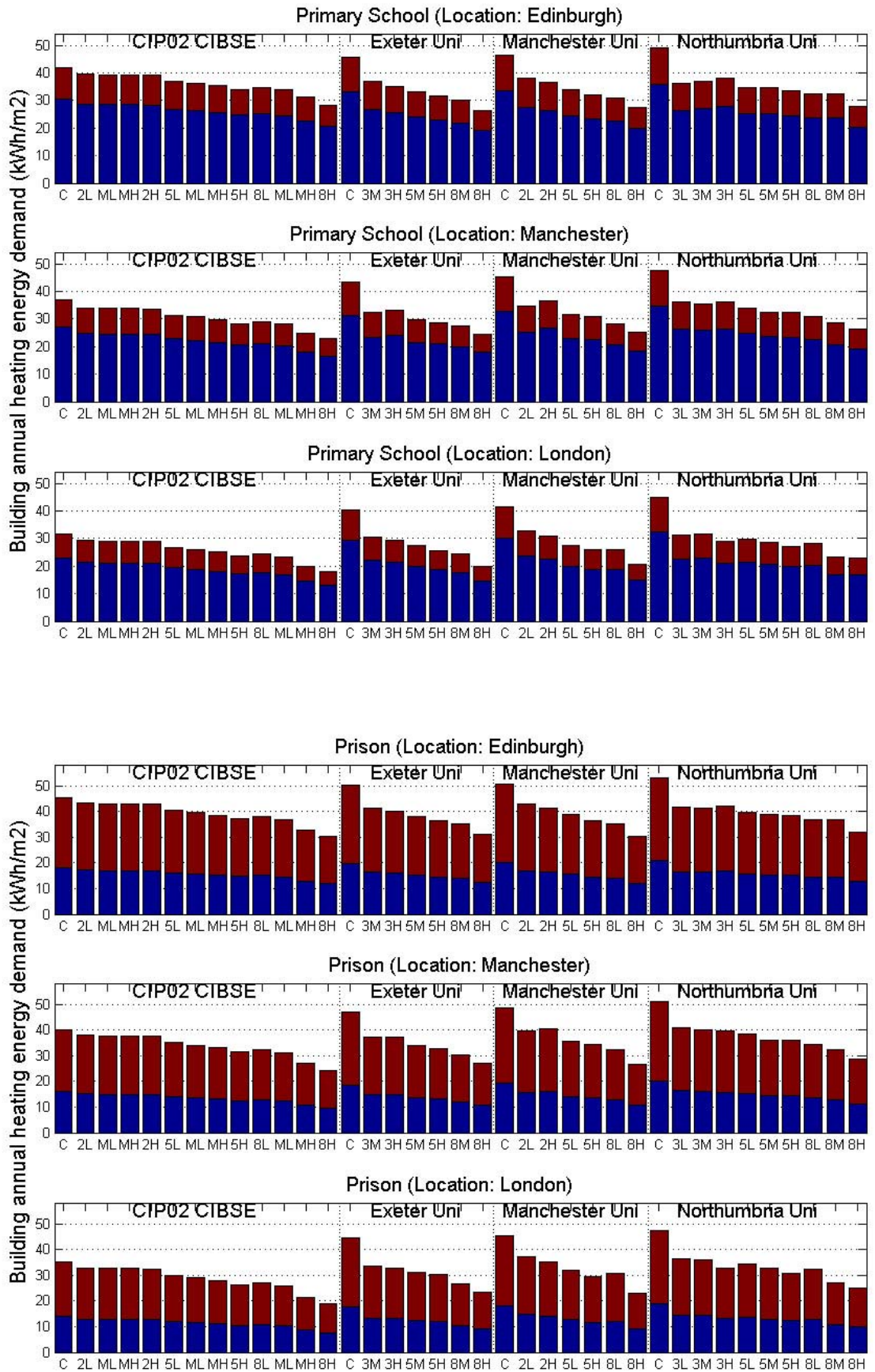


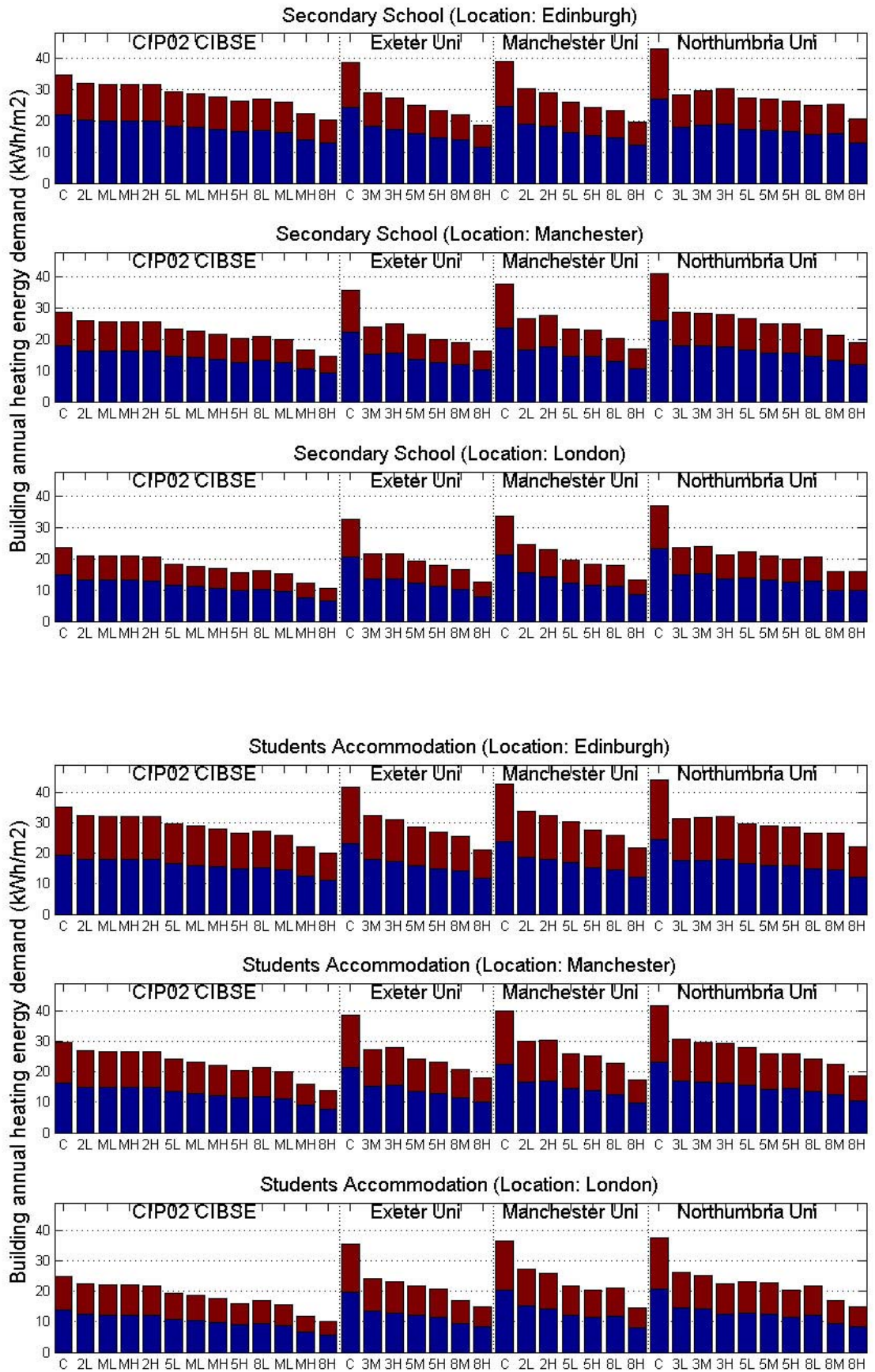


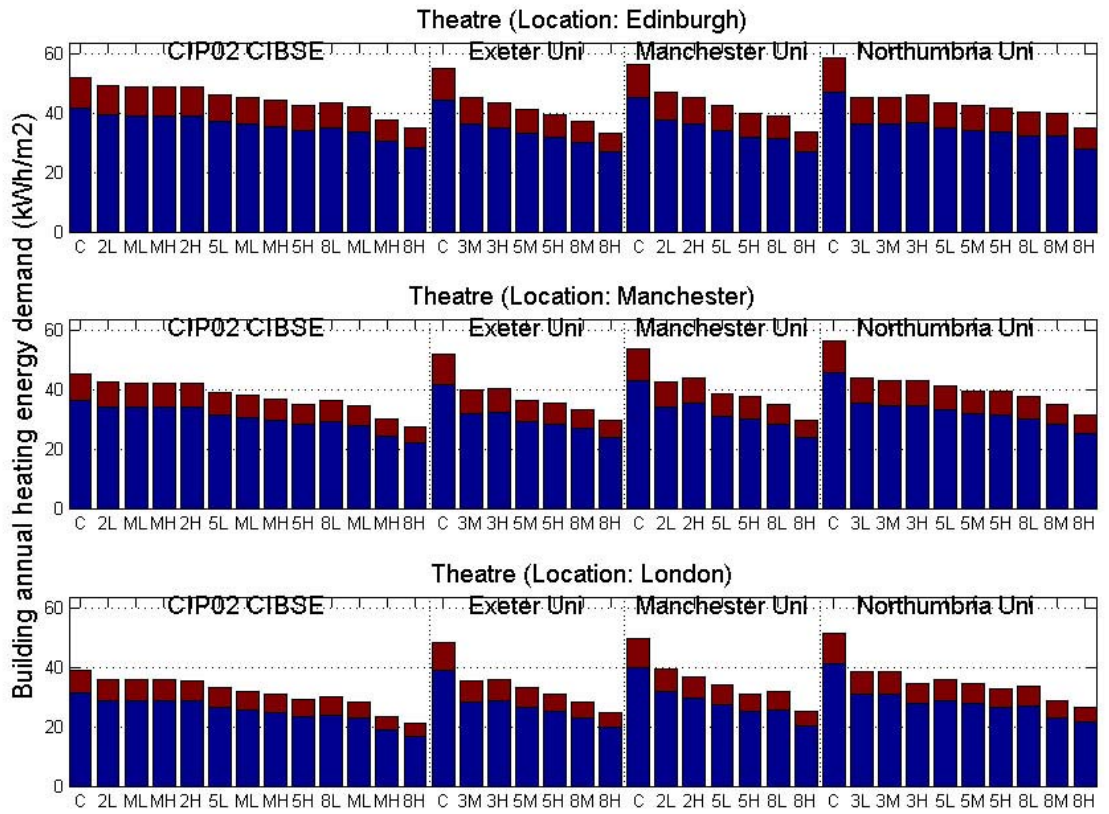




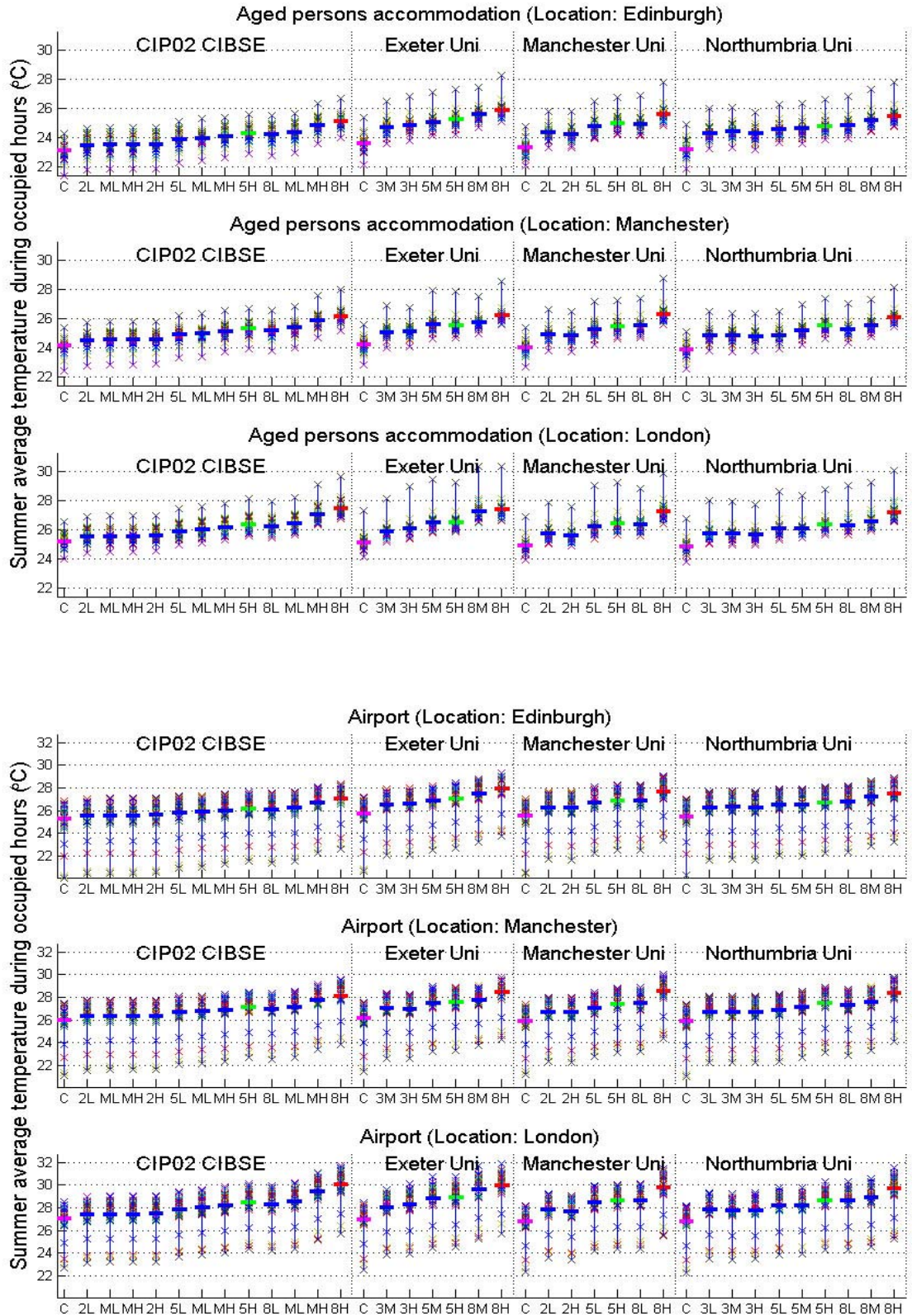


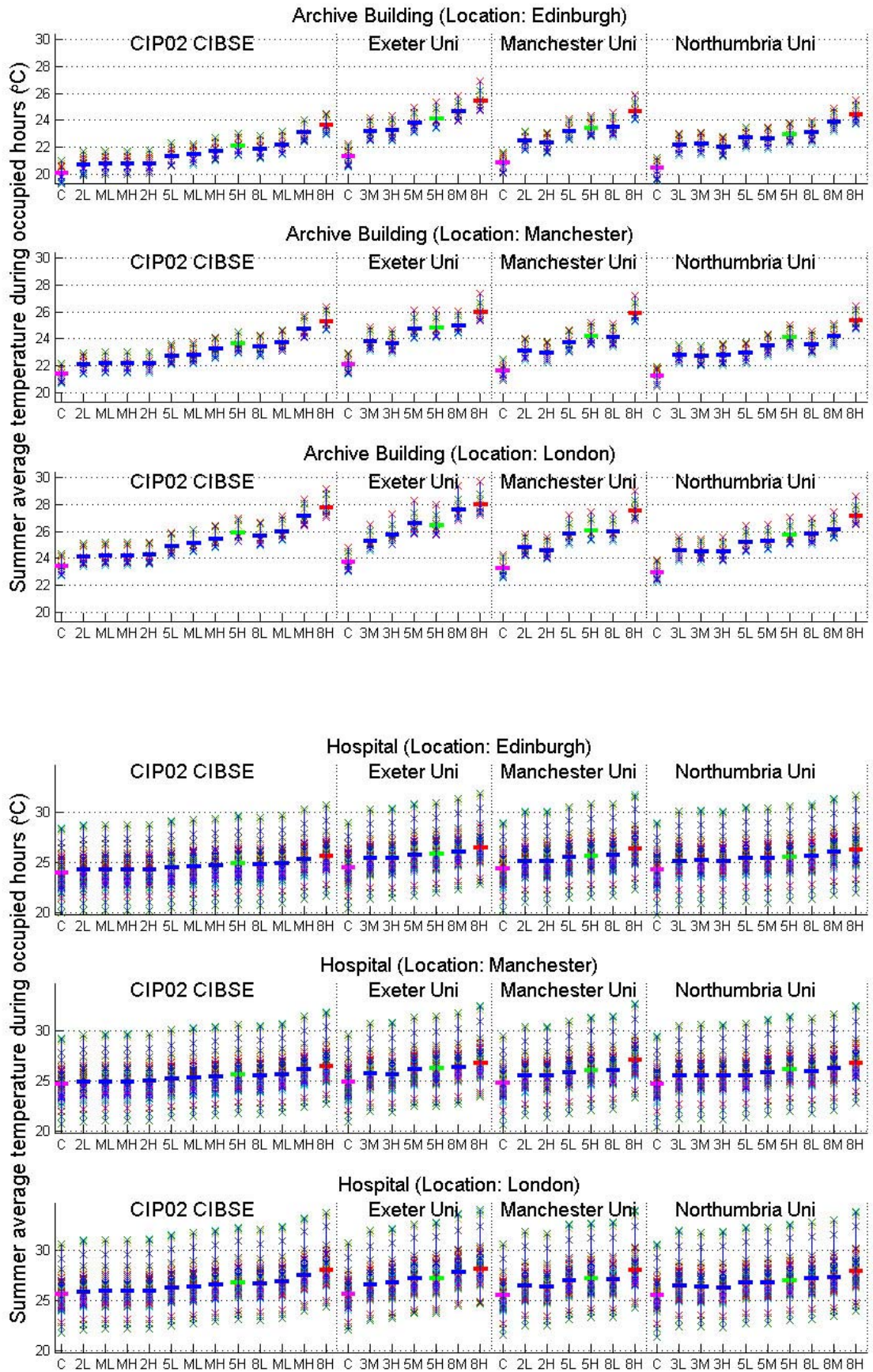


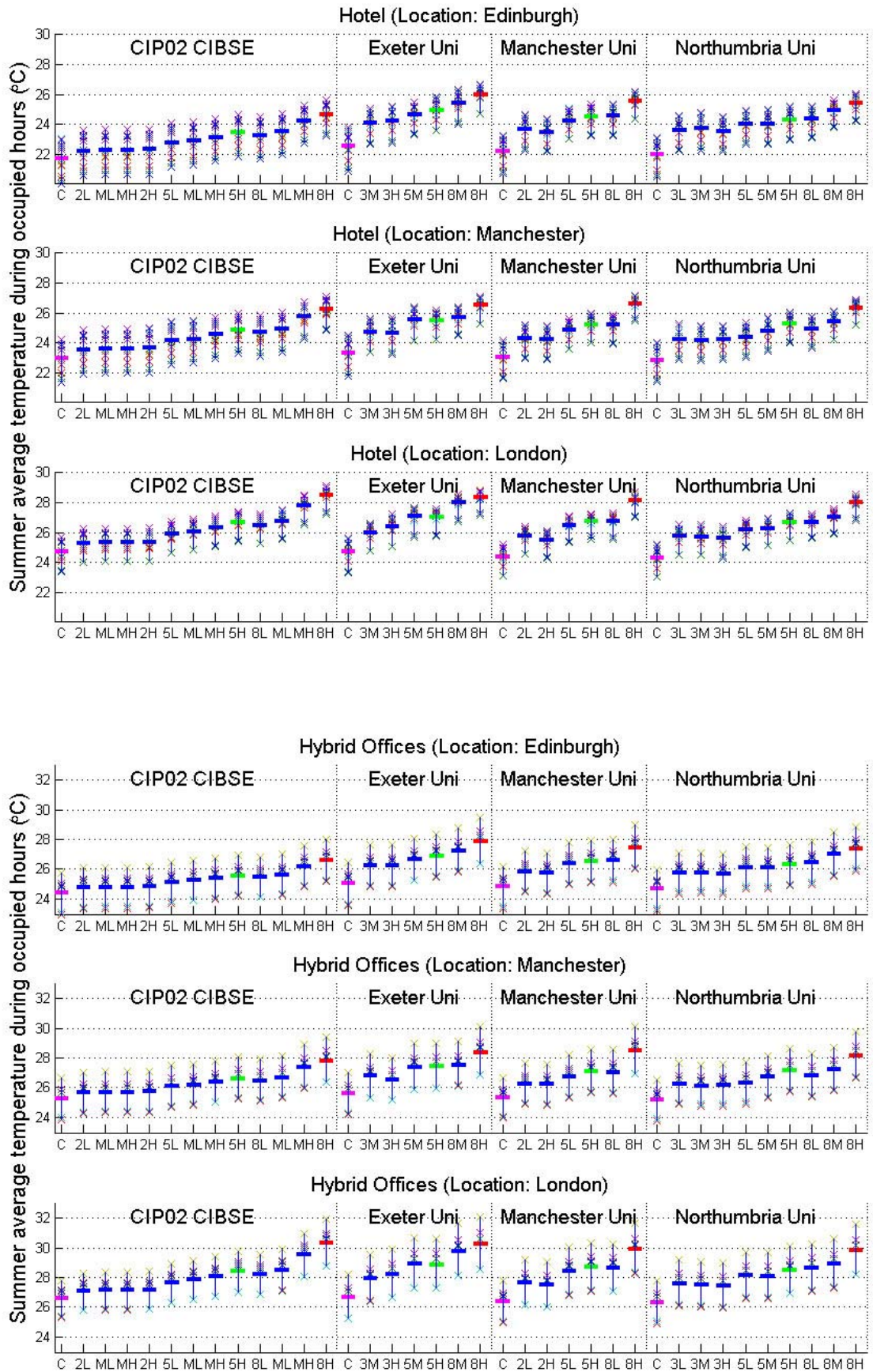


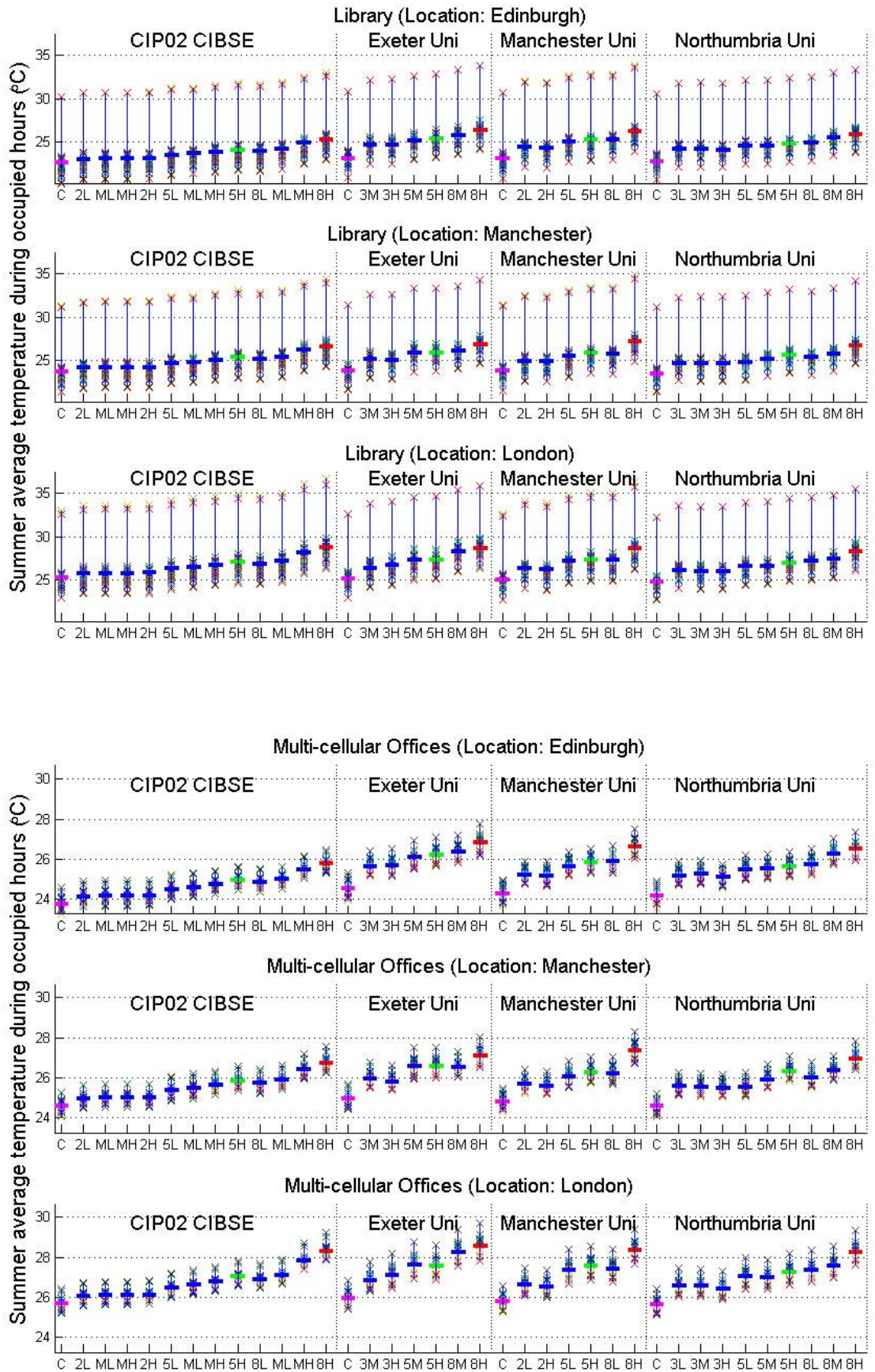


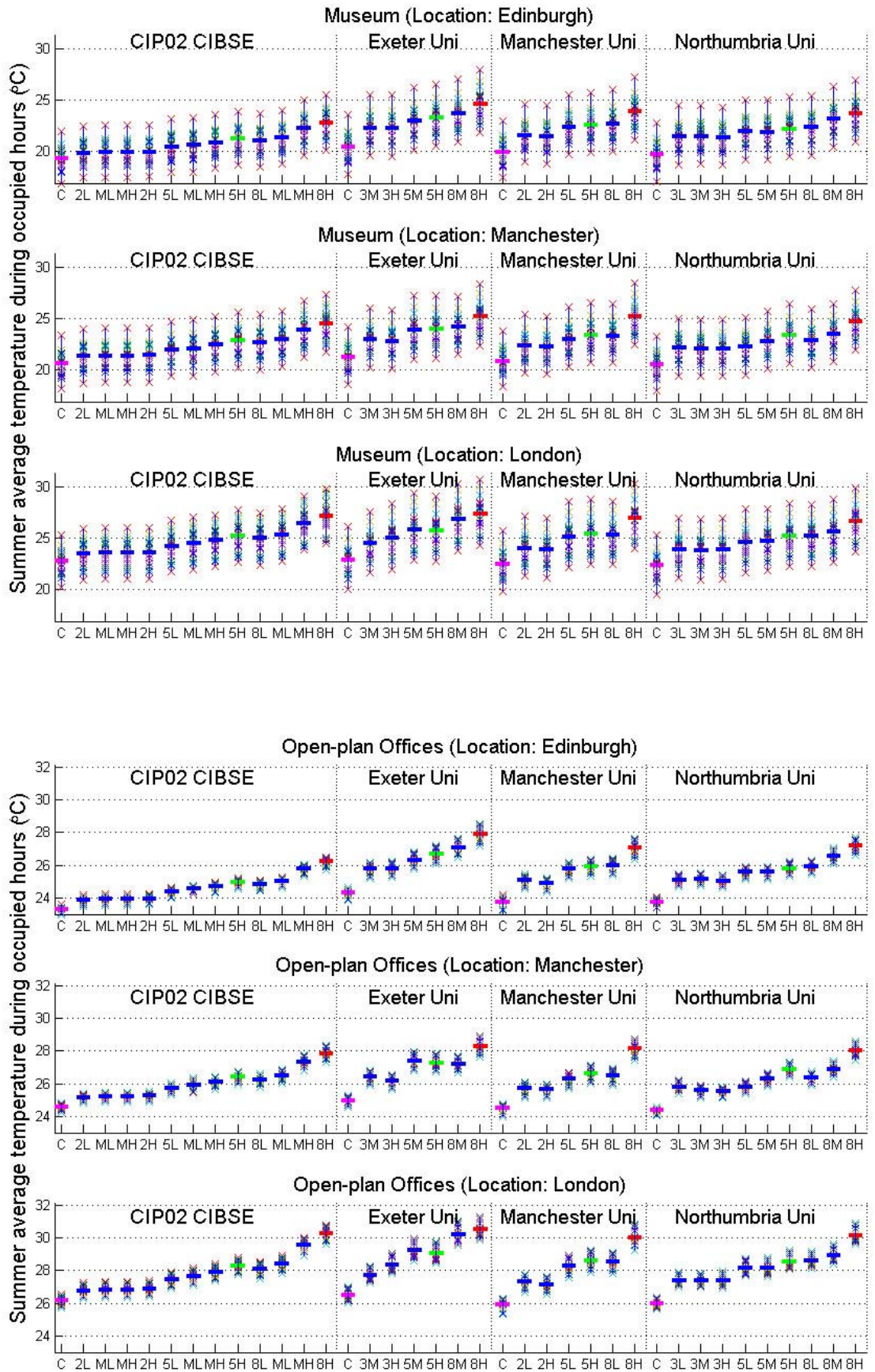
Appendix A3: TRY results: Summer average temperature during occupied hours

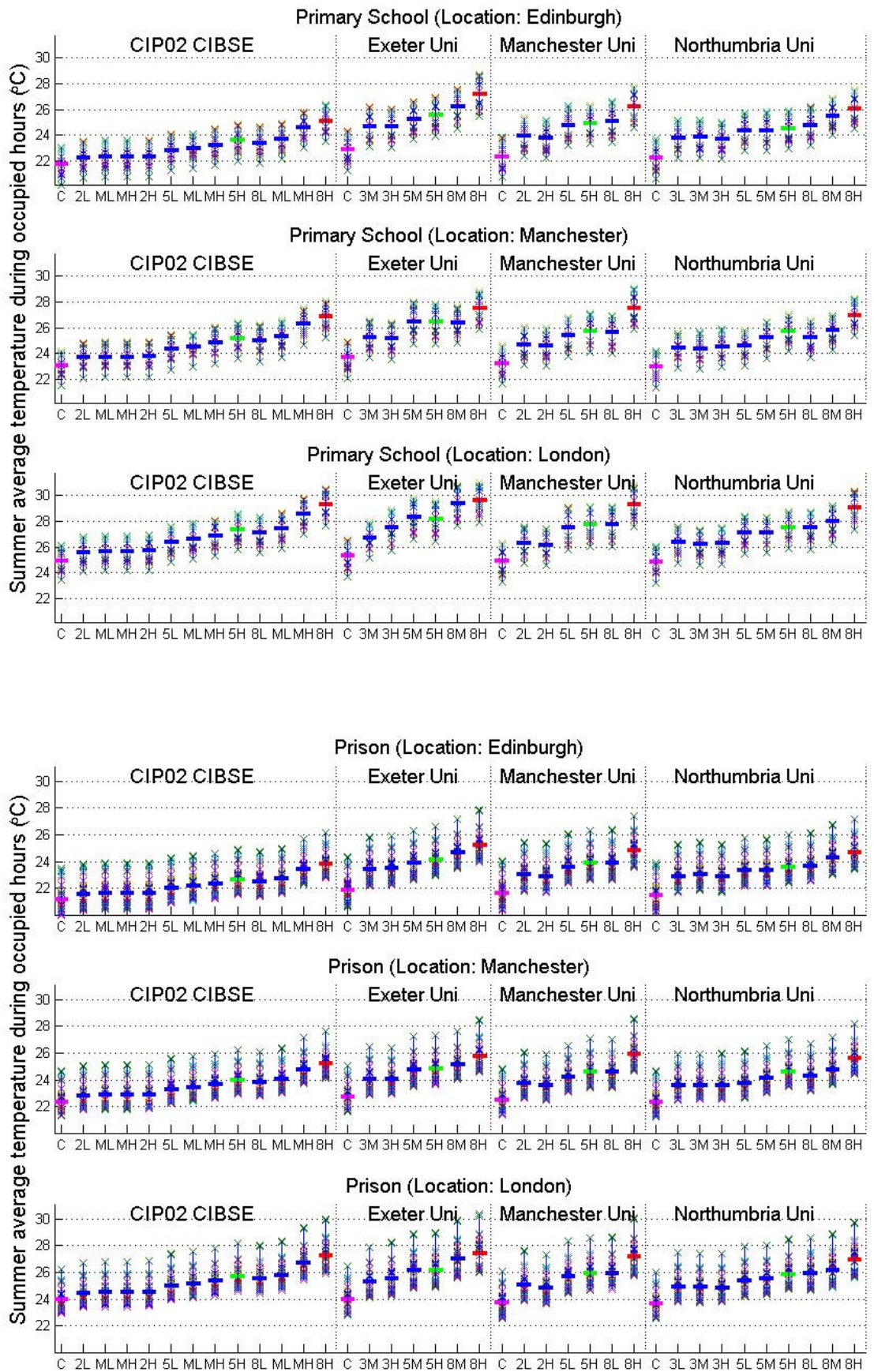


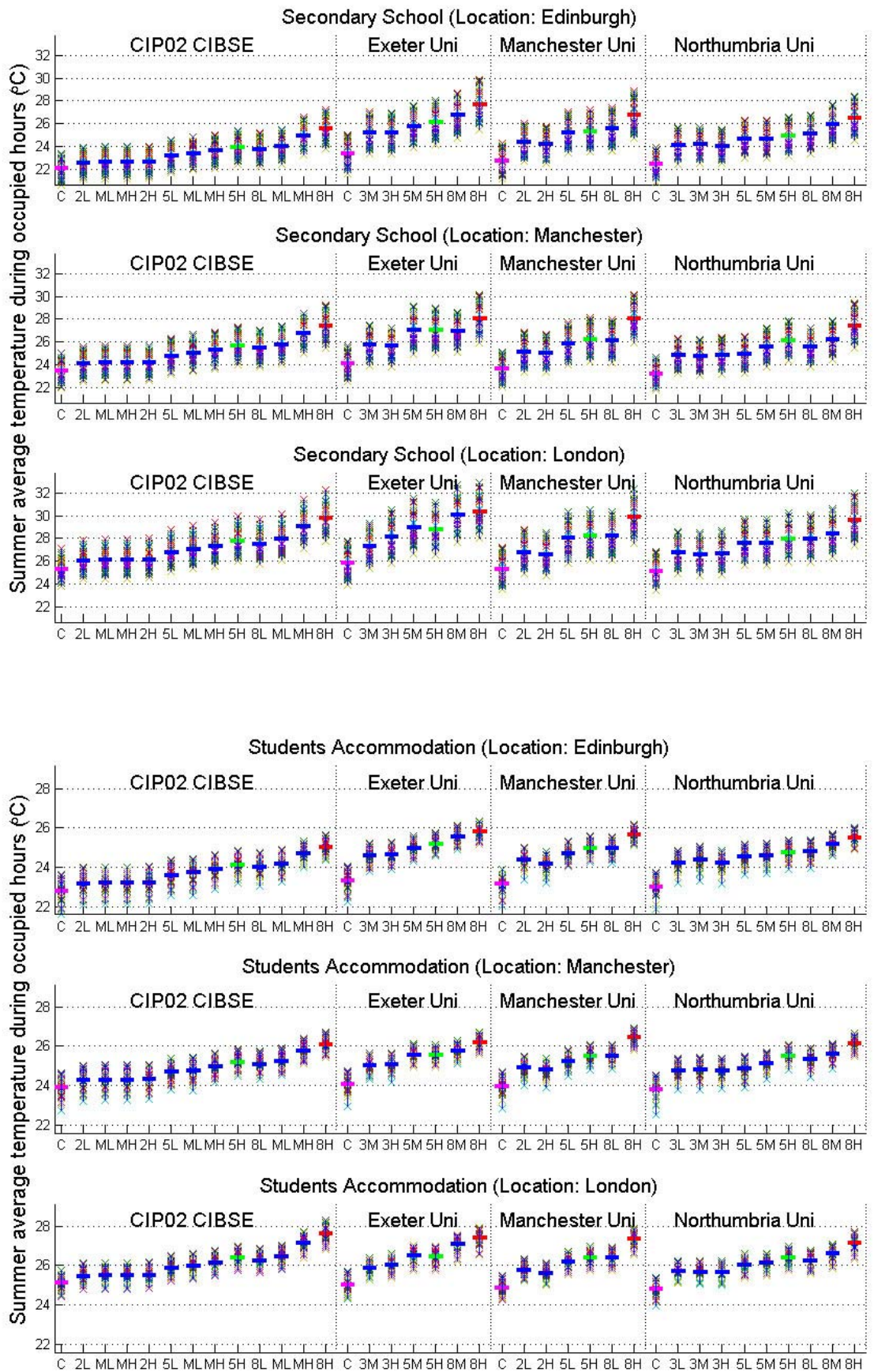


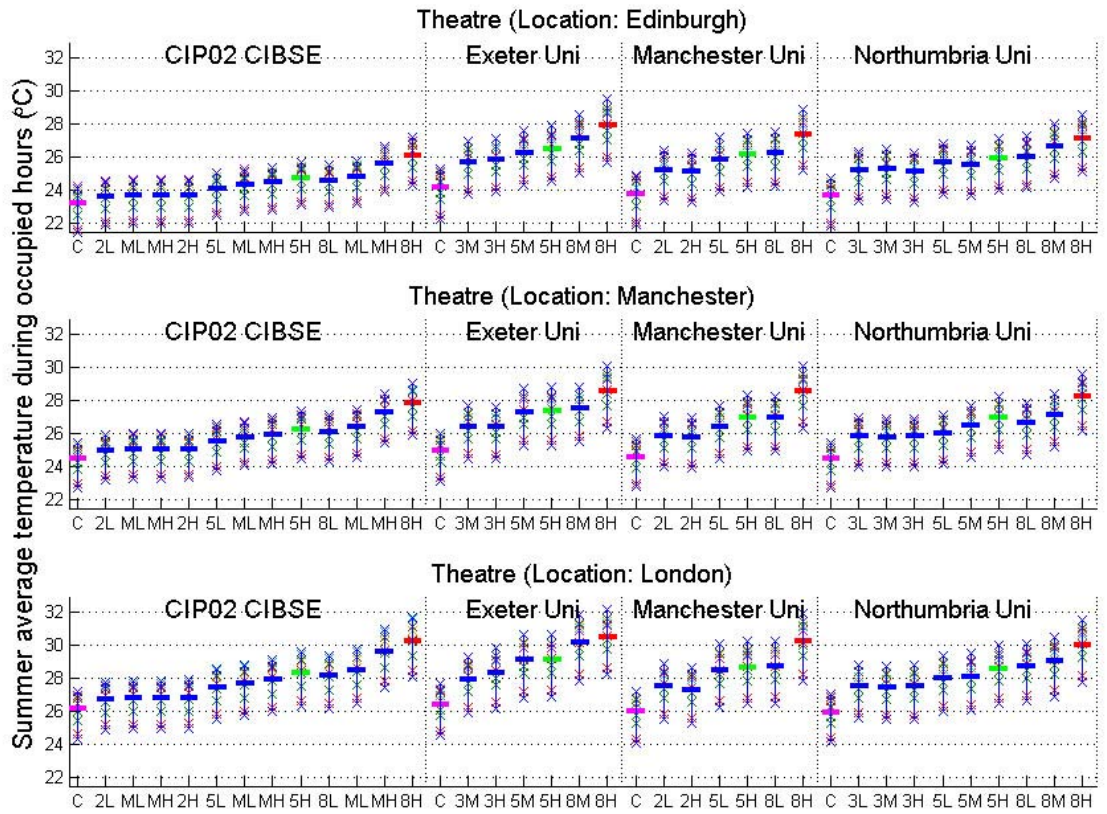




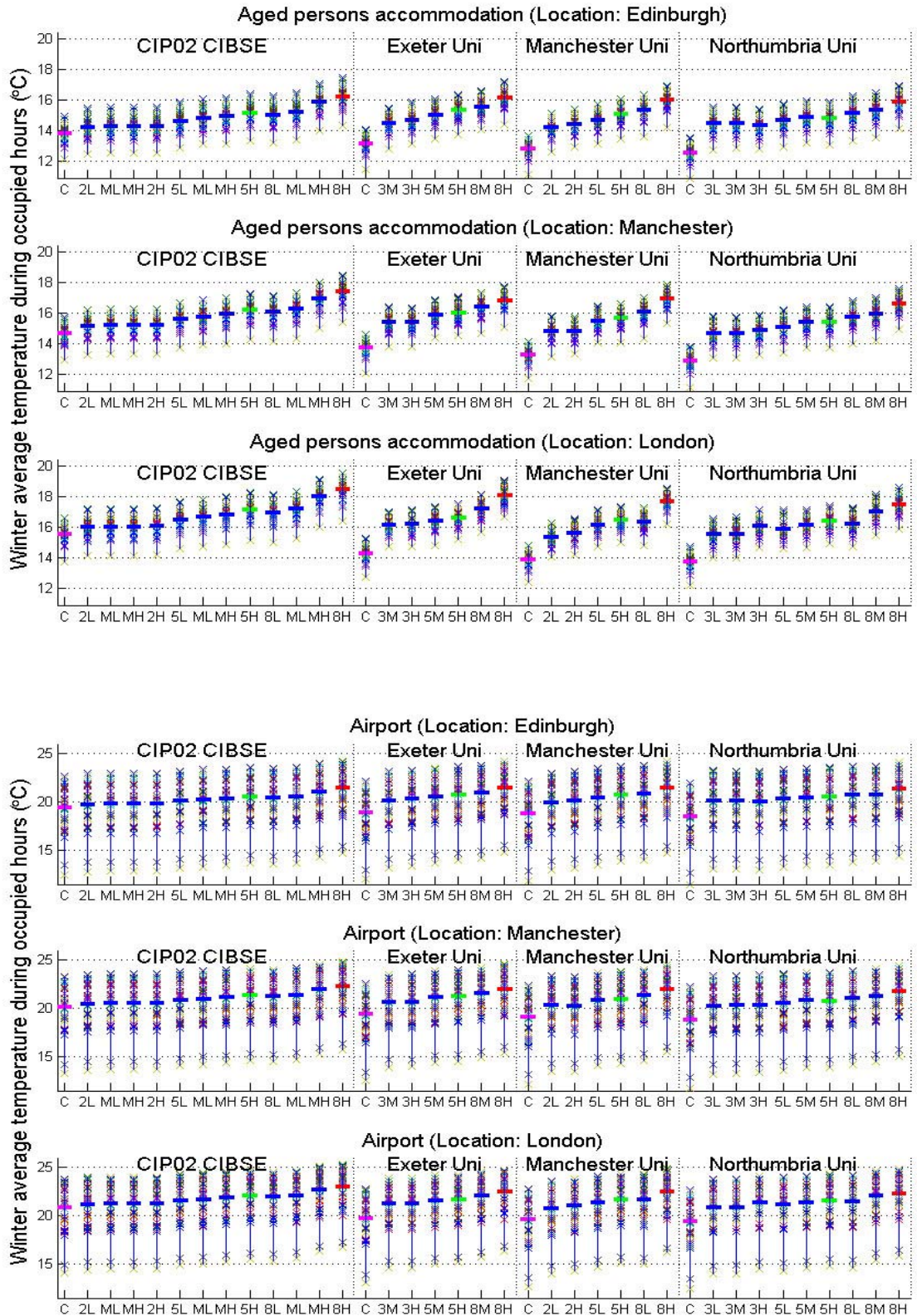


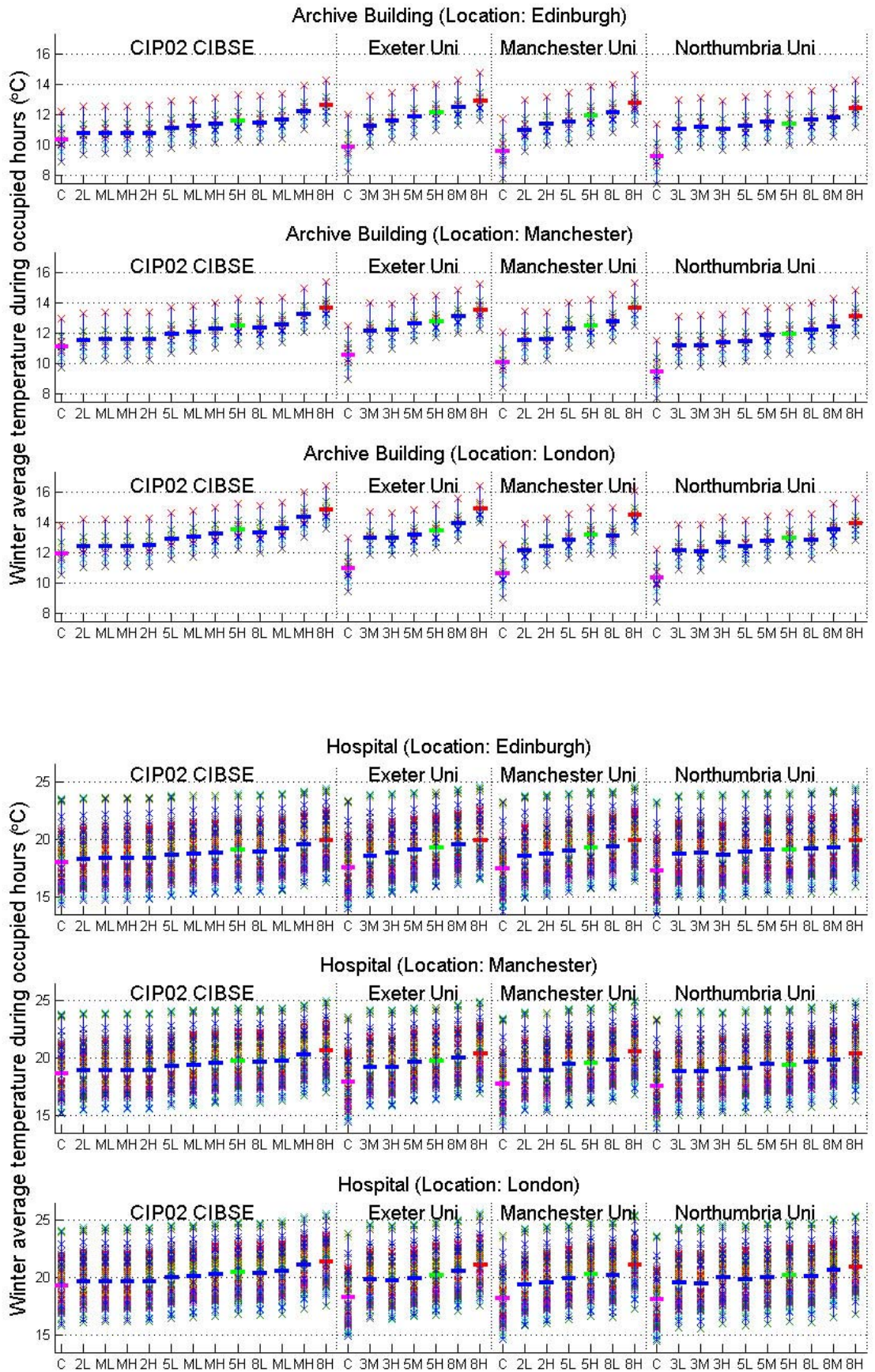


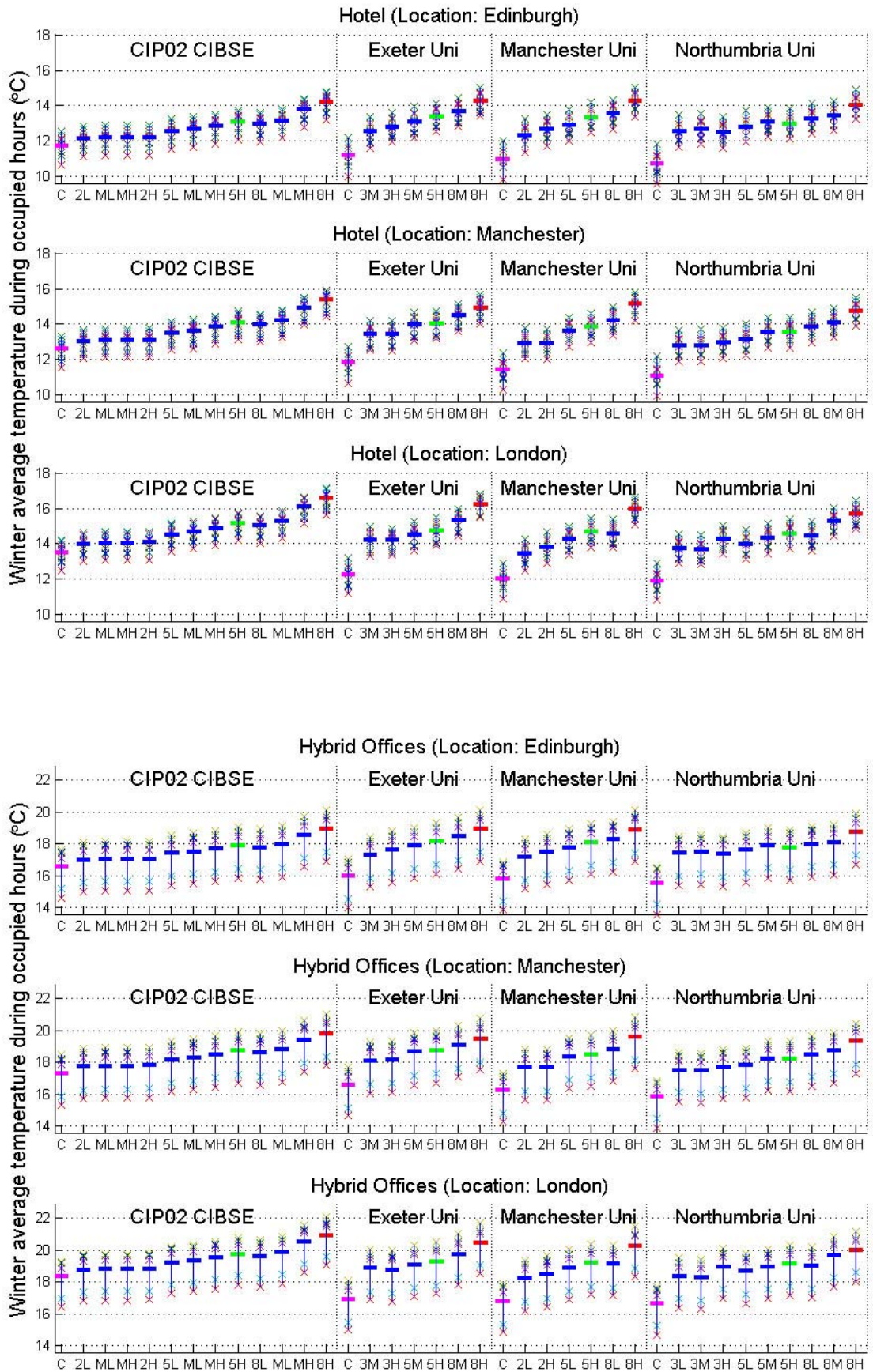


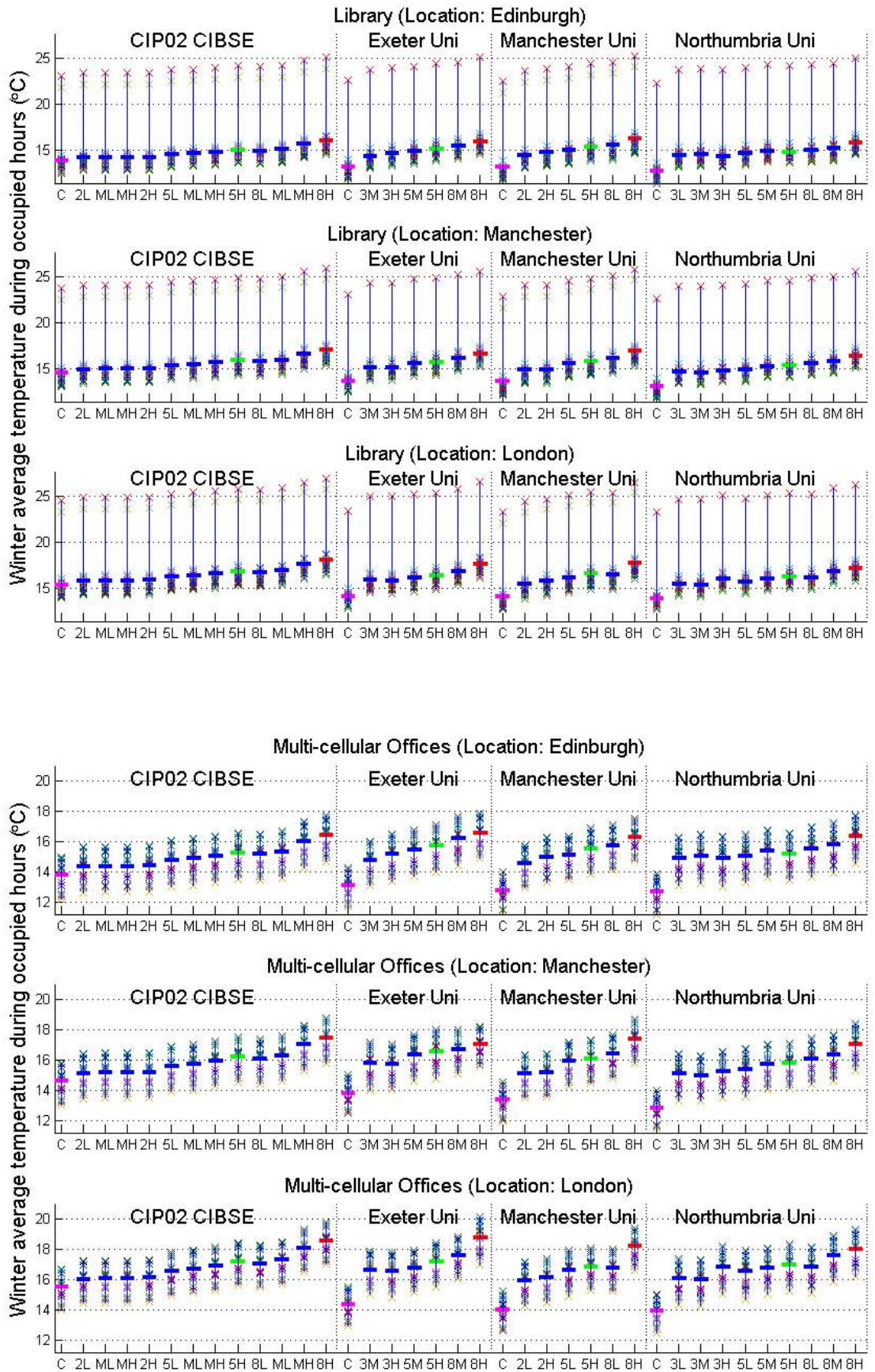


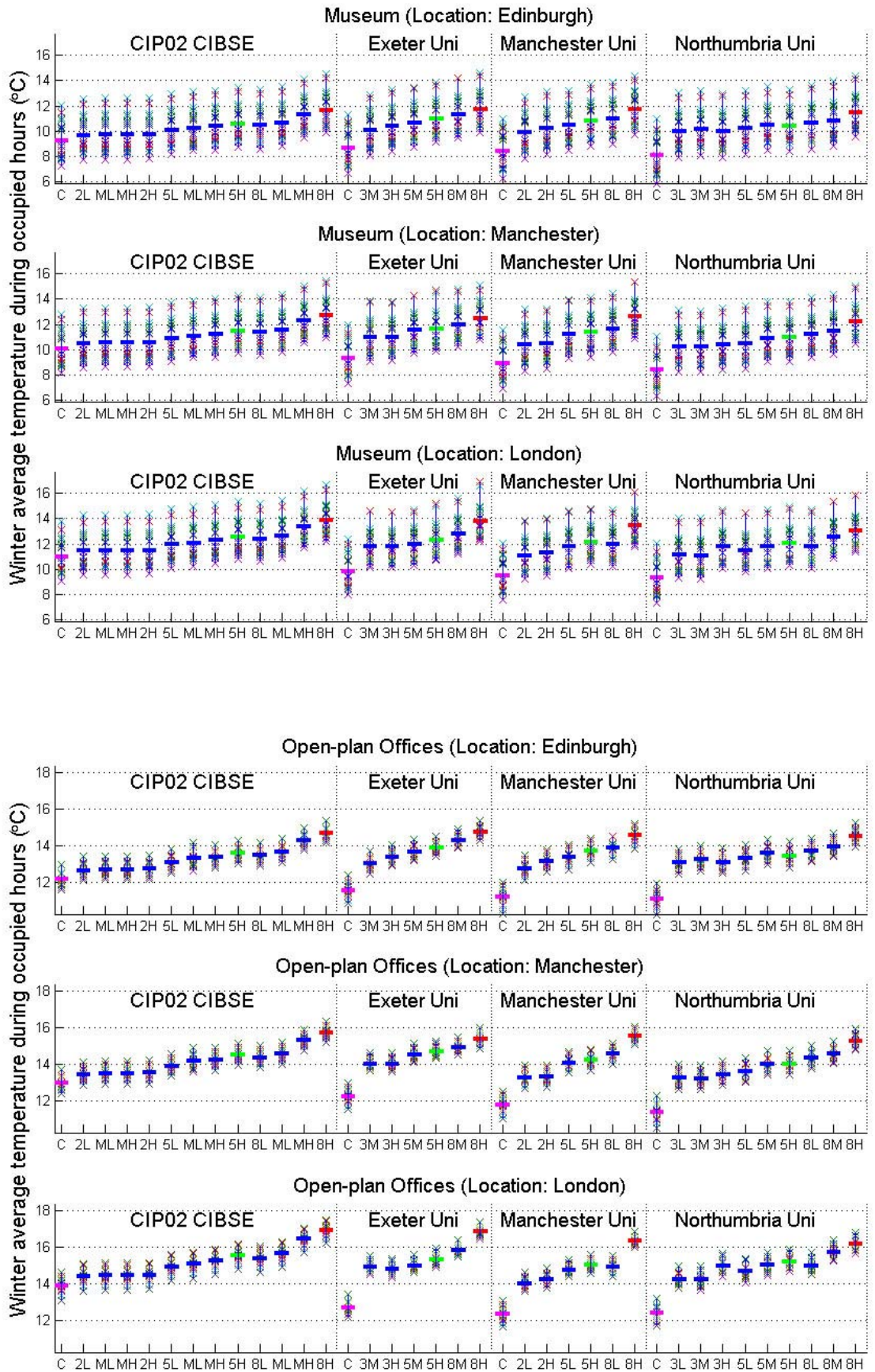
Appendix A4: TRY results: Winter average temperature during occupied hours

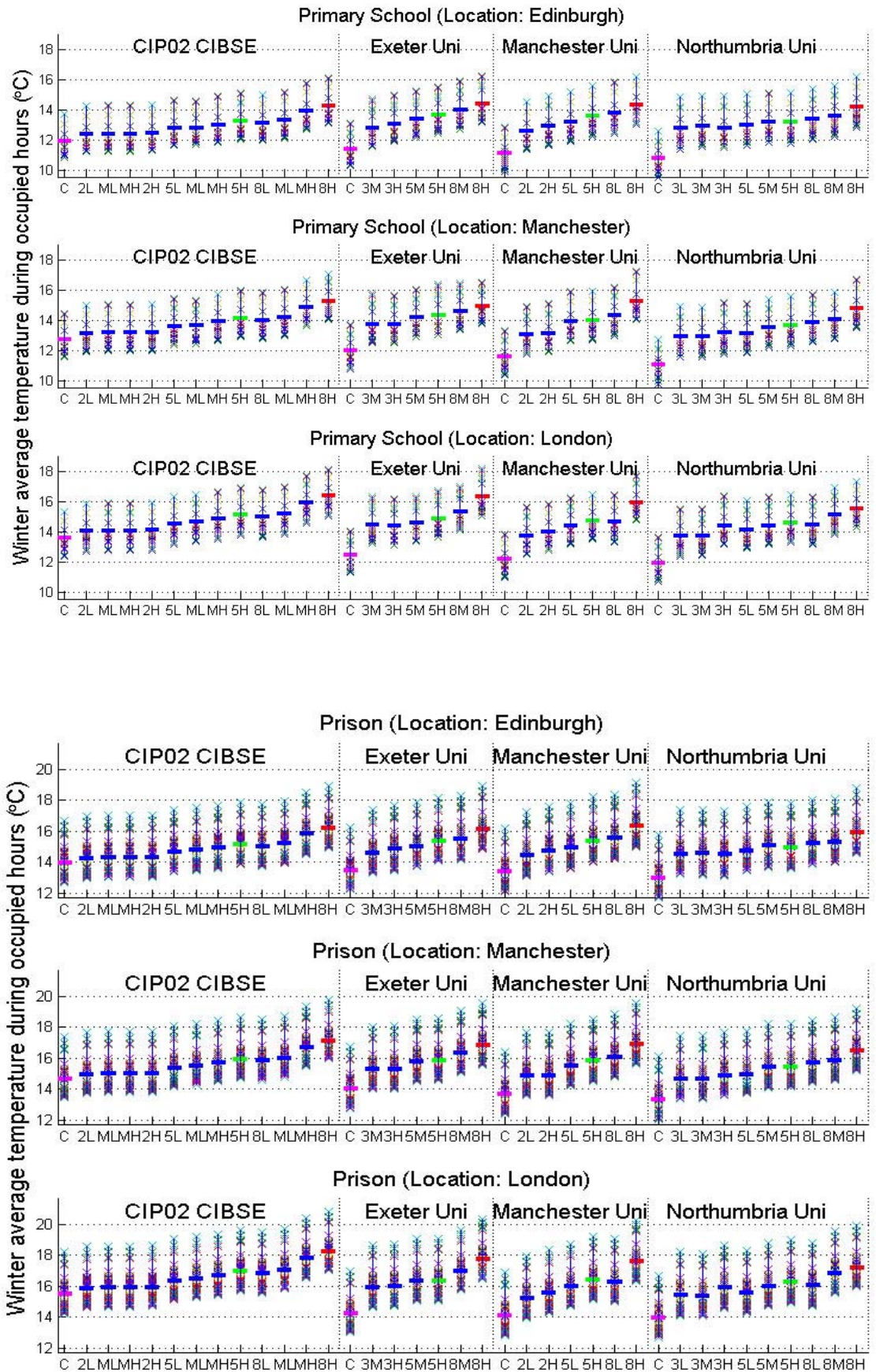


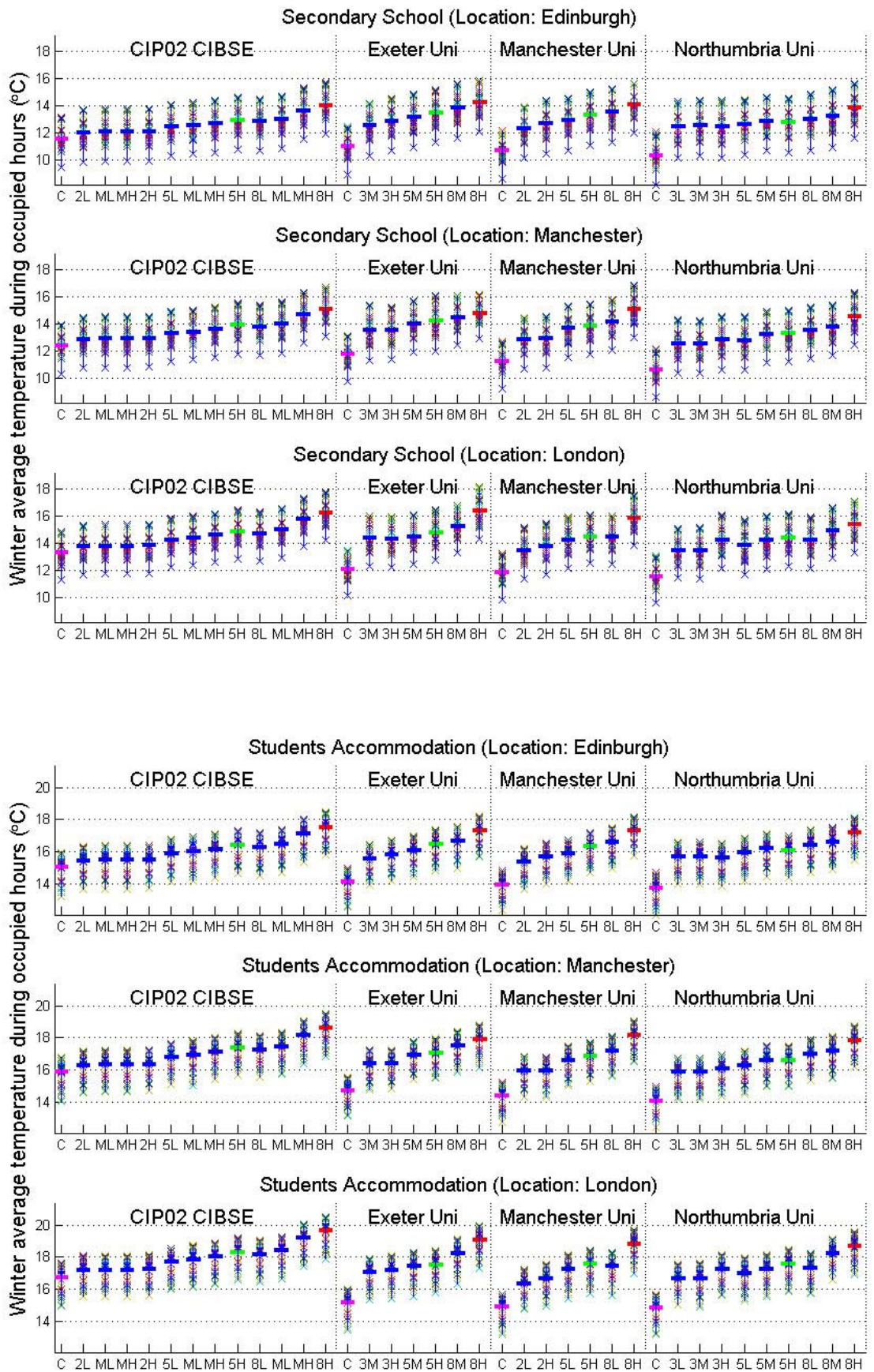


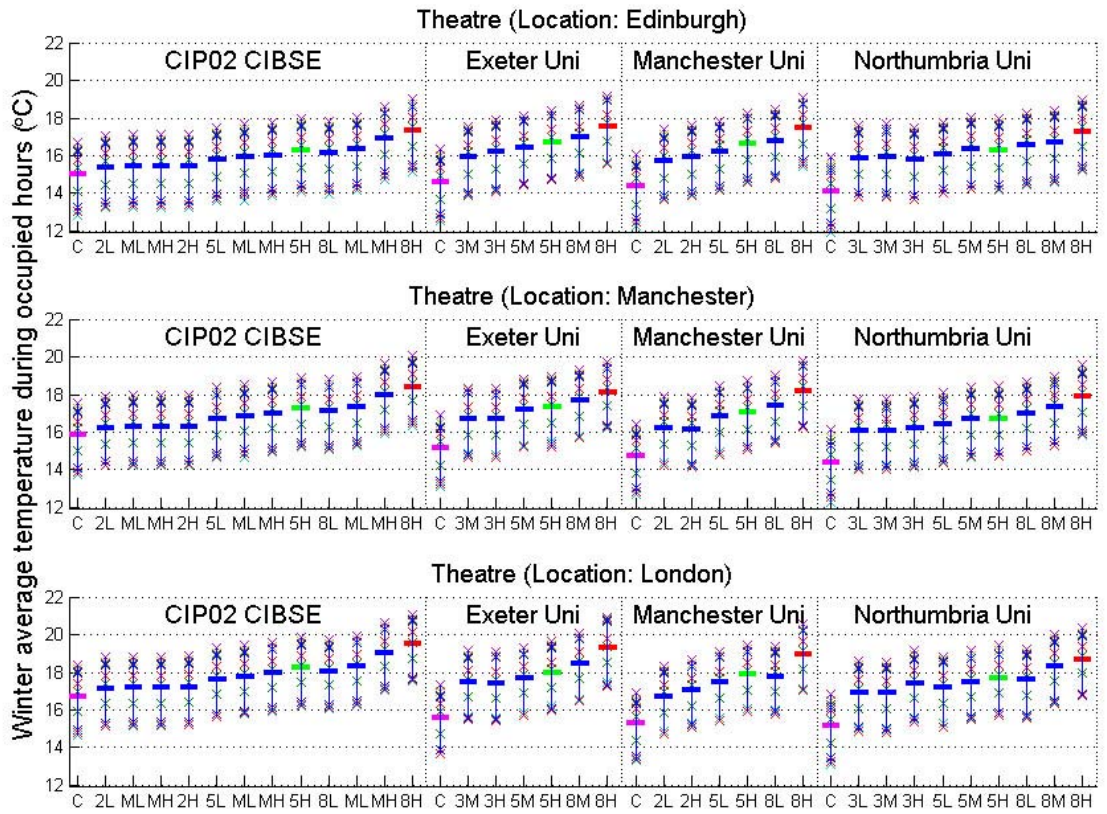




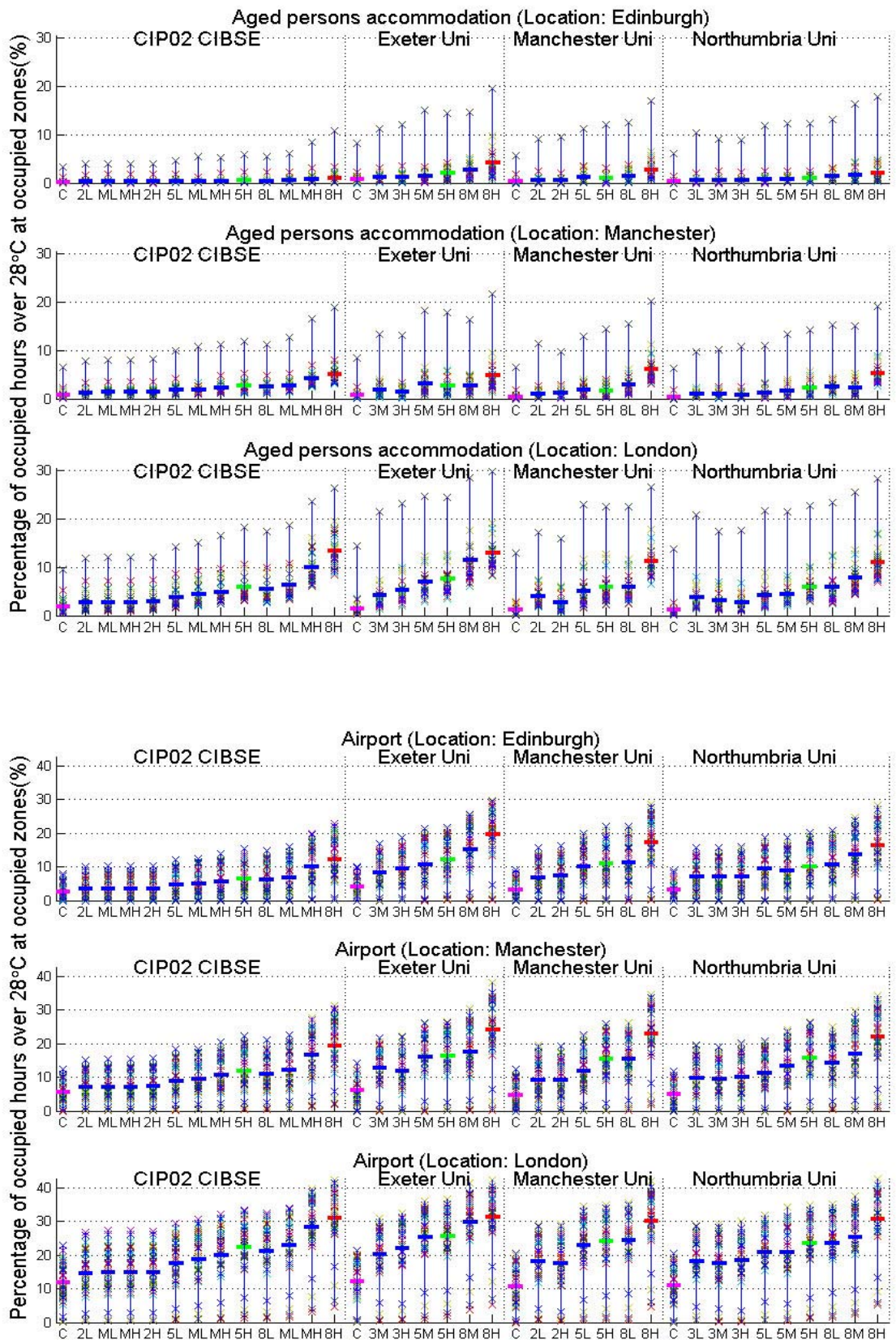


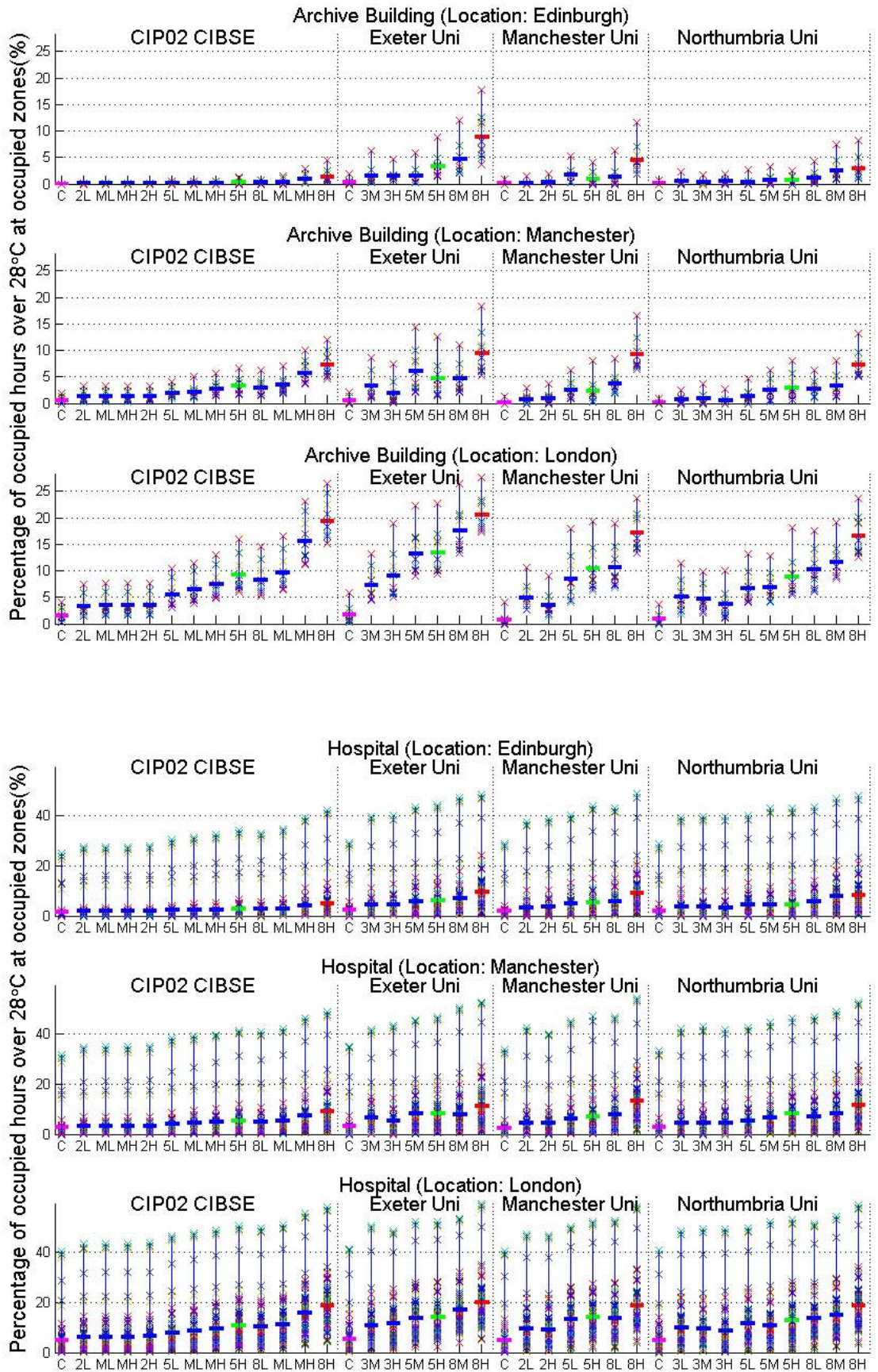


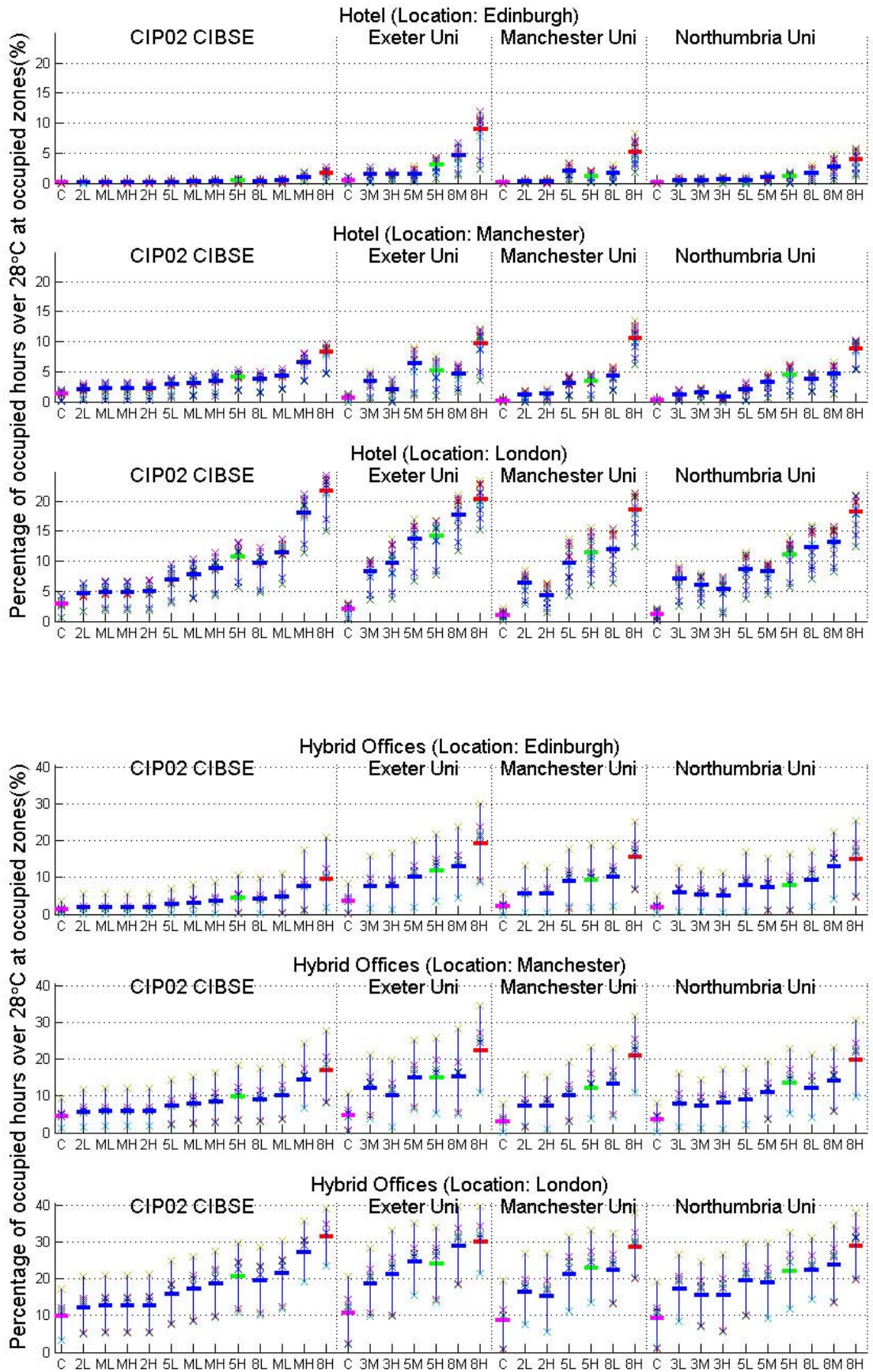


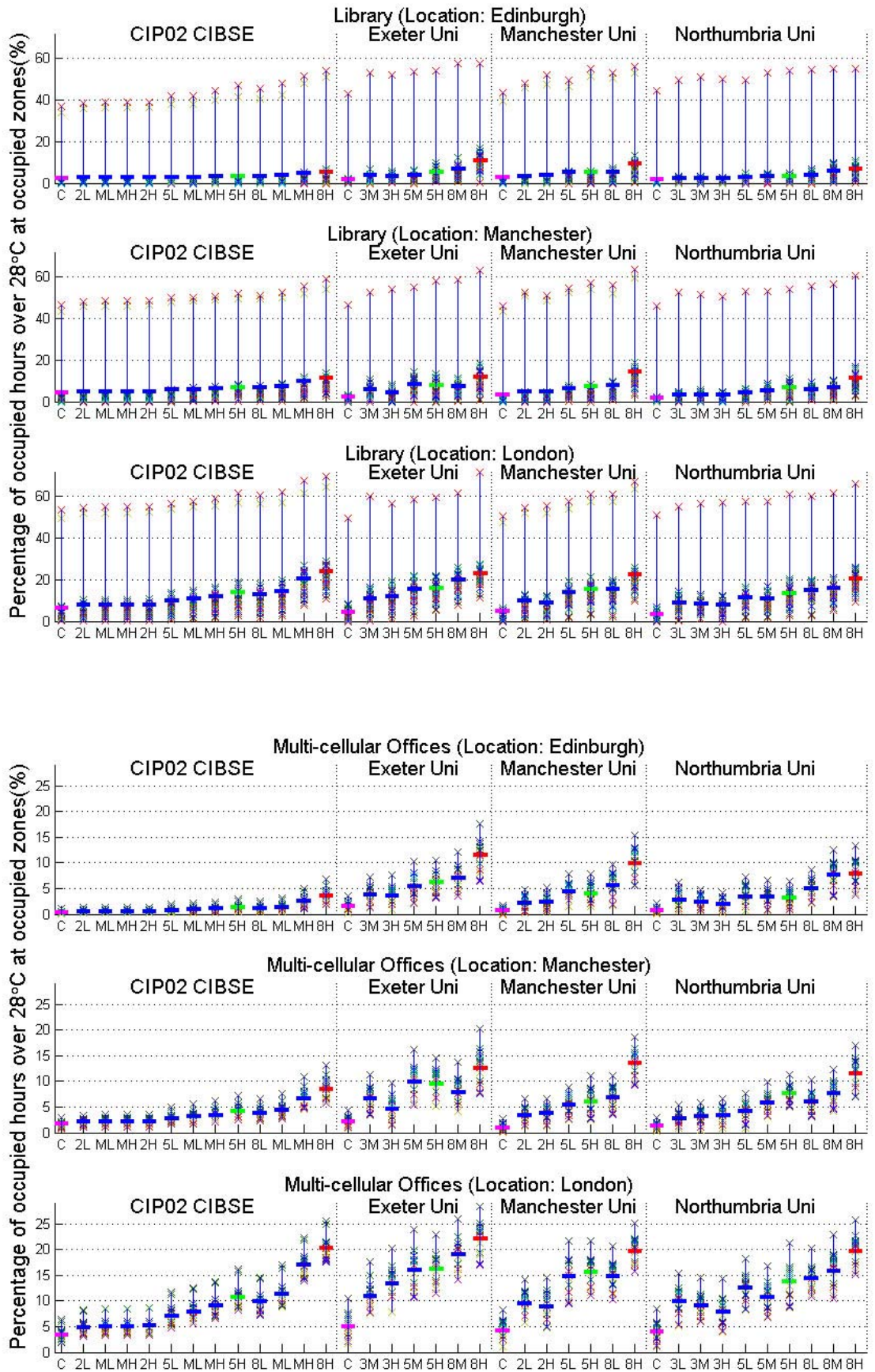


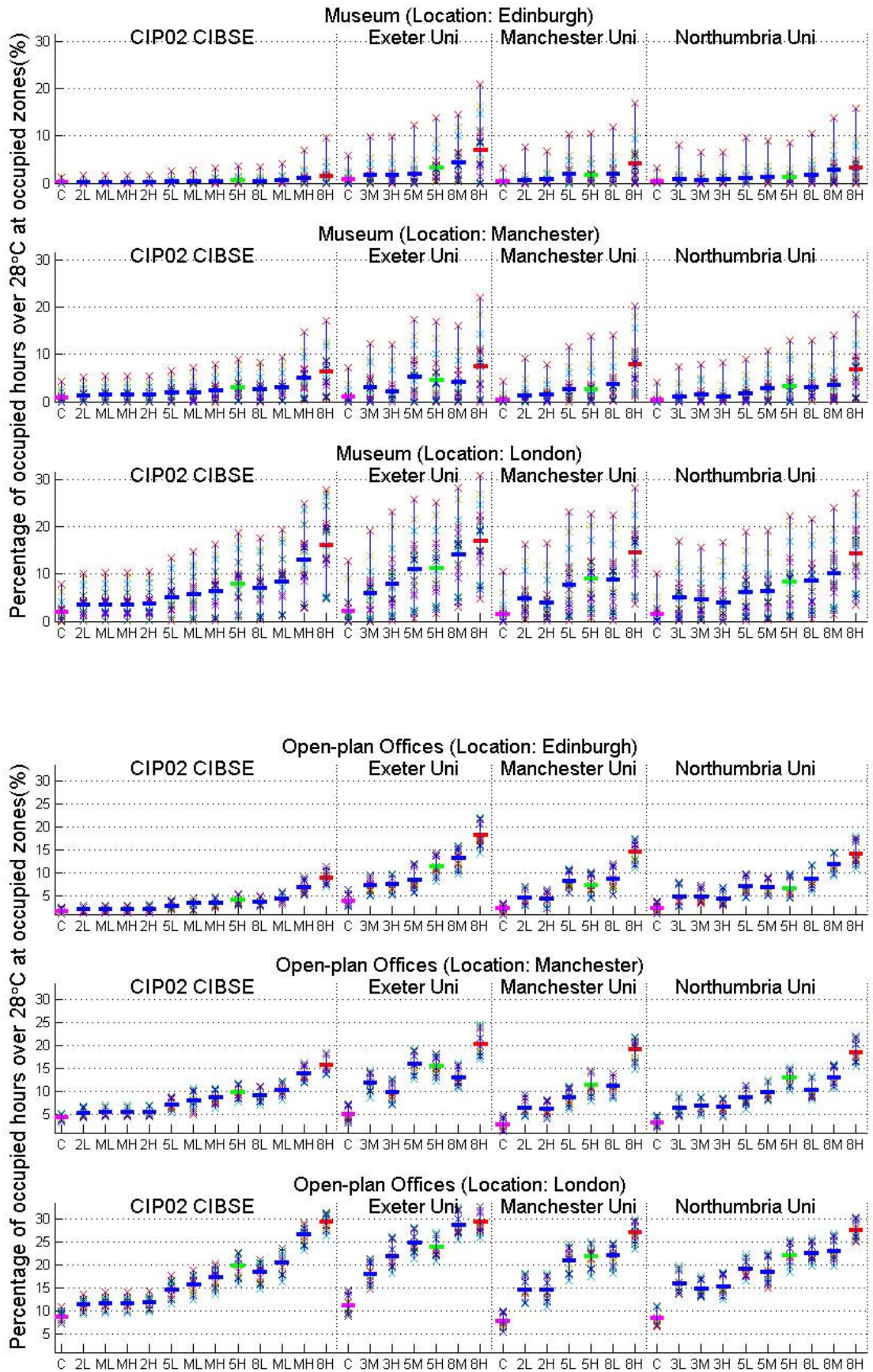
Appendix A5: TRY results: Overheat percentage of occupied hours

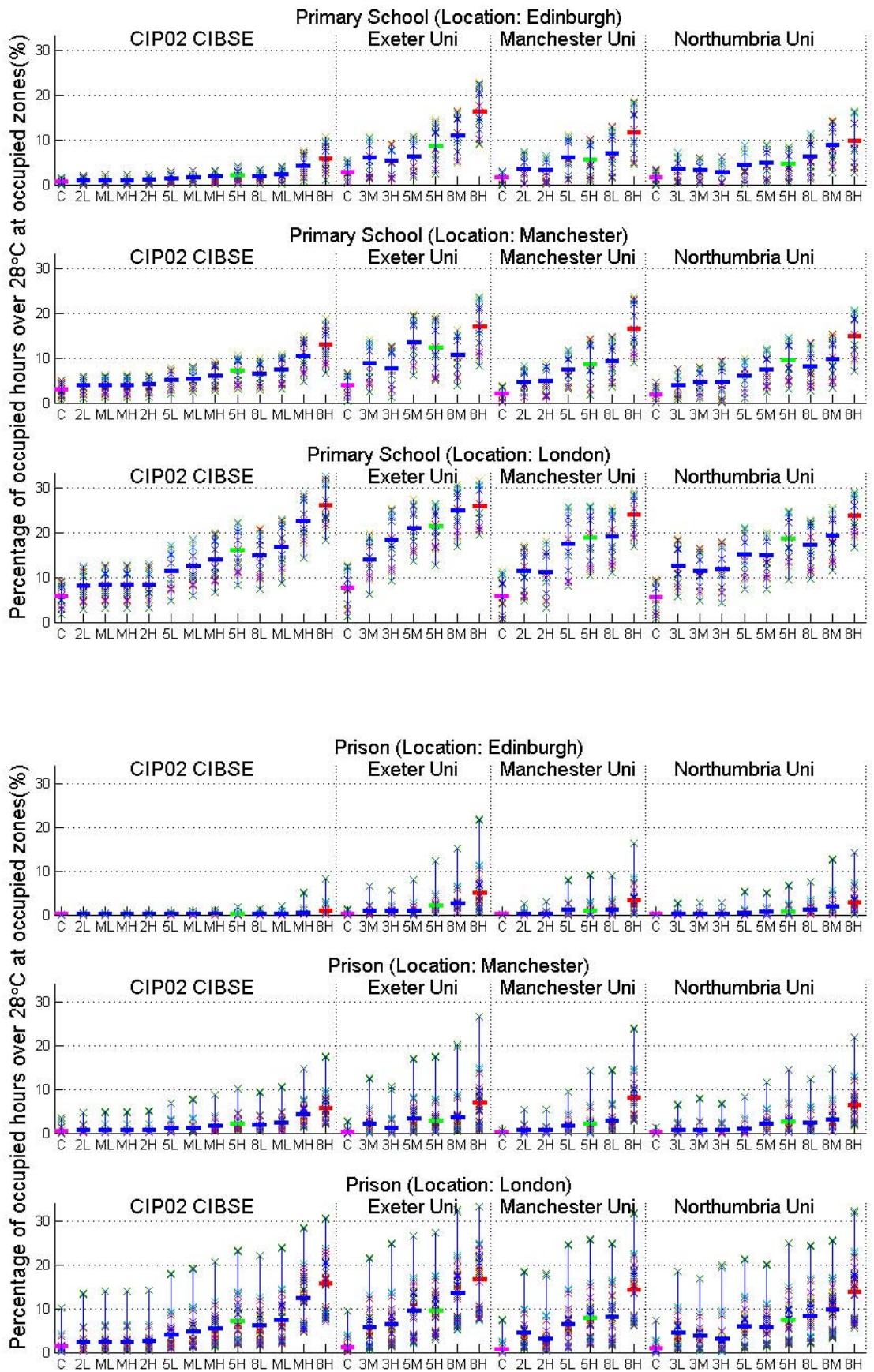


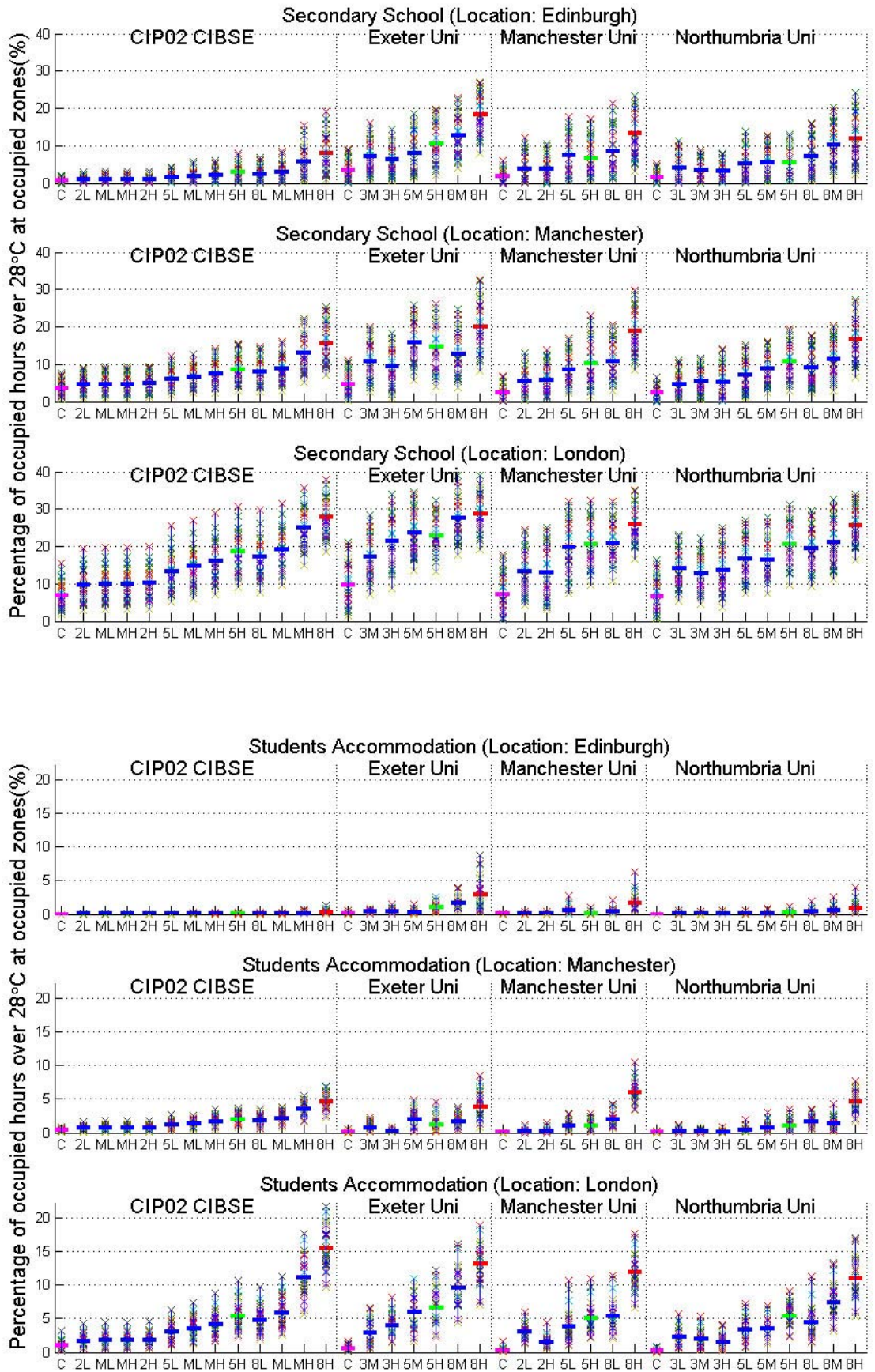


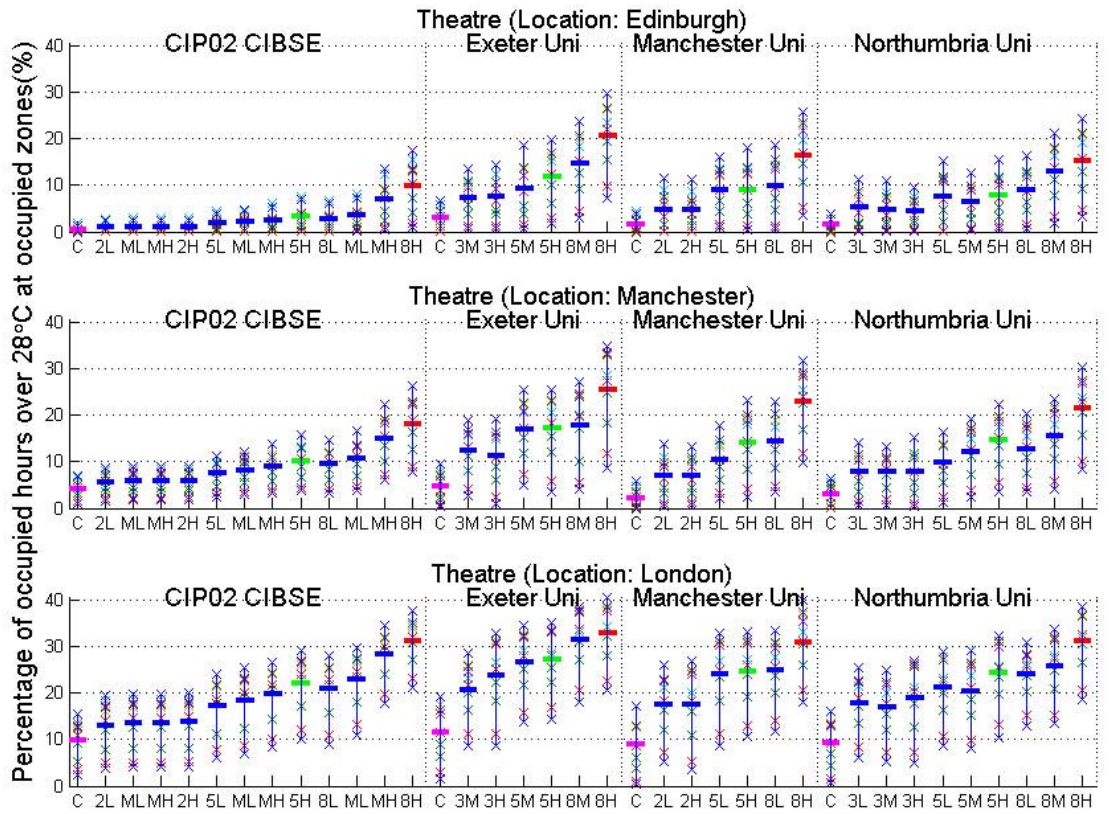




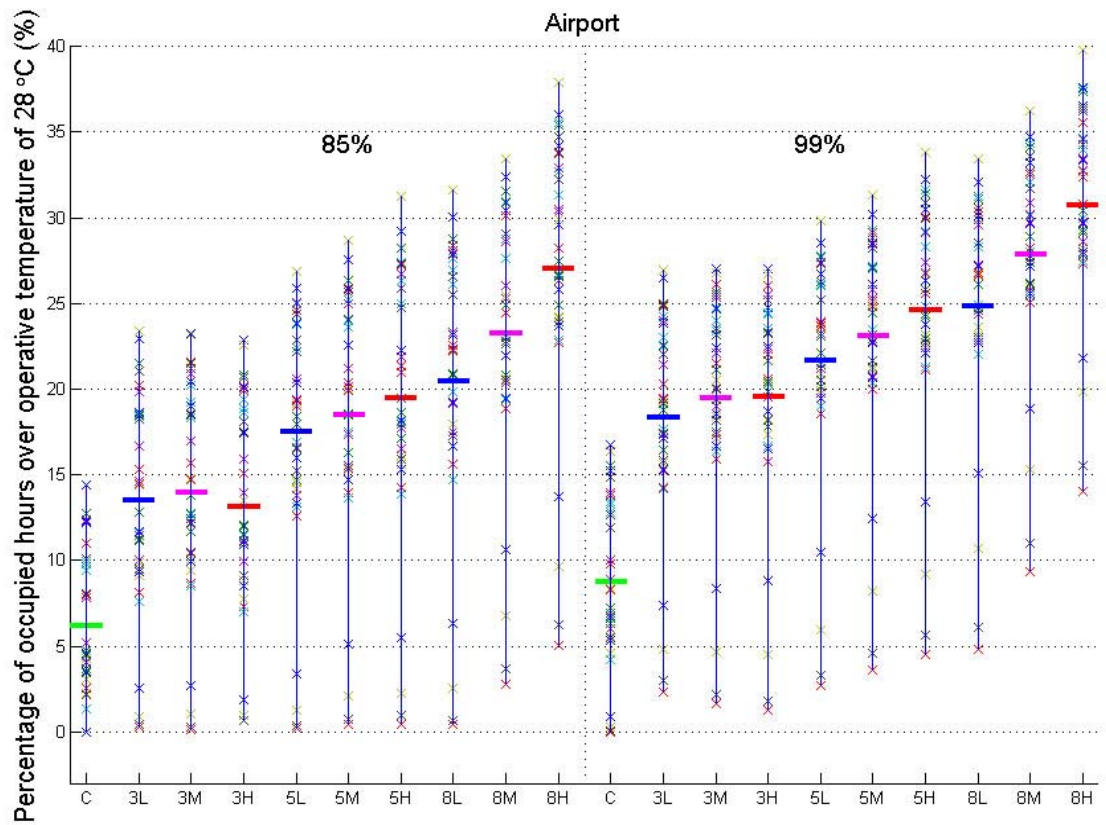
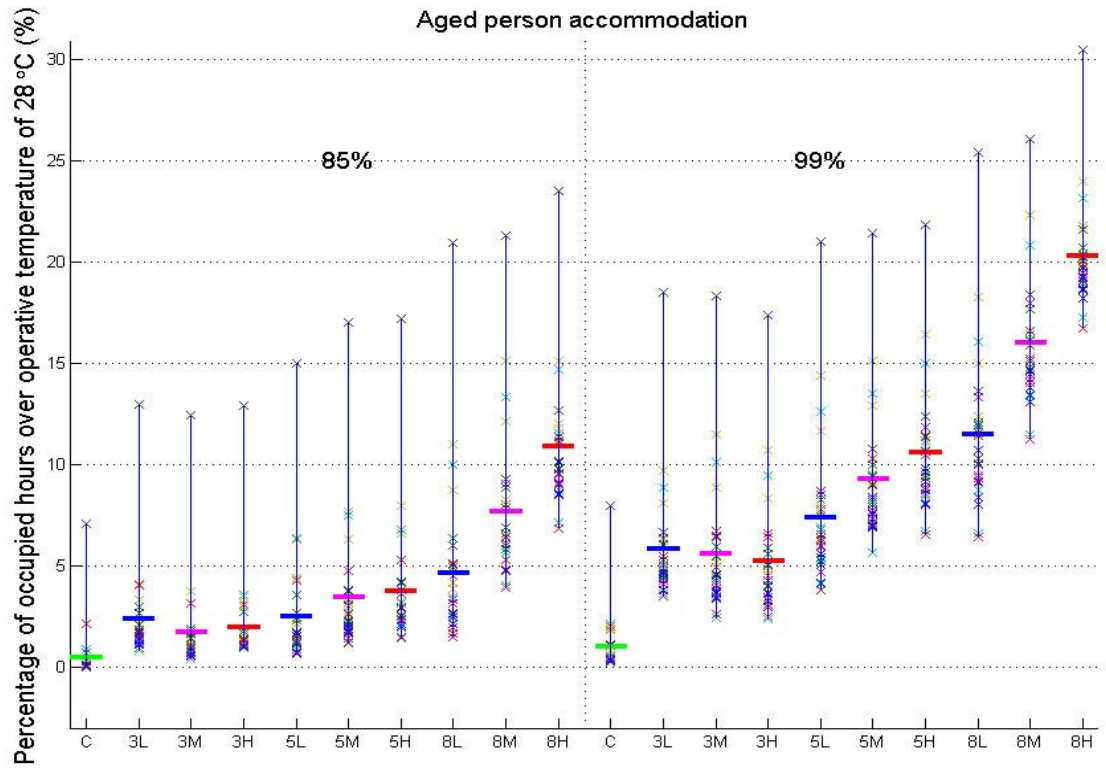


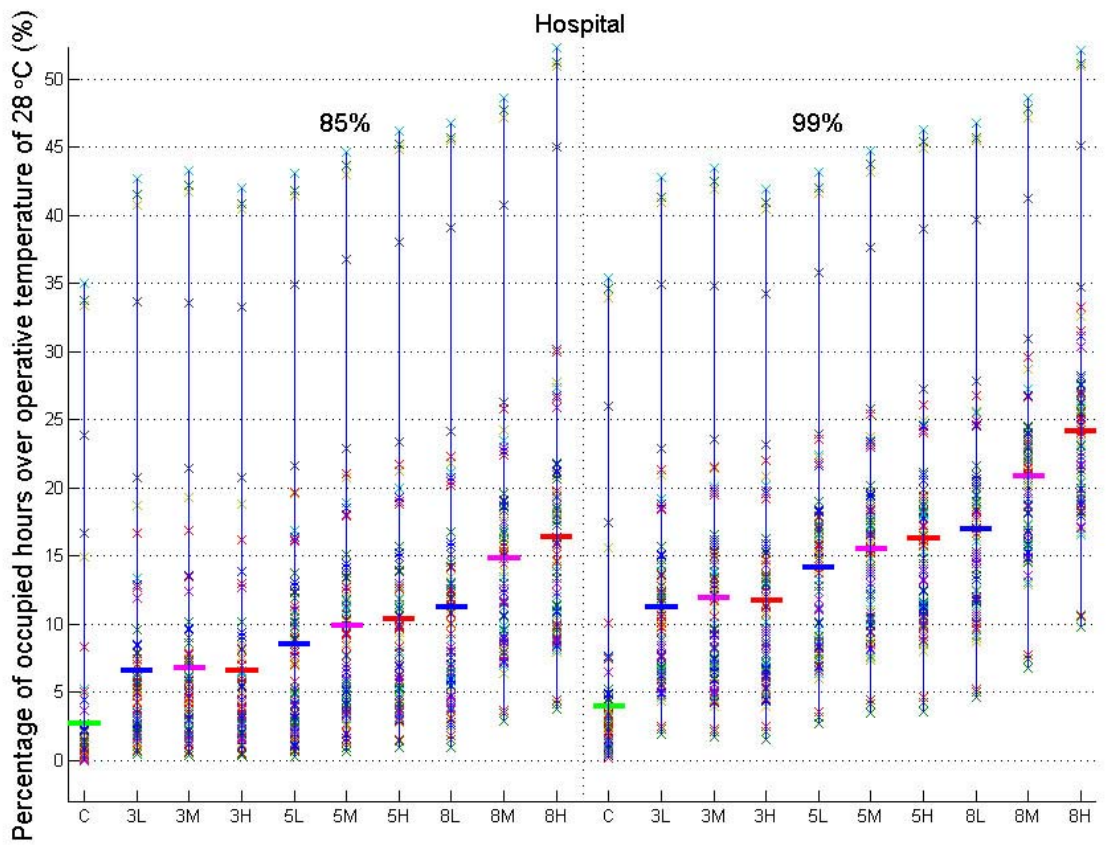
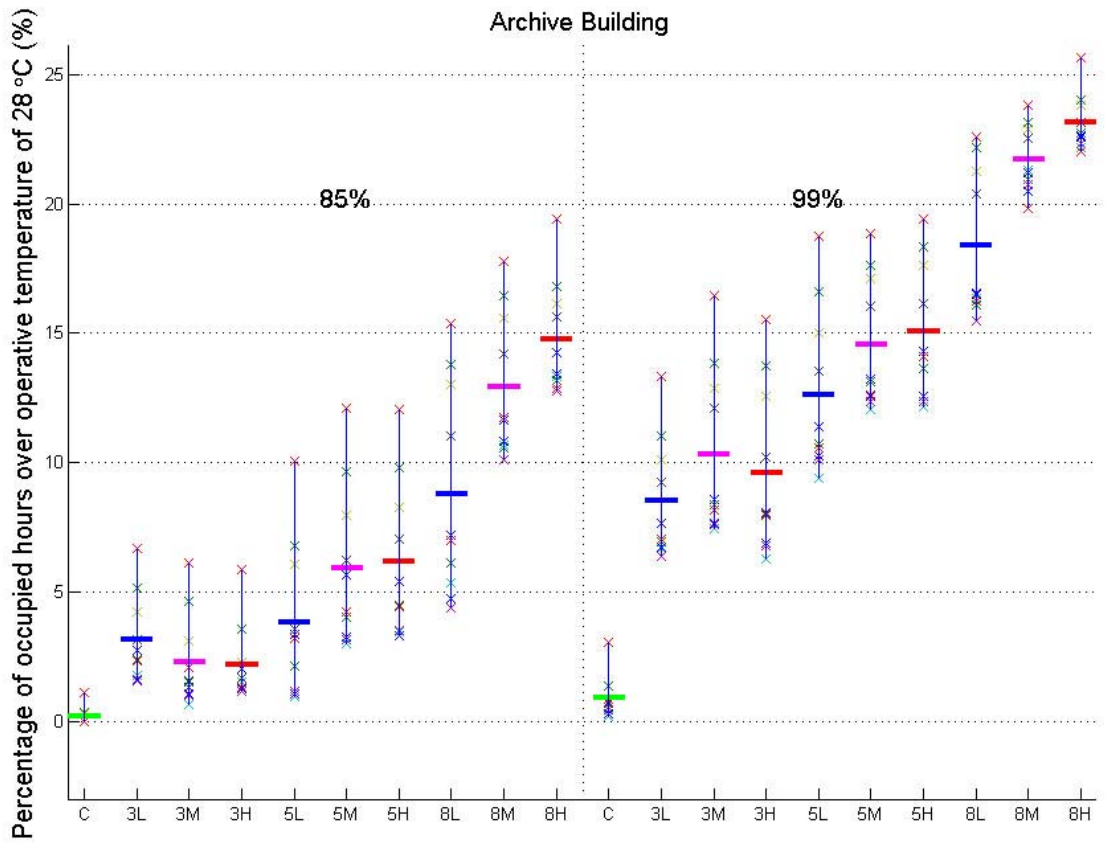


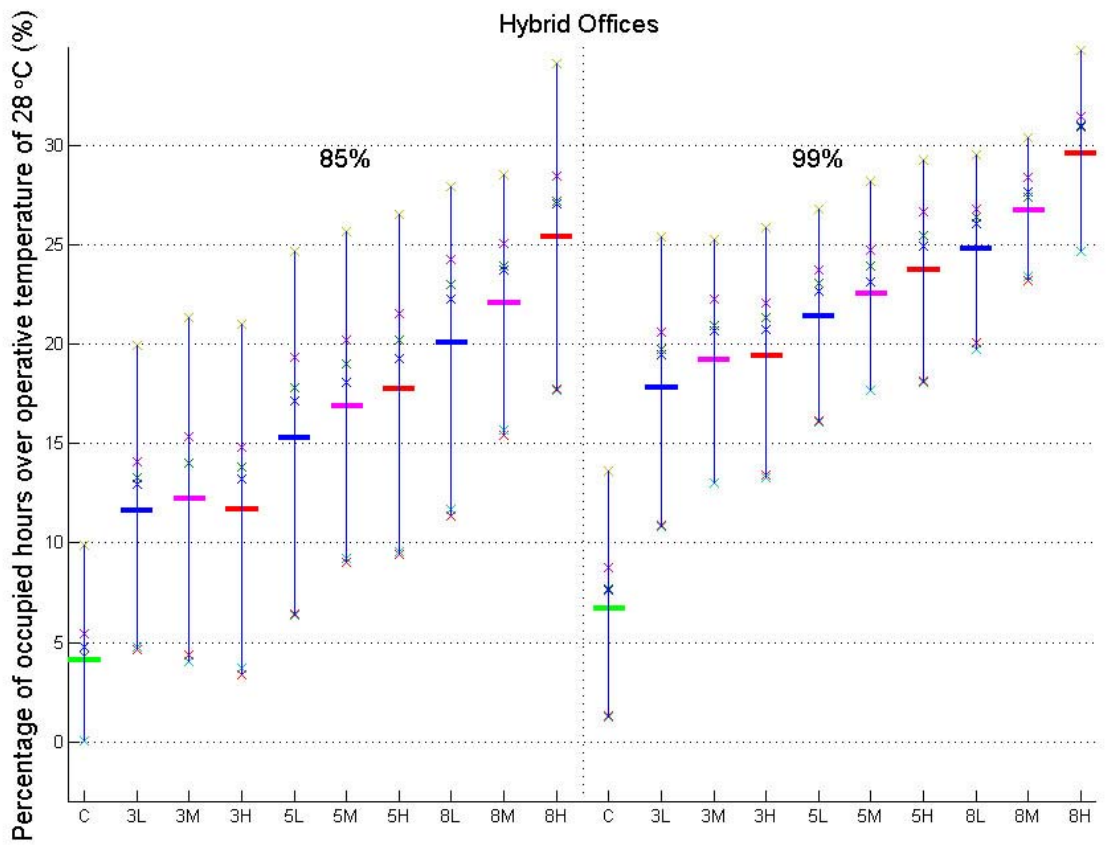
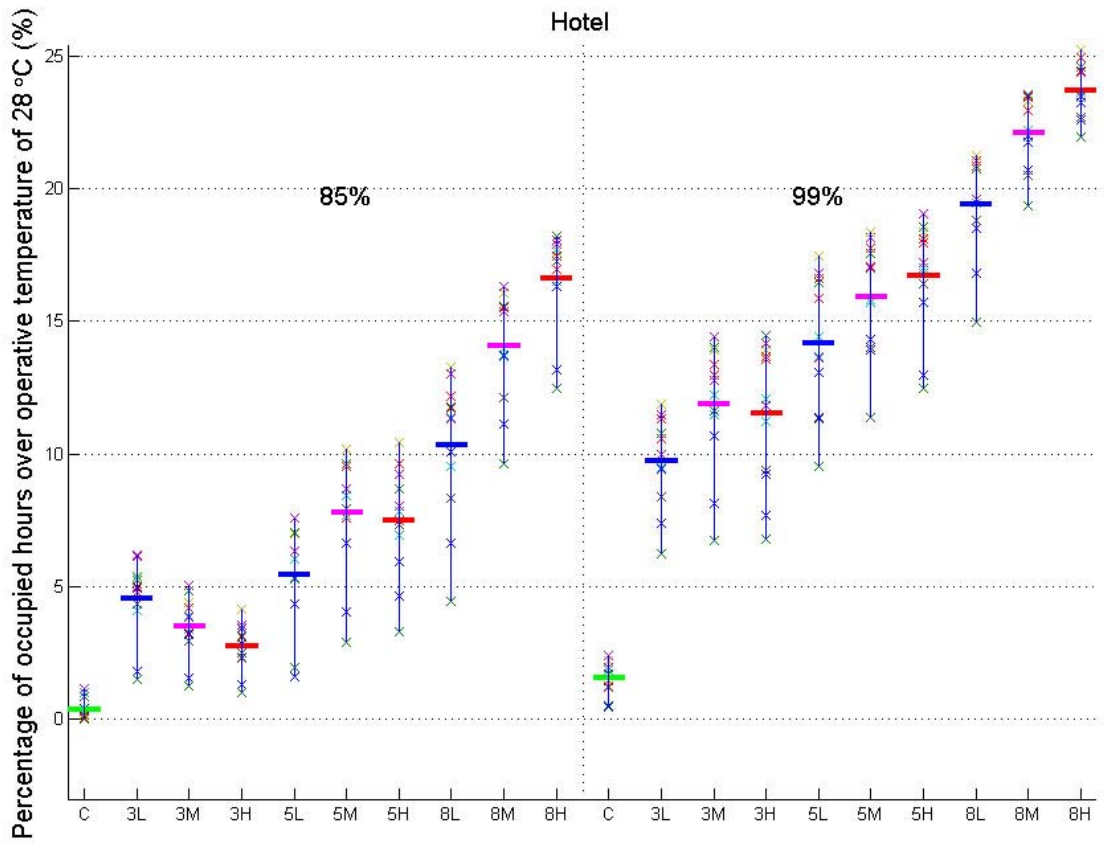


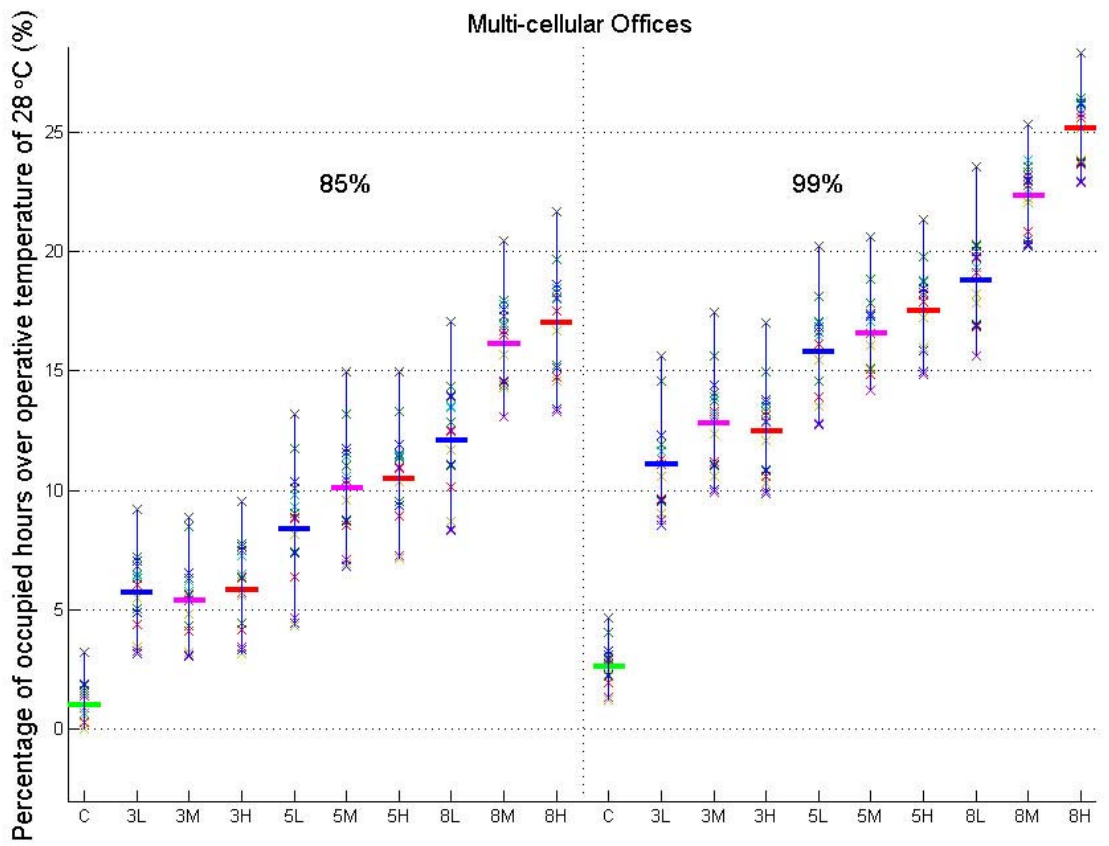
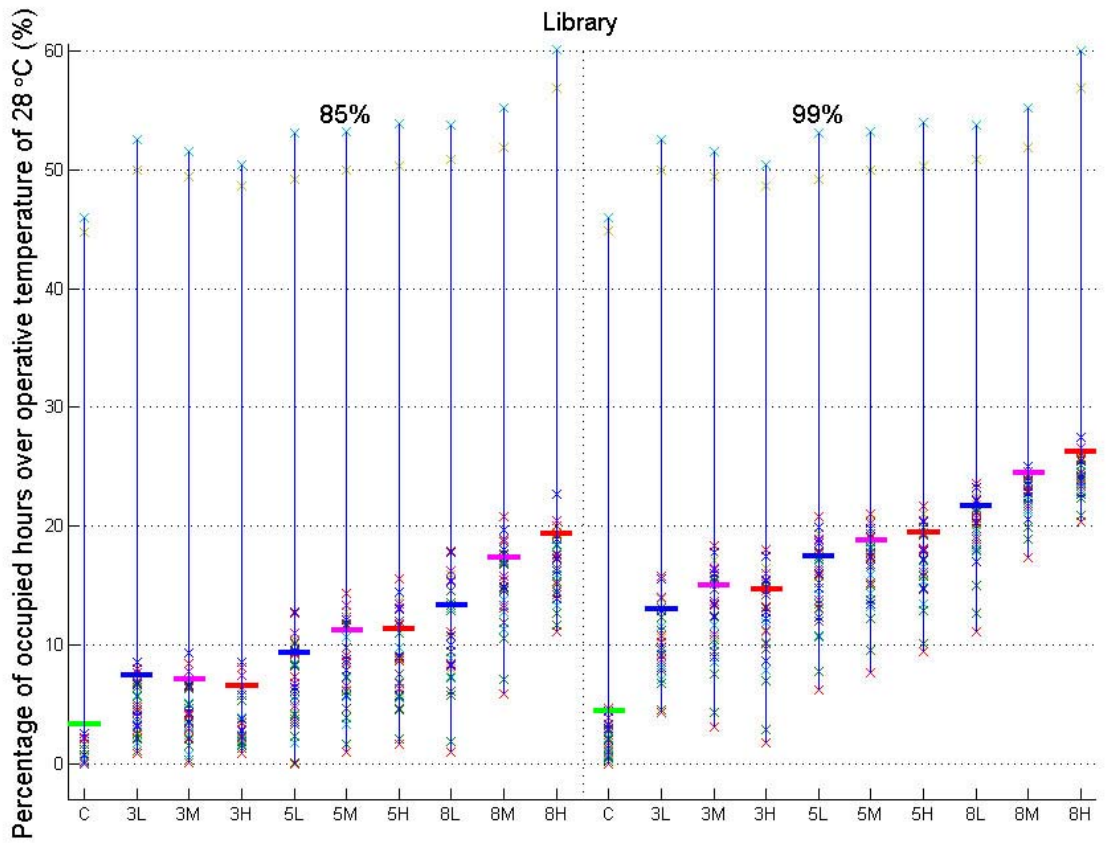


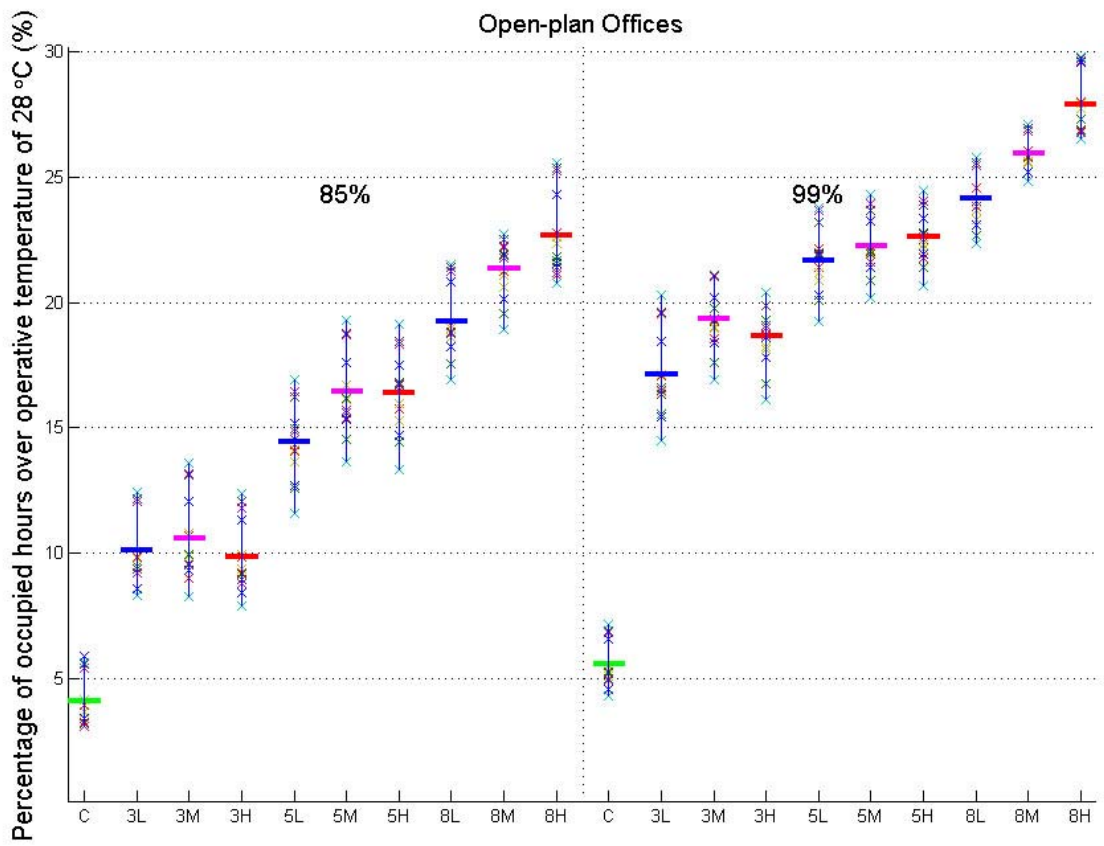
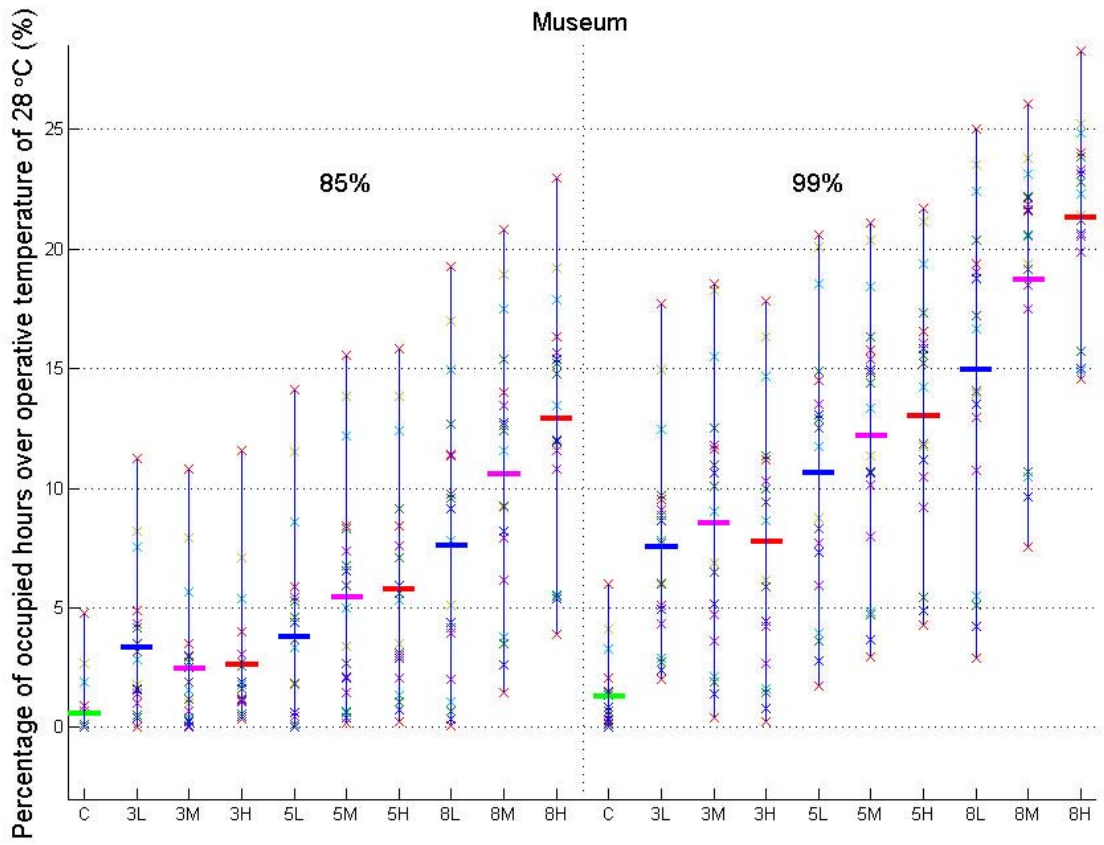
Appendix B1: DRY results: Overheat percentage of occupied hours

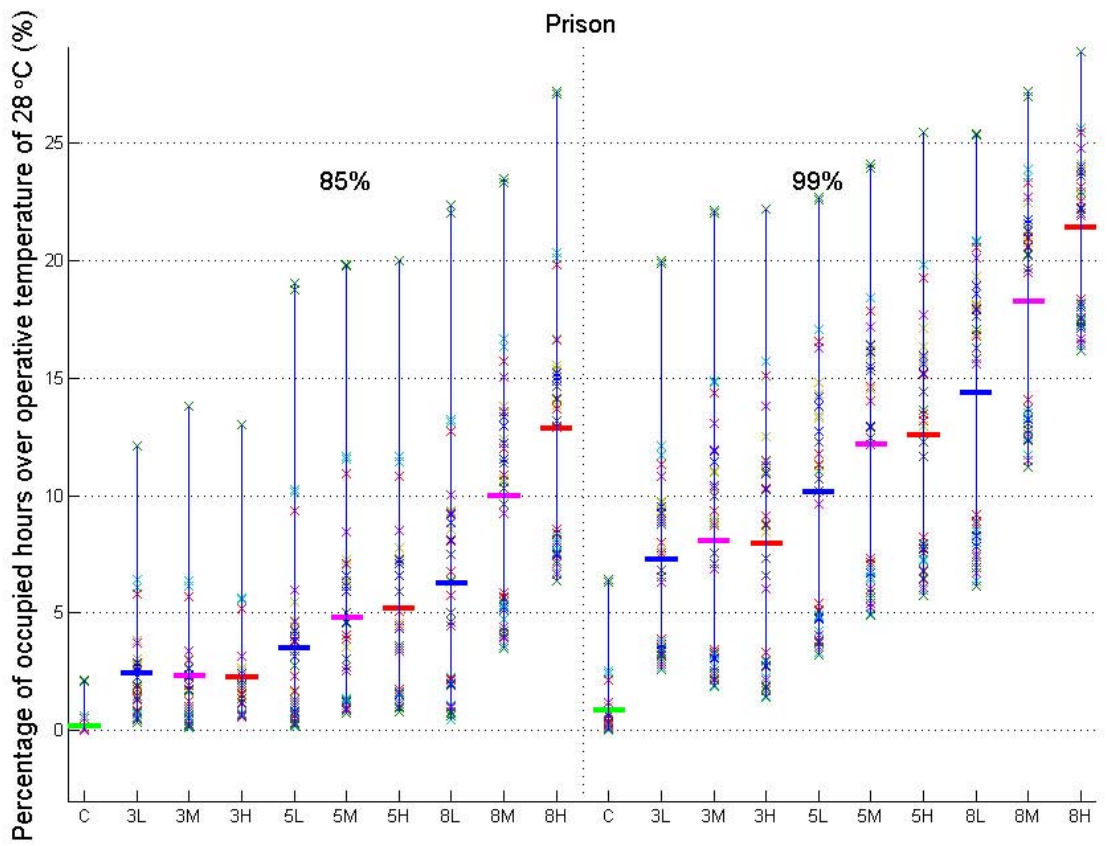
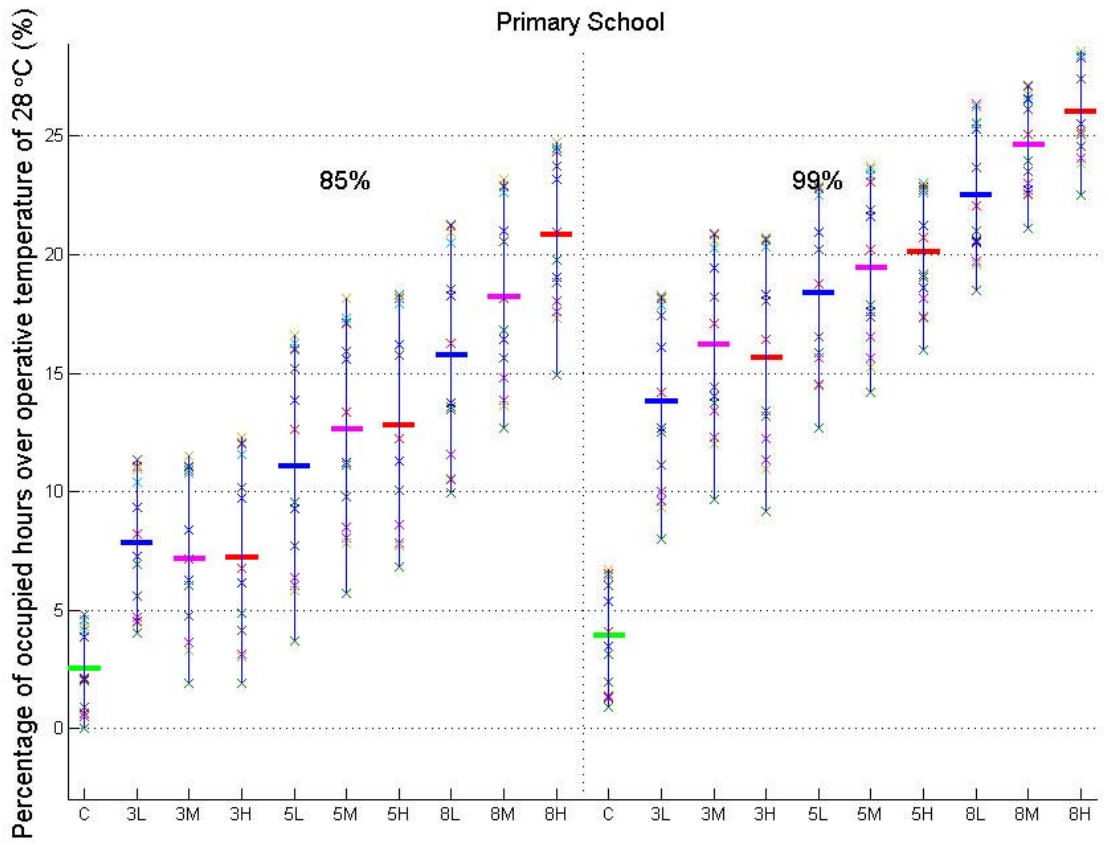


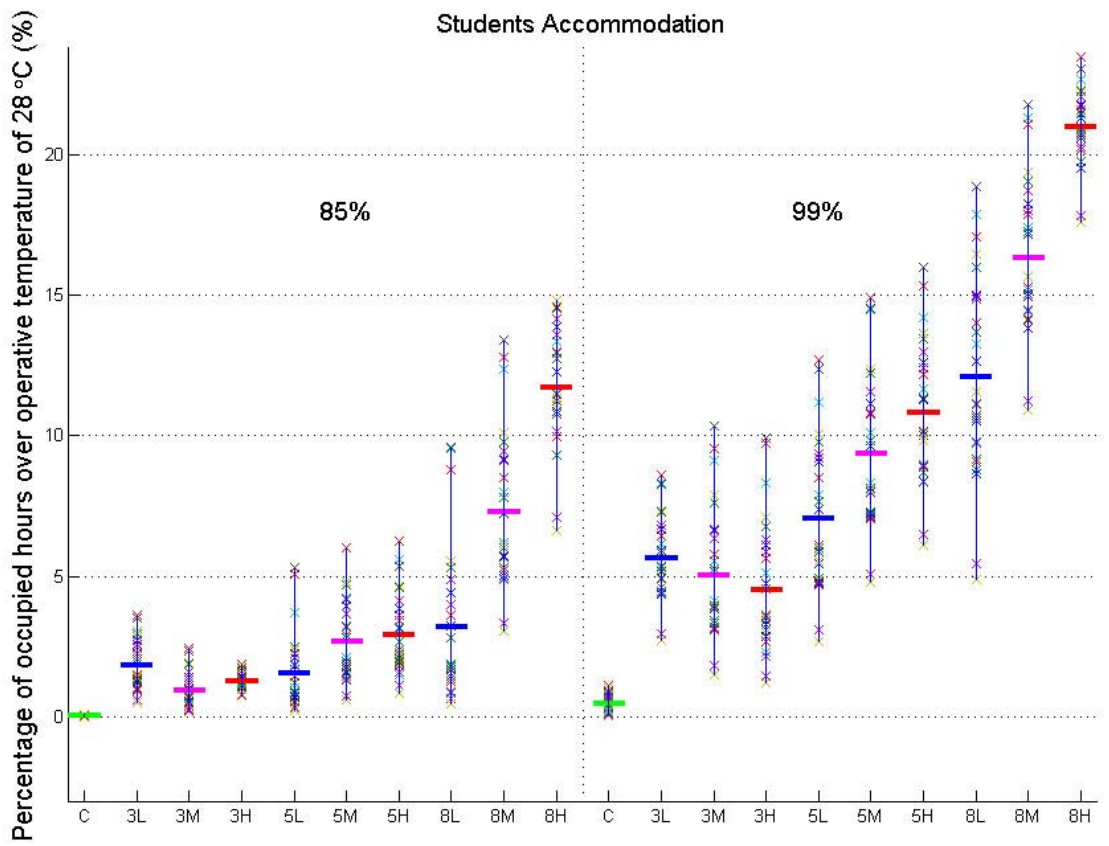
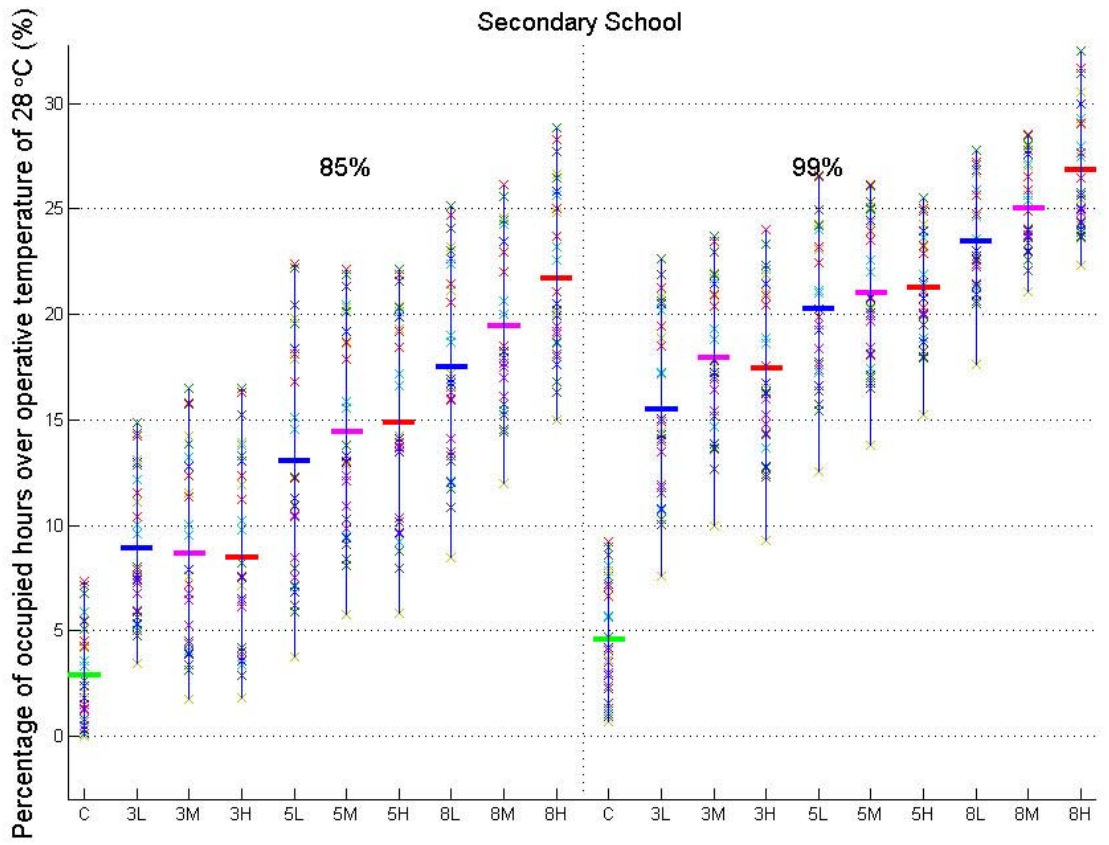


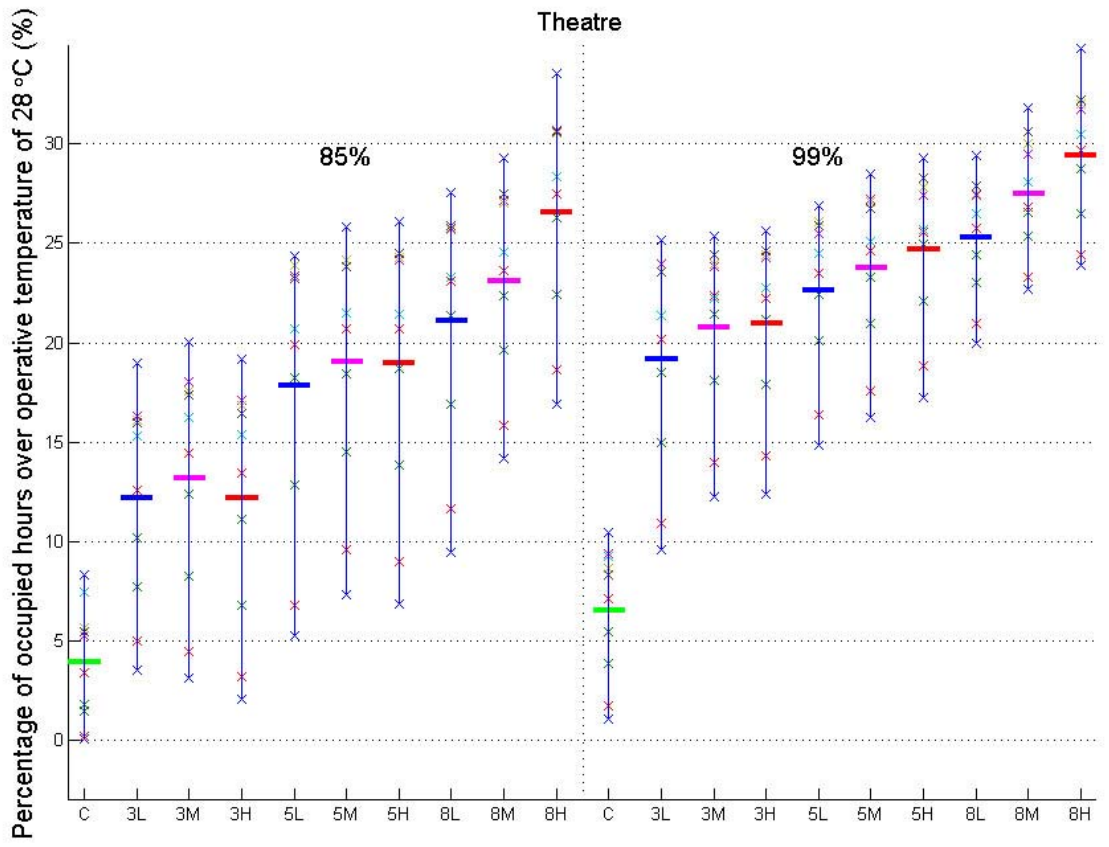




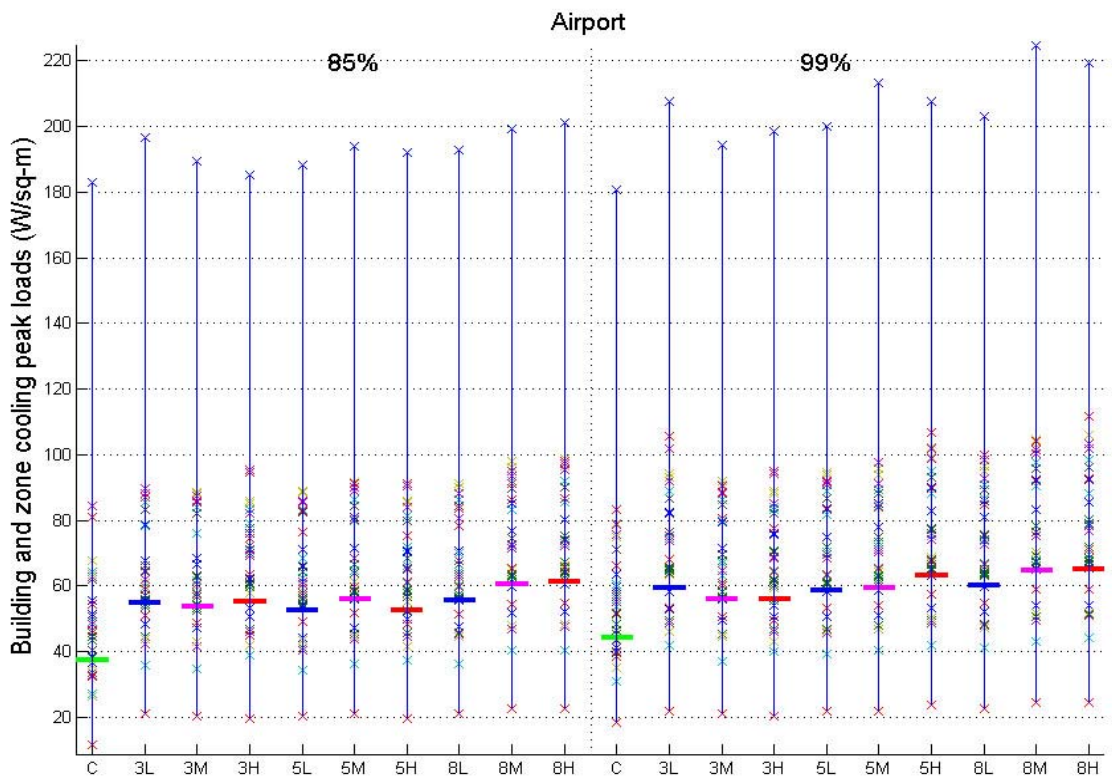
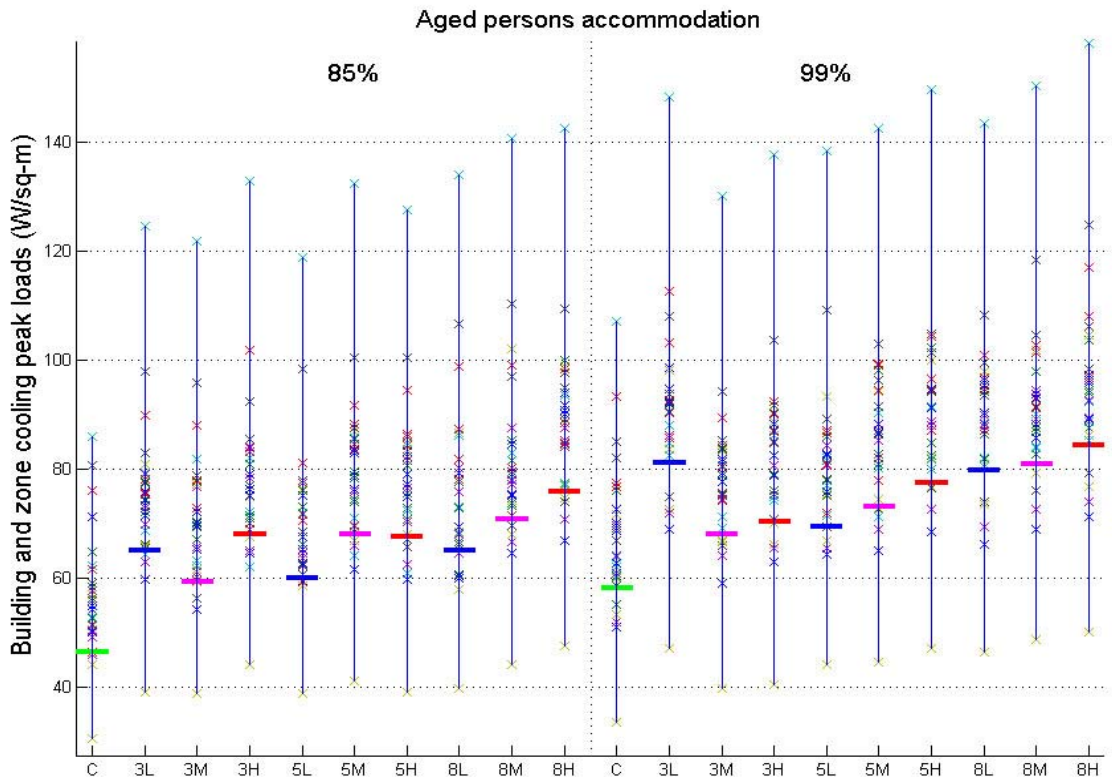


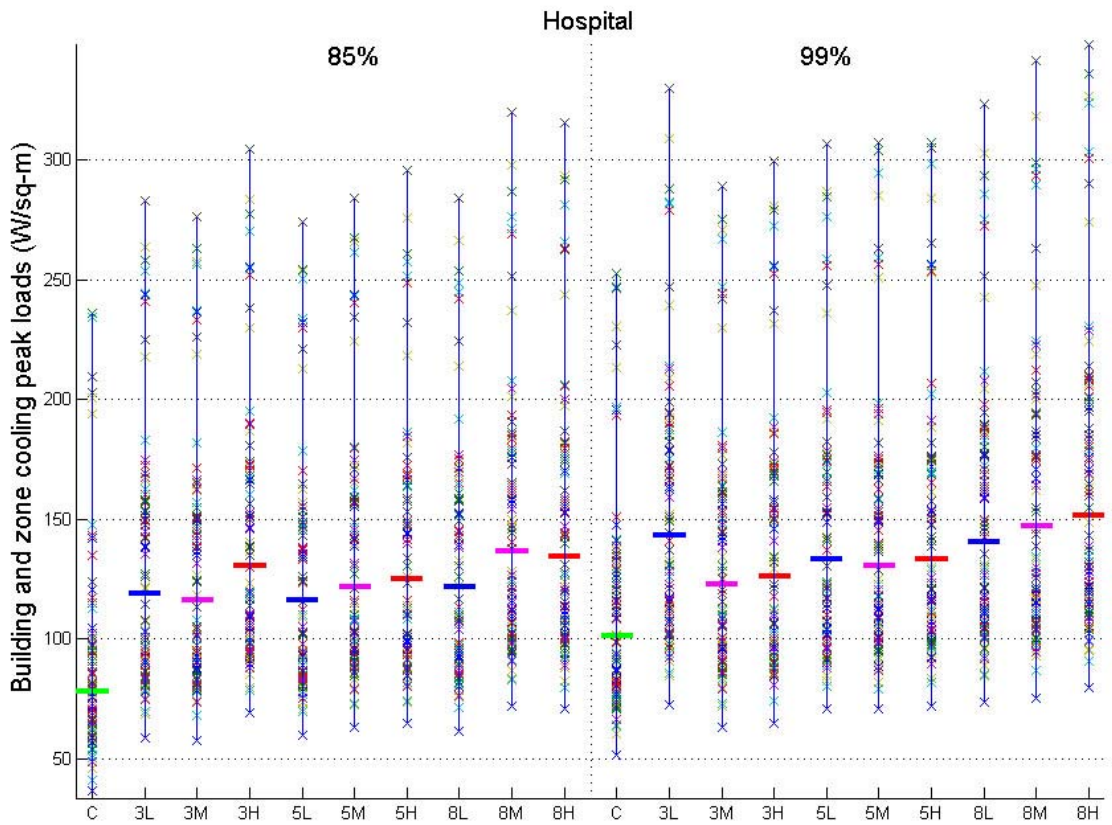
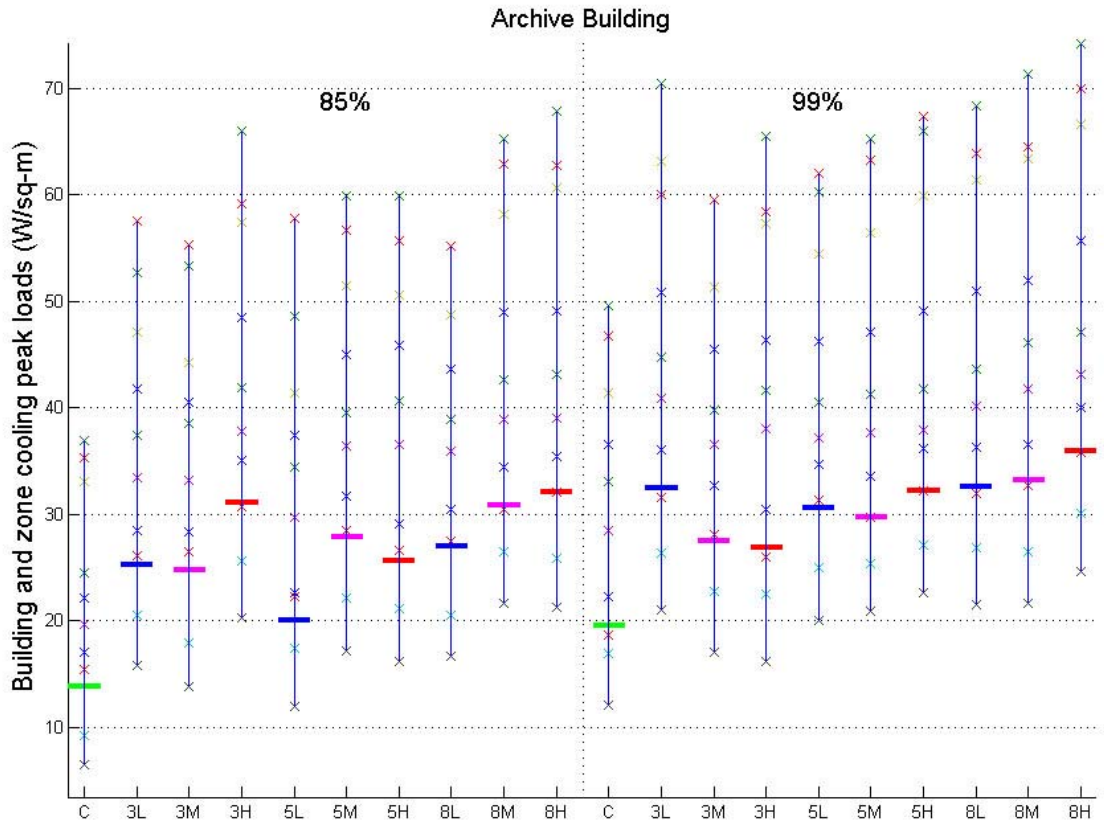


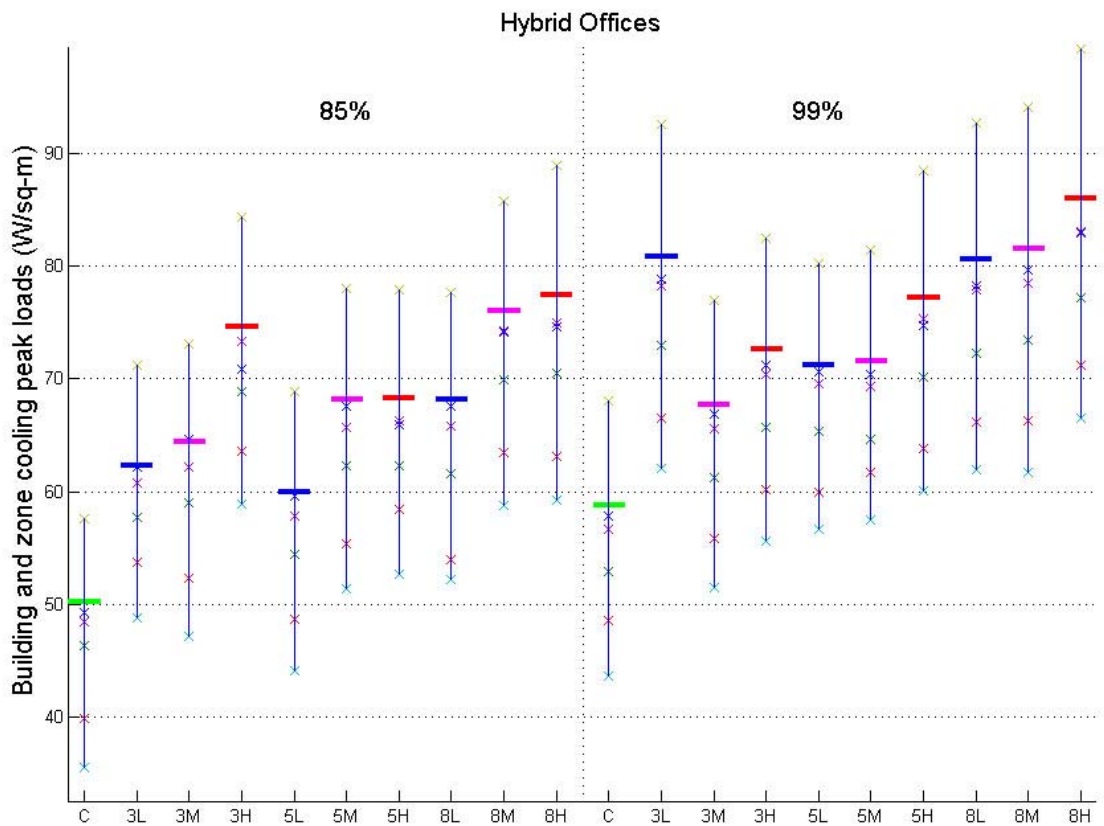
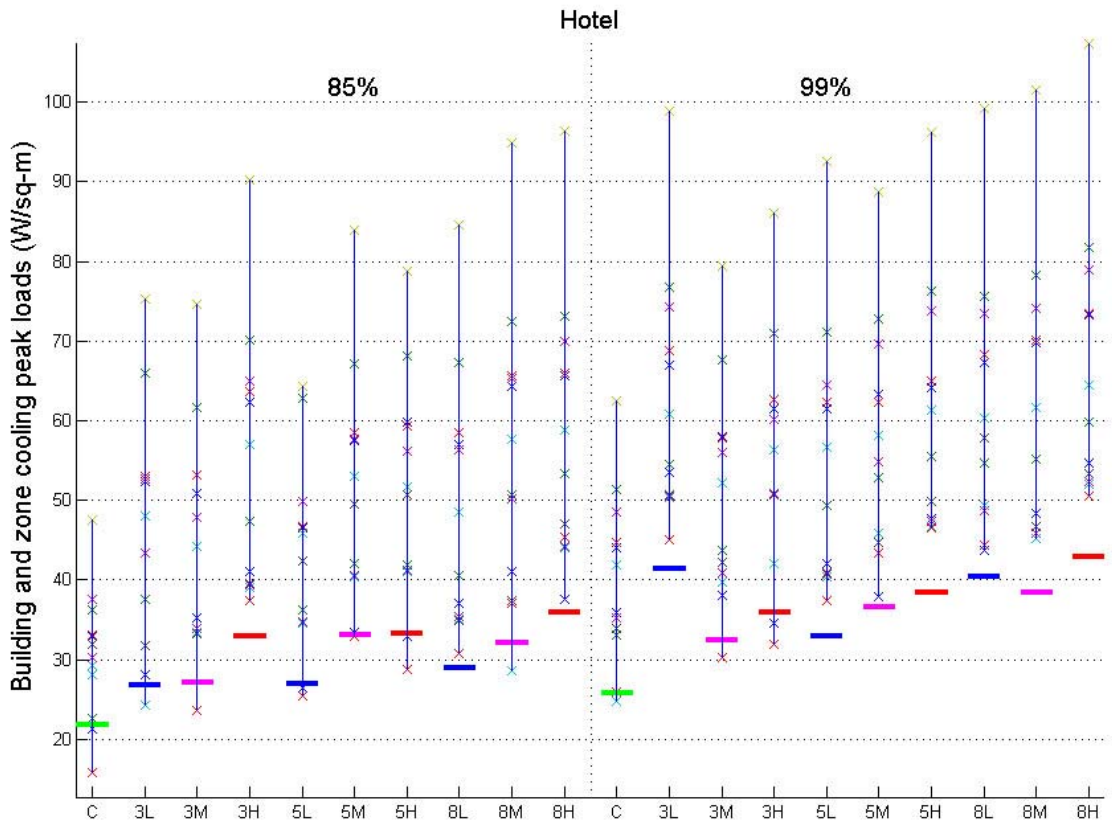


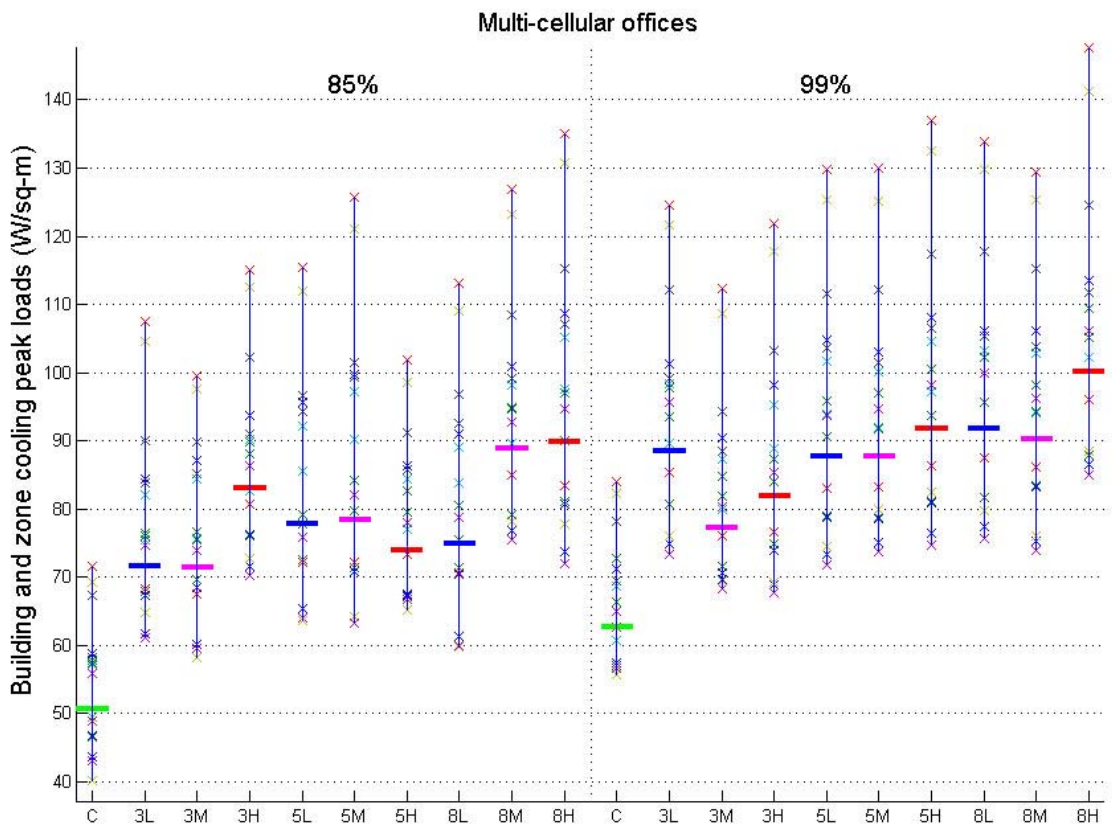
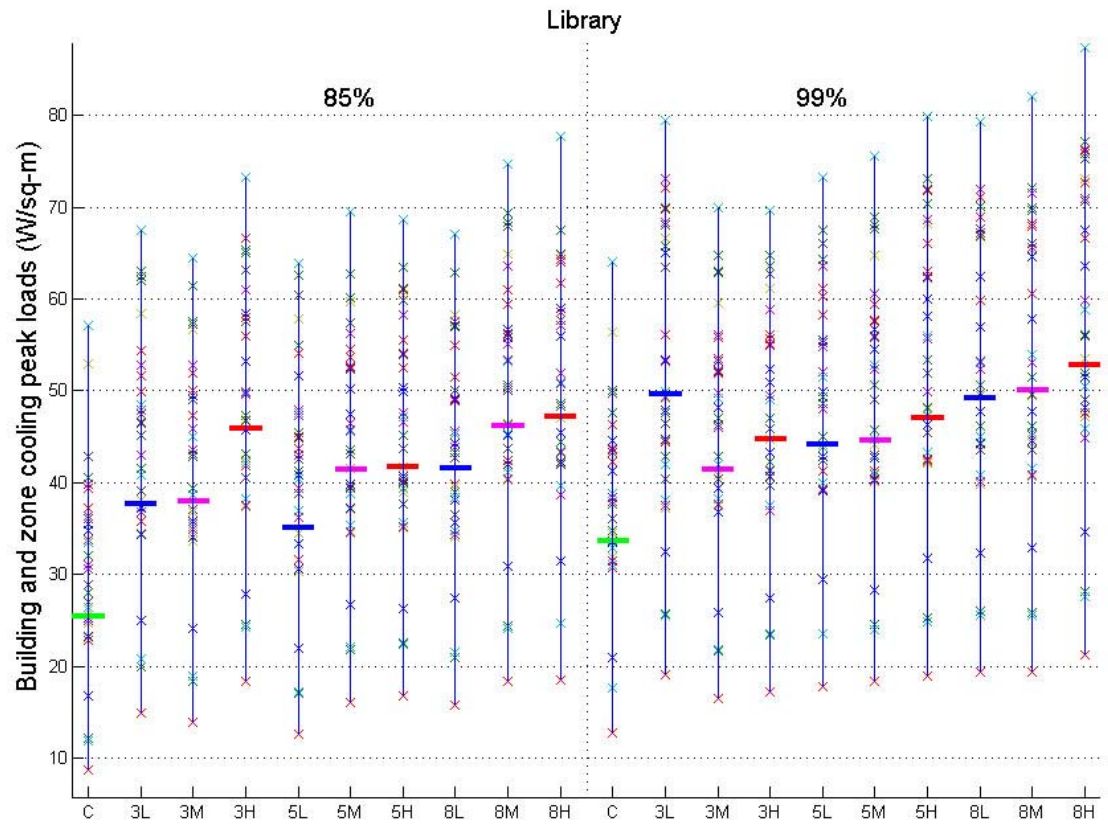


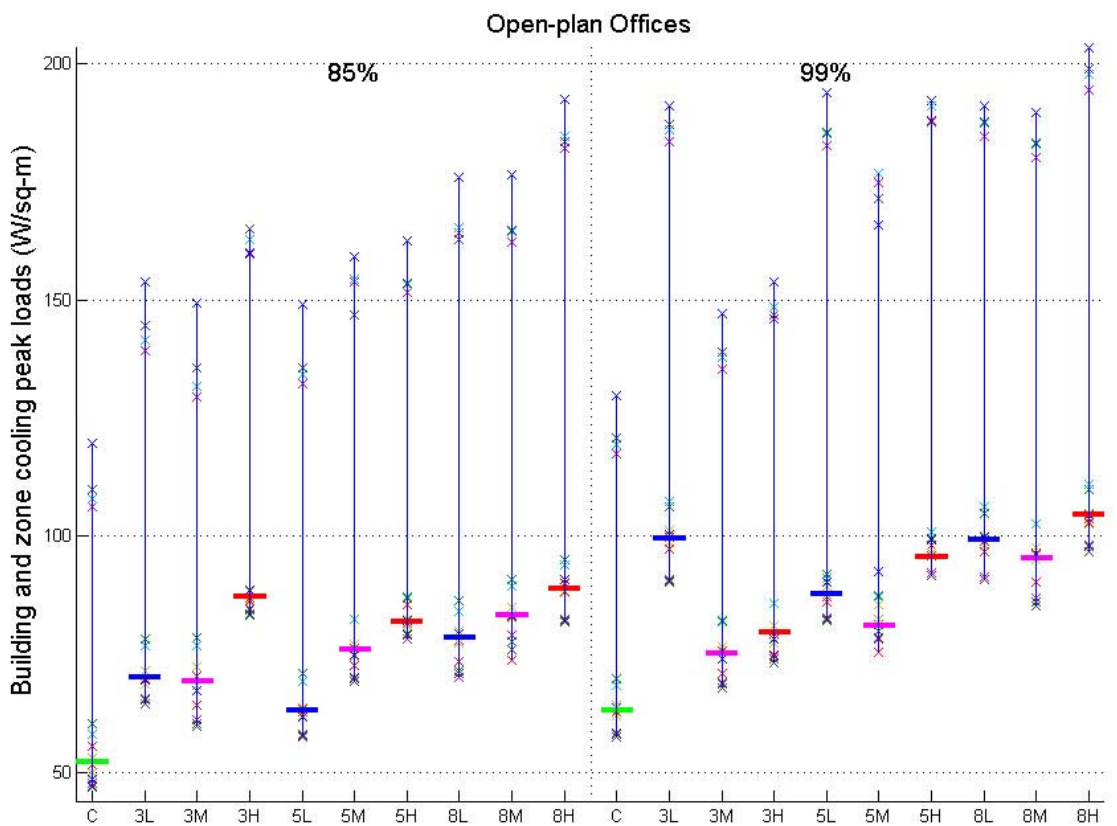
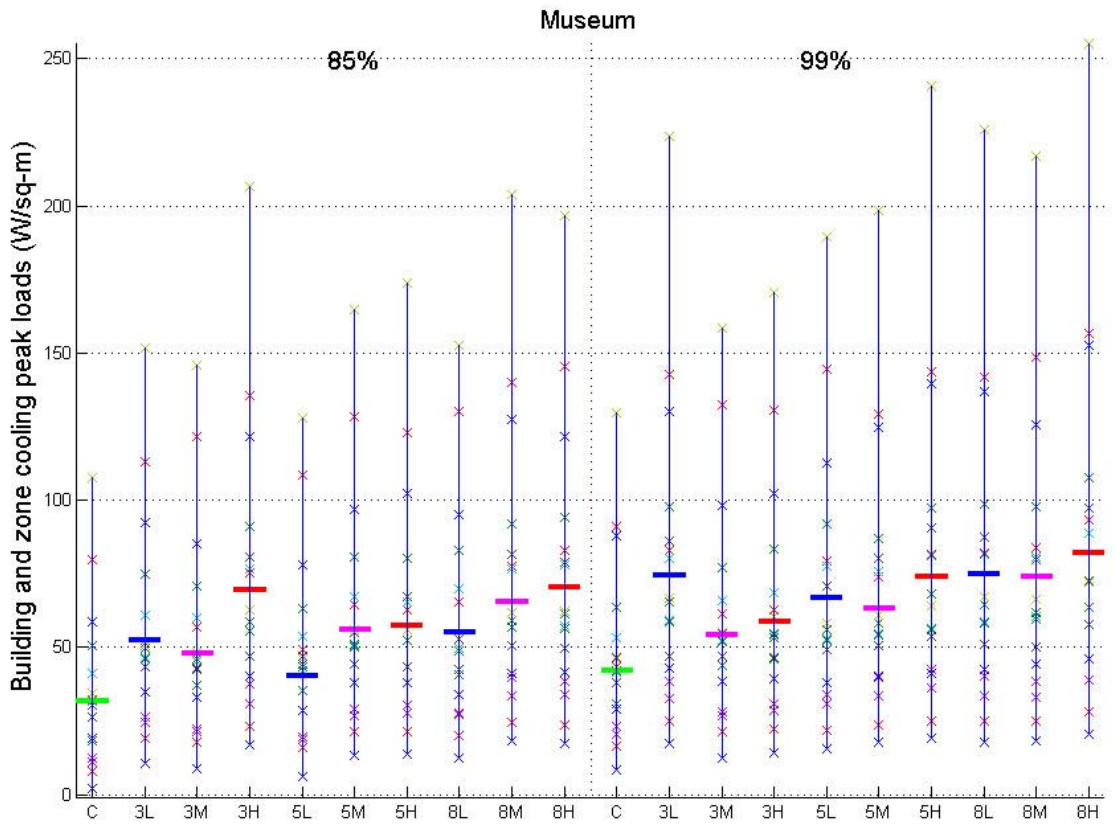
Appendix B2: DRY results: Building and zones cooling design loads

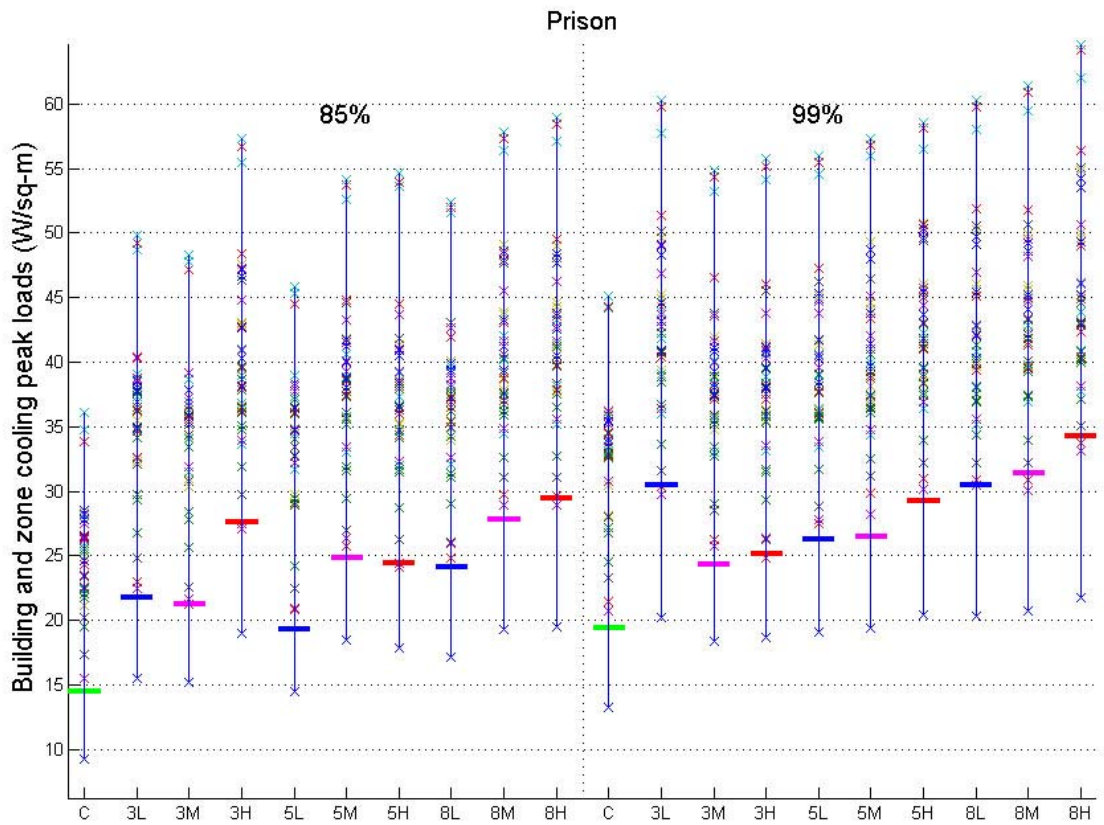
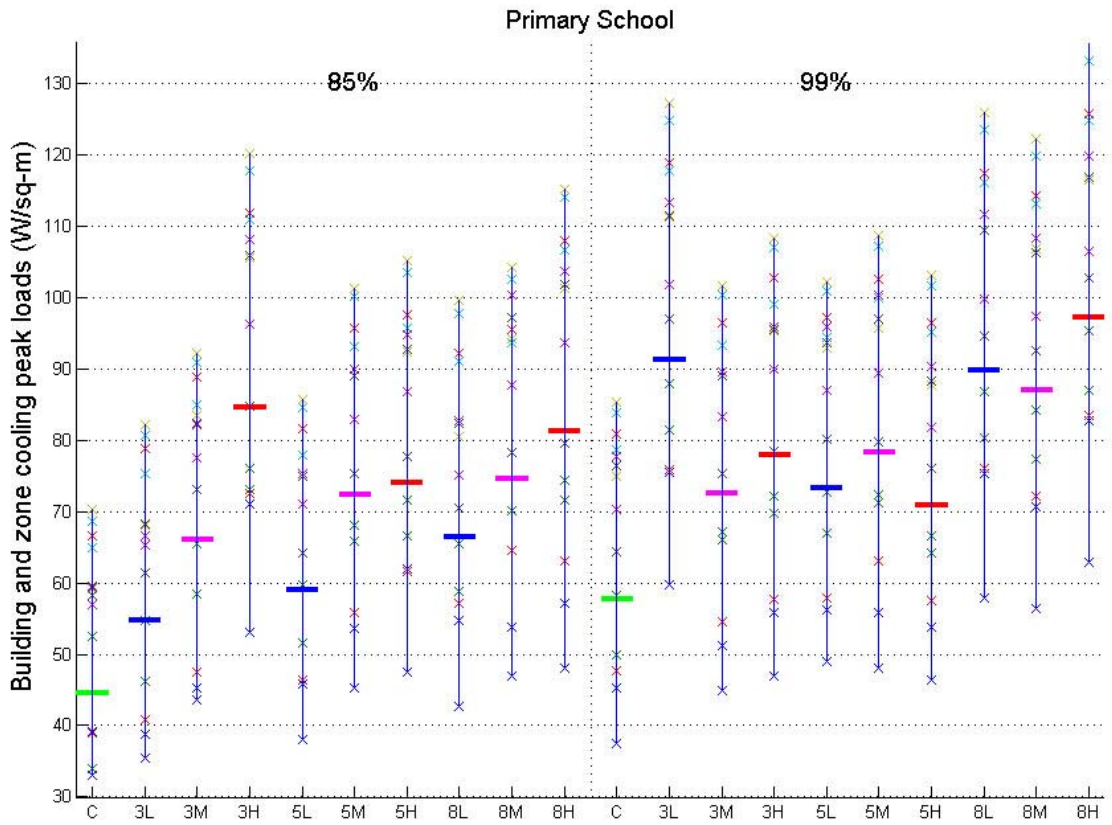


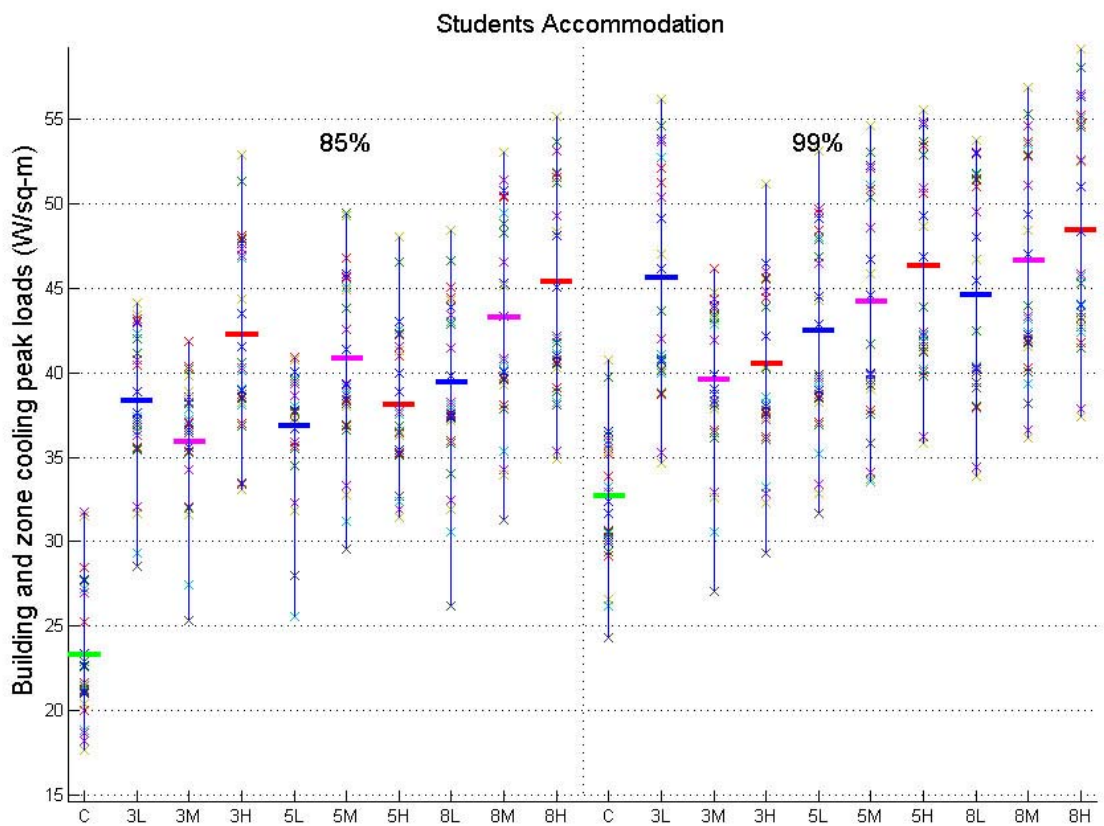
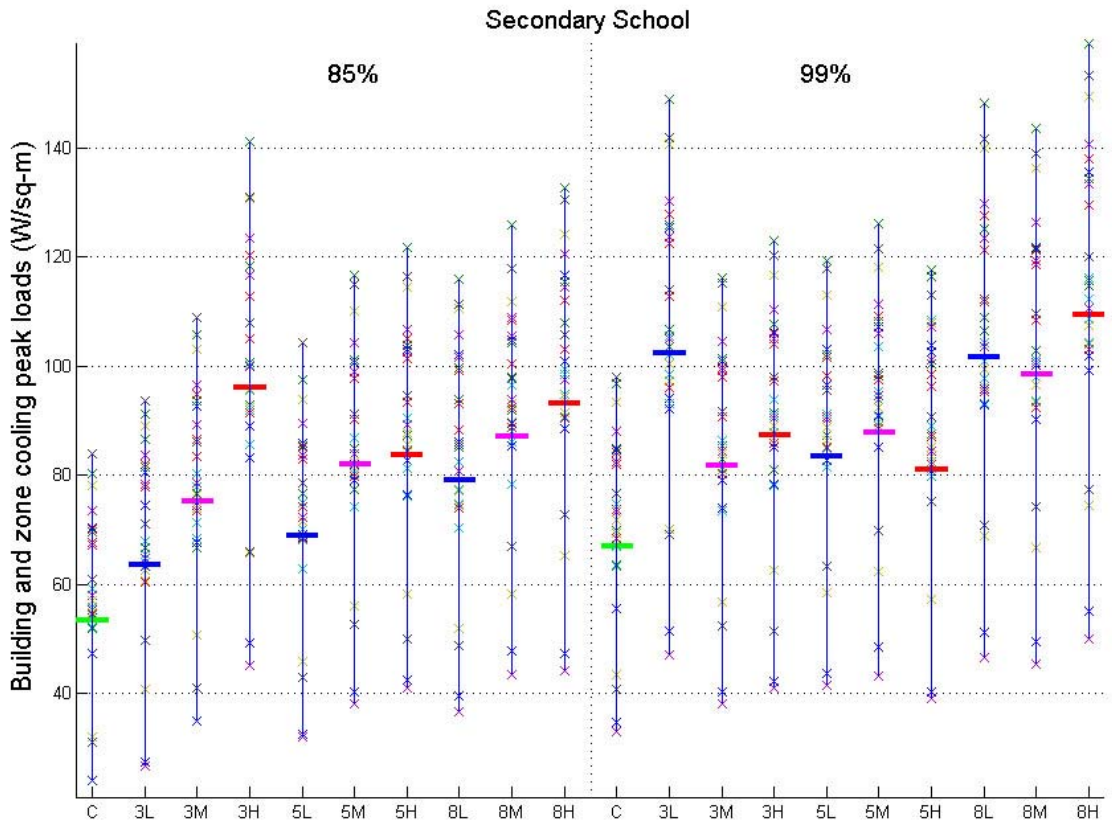


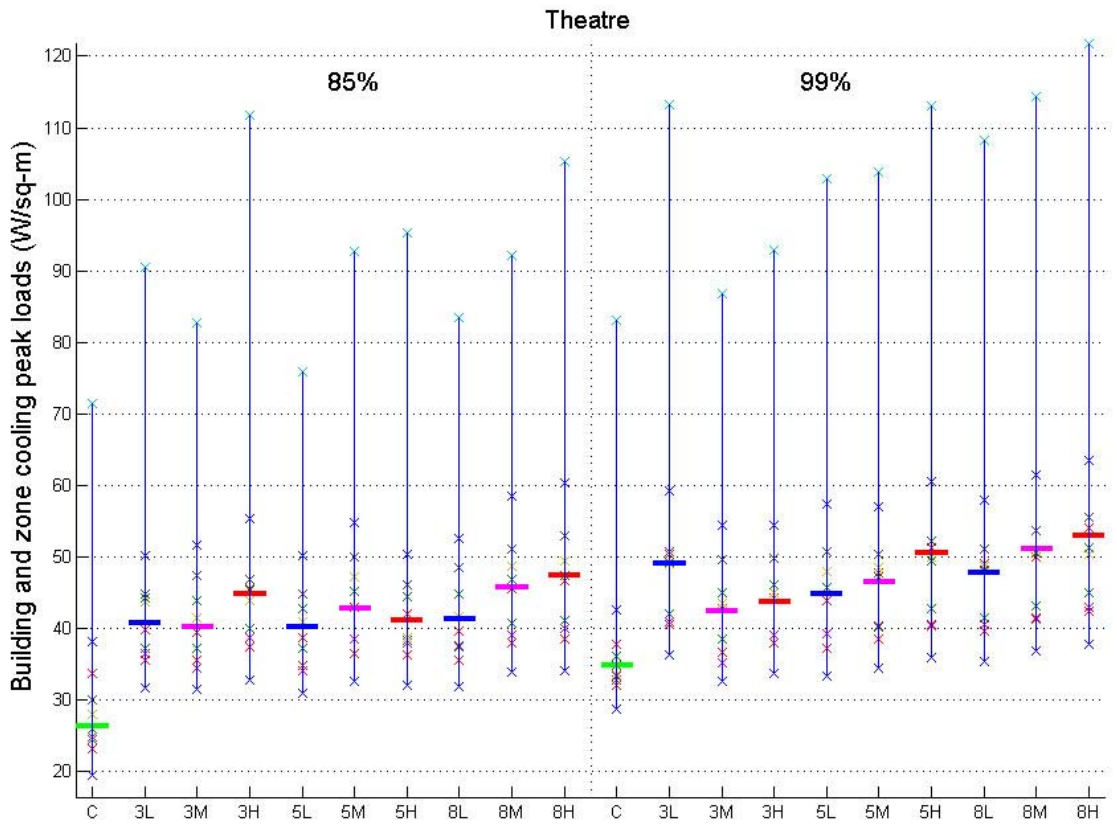




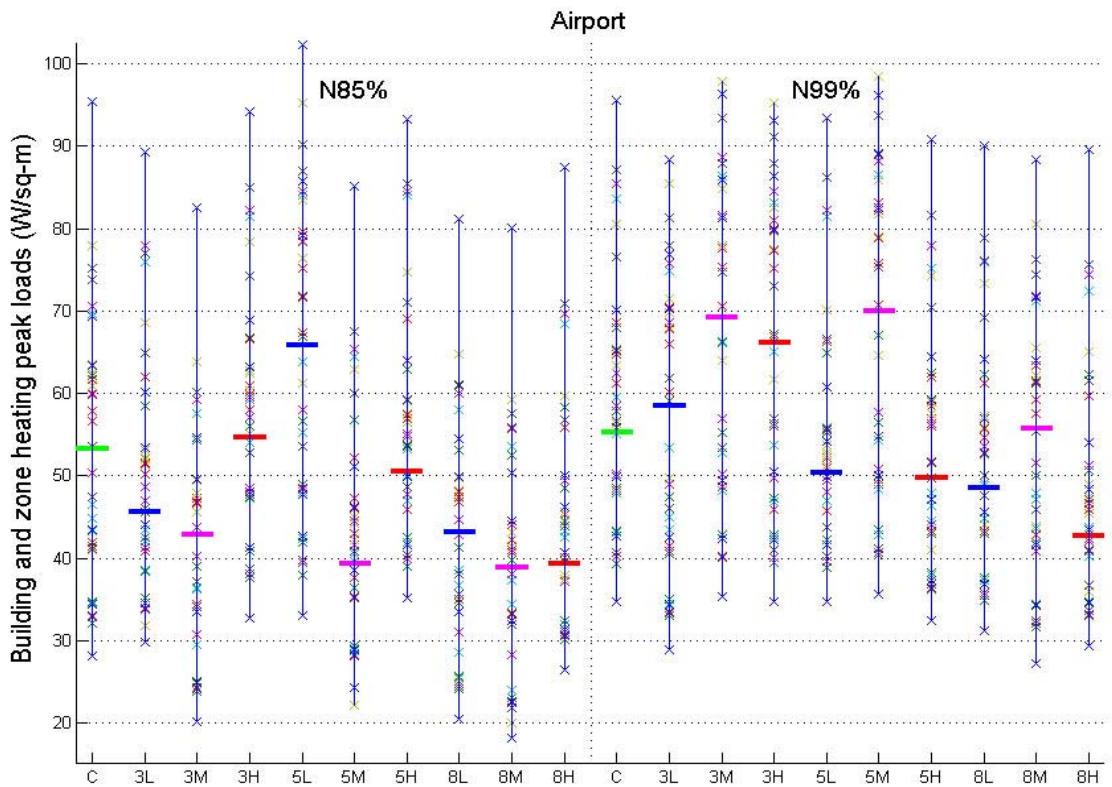
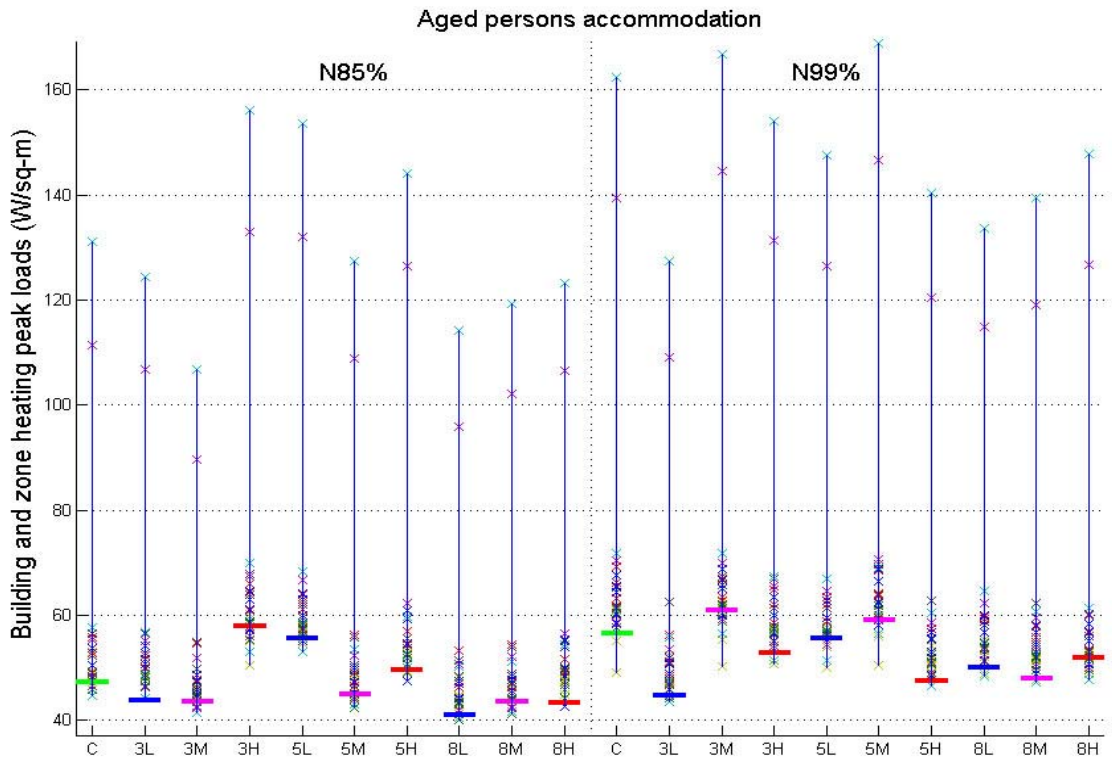


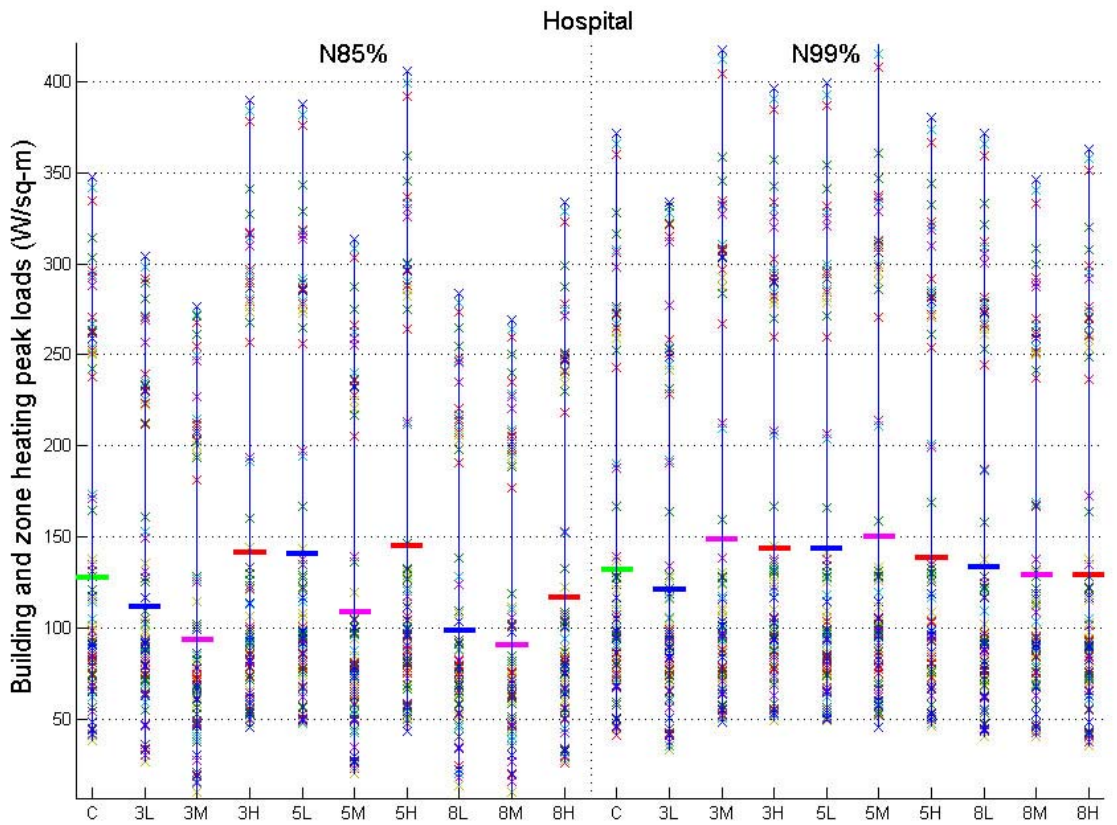
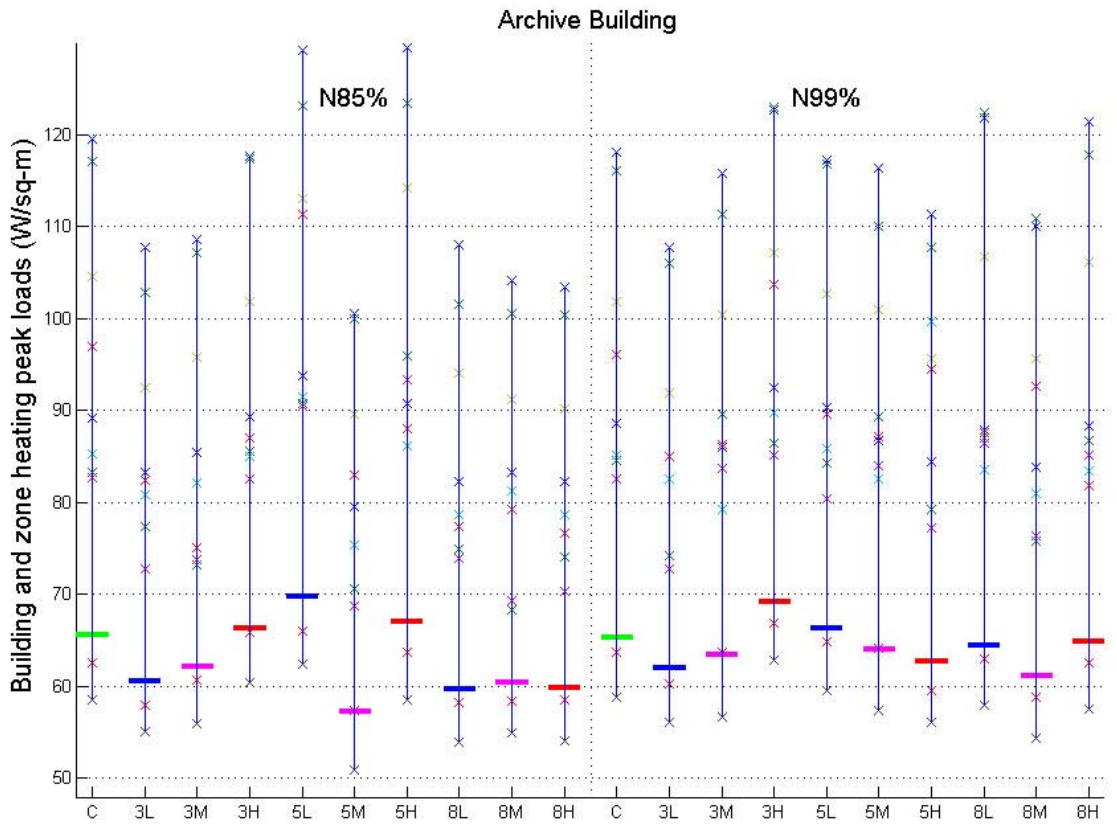


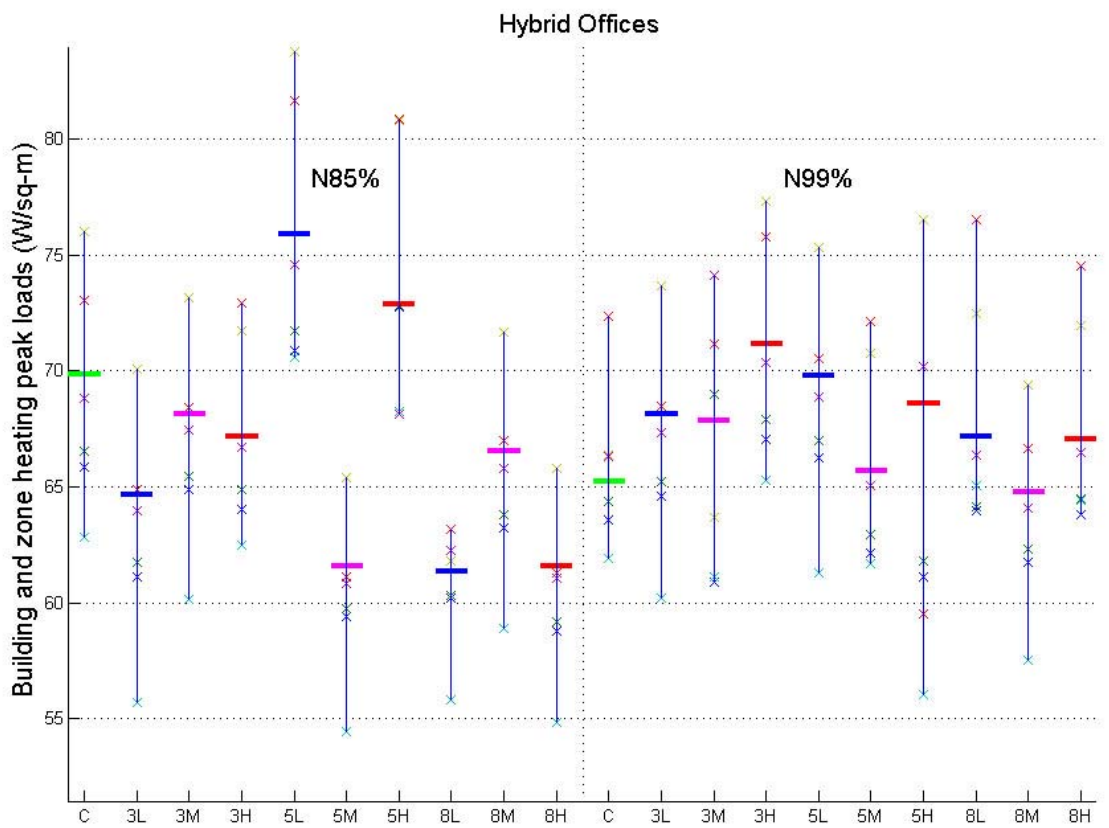
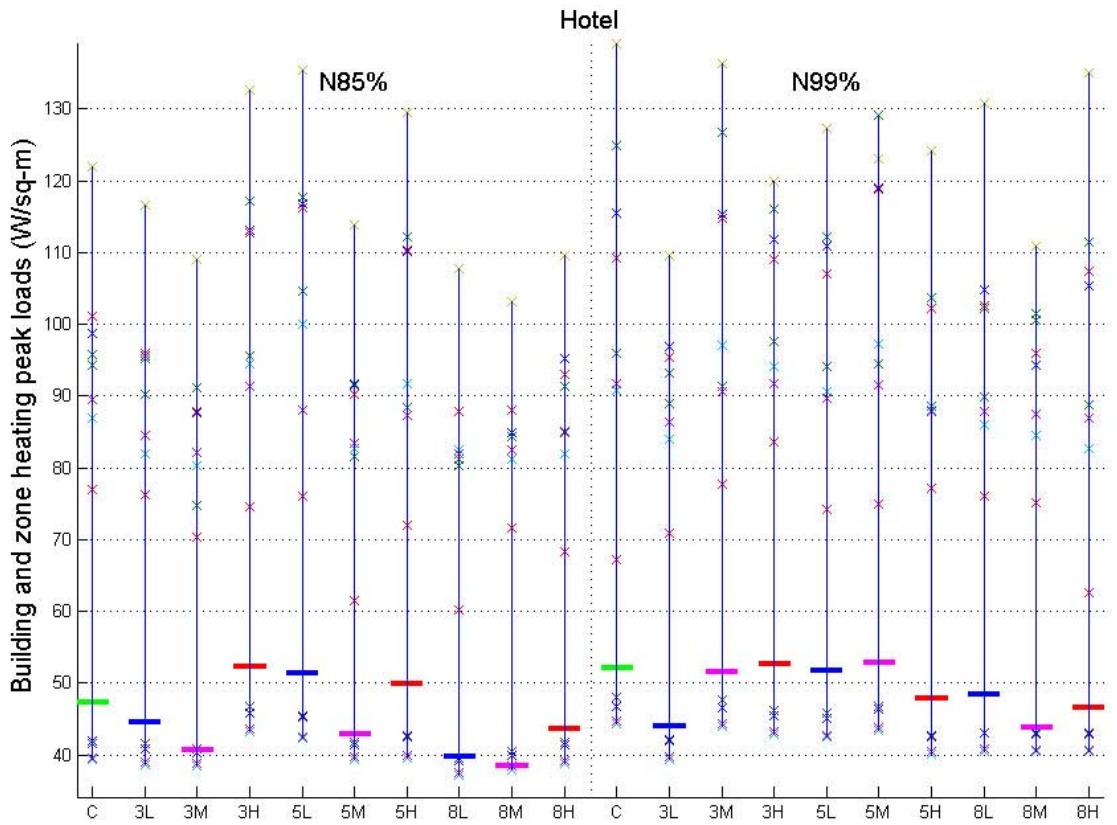


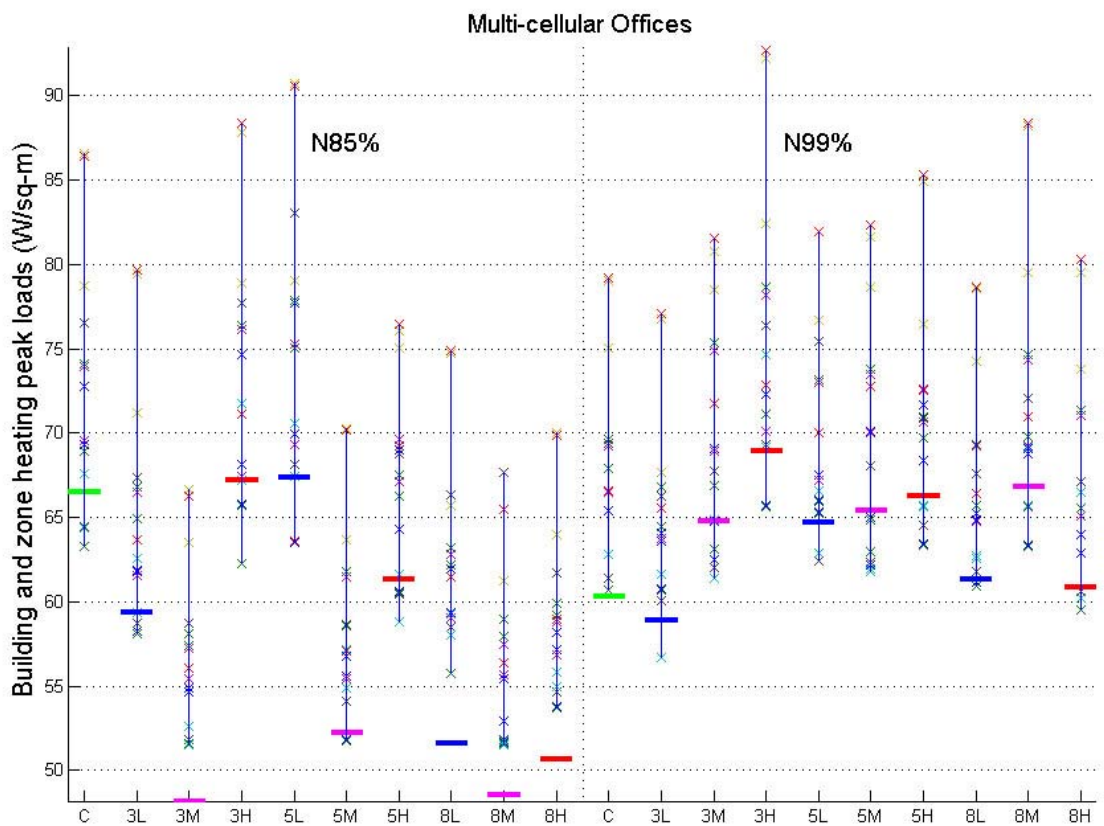
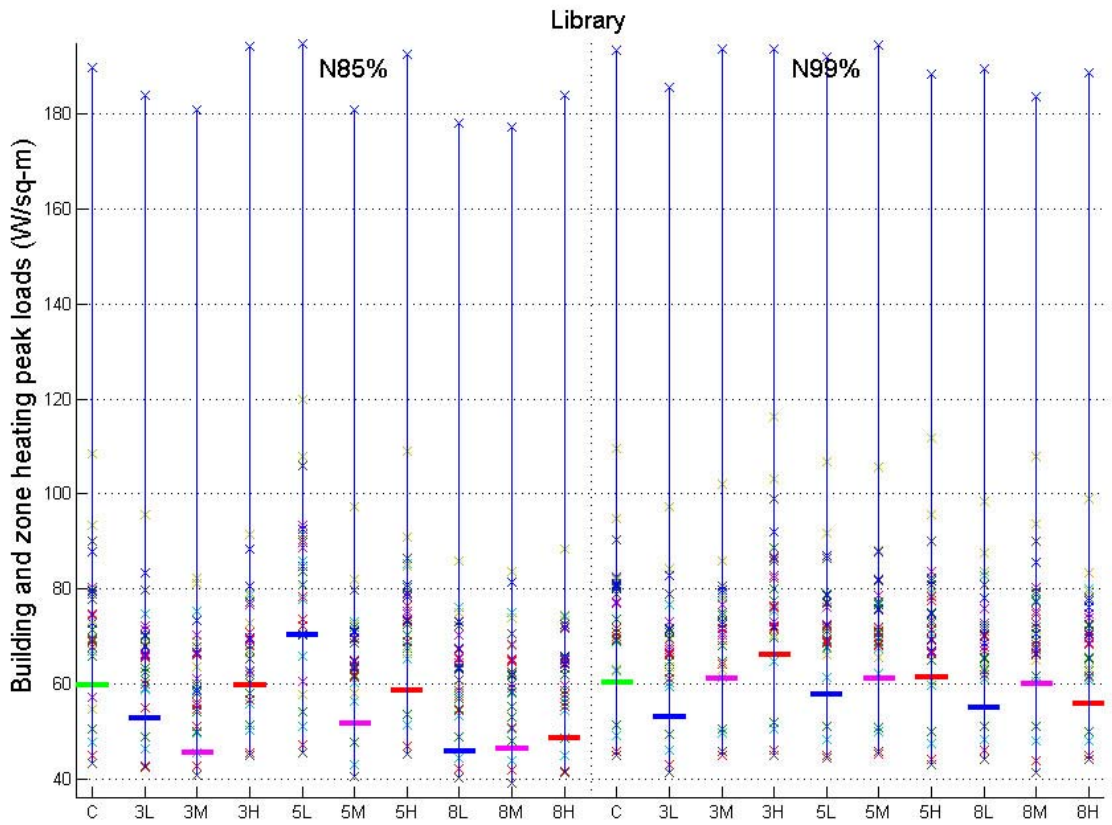


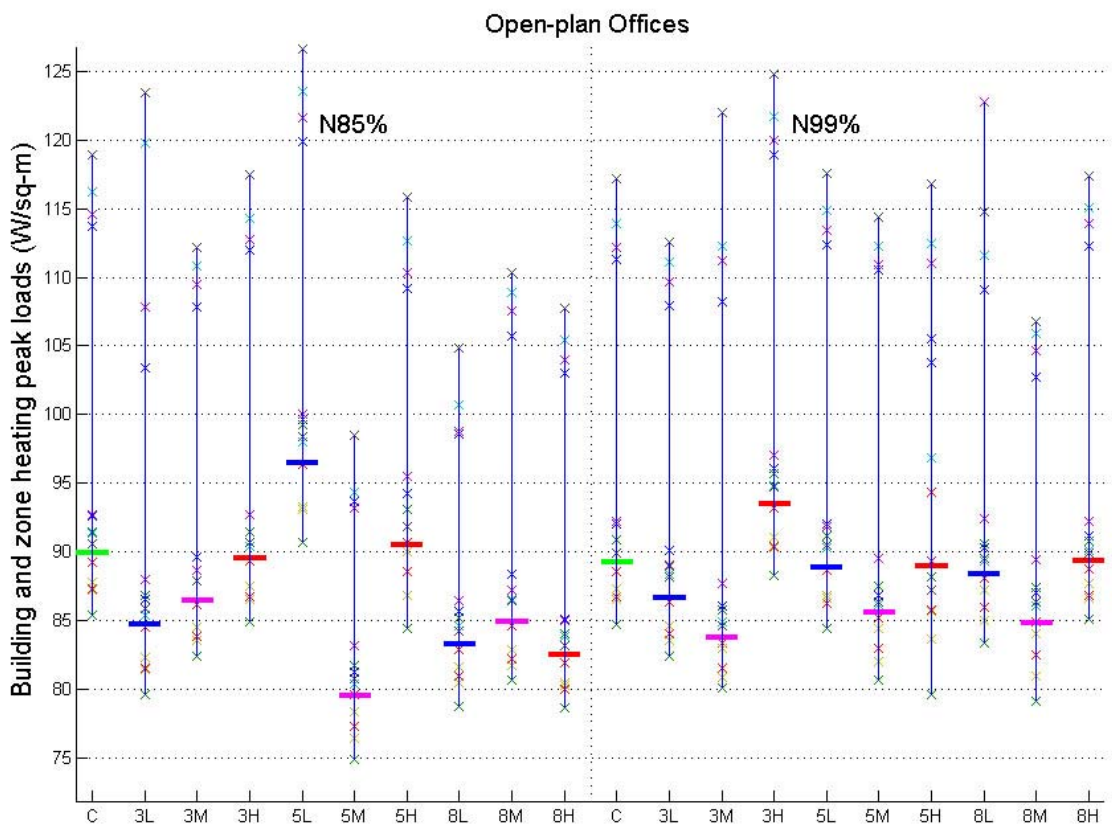
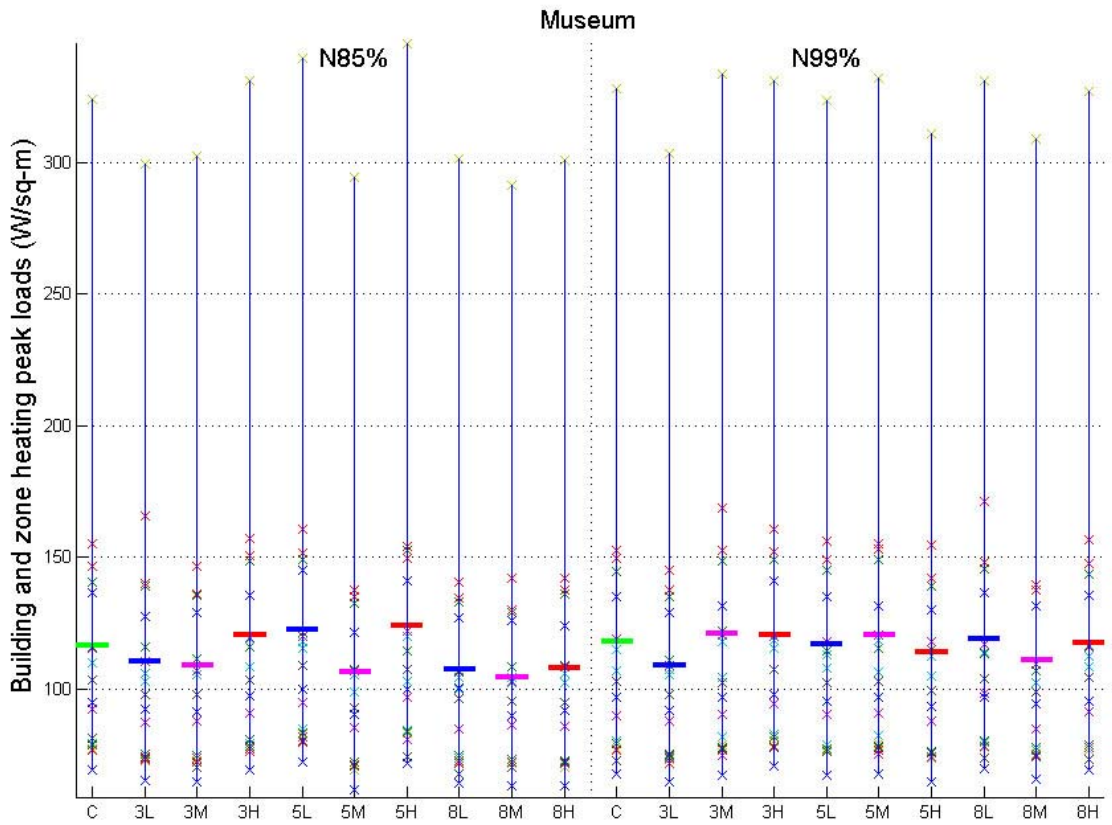
Appendix B3: DRY results: Building and zones heating design loads

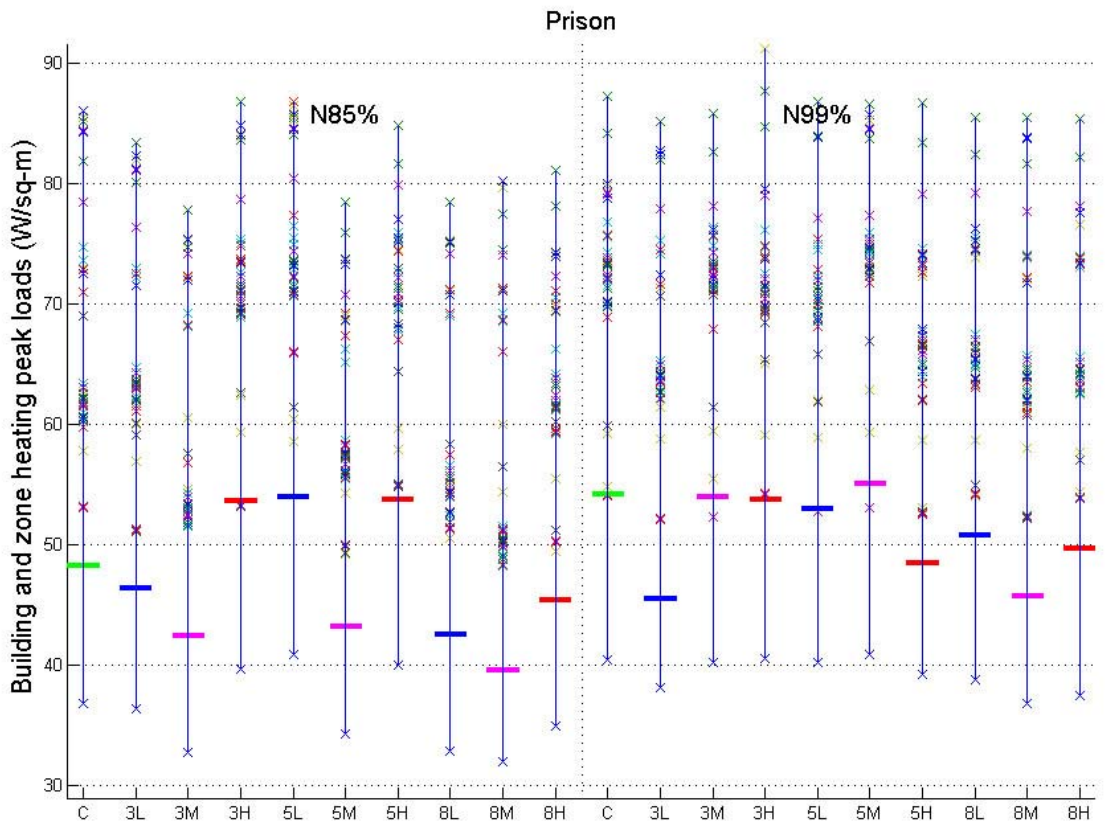
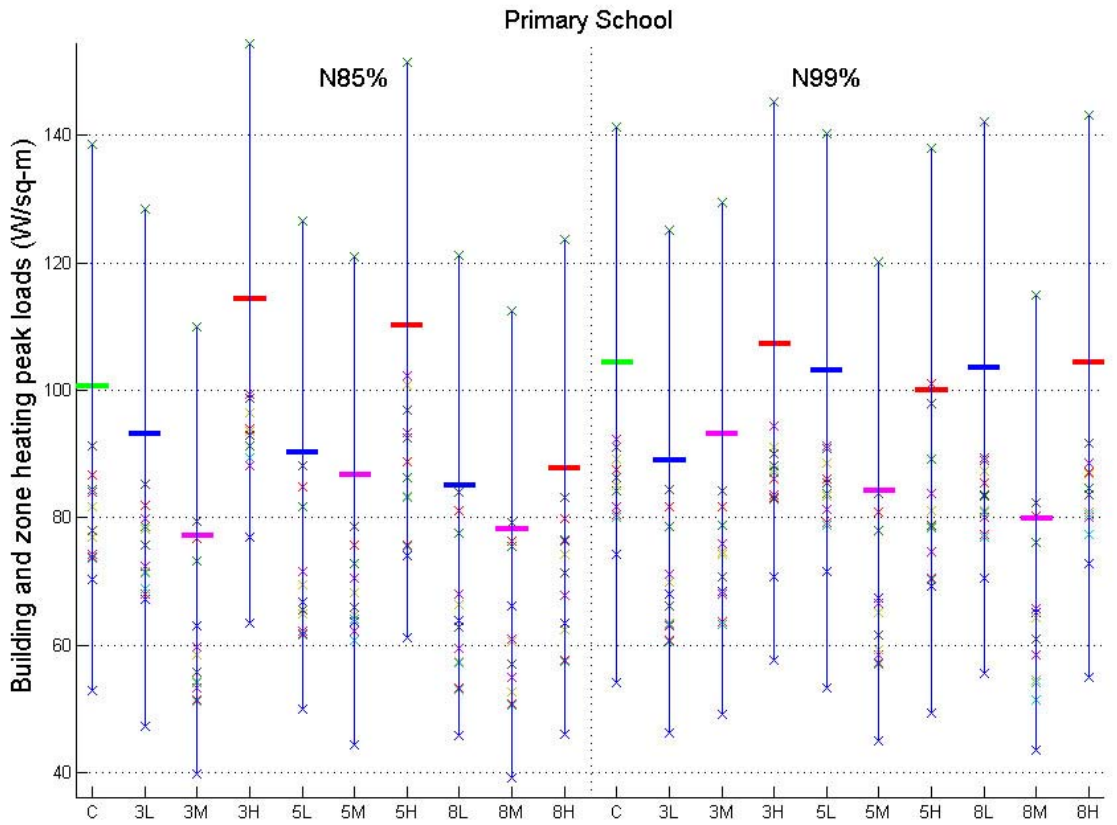


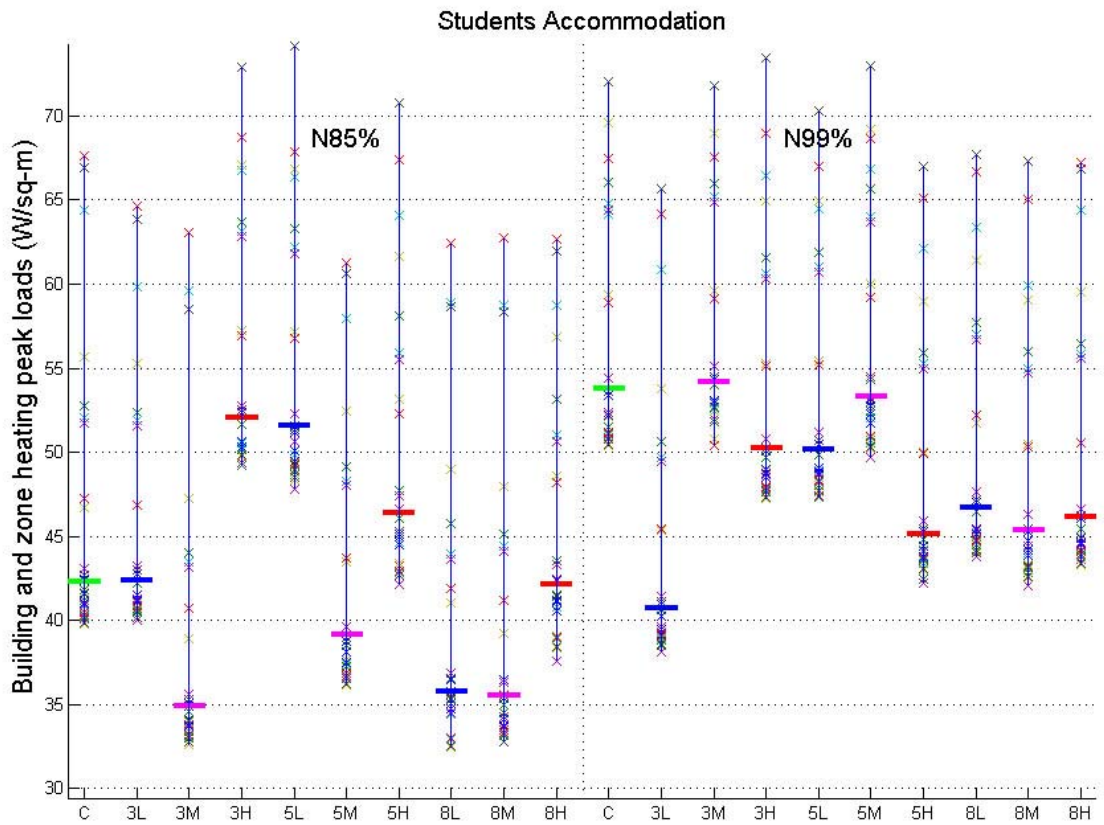
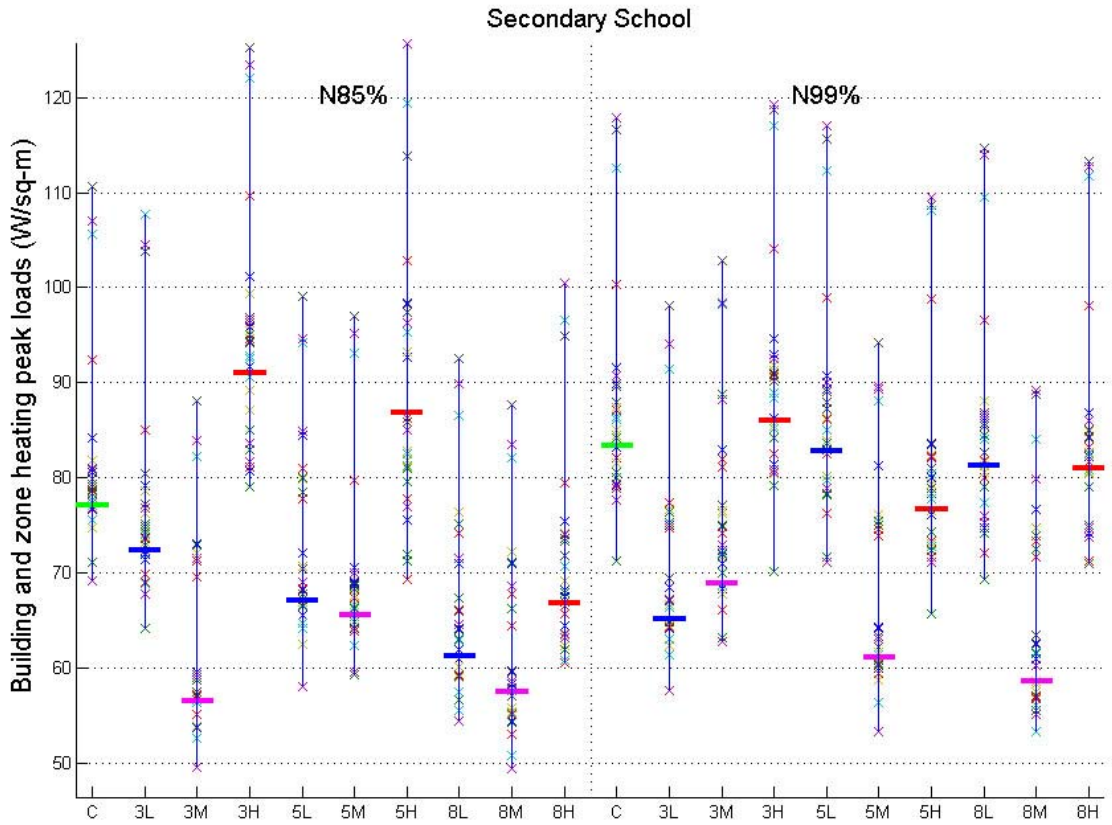


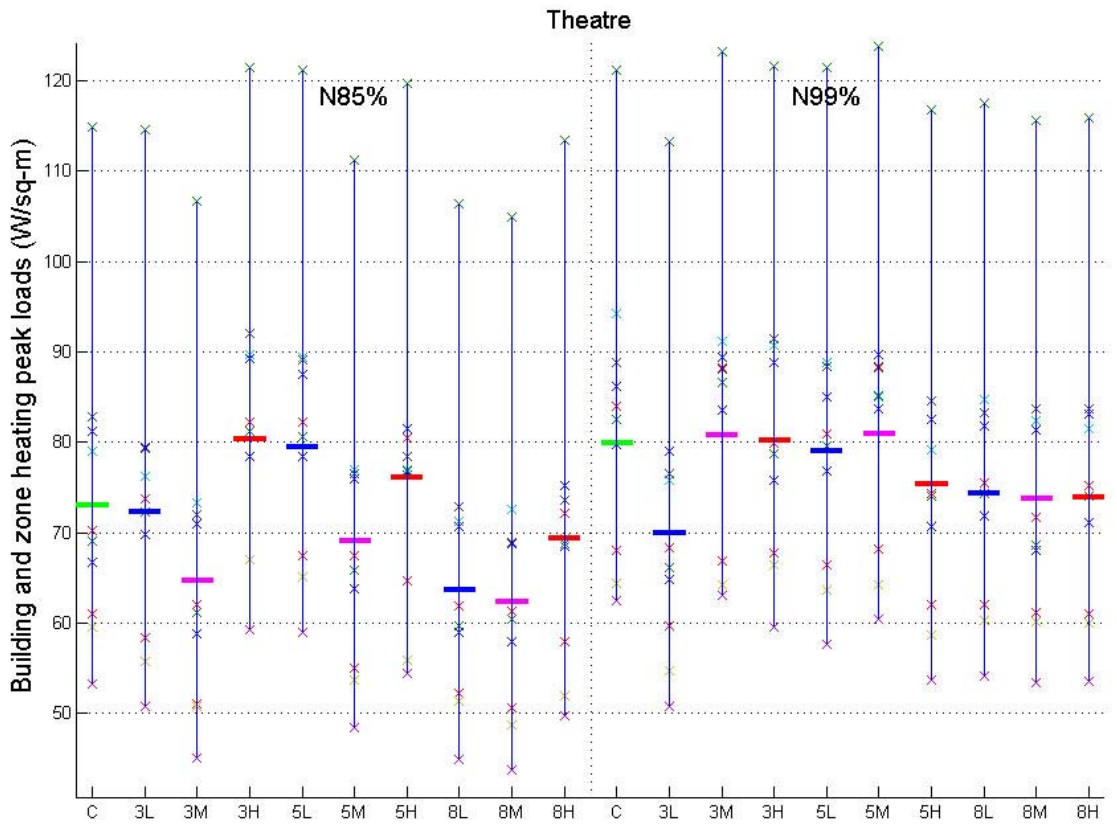












Appendix C: Published outputs

XML Template (2011)
K:/BSE/BSE 4181323d

[28.7.2011-8:01pm]
(BSE)

[1-20]
[PREPINTER stage]

Building Serv. Eng. Res. Technol. 00,00 (2011) pp. 1-20

Generating test reference years from the UKCP09 projections and their application in building energy simulations

H Du BEng, PgDip, **CP Underwood** BSc PhD CEng MCIBSE MASHRAE and **JS Edge** BSc PhD CEng MCIBSE
School of the Built and Natural Environment, University of Northumbria, Newcastle upon Tyne NE1 8ST, UK

In this study, test reference year (TRY) data for three UK cities are generated from the new UKCP09 climate change projections¹ for a variety of future time horizons and carbon emission scenario assumptions. The data are applied to the energy simulation of three commercial buildings and one house for the three city locations (London, Manchester and Edinburgh), three future time horizons in this century and three carbon emission scenarios. Results are compared with those generated using alternative TRYs from two other research groups who used UKCP09¹ as well as with the existing TRY data sets which form the CIBSE Future Weather Years² in order to produce robust results. Results of future simulations of peak summer operative temperatures, peak cooling demand, annual cooling energy, peak heating demand and annual heating energy are presented for the four building case studies benchmarked against control weather data for the period 1960-1989. The results show increasing internal operative temperatures (non-air-conditioned) and increasing air-conditioning demands (air-conditioned) throughout this century and though peak heating demands remain similar to control data, annual heating energy consumptions can be expected to fall sharply.

Practical applications: Currently, practitioners can use Test Reference Years for use in building energy simulations. In 2009, the CIBSE released Future Weather Years, which go further by allowing practitioners to explore the thermal and comfort behaviour of buildings at future time horizons thus helping to "future proof" a design. In 2009, the United Kingdom Climate Impacts Programme released a new generation of climate change scenario data (the UKCP09 climate change projections) using probabilistic methods. These are the most comprehensive data yet and provides a greater degree of detail than was available to generate the CIBSE Future Weather Years. It is therefore likely that the new data will gradually become the normal basis for investigating future building thermal and comfort response. In this study, a sample of TRY is generated from the UKCP09 data and applied to the simulation of a sample of 'real' buildings. The results are compared with both the existing CIBSE Future Weather Years as well as with Test Reference Years generated using UKCP09 by two other research groups. The results provide a robust way forward for simulating building thermal and comfort response using future weather data.

1 Introduction

Address for correspondence: Address for correspondence: CP Underwood, School of the Built and Natural Environment, University of Northumbria, Newcastle upon Tyne NE1 8ST, UK.
E-mail: chris.underwood@northumbria.ac.uk

Predictions published by the Intergovernmental Panel on Climate Change (IPCC) indicate an increase in global average surface

© The Chartered Institution of Building Services Engineers 2011

10.1177/0143624411418132

2 Generating test reference years from the UKCP09 projections

temperature in different scenario ranges of 1.1–2.9°C to 2.4–6.4°C from a 1990s baseline towards the end of the twenty-first century³. The growing impact of this on the built environment will be increased internal temperatures, particularly during summer, increased air-conditioning demands and reduced winter heating demands. Since most buildings in the UK are either not air conditioned or partially air conditioned, the implications of this for the design of future buildings, and in the operation and refurbishment of existing buildings are profound. Many of the buildings that will be in use in the later part of this century already exist. It is therefore of considerable interest to establish how these buildings will respond to the effects of a changing climate both from the point of view of the design of new buildings in the immediate years ahead as well as from the point of view of the development of mitigation strategies for application in the periodic refurbishment of existing buildings.

The United Kingdom Climate Impacts Programme (UKCIP) is a UK-based agency, which was established to provide support and advice to organisations concerning adaptive-ness and resilience to climate change. Among other things, it has coordinated the generation and dissemination of predicted climate change scenarios to assist organisations to assess levels of risk and strategies for remediation arising from a changing climate in the UK. There have been five of these scenarios during the past 20 years, the most recent and sophisticated of which were published in 2009 and termed the UKCP09 climate change projections¹ (abbreviated simply to UKCP09). UKCP09 superseded the previous (UKCIP02⁴) climate change scenarios which form the basis of the current Future Weather Years (FWY)² recommended by the Chartered Institution of Building Services Engineers (CIBSE) for use in the simulation modelling of buildings in the UK.

UKCP09 differs from the UKCIP02 climate change scenarios in two fundamental respects. UKCP09 provides monthly projections of

climate change and absolute future climate data on a 25 km grid-scale over seven 30-year time-slices starting, with a baseline of 1961–1990 and for three carbon emission scenarios. The data were generated by the UK's Meteorological Office Hadley Centre Climate Model 'HadCM3'.¹ An accompanying Weather Generator is used to spatially downscale the 25 km data to 5 km and to temporally downscale the monthly data to daily or hourly data. The Weather Generator uses stochastic modelling methods to perform the downscaling.¹ The earlier UKCIP02 climate change scenario data were generated by downscaling an existing climate model to give, at 50 km resolution, predictions of changes in the monthly average values of 15 climate variables at three time slices and four carbon emission scenarios. Uncertainty bounds were attached based on results from other climate models. Extraction of future weather data for building simulation requires to be constructed from an existing hourly time series (described in detail later), whereas hourly time series data can be extracted directly from UKCP09 and uncertainties form an inherent part of the probabilistic method used.

UKCP09 expresses a probability that a give climate change outcome will arise. Results are usually expressed as a cumulative distribution function (CDF), which gives a plot of the probability (%) of a climate variable's change being less than a given amount. Key thresholds are the central estimate (50% probability) at which a climate change amount is as likely to be exceeded as not, and UKCP09 interprets a cumulative probability of 90% as 'very likely to be less than' (or very unlikely to be greater than) and 10% as 'very unlikely to be less than' (or very likely to be greater than).¹

The aim of this study is to generate test reference years (TRY) from UKCP09 for a variety of future time slices and carbon emission scenarios and to apply the data to the simulation modelling of a variety of building case studies in order to investigate probable

patterns of overheating and likely changes in air-conditioning and heating demands over time.

The research objectives are:

- (1) To apply a suitable statistical method to the extraction of annual TRY data from probabilistic raw data produced by the Weather Generator in UKCP09.¹
- (2) To apply the data to the simulation modelling of a sample of UK building types using a dynamic thermal modelling tool for a range of carbon emissions and future time slices.
- (3) To generate and present time series results of summertime internal zone operative temperatures, heating demand and cooling demand for comparison with current (control) weather data.
- (4) To compare the results with those generated using alternative weather data-generating methods including UKCIP02-based FWY.

2 Literature review

In some of the earliest work seeking to predict the impact of future weather on buildings, Lea and Cullen⁵ attempted to create a predicted 2050 weather pattern by scaling external dry bulb temperature by 2 K above an established 1961–1990 mean value of 15.3°C. In a further development of this approach, Belcher et al.⁶ developed a method (called ‘morphing’) for transforming existing CIBSE TRY and the Design Standard Year (DSY) weather files to future weather data. Current hourly CIBSE weather data were adjusted according to the monthly climate change prediction values of the UKCIP02⁴ scenario data sets. A ‘shift’ (i.e. scale), ‘stretch’ (i.e. project) and a combination of ‘shift’ and ‘stretch’ methods are used to modify total solar irradiance on the horizontal, diffuse solar irradiance on the horizontal, sunshine duration, cloud cover, dry bulb

temperature, wet bulb temperature, atmospheric pressure and wind speed.

Guan⁷ reviewed methods of preparing future weather data to study the impact of climate change on building performance and compared the following four techniques: the extrapolating statistical method, the imposed offset method (morphing), stochastic weather models and global climate models. A conclusion was that the imposed offset method (morphing) may be the most suitable method to be adopted by building consultants for building simulation studies.

Jensch et al.⁸ recognised that no bespoke climate change weather files are readily available that can be loaded directly into environmental simulation software. Again, they used a morphing method to transform current CIBSE TRYs and DSYs into climate change weather years and presented a tool to convert these to a Typical Meteorological Year and other file formats readily readable by building simulation packages. These weather data were used to perform simulations of a naturally ventilated building to assess the potential summer overheating problems caused by climate change. They found a ‘significant difference’ in applying current and future weather data in building simulation and compare the predicted results with some observed temperature readings in a case study building. Numerous modelling studies have since been conducted using morphed weather data based on the UKCIP02 climate change scenarios applied to building comfort, energy use and ventilation performance analyses.^{9–13}

More recently, work has been carried out using the UKCP09 projections.¹ UKCP09, UKCIP02 and historical measured data were used to analyse likely changes in temperature, sunshine duration and solar irradiation by Tham and Muneer.¹⁴ They studied three locations in the UK and found that both data sets showed an increase in these three variables when compared to the measured historical data as well as concluding that data

4 Generating test reference years from the UKCP09 projections

based on UKCP09 produced abnormally elongated sunshine duration for some scenarios. Eames et al.¹⁵ discuss a method for the creation of future probabilistic reference years using UKCP09 for use in simulating the thermal performance of buildings. They identify a number of parameters not produced by the generator such as wind speed and direction, air pressure and cloud cover which have to be calculated separately. Kershaw et al.¹⁶ used the UKCP09 weather generator to generate 3000 example weather years and created probabilistic future reference years using the method detailed in Eames et al.¹⁵ They found that the external data from the reference years compared very well to the 3000-year weather data. Building simulations were then carried out for all 3000 example years and the reference years to compare the results. They found that the probabilistic reference years can be adequately used to assess the risk of building failure and risk to occupants but a number of these reference years need to be considered in order to represent the variation in possible future climates.

Watkins et al.¹⁷ present a method to construct a future weather file using UKCP09. They highlight that the UKCP09 data have no wind or cloud data and detail algorithms to produce these for their inclusion in a TRY. They use the 3000-year weather data in a method similar to Eames et al.¹⁵ Wind speed was calculated from the potential evapotranspiration values included in the UKCP09 data. Historical weather files were used to provide typical wind directional data. The UKCP09 data only include diffuse and direct solar irradiation on the horizontal plane; so they adjust the solar data so that the direct normal radiation can be correctly calculated. Day time cloud cover is generated from sunshine hours and linear interpolation is used to produce night time cloud cover data. They produce a single composite TRY to provide a common, practical weather year against which designers can compare the average performance of their

buildings. In related work, Watkins and Levermore¹⁸ use the CIBSE calculation method (CIBSE Guide A) to examine the effect future increasing external temperature has on the peak cooling load on a building. They found that relatively small increases in external temperature could have a significant effect on the peak load and its associated plant items. Patidar et al.¹⁹ investigate the use of a probabilistic method of analysing the overheating of buildings in the future. They use a domestic dwelling to demonstrate a technique of linear filtering and regression analysis to analyse its thermal performance for various climate change scenarios and compare the results to building simulation software analysis. A linear predictor is constructed for the bedroom temperature corresponding to climate data from a preceding period of time. Least squares regression is used to fit the model. They found that results from their model were just as reliable as a detailed building simulation for many different climates; however, the regression relationship might not be suitable for more complex buildings.

3 Method

3.1 Test reference years

The method adopted to generate TRYs is broadly that described in British Standard BS EN ISO 15927-4:2005.²⁰ Raw data consisting of 30 years of hourly weather data were obtained from UKCP09 using version 1 of the accompanying Weather Generator¹ (further details of the Weather Generator are given in Kilsby et al.²¹). The time slices available are summarised in Table 1.

In this study, the nominal time periods of 2030s, 2050s and 2080s were chosen together with the control period data, the former representing a sample of future time slices looking sufficiently far towards a time horizon likely to be of interest for the life span of buildings currently under development and construction. The number of probabilistic

Table 1 Available time slices of the UKCP09 projections¹

Nominal time period	Time slice
Control (reference) data	1960–1989
2020s	2010–2039
2030s	2020–2049
2040s	2030–2059
2050s	2040–2069
2060s	2050–2079
2070s	2060–2089
2080s	2070–2099

variations (or change factors) used by the UKCP09 Weather Generator for hourly data is 100. Thus, for each 30-year band of climate data, 3000 annual files of hourly and daily weather data were extracted to represent each of the four selected time slices (including the control data) at each of three carbon emission scenarios. The following procedure was then used:²⁰

- (1) The average of daily maximum and minimum dry bulb temperatures, T (°C), and relative humidity, H , and the total daily horizontal solar radiation, I (Whm^{-2}), were captured from the 3000 daily weather files.
- (2) For each calendar month in all years of data, the daily values of each variable from (1) were ranked in increasing order and the following was evaluated in order to arrive at a CDF of the daily means for all years in the data set and for each variable $f(T_{m,i}, I_{m,i}, H_{m,i})$:

$$f(T_{m,i}, I_{m,i}, H_{m,i}) = \frac{K(i)}{N+1} \quad (1)$$

where $K(i)$ is the rank order of the i th value of the daily mean within that calendar month across the entire data set, N the total number of days for that calendar month in the whole data set and m the month number in the year.

- (3) For each month in each year, the CDF of the daily mean of each variable within each calendar month, $F(T_{y,m,i}, I_{y,m,i},$

$H_{y,m,i})$, was then obtained by ranking the variables in each month in increasing order and then applying the following:

$$F(T_{y,m,i}, I_{y,m,i}, H_{y,m,i}) = \frac{J(i)}{n+1} \quad (2)$$

where $J(i)$ is the rank order of the i th daily mean within a calendar month in 1 year, y the year number and n the number of days in each individual month.

- (4) For each month in each year of the data set, the Finkelstein–Schafer statistic, $\text{FS}(T_{y,m}, I_{y,m}, H_{y,m})$, was then obtained:

$$\text{FS}(T_{y,m}, I_{y,m}, H_{y,m}) = \sum_{i=1}^n |F(T_{y,m,i}, I_{y,m,i}, H_{y,m,i}) - f(T_{m,i}, I_{m,i}, H_{m,i})| \quad (3)$$

- (5) The FS statistic of each variable in each individual month for the whole data set were then ranked in order of increasing value and, for each month in each year, the individual variable rank values were added.
- (6) For the 3 months with the lowest total ranking, the deviation of the monthly mean wind speed from the corresponding mean value for each set of calendar months in the data set were then obtained and the month with the lowest deviation in wind speed was selected to be included in the TRY.

The first release of UKCP09 data excluded daily or hourly wind speed data from which monthly mean values could be obtained. However, evapotranspiration rates were provided from which daily wind speed can be obtained by the Penman–Monteith equation²² which is re-arranged here for that purpose:

$$u_w = \frac{E(\delta + \gamma) + 0.408\delta(G - R)}{900\gamma^{0.5} \frac{(P_w - P_a)}{(T + 273)} - 0.34\gamma E} \quad (4)$$

6 Generating test reference years from the UKCP09 projections

where E is the reference evapotranspiration (mm/day), P_v the vapour pressure (kNm^{-2}), P_{vs} the saturation vapour pressure (kNm^{-2}), T the mean daily temperature at 2m height ($^{\circ}\text{C}$), G the surface heat flux density ($\text{MJm}^{-2}\text{day}^{-1}$), R the net radiation at the surface ($\text{MJm}^{-2}\text{day}^{-1}$), δ the slope of the vapour pressure curve ($\text{kNm}^{-2}\text{K}^{-1}$) and γ the psychrometric constant ($\text{kNm}^{-2}\text{K}^{-1}$)

Watkins et al.¹⁷ evaluated the reliability of extracted windspeed data from evapotranspiration using Equation (4) based on a (non-UKCP09) data set containing evapotranspiration rates and windspeed. They obtained a good agreement between Equation (4) windspeeds and the windspeed in the original data (coefficient of determination 0.94). They also concluded small instances of negative windspeeds (affecting less than 5% of the data). In this study, negative windspeed results were set to zero and the very small instances of implausibly high windspeed were cropped at 20 ms^{-1} .

Because each TRY consists of different statistically representative months 'stitched' together to form 1 year, there were inevitable step transitions in the values of certain variables at midnight on the last day of each calendar month. These transitions were smoothed using cubic-spline fitting. The fitting interval used was a 16-h period centred at the relevant midnight instants as recommended in BS EN ISO 15927-4:2005.²⁰ The variables affected were dry bulb temperature, vapour pressure and relative humidity.

The above procedure was coded into a Matlab script. Processing times for 3000 years of input files to a single TRY were typically less than 5 min on a conventional personal computer.

3.2 Verification

Verification of the results of the TRY data sets generated in this study was carried out

with reference to two alternative sets of methods:

- (1) The CIBSE FWY series.²
- (2) Alternative generations of TRY data based on UKCP09¹ carried out by Exeter University¹⁵ and Manchester University.¹⁷

The CIBSE FWY series forms an important reference point because it is the currently available data in use by practitioners. These data were generated using the climate change scenario data forming the earlier UKCIP02. Because these scenarios were presented in the form of monthly data, it was necessary to decompose the data into hourly time series suitable for building simulation such that the hourly data preserve the same statistical distribution as the original monthly data. This was done using a technique called morphing full details of which can be found in Belcher et al.⁶ Briefly, files of existing CIBSE TRY climate data each consisting of 'typical' months derived from 1983–2004 records of actual weather data were used. These files were used to generate projected future weather data by either 'shifting', 'stretching' or shifting and stretching each existing climate variable. A shift involves adding the absolute mean change (from the UKCIP02 scenario data) to each existing hourly value for the relevant month and is applied when the climate change scenario is in the form of an absolute change to the monthly mean. A stretch involves a multiplicative adjustment of the existing variable based on the fractional change in the monthly mean value for the relevant month and is used when the scenario data are defined as a fractional or percentage change. A combination of shift and stretch is applied when both the mean and variance are required (e.g. a daily mean and its maximum and minimum values).

In the selection procedure applied by Exeter University,¹⁵ 100 'typical' years from 100

samples of each year in each 30-year band were captured using the FS statistic (using a procedure similar to that described above but involving different variables). Each set of 100 months was then ranked based on ascending values of the mean monthly temperatures. They then select each month based on the same chosen percentile value (e.g. 50th, 90th, etc). Thus, the 50th percentile January is joined by the 50th percentile February and so on to form a complete year. This two-stage process places a strong emphasis on dry bulb temperature which, it is argued, will form greater coherence between variables in each month. However, there is virtually no concurrency between months with this method (i.e. there is a negligible chance that a January from the original set of 100 Januaries will be joined by the corresponding February in the February set). Step changes in variables occurring at midnight on the last day of each month were smoothed by taking the average of the 5 h of data either side of midnight. In this study, the 50th percentile weather files from Exeter were used as TRY with the assumption that they would be most 'typical'.

The method used by Manchester University¹⁷ is very similar to that used in this study. Both Manchester University and Northumbria University used the method recommended by BS EN ISO 15927-4:2005, but applied the method directly to 3000 years of weather data (100 probabilistic sets of 30 years data). There are two significant differences between this method and the method used by Exeter University. First, Exeter University applied the FS statistic equally to dry bulb temperature, global horizontal solar irradiation and wind speed, whereas this method applied the FS statistic to dry bulb temperature, global horizontal solar irradiation and relative humidity (step 4 above) to select three candidate months, and then one month out of the three with lowest wind speed deviation was selected as the 'best' month to be included in the TRY. The second difference

was the method of ranking. The method reported here added the separate ranks of the FS statistic values of the three climate variables together then chose three months with lowest total rank, while Exeter added absolute values of FS statistic of their three climate variables together, and then chose the month with lowest total FS statistic value. In terms of interpretation, users may choose an Exeter file with a high percentile (e.g. 90th) to factor in risk. In this study, design and risk are dealt with using an alternative 'Design Reference Year' file of climate data which involves selections of candidate months using probabilistic percentiles. This study is currently under development and will be reported at a later date.

As to the relatively minor differences between the Manchester and Northumbria approaches, Manchester University implemented the ISO method in Turbo Pascal using conventional programming based on element-wise calculations, while Northumbria University applied the same method in Matlab to take advantage of superior array-handling, resulting in a significant reduction of computation time. The results of both methods were cross-checked and there are two minor differences in calculation procedures. First, Manchester included weather data of the 29th February in leap years, whereas Northumbria did not include these days in order to compare the annual energy consumption among 365-day years only. Second, Manchester used 15 ms^{-1} as an upper limit when generating daily wind speed from Equation (4), whereas Northumbria used 20 ms^{-1} after examining the typical distribution ranges of windspeeds in historical UK weather data. The two differences will occasionally cause different selections of 'typical' months when precisely the same raw data are used; so they are not expected to give exactly the same climate data, but the both will result in reasonably comparable 'typical' climate data files.

Results of two key weather variables are compared in Figures 1 and 2 for three UK

8 *Generating test reference years from the UKCP09 projections*

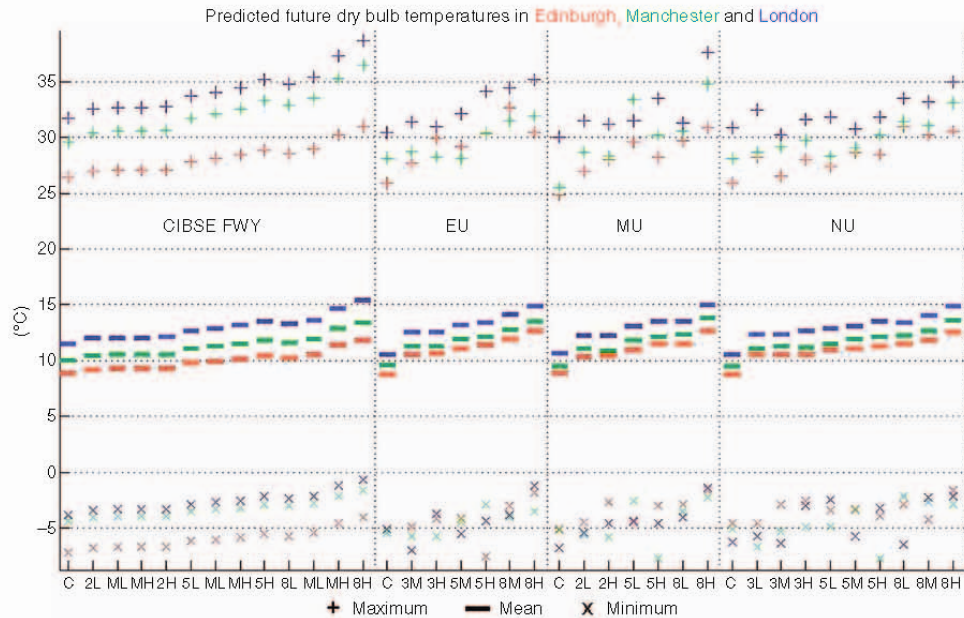


Figure 1 Comparison of data sets: air temperature

cities (Edinburgh, Manchester and London), a variety of future time slices and carbon emission scenarios. Figure 1 shows air dry bulb temperatures and Figure 2 the global horizontal solar radiation. Additionally, the deviations from Northumbria data arising from the CIBSE FWY, Exeter and Manchester climate data are given in Figures 3 and 4 (see Box 1 for key to symbols).

For dry bulb temperature, there is good agreement between the various data sets, all of which support an increasing trend in temperature throughout this century, the precise extent of which depends on the carbon emission scenario. The maximum dry bulb temperatures are notably higher for the CIBSE FWY data set than for all of the UKCP09-based results. This is considered to be due to the higher control temperatures (also evident in Figure 1) which form the baseline for the

CIBSE FWY data. Control data for the latter are based on original data from the period 1983 to 2004, whereas all UKCP09-based methods use a control period from 1960 to 1989. Whilst there is some inevitable scatter in predictions of absolute maximum and minimum external dry bulb temperatures due to the differences in the methods described above, the deviations in mean external air temperature between those methods using UKCP09 are negligible (Figure 3).

For global horizontal solar radiation, there is again good agreement between the various data sets though the UKCP09-derived data all suggest higher peak radiation intensities than those predicted using the morphed UKCIP02-based data of the CIBSE FWYs. An inspection of the data suggests that UKCP09¹ tends to predict higher periods of bright clear sunshine than existing data would suggest as

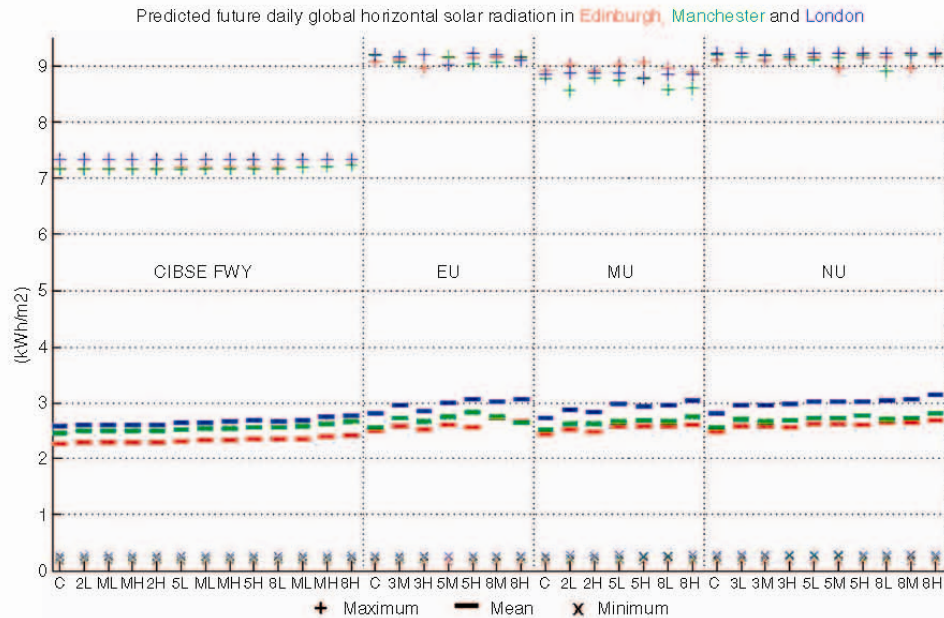


Figure 2 Comparison of data sets: solar radiation

first reported by Tham and Muneer.¹⁴ Deviations between methods for those cases using UKCP09 are, however, very small (Figure 4).

3.3 Modelling

The weather data generated as described above were used in a variety of energy simulations carried out using EnergyPlus (version 6).²³ To meet the formatting and content requirements of the bespoke EnergyPlus weather file 'EPW' format, further adjustments were needed to the TRY data generated earlier:

- (1) Disjointed dry bulb temperature, vapour pressure and relative humidity values at midnight on the last day of each month were smoothed using an interpolation method.

- (2) The EPW format requires the hourly dew point temperatures. This was calculated using hygrometric properties of humid air based on the known TRY dry bulb temperature, vapour pressure and relative humidity values.
- (3) The direct-normal solar radiation (also required by the EPW format) was obtained from the known direct-horizontal radiation using standard solar geometry calculations.
- (4) The cloud cover was expressed for EPW purposes in tenths, based on the known daily hours of sunshine duration.
- (5) The EPW format requires the horizontal infrared radiation flux. This was obtained by first calculating the sky emissivity from the opaque cloud cover (in tenths) and the dew point temperature²⁴ and then multiplying the sky

10 Generating test reference years from the UKCP09 projections

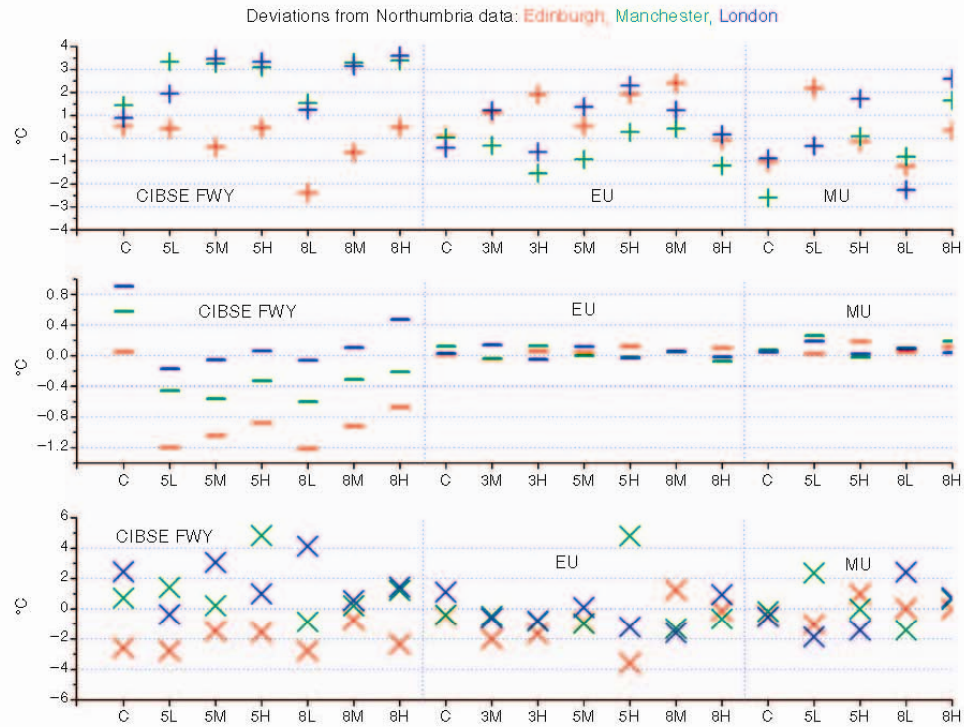


Figure 3 Deviations from Northumbria data in external air temperature (top: max middle: mean bottom: min)

emissivity by the Stefan–Boltzmann constant and the hourly dry bulb temperature (K) to the fourth power. Very little information is available regarding UK *opaque* cloud cover values and this is clearly an avenue for further work. In this study, it was assumed to be constant at 0.5 of the cloud cover value as previously used by Jensch et al.⁸ in the work they did using the CIBSE FWY data set.

4 Case study buildings

Four contrasting buildings were selected for energy simulation using the new TRY data sets

described in Section 3. The intention was to select ‘real’ buildings that either exist or have received planning consent and are therefore likely to be built, as well as to capture a range of construction styles and activity levels that would ensure contrasting thermal comfort and energy demand results. Thumbnails of the buildings selected are given in Figure 5 and key physical attributes of each building are given in Table 2. The aged persons’ accommodation was selected because it is used by a vulnerable social group sensitive to extremes in thermal comfort standards. The hospital building is a recently constructed oncology department which was selected due to extensive deep space planning, high internal heat gains due

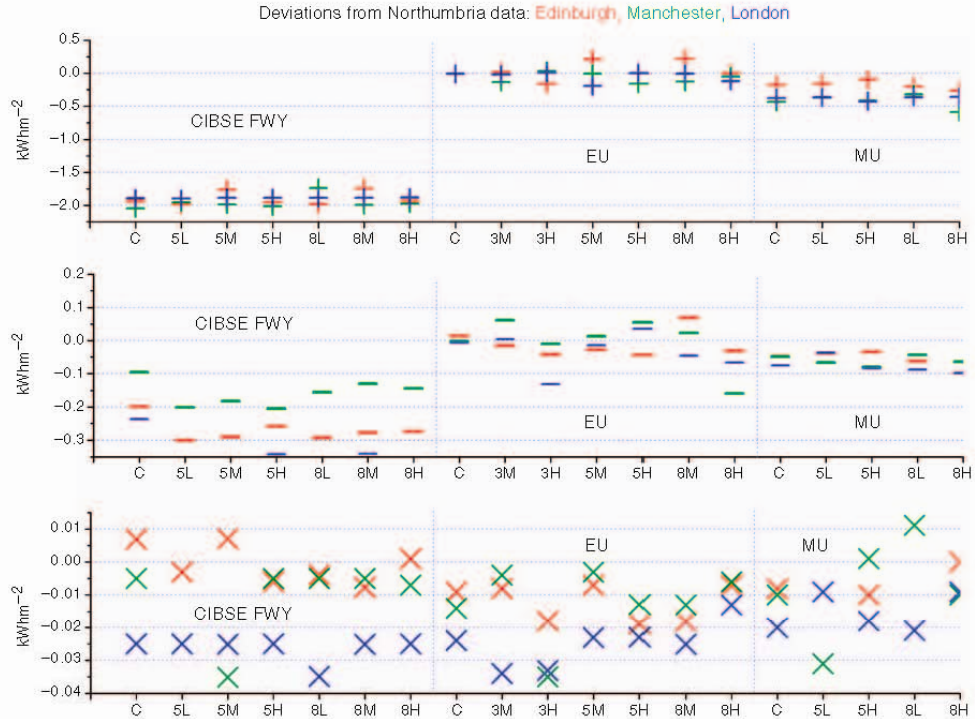


Figure 4 Deviations from Northumbria data in solar radiation (top: max middle: mean bottom: min)

to scanning equipment, etc. The house is a generic type from a commercial house builder's prospectus and depicts a small terraced row. In this study, only the end-terraced unit is used. Both the aged persons' accommodation and hospital are in continuous use, whereas the office building is used during normal weekday office hours only and the house is occupied by a family of four during weekday nights and weekends. A constant effective mean allowance for infiltration of 0.5 air changes per hour was applied to all buildings and, additionally, an allowance for natural/mechanical fresh air ventilation during occupied hours only of 10 L s^{-1} per person was applied.

With the exception of the office building, the buildings have been recently built and conform to the UK Building Regulations, Part L, 2006 edition. Briefly, the 2002 edition of these Regulations sets minimum standards of u -values for external walls and roofs of $0.35 \text{ W m}^{-2} \text{ K}^{-1}$ and $0.25 \text{ W m}^{-2} \text{ K}^{-1}$, respectively, and external elevations glazed to a maximum of 35% of the overall envelope area using double air-cavity glazing. The later 2006 edition of the regulations sets the same 'notional' standard but goes on to require a 23–28% reduction in carbon emission beyond that standard. The office building was refurbished to an earlier standard not greatly different to the current standards. The thermal

12 Generating test reference years from the UKCP09 projections

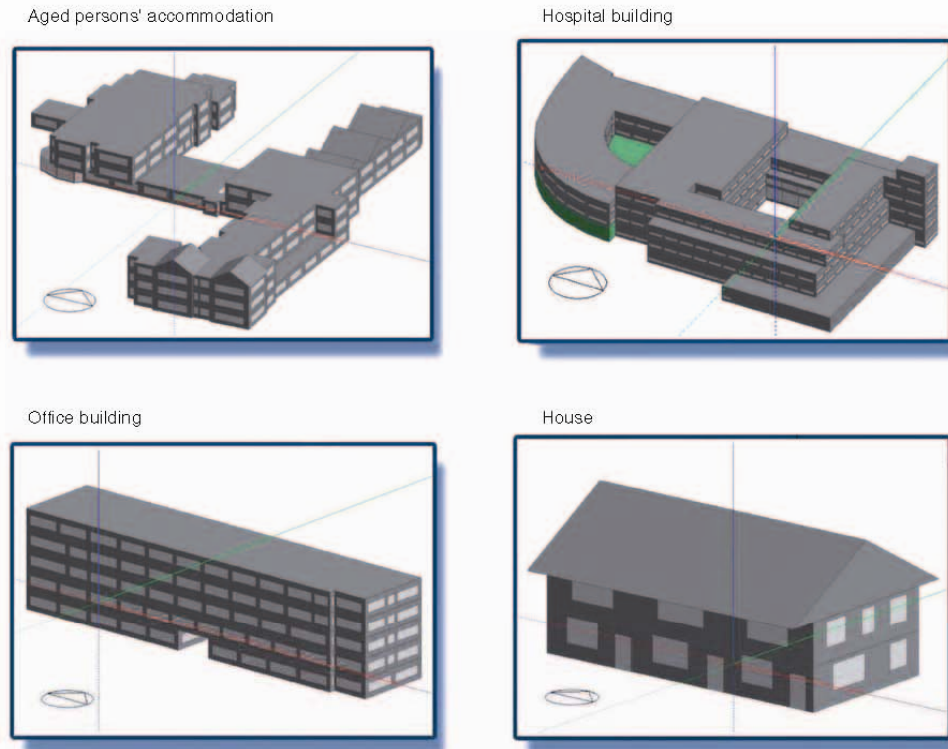


Figure 5 Building thumbnails

capacity of each zone was calculated using the simplified method set out in ISO 13786:2007 based on a maximum effective element thickness of 0.1 m. Total values for each zone were added to give a building total and this value was then divided by the gross building floor area for comparative purposes.

The occupancy densities, occupied period profiles and internal heat gain allowances for all zone types in all buildings were selected according to standard data presented in the UK National Calculation Method database.²⁵ The values selected would be used in current practice for, among other things, building regulation compliance modelling.

Three simulations were then carried out on all buildings using the new TRY weather files for London, Manchester and Edinburgh:

- (1) A 'freefloat' simulation to generate the average of zone peak operative temperatures for each building under conditions of natural ventilation. In all cases, a natural ventilation rate of 4 air changes per hour was used and this was switched to become active in any zone when the internal operative temperature reached 25°C. Results from these simulations were extracted during the warmest

Table 2 Generic building features

Building	Total zones	Occupied zones	Gross floor area (m ²)	Treated floor area (m ²)	Effective thermal capacity (kJm ⁻² K ⁻¹)
Aged persons' accommodation	51	29	5657	4062	425
Hospital	145	84	21 897	12 786	259
Office	36	16	4269	2977	466
House	16	10	183	140	328

summer months (June–August). In practice, these results would be used to help inform design decisions regarding the need for zone air conditioning.

- (2) A cooling simulation in which it was now assumed that all treated zones would be air conditioned to a nominal set point temperature of 22°C (dry bulb). Results from these simulations include both hourly time series cooling demands as well as annually integrated total cooling energy consumption.
- (3) A heating simulation with all treated zones heated to set points of between 19°C and 21°C (depending on the nature of usage). Again, results from these simulations include both hourly time series heating demands as well as annually integrated total heating energy consumption.

In the 'freefloat' case, the winter heating was not activated which had the advantage of reducing simulation run times slightly. In practice, the heating would in any case be inactive outside the normal heating season periods (typically from May through to October). Therefore, at least 1 month will elapse from the end of the heating cycle and the start of cooling or peak summertime temperature cycle such that the heating cycle is unlikely to influence the cooling cycle significantly.

5 Results

Results of simulations are presented in Figures 6–10 (Box 1).

In general, the trend lines for advancing time (and carbon emission intensity assumption) suggest a smoother growth in values due to the scaled and stretched CIBSE FWY² data than is the case with the probabilistic data from UKCP09.¹ The Manchester and Northumbria results are generally in reasonably close agreement but there are minor anomalies mainly due to the different maximum windspeed assumptions used as detailed in Section 3. The more pronounced differences between the Exeter results and those from both Manchester and Northumbria are due to differences in the methods used to select climate data as discussed in detail in Section 3. Nonetheless, results from any of the methods selected here point to broadly similar conclusions which are summarised below.

Figure 6 shows the results of the average zone peak temperatures during the warmest summer months for all buildings in all selected UK cities, all TRY data sets, time slices and carbon emission scenario assumptions. These values represent the average of all absolute peak zone operative temperatures (whenever they occur) for each building. All data sets for all city locations chosen are suggesting internal comfort temperature growth of around 5 K through to the end of the present century from typical control data values of around 30°C (Figure 6). The spread in values across the four contrasting buildings is quite narrow – typically 1–2K though it is slightly wider for the UKCP09 data than is the case with the CIBSE FWY-based data. All data tend to point to a higher degree of warming in London towards the end of the century than is the case in the two northern cities chosen though there are

Box 1 Key to symbols on figures

CIBSE FWY TRY data from the CIBSE Future Weather Year² series (based on UKCIP02).

- EU UKCP09-based TRY data generated by Exeter University.¹⁵
- MU UKCP09-based TRY data generated by Manchester University.¹⁷
- NU UKCP09-based TRY data generated in this study.
- C Control data (1960–1989 for UKCP09; 1983–2004 for CIBSE FWY).
- 2L 2020s (2010–2039) ‘low’¹ carbon emission scenario.
- 2H 2020s (2010–2039) ‘high’¹ carbon emission scenario.
- ML ‘Medium low’¹ carbon emission scenario.
- MH ‘Medium high’¹ carbon emission scenario.
- 3L 2030s (2020–2049) ‘low’¹ carbon emission scenario.
- 3M 2030s (2020–2049) ‘medium’¹ carbon emission scenario.
- 3H 2030s (2020–2049) ‘high’¹ carbon emission scenario.
- 5L 2050s (2040–2069) ‘low’¹ carbon emission scenario.
- 5M 2050s (2040–2069) ‘medium’¹ carbon emission scenario.
- 5H 2050s (2040–2069) ‘high’¹ carbon emission scenario.
- 8L 2080s (2070–2099) ‘low’¹ carbon emission scenario.
- 8M 2080s (2070–2099) ‘medium’¹ carbon emission scenario.
- 8H 2080s (2070–2099) ‘high’¹ carbon emission scenario.

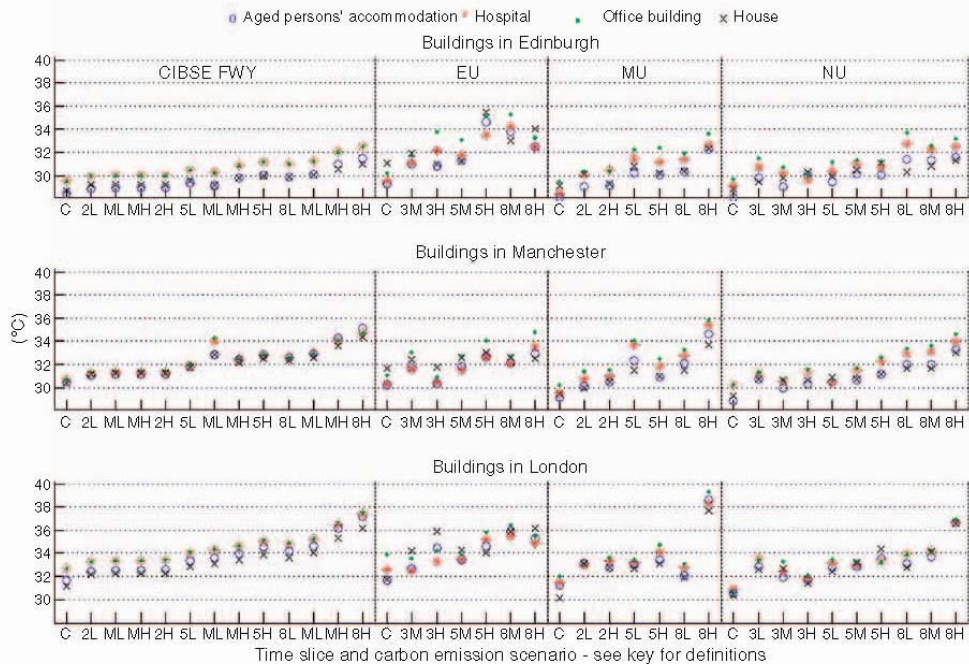


Figure 6 Simulated averages of zone peak operative temperatures

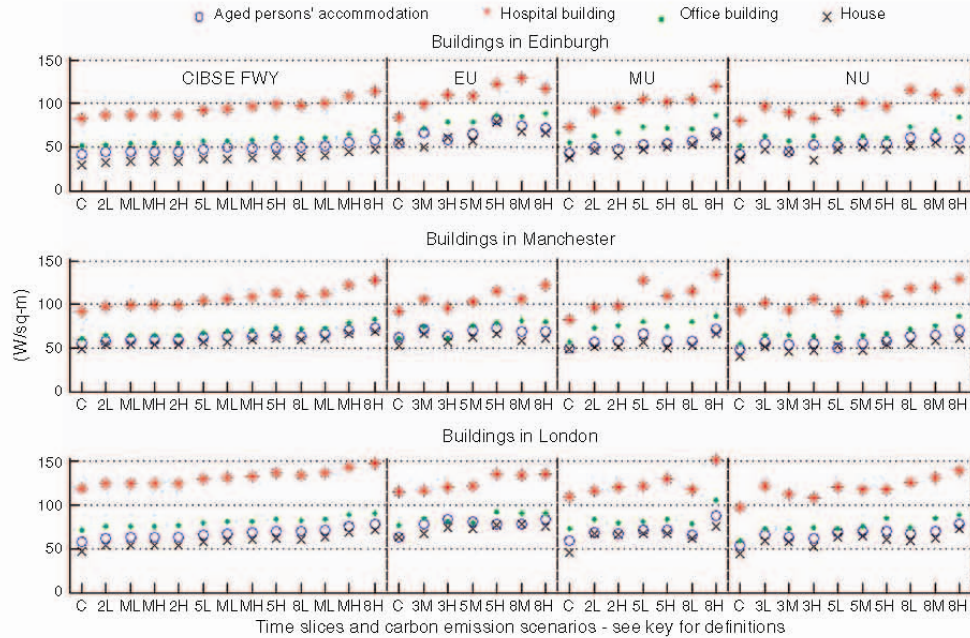


Figure 7 Simulated peak of the total zone cooling loads per unit of treated floor area

apparent anomalies in some results (2080s Edinburgh from the Exeter set¹⁵ and 2080s London 'high' carbon from the Manchester set¹⁷). In particular, the house is exhibiting mean peak operative temperatures in excess of 30°C from the middle of this century which has major implications for a trend towards at least partial air conditioning in the UK for the first time.

Figure 7 shows results of the spread of simulated zone (sensible) cooling loads expressed here as the peak of the sum of simultaneous zone cooling loads divided by the treated floor area of the building. The much higher peak cooling loads evident in the hospital example reflects high internal heat gains in this case due to scanning, diagnostic and radio therapy equipment. Figure 8 gives the simulated annual zone sensible cooling

energy demand (whole building) expressed in kilowatt hour per unit of treated floor area. Sensible room (zone) cooling demands can be expected to increase throughout this century towards 100 Wm⁻² from control values of around 50 Wm⁻² for conventional narrow-plan buildings and from 100 Wm⁻² towards 150 Wm⁻² for the high-intensity deep plan hospital building used in this study. However, the impact on annual cooling energy use is, if anything, even more pronounced (Figure 8) with most results suggesting a near doubling in annual energy use for room cooling in air-conditioned buildings with reference to control data. The house example suggests a lower trend due to the operational assumption of it being unoccupied during weekday periods as family members attend work and school, etc.

16 *Generating test reference years from the UKCP09 projections*

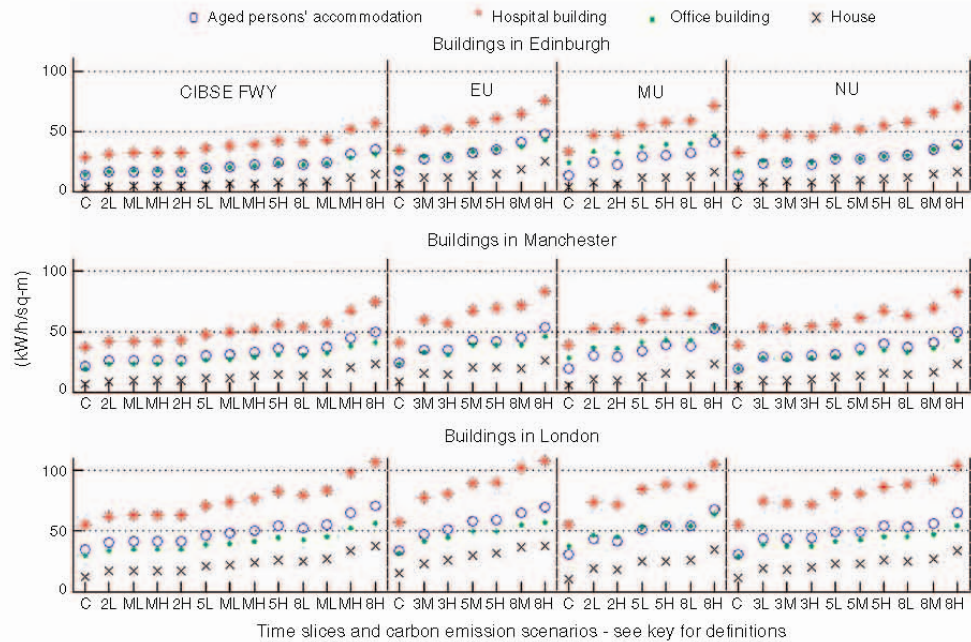


Figure 8 Simulated annual building sensible cooling energy use

Figure 9 shows results of the spread of simulated zone heating loads, again expressed as the peak of the sum of simultaneous zone heating loads divided by the treated floor area of the building. Note that the higher peak heating loads evident in the hospital example reflect high mechanical air heating loads due to the deep plan nature of this building. Figure 10 gives the simulated annual zone heating energy demand (whole building) expressed in kilowatt hour per unit of treated floor area. Heating demand simulations tend to suggest very little decline (contrary to what at first might be expected, Figure 9) with conventional narrow-plan building types continuing to have typical peak demands of around 50 Wm^{-2} if trends in insulation and air tightness were to remain unchanged. However, there are likely to be significant

improvements in the latter over the course of the next few years if the UK is to meet its various carbon reduction targets and so sharp reductions unrelated to climate change might be expected as existing buildings receive refurbishment and future new buildings roll through. An investigation of the impact of these expected improving standards is a matter for further work. Of interest, though the peak heating demands are barely affected by the climate change features captured in our data, the annual energy use due to heating shows a marked reduction (Figure 10) of, typically, 50% of the control values. This would seem to suggest that a need towards radical improvement in thermal insulation standards in the UK, as mentioned above may require to be considered in a measured and incremental manner.

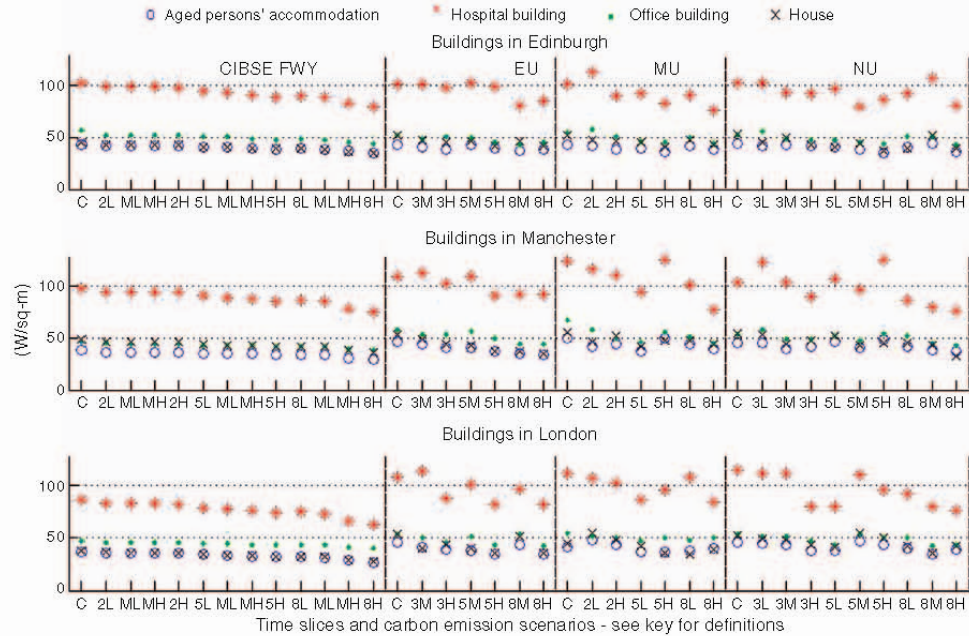


Figure 9 Simulated peak of the total zone heating loads per unit of treated floor area

All the results point to a generally good predictive agreement between simulation results obtained using the former (UKCIP02) climate change scenario data which form the CIBSE FWY set,² and methods that draw from UKCP09.¹

6 Conclusions

Data from the new UKCP09 climate change projections¹ can be more easily and directly translated into future TRY suitable for building energy simulation than was the case with previous data sets of this kind. In this study, TRY data have been generated for a range of future time slices based on UKCP09 and used to simulate the future response of four contrasting building types. The results have been

compared with future weather data produced by other researchers including the CIBSE FWY which forms the basis of current practice as far as the simulation of future building behaviour is concerned. The results of this study show that UKCP09¹ produces simulated building performances that give a good agreement with those obtained from the CIBSE FWY in spite of radically different methods being used to generate the two data sets. Results also confirm the findings of a growing number of studies which point to steady increases in comfort temperature throughout this century for buildings without air conditioning and increased cooling demands and annual cooling energy use for buildings with air conditioning. Though the results also point to negligible reductions in peak winter heating demands through this century due to climate change

18 *Generating test reference years from the UKCP09 projections*

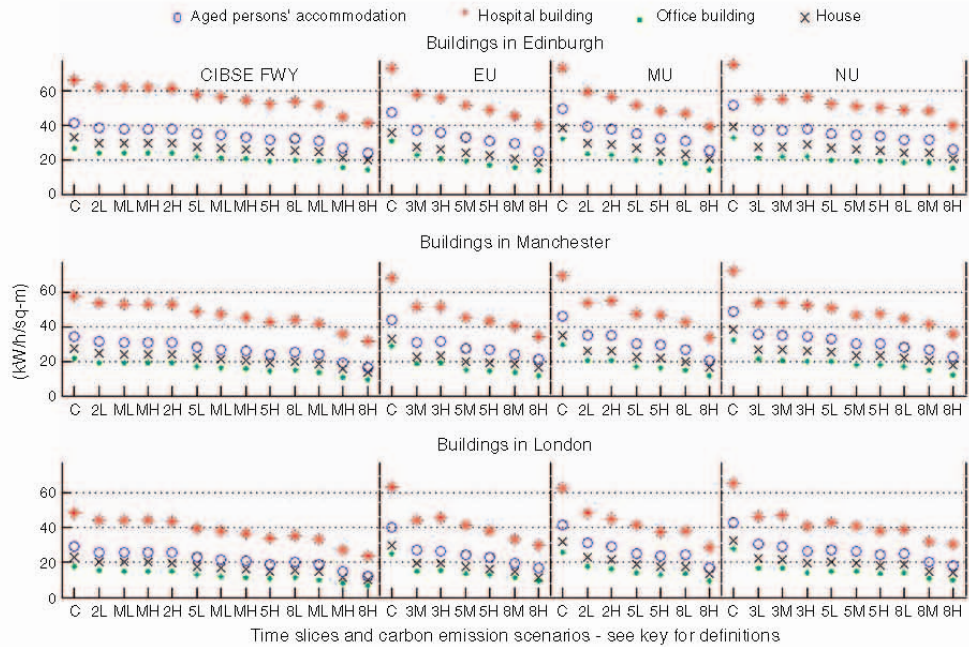


Figure 10 Simulated annual building heating energy use

alone, they do suggest a significant reduction in overall seasonal heating energy use.

Further work is required in five areas. First, the need to develop robust methods for obtaining values of variables and climate modelling parameters that are currently either not defined or badly defined. In particular, hourly wind speed (and direction) from UKCP09¹ and data leading to the opaque could cover parameter which is needed for surface-to-sky radiation heat transfer modelling. Second, work is needed to develop mechanisms for adjusting the TRY data in inner-city areas to account for the impact of urban heat island effect. Third, there is a need to explore alternative future insulation, massing, shading and air tightness standards as future buildings inherit these standards and existing buildings undergo refurbishment

cycles, and to harmonise the results of this with changing energy use due to climate change. This is particularly important both from the viewpoint of increasing insulation standards (reduced winter heating) and improved shading and massing (reduced summertime overheating). Fourth, a better understanding of how occupancy patterns (including patterns of use) in buildings might be expected to evolve in future will help in the development of mitigation strategies such as adaptive comfort algorithms and exposure limits in building inclined to overheating. Finally, there is a need to construct alternative file types containing weather data that can be used for future plant and equipment sizing together with simplified methods for practitioners to use to help to arrive at these design decisions.

Acknowledgements

This study is part of a programme of research funded by the Engineering and Physical Sciences Research Council in the UK (grant reference EP/F038135/1). The authors thankfully acknowledge the sample TRY data supplied for comparison by Dr Richard Watkins at Manchester University and Dr David Coley at Exeter University.

References

- 1 UK Climate Projections. Available from: <http://ukclimateprojections.defra.gov.uk/> (accessed 27 August 2010; version 1). London: Department of Environment, Food and Rural Affairs.
- 2 CIBSE TM48. *Use of climate change scenarios for building simulation: The CIBSE future weather years*, London: Chartered Institution of Building Services Engineers, 2009.
- 3 Climate change 2007. *The physical science basis: Contribution of Working Group I 2007*; Cambridge, Cambridge University Press.
- 4 Hulme M, Jenkins GJ, Lu X, Turnberry JR, Mitchell TD, Jones RG, Lowe J, Murphy JM, Hassell D, Boorman P, McDonald R, Hill S. Climate change scenarios for the United Kingdom. *The UKCIP02 Scientific Report* (2002); Norwich, Tyndall Centre for Climate Change Research, University of East Anglia.
- 5 Cullen NJ, Lea H. *Climate change designing buildings with a future: Proceedings of the CIBSE National Conference 2001*; London, The Chartered Institution of Building Services Engineers.
- 6 Belcher SE, Hacker JN, Powell DS. Constructing design weather data for future climates. *Building Services Engineering Research and Technology* 2005; 26(1): 49–61.
- 7 Guan L. Preparation of future weather data to study the impact of climate change on buildings. *Building and Environment* 2009; 44(4): 793–800.
- 8 Jentsch MF, Bahaj AS, James PAB. Climate change future proofing of buildings generation and assessment of building simulation weather files. *Energy and Buildings* 2008; 40(12): 2148–68.
- 9 Holmes MJ, Hacker JN. Climate change, thermal comfort and energy: Meeting the design challenges of the 21st century. *Energy and Buildings* 2007; 33(7): 802–14.
- 10 Hacker JN, De Saulles TP, Minson AJ, Holmes MJ. Embodied and operational carbon dioxide emissions from housing: A case study on the effects of thermal mass and climate change. *Energy and Buildings* 2008; 40(3): 375–84.
- 11 Coley D, Kershaw T. Changes in internal temperatures within the built environment as a response to a changing climate. *Building and Environment* 2010; 45: 89–93.
- 12 Du H, Underwood CP, Edge JS. *Modelling the impact of a warming climate on commercial buildings in the UK: Proceedings of the 10th REHVA World Congress, Clima 10, Antalya 2010*; Brussels, Federation of European HVAC Associations.
- 13 de Wilde P, Tian W. The role of adaptive thermal comfort in the prediction of the thermal performance of a modern mixed-mode office building in the UK under climate change. *Journal of Building Performance Simulation* 2010; 3(2): 87–101.
- 14 Tham Y, Muneer T. Sol-air temperature and daylight illuminance profiles for the UKCP09 data sets. *Building and Environment* 2010; 46(4): 1243–50.
- 15 Eames M, Kershaw T, Coley D. On the creation of future probabilistic design weather years from UKCP09. *Building Services Engineering Research and Technology* 2011; 32(2): 127–42.
- 16 Kershaw T, Eames M, Coley D. Assessing the risk of climate change for buildings: A comparison between multi-year and probabilistic reference year simulations. *Building and Environment* 2011; 46(6): 1303–08.
- 17 Watkins R, Levermore GJ, Parkinson JB. Constructing a future weather file for use in building simulation using UKCP09 projections. *Building Services Engineering Research and Technology* 2011; doi: 10.1177/0143624410396661 (accessed 6 May 2011).
- 18 Watkins R, Levermore G. Quantifying the effects of climate change and risk level on peak load design in buildings. *Building Services Engineering Research and Technology* 2011; 32(1): 9–19.

20 *Generating test reference years from the UKCP09 projections*

- 19 Patidar S, Jenkins DP, Gibson GJ, Banfill PFG. Statistical techniques to emulate dynamic building simulations for overheating analyses in future probabilistic climates. *Journal of Building Performance Simulation* 2011; doi: 10.1080/19401493.2010.531144 (accessed 6 May 2011).
- 20 British Standard BS EN ISO 15927-4:2005. *Hygrothermal performance of buildings calculation and presentation of data. Part 4: Hourly data for assessing the annual energy use for heating and cooling* 2005; London, British Standards Institute.
- 21 Kilsby CG, Jones PD, Burton A, Ford AC, Fowler HJ, Harpham C, James P, Smith A, Wilby RL. A daily weather generator for use in climate change studies. *Environmental Modelling and Software* 2007; 22: 1705-19.
- 22 Allen RG, Pereira LS, Raes D, Smith M. *Food and agriculture organisation paper 56: Crop evapotranspiration guidelines for computing water requirements*. Rome: Food and Agriculture Organisation of the United Nations, 1998.
- 23 EnergyPlus Energy Simulation Software. Available at: <http://apps1.eere.energy.gov/buildings/energyplus/> (accessed 9th May 2011). U.S. Department of Energy..
- 24 Auxiliary EnergyPlus Programs Manual2010; USA, US Department of Energy.
- 25 Department for Communities and Local Government: National Calculation Method SBEM Software. [Online] Available at: <http://www.ncm.bre.co.uk/>(accessed 10 May 2011).

Generating design reference years from the UKCP09 projections and their application to future air conditioning loads

H Du BEng PgDip **CP Underwood** BSc PhD CEng MCIBSE MASHRAE and **JS Edge** BSc PhD CEng MCIBSE

School of the Built and Natural Environment, University of Northumbria, Newcastle upon Tyne NE1 8ST, United Kingdom.

(Corresponding author: chris.underwood@northumbria.ac.uk)

Keywords

Weather data, climate change, UKCP09 projections, design reference year, air conditioning loads.

A method is developed to generate future design reference year (DRY) data from the UKCP09 climate change projections for a variety of future time horizons and carbon emission assumptions. The method selects three near-extreme summer months and three near-extreme winter months and weaves them into an existing Test Reference Year. Risk levels associated with the 85th percentile (broadly equivalent to existing CIBSE Design Summer Years) of the cumulative distribution function of dry bulb temperature and, for comparison, the 99th percentile are used. A comparison is made with DRYs generated using alternative methods from other research groups. The data are applied to future air conditioning (cooling) loads analysis for a wide range of non-domestic case study building types. Simulations using a control DRY set applied to these buildings are used to develop a simplified regression-based calculation method for predicting future air conditioning loads. The simplified model is shown to be applicable to future weather data without loss of accuracy which makes it possible to carry out large numbers of future cooling loads predictions without the need to perform extensive and complex energy simulations.

Practical applications:

It is becoming increasingly necessary to design energy and comfort services for buildings with a whole-life perspective. To assist with this, the CIBSE Future Weather Years can be used for building simulations through to the 2080s. In June 2009, the United Kingdom's Department of the Environment, Food and Rural Affairs (Defra) with the support of the UK Climate Impacts Programme (UKCIP) published updated climate change projections using a probabilistic method. In future, the responsibility will rest with designers to select design data from a large number of probabilistic outcomes. This work develops a technique to select design weather data called a Design Reference Year at two alternative risk levels for use in building simulations through to the 2080s. A simplified method is also proposed to allow practitioners to generate large numbers of probabilistic design cooling loads without the need to perform extensive simulations.

1. Introduction

It is widely accepted that increases in global temperatures through the 21st century will increase the need for air conditioning in UK buildings. Most of the buildings that will be in use throughout this period either already exist or will be designed, planned and constructed in the immediate years ahead. Furthermore, a majority of these buildings in the UK continue to either have no air conditioning or selective air conditioning. This places a significant responsibility on architects, planners, engineers and construction organisations to ensure that the provision of air conditioning in new buildings and those expected to undergo refurbishment in the immediate years ahead can be designed-in when necessary and with minimum adaptation, disruption and inconvenience to users. Whilst it is true that a building enjoying a typical lifespan of 60-100 years will undergo several major refurbishments through life including replacement of building services assets typically every 15-20 years for primary plant such as boilers and chillers and 20-30 years for end-use plant such as room units, heat emitters and distribution services it nonetheless makes clear sense to plan at the very outset for the introduction of air conditioning as well as other building adaptations such as massing and shading that might mitigate the impacts of a warming climate. A key consideration in this is the availability of predictions of future weather data that can be used to inform the design and planning processes of new and refurbished buildings.

The United Kingdom Climate Impacts Programme (UKCIP) provides support and advice to organisations concerning adaptiveness and resilience to climate change. Its key role is the dissemination of climate information to assist in the assessment of climate change risk and in the development of strategies for the remediation of the impacts of climate change. There have been five of these sets of climate information during the past 20 years the most recent and sophisticated of which were published in 2009 and termed the UKCP09 climate change projections¹ (abbreviated simply to UKCP09). UKCP09 superseded the previous (UKCIP02²) climate change scenarios which form the basis of the current Future Weather Years³ recommended by the Chartered Institution of Building Services Engineers (CIBSE) for use in the simulation modelling and the assessment of overheating risk for buildings in the UK.

Data derived from UKCP09 express probabilities of a given climate change outcome. Results are presented either as cumulative distribution functions (CDF) or probability density functions (PDF) (UK Climate Change Projections¹). A CDF in this context is a plot of the probability (%) of a climate variable's change being less than a given amount. Thus, a CDF percentile of 50% reflects a climate change amount which is as likely to be exceeded as not whereas 90% reflects an amount which is very unlikely to be exceeded (or very likely to be less than). The raw UKCP09 data were generated by the UK's Meteorological Office Hadley Centre Climate Model 'HadCM3' and presented as monthly data on a 25km grid scale. A Weather Generator⁴ is available which enables the data to be spatially downscaled to a 5km grid scale and to temporally downscale the monthly data to either daily data or hourly data. The Weather Generator⁴ uses stochastic modelling methods and, thus, results are innately probabilistic.

It is usually assumed that climate change will be mainly evident in future dry bulb temperature growth whereas solar radiation intensity, which is very influential in design cooling loads, is unlikely to stray much beyond current and historical patterns of variation. However Tham and Muneer⁵ reported that weather data derived from both the UKCIP02 climate change scenarios and the UKCP09 projections suggest greater periods of clear skies with low atmospheric turbidity suggesting higher solar radiation intensities overall in future. A further issue with the current data concerns the lack of wind speed data. Currently, this is dealt with by extracting wind speeds from UKCP09 Weather Generator⁴ surface evapotranspiration rates.^{6,7}

In this work, a method is developed to generate future design reference years (DRY) – yearly data which contains near extreme winter and summer conditions for use in the design capacity sizing of building plant. Though a DRY defined in this way can be used for both winter heating and summer air conditioning equipment the present work concerns itself with the latter only. A simple method is developed for the estimation of future design loads for room-based air conditioning equipment avoiding the need for extensive detailed energy simulations. The work reported here is focused on non-domestic buildings and builds on earlier work which concerned itself with the generation of test reference years for use in building energy and comfort performance simulations⁸.

The objectives of this work are as follows:

1. To develop a statistically-based procedure for extracting future design reference years from UKCP09.
2. To compare and verify results with those from co-workers as well as from UKCIP02-based methods which form current practice.
3. To apply a representative sample of design reference years to a range of case study buildings and extract future room cooling loads for a range of conditions.
4. To develop a simple load estimation model for future cooling load calculations in order to simplify design analysis by reducing the number of complex energy simulations needed.

2. Literature review

Historically, test reference year (TRY) data consisting of a statistically-typical year of weather data are used for seasonal energy simulations of buildings whilst design summer year (DSY) data are used to assess near-extreme summer comfort conditions as well as for use in air conditioning sizing. Design summer years have previously been extracted by choosing the third warmest summer (from April to September) from typically 20 alternative weather files giving near-extreme conditions. Until the UKCIP02 climate change scenarios² these data were based on historical records and, thus, offered no future perspective on weather data trends. Chow et al.⁹ were among the first to suggest that future building design should take account of future patterns of weather data in order to account for a warming climate. They utilised predicted future climate data from the UK Met. Office's HadCM3 general circulation model to provide confidence in future plant capacities for new buildings.

Levermore and Parkinson¹⁰ presented a method for extracting Test Reference Year and Design Summer Year data from historical weather data records using a relatively simple approach involving the Finkelstein-Schafer statistic acting on cumulative distribution functions (CDF) of external dry bulb temperatures for individual months compared with the overall CDF for all months in the data set. Their Design Summer Year was selected from 22 years of historical data (with some years having missing months). Recognising a need for weather files that can be readily loaded directly into environmental simulation software Jentsch et al.¹¹ used a stretching and scaling method (called 'morphing' as first developed by Belcher et al.¹²) to transform current CIBSE design summer years (and test reference years) into climate change weather years and developed a tool to convert these into file formats readily readable by building simulation packages. They performed simulations of a naturally ventilated building to assess the potential summer overheating problems caused by climate change. Their work was based on the UKCIP02 climate change scenarios². Chow and Levermore¹³ use a second order room modelling method to investigate heating and cooling energy demands in office buildings constructed to UK Building Regulations standards, the choice of modelling method designed to explore the impact of room

thermal capacity on cooling demand. Their method also used data from the earlier (UKCIP02) climate change scenario data.

More recently, developments have centred on the use of the UKCP09 data. Eames et al.¹⁴ developed a single method to extract both TRYs and DSYs from UKCP09. Typically, the 50th percentile would be chosen in order to construct a TRY and a higher percentile chosen to generate a DSY. Results were found to be consistent with the CIBSE future weather years³. Similar tools were developed by Watkins et al.⁶ and Du et al.⁸ although these methods were restricted to the generation of TRYs only. Kershaw et al.¹⁵ compared results from TRY and DSY simulations of buildings with numerous simulations carried out using all of the weather files from which the reference years were selected. They found that a DSY will often underestimate the risk of over-heating in summer compared with individual simulations using many weather files. Watkins and Levermore¹⁶ investigated the effects of climate change on the peak design loads of buildings using the conventional CIBSE cooling load calculation method. They evaluated the impact on plant size of designing to a fixed percentile of risk attached to the choice of weather data by evaluating results at the 90th, 95th and 98th percentiles. They found for instance that a building designed at the 95th percentile against over-heating (i.e. 5% risk of over-heating) during 1960-1990 would require 41% more cooling capacity to avoid exceeding the same comfort threshold in 2070-2100.

Jenkins et al.¹⁷ investigated overheating in a domestic dwelling by means of a linear filtering and regression technique. A principal component analysis is used to decompose the extensive climate data (504 potential input variables) to a much smaller set (33) of variables and a linear predictor is constructed for the bedroom temperature of the house corresponding to climate data from a preceding period of time. Least squares regression is used to fit the model. They found that results from their model were just as reliable as a detailed building simulation for many different climates however the regression relationship might not be suitable for more complex buildings. Lam et al.¹⁸ also used principal component analysis to decompose otherwise large data sets in the process of fitting energy demand models to weather data (in this case for application to building cooling load assessment in the humid sub-tropical climate of Hong Kong). Other work seeking to simplify load calculations based on pseudo variables is due to Chen et al.¹⁹ who combine solar irradiance, dry bulb temperature and wet bulb temperature into a single variable called the effective temperature. This method is based on the critique that most existing design methods consider these three dominant variables for cooling load calculations independently and thus their method ensures that the probable coincident impact of all three is better accounted for as well as resulting in a very simply model structure. However the approach is restricted to buildings of very low thermal capacity.

Smith et al.²⁰ noted increasing trends in wet-bulb temperature depression in the UKCP09 projections and used this to explore the potential of evaporative cooling as a way of tackling the expected increases in cooling demand. They conclude that evaporative cooling, as part of a mixed-mode strategy, offers a promising solution to future air-conditioning. Besides this, there has been very little work that has considered the impact of alternative air conditioning methods in response to a changing climate.

In summary, there is significant evidence of progress concerning the extraction of statistically-representative weather data for building simulation and for extreme summer design purposes. There is a limited but growing body of work dealing with the translation of the UKCP09 data into appropriate file formats for building modelling and design but somewhat less progress on the direct application of these data sets to the broad context of building design. This work seeks to contribute to the former and address a key aspect of the latter.

3. Method for generating design reference years

Design Reference Years were generated from the UKCP09 projections using the following procedure. Raw data consisting of 30-year periods of hourly weather data were obtained using the UKCP09 Weather Generator.⁴ The UKCP09 data can be partitioned into the time periods shown in Table 1. In this work, the nominal time periods of 2030s, 2050s and 2080s were used together with the control period data; the former represents a sample of future time periods looking sufficiently far towards a time horizon likely to be of interest for the life span of buildings currently under development and construction or refurbishment.

Table 1 Time periods of the UKCP09 data

Time Period	Interval
Control (reference) data	1961-1990
2020s	2010-2039
2030s	2020-2049
2040s	2030-2059
2050s	2040-2069
2060s	2050-2079
2070s	2060-2089
2080s	2070-2099

The number of probabilistic variations used in the UKCP09 Weather Generator⁴ for hourly data output is 100. Thus, for each 30-year band of climate data, 3000 annual files of hourly and daily weather data were extracted to represent each of the 4 selected times periods (including the control data) at each of three (low, medium and high) carbon emission scenarios. In the procedure reported here, weather data are selected at the 85th and 99th percentiles. Because CIBSE design summer data has historically selected the third warmest period from 20 individual weather files (i.e. $3/20 = 0.15$ or 15%) the 85th was chosen for consistency with this. For comparison, for a much lower design risk of overheating, the 99th percentile was also used because it forms the medium-risk value of the three percentiles (98%, 99% and 99.6%) recommended for use in current practice for UK design cooling loads²¹. The following procedure was used:

- 1) A Test Reference Year for each time period (including control) was generated using the method previously reported by Du et al.⁸
- 2) Daily maximum dry bulb temperatures (T_{\max}) and daily minimum dry bulb temperatures (T_{\min}) were captured from the UKCP09 Weather Generator⁴ daily data for each complete time period, and daily mean dry bulb temperatures were then calculated from these by averaging.
- 3) For the two three month sets only: December-February and June-August, the monthly mean dry bulb temperatures were calculated by averaging the daily mean dry bulb temperatures, and then for each of these calendar month sets, 3000 monthly mean temperatures were ranked in ascending order.
- 4) For the June-August set, 30 of each of these months with the 31st – 60th highest monthly mean temperatures (i.e. 99th percentile) were selected, from which one of each was selected by applying the Finklestein-Schafer (FS) statistic to temperature, solar radiation and relative humidity as described by Du et al.⁸ This resulted in the summer DRY month selections

- 5) Step 4 was repeated for the December-February set to obtain the lowest mean monthly mean temperature (1st percentile) and, again, one of each of these months was selected by applying the FS-statistic to obtain the winter DRY month selections.
- 6) The 3 summer and 3 winter month selections from steps 4 and 5 above were merged with 6 other months from the Test Reference Year (Step 1) to form the 99th percentile Design Reference Year.
- 7) Steps 4-6 were repeated using the 451st – 480th highest monthly mean temperatures among the summer months and the 451st – 480th lowest monthly mean temperatures among the winter months to form the 85th and 15th percentile summer and winter DRYs respectively.
- 8) To deal with spikes in the data at midnight (arising from non-chronological months being joined), the last eight hours of each month and the first eight hours of the next month were smoothed by cubic-spline interpolation. This adjustment included the December-January connections so that the Design Reference Year could be used repeatedly in simulations.

Completion of each DRY file of data required further trivial completion steps before conversion to the relevant file format for use in a dynamic energy simulation program. The precise nature of these would depend on what data fields were needed for the particular simulation program intended. In this work, the simulation program EnergyPlus²² has been used. Completing steps for EnergyPlus²² required the following:

- Calculation of the hourly dew point temperature based on the existing hourly dry bulb temperature and relative humidity from the DRY file, using hygrometric properties of air.
- Calculation of the hourly direct-normal solar radiation based on the existing direct horizontal solar radiation from the DRY file using conventional sun-earth geometry procedures.
- Translation of cloud cover into tenths using the sunshine hours data in the existing DRY file, and the addition of night-time cloud cover data which was assumed in this work to be based on a linear interpolation of sunset and subsequent sunrise values.
- Calculation of the hourly horizontal infrared radiation flux²² in which the opaque cloud cover was assumed constant at 0.5 as used previously by Jentsch et al.¹¹

The entire procedure described above was carried out using a bespoke Matlab script. Processing times to completion based on 3000 years of initial input files resulting in one TRY file and two DRY files (85th and 99th percentiles) were typically 6 minutes on a conventional personal computer.

A sample of control and future external dry bulb temperatures for the June-August period are compared with results from other sources for DRY files at Manchester Ringway. The other sources are from the CIBSE future weather years³ (these data are based on the earlier UKCIP02 climate change scenarios²), a sample of results from Manchester University⁶, and a sample of results from Exeter University¹⁴. The CIBSE data were generated using ‘morphing’¹² applied to existing Design Summer Year data the latter consisting of the third warmest April-September period based on average dry bulb temperature from a sample of 21 historical data sets. Manchester University⁶ calculated monthly average temperatures for each calendar month (3000 Januaries, 3000 Februaries, etc) and ranked them separately in ascending order. For each calendar month, one month was then selected from 20-year bands at the 87.5th percentile using the FS-statistic. Besides these dry-bulb temperature based files, Manchester also used a similar approach to select alternative DRY files based on relative humidity and solar radiation. Exeter University¹⁴ captured 100 design summer years from 3000 years of UKCPO9 data (100 samples of 30-year data) by choosing the fourth warmest April-September periods in each 30-year band based on 6-monthly mean dry bulb temperatures. They then ranked each 100 year month set

based on ascending order of mean monthly temperatures and picked off each month in each set at the same percentile (10th, 33rd, etc through to 90th) and joined them together to form a complete year of data.

The results of dry bulb temperatures from the DRY file of Manchester Ringway created in this work (at the 85th and 99th percentiles) are compared with the results from Manchester University (87.5th percentile) and Exeter University (90th percentile) in Figure 1. Note that the symbols used along the horizontal axis of this Figure (as well as Figures 3-5) are as detailed in Box 1. Note also that Manchester University data are not available for the 2030s period but instead the 2020s period is included. The results confirm a broad agreement in the trends of the growth in dry bulb temperatures with advancing time and carbon emission scenario.

Box 1 Symbols used in Figures 1, 3, 4 & 5

C	Control data
2L	2020s (2010-2039) low carbon emission
2H	2020s (2010-2039) high carbon emission
ML	Medium low carbon emission (UKCIP02 data)
MH	Medium high carbon emission (UKCIP02 data)
3L	2030s low carbon emission
3M	2030s medium carbon emission
3H	2030s high carbon emission
5L	2050s low carbon emission
5M	2030s medium carbon emission
5H	2030s high carbon emission
8L	2080s low carbon emission
8M	2030s medium carbon emission
8H	2030s high carbon emission

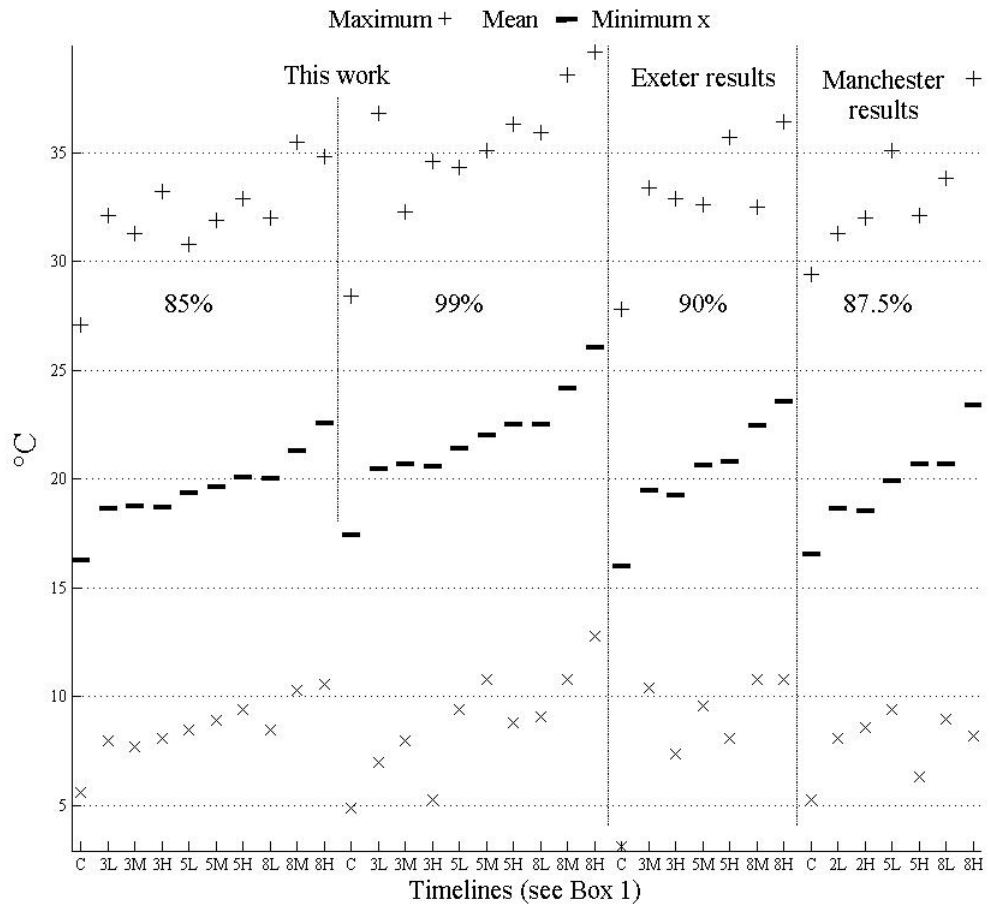


Figure 1 Comparison of external dry bulb temperatures from Manchester Design Reference Years

4. Application to future building loads

This work has been supported by a range of non-domestic building case studies selected from a widely varying mix of building types with some in continuous use and others in intermittent use. Details of the buildings are given in Figure 2 and Table 2. It is neither practical nor possible to give full details of the buildings because some of this information is commercially sensitive however all of the buildings exist and so the modelling was carried out to reflect, as closely as practicable, the actual nature of current usage. In order to gain a consistent insight into the behaviour of these buildings, it has been assumed that they have all been either constructed to, or upgraded (through refurbishment), to the same nominal construction standard. Since many of the buildings detailed were actually constructed to the 2006 edition of the Building Regulations rather than the current (2010) edition, it was assumed that all of the buildings modelled conformed to this earlier standard. The thermal capacity of each zone was calculated using the simplified method set out in ISO 13786:2007 based on a maximum effective element thickness of 0.1m. Total values for each zone were added to give a building total and this value was then divided by the gross building floor area for comparative purposes and results are given in Table 2.

The occupancy densities, occupied period profiles and internal heat gain allowances for all zone types in all buildings were selected according to standard data presented in the UK National Calculation Method database.²³ The values selected would be used in current practice for, among other things, building regulation compliance modelling.

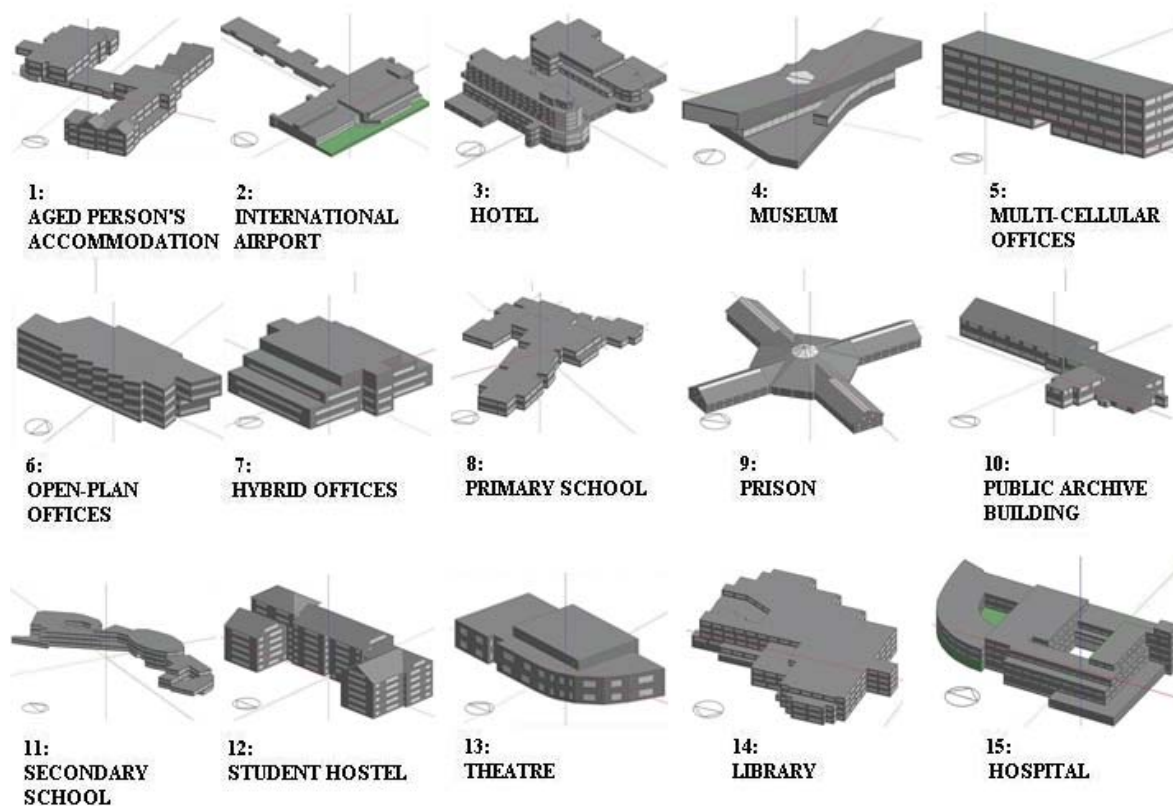


Figure 2 Building thumbnails

Table 2 Building details

KEY: GFA gross floor area TFA occupied/treated floor area C_{Eff} effective thermal capacity per unit GFA

Building (Figure 2)	Zones	GFA (m ²)	TFA (m ²)	C_{Eff} (kJm ⁻² K ⁻¹)
1	51	5683	5345	425
2	77	49795	37445	305
3	51	21275	17910	338
4	40	12802	10518	300
5	36	4269	2977	466
6	24	3779	2632	476
7	22	8682	6172	357
8	25	4870	2844	285
9	67	10063	9411	500
10	23	2347	2201	470

11	64	13200	8259	397
12	86	9256	6053	503
13	14	1257	1010	409
14	64	20289	18530	348
15	145	21897	12786	259

As an example, results of design simulations using a sample of the Design Reference Year data generated in this work were applied to Building 5 (multi-cellular office building) only (more extensive use will be made of the buildings discussed in this section a little later). Simulations were carried out using EnergyPlus.²² Figure 3 shows simulated maximum heating demands for the building, thus forming design heating loads when using a Design Reference Year weather file. The vertical bars on this Figure (and Figures 4 and 5) represent the spread of individual zone heating demands with crosses along this line representing individual zone loads. The short horizontal bars represent the overall design loads for the whole building. Note that the zone design loads and overall building design loads will occur at different time which is why, in some cases, the horizontal bar appears outside the range of the zone spread. For example, suppose that a building consists of 2 zones of identical floor area but different heat transfer characteristics and, during 2 consecutive hours, the first zone has a load of 50Wm^{-2} (which is its peak value) and 10Wm^{-2} respectively whilst the second zone has loads of 10Wm^{-2} and 40Wm^{-2} (which is its peak value), respectively. Zone design loads of 50Wm^{-2} (zone 1) and 40Wm^{-2} (zone 2) would be returned for the two zones whilst the overall design load for the building would be the higher of the two combined and coincident values (i.e. 30Wm^{-2}). An interesting feature in the results given in Figure 3 concerns the trend in heating design loads over time and with increasing emissions scenario in that they do not reduce as might at first be expected but stay broadly the same subject to some randomness. This was found in earlier work when using TRY data for simulating heating demands⁸. The earlier work found that annual heating energy demands did indeed decline with time and emissions scenario whereas peak instantaneous values did not. This suggests that short instances of cold winter weather might be expected to continue to occur more or less as they do now.

Box 1 may be consulted for details of the symbols used along the horizontal axis. It is evident that the design heating demand pattern for this building is not greatly influenced by climate change regardless of the emission scenario assumption. Figure 4 gives the percentage of occupied hours for this building during which internal zone operative temperatures exceed a notional threshold of 28°C (the typical value currently used to assess summer overheating). These results were generated by assuming that natural ventilation at a constant rate of 4 air changes per hour would be introduced to each zone when the zone internal operative temperature exceeds 25°C and the external dry bulb temperature is less than the zone dry bulb temperature. From the control data, a steady rise in this comfort violation is evident with time and emissions scenario. This has significant implications for the introduction of remediation measures, such as shading and increased thermal mass, or for the uptake of air conditioning. Figure 5 shows simulated maximum cooling demands for those zones of the building that fail the previous overheating criterion for 1% or more of the occupied hours, thus forming design cooling loads when using a Design Reference Year. Note that, again, the horizontal bar represents the overall building design loads and that all values will occur at different times. A steady increase in design cooling demand is evident with time and emissions scenario. The implication of this is that for buildings constructed today in which it is adjudged unnecessary to provide air conditioning or special measures to reduce solar heat gain (etc) in current conditions, designers would be well-advised to factor-in features that would make the addition of such services in the future, easy to implement. Such features might include contingency space allowances for future plant and ductwork/pipework services distribution.

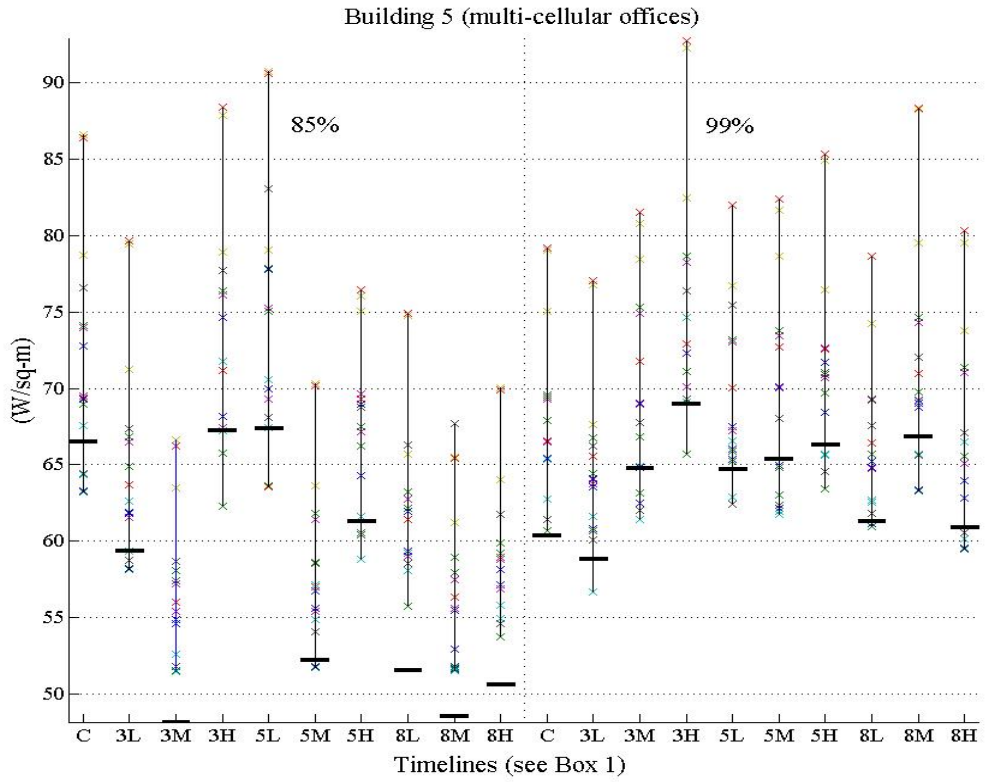


Figure 3 Sample of heating design load results

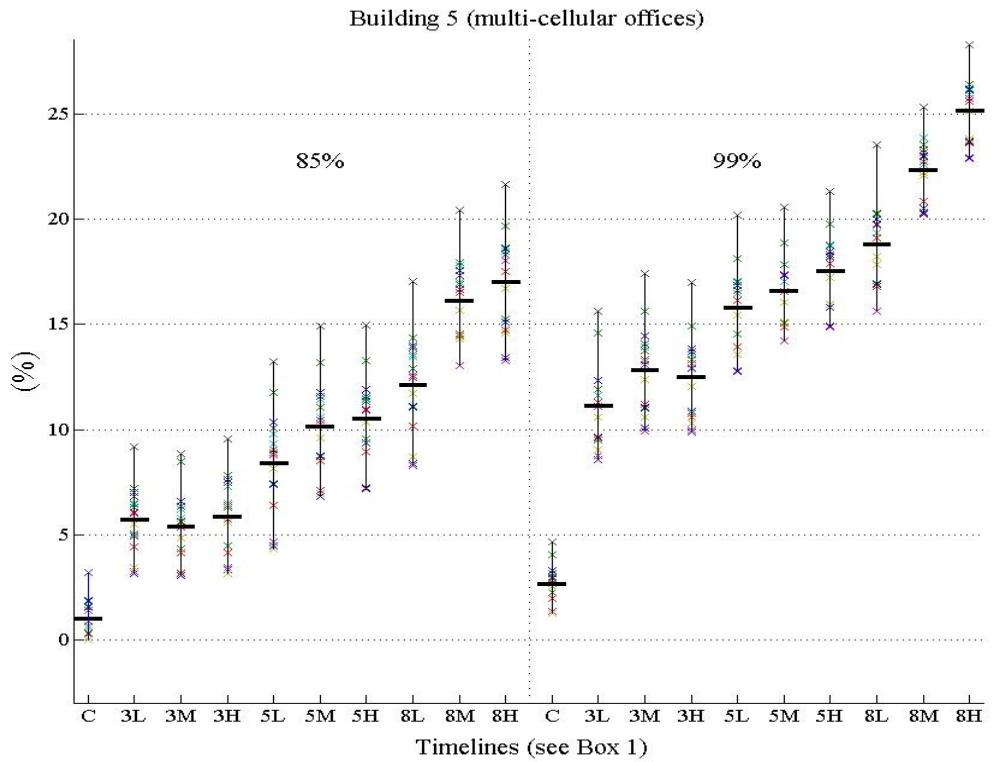


Figure 4 Sample of summer percentage overheating results

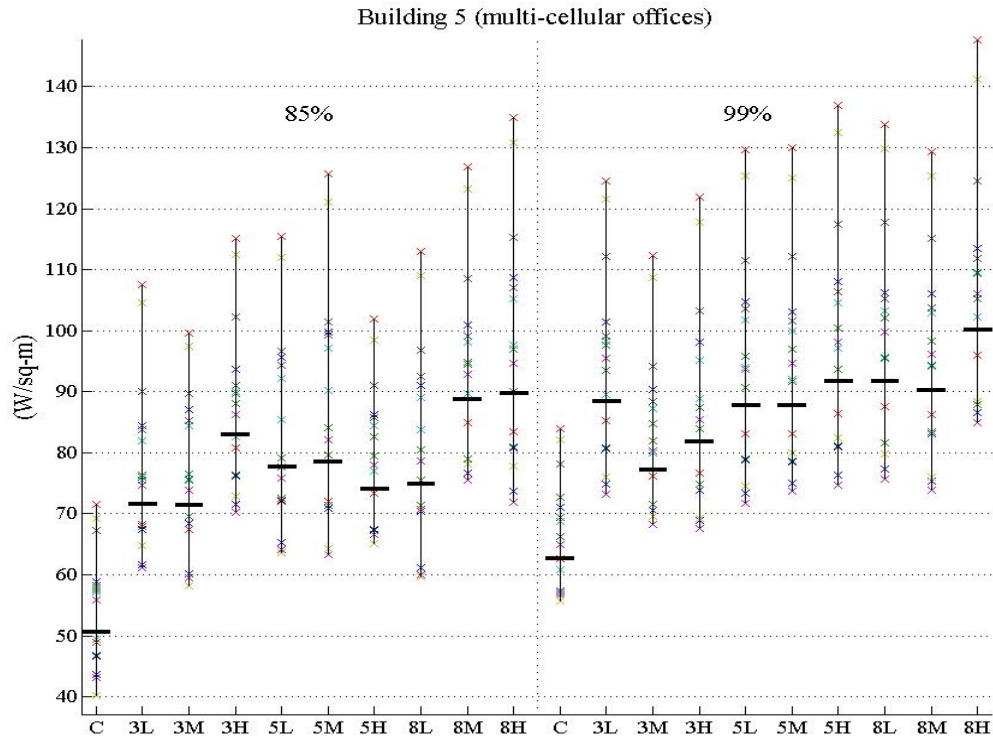


Figure 5 Sample of cooling design load results

5. A simplified method for predicting future air conditioning loads

In the previous section, results based on energy simulations using DRY weather data for an example building were compared. It is recommended that this method be adopted for future design and design-risk analysis for new and refurbished building proposals using dynamic energy modelling tools such as EnergyPlus²² (as used here) or one of the numerous other simulation tools that have become available in recent years. It is however acknowledged that the resources of time and effort to conduct such design studies are not trivial particularly when applied during the early design and planning processes that most new building proposal undergo. At this stage, the availability of a simpler approximate method would be invaluable to practitioners. In this section, the development of such a method is considered and applied to the calculation of future room design cooling loads.

Simple reasoning and an inspection of results similar to those presented in the previous section suggests that the room maximum (design) sensible cooling load for a given building is dependent on current and historical values of solar radiation, external dry bulb temperature and internal casual heat gains due to lighting, equipment and occupancy. The extent of historical data among these key independent variables will depend on the thermal capacity of the room. The objective was to ascertain the extent to room design cooling loads could be fitted to sets of these variables through linear regression. All independent weather data variables (and internal casual heat gain values) were arranged to consist of the current time-row values; the average of the current and previous hour values; the average of the current, and previous two hours' values, and so on to a maximum of 96 (4-days worth) of instantaneous and historical values for each variable. A total of 44 arbitrarily selected occupied zones from the 15 buildings detailed in Figure 2 and Table 2 were

selected. After extensive step-wise multiple regression analysis, it was found that 38 (out of 44) zone cooling loads could be expressed reasonably well ($R^2 > 0.7$ with respect to simulated values) using only four independent variables, however the four independent variables were not the same for different zones. The choice of R^2 at > 0.7 as a threshold for goodness of fit was somewhat arbitrary but it was felt that a threshold that describes a model that can describe a substantial majority of the variance was better than simply selecting a threshold of > 0.5 . Indeed most of the results obtained values of > 0.8 as illustrated in table 4. A repeat times count of the 4 independent variables for each zone was carried out. In this context, a repeat times count is the number of occasions in which a particular variable was selected across all zones by the regression analysis. The repeat times were ranked in ascending order from which it was evident that 9 different variables would be able to give good results for the 38 selected zones. These are summarised in Table 3 (together with the repeat times count values). It was found that the peak cooling load always occurred on a day with a high average external air dry bulb temperature during 10:00h – 22:00h following a period of strong global horizontal solar radiation which confirmed the selection of the 9 independent variables used.

Table 3 Independent variables repeat times count results

Variable	Symbol used	Repeat times count
Current air dry bulb temperature	T_0 ($^{\circ}\text{C}$)	21
Dry bulb temperature at the previous hour	T_{-1} ($^{\circ}\text{C}$)	12
Average of current and previous 2h dry bulb temperature	T_{0-2} ($^{\circ}\text{C}$)	7
Dry bulb temperature 7h ago	T_{-7} ($^{\circ}\text{C}$)	7
Current global horizontal solar radiation	I_0 (Whm^{-2})	12
Average of current and previous 2h solar radiation	I_{0-2} (Whm^{-2})	8
Average of current and previous 7h solar radiation	I_{0-7} (Whm^{-2})	13
Current internal casual heat gain	q_0 (Wm^{-2})	29
Average of current and previous 2h casual heat gain	q_{0-2} (Wm^{-2})	5

The simplified zone sensible cooling load model can therefore be expressed to give the current time-row zone sensible cooling load, $Q_{0,\text{plant}}$, as follows (Equation 1),

$$Q_{0,\text{plant}} = k_1 + k_2T_0 + k_3T_{-1} + k_4T_{0-2} + k_5T_{-7} + k_6I_0 + k_7I_{0-2} + k_8I_{0-7} + k_9q_0 + k_{10}q_{0-2} \quad [1]$$

in which k_1, \dots, k_{10} are constants fitted by multiple-regression. Typical fitted values for these constants for a sample zone in each of the 15 case study buildings are summarised in Table 4.

Table 4 Typical results of fitted constants (Equation 1)

Building & Zone	k_1, \dots, k_{10} & R^2
1: 1 st floor flat (east-facing)	-36.76, 1.405, 1.462, 1.337, -1.629, 0.018, -0.022, 0.054, 0.180, 0.198 ($R^2 = 0.820$)
2: 2 nd floor large public space	-33.75, 1.392, 1.790, 0.388, -1.372, 0.003, 0, 0.003, -0.018, 0.054 ($R^2 = 0.829$)
3: Grd. floor conference room	-65.91, 1.423, 0.893, 0.160, 0.293, 0.002, -0.002, 0.004, 0.474, 0.017 ($R^2 = 0.855$)
4: Grd. floor gallery	-53.38, 13.79, 0, 2.713, -14.25, 0.007, -0.005, 0.030, 0.014, -34.11, 46.44 ($R^2 = 0.906$)
5: Grd. floor office	-28.84, 4.814, -2.810, 0.630, -0.711, -0.002, -0.012, 0.048, 0.374, -0.273 ($R^2 = 0.683$)
6: 2 nd floor office	-20.52, 3.983, -3.015, 0.009, 1.461, 0.003, 0.017, 0.013, 0.078, -0.366 ($R^2 = 0.846$)
7: 4 th floor office	-26.80, 3.557, -2.818, 0.379, 1.646, 0.003, 0.001, 0.010, 0.268, -0.101 ($R^2 = 0.867$)
8: Grd. floor classroom	-64.69, 8.669, -18.121, 0.009, 13.215, 0.007, -0.004, 0.009, 0.314, -0.076 ($R^2 = 0.855$)
9: Grd. floor cells	-37.31, 0.779, 7.020, 1.411, -7.136, 0.007, -0.006, 0.006, 0.434, -0.115 ($R^2 = 0.790$)
10: Deep plan archive room	-24.899, -0.542, 10.83, 0.825, -9.794, 0.007, -0.002, 0.010, 0, 0 ($R^2 = 0.842$)
11: 2 nd floor classroom	-66.58, 13.08, -33.18, -0.054, 23.95, 0.017, 0.013, 0.003, 0.317, -0.094 ($R^2 = 0.840$)
12: 1 st floor bedsit	-28.26, 1.380, 0.343, 0.516, -0.555, -0.012, -0.008, 0.009, 0.224, 0.012 ($R^2 = 0.709$)
13: Theatre space	-48.17, 2.063, 0.357, 0.710, -1.058, 0.001, 0.001, 0.002, 0.291, 0.230 ($R^2 = 0.800$)
14: 1 st floor book stack	-34.13, 2.587, -0.854, 0.271, -0.097, 0.005, -0.004, 0.007, 0.252, -0.025 ($R^2 = 0.725$)
15: 3 rd floor treatment room	-37.84, 5.271, -6.084, 0.310, 4.291, 0.003, 0.017, 0.010, 0.158, -0.158 ($R^2 = 0.933$)

All of the fitted constants illustrated in Table 4 were generated using simulated cooling load results for the control period. As an illustration, cooling loads based on the control Design Reference Year data for the period June-August were calculated using the regression model for the 4th floor office zone example of Office Building 7 and plotted against the corresponding simulated results in Figure 6. To test the application of the model using data other than that used to generate it, the same model was also used with the 2030s DRY data (medium emissions scenario), 2050s (medium emissions scenario) and 2080s (medium emissions scenario) and these results are also plotted in Figure 6. The results show that the performance of the fitted model remains good (all points lie close to the regression line) regardless of the future weather data used.

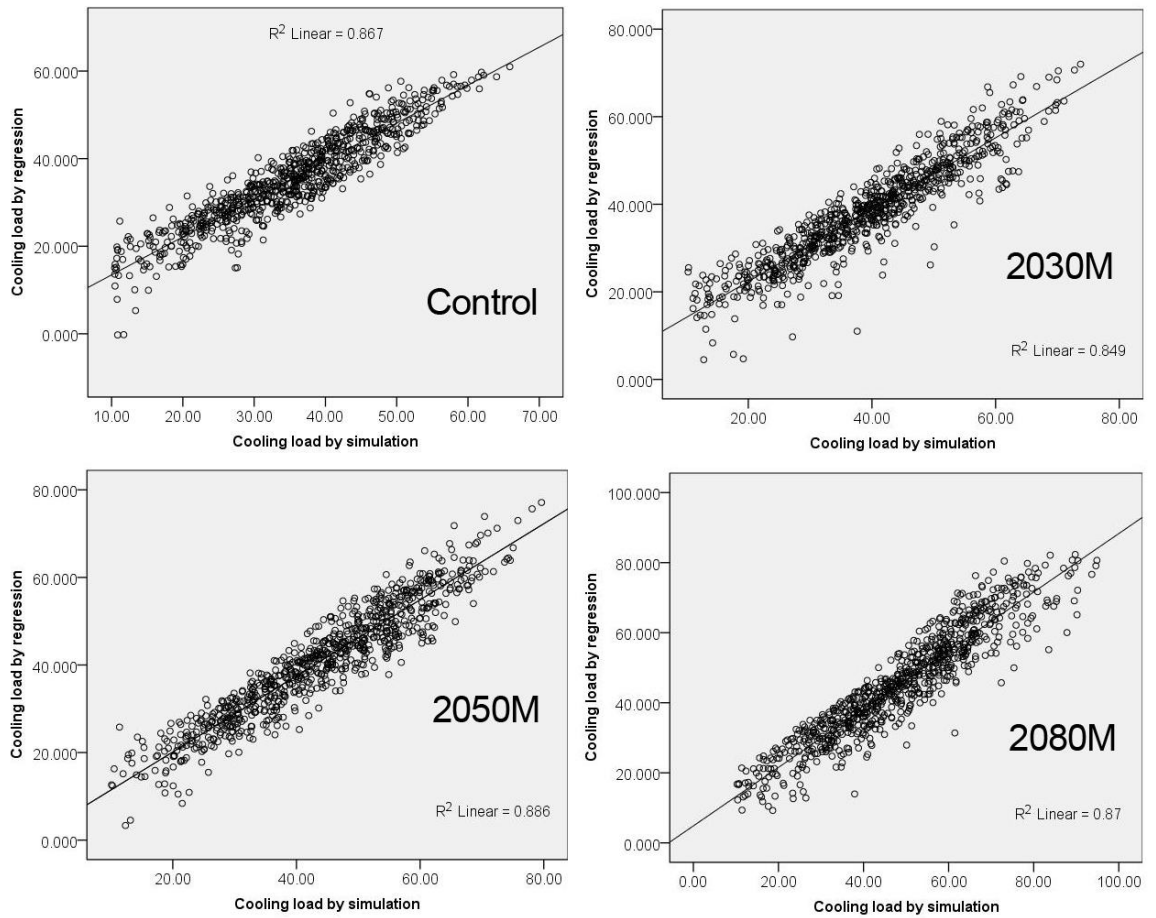


Figure 6 Example estimated vs. simulated cooling loads (control and future DRY data)

To obtain the design cooling load, the highest hourly load during the June-August period is selected. A comparison between the simulated design cooling load with the corresponding load predicted by the simple model for this example case is given in Figure 7 for all of the DRY files generated in this work. This confirms that the compromises concerning the reduced number of independent variables used for model fitting has not impaired the predictive quality of the simple model greatly.

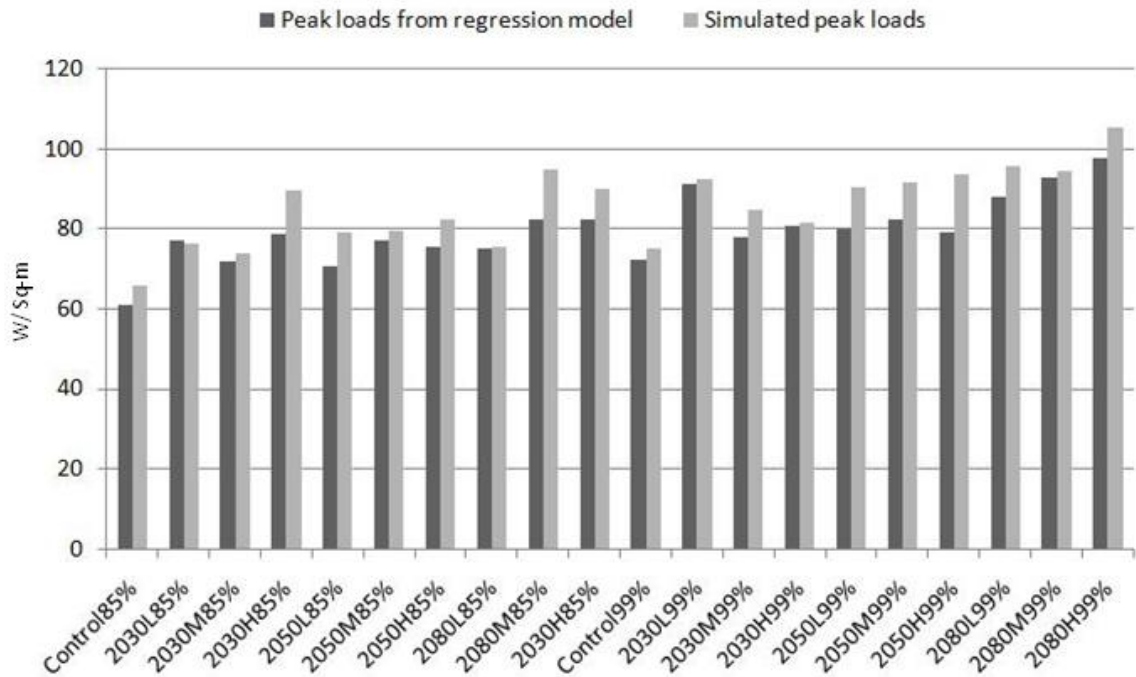


Figure 7 Example estimated vs. simulated design cooling loads (all DRY data)

The simplified zone cooling load model can be used through the application of the following procedure avoiding the need to engage in repeated iterations of complicated energy simulation modelling.

- Step 1 Using a reference Design Reference Year (e.g. based on existing data or some other control set), conduct a single energy simulation of the building of interest and fit regression constants according to Equation 1 for all building zones of interest. It is suggested that a lower threshold be applied below which cooling is deemed unnecessary (e.g. 10Wm^{-2}). Regression constants may be fitted routinely using most statistical packages or spreadsheets.
- Step 2 Prepare time series files of future weather data consisting of summer (June-August) dry bulb temperatures and global horizontal solar radiation data and prepare the independent variable set as summarised in Table 3. Using the UKCIP09¹, 3000 such time series files will be available.
- Step 3 Calculate the time series cooling loads for each summer period using the fitted model and the synoptic files of input data and select the highest cooling load result for each summer as the design cooling load for that year. This can be carried out using a spreadsheet.
- Step 4 Rank the 3000 design cooling loads in ascending order and select the design cooling load results at the desired risk percentile.

As an illustration, the distribution of the 3000 design cooling loads predicted by the simple model for the example building zone are shown in Figures 8 for the control data and in Figure 9 for all DRY data. In Figure 9, the central values (shown as small circles) are at the 50th percentile (i.e. design cooling loads as likely to occur as not) whereas the bars represent the extents of the design

cooling loads at +/- two standard deviations from the central values (i.e. 2.2 percentile and 97.8 percentile).

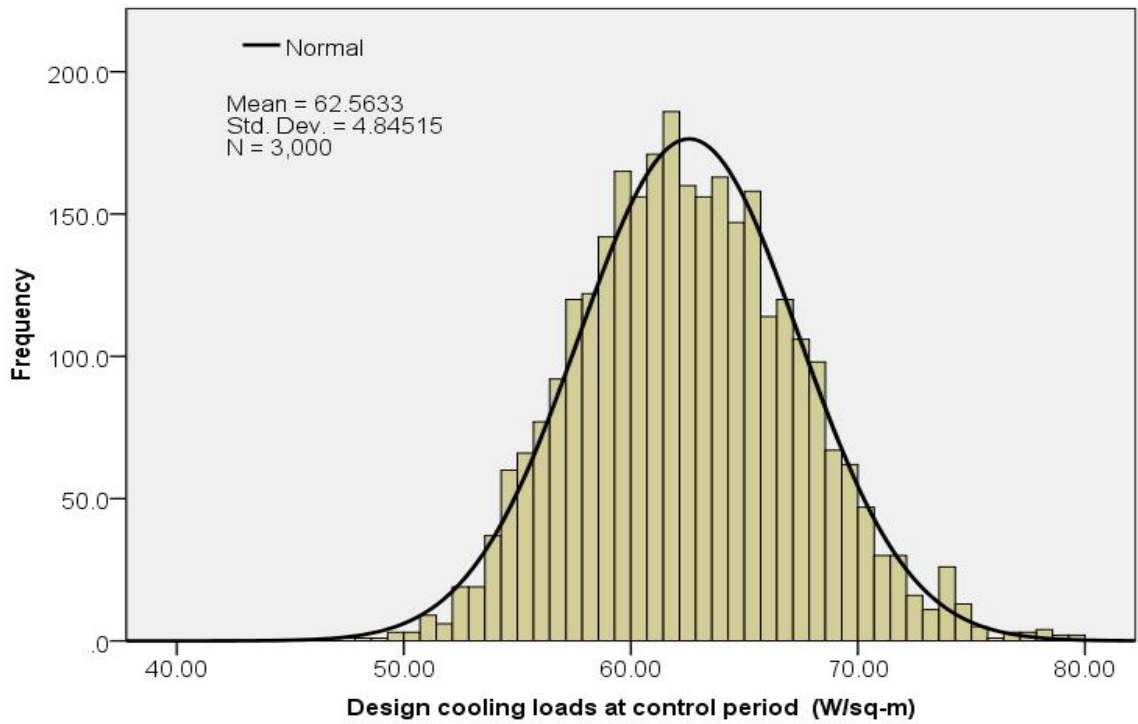


Figure 8 Example distribution of 3000 design cooling loads (control data)

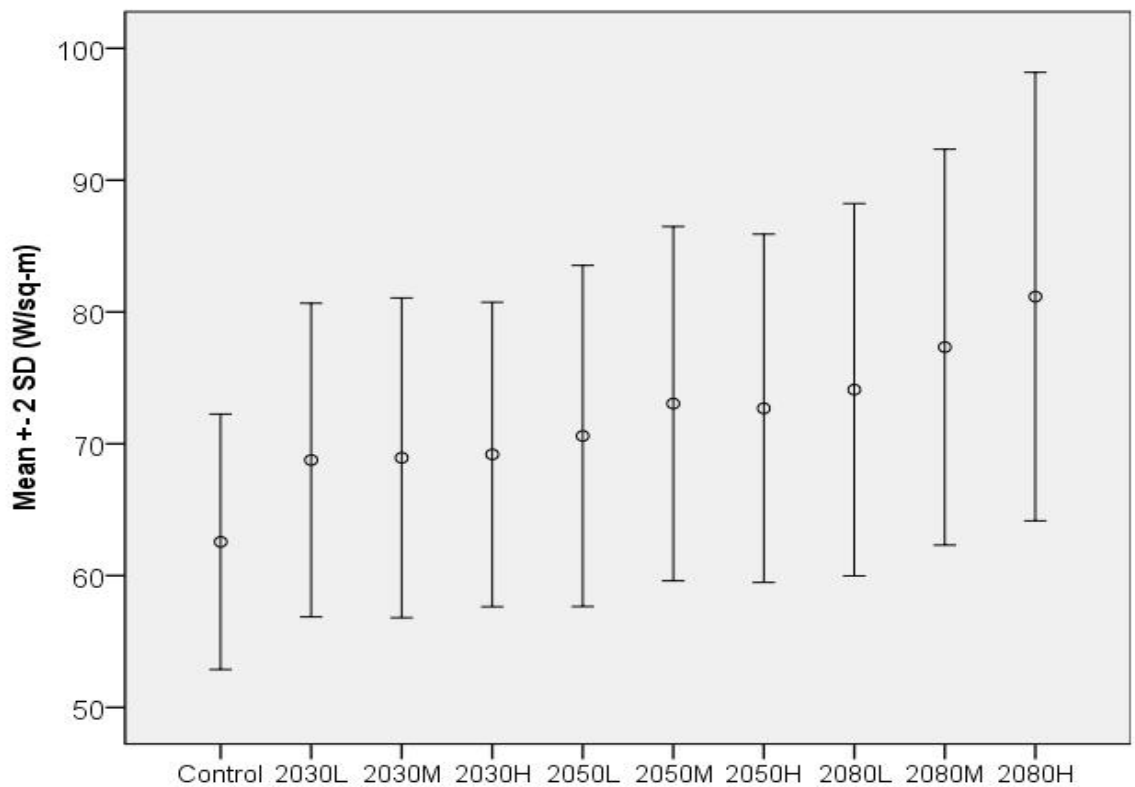


Figure 9 Example distribution based on 3000 control and future design cooling loads

6. Conclusions

It is becoming abundantly clear that the design of energy and comfort services for buildings should take a whole-life perspective by considering the impact of, *inter alia*, climate change during building life. Measures to mitigate the impact of climate change as well as to make provision for the possible future addition of air conditioning in buildings planned and constructed today are better considered at design outset rather than when they become necessary during a future refurbishment episode. To assist with the provision of design data for this, a method for generating future Design Reference Years consisting of near extreme summer months and near extreme winter months woven into an existing Test Reference Year is described. Three near extreme months are selected for each season in order to provide results that are suitable for buildings with the highest thermal mass. Data are selected from 3000 years of time series data from the UKCP09 Weather Generator⁴ based on 85th and 99th percentile risk thresholds. The results compare favourably with alternative DRY methods produced by other research groups.

To avoid the need for large numbers of energy simulations in order to predict future cooling load changes as climate change takes effect, a simple load estimating procedure is proposed which enables a simple zone cooling load model to be fitted to results from a single reference simulation using existing weather data. The simple model may then be used repeatedly to generate a large number of future probabilistic design cooling load results from which results can be obtained at any chosen risk percentile.

This work has dealt with sensible zone cooling loads only applied to non-domestic buildings. Further work is needed to consider simplified procedures for analysing future overheating risk and future design space heating loads in both domestic and non-domestic buildings as well as the impact of other variables such as those influencing humidity loads. There is a need for ongoing work to take account of likely future changes in building thermal insulation standards as new editions to building (and other) regulations come into force. There is also a need to investigate alternative air conditioning methods in order to identify plant, control and thermal storage options that operate best in conditions of a changing climate.

Acknowledgements

This work is part of a programme of research funded by the Engineering and Physical Sciences Research Council in the UK (grant reference EP/F038135/1). The authors acknowledge with thanks the sample Design Reference Year data supplied for comparison by Dr Richard Watkins at Manchester University and the Design Summer Year data supplied by Dr David Coley at Exeter University.

References

1. UK Climate Projections. Available from: <http://ukclimateprojections.defra.gov.uk/>. London: Department of Environment, Food and Rural Affairs. (Accessed: 27th August 2010; version 1).
2. Hulme M, Jenkins GJ, Lu X, Turnberry JR, Mitchell TD, Jones RG, Lowe J, Murphy JM, Hassell D, Boorman P, McDonald R, Hill S. *Climate Change Scenarios for the United Kingdom: The UKCIP02 Scientific Report*. Norwich: Tyndall Centre for Climate Change Research, University of East Anglia, 2002.
3. *CIBSE TM48: Use of climate change scenarios for building simulation: the CIBSE future weather years*. London: Chartered Institution of Building Services Engineers, 2009.

4. Kilsby CG, Jones PD, Burton A, Ford AC, Fowler HJ, Harpham C, James P, Smith A and Wilby RL. A daily weather generator for use in climate change studies. *Env. Modelling and Software* 2007; 22: 1705-19.
5. Tham Y, Muneer T, Levermore GJ, Chow D. An examination of UKCIP02 and UKCIP09 solar radiation data sets for the UK climate related to their use in building design. *Building Serv. Eng. Res. Technol.* 2011; 32(3): 207-28.
6. Watkins R, Levermore GJ, Parkinson JB. Constructing a future weather file for use in building simulation using UKCIP09 projections. *Building Serv. Eng. Res. Technol.* 2011; 32(3): 293-9.
7. Eames M, Kershaw T, Coley D. The creation of wind speed and direction for the use in probabilistic future weather files. *Building Serv. Eng. Res. Technol.* 2011; 32(2): 143-58.
8. Du H, Underwood CP, Edge JS. Generating Test Reference Years from the UKCIP09 Projections and their application in building energy simulation. *Building Serv. Eng. Res. Technol.* 2011; DOI: 10.1177/0143624411418132.
9. Chow DHC, Levermore GJ, Jones P, Lister D, Laycock PJ, Page J. Extreme and near-extreme climate change data in relation to building and plant design. *Building Serv. Eng. Res. Technol.* 2002; 23(4): 233-42.
10. Levermore GJ, Parkinson JB. Analyses and algorithms for new Test Reference Years and Design Summer Years for the UK. *Building Serv. Eng. Res. Technol.* 2006; 27(4): 311-26.
11. Jentsch MF, Bahaj AS, James PAB. Climate change future proofing of buildings – generation and assessment of building simulation weather files. *Energy and Buildings* 2008; 40(12): 2148-68.
12. Belcher SE, Hacker JN, Powell DS. Constructing design weather data for future climates. *Building Serv. Eng. Res. Technol.* 2005; 26(1): 49-61.
13. Chow DHC, Levermore GJ. The effects of future climate on heating and cooling demands in office buildings in the UK. *Building Serv. Eng. Res. Technol.* 2010; 31(4): 307-24.
14. Eames M, Kershaw T, Coley D. On the creation of future probabilistic design weather years from UKCIP09. *Building Serv. Eng. Res. Technol.* 2011; 32(2): 127-42.
15. Kershaw T, Eames M, Coley D. Comparison of multi-year and reference year building simulations. *Building Serv. Eng. Res. Technol.* 2010; 31(4): 357-70.
16. Watkins R, Levermore GJ. Quantifying the effects of climate change and risk level on peak load design in buildings. *Building Serv. Eng. Res. Technol.* 2011; 32(1): 9-20.
17. Jenkins DP, Patidar S, Banfill PFG, Gibson GJ. Probabilistic climate projections with dynamic building simulation: Predicting overheating in dwellings. *Energy and Buildings* 2011; 43: 1723-31.
18. Lam JC, Wan KKW, Lam TNT, Wong SL. An analysis of future building energy use in subtropical Hong Kong. *Energy* 2010; 35: 1482-90.
19. Chen T, Chen Y, Yik FWH. Rational selection of near-extreme coincident weather data with solar irradiation for risk-based air-conditioning design. *Energy and Buildings* 2007; 39: 1193-201.
20. Smith ST, Hanby VI, Harpham C. A probabilistic analysis of the future potential of evaporative cooling systems in a temperate climate. *Energy and Buildings* 2011; 43: 507-16.
21. *EnergyPlus Energy Simulation Software*. Available at: <http://apps1.eere.energy.gov/buildings/energyplus/> (accessed 9th May 2011). U.S. Department of Energy.
22. CIBSE Guide A. *Environmental Design – Chapter 2 External Design Data*. London: Chartered Institution of Building Services Engineers, 2006.
23. Department for Communities and Local Government: National Calculation Method SBEM Software. [Online] Available at: <http://www.ncm.bre.co.uk/> (accessed 10th May 2011).

MODELLING THE IMPACTS OF NEW UK FUTURE WEATHER DATA ON A SCHOOL BUILDING

Hu Du, Jerry Edge, Chris Underwood
School of Built and Natural Environment, Northumbria University,
Newcastle upon Tyne, United Kingdom

ABSTRACT

To investigate the impact of the new UK Climate Projections on building performance, a primary school building has been simulated with help of a dynamic building performance simulation package (EnergyPlus Version 6) using 4 sets of future test reference year data which were produced by the UK Chartered Institution of Building Services Engineers, Exeter University, Manchester University and Northumbria University respectively.

Indoor operative temperatures, heating and cooling energy demand of the sample building at three locations (Edinburgh, Manchester and London) under future climate conditions (time slices: 2020s 2030s, 2050s and 2080s; carbon emission scenarios: low, medium and high) were calculated to compare the impacts of four sets of future weather data on building performance.

INTRODUCTION

It is widely agreed that the increase of greenhouse gases emissions has caused, or at least contributed significantly to, the observed changes in global climate conditions. The Inter-governmental Panel on Climate Change fourth assessment report (IPCC, 2007) stated that world temperatures could rise by between 1.1 and 6.4 °C during the 21st century.

In the UK, designing buildings towards future climate conditions were widely implemented by building designers and building simulation practitioners. Hence, future weather data were used intensively for building simulation. The impact of the future warming of climate on building performance (such as thermal comfort conditions and heating/cooling energy consumption) has been predicted previously based on different climate model, however for the UK Climate Projection 2009 (the most comprehensive package of climate information for the 21st century to be made available for the UK to date), very few research has been done to investigate its impacts on buildings. As one of most important input parameter for building simulation, weather data directly influence the reliability and accuracy of simulation results; therefore, it is crucial to let practitioners understand the usage of appropriate future weather data for building simulation.

The UK Climate Projections

For the UK, two projections were made available in the last decade. The first one, the UKCIP02 climate change scenarios (UK Climate Impacts Programme, 2002) were generated in 2002 from a climate model developed by the Hadley Centre. In 2009, the latest version, the UK Climate Projections 09 (UKCP09), was released to supersede the UKCIP02 projections.

The UKCP09 Projections (Jenkins et al., 2009) indicated that the changes in summer mean temperatures were greatest in parts of Southern England (up to 4.2°C (in range of 2.2 to 6.8°C)) and least in the Scottish islands (just over 2.5°C (in range of 1.2 to 4.1°C)) from a 1970s baseline towards the 2080s (refer to the time slices definition in Table 1).

Table 1
Time slices definition

1970s	1960-1989
2020s	2010-2039
2030s	2020-2049
2050s	2040-2069
2080s	2070-2099

As a main product of the Projections, the UKCP09 Weather Generator (UK Climate Projections, 2010) can generate a set of daily and hourly future climate variables at different time periods (2020s to 2080s) and carbon emission scenarios (low, medium and high) for every 5km² in the UK. For each specific location, time period and carbon emission scenario, 100 sets of 30-year period hourly and daily data could be generated by the Weather Generator to indicate 100 probabilities of future weather for 30-year period. The hourly climate variables were temperature, vapour pressure, relative humidity, sunshine hours, diffuse and direct horizontal radiation. This provided an opportunity to construct future weather files for building simulation.

Weather data for simulation

Due to the computational limit of most building simulation packages, there was a need to generate typical year data (also called test reference year data) from the Climate Projections Weather Generator raw data (multi-year data).

The UK Chartered Institution of Building Services Engineers (CIBSE, 2009) released future hourly weather data (named CIBSE data) in 2008 which incorporated the UKCIP02 Projections, for three time lines (2020s, 2050s and 2080s) and for four carbon emissions scenarios (low, medium-low, medium-high and high). The method (Belcher, Hacker & Powell, 2005) used to create this CIBSE future weather data was to ‘morph’ the historical weather data, thus retaining historical weather patterns in the future data.

Due to the probabilistic feature of the UKCP09 Projections, for a specific location, time slice and carbon emission scenario, 3000 years hourly data (100 sets of 30 years data) were provided by the Weather Generator (UK Climate Projections, 2010). Researchers (Eames, Kershaw & Coley, 2011) at Exeter University created a method of generating five Probabilistic Reference Year data from a set of UKCP09 data. In their method, for each calendar month, 100 sets of typical month data were derived from 3000 months data, and then they were ranked in ascending order of monthly mean temperatures. Five months at 10th, 33rd, 50th, 66th and 90th percentile positions were then picked to construct five sets of Probabilistic Reference Year data. In this article, only the 50th percentile data (named Exeter University data) were employed to do the building simulations.

Researchers (Watkins, Levermore & Parkinson, 2011) at Manchester University developed another method of generating one future test reference year data (named Manchester University data) from a set of UKCP09 data. The method followed BS EN ISO 15927-4:2005 (ISO, 2005) standard, but they directly applied the method to 3000 years data, rather than 20-30 years historical data.

A similar method (Du, Underwood & Edge, 2011) was implemented in Matlab by authors at Northumbria University to quickly extract a future Test Reference Year from UKCP09 data for a specific location, time slice and carbon emission scenario. This approach was more computationally efficient.

The Northumbria University dataset covered three time lines (2030s, 2050s and 2080s) and three carbon emissions scenarios (Low, Medium and High); whilst the Manchester University dataset only covered two emission scenarios (Low and High) for the 2020s, 2050s and 2080s. More detailed information about time lines and carbon emission scenarios of weather data from four organisations are listed in Table 2. The letters in column 2 of Table 2 were used to indicate time lines and emission scenarios in Figures 2-8.

The maximum daily global horizontal solar radiations of all typical year data at Edinburgh, Manchester and London from four organisations’ datasets are plotted in Figure 2. There was a significant difference between the maximum values

of three universities’ data (derived from the UKCP09 Projections) and the values from CIBSE data (based on the UKCIP02 Projections). This might be attributed to the changing clarity of sky condition (Tham & Muneer, 2010) in the UKCP09 Projections.

Table 2
Weather data for simulation

WEATHER DATA FOR SIMULATION		
CIBSE	C	Control data (1983-2004)
	2L	2020s low carbon emission scenario
	ML	2020s medium low carbon emission scenario
	MH	2020s medium high carbon emission scenario
	2H	2020s high carbon emission scenario
	5L	2050s low carbon emission scenario
	ML	2050s medium low carbon emission scenario
	MH	2050s medium high carbon emission scenario
	5H	2050s high carbon emission scenario
	8L	2080s low carbon emission scenario
	ML	2080s medium low carbon emission scenario
	HL	2080s medium high carbon emission scenario
Exeter Uni	8H	2080s high carbon emission scenario
	C	Control data (1960-1989)
	3M	2030s medium carbon emission scenario
	3H	2030s high carbon emission scenario
	5M	2050s medium carbon emission scenario
	5H	2050s high carbon emission scenario
Manchester Uni	8M	2080s medium carbon emission scenario
	8H	2080s high carbon emission scenario
	C	Control data (1960-1989)
	2L	2020s low carbon emission scenario
	2H	2020s high carbon emission scenario
	5L	2050s low carbon emission scenario
Northumbria Uni	5H	2050s high carbon emission scenario
	8L	2080s low carbon emission scenario
	8H	2080s high carbon emission scenario
	C	Control data (1960-1989)
	3L	2030s low carbon emission scenario
	3M	2030s medium carbon emission scenario
	3H	2030s high carbon emission scenario
	5L	2050s low carbon emission scenario
	5M	2050s medium carbon emission scenario
5H	2050s high carbon emission scenario	

The annual maximum, annual minimum, annual mean, summer mean and winter mean dry bulb temperatures of test reference year data at Edinburgh, Manchester and London from four organisations (CIBSE, Exeter University, Manchester University and Northumbria University) are illustrated in Figure 3. The increase of annual mean and summer mean temperatures from four organisations’ datasets were identical although their methods of generating typical year weather data were different. The maximum

hourly temperature and winter mean temperatures from three universities (derived from the UKCP09 Projections) were generally lower than CIBSE data (based on the UKCIP02 Projections). Both projections show that the mean temperature in Edinburgh will be about 3 °C lower than the mean temperature in London, while the mean temperatures of Manchester lies between the temperatures of Edinburgh and London.

SIMULATION

Building

A recently built primary school (Figure 1) was selected for building performance simulation using the future weather data sets described in Table 2, because the users (age from 4 to 11) of the building are sensitive to extremes of thermal comfort which are very likely to occur in future according to climate projections.

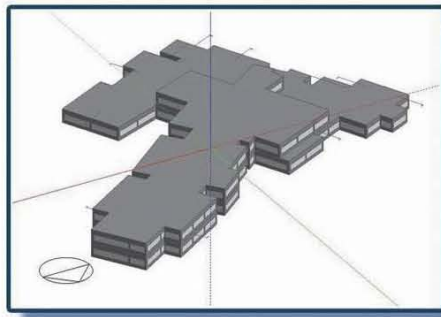


Figure 1 Primary school building

This two-storey building comprised of 25 zones which included 14 main occupied zones, such as meeting rooms, classrooms, offices and a library. The main occupied area was 3081.8 m² out of 4246.4 m² of gross floor area.

The occupancy densities and occupied period profiles of all zones were configured according to the UK National Calculation Method database (The Department for Communities and Local Government, 2010). For example, classrooms were occupied from 8:01 to 17:00 with difference occupancy densities at school term days.

Table 3
Building U-value and thermal capacity

	U-VALUE (W/m ² K)	KM (kJ/m ² K)
External wall	0.350	134.9
External roof	0.250	\
Groundfloor	0.257	\
Partition wall	1.690	126.1
Double glazing	2.725	\

The U-values and thermal capacities of the building material are shown in Table 3. The total solar transmission (Solar Heat Gain Coefficient, SHGC) of glazing was 0.742 and the area of glazing was 40% of the façade area.

Modelling assumptions

The same building was assumed to be located in three major cities in the UK: Edinburgh (55.95N, 3.34W), Manchester (53.36N, 2.28W) and London (51.48N, 0.45W) in order to compare the climate change impacts at different locations cross the UK.

A constant effective mean allowance for infiltration of 0.5 air changes per hour was applied to all zones, and additionally, an allowance for natural fresh air ventilation during occupied hours of 10L/s per person was applied for all the simulations.

Three simulations were conducted for the building at each specific location, timeline and carbon emission scenario. These simulations were ‘freefloat’ (no heating or cooling), heating and cooling conditions.

The ‘freefloat’ condition simulation was aimed to generate the summer, winter and annual mean indoor operative temperatures at occupied hours and the percentage of occupied hours over 28 °C. Apart from the basic infiltration and fresh air allowance, 4 air changes per hour of natural ventilation were added when indoor air temperatures went over 25 °C during the occupied hours and the indoor air temperatures were higher than the outdoor temperature. This assumes that users would open windows when they feel warm inside rooms.

For the heating and cooling simulations, profiles of all main occupied zones were configured according to the UK National Calculation Method database (The Department for Communities and Local Government, 2010). In brief, heating setpoints ranged from 18 to 22 °C, and cooling setpoints ranged from 23 to 25 °C depending on the usage of rooms.

To test the impact of different future weather data only on existing building, it was assumed that building materials, user behaviour and HVAC systems would be as they would be defined at the present time. Although it is debatable that this assumption could stand until 2080s because of the adaptive thermal comfort behaviour of occupancy, policy, economy and technology influence on occupancy. For this study, cooling and heating energy demand of each zone and the building were simulated. This energy demand does not include HVAC system energy consumption, because HVAC system is going to be replaced at 20-30 years cycle in future, and the efficient of system will change as well.

The usage of school is very unlikely to change in the future. The type of fuel source could influence total energy consumption, but it would not influence heating and cooling energy demand.

RESULTS AND DISCUSSION

Winter mean temperatures

Figure 4 shows results of indoor mean operative temperatures at occupied hours in winter for each zone and building at different locations, time slices and carbon emission scenarios. The occupied hours are working hours of weekdays in December, January and February, and they do not include Christmas (22nd Dec- 9th Jan) and middle term holiday (13th Feb- 20th Feb).

The top, middle and bottom rows show simulation results of the building at the Edinburgh, Manchester and London locations respectively.

The figure was broken into 4 columns to represent results from 4 organisations' datasets (CIBSE, Exeter University, Manchester University and Northumbria University, ordered from left to right in the figure).

Tests under the X axis indicate timelines and carbon emission scenarios (refer to Table 2).

The symbol 'x' in the figure indicates the mean temperature of one zone, and the bar in the figure indicates the mean temperature of the whole building. The pink, green and red bars in the figure highlight control, 2050 high emission scenario and 2080 high emission scenario results respectively which were common in the 4 organisations weather files.

This pattern of visualising the results was also used in Figures 5 and 6.

Figure 4 shows that results from the CIBSE control period were higher than other three control periods. This is because the CIBSE control weather data was historical recorded data from 1983-2004, whilst the other control data was simulated historical data for 1960-1989. For future timelines, results were identical, and they indicated that there would be a 2-4 °C mean operative temperature increase inside the building in winter by the 2080s high carbon emission scenario.

Summer mean temperatures

Figure 5 shows results of indoor mean operative temperatures at occupied hours in summer for each zone and building at different locations, time slices and carbon emission scenarios. The occupied hours are working hours of weekdays in June, July and August. Middle term (29th May- 5th Jun) and summer holiday (24th July- 4th Sep) are not included.

For London, results from the UKCP09 Projections (three universities' datasets) are similar to results from the UKCIP02 Projections (CIBSE dataset), however, for Edinburgh, the UKCP09 Projections indicate warmer indoor conditions in summer than the UKCIP02 Projections.

The Figure also shows that overheating issues would be significant by the second half of this century, especially in London, because indoor summer mean operative temperature could reach 28 °C.

Overheat percentages

CIBSE Guide A (CIBSE, 2006) recommends 1% of annual occupied hours over an operative temperature of 28 °C as a criteria to assess the overheating risk of a school building. Figure 6 demonstrates the potential overheating situation for this building.

This figure shows that the duration of overheating by the end of this century would be 4 times that of current conditions.

Similar to summer mean temperature results, both UKCP09 and UKCIP02 Projections in London indicate similar overheat percentages, but for northern city (Edinburgh), UKCP09 indicate more overheat risks in late part of this century than UKCIP02. The overheat percentage from Exeter data is significantly higher than the percentage from other organizations.

Heating energy demand

Figure 7 shows the simulated annual heating energy demand for the building at different locations, time slices and carbon emission scenarios.

The blue bar indicates heating energy demand per gross floor area, and the blue and dark red bar together represent heating energy demand per treated floor area. The similar format was used in Figure 8 (for cooling energy demand).

Figure 7 shows a decreasing trend of heating energy demand. This would be one of benefits from a warmer winter in the future.

For control period, there is a difference between three universities' results and CIBSE's results due to the timeline difference. For future periods, the results are identical.

Cooling energy demand

Figure 8 gives the simulated annual cooling energy demand (sensible room load only) for the building at different locations, time slices and carbon emission scenarios. Sensible room load is the main cooling load for the UK buildings at this moment, and there is no evidence showing the change of relative humidity in future.

Both UKCIP02 (CIBSE data) and UKCP09 (three universities datasets) projections give identical results for the building in London, while the UKCP09 projections indicate more cooling energy demand in Edinburgh than UKCIP02 projections.

Figure 8 also shows that annual cooling energy demand could be tripled by the 2080s for the high carbon emission scenarios compared with the baseline results.

CONCLUSION

In this work, simulation results from four organisations' future test reference year data were compared. All of them show that summer overheating and higher cooling energy demand are very likely to occur in the second half of this century,

though winter heating energy consumption could reduce.

In general, there is a good agreement among results from all weather data sets, although the CIBSE dataset and the three universities' datasets have slightly different predictions for the three cities due to geographical distribution. Three universities' test reference year results are identical although their methods of generating test reference year data are different.

This work provides an example for practitioners to understand the agreement and differences between four sets of future weather data, and it gives information for policy makers to choose appropriate weather data to conduct future proofed building design assessment.

Future work is required in four areas. First, a comparison of future Design Summer Year data and Design Reference Year data from four organisations will be conducted, as those data are important for peak load calculation and risk analysis. Second, more building types will be included as case studies, as they will give better understanding of how buildings perform in the future. Third, the adaptation towards future climate would be investigated. Fourth, user behaviour changes due to policy and economy factors will be investigated.

ACKNOWLEDGEMENTS

The research described in this paper is funded by the Engineering and Physical Sciences Research Council (EPSRC) under grant EP/F038135/1 'COincident Probabilistic climate change weather data for a Sustainable built Environment (COPSE)' project. We would thank the following researchers for providing weather data: Dr. Richard Watkins at Manchester University and Dr. David Coley at Exeter University.

REFERENCES

Belcher, S., Hacker, J. & Powell, D. (2005) 'Constructing design weather data for future climates', Building Service Engineering Research and Technology, 26 (1), pp. 49-61.

CIBSE. (2006) Environmental Design: CIBSE Guide A. London: Chartered Institution of Building Services Engineers.

CIBSE. (2009) TM48: The use of Climate Change Scenarios for Building Simulation: the CIBSE

Future Weather Years. London: Chartered Institution of Building Services Engineers.

Du, H., Underwood, C. P. & Edge, J. S. (2011) 'Generating test reference years from the UKCP09 projections and their application in building energy simulations', Building Services Engineering Research and Technology (accepted).

Eames, M., Kershaw, T. & Coley, D. (2011) 'On the creation of future probabilistic design weather years from UKCP09', Building Services Engineering Research and Technology, 32 (2), pp. 127-142.

IPCC (2007) Climate change 2007: the physical science basis: Contribution of Working Group I. Cambridge, UK and New York: Cambridge University Press.

ISO (2005). ISO 15927-4: Hourly data for assessing the annual energy use for heating and cooling.

Jenkins, G. J., Murphy, J. M., Sexton, D. S., Lowe, J. A., Jones, P. & Kilsby, C. G. (2009) UK Climate Projections: Briefing report. Exeter: Met Office Hadley Centre.

Tham, Y. & Muneer, T. (2010) 'Sol-air temperature and daylight illuminance profiles for the UKCP09 data sets', Building and Environment.

The Department for Communities and Local Government (2010) National Calculation Method SBEM software. [Online]. Available at: <http://www.ncm.bre.co.uk/> (Accessed: 10th May 2010).

UK Climate Impacts Programme (2002) Climate Change Scenarios for the United Kingdom: The UKCIP02 Scientific Report.

UK Climate Projections (2010) UK Climate Projections 2009 Weather Generator User Interface (Version 1). [Online]. Available at: <http://ukclimateprojections-ui.defra.gov.uk/ui/admin/login.php> (Accessed: 27th August 2010).

Watkins, R., Levermore, G. & Parkinson, J. (2011) 'Constructing a future weather file for use in building simulation using UKCP09 projections', Building Services Engineering Research and Technology, 32 (3), pp. 293-299.

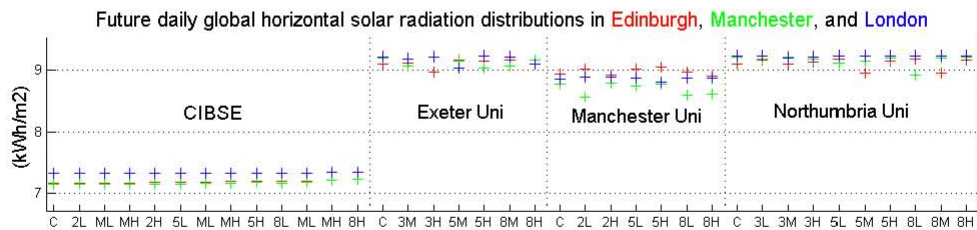


Figure 2 Maximum daily global horizontal solar radiation in Edinburgh, Manchester, and London

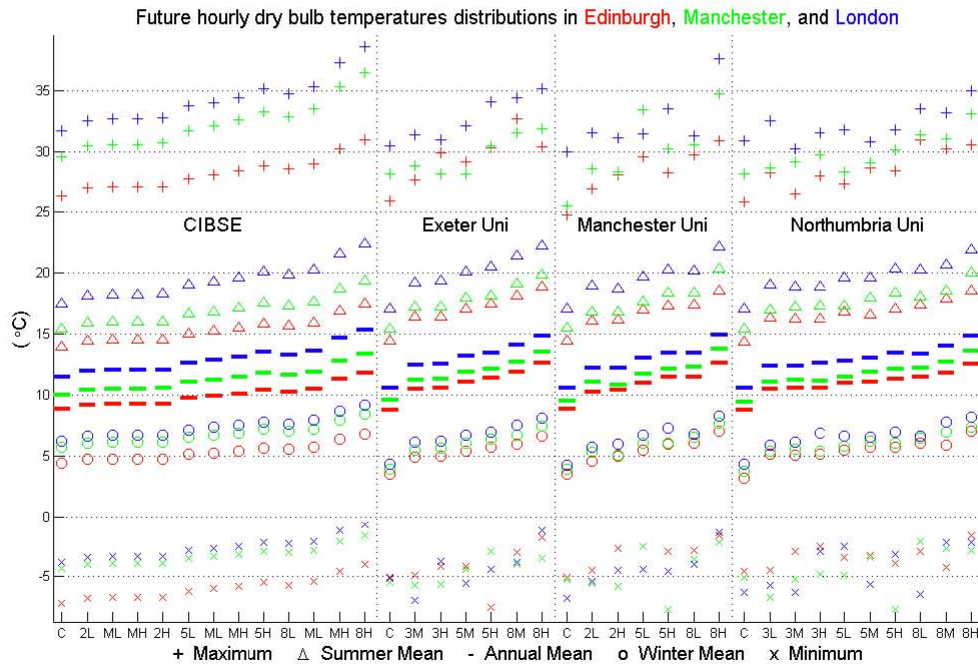


Figure 3 Hourly dry bulb temperatures distributions in Edinburgh, Manchester, and London

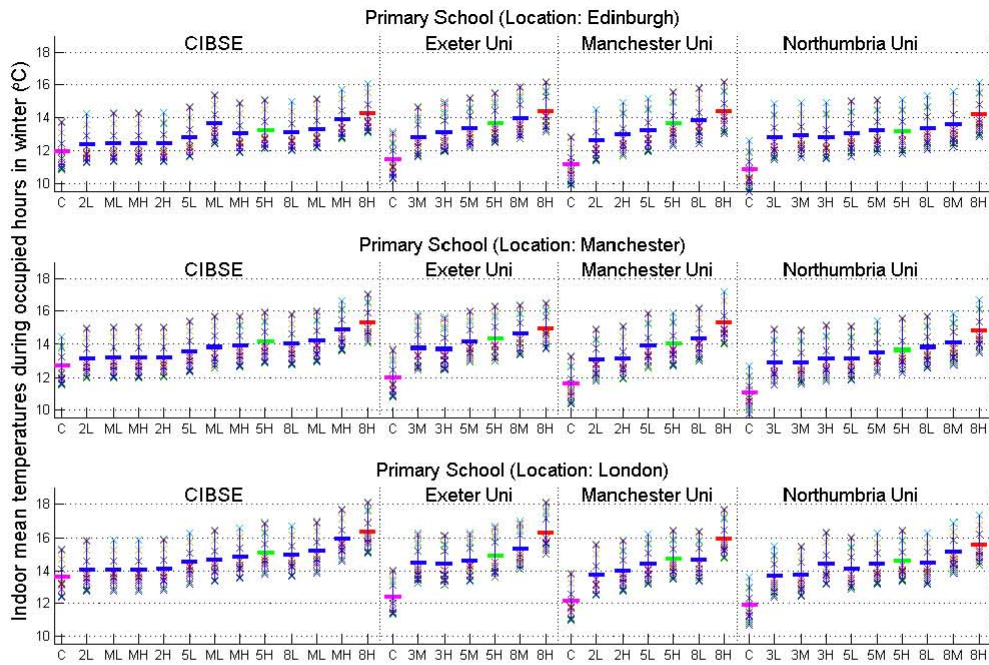


Figure 4 Indoor mean temperatures during occupied hours in winter

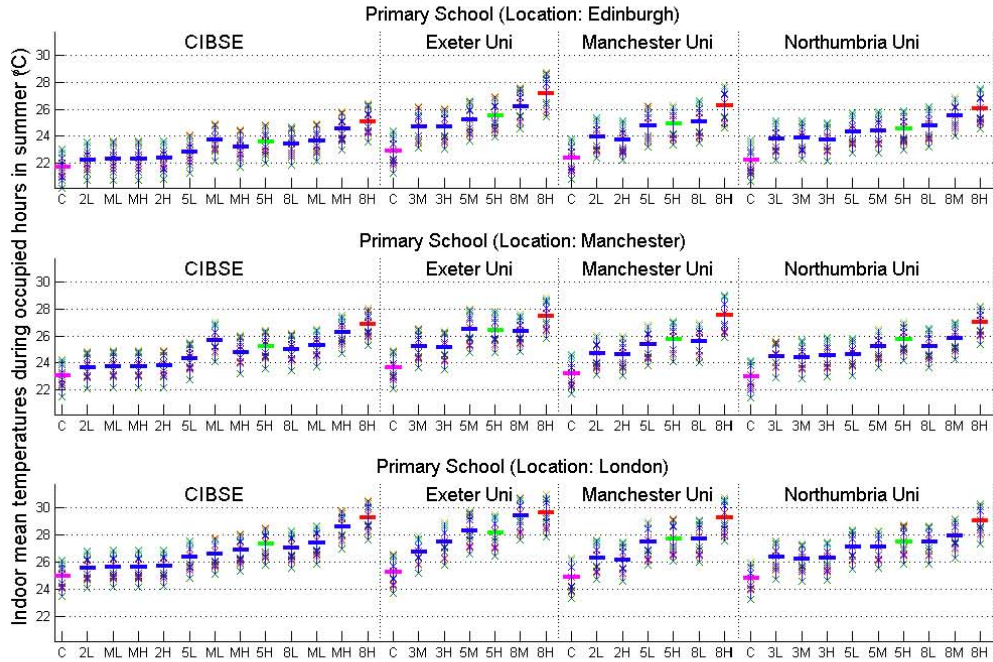


Figure 5 Indoor mean temperatures during occupied hours in summer

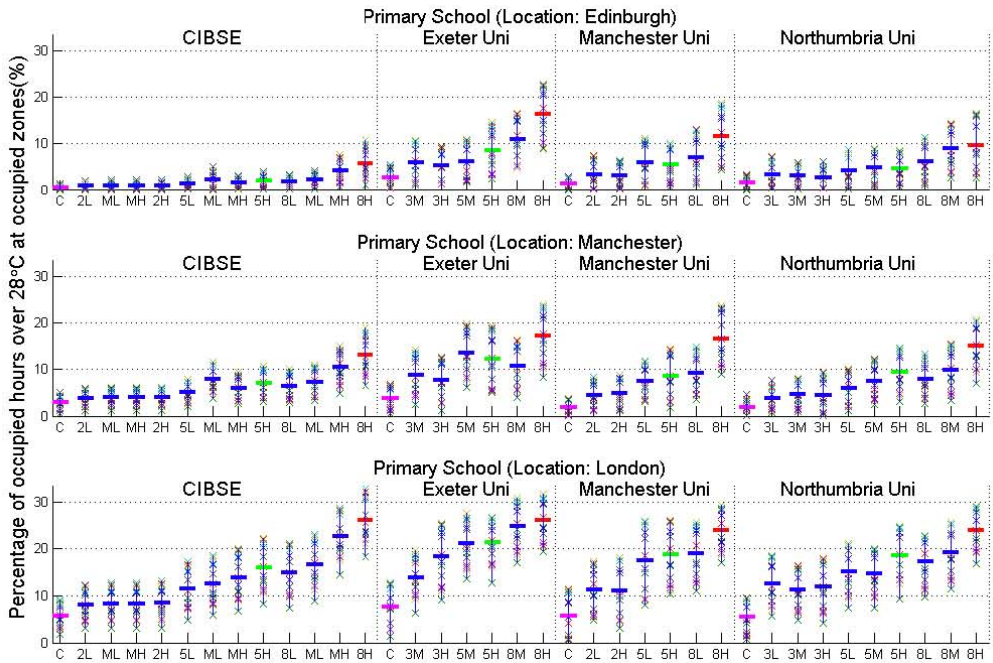


Figure 6 Percentage of occupied hours over 28°C at occupied zones

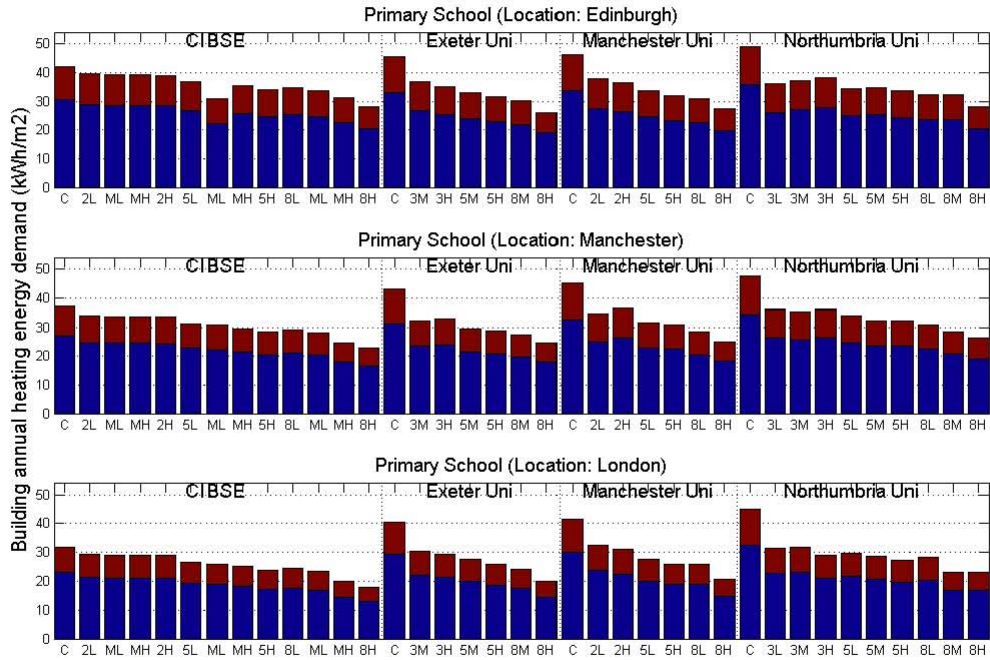


Figure 7 Building annual heating energy demand

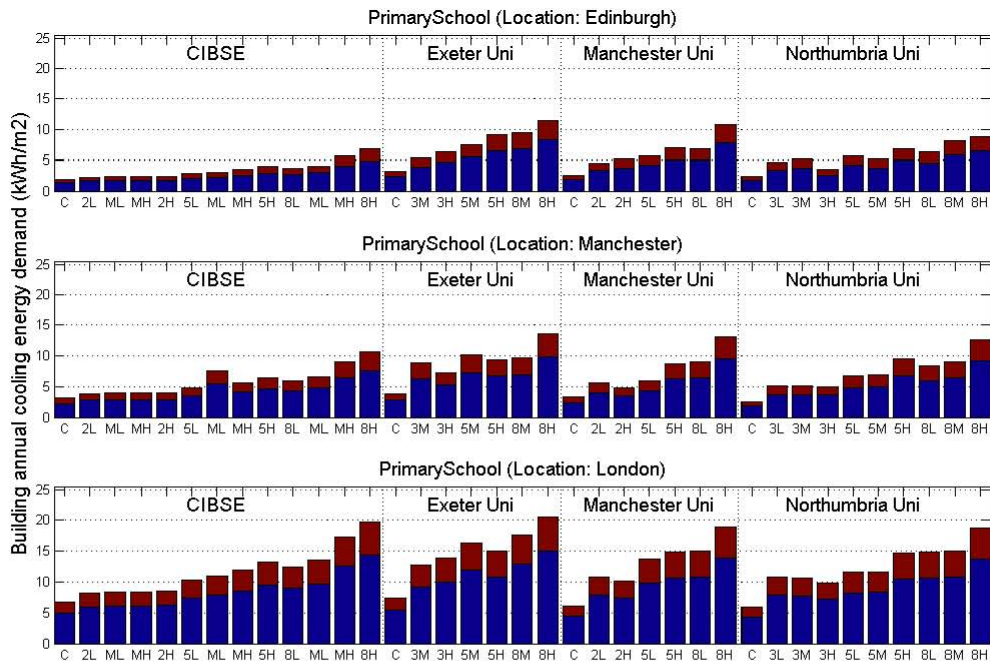


Figure 8 Building annual cooling energy demand

Modelling the impact of a warming climate on commercial buildings in the UK

Hu Du, Chris Underwood and Jerry Edge

University of Northumbria, Newcastle upon Tyne, UK

Corresponding email: hu.du@northumbria.ac.uk

SUMMARY

The impact of a warming climate on the internal operative temperatures of commercial buildings in the UK is considered in this article. The CIBSE future weather years based on the United Kingdom Climate Impacts Programme's 2002 projections are applied using dynamic thermal modelling of a set of 14 buildings with widely differing construction types and patterns of use. Predictions corresponding to 2020, 2050 and 2080 were carried out together with one control case (1989) under 4 alternative carbon emission scenarios. Results show a strong linear relationship between internal temperature increase and external dry bulb temperature increase for overall July peak, overall July average and average of July zone peak temperatures. The gradient of this increase varies between 0.817 and 1.009 suggesting that future building design and management processes might expect internal operative temperature increases of one degree (or a little under) for each degree of global temperature increase.

INTRODUCTION

Predictions published by the Intergovernmental Panel on Climate Change (IPCC) indicate an increase in global average surface temperature in different scenario ranges of 1.1–2.9°C to 2.4–6.4°C from a 1990s baseline towards the end of the 21st century [1]. The immediate impact of this on the built environment will be increased internal temperatures particularly during summer. Since many of the commercial buildings in the UK are either not air conditioned or partially air conditioned, the implications of this for health and well-being are profound. Many of the buildings that will be in use in the later part of this century already exist. It is therefore of considerable interest to establish how these building will behave as global warming takes effect.

Previous work has been done on the development of weather data suitable for use in energy simulations of buildings [2,3]. Most of this work has focused on adjusted time series methods (or 'morphing') in which predicted monthly mean climate variables from general circulation models are used to stretch and scale the time series data of a current weather file such that the mean statistical properties of the adjusted current file are the same as the predictions.

Other studies (including the work reported here) have dealt with the application of future weather files using simulation modelling to predict the likely behaviour of

buildings in the future in response to a warming climate [4,5,6]. Much of this work has focused on housing.

The aim of this work is to estimate how internal comfort temperatures in non air conditioned commercial buildings in the UK are likely to change during the next 70 years. The work will adopt a dynamic thermal modelling approach and will make use of the CIBSE 'future weather years' data set [7]. The objectives of the work were:

1. To select a contrasting sample of existing commercial buildings and submit them to dynamic thermal modelling.
2. Generate internal thermal responses under 'free float' conditions in summer based on a current (control) climate data set as well as predicted future climate data under a variety of global carbon emission scenarios.
3. Show how internal comfort temperatures are likely to evolve in response to global warming during the present century.
4. Compare the results with predictions carried out in other studies for alternative building types.

METHOD

Dynamic thermal modelling of a contrasting sample of UK commercial buildings formed the core of the method adopted in this work. EnergyPlus v4.0 with the DesignBuilder graphical user interface were used partly due to the wide international usage of the former by both research and practice communities, and partly due to the extensive historical testing and verification to which the program had previously been exposed [8].

The selected buildings were chosen with reference to the following criteria:

- Range – to ensure a contrasting spread of commercial building types.
- Realism – to use only recently constructed buildings, or buildings that had recently been given planning consent (and would, therefore, most likely get built).
- Treatment – to ensure buildings that, at least in UK terms, could conceivably be designed to operate without any specific requirement for air conditioning based on current climate data.
- Usage – to ensure a range of usage patterns; some buildings in continuous use and others operated during normal business hours only.
- To include buildings occupied by comfort-vulnerable groups such as children and the elderly.

Accordingly, details of 14 buildings were obtained to form the basis of the modelling and, though most of these buildings actually exist in different towns and cities in the UK, they were all exposed to the same climate data so that direct comparisons could be made. Thumbnail summaries of buildings selected are given in Figure 1 (a) – (n).

Most of the buildings have been either newly built or refurbished to recent standards – either the 2002 edition of the UK Building regulations, Part L, or the 2006 edition. Briefly, the 2002 edition sets minimum standards of u -values for external walls and roofs of $0.35\text{Wm}^{-2}\text{K}^{-1}$ and $0.25\text{Wm}^{-2}\text{K}^{-1}$ respectively, and external elevations glazed to a maximum of 35% of the overall envelope area using double air-cavity glazing. The maximum building leakage to be equivalent to $10\text{m}^3\text{h}^{-1}\text{m}^{-2}$ of facade at 50Nm^{-2} . The later 2006 edition of the Regulations sets the same ‘notional’ standard but goes on to require a 23-28% reduction in carbon emission beyond that standard. Buildings (b) and (g) were constructed to earlier standards; the main differences of which were slightly higher u -values in external elements (i.e. external walls and roofs).

Buildings (d) – (h), (j), (k), (m) and (n) were scheduled to operate during normal business hours with, in some instances, additional weekend opening such as in the cases of the Library and Theatre. All other buildings were scheduled for continuous use. Allowances were made for occupancy density and casual heat gains due to electrical equipment and lighting using loadings typical for the building types involved. During summer, all buildings were excited with a scheduled natural ventilation rate of 3 air changes per hour (this being a typical value that might be expected for mainly single-sided building spaces on still, or virtually still, warm summer days) plus a constant allowance for infiltration of 0.5 air changes per hour.





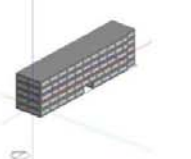
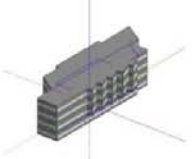

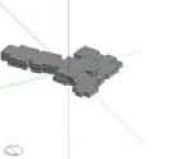

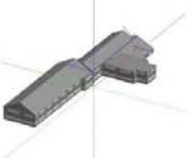

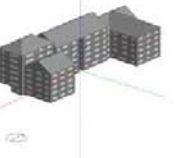
The thermal capacity of each zone was calculated using the simplified method set out in ISO 13786:2007 based on a maximum effective element thickness of 0.1m. Total values for each zone were added to give a building total and this value was then divided by the gross building floor area for comparative purposes. The construction element heat capacities ranged from $3.8\text{kJm}^{-2}\text{K}^{-1}$ to $312.8\text{kJm}^{-2}\text{K}^{-1}$ for all buildings (the building heat capacities per unit floor area are given in the footnotes of Figure 1).

The completed building models were simulated using the following alternative weather files from the CIBSE ‘future weather years’ set [7]:

- Control data: London 1989 design summer year
- Future set 1: London 2020 predictions based on ‘low’, ‘medium low’, ‘medium high’ and ‘high’ carbon emission scenarios
- Future set 2: London 2050 predictions based on ‘low’, ‘medium low’, ‘medium high’ and ‘high’ carbon emission scenarios
- Future set 3: London 2080 predictions based on ‘low’, ‘medium low’, ‘medium high’ and ‘high’ carbon emission scenarios

The ‘future weather years’ data are based on the use of the UK Meteorological Office’s general circulation model results of predictions of changes in monthly average values of climate variables for the period 1962-2100 based on four future carbon emission scenarios (‘low’, ‘medium low’, ‘medium high’ and ‘high’). These were first published under the United Kingdom Climate Impacts Programme in 2002

[9]. To obtain annual sets of hourly time series data required for energy simulations, the mean monthly predictions of changes to climate variables were used to generate time series adjustments (sometimes called 'morphing') to current time series weather data. These adjustments involved 'stretching' (i.e. scaling) and 'shifting' (i.e. time-adjusting) the current climate variable values so that they have the same monthly average statistics as the predicted climate change variable. Full details of the method can be found in Belcher *et al.* (2005).

<p>(a) <u>Aged persons home</u></p>  <p>$GFA = 5683(5345)m^2$ $\bar{C} = 425kJm^{-2}K^{-1}$ $Q_H = 22.8Wm^{-2}$</p>	<p>(b) <u>International airport</u></p>  <p>$GFA = 49795(37445)m^2$ $\bar{C} = 305kJm^{-2}K^{-1}$ $Q_H = 28.0Wm^{-2}$</p>	<p>(c) <u>Hotel</u></p>  <p>$GFA = 21275(17910)m^2$ $\bar{C} = 338kJm^{-2}K^{-1}$ $Q_H = 17.9Wm^{-2}$</p>	<p>(d) <u>Museum</u></p>  <p>$GFA = 12802(10518)m^2$ $\bar{C} = 300kJm^{-2}K^{-1}$ $Q_H = 33.8Wm^{-2}$</p>
<p>(e) <u>Multi-cell offices</u></p>  <p>$GFA = 4269(2977)m^2$ $\bar{C} = 466kJm^{-2}K^{-1}$ $Q_H = 32.7Wm^{-2}$</p>	<p>(f) <u>Open-plan offices</u></p>  <p>$GFA = 3779(2632)m^2$ $\bar{C} = 476kJm^{-2}K^{-1}$ $Q_H = 33.9Wm^{-2}$</p>	<p>(g) <u>Hybrid offices</u></p>  <p>$GFA = 8682(6172)m^2$ $\bar{C} = 357kJm^{-2}K^{-1}$ $Q_H = 27.8Wm^{-2}$</p>	<p>(h) <u>Primary school</u></p>  <p>$GFA = 4870(2844)m^2$ $\bar{C} = 285kJm^{-2}K^{-1}$ $Q_H = 38.4Wm^{-2}$</p>
<p>(i) <u>Prison</u></p>  <p>$GFA = 10063(9411)m^2$ $\bar{C} = 500kJm^{-2}K^{-1}$ $Q_H = 16.7Wm^{-2}$</p>	<p>(j) <u>Public archive building</u></p>  <p>$GFA = 2347(2201)m^2$ $\bar{C} = 470kJm^{-2}K^{-1}$ $Q_H = 29.2Wm^{-2}$</p>	<p>(k) <u>Secondary school</u></p>  <p>$GFA = 13200(8259)m^2$ $\bar{C} = 397kJm^{-2}K^{-1}$ $Q_H = 41.9Wm^{-2}$</p>	<p>(l) <u>Student hostel</u></p>  <p>$GFA = 9256(6053)m^2$ $\bar{C} = 503kJm^{-2}K^{-1}$ $Q_H = 17.2Wm^{-2}$</p>

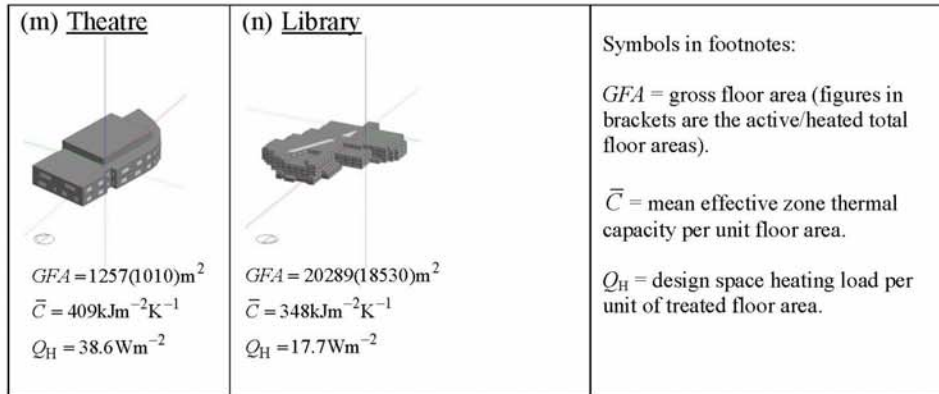


Figure 1. Building model set.

RESULTS

Results of simulated internal temperatures (T_{oi} , T_{ai} denoting operative and air temperatures respectively) are plotted against external (peak) temperature change, ΔT_e in figures 2 – 4.

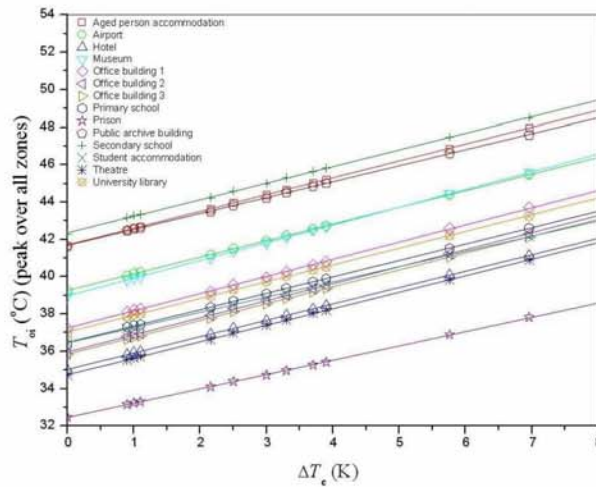


Figure 2. Internal overall peak operative temperature against external peak temperature change.

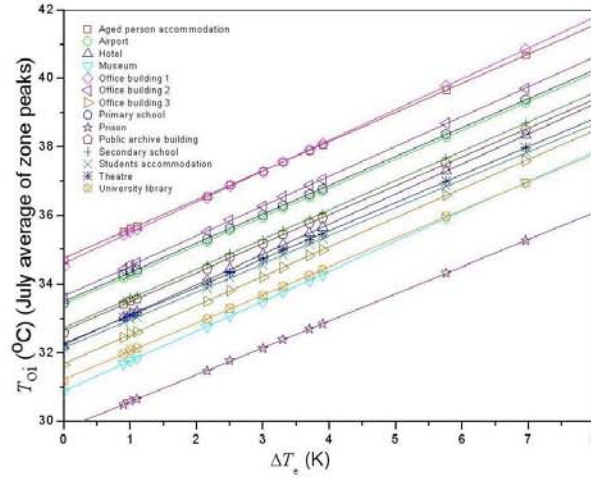


Figure 3. Predicted operative temperature – internal averaged zone peaks against external peak temperature change

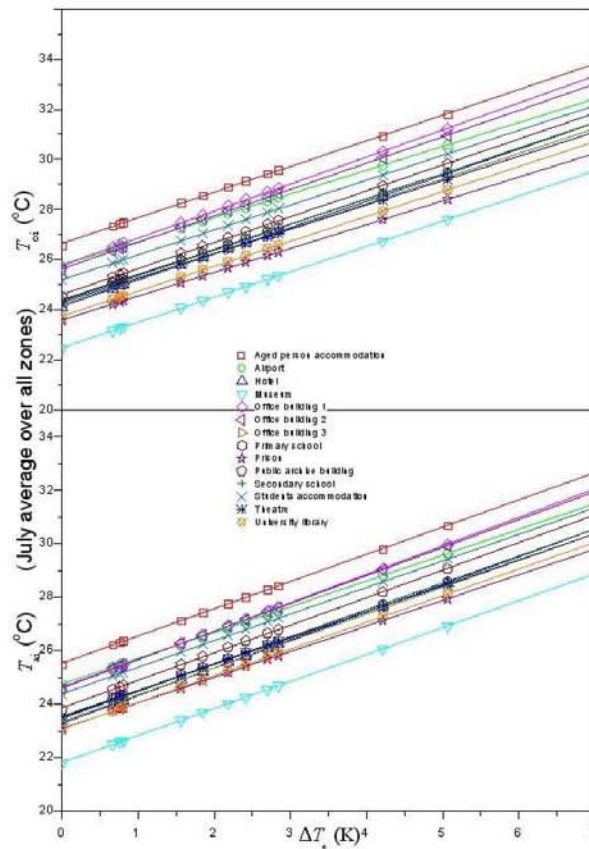


Figure 4. Comparison of predicted dry bulb and operative temperatures (average over all zones) against external average temperature change

DISCUSSION

A strong linear relationship between internal operative (or air) temperature and external air temperature is evident in all results obtained (figures 2-4). Figure 4 shows that the operative temperatures are generally slightly higher than the internal air temperatures as might be expected due to elevated internal surface temperatures arising from higher rates of solar radiation absorbed into these surfaces in summer.

Coley and Kershaw [6] define a 'global warming amplification factor' as:

$$C_{\text{mean}} = \frac{\Delta T_{i,\text{mean}}}{\Delta T_e} \quad \& \quad C_{\text{max}} = \frac{\Delta T_{i,\text{max}}}{\Delta T_e}$$

(where $\Delta T_{i,\text{mean}}$, $\Delta T_{i,\text{max}}$ is the difference in internal air or operative temperature at some time in the future based on mean and maximum values respectively and ΔT_e is the corresponding difference in external air temperature). Evidently, this is essentially the gradient of the slopes given in figures 2-4 based on either internal air temperature or operative temperature as appropriate.

Coley and Kershaw [6] dealt with houses, schools, apartments and offices. For their housing sample, they obtained results with the same linear characteristics as obtained in this work with warming gradients of between 0.817 and 0.958 (based on internal air dry bulb temperature only). In this work, a much wider range of commercial building types has been considered and the operative temperature was used as a better index for thermal comfort sensation (defined in this work as the average of the air dry bulb temperature and mean radiant temperature). A mean warming gradient of 0.882 (standard deviation: 0.045) has been obtained based on the peak (over all zones) operative temperature; 1.009 (standard deviation: 0.037) based on the overall average internal operative temperature for July; and 0.846 (standard deviation: 0.029) based on the average of the individual zone peak operative temperatures for July. Differences between internal overall average air dry bulb temperature and overall average operative temperature gradients were found to be very small.

CONCLUSION

The response in internal operative temperature to a warming climate by commercial buildings in the UK has been addressed in this article. Overall maxima, overall July averages, and the July average of zone peak temperature increases were obtained. Results indicate a strong linear relationship between internal operative temperature increase and corresponding external dry bulb temperature increase. The gradient of this increase was found to vary between 0.767 and 1.009 for a wide range of contrasting commercial building types with differing constructions and were consistent for either dry bulb or operative temperature results. The results were found to agree with similar findings of an earlier study which dealt with housing, schools and offices. The results of this (and the earlier) work provides valuable information to assist the development of adaptive thermal comfort algorithms as well as to predict

a timeline for the introduction of air conditioning in existing buildings as the climate warms.

This work forms the preliminary stage of a larger study to develop design procedures and gain a better understanding of comfort and internal warming using the recently released 2009 Projections from the United Kingdom Climate Impact Programme. These new probabilistic climate projections represent a radically new way of assessing future climate impacts. Future work will focus on investigating warming impacts using the new Projections by adopting the methods described in the present work together with the development of new methods of determining future-proof design capacities of heating and cooling plant for buildings.

ACKNOWLEDGMENTS

This work is part of a programme of research funded by the Engineering and Physical Sciences Research Council in the UK (grant reference EP/F038135/1).

REFERENCES

1. IPCC (2007) *Climate change 2007: the physical science basis: Contribution of Working Group I*. (Cambridge: Cambridge University Press).
2. Beleher, S.E., Hacker, J.N. and Powell, D.S. (2005) Constructing design weather data for future climates. *Building Serv. Eng. Res. Technol.* 26 (1) pp. 49-61.
3. Jentsch, M. F., Bahaj, A. S. & James, P. A. B. (2008) Climate change future proofing of buildings – generation and assessment of building simulation weather files. *Energy and Buildings*, 40 (12), pp. 2148-68.
4. Holmes, M.J. & Hacker, J.N. (2007) Climate change, thermal comfort and energy: Meeting the design challenges of the 21st century. *Energy and Buildings*, 33 (7), pp. 802-14.
5. Hacker, J.N., De Saulles, T.P., Minson, A.J. & Holmes, M.J. (2008) Embodied and operational carbon dioxide emissions from housing: A case study on the effects of thermal mass and climate change. *Energy and Buildings*, 40 (3), pp. 375-84.
6. Coley, D. & Kershaw, T. (2010) Changes in internal temperatures within the built environment as a response to a changing climate. *Building and Environment*, 45, pp. 89-93.
7. CIBSE (2009) *CIBSE Technical Memorandum 48: Use of Climate Change Scenarios for Building Simulation: the CIBSE Future Weather Years*. (London: Chartered Institution of Building Services Engineers).
8. Neymark, J. & Judkoff, R. (2002) *International Energy Agency Building Energy Simulation Test and Diagnostic Method for Heating, Ventilating, and Air-Conditioning Equipment Models (HVAC BESTEST)* (Golden, CO: National Renewable Energy Laboratory).
9. UKCIP02 (2002) *United Kingdom Climate Impacts Programme* [Online]. Available at: http://www.ukcip.org.uk/index.php?id=161&option=com_content&task=view (accessed 27th January 2010)

Appendix D: Matlab scripts

```
%***** runcontrol.m*****
%% generate TRY/DRY for control period
cd M:\UKCP09Control;
[num, txtlist]= xlsread('M:\UKCP09Control\fileslist.xlsx',2);
[m,n]=size(txtlist);
save txtlist.mat
for i=1:4
    load txtlist;
    location=char(txtlist(i,1));
    WMOcode=num(i,1);
    latitude=num(i,2);
    longitude=num(i,3);
    elevation=num(i,4);
    UKCP09Grid=num(i,5);
    year=num(i,6);
    senario=char(txtlist(i,8));
    s1=['cd ' char(txtlist(i,11)) ';'];
    eval(s1);
    copyfile('M:\UKCP09\TRYDRY_Hu_control.m',char(txtlist(i,11)));
    copyfile('M:\UKCP09\DRY85_Hu_Part_control.m',char(txtlist(i,11)));
    copyfile('M:\UKCP09\DRY99_Hu_Part_control.m',char(txtlist(i,11)));
    copyfile('M:\UKCP09\PlotDRYTRY.m',char(txtlist(i,11)));
    copyfile('M:\UKCP09\GenDef.m',char(txtlist(i,11)));
    copyfile('M:\UKCP09\CDFiso.m',char(txtlist(i,11)));
    copyfile('M:\UKCP09\filename.mat',char(txtlist(i,11)));
    copyfile('M:\UKCP09\rankt.m',char(txtlist(i,11)));
    GenDef(location, WMOcode, latitude, longitude, elevation, UKCP09Grid,
year,senario);
    copyfile('TRY.def','DRY99.def');
    copyfile('TRY.def','DRY85.def');
    % copy necessary files to destination folder
```



```

TRYDRY_Hu_control;
% generate TRY/DRY for control period
clear all;
cd M:\UKCP09Control;
end

%% generate TRY/DRY for future
cd M:\UKCP09;
[num, txtlist]= xlsread('M:\UKCP09\fileslist.xlsx',1);
[m,n]=size(txtlist);
save txtlist.mat
for i=1:63
    fprintf('\n Generating  %2d th set of file, 63 in total', i);
    load txtlist;
    location=char(txtlist(i,1));
    WMOcode=num(i,1);
    latitude=num(i,2);
    longitude=num(i,3);
    elevation=num(i,4);
    UKCP09Grid=num(i,5);
    year=num(i,6);
    senario=char(txtlist(i,8));
    s1=['cd ' char(txtlist(i,11)) ';'];
    eval(s1);
    copyfile('M:\UKCP09\TRYDRY_Hu.m',char(txtlist(i,11)));
    copyfile('M:\UKCP09\DRY85_Hu_Part.m',char(txtlist(i,11)));
    copyfile('M:\UKCP09\DRY99_Hu_Part.m',char(txtlist(i,11)));
    copyfile('M:\UKCP09\PlotDRYTRY.m',char(txtlist(i,11)));
    copyfile('M:\UKCP09\GenDef.m',char(txtlist(i,11)));
    copyfile('M:\UKCP09\CDFiso.m',char(txtlist(i,11)));
    copyfile('M:\UKCP09\filename.mat',char(txtlist(i,11)));

```

```
copyfile('M:\UKCP09\rankt.m',char(txtlist(i,11)));
GenDef(location, WMOcode, latitude, longitude, elevation, UKCP09Grid,
year,senario);
copyfile('TRY.def','DRY99.def');
copyfile('TRY.def','DRY85.def');
% copy necessary files to destination folder
TRYDRY_Hu;
% generate TRY/DRY for future
clear all;
cd M:\UKCP09;
end
%!shutdown -s
% auto shutdown computer
```

```

%***** TRYDRY_Hu.m *****
%% Step 1: Capturing daily mean value from UKCP09 data
tic;
fprintf('\n Step 1: Reading daily data.....(Estimated time: 1
mins)')
time=clock;
a1=time(4:6);
%fprintf('\n Starting at %4d hour %4d min %4.2f second', a1);

%read file name of daily CSV files
load filename.mat;
%read 100 daily csv files
pday=[];
for i=1:100
%read a csv files % G temp_dmin; H temp_dmax; I vapourpressure_dmean;
% K sunshie hour; L diffuse radiation; M direct radiation; N pet_dmean
p0=dlmread(char(txt(i,4)),',', 'D1..N10957'); % txt(i,4) read scenario data;
%p0=dlmread(char(txt(i,3)),',', 'D1..N10957'); % txt(i,3) read control data;

pday=cat(1,pday,p0);
fprintf('\n Reading %3d th daily file.....', i);
end

save pday.mat pday; %save raw daily data
save txt.mat txt; %save file name
clear p0 i txt;
pdaily(:,1)=(pday(:,4)+pday(:,5))/2; %daily mean temperature
pdaily(:,2)=pday(:,7); %reltive humility
pdaily(:,3)=pday(:,9)+pday(:,10); % total incoming solar radiation, kWh/m2
save daily.mat pdaily; % save hourly temperature, solar radiation and relative
humidity

```

```

time=clock;
a2=time(4:6);
%fprintf('\n Ending at  %4d hour %4d min %4.2f second', a2);
a=a2-a1;
fprintf('\n Time spent: %4d hour %4d min %4.2f second', a);
clear all;

```

% Step 2.1: Capture temperature data for each month in that year and in whole 100 years

```

load daily;
fprintf('\n Step 2.1: Capturing temperature data for each month
.....(Estimated time: 1 min)')
Tempdaily=pdaily(:,1); % capture temperature data from daily data
clear pdaily;
%Tempdaily=double(Tempdaily);
time=clock;
a1=time(4:6);
%fprintf('\n Starting at %4d hour %4d min %4.2f second', a1);

%capture daily average data from each month; format is Jand_i, such as
Jan3000_100
for i=1:100
    for d=3001:3030
        s01=['Jan' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',1,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',1,31)-1096093+10957*(i-
1)))']; %1096093=datenum(3000,12,31);10957=datenum(3030,12,31)-
datenum(3000,12,31)

```

```

s02=['Feb' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',2,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',2,28)-1096093+10957*(i-
1))))];

s03=['Mar' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',3,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',3,31)-1096093+10957*(i-
1))))];

s04=['Apr' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',4,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',4,30)-1096093+10957*(i-
1))))];

s05=['May' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',5,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',5,31)-1096093+10957*(i-
1))))];

s06=['Jun' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',6,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',6,30)-1096093+10957*(i-
1))))];

s07=['Jul' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',7,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',7,31)-1096093+10957*(i-
1))))];

s08=['Aug' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',8,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',8,31)-1096093+10957*(i-
1))))];

s09=['Sep' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',9,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',9,30)-1096093+10957*(i-
1))))];

s10=['Oct' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',10,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',10,31)-1096093+10957*(i-
1))))];

s11=['Nov' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',11,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',11,30)-1096093+10957*(i-
1))))];

```

```
s12=['Dec' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',12,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',12,31)-1096093+10957*(i-
1)))'];
```

```
eval(s01);
```

```
eval(s02);
```

```
eval(s03);
```

```
eval(s04);
```

```
eval(s05);
```

```
eval(s06);
```

```
eval(s07);
```

```
eval(s08);
```

```
eval(s09);
```

```
eval(s10);
```

```
eval(s11);
```

```
eval(s12);
```

```
end
```

```
end
```

```
clear d s01 s02 s03 s04 s05 s06 s07 s08 s09 s10 s11 s12
```

```
%Generate matrix for a calendar month in the whole data set;
```

```
%size(Jan)=90000
```

```
Jan=[];
```

```
Feb=[];
```

```
Mar=[];
```

```
Apr=[];
```

```
May=[];
```

```
Jun=[];
```

```
Jul=[];
```

```
Aug=[];
```

```
Sep=[];
```

```
Oct=[];
```

```

Nov=[];
Dec=[];

for i=1:100
for d=3001:3030
s1=['Jan=[Jan;Jan' int2str(d) '_' int2str(i) '];'];
s2=['Feb=[Feb;Feb' int2str(d) '_' int2str(i) '];'];
s3=['Mar=[Mar;Mar' int2str(d) '_' int2str(i) '];'];
s4=['Apr=[Apr;Apr' int2str(d) '_' int2str(i) '];'];
s5=['May=[May;May' int2str(d) '_' int2str(i) '];'];
s6=['Jun=[Jun;Jun' int2str(d) '_' int2str(i) '];'];
s7=['Jul=[Jul;Jul' int2str(d) '_' int2str(i) '];'];
s8=['Aug=[Aug;Aug' int2str(d) '_' int2str(i) '];'];
s9=['Sep=[Sep;Sep' int2str(d) '_' int2str(i) '];'];
s10=['Oct=[Oct;Oct' int2str(d) '_' int2str(i) '];'];
s11=['Nov=[Nov;Nov' int2str(d) '_' int2str(i) '];'];
s12=['Dec=[Dec;Dec' int2str(d) '_' int2str(i) '];'];
eval(s1);
eval(s2);
eval(s3);
eval(s4);
eval(s5);
eval(s6);
eval(s7);
eval(s8);
eval(s9);
eval(s10);
eval(s11);
eval(s12);
end
end
clear d s1 s2 s3 s4 s5 s6 s7 s8 s9 s10 s11 s12

```

```

save temperature.mat
time=clock;
a2=time(4:6);
fprintf('\n Ending at  %4d hour %4d min %4.2f second', a2);
a=a2-a1;
fprintf('\n Time spent: %4d hour %4d min %4.2f second', a);
clear time a1 a2 a i;      %take 50 seconds

```

% Step 2.2: Calculating Cumulative Distribution of temperature

```

fprintf('\n Step 2.2: Calculating Cumulative Distribution of
temperature...(Estimated time: 1 min)')
time=clock;
a1=time(4:6);
fprintf('\n Starting at %4d hour %4d min %4.2f second', a1);

```

%Tie rank percentage of the ith value of each daily temperature data within that calender month in the whole data set

```

Jan=CDFiso(Jan);
Feb=CDFiso(Feb);
Mar=CDFiso(Mar);
Apr=CDFiso(Apr);
May=CDFiso(May);
Jun=CDFiso(Jun);
Jul=CDFiso(Jul);
Aug=CDFiso(Aug);
Sep=CDFiso(Sep);
Oct=CDFiso(Oct);
Nov=CDFiso(Nov);

```



```
Dec=CDFiso(Dec);
```

```
%Tie rank percentage of the ith value of each daily temperature data within that  
month and that year
```

```
for i=1:100
```

```
for d=3001:3030
```

```
s1=['Jan' int2str(d) '_' int2str(i) '=CDFiso(Jan' int2str(d) '_' int2str(i) ');'];
```

```
s2=['Feb' int2str(d) '_' int2str(i) '=CDFiso(Feb' int2str(d) '_' int2str(i) ');'];
```

```
s3=['Mar' int2str(d) '_' int2str(i) '=CDFiso(Mar' int2str(d) '_' int2str(i) ');'];
```

```
s4=['Apr' int2str(d) '_' int2str(i) '=CDFiso(Apr' int2str(d) '_' int2str(i) ');'];
```

```
s5=['May' int2str(d) '_' int2str(i) '=CDFiso(May' int2str(d) '_' int2str(i) ');'];
```

```
s6=['Jun' int2str(d) '_' int2str(i) '=CDFiso(Jun' int2str(d) '_' int2str(i) ');'];
```

```
s7=['Jul' int2str(d) '_' int2str(i) '=CDFiso(Jul' int2str(d) '_' int2str(i) ');'];
```

```
s8=['Aug' int2str(d) '_' int2str(i) '=CDFiso(Aug' int2str(d) '_' int2str(i) ');'];
```

```
s9=['Sep' int2str(d) '_' int2str(i) '=CDFiso(Sep' int2str(d) '_' int2str(i) ');'];
```

```
s10=['Oct' int2str(d) '_' int2str(i) '=CDFiso(Oct' int2str(d) '_' int2str(i) ');'];
```

```
s11=['Nov' int2str(d) '_' int2str(i) '=CDFiso(Nov' int2str(d) '_' int2str(i) ');'];
```

```
s12=['Dec' int2str(d) '_' int2str(i) '=CDFiso(Dec' int2str(d) '_' int2str(i) ');'];
```

```
eval(s1);
```

```
eval(s2);
```

```
eval(s3);
```

```
eval(s4);
```

```
eval(s5);
```

```
eval(s6);
```

```
eval(s7);
```

```
eval(s8);
```

```
eval(s9);
```

```
eval(s10);
```

```
eval(s11);
```

```

eval(s12);
end
end
clear d s1 s2 s3 s4 s5 s6 s7 s8 s9 s10 s11 s12

save month_rank_temperature.mat % save month value with rank order

time=clock;
a2=time(4:6);
fprintf('\n Ending at %4d hour %4d min %4.2f second', a2);
a=a2-a1;
fprintf('\n Time spent: %4d hour %4d min %4.2f second', a);
clear time a1 a2 a i; %take 50 seconds

% Step 2.3: Calculate Finkelstein-Schafer statistic of temperature for each
month
fprintf('\n Step 2.3: Calculating Finkelstein-Schafer statistic of
temperature....(Estimated time: 1 mins)')
time=clock;

a1=time(4:6);
fprintf('\n Starting at %4d hour %4d min %4.2f second', a1);

Jan2=[];
Feb2=[];
Mar2=[];
Apr2=[];
May2=[];
Jun2=[];
Jul2=[];

```

```

Aug2=[];
Sep2=[];
Oct2=[];
Nov2=[];
Dec2=[];
for i=1:100
    Jan_i=[];
    Feb_i=[];
    Mar_i=[];
    Apr_i=[];
    May_i=[];
    Jun_i=[];
    Jul_i=[];
    Aug_i=[];
    Sep_i=[];
    Oct_i=[];
    Nov_i=[];
    Dec_i=[];
for y=3001:3030
    s1=['Jan_y=Jan' int2str(y) '_' int2str(i) '(:,1)'];
    s2=['Feb_y=Feb' int2str(y) '_' int2str(i) '(:,1)'];
    s3=['Mar_y=Mar' int2str(y) '_' int2str(i) '(:,1)'];
    s4=['Apr_y=Apr' int2str(y) '_' int2str(i) '(:,1)'];
    s5=['May_y=May' int2str(y) '_' int2str(i) '(:,1)'];
    s6=['Jun_y=Jun' int2str(y) '_' int2str(i) '(:,1)'];
    s7=['Jul_y=Jul' int2str(y) '_' int2str(i) '(:,1)'];
    s8=['Aug_y=Aug' int2str(y) '_' int2str(i) '(:,1)'];
    s9=['Sep_y=Sep' int2str(y) '_' int2str(i) '(:,1)'];
    s10=['Oct_y=Oct' int2str(y) '_' int2str(i) '(:,1)'];
    s11=['Nov_y=Nov' int2str(y) '_' int2str(i) '(:,1)'];
    s12=['Dec_y=Dec' int2str(y) '_' int2str(i) '(:,1)'];
    eval(s1);

```

```

eval(s2);
eval(s3);
eval(s4);
eval(s5);
eval(s6);
eval(s7);
eval(s8);
eval(s9);
eval(s10);
eval(s11);
eval(s12);
Jan_i=cat(1,Jan_i,Jan_y);
Feb_i=cat(1,Feb_i,Feb_y);
Mar_i=cat(1,Mar_i,Mar_y);
Apr_i=cat(1,Apr_i,Apr_y);
May_i=cat(1,May_i,May_y);
Jun_i=cat(1,Jun_i,Jun_y);
Jul_i=cat(1,Jul_i,Jul_y);
Aug_i=cat(1,Aug_i,Aug_y);
Sep_i=cat(1,Sep_i,Sep_y);
Oct_i=cat(1,Oct_i,Oct_y);
Nov_i=cat(1,Nov_i,Nov_y);
Dec_i=cat(1,Dec_i,Dec_y);
end
Jan2=cat(1,Jan2,Jan_i);
Feb2=cat(1,Feb2,Feb_i);
Mar2=cat(1,Mar2,Mar_i);
Apr2=cat(1,Apr2,Apr_i);
May2=cat(1,May2,May_i);
Jun2=cat(1,Jun2,Jun_i);
Jul2=cat(1,Jul2,Jul_i);
Aug2=cat(1,Aug2,Aug_i);

```

```

Sep2=cat(1,Sep2,Sep_i);
Oct2=cat(1,Oct2,Oct_i);
Nov2=cat(1,Nov2,Nov_i);
Dec2=cat(1,Dec2,Dec_i);
end

```

```

CDFdiff1=abs(Jan-Jan2);
CDFdiff2=abs(Feb-Feb2);
CDFdiff3=abs(Mar-Mar2);
CDFdiff4=abs(Apr-Apr2);
CDFdiff5=abs(May-May2);
CDFdiff6=abs(Jun-Jun2);
CDFdiff7=abs(Jul-Jul2);
CDFdiff8=abs(Aug-Aug2);
CDFdiff9=abs(Sep-Sep2);
CDFdiff10=abs(Oct-Oct2);
CDFdiff11=abs(Nov-Nov2);
CDFdiff12=abs(Dec-Dec2);
%
%FS(1,:)=sum(reshape(CDFdiff1,31,3000));
%FS(2,:)=sum(reshape(CDFdiff2,28,3000));
%FS(3,:)=sum(reshape(CDFdiff3,31,3000));
%FS(4,:)=sum(reshape(CDFdiff4,30,3000));
%FS(5,:)=sum(reshape(CDFdiff5,31,3000));
%FS(6,:)=sum(reshape(CDFdiff6,30,3000));
%FS(7,:)=sum(reshape(CDFdiff7,31,3000));
%FS(8,:)=sum(reshape(CDFdiff8,31,3000));
%FS(9,:)=sum(reshape(CDFdiff9,30,3000));
%FS(10,:)=sum(reshape(CDFdiff10,31,3000));
%FS(11,:)=sum(reshape(CDFdiff11,30,3000));
%FS(12,:)=sum(reshape(CDFdiff12,31,3000));
% ISO above

```

```

FS(1,:)=sum(reshape(CDFdiff1,31,3000))/31;
FS(2,:)=sum(reshape(CDFdiff2,28,3000))/28;
FS(3,:)=sum(reshape(CDFdiff3,31,3000))/31;
FS(4,:)=sum(reshape(CDFdiff4,30,3000))/30;
FS(5,:)=sum(reshape(CDFdiff5,31,3000))/31;
FS(6,:)=sum(reshape(CDFdiff6,30,3000))/30;
FS(7,:)=sum(reshape(CDFdiff7,31,3000))/31;
FS(8,:)=sum(reshape(CDFdiff8,31,3000))/31;
FS(9,:)=sum(reshape(CDFdiff9,30,3000))/30;
FS(10,:)=sum(reshape(CDFdiff10,31,3000))/31;
FS(11,:)=sum(reshape(CDFdiff11,30,3000))/30;
FS(12,:)=sum(reshape(CDFdiff12,31,3000))/31;

FS_temp=FS';
save FS_temp.mat FS_temp;

save CDFdiff_temp.mat CDFdiff1 CDFdiff2 CDFdiff3 CDFdiff4 CDFdiff5
CDFdiff6 CDFdiff7 CDFdiff8 CDFdiff9 CDFdiff10 CDFdiff11 CDFdiff12;

time=clock;
a2=time(4:6);
fprintf('\n Ending at  %4d hour %4d min %4.2f second', a2);
a=a2-a1;
fprintf('\n Time spent: %4d hour %4d min %4.2f second', a);
clear all;

% Step 3.1: Capture solar radiation data for each month in that year and in
whole 100 years
fprintf('\n Step 3.1: Capturing solar radiation for each month .....(Estimated
time: 1 min)')

```

```

load daily;
Tempdaily=pdaily(:,3); % capture solar radiation data from daily data
clear pdaily;
%Tempdaily=double(Tempdaily);
time=clock;
a1=time(4:6);
%fprintf('\n Starting at %4d hour %4d min %4.2f second', a1);

%capture daily average data from each month; format is Jand_i, such as
Jan3000_100
for i=1:100
    for d=3001:3030
        s01=['Jan' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',1,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',1,31)-1096093+10957*(i-
1))))]; %1096093=datenum(3000,12,31);10957=datenum(3030,12,31)-
datenum(3000,12,31)
        s02=['Feb' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',2,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',2,28)-1096093+10957*(i-
1))))];
        s03=['Mar' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',3,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',3,31)-1096093+10957*(i-
1))))];
        s04=['Apr' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',4,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',4,30)-1096093+10957*(i-
1))))];
        s05=['May' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',5,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',5,31)-1096093+10957*(i-
1))))];
        s06=['Jun' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',6,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',6,30)-1096093+10957*(i-
1))))];

```

```

s07=['Jul' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',7,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',7,31)-1096093+10957*(i-
1))))'];

s08=['Aug' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',8,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',8,31)-1096093+10957*(i-
1))))'];

s09=['Sep' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',9,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',9,30)-1096093+10957*(i-
1))))'];

s10=['Oct' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',10,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',10,31)-1096093+10957*(i-
1))))'];

s11=['Nov' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',11,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',11,30)-1096093+10957*(i-
1))))'];

s12=['Dec' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',12,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',12,31)-1096093+10957*(i-
1))))'];

eval(s01);
eval(s02);
eval(s03);
eval(s04);
eval(s05);
eval(s06);
eval(s07);
eval(s08);
eval(s09);
eval(s10);
eval(s11);
eval(s12);

end

end

```



```
clear d s01 s02 s03 s04 s05 s06 s07 s08 s09 s10 s11 s12
```

```
%Generate matrix for a calendar month in the whole data set;
```

```
%size(Jan)=90000
```

```
Jan=[];
```

```
Feb=[];
```

```
Mar=[];
```

```
Apr=[];
```

```
May=[];
```

```
Jun=[];
```

```
Jul=[];
```

```
Aug=[];
```

```
Sep=[];
```

```
Oct=[];
```

```
Nov=[];
```

```
Dec=[];
```

```
for i=1:100
```

```
for d=3001:3030
```

```
s1=['Jan=[Jan;Jan' int2str(d) '_' int2str(i) '];'];
```

```
s2=['Feb=[Feb;Feb' int2str(d) '_' int2str(i) '];'];
```

```
s3=['Mar=[Mar;Mar' int2str(d) '_' int2str(i) '];'];
```

```
s4=['Apr=[Apr;Apr' int2str(d) '_' int2str(i) '];'];
```

```
s5=['May=[May;May' int2str(d) '_' int2str(i) '];'];
```

```
s6=['Jun=[Jun;Jun' int2str(d) '_' int2str(i) '];'];
```

```
s7=['Jul=[Jul;Jul' int2str(d) '_' int2str(i) '];'];
```

```
s8=['Aug=[Aug;Aug' int2str(d) '_' int2str(i) '];'];
```

```
s9=['Sep=[Sep;Sep' int2str(d) '_' int2str(i) '];'];
```

```
s10=['Oct=[Oct;Oct' int2str(d) '_' int2str(i) '];'];
```

```
s11=['Nov=[Nov;Nov' int2str(d) '_' int2str(i) '];'];
```

```
s12=['Dec=[Dec;Dec' int2str(d) '_' int2str(i) '];'];
```

```

eval(s1);
eval(s2);
eval(s3);
eval(s4);
eval(s5);
eval(s6);
eval(s7);
eval(s8);
eval(s9);
eval(s10);
eval(s11);
eval(s12);
end
end
clear d s1 s2 s3 s4 s5 s6 s7 s8 s9 s10 s11 s12
save radiation.mat;

time=clock;
a2=time(4:6);
%fprintf('\n Ending at  %4d hour %4d min %4.2f second', a2);
a=a2-a1;
fprintf('\n Time spent: %4d hour %4d min %4.2f second', a);
clear all;          %take 50 seconds

% Step 3.2: Calculating Cumulative Distribution of solar radiation
time=clock;
load radiation
fprintf('\n Step 3.2: Calculating Cumulative Distribution of solar
radiation...(Estimated time: 1 min)');
a1=time(4:6);
%fprintf('\n Starting at %4d hour %4d min %4.2f second', a1);

```

%Tie rank percentage of the ith value of each daily temperature data within that calender month in the whole data set

```
Jan=CDFiso(Jan);  
Feb=CDFiso(Feb);  
Mar=CDFiso(Mar);  
Apr=CDFiso(Apr);  
May=CDFiso(May);  
Jun=CDFiso(Jun);  
Jul=CDFiso(Jul);  
Aug=CDFiso(Aug);  
Sep=CDFiso(Sep);  
Oct=CDFiso(Oct);  
Nov=CDFiso(Nov);  
Dec=CDFiso(Dec);
```

%Tie rank percentage of the ith value of each daily temperature data within that month and that year

```
for i=1:100
```

```
for d=3001:3030
```

```
s1=['Jan' int2str(d) '_' int2str(i) '=CDFiso(Jan' int2str(d) '_' int2str(i) ');'];  
s2=['Feb' int2str(d) '_' int2str(i) '=CDFiso(Feb' int2str(d) '_' int2str(i) ');'];  
s3=['Mar' int2str(d) '_' int2str(i) '=CDFiso(Mar' int2str(d) '_' int2str(i) ');'];  
s4=['Apr' int2str(d) '_' int2str(i) '=CDFiso(Apr' int2str(d) '_' int2str(i) ');'];  
s5=['May' int2str(d) '_' int2str(i) '=CDFiso(May' int2str(d) '_' int2str(i) ');'];  
s6=['Jun' int2str(d) '_' int2str(i) '=CDFiso(Jun' int2str(d) '_' int2str(i) ');'];  
s7=['Jul' int2str(d) '_' int2str(i) '=CDFiso(Jul' int2str(d) '_' int2str(i) ');'];
```

```

s8=['Aug' int2str(d) '_' int2str(i) '=CDFiso(Aug' int2str(d) '_' int2str(i) ');'];
s9=['Sep' int2str(d) '_' int2str(i) '=CDFiso(Sep' int2str(d) '_' int2str(i) ');'];
s10=['Oct' int2str(d) '_' int2str(i) '=CDFiso(Oct' int2str(d) '_' int2str(i) ');'];
s11=['Nov' int2str(d) '_' int2str(i) '=CDFiso(Nov' int2str(d) '_' int2str(i) ');'];
s12=['Dec' int2str(d) '_' int2str(i) '=CDFiso(Dec' int2str(d) '_' int2str(i) ');'];
eval(s1);
eval(s2);
eval(s3);
eval(s4);
eval(s5);
eval(s6);
eval(s7);
eval(s8);
eval(s9);
eval(s10);
eval(s11);
eval(s12);
end
end
clear d s1 s2 s3 s4 s5 s6 s7 s8 s9 s10 s11 s12

save month_rank_radiation.mat % save month value with rank order

time=clock;
a2=time(4:6);
%fprintf('\n Ending at %4d hour %4d min %4.2f second', a2);
a=a2-a1;
fprintf('\n Time spent: %4d hour %4d min %4.2f second', a);
clear time a1 a2 a i; %take 50 seconds

```

```
% Step 3.3: Calculate Finkelstein-Schafer statistic of solar radiation for each month
```

```
fprintf('\n Step 3.3: Calculating Finkelstein-Schafer statistic of solar radiation.....(Estimated time: 1 mins)')
```

```
time=clock;
```

```
a1=time(4:6);
```

```
%fprintf('\n Starting at %4d hour %4d min %4.2f second', a1);
```

```
Jan2=[];
```

```
Feb2=[];
```

```
Mar2=[];
```

```
Apr2=[];
```

```
May2=[];
```

```
Jun2=[];
```

```
Jul2=[];
```

```
Aug2=[];
```

```
Sep2=[];
```

```
Oct2=[];
```

```
Nov2=[];
```

```
Dec2=[];
```

```
for i=1:100
```

```
    Jan_i=[];
```

```
    Feb_i=[];
```

```
    Mar_i=[];
```

```
    Apr_i=[];
```

```
    May_i=[];
```

```
    Jun_i=[];
```

```
    Jul_i=[];
```

```
    Aug_i=[];
```

```
    Sep_i=[];
```

```

Oct_i=[];
Nov_i=[];
Dec_i=[];
for y=3001:3030
    s1=['Jan_y=Jan' int2str(y) '_' int2str(i) '(:,1)'];
    s2=['Feb_y=Feb' int2str(y) '_' int2str(i) '(:,1)'];
    s3=['Mar_y=Mar' int2str(y) '_' int2str(i) '(:,1)'];
    s4=['Apr_y=Apr' int2str(y) '_' int2str(i) '(:,1)'];
    s5=['May_y=May' int2str(y) '_' int2str(i) '(:,1)'];
    s6=['Jun_y=Jun' int2str(y) '_' int2str(i) '(:,1)'];
    s7=['Jul_y=Jul' int2str(y) '_' int2str(i) '(:,1)'];
    s8=['Aug_y=Aug' int2str(y) '_' int2str(i) '(:,1)'];
    s9=['Sep_y=Sep' int2str(y) '_' int2str(i) '(:,1)'];
    s10=['Oct_y=Oct' int2str(y) '_' int2str(i) '(:,1)'];
    s11=['Nov_y=Nov' int2str(y) '_' int2str(i) '(:,1)'];
    s12=['Dec_y=Dec' int2str(y) '_' int2str(i) '(:,1)'];
    eval(s1);
    eval(s2);
    eval(s3);
    eval(s4);
    eval(s5);
    eval(s6);
    eval(s7);
    eval(s8);
    eval(s9);
    eval(s10);
    eval(s11);
    eval(s12);
    Jan_i=cat(1,Jan_i,Jan_y);
    Feb_i=cat(1,Feb_i,Feb_y);
    Mar_i=cat(1,Mar_i,Mar_y);
    Apr_i=cat(1,Apr_i,Apr_y);

```

```

    May_i=cat(1,May_i,May_y);
    Jun_i=cat(1,Jun_i,Jun_y);
    Jul_i=cat(1,Jul_i,Jul_y);
    Aug_i=cat(1,Aug_i,Aug_y);
    Sep_i=cat(1,Sep_i,Sep_y);
    Oct_i=cat(1,Oct_i,Oct_y);
    Nov_i=cat(1,Nov_i,Nov_y);
    Dec_i=cat(1,Dec_i,Dec_y);
end
Jan2=cat(1,Jan2,Jan_i);
Feb2=cat(1,Feb2,Feb_i);
Mar2=cat(1,Mar2,Mar_i);
Apr2=cat(1,Apr2,Apr_i);
May2=cat(1,May2,May_i);
Jun2=cat(1,Jun2,Jun_i);
Jul2=cat(1,Jul2,Jul_i);
Aug2=cat(1,Aug2,Aug_i);
Sep2=cat(1,Sep2,Sep_i);
Oct2=cat(1,Oct2,Oct_i);
Nov2=cat(1,Nov2,Nov_i);
Dec2=cat(1,Dec2,Dec_i);
end

CDFdiff1=abs(Jan-Jan2);
CDFdiff2=abs(Feb-Feb2);
CDFdiff3=abs(Mar-Mar2);
CDFdiff4=abs(Apr-Apr2);
CDFdiff5=abs(May-May2);
CDFdiff6=abs(Jun-Jun2);
CDFdiff7=abs(Jul-Jul2);
CDFdiff8=abs(Aug-Aug2);
CDFdiff9=abs(Sep-Sep2);

```

```

CDFdiff10=abs(Oct-Oct2);
CDFdiff11=abs(Nov-Nov2);
CDFdiff12=abs(Dec-Dec2);

%FS(1,:)=sum(reshape(CDFdiff1,31,3000));
%FS(2,:)=sum(reshape(CDFdiff2,28,3000));
%FS(3,:)=sum(reshape(CDFdiff3,31,3000));
%FS(4,:)=sum(reshape(CDFdiff4,30,3000));
%FS(5,:)=sum(reshape(CDFdiff5,31,3000));
%FS(6,:)=sum(reshape(CDFdiff6,30,3000));
%FS(7,:)=sum(reshape(CDFdiff7,31,3000));
%FS(8,:)=sum(reshape(CDFdiff8,31,3000));
%FS(9,:)=sum(reshape(CDFdiff9,30,3000));
%FS(10,:)=sum(reshape(CDFdiff10,31,3000));
%FS(11,:)=sum(reshape(CDFdiff11,30,3000));
%FS(12,:)=sum(reshape(CDFdiff12,31,3000));
% ISO above
FS(1,:)=sum(reshape(CDFdiff1,31,3000))/31;
FS(2,:)=sum(reshape(CDFdiff2,28,3000))/28;
FS(3,:)=sum(reshape(CDFdiff3,31,3000))/31;
FS(4,:)=sum(reshape(CDFdiff4,30,3000))/30;
FS(5,:)=sum(reshape(CDFdiff5,31,3000))/31;
FS(6,:)=sum(reshape(CDFdiff6,30,3000))/30;
FS(7,:)=sum(reshape(CDFdiff7,31,3000))/31;
FS(8,:)=sum(reshape(CDFdiff8,31,3000))/31;
FS(9,:)=sum(reshape(CDFdiff9,30,3000))/30;
FS(10,:)=sum(reshape(CDFdiff10,31,3000))/31;
FS(11,:)=sum(reshape(CDFdiff11,30,3000))/30;
FS(12,:)=sum(reshape(CDFdiff12,31,3000))/31;

FS_rad=FS';
save FS_rad.mat FS_rad;

```



```
save CDFdiff_rad.mat CDFdiff1 CDFdiff2 CDFdiff3 CDFdiff4 CDFdiff5 CDFdiff6
CDFdiff7 CDFdiff8 CDFdiff9 CDFdiff10 CDFdiff11 CDFdiff12;
```

```
time=clock;
a2=time(4:6);
fprintf('\n Ending at %4d hour %4d min %4.2f second', a2);
a=a2-a1;
fprintf('\n Time spent: %4d hour %4d min %4.2f second', a);
clear all;
```

```
% Step 4.1: Capture solar relative humidity for each month in that year and in
whole 100 years
```

```
time=clock;
fprintf('\n Step 4.1: Capturing relative humidity for each month .....(Estimated
time: 1 min)')
load daily;
Tempdaily=pdaily(:,2); % capture relative humidity data from daily data
clear pdaily;
%Tempdaily=double(Tempdaily);
a1=time(4:6);
fprintf('\n Starting at %4d hour %4d min %4.2f second', a1);
```

```
%capture daily average data from each month; format is Jand_i, such as
Jan3000_100
```

```
for i=1:100
    for d=3001:3030
        s01=['Jan' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',1,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',1,31)-1096093+10957*(i-
```

```

1))))]; %1096093=datenum(3000,12,31);10957=datenum(3030,12,31)-
datenum(3000,12,31)
s02=['Feb' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',2,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',2,28)-1096093+10957*(i-
1))))];
s03=['Mar' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',3,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',3,31)-1096093+10957*(i-
1))))];
s04=['Apr' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',4,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',4,30)-1096093+10957*(i-
1))))];
s05=['May' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',5,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',5,31)-1096093+10957*(i-
1))))];
s06=['Jun' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',6,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',6,30)-1096093+10957*(i-
1))))];
s07=['Jul' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',7,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',7,31)-1096093+10957*(i-
1))))];
s08=['Aug' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',8,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',8,31)-1096093+10957*(i-
1))))];
s09=['Sep' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',9,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',9,30)-1096093+10957*(i-
1))))];
s10=['Oct' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',10,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',10,31)-1096093+10957*(i-
1))))];
s11=['Nov' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',11,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',11,30)-1096093+10957*(i-
1))))];

```

```
s12=['Dec' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',12,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',12,31)-1096093+10957*(i-
1)))'];
```

```
eval(s01);
```

```
eval(s02);
```

```
eval(s03);
```

```
eval(s04);
```

```
eval(s05);
```

```
eval(s06);
```

```
eval(s07);
```

```
eval(s08);
```

```
eval(s09);
```

```
eval(s10);
```

```
eval(s11);
```

```
eval(s12);
```

```
end
```

```
end
```

```
clear d s01 s02 s03 s04 s05 s06 s07 s08 s09 s10 s11 s12
```

```
%Generate matrix for a calendar month in the whole data set;
```

```
%size(Jan)=90000
```

```
Jan=[];
```

```
Feb=[];
```

```
Mar=[];
```

```
Apr=[];
```

```
May=[];
```

```
Jun=[];
```

```
Jul=[];
```

```
Aug=[];
```

```
Sep=[];
```

```
Oct=[];
```

```

Nov=[];
Dec=[];

for i=1:100
for d=3001:3030
s1=['Jan=[Jan;Jan' int2str(d) '_' int2str(i) '];'];
s2=['Feb=[Feb;Feb' int2str(d) '_' int2str(i) '];'];
s3=['Mar=[Mar;Mar' int2str(d) '_' int2str(i) '];'];
s4=['Apr=[Apr;Apr' int2str(d) '_' int2str(i) '];'];
s5=['May=[May;May' int2str(d) '_' int2str(i) '];'];
s6=['Jun=[Jun;Jun' int2str(d) '_' int2str(i) '];'];
s7=['Jul=[Jul;Jul' int2str(d) '_' int2str(i) '];'];
s8=['Aug=[Aug;Aug' int2str(d) '_' int2str(i) '];'];
s9=['Sep=[Sep;Sep' int2str(d) '_' int2str(i) '];'];
s10=['Oct=[Oct;Oct' int2str(d) '_' int2str(i) '];'];
s11=['Nov=[Nov;Nov' int2str(d) '_' int2str(i) '];'];
s12=['Dec=[Dec;Dec' int2str(d) '_' int2str(i) '];'];
eval(s1);
eval(s2);
eval(s3);
eval(s4);
eval(s5);
eval(s6);
eval(s7);
eval(s8);
eval(s9);
eval(s10);
eval(s11);
eval(s12);
end
end
clear d s1 s2 s3 s4 s5 s6 s7 s8 s9 s10 s11 s12

```

```

save humidity.mat;
time=clock;
a2=time(4:6);
%fprintf('\n Ending at  %4d hour %4d min %4.2f second', a2);
a=a2-a1;
fprintf('\n Time spent: %4d hour %4d min %4.2f second', a);
clear all;          %take 50 seconds

```

```

% Step 4.2: Calculating Cumulative Distribution of relative humidity
fprintf('\n Step 4.2: Calculating Cumulative Distribution of relative
humidity...(Estimated time: 1 min)')
time=clock;
a1=time(4:6);
%fprintf('\n Starting at %4d hour %4d min %4.2f second', a1);
load humidity
%Tie rank percentage of the ith value of each daily temperature data within that
calender month in the whole data set

```

```

Jan=CDFiso(Jan);
Feb=CDFiso(Feb);
Mar=CDFiso(Mar);
Apr=CDFiso(Apr);
May=CDFiso(May);
Jun=CDFiso(Jun);
Jul=CDFiso(Jul);
Aug=CDFiso(Aug);
Sep=CDFiso(Sep);
Oct=CDFiso(Oct);
Nov=CDFiso(Nov);
Dec=CDFiso(Dec);

```

```
%Tie rank percentage of the ith value of each daily temperature data within that month and that year
```

```
for i=1:100
```

```
for d=3001:3030
```

```
s1=['Jan' int2str(d) '_' int2str(i) '=CDFiso(Jan' int2str(d) '_' int2str(i) ');'];  
s2=['Feb' int2str(d) '_' int2str(i) '=CDFiso(Feb' int2str(d) '_' int2str(i) ');'];  
s3=['Mar' int2str(d) '_' int2str(i) '=CDFiso(Mar' int2str(d) '_' int2str(i) ');'];  
s4=['Apr' int2str(d) '_' int2str(i) '=CDFiso(Apr' int2str(d) '_' int2str(i) ');'];  
s5=['May' int2str(d) '_' int2str(i) '=CDFiso(May' int2str(d) '_' int2str(i) ');'];  
s6=['Jun' int2str(d) '_' int2str(i) '=CDFiso(Jun' int2str(d) '_' int2str(i) ');'];  
s7=['Jul' int2str(d) '_' int2str(i) '=CDFiso(Jul' int2str(d) '_' int2str(i) ');'];  
s8=['Aug' int2str(d) '_' int2str(i) '=CDFiso(Aug' int2str(d) '_' int2str(i) ');'];  
s9=['Sep' int2str(d) '_' int2str(i) '=CDFiso(Sep' int2str(d) '_' int2str(i) ');'];  
s10=['Oct' int2str(d) '_' int2str(i) '=CDFiso(Oct' int2str(d) '_' int2str(i) ');'];  
s11=['Nov' int2str(d) '_' int2str(i) '=CDFiso(Nov' int2str(d) '_' int2str(i) ');'];  
s12=['Dec' int2str(d) '_' int2str(i) '=CDFiso(Dec' int2str(d) '_' int2str(i) ');'];  
eval(s1);  
eval(s2);  
eval(s3);  
eval(s4);  
eval(s5);  
eval(s6);  
eval(s7);  
eval(s8);  
eval(s9);  
eval(s10);  
eval(s11);  
eval(s12);
```

```

end
end
clear d s1 s2 s3 s4 s5 s6 s7 s8 s9 s10 s11 s12

save month_rank_relhum.mat % save month value with rank order

time=clock;
a2=time(4:6);
%fprintf('\n Ending at %4d hour %4d min %4.2f second', a2);
a=a2-a1;
fprintf('\n Time spent: %4d hour %4d min %4.2f second', a);
clear time a1 a2 a i; %take 50 seconds

% Step 4.3: Calculate Finkelstein-Schafer statistic of relative humidity for each
month
fprintf('\n Step 4.3: Calculating Finkelstein-Schafer statistic of relative humidity
...(Estimated time: 1 mins)')
time=clock;

a1=time(4:6);
%fprintf('\n Starting at %4d hour %4d min %4.2f second', a1);

Jan2=[];
Feb2=[];
Mar2=[];
Apr2=[];
May2=[];
Jun2=[];
Jul2=[];
Aug2=[];

```

```

Sep2=[];
Oct2=[];
Nov2=[];
Dec2=[];
for i=1:100
    Jan_i=[];
    Feb_i=[];
    Mar_i=[];
    Apr_i=[];
    May_i=[];
    Jun_i=[];
    Jul_i=[];
    Aug_i=[];
    Sep_i=[];
    Oct_i=[];
    Nov_i=[];
    Dec_i=[];
for y=3001:3030
    s1=['Jan_y=Jan' int2str(y) '_' int2str(i) '(:,1)'];
    s2=['Feb_y=Feb' int2str(y) '_' int2str(i) '(:,1)'];
    s3=['Mar_y=Mar' int2str(y) '_' int2str(i) '(:,1)'];
    s4=['Apr_y=Apr' int2str(y) '_' int2str(i) '(:,1)'];
    s5=['May_y=May' int2str(y) '_' int2str(i) '(:,1)'];
    s6=['Jun_y=Jun' int2str(y) '_' int2str(i) '(:,1)'];
    s7=['Jul_y=Jul' int2str(y) '_' int2str(i) '(:,1)'];
    s8=['Aug_y=Aug' int2str(y) '_' int2str(i) '(:,1)'];
    s9=['Sep_y=Sep' int2str(y) '_' int2str(i) '(:,1)'];
    s10=['Oct_y=Oct' int2str(y) '_' int2str(i) '(:,1)'];
    s11=['Nov_y=Nov' int2str(y) '_' int2str(i) '(:,1)'];
    s12=['Dec_y=Dec' int2str(y) '_' int2str(i) '(:,1)'];
    eval(s1);
    eval(s2);

```



```

eval(s3);
eval(s4);
eval(s5);
eval(s6);
eval(s7);
eval(s8);
eval(s9);
eval(s10);
eval(s11);
eval(s12);
Jan_i=cat(1,Jan_i,Jan_y);
Feb_i=cat(1,Feb_i,Feb_y);
Mar_i=cat(1,Mar_i,Mar_y);
Apr_i=cat(1,Apr_i,Apr_y);
May_i=cat(1,May_i,May_y);
Jun_i=cat(1,Jun_i,Jun_y);
Jul_i=cat(1,Jul_i,Jul_y);
Aug_i=cat(1,Aug_i,Aug_y);
Sep_i=cat(1,Sep_i,Sep_y);
Oct_i=cat(1,Oct_i,Oct_y);
Nov_i=cat(1,Nov_i,Nov_y);
Dec_i=cat(1,Dec_i,Dec_y);
end
Jan2=cat(1,Jan2,Jan_i);
Feb2=cat(1,Feb2,Feb_i);
Mar2=cat(1,Mar2,Mar_i);
Apr2=cat(1,Apr2,Apr_i);
May2=cat(1,May2,May_i);
Jun2=cat(1,Jun2,Jun_i);
Jul2=cat(1,Jul2,Jul_i);
Aug2=cat(1,Aug2,Aug_i);
Sep2=cat(1,Sep2,Sep_i);

```

```

Oct2=cat(1,Oct2,Oct_i);
Nov2=cat(1,Nov2,Nov_i);
Dec2=cat(1,Dec2,Dec_i);
end

CDFdiff1=abs(Jan-Jan2);
CDFdiff2=abs(Feb-Feb2);
CDFdiff3=abs(Mar-Mar2);
CDFdiff4=abs(Apr-Apr2);
CDFdiff5=abs(May-May2);
CDFdiff6=abs(Jun-Jun2);
CDFdiff7=abs(Jul-Jul2);
CDFdiff8=abs(Aug-Aug2);
CDFdiff9=abs(Sep-Sep2);
CDFdiff10=abs(Oct-Oct2);
CDFdiff11=abs(Nov-Nov2);
CDFdiff12=abs(Dec-Dec2);
%
%FS(1,:)=sum(reshape(CDFdiff1,31,3000));
%FS(2,:)=sum(reshape(CDFdiff2,28,3000));
%FS(3,:)=sum(reshape(CDFdiff3,31,3000));
%FS(4,:)=sum(reshape(CDFdiff4,30,3000));
%FS(5,:)=sum(reshape(CDFdiff5,31,3000));
%FS(6,:)=sum(reshape(CDFdiff6,30,3000));
%FS(7,:)=sum(reshape(CDFdiff7,31,3000));
%FS(8,:)=sum(reshape(CDFdiff8,31,3000));
%FS(9,:)=sum(reshape(CDFdiff9,30,3000));
%FS(10,:)=sum(reshape(CDFdiff10,31,3000));
%FS(11,:)=sum(reshape(CDFdiff11,30,3000));
%FS(12,:)=sum(reshape(CDFdiff12,31,3000));
% ISO above
FS(1,:)=sum(reshape(CDFdiff1,31,3000))/31;

```

```

FS(2,:)=sum(reshape(CDFdiff2,28,3000))/28;
FS(3,:)=sum(reshape(CDFdiff3,31,3000))/31;
FS(4,:)=sum(reshape(CDFdiff4,30,3000))/30;
FS(5,:)=sum(reshape(CDFdiff5,31,3000))/31;
FS(6,:)=sum(reshape(CDFdiff6,30,3000))/30;
FS(7,:)=sum(reshape(CDFdiff7,31,3000))/31;
FS(8,:)=sum(reshape(CDFdiff8,31,3000))/31;
FS(9,:)=sum(reshape(CDFdiff9,30,3000))/30;
FS(10,:)=sum(reshape(CDFdiff10,31,3000))/31;
FS(11,:)=sum(reshape(CDFdiff11,30,3000))/30;
FS(12,:)=sum(reshape(CDFdiff12,31,3000))/31;

FS_relhum=FS';
save FS_relhum.mat FS_relhum;

save CDFdiff_relhum.mat CDFdiff1 CDFdiff2 CDFdiff3 CDFdiff4 CDFdiff5
CDFdiff6 CDFdiff7 CDFdiff8 CDFdiff9 CDFdiff10 CDFdiff11 CDFdiff12;

time=clock;
a2=time(4:6);
fprintf('\n Ending at  %4d hour %4d min %4.2f second', a2);
a=a2-a1;
fprintf('\n Time spent: %4d hour %4d min %4.2f second', a);
clear all;

% Step 5: Selecting three months with the lowest FS ranking
fprintf('\n Step 5: Selecting three months with the lowest FS
ranking.....(Estimated time: 1 mins)');
load FS_relhum;

```

```

load FS_temp;
load FS_rad;
[~,a]=sort(FS_temp);
[~,XI_temp]=sort(a);
[~,a]=sort(FS_rad);
[~,XI_rad]=sort(a);
[~,a]=sort(FS_relhum);
[~,XI_relhum]=sort(a);

XI=XI_relhum+XI_rad+XI_temp; %sum order of three climate parameters

[~,a]=sort(XI);
n=zeros(3,12);y=zeros(3,12);
for o=1:12      %12 months
    for z=1:3    %first three low value
        n(z,o)=floor((a(z,o)-1)/30)+1; % n is set of data
        y(z,o)=a(z,o)-30*(n(z,o)-1)+3000; % y is year
    end
end
end

clear XI XI_rad XI_relhum XI_temp o z

save yearall.mat;
save year.mat n y;

% Step 6: Calculate daily wind speed
fprintf('\n Step 6: Calculate daily wind speed .....(Estimated time:
3 secs)');
%time=clock;
%a1=time(4:6);
%fprintf('\n Starting at %4d hour %4d min %4.2f second', a1);

```

```
load pday; % load raw daily data
```

```
JD=pday(:,1); %Day Number of the year
```

```
Tmax=pday(:,5)+273.16; %Tmax, K
```

```
Tmin=pday(:,4)+273.16; %Tmin, K
```

```
temp1=(pday(:,4)+pday(:,5))/2; %daily mean temperature
```

```
ss=pday(:,8); % sunshine hours day total
```

```
Rs=pday(:,9)+pday(:,10); % total incoming solar radiation, MJ/m2/d
```

```
PET=pday(:,11);
```

```
ea=pday(:,6)/10;
```

```
temp2(1,1)=temp1(size(temp1,1),1);%generate temperature for previous day
```

```
temp2(2:size(temp1,1),1)=temp1(1:size(temp1,1)-1,1);
```

```
%calculate DEC solar declination in radians
```

```
DEC=0.409*sin(2*pi/365*JD-1.39);
```

```
%DEC=(0.33281-22.984*cos(JD)+3.7872*sin(JD)-
```

```
0.3499*cos(2*JD)+0.03205*sin(2*JD)-
```

```
0.1398*cos(3*JD)+0.07187*sin(3*JD))*pi/180; %results in radians
```

```
% simplified DEC=0.409*sin(JD-1.39);
```

```
load latitude;
```

```
lat=latitude*pi/180;
```

```
Omega=acos(-tan(lat).*tan(DEC)); %calcuete sunset hour angle
```

```

dyln=7.64*Omega; %dyln, sunshine hour angle, from Richard Excel and
pet_penmon.f90

ssf=ss./dyln;
for i=1:size(ssf,1)
    if ssf(i,1)>1
        ssf(i,1)=1;
    end
end

JD=2*pi*JD/366; %Julian day in radians
dr=1+0.033*cos(JD); %inverse relative distance from Earth to sun
Gsc=0.0820; %solar constant, MJ/m2/min

Ra=1440/pi*Gsc.*dr.*(Omega.*sin(lat).*sin(DEC)+cos(lat).*cos(DEC).*sin(Omega
)); %extraterrestrial radiation, ML/m2/d
z=0; % station elevation, meter
Rso=(0.75+2e-5*z)*Ra; %daily clear sky solar radiation Rso at z meter,
ML/m2/d

Sigma=4.903e-9; %Stefan-Boltzmann constant, MJ/K4/m2/d

Rnl=Sigma*((Tmax.^4+Tmin.^4)/2).*(0.34-0.14*ea.^0.5).*(0.9*ssf+0.1);
%Rnl=Sigma*((Tmax.^4+Tmin.^4)/2).*(0.34-0.14*ea.^0.5).*(1.35*Rs./Rso-0.35);
% outgoing net longwave radiation, from Irmak's paper

alpha=0.23; %albedo or canopy reflection coefficient, 0.23 for a grass reference
crop surface
Rns=0.77*(0.25+0.5*ssf).*Ra; % incoming net shortwave raditaion, Rns,
balance between incoming and reflected solar radiation
%Rns=(1-alpha)*Rs, Irmak's paper

Rn=Rns-Rnl; %net radiation at the crop surface, MJ/m2/day

```

```

%calculate G, soil heat flux density, MJ/m2/day
G=0.38*(temp1-temp2);

%calculate lambda, latent heat of vaporization, MJ*kg-1
lambda=2.501-2.361e-3*temp1;
%calculate P, atmospheric pressure at elevation z, kPa
P=101.3;
%calculate r, psychrometric constant, kPa/K
r=0.00163*P./lambda;
%calculate es, saturated vapour pressure, kPa
es=(0.6108*exp((17.27*(Tmax-273.16))./(Tmax+237.3-
273.16))+0.6108*exp((17.27*(Tmin-273.16))./(Tmin-273.16+237.3)))/2;
%es=0.611*exp((17.27*temp1)./(temp1+237.3));%
%calculate delta, gradient of vapour pressure against temperature curve at
%temperature, kPa/K
delta=4098*es./((temp1+237.3).^2);

wind2=(PET.*delta+PET.*r-0.408*delta.*(Rn-G))./(900*r.*(es-
ea)./(temp1+273.16)-0.34*PET.*r); %wind speed at 2m

wnf=log((2-0.08)/0.015)/log((10-0.08)/0.015); %convert wind speed at 2m to
10m
wind10=wind2/wnf; %wind speed at 10meter
windspeed=wind10;
index1=0;
index2=0;
for i=1:size(windspeed,1)
    if windspeed(i,1)<0
        windspeed(i,1)=-windspeed(i,1);
        index1=index1-1;
    end %delete negative values

```

```

        if windspeed(i,1)>21
            windspeed(i,1)=21;
            index2=index2+1;
        end %set 21 m/s as threshold, if the windspeed over 21, set to 21
    end

if windspeed(1,1)>20 % for i=1
    windspeed(1,1)=(windspeed(size(windspeed,1),1)+windspeed(2,1))/2;
end

for i=2:(size(windspeed,1)-1)
    if windspeed(i,1)>20
        windspeed(i,1)=(windspeed(i-1,1)+windspeed(i+1,1))/2;
    end %if the windspeed over 20, set the windspeed to the average of
nearby values
end

if windspeed(size(windspeed,1),1)>20 % for i=size(windspeed,1)
    windspeed(size(windspeed,1),1)=(windspeed(size(windspeed,1)-
1,1)+windspeed(1,1))/2;
end

%time=clock;
%a2=time(4:6);
%fprintf('\n Ending at %4d hour %4d min %4.2f second', a2);
%a=a2-a1;
%fprintf('\n Time spent: %4d hour %4d min %4.2f second', a);
%clear a1 a2 a
save windall.mat;
save wind.mat windspeed;
clear all

```



```

% Step 7: Calculate monthly mean wind speed
load wind.mat
fprintf('\n Step 7: Calculate monthly mean wind speed.....(Estimated
time: 3 secs)');
WindDev=zeros(3000,12);
for i=1:100
    for d=3001:3030
        WindDev((i-1)*30+d-3000,1)=mean(windspeed((datenum(d,1,1)-
1096093+10957*(i-1)):(datenum(d,1,31)-1096093+10957*(i-1))));
        WindDev((i-1)*30+d-3000,2)=mean(windspeed((datenum(d,2,1)-
1096093+10957*(i-1)):(datenum(d,2,28)-1096093+10957*(i-1))));
        WindDev((i-1)*30+d-3000,3)=mean(windspeed((datenum(d,3,1)-
1096093+10957*(i-1)):(datenum(d,3,31)-1096093+10957*(i-1))));
        WindDev((i-1)*30+d-3000,4)=mean(windspeed((datenum(d,4,1)-
1096093+10957*(i-1)):(datenum(d,4,30)-1096093+10957*(i-1))));
        WindDev((i-1)*30+d-3000,5)=mean(windspeed((datenum(d,5,1)-
1096093+10957*(i-1)):(datenum(d,5,31)-1096093+10957*(i-1))));
        WindDev((i-1)*30+d-3000,6)=mean(windspeed((datenum(d,6,1)-
1096093+10957*(i-1)):(datenum(d,6,30)-1096093+10957*(i-1))));
        WindDev((i-1)*30+d-3000,7)=mean(windspeed((datenum(d,7,1)-
1096093+10957*(i-1)):(datenum(d,7,31)-1096093+10957*(i-1))));
        WindDev((i-1)*30+d-3000,8)=mean(windspeed((datenum(d,8,1)-
1096093+10957*(i-1)):(datenum(d,8,31)-1096093+10957*(i-1))));
        WindDev((i-1)*30+d-3000,9)=mean(windspeed((datenum(d,9,1)-
1096093+10957*(i-1)):(datenum(d,9,30)-1096093+10957*(i-1))));
        WindDev((i-1)*30+d-3000,10)=mean(windspeed((datenum(d,10,1)-
1096093+10957*(i-1)):(datenum(d,10,31)-1096093+10957*(i-1))));
        WindDev((i-1)*30+d-3000,11)=mean(windspeed((datenum(d,11,1)-
1096093+10957*(i-1)):(datenum(d,11,30)-1096093+10957*(i-1))));
        WindDev((i-1)*30+d-3000,12)=mean(windspeed((datenum(d,12,1)-
1096093+10957*(i-1)):(datenum(d,12,31)-1096093+10957*(i-1))));

```

```

        %1096093=datenum(3000,12,31);10957=datenum(3030,12,31)-
datenum(3000,12,31)
    end
end
clear d i windspeed;
save WindDev.mat WindDev;
clear all;

% Step 8: Calculate the deviation of the monthly mean wind speed from the
% corresponding multi-year calendar month mean
load WindDev;
fprintf('\n Step 8: Calculate monthly mean wind speed
deviation.....(Estimated time: 3 secs)');
load year.mat;
CalenderM=mean(WindDev);
Dev=zeros(3,12);
for i=1:12
    for o=1:3
        Dev(o,i)=WindDev((n(o,i)-1)*30+y(o,i)-3000,i)-CalenderM(i);
    end
end

[~,A]=sort(Dev);
year=zeros(2,12);
for i=1:12
    year(1,i)=y(A(1,i),i);
    year(2,i)=n(A(1,i),i);
end

save yearnumber.mat year;

```

```

fprintf('\n Selected 12 months for TRY:');
fprintf('\n Jan is from year %4d _ %2d th data set', year(:,1));
fprintf('\n Feb is from year %4d _ %2d th data set', year(:,2));
fprintf('\n Mar is from year %4d _ %2d th data set', year(:,3));
fprintf('\n Apr is from year %4d _ %2d th data set', year(:,4));
fprintf('\n May is from year %4d _ %2d th data set', year(:,5));
fprintf('\n Jun is from year %4d _ %2d th data set', year(:,6));
fprintf('\n Jul is from year %4d _ %2d th data set', year(:,7));
fprintf('\n Aug is from year %4d _ %2d th data set', year(:,8));
fprintf('\n Sep is from year %4d _ %2d th data set', year(:,9));
fprintf('\n Oct is from year %4d _ %2d th data set', year(:,10));
fprintf('\n Nov is from year %4d _ %2d th data set', year(:,11));
fprintf('\n Dec is from year %4d _ %2d th data set', year(:,12));

% Step 9: Generating TRY data(CIBSE format)
clear all;
fprintf('\n Step 9: Generating TRY data(CIBSE format).....(Estimated
time: 25 secs)');
load yearnumber;
DayNu=[31,28,31,30,31,30,31,31,30,31,30,31];

load txt;

a=1;
TRY=zeros(8760,11);
for i=1:12
    %p0=dlmread(char(txt(year(2,i),1)),',', 'A1..K262968'); %1 control data
    p0=dlmread(char(txt(year(2,i),2)),',', 'A1..K262968'); %2 senario data
    for m=1:262968
        if ((p0(m,1)==year(1,i)) && (p0(m,2)==i)&&(p0(m,3)==1)&&(p0(m,4)==0))
            TRY(a:(a+DayNu(i)*24-1),:)=p0(m:m+DayNu(i)*24-1,:);
        end
    end
end

```

```

    end
    a=a+24*DayNu(i);
end
save TestReferenceYear.mat TRY
clear DayNu a i m p0 txt;

% Step 10: Adjusting the hourly value at the beginning and end of each
% month
fprintf('\n Step 10: Adjusting hourly value at beginning and end of each
month...(Estimated time: 25 secs)');
TRY_S=TRY;
for q=6:8 %column 6,7,8 are temp_hmean,vapourpressure_hmean and
relhum_hmean
% smooth beginning of Jan and end of Dec
y1=TRY(1:8,q);
y2=TRY(8760-7:8760,q);
y0=cat(1,y2,y1);
y(1)=y0(1);
y(5)=y0(16);
y(3)=mean(y0);
y(2)=mean(y2);
y(4)=mean(y1);
x=[1,4.75,8.5,13.25,16];
xx=1:16;
yy=spline(x,y,xx);
TRY_S(8760-7:8760,q)=yy(1:8)';
TRY_S(1:8,q)=yy(9:16)';
% smooth other months
for i=10:8760
    if (TRY(i,2)>TRY(i-1,2))
        y(1)=TRY(i-8,q);

```

```

y(5)=TRY(i+7,q);
y(3)=mean(TRY(i-8:i+7,q));
y(2)=mean(TRY(i-8:i-1,q));
y(4)=mean(TRY(i:i+7,q));
x=[1,4.75,8.5,13.25,16];
xx=1:16;
yy=spline(x,y,xx);
TRY_S(i-8:i+7,q)=yy';
end
end
end
save TestReferenceYear_Smoothed.mat TRY_S;
clear y1 y2 y0 y x xx yy i q;

% Step 11: Caculate dew point temeprature, horizontal infrared and direct
normal radiation
fprintf('\n Step 11: Generating TRY data (EPW format:');
fprintf('\n Step 11.1: Calculating dew point temeprature.....(Estimated
time: 1 sec)');
r=17.271*TRY_S(:,6)./(237.7+TRY_S(:,6))+log(TRY_S(:,8));
TRY_S(:,12)=237.7*r./(17.271-r); %column 12, dew point temperature,

for i=1:8760
    if TRY_S(:,12)>TRY_S(:,6)
        TRY_S(:,12)=TRY_S(:,6);
    end
end
end

clear r

```

```

fprintf('\n Step 11.2: Calculating direct normal radiation.....(Estimated
time: 5 secs)');
%column 13, date number OF the year
TRY_S(1,13)=1; % first day number is 1
for i=2:8760
    if or(TRY_S(i,3)>TRY_S(i-1,3),TRY_S(i,2)>TRY_S(i-1,2))
        TRY_S(i,13)=TRY_S(i-1,13)+1;
    else
        TRY_S(i,13)=TRY_S(i-1,13);
    end
end
clear i;
%column 15, DEC, solar Declination (between the earth-sun line and the
equator plane) in radians
TRY_S(:,14)=2*pi*((TRY_S(:,13))/366); %N
TRY_S(:,15)=(0.33281-22.984*cos(TRY_S(:,14))+3.7872*sin(TRY_S(:,14))-
0.3499*cos(2*TRY_S(:,14))+0.03205*sin(2*TRY_S(:,14))-
0.1398*cos(3*TRY_S(:,14))+0.07187*sin(3*TRY_S(:,14)))*pi/180;
%column 16, HRA, hour angle from solar noon, 15 degree per hour, in radians
TRY_S(:,16)=15*(TRY_S(:,4)/100-11.5)*pi/180;
%LAT, geographical latitude (south negative), in radians
load latitude
LAT=latitude*pi/180;
%column 17, ALT, solar altitude(from horizontal max 90 zenith), in radians,
TRY_S(:,17)=asin(sin(TRY_S(:,15))*sin(LAT)+cos(LAT)*cos(TRY_S(:,16)).*cos(
TRY_S(:,15)));
%column 18, direct normal=direct horizontal/sin(solar altitude),
TRY_S(:,18)=TRY_S(:,11)./sin(TRY_S(:,17));
a=0;
for i=2:8760
    if TRY_S(i,18)<0
        TRY_S(i,18)=0; %delete the negative value
    end
end

```

```

        end
    end

    %delete unreasonable value at sunrise and sunset, (solar altitude <11 degree,
    direct normal>100)
    TRY_S(:,19)=TRY_S(:,17)*180/pi; %column 19, solar altitude in degree

    TRY_SS=TRY_S;
    c=0;
    for i=1:8760
        if and(TRY_S(i,19)<11,TRY_S(i,18)>200)
            TRY_SS(i,18)=200;
            c=c+1;
            A(c,1)=TRY_S(i,18);
            A(c,2)=TRY_S(i,19);
        end
    end %when direct normal over 200, set to 200

    c=0;
    for i=1:8760
        if and(TRY_S(i,19)<11,TRY_S(i,18)>100)
            TRY_SS(i,18)=(TRY_SS(i-1,18)+TRY_SS(i+1,18))/2;
            c=c+1;
        end
    end %re-run, when direct normal over 100, set to avearge of nearby values

    fprintf('\n Step 11.3: Calculating cloud cover.....(Estimated time:
    2 secs)');
    TRY_SS(:,20)=10*(1-TRY_SS(:,9)); %column 20, total sky cover in tenth
    for i=1:8760
        if TRY_SS(i,9)==0

```

```

        TRY_SS(i,20)=0;
    end
end

% night cloud covers are equal to interpolation of cloud covers at sunrise and
sunset time
c1=0;
for i=2:8760
    if TRY_SS(i,19)*TRY_SS(i-1,19)<0
        c1=c1+1;
        Index(c1)=i;
    end %Identify night time
end

for i=1:(size(Index,2)-2)/2
    z(1)=TRY_SS(Index(i*2)-1,20);
    z(2)=TRY_SS(Index(i*2+1),20);
    TRY_SS(Index(i*2)-1:(Index(i*2+1)),20)=interp1(0:1,z,0:1/(Index(i*2+1)-
Index(i*2)+1):1);
end %liner interpolate cloud cover at night time

for i=1:8760
    TRY_SS(i,20)=round(TRY_SS(i,20));
end %integral function
%
fprintf('\n Step 11.4: Calculating horizontal infrared radiation
intensity...(Estimated time: 2 secs)');
TRY_SS(:,21)=round(TRY_SS(:,20)/2); %column 21, opaque sky cover,
assumed as half the value of total sky cover
SkyE=(0.787+0.764*log((TRY_SS(:,12)+273)/273)).*(1+0.0224*TRY_SS(:,21)+
0.0035*TRY_SS(:,21).^2+0.00028*TRY_SS(:,21).^3);

```



```

TRY_SS(:,22)=5.6697e-8*SkyE.*(TRY_SS(:,6)+273).^4; %column 22,
horizontal infrared radiation intensty

TRY_SS(:,23)=101300; %column 23, atmospheric pressure
TRY_SS(:,24)=TRY_SS(:,10)+TRY_SS(:,11); %column 24, global horizontal
radiation,
TRY_SS(:,8)=floor(100*TRY_SS(:,8)); %column 8, relative humidity, in
percentage
save TRY_EPW TRY_SS
dlmwrite('TRY.csv',TRY_SS);
fprintf('\n Congratulation!!! TRY is saved as "TRY.csv"');
clear;
%%
DRY99_Hu_Part; % to run script to generate DRY
DRY85_Hu_Part;
clear;
%PlotDRYTRY;
fprintf('\n Total ');
toc;

%column 1, year
%column 2, month
%column 3, date of the month
%column 4, hour
%column 5, precip htotal, mm/hour
%column 6, hourly temperature, degree C
%column 7, vapour pressure, hPa
%column 8, relative humidity, %
%column 9, sunshine hour, hours
%column 10, diffuse solar radiation, Wh/m2
%column 11, direct solar radiation in horizontal, Wh/m2
%column 12, dew point temperature, C

```

%column 13, date number of the year
%column 14, date number, in radians
%column 15, solar declination, in radians
%column 16, hour angle from solar noon
%column 17, solar altitude, in radians
%column 18, direct normal radiation, Wh/m²
%column 19, solar altitude, in degree
%column 20, total sky cover
%column 21, opaque sky cover
%column 22, horizontal infrared radiation intensity
%column 23, atmospheric pressure
%column 24, global horizontal radiation,

```

%***** DRY85_Hu_Part.m *****
%% Step 12: Calculating monthly mean temperature for 3000 years
fprintf('\n Calculating DRY at 85 percentile...');
fprintf('\n Step 12: Calculating monthly mean temperature for 3000
years...(Estimated time: 1 min)')

load temperature;
save JanFebJunJulAug.mat Jan Feb Jun Jul Aug Dec;
SummerYearNumber=zeros(100,1);
m=0;
for i=1:100
    for d=3001:3030
        m=m+1;
        s1=['MonthMeanTemp(m,1)=mean(Jan' int2str(d) '_' int2str(i) ');'];
        s2=['MonthMeanTemp(m,2)=mean(Feb' int2str(d) '_' int2str(i) ');'];
        s3=['MonthMeanTemp(m,3)=mean(Mar' int2str(d) '_' int2str(i) ');'];
        s4=['MonthMeanTemp(m,4)=mean(Apr' int2str(d) '_' int2str(i) ');'];
        s5=['MonthMeanTemp(m,5)=mean(May' int2str(d) '_' int2str(i) ');'];
        s6=['MonthMeanTemp(m,6)=mean(Jun' int2str(d) '_' int2str(i) ');'];
        s7=['MonthMeanTemp(m,7)=mean(Jul' int2str(d) '_' int2str(i) ');'];
        s8=['MonthMeanTemp(m,8)=mean(Aug' int2str(d) '_' int2str(i) ');'];
        s9=['MonthMeanTemp(m,9)=mean(Sep' int2str(d) '_' int2str(i) ');'];
        s10=['MonthMeanTemp(m,10)=mean(Oct' int2str(d) '_' int2str(i) ');'];
        s11=['MonthMeanTemp(m,11)=mean(Nov' int2str(d) '_' int2str(i) ');'];
        s12=['MonthMeanTemp(m,12)=mean(Dec' int2str(d) '_' int2str(i) ');'];
        eval(s1);
        eval(s2);
        eval(s3);
        eval(s4);
        eval(s5);
        eval(s6);
        eval(s7);
    end
end

```

```

        eval(s8);
        eval(s9);
        eval(s10);
        eval(s11);
        eval(s12);
    end
end

MeanTemp(1)=mean(Jan);
MeanTemp(2)=mean(Feb);
MeanTemp(3)=mean(Mar);
MeanTemp(4)=mean(Apr);
MeanTemp(5)=mean(May);
MeanTemp(6)=mean(Jun);
MeanTemp(7)=mean(Jul);
MeanTemp(8)=mean(Aug);
MeanTemp(9)=mean(Sep);
MeanTemp(10)=mean(Oct);
MeanTemp(11)=mean(Nov);
MeanTemp(12)=mean(Dec);
save MonthMeanTemp.mat MonthMeanTemp MeanTemp

clear d s1 s2 s3 s4 s5 s6 s7 s8 s9 s10 s11 s12

clear;
%% Step 13: Selecting month for Design Reference Year
fprintf('\n Step 13: Selecting month for Design Reference
Year.....(Estimated time: 1 sec)')
load MonthMeanTemp
for i=1:12
    [RankedMeanTemp(:,i),X(:,i)]=sort(MonthMeanTemp(:,i));
end

```

% 99th percentile

```
YearJanFebJunJulAug(:,1)=X(451:480,1);  
YearJanFebJunJulAug(:,2)=X(451:480,2);  
YearJanFebJunJulAug(:,3)=X(2521:2550,6);  
YearJanFebJunJulAug(:,4)=X(2521:2550,7);  
YearJanFebJunJulAug(:,5)=X(2521:2550,8);  
YearJanFebJunJulAug(:,6)=X(451:480,12);
```

```
load JanFebJunJulAug;
```

```
Jan30=[];
```

```
Feb30=[];
```

```
Jun30=[];
```

```
Jul30=[];
```

```
Aug30=[];
```

```
Dec30=[];
```

```
for i=1:30
```

```
    yearnumberJan=YearJanFebJunJulAug(i,1);
```

```
    yearnumberFeb=YearJanFebJunJulAug(i,2);
```

```
    yearnumberJun=YearJanFebJunJulAug(i,3);
```

```
    yearnumberJul=YearJanFebJunJulAug(i,4);
```

```
    yearnumberAug=YearJanFebJunJulAug(i,5);
```

```
    yearnumberDec=YearJanFebJunJulAug(i,6);
```

```
    JanMonth=Jan((yearnumberJan-1)*31+1:(yearnumberJan-1)*31+31);
```

```
    FebMonth=Feb((yearnumberFeb-1)*28+1:(yearnumberFeb-1)*28+28);
```

```
    JunMonth=Jun((yearnumberJun-1)*30+1:(yearnumberJun-1)*30+30);
```

```
    JulMonth=Jul((yearnumberJul-1)*31+1:(yearnumberJul-1)*31+31);
```

```
    AugMonth=Aug((yearnumberAug-1)*31+1:(yearnumberAug-1)*31+31);
```

```
    DecMonth=Dec((yearnumberDec-1)*31+1:(yearnumberDec-1)*31+31);
```

```
    Jan30=cat(1,JanMonth,Jan30);
```

```
    Feb30=cat(1,FebMonth,Feb30);
```

```

Jun30=cat(1,JunMonth,Jun30);
Jul30=cat(1,JulMonth,Jul30);
Aug30=cat(1,AugMonth,Aug30);
Dec30=cat(1,DecMonth,Dec30);
end
Jan30Month=reshape(Jan30,31,30); % daily mean of selected 30 months
Feb30Month=reshape(Feb30,28,30);
Jun30Month=reshape(Jun30,30,30);
Jul30Month=reshape(Jul30,31,30);
Aug30Month=reshape(Aug30,31,30);
Dec30Month=reshape(Dec30,31,30);
% calculate FS-stat for selected 30 months
for i=1:30
    CDFJan(:,i)=CDFIso(Jan30Month(:,i));
    CDFFeb(:,i)=CDFIso(Feb30Month(:,i));
    CDFJun(:,i)=CDFIso(Jun30Month(:,i));
    CDFJul(:,i)=CDFIso(Jul30Month(:,i));
    CDFAug(:,i)=CDFIso(Aug30Month(:,i));
    CDFDec(:,i)=CDFIso(Dec30Month(:,i));
end
CDFJanAll=CDFIso(Jan30);
CDFFebAll=CDFIso(Feb30);
CDFJunAll=CDFIso(Jun30);
CDFJulAll=CDFIso(Jul30);
CDFAugAll=CDFIso(Aug30);
CDFDecAll=CDFIso(Dec30);

CDFJanA=reshape(CDFJanAll,31,30);
CDFFebA=reshape(CDFFebAll,28,30);
CDFJunA=reshape(CDFJunAll,30,30);
CDFJulA=reshape(CDFJulAll,31,30);
CDFAugA=reshape(CDFAugAll,31,30);

```

```
CDFDecA=reshape(CDFDecAll,31,30);
```

```
JanFS=sum(abs(CDFJanA-CDFJan));
```

```
FebFS=sum(abs(CDFFebA-CDFFeb));
```

```
JunFS=sum(abs(CDFJunA-CDFJun));
```

```
JulFS=sum(abs(CDFJulA-CDFJul));
```

```
AugFS=sum(abs(CDFAugA-CDFAug));
```

```
DecFS=sum(abs(CDFDecA-CDFDec));
```

```
[~,AJan]=sort(JanFS);
```

```
[~,AFeb]=sort(FebFS);
```

```
[~,AJun]=sort(JunFS);
```

```
[~,AJul]=sort(JulFS);
```

```
[~,AAug]=sort(AugFS);
```

```
[~,ADec]=sort(DecFS);
```

```
YearNumberDRY(1,1)=YearJanFebJunJulAug(AJan(1),1);
```

```
YearNumberDRY(2,1)=YearJanFebJunJulAug(AFeb(1),2);
```

```
YearNumberDRY(6,1)=YearJanFebJunJulAug(AJun(1),3);
```

```
YearNumberDRY(7,1)=YearJanFebJunJulAug(AJul(1),4);
```

```
YearNumberDRY(8,1)=YearJanFebJunJulAug(AAug(1),5);
```

```
YearNumberDRY(12,1)=YearJanFebJunJulAug(ADec(1),6);
```

```
YearNumberDRY(1,2)=YearJanFebJunJulAug(AJan(2),1);
```

```
YearNumberDRY(2,2)=YearJanFebJunJulAug(AFeb(2),2);
```

```
YearNumberDRY(6,2)=YearJanFebJunJulAug(AJun(2),3);
```

```
YearNumberDRY(7,2)=YearJanFebJunJulAug(AJul(2),4);
```

```
YearNumberDRY(8,2)=YearJanFebJunJulAug(AAug(2),5);
```

```
YearNumberDRY(12,2)=YearJanFebJunJulAug(ADec(2),6);
```

```
YearNumberDRY(1,3)=YearJanFebJunJulAug(AJan(3),1);
```

```
YearNumberDRY(2,3)=YearJanFebJunJulAug(AFeb(3),2);
```

```

YearNumberDRY(6,3)=YearJanFebJunJulAug(AJun(3),3);
YearNumberDRY(7,3)=YearJanFebJunJulAug(AJul(3),4);
YearNumberDRY(8,3)=YearJanFebJunJulAug(AAug(3),5);
YearNumberDRY(12,3)=YearJanFebJunJulAug(ADec(3),6);

```

```

YearNumberDRY(1,4)=YearJanFebJunJulAug(AJan(4),1);
YearNumberDRY(2,4)=YearJanFebJunJulAug(AFeb(4),2);
YearNumberDRY(6,4)=YearJanFebJunJulAug(AJun(4),3);
YearNumberDRY(7,4)=YearJanFebJunJulAug(AJul(4),4);
YearNumberDRY(8,4)=YearJanFebJunJulAug(AAug(4),5);
YearNumberDRY(12,4)=YearJanFebJunJulAug(ADec(4),6);

```

```

YearNumberDRY(1,5)=YearJanFebJunJulAug(AJan(5),1);
YearNumberDRY(2,5)=YearJanFebJunJulAug(AFeb(5),2);
YearNumberDRY(6,5)=YearJanFebJunJulAug(AJun(5),3);
YearNumberDRY(7,5)=YearJanFebJunJulAug(AJul(5),4);
YearNumberDRY(8,5)=YearJanFebJunJulAug(AAug(5),5);
YearNumberDRY(12,5)=YearJanFebJunJulAug(ADec(5),6);

```

```
save YearnumberDRY.mat YearNumberDRY
```

```
load radiation.mat
```

```
m=0;
```

```
for i=1:100
```

```
    for d=3001:3030
```

```
        m=m+1;
```

```
        s1=['MonthMeanRad(m,1)=mean(Jan' int2str(d) ' ' int2str(i) ');'];
```

```
        s2=['MonthMeanRad(m,2)=mean(Feb' int2str(d) ' ' int2str(i) ');'];
```

```
        s3=['MonthMeanRad(m,3)=mean(Mar' int2str(d) ' ' int2str(i) ');'];
```

```
        s4=['MonthMeanRad(m,4)=mean(Apr' int2str(d) ' ' int2str(i) ');'];
```

```
        s5=['MonthMeanRad(m,5)=mean(May' int2str(d) ' ' int2str(i) ');'];
```

```
        s6=['MonthMeanRad(m,6)=mean(Jun' int2str(d) ' ' int2str(i) ');'];
```

```
        s7=['MonthMeanRad(m,7)=mean(Jul' int2str(d) ' ' int2str(i) ');'];
```



```

s8=['MonthMeanRad(m,8)=mean(Aug' int2str(d) '_' int2str(i) ');'];
s9=['MonthMeanRad(m,9)=mean(Sep' int2str(d) '_' int2str(i) ');'];
s10=['MonthMeanRad(m,10)=mean(Oct' int2str(d) '_' int2str(i) ');'];
s11=['MonthMeanRad(m,11)=mean(Nov' int2str(d) '_' int2str(i) ');'];
s12=['MonthMeanRad(m,12)=mean(Dec' int2str(d) '_' int2str(i) ');'];
eval(s1);
eval(s2);
eval(s3);
eval(s4);
eval(s5);
eval(s6);
eval(s7);
eval(s8);
eval(s9);
eval(s10);
eval(s11);
eval(s12);
end
end
save MonthMeanRad.mat MonthMeanRad

```

```

FiveMonthRadMean(:,1)=MonthMeanRad(YearNumberDRY(1,:),1); %Selected
5 Jan mean radiation
FiveMonthRadMean(:,2)=MonthMeanRad(YearNumberDRY(2,:),1);
FiveMonthRadMean(:,3)=MonthMeanRad(YearNumberDRY(6,:),1);
FiveMonthRadMean(:,4)=MonthMeanRad(YearNumberDRY(7,:),1);
FiveMonthRadMean(:,5)=MonthMeanRad(YearNumberDRY(8,:),1);
FiveMonthRadMean(:,6)=MonthMeanRad(YearNumberDRY(12,:),1);

[~,XX]=sort(FiveMonthRadMean);
YearNumberDRYFinal(1)=YearNumberDRY(1,XX(1,1)); %Select the month
having lowest solar radiation

```

```

YearNumberDRYFinal(2)=YearNumberDRY(2,XX(1,2)); %Select the month
having lowest solar radiation
YearNumberDRYFinal(6)=YearNumberDRY(6,XX(5,3)); %Select the month
having highest solar radiation
YearNumberDRYFinal(7)=YearNumberDRY(7,XX(5,4)); %Select the month
having highest solar radiation
YearNumberDRYFinal(8)=YearNumberDRY(8,XX(5,5)); %Select the month
having highest solar radiation
YearNumberDRYFinal(12)=YearNumberDRY(12,XX(5,6)); %Select the month
having highest solar radiation
save YearNumberDRYFinal.mat YearNumberDRYFinal

```

```

n=zeros(1,12);y=zeros(1,12);
a=YearNumberDRYFinal;
for o=1:12          %12 months
    n(o)=floor((a(o)-1)/30)+1; % n is set of data
    y(o)=a(o)-30*(n(o)-1)+3000; % y is year
end

```

```

load YearNumber
y0=year(1,:);
n0=year(2,:);
n(3:5)=n0(3:5);
y(3:5)=y0(3:5);
n(9:11)=n0(9:11);
y(9:11)=y0(9:11);

```

```

year(1,:)=y;
year(2,:)=n;

```

```

fprintf('\n Selected 5 months for DRY:');

```

```

fprintf('\n Jan is from year %4d _ %2d th data set', year(:,1));
fprintf('\n Feb is from year %4d _ %2d th data set', year(:,2));
fprintf('\n Jun is from year %4d _ %2d th data set', year(:,6));
fprintf('\n Jul is from year %4d _ %2d th data set', year(:,7));
fprintf('\n Aug is from year %4d _ %2d th data set', year(:,8));
fprintf('\n Dec is from year %4d _ %2d th data set', year(:,12));
save yearDRY.mat n y;
clear all;

```

%% Step 14: Generating DSY data(CIBSE format)

```

fprintf('\n Step 14: Generating DSY data(CIBSE format).....(Estimated
time: 25 secs)');
load yearDRY;
load txt;
year(1,:)=y;
year(2,:)=n;

```

```

DayNu=[31,28,31,30,31,30,31,31,30,31,30,31];
a=1;
DRY=zeros(8760,11);
for i=1:12
    %p0=dlmread(char(txt(year(2,i),1)),',', 'A1..K262968'); %1 control data
    p0=dlmread(char(txt(year(2,i),2)),',', 'A1..K262968'); %2 senario data
    for m=1:262968
        if ((p0(m,1)==year(1,i)) && (p0(m,2)==i)&&(p0(m,3)==1)&&(p0(m,4)==0))
            DRY(a:(a+DayNu(i)*24-1,:)=p0(m:m+DayNu(i)*24-1,:);
        end
    end
    a=a+24*DayNu(i);
end
save DesignReferenceYear.mat DRY
clear;

```

```

% Step 15: Adjusting the hourly value at the beginning and end of each
% month
fprintf('\n Step 15: Adjusting hourly value at beginning and end of each
month...(Estimated time: 25 secs)');
load DesignReferenceYear
DRY_S=DRY;
for q=6:8 %column 6,7,8 are temp_hmean,vapourpressure_hmean and
relhum_hmean
% smooth beginning of Jan and end of Dec
y1=DRY(1:8,q);
y2=DRY(8760-7:8760,q);
y0=cat(1,y2,y1);
y(1)=y0(1);
y(5)=y0(16);
y(3)=mean(y0);
y(2)=mean(y2);
y(4)=mean(y1);
x=[1,4.75,8.5,13.25,16];
xx=1:16;
yy=spline(x,y,xx);
DRY_S(8760-7:8760,q)=yy(1:8)';
DRY_S(1:8,q)=yy(9:16)';
% smooth other months
for i=10:8760
    if (DRY(i,2)>DRY(i-1,2))
        y(1)=DRY(i-8,q);
        y(5)=DRY(i+7,q);
        y(3)=mean(DRY(i-8:i+7,q));
        y(2)=mean(DRY(i-8:i-1,q));
        y(4)=mean(DRY(i:i+7,q));
        x=[1,4.75,8.5,13.25,16];
    end
end

```

```

        xx=1:16;
        yy=spline(x,y,xx);
        DRY_S(i-8:i+7,q)=yy';
    end
end
end
save DesignReferenceYear_Smoothed.mat DRY_S;
clear y1 y2 y0 y x xx yy i q;

% Step 16: Caculate dew point temeprature, horizontal infrared and direct
normal radiation
fprintf('\n Step 16: Caculating parameters for EPW format!');
fprintf('\n Step 16.1: Caculating dew point temeprature.....(Estimated
time: 1 secs)');
r=17.271*DRY_S(:,6)./(237.7+DRY_S(:,6))+log(DRY_S(:,8));
DRY_S(:,12)=237.7*r./(17.271-r); %column 12, dew point temperature,

for i=1:8760
    if DRY_S(:,12)>DRY_S(:,6)
        DRY_S(:,12)=DRY_S(:,6);
    end
end

clear r

fprintf('\n Step 16.2: Caculating direct normal radiation.....(Estimated
time: 5 secs)');
%column 13, date number OF the year
DRY_S(1,13)=1; % first day number is 1
for i=2:8760
    if or(DRY_S(i,3)>DRY_S(i-1,3),DRY_S(i,2)>DRY_S(i-1,2))

```

```

        DRY_S(i,13)=DRY_S(i-1,13)+1;
    else
        DRY_S(i,13)=DRY_S(i-1,13);
    end
end
clear i;
%column 15, DEC, solar Declination (between the earth-sun line and the
equator plane) in radians
DRY_S(:,14)=2*pi*((DRY_S(:,13))/366); %N
DRY_S(:,15)=(0.33281-22.984*cos(DRY_S(:,14))+3.7872*sin(DRY_S(:,14))-
0.3499*cos(2*DRY_S(:,14))+0.03205*sin(2*DRY_S(:,14))-
0.1398*cos(3*DRY_S(:,14))+0.07187*sin(3*DRY_S(:,14)))*pi/180;
%column 16, HRA, hour angle from solar noon, 15 degree per hour, in radians
DRY_S(:,16)=15*(DRY_S(:,4)/100-11.5)*pi/180;
%LAT, geographical latitude (south negative), in radians
load latitude
LAT=latitude*pi/180;
%column 17, ALT, solar altitude(from horizontal max 90 zenith), in radians,
DRY_S(:,17)=asin(sin(DRY_S(:,15))*sin(LAT)+cos(LAT)*cos(DRY_S(:,16)).*cos
(DRY_S(:,15)));
%column 18, direct normal=direct horizontal/sin(solar altitude),
DRY_S(:,18)=DRY_S(:,11)./sin(DRY_S(:,17));
a=0;
for i=2:8760
    if DRY_S(i,18)<0
        DRY_S(i,18)=0; %delect the negative value
    end
end
end

%delete unreasonable value at sunrise and sunset, (solar altitude <11 degree,
direct normal>100)
DRY_S(:,19)=DRY_S(:,17)*180/pi; %column 19, solar altitude in degree

```

```

DRY_SS=DRY_S;
c=0;
for i=1:8760
    if and(DRY_S(i,19)<11,DRY_S(i,18)>200)
        DRY_SS(i,18)=200;
        c=c+1;
        A(c,1)=DRY_S(i,18);
        A(c,2)=DRY_S(i,19);
    end
end %when direct normal over 200, set to 200

c=0;
for i=1:8760
    if and(DRY_S(i,19)<11,DRY_S(i,18)>100)
        DRY_SS(i,18)=(DRY_SS(i-1,18)+DRY_SS(i+1,18))/2;
        c=c+1;
    end
end %re-run, when direct normal over 100, set to average of nearby values

fprintf('\n Step 16.3: Calculating cloud cover.....(Estimated time:
2 secs)');
DRY_SS(:,20)=10*(1-DRY_SS(:,9)); %column 20, total sky cover in tenth
for i=1:8760
    if DRY_SS(i,9)==0
        DRY_SS(i,20)=0;
    end
end

% night cloud covers are equal to interpolation of cloud covers at sunrise and
sunset time

```

```

c1=0;
for i=2:8760
    if DRY_SS(i,19)*DRY_SS(i-1,19)<0
        c1=c1+1;
        Index(c1)=i;
    end %Identify night time
end

for i=1:(size(Index,2)-2)/2
    z(1)=DRY_SS(Index(i*2)-1,20);
    z(2)=DRY_SS(Index(i*2+1),20);
    DRY_SS(Index(i*2)-1:(Index(i*2+1)),20)=interp1(0:1,z,0:1/(Index(i*2+1)-
Index(i*2)+1):1);
end %liner interpolate cloud cover at night time

for i=1:8760
    DRY_SS(i,20)=round(DRY_SS(i,20));
end %integral function
%
fprintf('\n Step 16.4: Caculating horizontal infrared radiation intensty...(Estimated
time: 2 secs)');
DRY_SS(:,21)=round(DRY_SS(:,20)/2); %column 21, opaque sky cover,
assumed as half the value of total sky cover
SkyE=(0.787+0.764*log((DRY_SS(:,12)+273)/273)).*(1+0.0224*DRY_SS(:,21)+
0.0035*DRY_SS(:,21).^2+0.00028*DRY_SS(:,21).^3);
DRY_SS(:,22)=5.6697e-8*SkyE.*(DRY_SS(:,6)+273).^4; %column 22,
horizontal infrared radiation intensty

DRY_SS(:,23)=101300; %column 23, atmospheric pressure
DRY_SS(:,24)=DRY_SS(:,10)+DRY_SS(:,11); %column 24, global horizontal
radiation,

```



```

DRY_SS(:,8)=floor(100*DRY_SS(:,8)); %column 8, relative humidity, in
percentage
DRY85_SS=DRY_SS;
save DRY85_EPW.mat DRY85_SS
dlmwrite('DRY85.csv',DRY85_SS);
fprintf("\n Congratulation!!! DRY at 85 centile is saved as "DRY85.csv");

```

```

%column 1, year
%column 2, month
%column 3, date of the month
%column 4, hour
%column 5, precip htotal, mm/hour
%column 6, hourly temperature, degree C
%column 7, vapour pressure, hPa
%column 8, relative humidity, %
%column 9, sunshine hour, hours
%column 10, diffuse solar radiation, Wh/m2
%column 11, direct solar radiation in horizontal, Wh/m2
%column 12, dew point temperature, C
%column 13, date number of the year
%column 14, date number, in radians
%column 15, solar declination, in radians
%column 16, hour angle from solar noon
%column 17, solar altitude, in radians
%column 18, direct normal radiation, Wh/m2
%column 19, solar altitude, in degree
%column 20, total sky cover
%column 21, opaque sky cover
%column 22, horizontal infrared radiation intensty
%column 23, atmospheric pressure
%column 24, global horizontal radiation,

```



```

%***** DRY99_Hu_Part.m *****
%% Step 12: Calculating monthly mean temperature for 3000 years
fprintf('\n Calculating DRY at 99 percentile...');
fprintf('\n Step 12: Calculating monthly mean temperature for 3000
years...(Estimated time: 1 min)')

load temperature;
save JanFebJunJulAug.mat Jan Feb Jun Jul Aug Dec;
SummerYearNumber=zeros(100,1);
m=0;
for i=1:100
    for d=3001:3030
        m=m+1;
        s1=['MonthMeanTemp(m,1)=mean(Jan' int2str(d) '_' int2str(i) ');'];
        s2=['MonthMeanTemp(m,2)=mean(Feb' int2str(d) '_' int2str(i) ');'];
        s3=['MonthMeanTemp(m,3)=mean(Mar' int2str(d) '_' int2str(i) ');'];
        s4=['MonthMeanTemp(m,4)=mean(Apr' int2str(d) '_' int2str(i) ');'];
        s5=['MonthMeanTemp(m,5)=mean(May' int2str(d) '_' int2str(i) ');'];
        s6=['MonthMeanTemp(m,6)=mean(Jun' int2str(d) '_' int2str(i) ');'];
        s7=['MonthMeanTemp(m,7)=mean(Jul' int2str(d) '_' int2str(i) ');'];
        s8=['MonthMeanTemp(m,8)=mean(Aug' int2str(d) '_' int2str(i) ');'];
        s9=['MonthMeanTemp(m,9)=mean(Sep' int2str(d) '_' int2str(i) ');'];
        s10=['MonthMeanTemp(m,10)=mean(Oct' int2str(d) '_' int2str(i) ');'];
        s11=['MonthMeanTemp(m,11)=mean(Nov' int2str(d) '_' int2str(i) ');'];
        s12=['MonthMeanTemp(m,12)=mean(Dec' int2str(d) '_' int2str(i) ');'];
        eval(s1);
        eval(s2);
        eval(s3);
        eval(s4);
        eval(s5);
        eval(s6);
        eval(s7);
    end
end

```

```

        eval(s8);
        eval(s9);
        eval(s10);
        eval(s11);
        eval(s12);
    end
end

MeanTemp(1)=mean(Jan);
MeanTemp(2)=mean(Feb);
MeanTemp(3)=mean(Mar);
MeanTemp(4)=mean(Apr);
MeanTemp(5)=mean(May);
MeanTemp(6)=mean(Jun);
MeanTemp(7)=mean(Jul);
MeanTemp(8)=mean(Aug);
MeanTemp(9)=mean(Sep);
MeanTemp(10)=mean(Oct);
MeanTemp(11)=mean(Nov);
MeanTemp(12)=mean(Dec);
save MonthMeanTemp.mat MonthMeanTemp MeanTemp

clear d s1 s2 s3 s4 s5 s6 s7 s8 s9 s10 s11 s12
clear;
%% Step 13: Selecting month for Design Reference Year
fprintf('\n Step 13: Selecting month for Design Reference
Year.....(Estimated time: 1 sec)')

load MonthMeanTemp
for i=1:12
    [RankedMeanTemp(:,i),X(:,i)]=sort(MonthMeanTemp(:,i));
end

```

% 99th percentile

```
YearJanFebJunJulAug(:,1)=X(31:60,1);  
YearJanFebJunJulAug(:,2)=X(31:60,2);  
YearJanFebJunJulAug(:,3)=X(2941:2970,6);  
YearJanFebJunJulAug(:,4)=X(2941:2970,7);  
YearJanFebJunJulAug(:,5)=X(2941:2970,8);  
YearJanFebJunJulAug(:,6)=X(31:60,12);
```

```
load JanFebJunJulAug;
```

```
Jan30=[];
```

```
Feb30=[];
```

```
Jun30=[];
```

```
Jul30=[];
```

```
Aug30=[];
```

```
Dec30=[];
```

```
for i=1:30
```

```
    yearnumberJan=YearJanFebJunJulAug(i,1);
```

```
    yearnumberFeb=YearJanFebJunJulAug(i,2);
```

```
    yearnumberJun=YearJanFebJunJulAug(i,3);
```

```
    yearnumberJul=YearJanFebJunJulAug(i,4);
```

```
    yearnumberAug=YearJanFebJunJulAug(i,5);
```

```
    yearnumberDec=YearJanFebJunJulAug(i,6);
```

```
    JanMonth=Jan((yearnumberJan-1)*31+1:(yearnumberJan-1)*31+31);
```

```
    FebMonth=Feb((yearnumberFeb-1)*28+1:(yearnumberFeb-1)*28+28);
```

```
    JunMonth=Jun((yearnumberJun-1)*30+1:(yearnumberJun-1)*30+30);
```

```
    JulMonth=Jul((yearnumberJul-1)*31+1:(yearnumberJul-1)*31+31);
```

```
    AugMonth=Aug((yearnumberAug-1)*31+1:(yearnumberAug-1)*31+31);
```

```
    DecMonth=Dec((yearnumberDec-1)*31+1:(yearnumberDec-1)*31+31);
```

```
    Jan30=cat(1,JanMonth,Jan30);
```

```
    Feb30=cat(1,FebMonth,Feb30);
```

```

Jun30=cat(1,JunMonth,Jun30);
Jul30=cat(1,JulMonth,Jul30);
Aug30=cat(1,AugMonth,Aug30);
Dec30=cat(1,DecMonth,Dec30);
end
Jan30Month=reshape(Jan30,31,30); % daily mean of selected 30 months
Feb30Month=reshape(Feb30,28,30);
Jun30Month=reshape(Jun30,30,30);
Jul30Month=reshape(Jul30,31,30);
Aug30Month=reshape(Aug30,31,30);
Dec30Month=reshape(Dec30,31,30);
% calculate FS-stat for selected 30 months
for i=1:30
    CDFJan(:,i)=CDFIso(Jan30Month(:,i));
    CDFFeb(:,i)=CDFIso(Feb30Month(:,i));
    CDFJun(:,i)=CDFIso(Jun30Month(:,i));
    CDFJul(:,i)=CDFIso(Jul30Month(:,i));
    CDFAug(:,i)=CDFIso(Aug30Month(:,i));
    CDFDec(:,i)=CDFIso(Dec30Month(:,i));
end
CDFJanAll=CDFIso(Jan30);
CDFFebAll=CDFIso(Feb30);
CDFJunAll=CDFIso(Jun30);
CDFJulAll=CDFIso(Jul30);
CDFAugAll=CDFIso(Aug30);
CDFDecAll=CDFIso(Dec30);

CDFJanA=reshape(CDFJanAll,31,30);
CDFFebA=reshape(CDFFebAll,28,30);
CDFJunA=reshape(CDFJunAll,30,30);
CDFJulA=reshape(CDFJulAll,31,30);
CDFAugA=reshape(CDFAugAll,31,30);

```

```
CDFDecA=reshape(CDFDecAll,31,30);
```

```
JanFS=sum(abs(CDFJanA-CDFJan));
```

```
FebFS=sum(abs(CDFFebA-CDFFeb));
```

```
JunFS=sum(abs(CDFJunA-CDFJun));
```

```
JulFS=sum(abs(CDFJulA-CDFJul));
```

```
AugFS=sum(abs(CDFAugA-CDFAug));
```

```
DecFS=sum(abs(CDFDecA-CDFDec));
```

```
[~,AJan]=sort(JanFS);
```

```
[~,AFeb]=sort(FebFS);
```

```
[~,AJun]=sort(JunFS);
```

```
[~,AJul]=sort(JulFS);
```

```
[~,AAug]=sort(AugFS);
```

```
[~,ADec]=sort(DecFS);
```

```
YearNumberDRY(1,1)=YearJanFebJunJulAug(AJan(1),1);
```

```
YearNumberDRY(2,1)=YearJanFebJunJulAug(AFeb(1),2);
```

```
YearNumberDRY(6,1)=YearJanFebJunJulAug(AJun(1),3);
```

```
YearNumberDRY(7,1)=YearJanFebJunJulAug(AJul(1),4);
```

```
YearNumberDRY(8,1)=YearJanFebJunJulAug(AAug(1),5);
```

```
YearNumberDRY(12,1)=YearJanFebJunJulAug(ADec(1),6);
```

```
YearNumberDRY(1,2)=YearJanFebJunJulAug(AJan(2),1);
```

```
YearNumberDRY(2,2)=YearJanFebJunJulAug(AFeb(2),2);
```

```
YearNumberDRY(6,2)=YearJanFebJunJulAug(AJun(2),3);
```

```
YearNumberDRY(7,2)=YearJanFebJunJulAug(AJul(2),4);
```

```
YearNumberDRY(8,2)=YearJanFebJunJulAug(AAug(2),5);
```

```
YearNumberDRY(12,2)=YearJanFebJunJulAug(ADec(2),6);
```

```
YearNumberDRY(1,3)=YearJanFebJunJulAug(AJan(3),1);
```

```
YearNumberDRY(2,3)=YearJanFebJunJulAug(AFeb(3),2);
```

```

YearNumberDRY(6,3)=YearJanFebJunJulAug(AJun(3),3);
YearNumberDRY(7,3)=YearJanFebJunJulAug(AJul(3),4);
YearNumberDRY(8,3)=YearJanFebJunJulAug(AAug(3),5);
YearNumberDRY(12,3)=YearJanFebJunJulAug(ADec(3),6);

```

```

YearNumberDRY(1,4)=YearJanFebJunJulAug(AJan(4),1);
YearNumberDRY(2,4)=YearJanFebJunJulAug(AFeb(4),2);
YearNumberDRY(6,4)=YearJanFebJunJulAug(AJun(4),3);
YearNumberDRY(7,4)=YearJanFebJunJulAug(AJul(4),4);
YearNumberDRY(8,4)=YearJanFebJunJulAug(AAug(4),5);
YearNumberDRY(12,4)=YearJanFebJunJulAug(ADec(4),6);

```

```

YearNumberDRY(1,5)=YearJanFebJunJulAug(AJan(5),1);
YearNumberDRY(2,5)=YearJanFebJunJulAug(AFeb(5),2);
YearNumberDRY(6,5)=YearJanFebJunJulAug(AJun(5),3);
YearNumberDRY(7,5)=YearJanFebJunJulAug(AJul(5),4);
YearNumberDRY(8,5)=YearJanFebJunJulAug(AAug(5),5);
YearNumberDRY(12,5)=YearJanFebJunJulAug(ADec(5),6);

```

```
save YearnumberDRY.mat YearNumberDRY
```

```
load radiation.mat
```

```
m=0;
```

```
for i=1:100
```

```
    for d=3001:3030
```

```
        m=m+1;
```

```
        s1=['MonthMeanRad(m,1)=mean(Jan' int2str(d) ' ' int2str(i) ');'];
```

```
        s2=['MonthMeanRad(m,2)=mean(Feb' int2str(d) ' ' int2str(i) ');'];
```

```
        s3=['MonthMeanRad(m,3)=mean(Mar' int2str(d) ' ' int2str(i) ');'];
```

```
        s4=['MonthMeanRad(m,4)=mean(Apr' int2str(d) ' ' int2str(i) ');'];
```

```
        s5=['MonthMeanRad(m,5)=mean(May' int2str(d) ' ' int2str(i) ');'];
```

```
        s6=['MonthMeanRad(m,6)=mean(Jun' int2str(d) ' ' int2str(i) ');'];
```

```
        s7=['MonthMeanRad(m,7)=mean(Jul' int2str(d) ' ' int2str(i) ');'];
```



```

s8=['MonthMeanRad(m,8)=mean(Aug' int2str(d) '_' int2str(i) ');'];
s9=['MonthMeanRad(m,9)=mean(Sep' int2str(d) '_' int2str(i) ');'];
s10=['MonthMeanRad(m,10)=mean(Oct' int2str(d) '_' int2str(i) ');'];
s11=['MonthMeanRad(m,11)=mean(Nov' int2str(d) '_' int2str(i) ');'];
s12=['MonthMeanRad(m,12)=mean(Dec' int2str(d) '_' int2str(i) ');'];
eval(s1);
eval(s2);
eval(s3);
eval(s4);
eval(s5);
eval(s6);
eval(s7);
eval(s8);
eval(s9);
eval(s10);
eval(s11);
eval(s12);
end
end
save MonthMeanRad.mat MonthMeanRad

```

```

FiveMonthRadMean(:,1)=MonthMeanRad(YearNumberDRY(1,:),1); %Selected
5 Jan mean radiation
FiveMonthRadMean(:,2)=MonthMeanRad(YearNumberDRY(2,:),1);
FiveMonthRadMean(:,3)=MonthMeanRad(YearNumberDRY(6,:),1);
FiveMonthRadMean(:,4)=MonthMeanRad(YearNumberDRY(7,:),1);
FiveMonthRadMean(:,5)=MonthMeanRad(YearNumberDRY(8,:),1);
FiveMonthRadMean(:,6)=MonthMeanRad(YearNumberDRY(12,:),1);

[~,XX]=sort(FiveMonthRadMean);
YearNumberDRYFinal(1)=YearNumberDRY(1,XX(1,1)); %Select the month
having lowest solar radiation

```

```

YearNumberDRYFinal(2)=YearNumberDRY(2,XX(1,2)); %Select the month
having lowest solar radiation
YearNumberDRYFinal(6)=YearNumberDRY(6,XX(5,3)); %Select the month
having highest solar radiation
YearNumberDRYFinal(7)=YearNumberDRY(7,XX(5,4)); %Select the month
having highest solar radiation
YearNumberDRYFinal(8)=YearNumberDRY(8,XX(5,5)); %Select the month
having highest solar radiation
YearNumberDRYFinal(12)=YearNumberDRY(12,XX(5,6)); %Select the month
having highest solar radiation
save YearNumberDRYFinal.mat YearNumberDRYFinal

```

```

n=zeros(1,12);y=zeros(1,12);
a=YearNumberDRYFinal;
for o=1:12          %12 months
    n(o)=floor((a(o)-1)/30)+1; % n is set of data
    y(o)=a(o)-30*(n(o)-1)+3000; % y is year
end

```

```

load YearNumber
y0=year(1,:);
n0=year(2,:);
n(3:5)=n0(3:5);
y(3:5)=y0(3:5);
n(9:11)=n0(9:11);
y(9:11)=y0(9:11);

```

```

year(1,:)=y;
year(2,:)=n;

```

```

fprintf('\n Selected 6 months for DRY:');

```

```

fprintf('\n Jan is from year %4d _ %2d th data set', year(:,1));
fprintf('\n Feb is from year %4d _ %2d th data set', year(:,2));
fprintf('\n Jun is from year %4d _ %2d th data set', year(:,6));
fprintf('\n Jul is from year %4d _ %2d th data set', year(:,7));
fprintf('\n Aug is from year %4d _ %2d th data set', year(:,8));
fprintf('\n Dec is from year %4d _ %2d th data set', year(:,12));
save yearDRY.mat n y;

```

```
clear all;
```

```
%% Step 14: Generating DSY data(CIBSE format)
```

```
fprintf('\n Step 14: Generating DSY data(CIBSE format).....(Estimated
time: 25 secs)');
```

```
load yearDRY;
```

```
load txt;
```

```
year(1,:)=y;
```

```
year(2,:)=n;
```

```
DayNu=[31,28,31,30,31,30,31,31,30,31,30,31];
```

```
a=1;
```

```
DRY=zeros(8760,11);
```

```
for i=1:12
```

```
    %p0=dlmread(char(txt(year(2,i),1)),',', 'A1..K262968'); %1 control data
```

```
    p0=dlmread(char(txt(year(2,i),2)),',', 'A1..K262968'); %2 senario data
```

```
    for m=1:262968
```

```
        if ((p0(m,1)==year(1,i)) && (p0(m,2)==i)&&(p0(m,3)==1)&&(p0(m,4)==0))
```

```
            DRY(a:(a+DayNu(i)*24-1),:)=p0(m:m+DayNu(i)*24-1,:);
```

```
        end
```

```
    end
```

```
    a=a+24*DayNu(i);
```

```
end
```

```
save DesignReferenceYear.mat DRY
```

```

clear;

% Step 15: Adjusting the hourly value at the beginning and end of each
% month
fprintf('\n Step 15: Adjusting hourly value at beginning and end of each
month...(Estimated time: 25 secs)');
load DesignReferenceYear
DRY_S=DRY;
for q=6:8 %column 6,7,8 are temp_hmean,vapourpressure_hmean and
relhum_hmean
% smooth beginning of Jan and end of Dec
y1=DRY(1:8,q);
y2=DRY(8760-7:8760,q);
y0=cat(1,y2,y1);
y(1)=y0(1);
y(5)=y0(16);
y(3)=mean(y0);
y(2)=mean(y2);
y(4)=mean(y1);
x=[1,4.75,8.5,13.25,16];
xx=1:16;
yy=spline(x,y,xx);
DRY_S(8760-7:8760,q)=yy(1:8)';
DRY_S(1:8,q)=yy(9:16)';
% smooth other months
for i=10:8760
    if (DRY(i,2)>DRY(i-1,2))
        y(1)=DRY(i-8,q);
        y(5)=DRY(i+7,q);
        y(3)=mean(DRY(i-8:i+7,q));
        y(2)=mean(DRY(i-8:i-1,q));
        y(4)=mean(DRY(i:i+7,q));
    end
end

```

```

        x=[1,4.75,8.5,13.25,16];
        xx=1:16;
        yy=spline(x,y,xx);
        DRY_S(i-8:i+7,q)=yy';
    end
end
end
save DesignReferenceYear_Smoothed.mat DRY_S;
clear y1 y2 y0 y x xx yy i q;

% Step 16: Caculate dew point temeperature, horizontal infrared and direct
normal radiation
fprintf('\n Step 16: Caculating parameters for EPW format:');
fprintf('\n Step 16.1: Caculating dew point temeperature.....(Estimated
time: 1 secs)');
r=17.271*DRY_S(:,6)./(237.7+DRY_S(:,6))+log(DRY_S(:,8));
DRY_S(:,12)=237.7*r./(17.271-r); %column 12, dew point temperature,

for i=1:8760
    if DRY_S(:,12)>DRY_S(:,6)
        DRY_S(:,12)=DRY_S(:,6);
    end
end
end

clear r

fprintf('\n Step 16.2: Caculating direct normal radiation.....(Estimated
time: 5 secs)');
%column 13, date number OF the year
DRY_S(1,13)=1; % first day number is 1
for i=2:8760

```

```

        if or(DRY_S(i,3)>DRY_S(i-1,3),DRY_S(i,2)>DRY_S(i-1,2))
            DRY_S(i,13)=DRY_S(i-1,13)+1;
        else
            DRY_S(i,13)=DRY_S(i-1,13);
        end
    end
end
clear i;
%column 15, DEC, solar Declination (between the earth-sun line and the
equator plane) in radians
DRY_S(:,14)=2*pi*((DRY_S(:,13))/366); %N
DRY_S(:,15)=(0.33281-22.984*cos(DRY_S(:,14))+3.7872*sin(DRY_S(:,14))-
0.3499*cos(2*DRY_S(:,14))+0.03205*sin(2*DRY_S(:,14))-
0.1398*cos(3*DRY_S(:,14))+0.07187*sin(3*DRY_S(:,14)))*pi/180;
%column 16, HRA, hour angle from solar noon, 15 degree per hour, in radians
DRY_S(:,16)=15*(DRY_S(:,4)/100-11.5)*pi/180;
%LAT, geographical latitude (south negative), in radians
load latitude
LAT=latitude*pi/180;
%column 17, ALT, solar altitude(from horizontal max 90 zenith), in radians,
DRY_S(:,17)=asin(sin(DRY_S(:,15))*sin(LAT)+cos(LAT)*cos(DRY_S(:,16))).*cos
(DRY_S(:,15));
%column 18, direct normal=direct horizontal/sin(solar altitude),
DRY_S(:,18)=DRY_S(:,11)./sin(DRY_S(:,17));
a=0;
for i=2:8760
    if DRY_S(i,18)<0
        DRY_S(i,18)=0; %delect the negative value
    end
end
end

%delete unreasonable value at sunrise and sunset, (solar altitude <11 degree,
direct normal>100)

```

```
DRY_S(:,19)=DRY_S(:,17)*180/pi; %column 19, solar altitude in degree
```

```
DRY_SS=DRY_S;
```

```
c=0;
```

```
for i=1:8760
```

```
    if and(DRY_S(i,19)<11,DRY_S(i,18)>200)
```

```
        DRY_SS(i,18)=200;
```

```
        c=c+1;
```

```
        A(c,1)=DRY_S(i,18);
```

```
        A(c,2)=DRY_S(i,19);
```

```
    end
```

```
end %when direct normal over 200, set to 200
```

```
c=0;
```

```
for i=1:8760
```

```
    if and(DRY_S(i,19)<11,DRY_S(i,18)>100)
```

```
        DRY_SS(i,18)=(DRY_SS(i-1,18)+DRY_SS(i+1,18))/2;
```

```
        c=c+1;
```

```
    end
```

```
end %re-run, when direct normal over 100, set to avearge of nearby values
```

```
fprintf('\n Step 16.3: Caculating cloud cover.....(Estimated time:  
2 secs)');
```

```
DRY_SS(:,20)=10*(1-DRY_SS(:,9)); %column 20, total sky cover in tenth
```

```
for i=1:8760
```

```
    if DRY_SS(i,9)==0
```

```
        DRY_SS(i,20)=0;
```

```
    end
```

```
end
```

```

% night cloud covers are equal to interpolation of cloud covers at sunrise and
sunset time
c1=0;
for i=2:8760
    if DRY_SS(i,19)*DRY_SS(i-1,19)<0
        c1=c1+1;
        Index(c1)=i;
    end %Identify night time
end

for i=1:(size(Index,2)-2)/2
    z(1)=DRY_SS(Index(i*2)-1,20);
    z(2)=DRY_SS(Index(i*2+1),20);
    DRY_SS(Index(i*2)-1:(Index(i*2+1)),20)=interp1(0:1,z,0:1/(Index(i*2+1)-
Index(i*2)+1):1);
end %liner interpolate cloud cover at night time

for i=1:8760
    DRY_SS(i,20)=round(DRY_SS(i,20));
end %integral function
%
fprintf('\n Step 16.4: Caculating horizontal infrared radiation intensty...(Estimated
time: 2 secs)');
DRY_SS(:,21)=round(DRY_SS(:,20)/2); %column 21, opaque sky cover,
assumed as half the value of total sky cover
SkyE=(0.787+0.764*log((DRY_SS(:,12)+273)/273)).*(1+0.0224*DRY_SS(:,21)+
0.0035*DRY_SS(:,21).^2+0.00028*DRY_SS(:,21).^3);
DRY_SS(:,22)=5.6697e-8*SkyE.*(DRY_SS(:,6)+273).^4; %column 22,
horizontal infrared radiation intensty

DRY_SS(:,23)=101300; %column 23, atmospheric pressure

```



```
DRY_SS(:,24)=DRY_SS(:,10)+DRY_SS(:,11); %column 24, global horizontal radiation,
```

```
DRY_SS(:,8)=floor(100*DRY_SS(:,8)); %column 8, relative humidity, in percentage
```

```
save DRY_EPW.mat DRY_SS
```

```
dlmwrite('DRY99.csv',DRY_SS);
```

```
fprintf("\n Congratulation!!! DRY at 99 centile is saved as "DRY99.csv");
```

```
%column 1, year
```

```
%column 2, month
```

```
%column 3, date of the month
```

```
%column 4, hour
```

```
%column 5, precip httotal, mm/hour
```

```
%column 6, hourly temperature, degree C
```

```
%column 7, vapour pressure, hPa
```

```
%column 8, relative humidity, %
```

```
%column 9, sunshine hour, hours
```

```
%column 10, diffuse solar radiation, Wh/m2
```

```
%column 11, direct solar radiation in horizontal, Wh/m2
```

```
%column 12, dew point temperature, C
```

```
%column 13, date number of the year
```

```
%column 14, date number, in radians
```

```
%column 15, solar declination, in radians
```

```
%column 16, hour angle from solar noon
```

```
%column 17, solar altitude, in radians
```

```
%column 18, direct normal radiation, Wh/m2
```

```
%column 19, solar altitude, in degree
```

```
%column 20, total sky cover
```

```
%column 21, opaque sky cover
```

```
%column 22, horizontal infrared radiation intensty
```

%column 23, atmospheric pressure

%column 24, global horizontal radiation,

```

%***** TRYDRY_Hu_control.m *****
%% Step 1: Capturing daily mean value from UKCP09 data
tic;
fprintf('\n Step 1: Reading daily data.....(Estimated time: 1
mins)')
time=clock;
a1=time(4:6);
%fprintf('\n Starting at %4d hour %4d min %4.2f second', a1);

%read file name of daily CSV files
load filename.mat;
%read 100 daily csv files
pday=[];
for i=1:100
%read a csv files % G temp_dmin; H temp_dmax; I vapourpressure_dmean;
% K sunshie hour; L diffuse radiation; M direct radiation; N pet_dmean
%p0=dlmread(char(txt(i,4)),',', 'D1..N10957'); % txt(i,4) read scenario data;
p0=dlmread(char(txt(i,3)),',', 'D1..N10957'); % txt(i,3) read control data;

pday=cat(1,pday,p0);
fprintf('\n Reading %3d th daily file.....', i);
end

save pday.mat pday; %save raw daily data
save txt.mat txt; %save file name
clear p0 i txt;
pdaily(:,1)=(pday(:,4)+pday(:,5))/2; %daily mean temperature
pdaily(:,2)=pday(:,7); %reltive humililty
pdaily(:,3)=pday(:,9)+pday(:,10); % total incoming solar radiation, kWh/m2
save daily.mat pdaily; % save hourly temperature, solar radiation and relative
humidity

```

```

time=clock;
a2=time(4:6);
%fprintf('\n Ending at  %4d hour %4d min %4.2f second', a2);
a=a2-a1;
fprintf('\n Time spent: %4d hour %4d min %4.2f second', a);
clear all;

```

% Step 2.1: Capture temperature data for each month in that year and in whole 100 years

```

load daily;
fprintf('\n Step 2.1: Capturing temperature data for each month
.....(Estimated time: 1 min)')
Tempdaily=pdaily(:,1); % capture temperature data from daily data
clear pdaily;
%Tempdaily=double(Tempdaily);
time=clock;
a1=time(4:6);
%fprintf('\n Starting at %4d hour %4d min %4.2f second', a1);

%capture daily average data from each month; format is Jand_i, such as
Jan3000_100
for i=1:100
    for d=3001:3030
        s01=['Jan' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',1,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',1,31)-1096093+10957*(i-
1)))']; %1096093=datenum(3000,12,31);10957=datenum(3030,12,31)-
datenum(3000,12,31)

```

```

s02=['Feb' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',2,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',2,28)-1096093+10957*(i-
1))))];

s03=['Mar' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',3,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',3,31)-1096093+10957*(i-
1))))];

s04=['Apr' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',4,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',4,30)-1096093+10957*(i-
1))))];

s05=['May' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',5,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',5,31)-1096093+10957*(i-
1))))];

s06=['Jun' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',6,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',6,30)-1096093+10957*(i-
1))))];

s07=['Jul' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',7,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',7,31)-1096093+10957*(i-
1))))];

s08=['Aug' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',8,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',8,31)-1096093+10957*(i-
1))))];

s09=['Sep' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',9,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',9,30)-1096093+10957*(i-
1))))];

s10=['Oct' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',10,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',10,31)-1096093+10957*(i-
1))))];

s11=['Nov' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',11,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',11,30)-1096093+10957*(i-
1))))];

```

```
s12=['Dec' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',12,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',12,31)-1096093+10957*(i-
1)))'];
```

```
eval(s01);
```

```
eval(s02);
```

```
eval(s03);
```

```
eval(s04);
```

```
eval(s05);
```

```
eval(s06);
```

```
eval(s07);
```

```
eval(s08);
```

```
eval(s09);
```

```
eval(s10);
```

```
eval(s11);
```

```
eval(s12);
```

```
end
```

```
end
```

```
clear d s01 s02 s03 s04 s05 s06 s07 s08 s09 s10 s11 s12
```

```
%Generate matrix for a calendar month in the whole data set;
```

```
%size(Jan)=90000
```

```
Jan=[];
```

```
Feb=[];
```

```
Mar=[];
```

```
Apr=[];
```

```
May=[];
```

```
Jun=[];
```

```
Jul=[];
```

```
Aug=[];
```

```
Sep=[];
```

```
Oct=[];
```

```

Nov=[];
Dec=[];

for i=1:100
for d=3001:3030
s1=['Jan=[Jan;Jan' int2str(d) '_' int2str(i) '];'];
s2=['Feb=[Feb;Feb' int2str(d) '_' int2str(i) '];'];
s3=['Mar=[Mar;Mar' int2str(d) '_' int2str(i) '];'];
s4=['Apr=[Apr;Apr' int2str(d) '_' int2str(i) '];'];
s5=['May=[May;May' int2str(d) '_' int2str(i) '];'];
s6=['Jun=[Jun;Jun' int2str(d) '_' int2str(i) '];'];
s7=['Jul=[Jul;Jul' int2str(d) '_' int2str(i) '];'];
s8=['Aug=[Aug;Aug' int2str(d) '_' int2str(i) '];'];
s9=['Sep=[Sep;Sep' int2str(d) '_' int2str(i) '];'];
s10=['Oct=[Oct;Oct' int2str(d) '_' int2str(i) '];'];
s11=['Nov=[Nov;Nov' int2str(d) '_' int2str(i) '];'];
s12=['Dec=[Dec;Dec' int2str(d) '_' int2str(i) '];'];
eval(s1);
eval(s2);
eval(s3);
eval(s4);
eval(s5);
eval(s6);
eval(s7);
eval(s8);
eval(s9);
eval(s10);
eval(s11);
eval(s12);
end
end
clear d s1 s2 s3 s4 s5 s6 s7 s8 s9 s10 s11 s12

```

```

save temperature.mat
time=clock;
a2=time(4:6);
%fprintf('\n Ending at  %4d hour %4d min %4.2f second', a2);
a=a2-a1;
fprintf('\n Time spent: %4d hour %4d min %4.2f second', a);
clear time a1 a2 a i;      %take 50 seconds

```

% Step 2.2: Calculating Cumulative Distribution of temperature

```

fprintf('\n Step 2.2: Calculating Cumulative Distribution of
temperature...(Estimated time: 1 min)')
time=clock;
a1=time(4:6);
%fprintf('\n Starting at %4d hour %4d min %4.2f second', a1);

```

%Tie rank percentage of the ith value of each daily temperature data within that calender month in the whole data set

```

Jan=CDFiso(Jan);
Feb=CDFiso(Feb);
Mar=CDFiso(Mar);
Apr=CDFiso(Apr);
May=CDFiso(May);
Jun=CDFiso(Jun);
Jul=CDFiso(Jul);
Aug=CDFiso(Aug);
Sep=CDFiso(Sep);
Oct=CDFiso(Oct);
Nov=CDFiso(Nov);
Dec=CDFiso(Dec);

```



```
%Tie rank percentage of the ith value of each daily temperature data within that month and that year
```

```
for i=1:100
```

```
for d=3001:3030
```

```
s1=['Jan' int2str(d) '_' int2str(i) '=CDFiso(Jan' int2str(d) '_' int2str(i) ');'];
```

```
s2=['Feb' int2str(d) '_' int2str(i) '=CDFiso(Feb' int2str(d) '_' int2str(i) ');'];
```

```
s3=['Mar' int2str(d) '_' int2str(i) '=CDFiso(Mar' int2str(d) '_' int2str(i) ');'];
```

```
s4=['Apr' int2str(d) '_' int2str(i) '=CDFiso(Apr' int2str(d) '_' int2str(i) ');'];
```

```
s5=['May' int2str(d) '_' int2str(i) '=CDFiso(May' int2str(d) '_' int2str(i) ');'];
```

```
s6=['Jun' int2str(d) '_' int2str(i) '=CDFiso(Jun' int2str(d) '_' int2str(i) ');'];
```

```
s7=['Jul' int2str(d) '_' int2str(i) '=CDFiso(Jul' int2str(d) '_' int2str(i) ');'];
```

```
s8=['Aug' int2str(d) '_' int2str(i) '=CDFiso(Aug' int2str(d) '_' int2str(i) ');'];
```

```
s9=['Sep' int2str(d) '_' int2str(i) '=CDFiso(Sep' int2str(d) '_' int2str(i) ');'];
```

```
s10=['Oct' int2str(d) '_' int2str(i) '=CDFiso(Oct' int2str(d) '_' int2str(i) ');'];
```

```
s11=['Nov' int2str(d) '_' int2str(i) '=CDFiso(Nov' int2str(d) '_' int2str(i) ');'];
```

```
s12=['Dec' int2str(d) '_' int2str(i) '=CDFiso(Dec' int2str(d) '_' int2str(i) ');'];
```

```
eval(s1);
```

```
eval(s2);
```

```
eval(s3);
```

```
eval(s4);
```

```
eval(s5);
```

```
eval(s6);
```

```
eval(s7);
```

```
eval(s8);
```

```
eval(s9);
```

```
eval(s10);
```

```
eval(s11);
```

```
eval(s12);
```

```

end
end
clear d s1 s2 s3 s4 s5 s6 s7 s8 s9 s10 s11 s12

save month_rank_temperature.mat % save month value with rank order

time=clock;
a2=time(4:6);
%fprintf('\n Ending at %4d hour %4d min %4.2f second', a2);
a=a2-a1;
fprintf('\n Time spent: %4d hour %4d min %4.2f second', a);
clear time a1 a2 a i; %take 50 seconds

% Step 2.3: Calculate Finkelstein-Schafer statistic of temperature for each
month
fprintf('\n Step 2.3: Calculating Finkelstein-Schafer statistic of
temperature....(Estimated time: 1 mins)')
time=clock;

a1=time(4:6);
%fprintf('\n Starting at %4d hour %4d min %4.2f second', a1);

Jan2=[];
Feb2=[];
Mar2=[];
Apr2=[];
May2=[];
Jun2=[];
Jul2=[];
Aug2=[];

```

```

Sep2=[];
Oct2=[];
Nov2=[];
Dec2=[];
for i=1:100
    Jan_i=[];
    Feb_i=[];
    Mar_i=[];
    Apr_i=[];
    May_i=[];
    Jun_i=[];
    Jul_i=[];
    Aug_i=[];
    Sep_i=[];
    Oct_i=[];
    Nov_i=[];
    Dec_i=[];
for y=3001:3030
    s1=['Jan_y=Jan' int2str(y) '_' int2str(i) '(:,1)'];
    s2=['Feb_y=Feb' int2str(y) '_' int2str(i) '(:,1)'];
    s3=['Mar_y=Mar' int2str(y) '_' int2str(i) '(:,1)'];
    s4=['Apr_y=Apr' int2str(y) '_' int2str(i) '(:,1)'];
    s5=['May_y=May' int2str(y) '_' int2str(i) '(:,1)'];
    s6=['Jun_y=Jun' int2str(y) '_' int2str(i) '(:,1)'];
    s7=['Jul_y=Jul' int2str(y) '_' int2str(i) '(:,1)'];
    s8=['Aug_y=Aug' int2str(y) '_' int2str(i) '(:,1)'];
    s9=['Sep_y=Sep' int2str(y) '_' int2str(i) '(:,1)'];
    s10=['Oct_y=Oct' int2str(y) '_' int2str(i) '(:,1)'];
    s11=['Nov_y=Nov' int2str(y) '_' int2str(i) '(:,1)'];
    s12=['Dec_y=Dec' int2str(y) '_' int2str(i) '(:,1)'];
    eval(s1);
    eval(s2);

```

```

eval(s3);
eval(s4);
eval(s5);
eval(s6);
eval(s7);
eval(s8);
eval(s9);
eval(s10);
eval(s11);
eval(s12);
Jan_i=cat(1,Jan_i,Jan_y);
Feb_i=cat(1,Feb_i,Feb_y);
Mar_i=cat(1,Mar_i,Mar_y);
Apr_i=cat(1,Apr_i,Apr_y);
May_i=cat(1,May_i,May_y);
Jun_i=cat(1,Jun_i,Jun_y);
Jul_i=cat(1,Jul_i,Jul_y);
Aug_i=cat(1,Aug_i,Aug_y);
Sep_i=cat(1,Sep_i,Sep_y);
Oct_i=cat(1,Oct_i,Oct_y);
Nov_i=cat(1,Nov_i,Nov_y);
Dec_i=cat(1,Dec_i,Dec_y);
end
Jan2=cat(1,Jan2,Jan_i);
Feb2=cat(1,Feb2,Feb_i);
Mar2=cat(1,Mar2,Mar_i);
Apr2=cat(1,Apr2,Apr_i);
May2=cat(1,May2,May_i);
Jun2=cat(1,Jun2,Jun_i);
Jul2=cat(1,Jul2,Jul_i);
Aug2=cat(1,Aug2,Aug_i);
Sep2=cat(1,Sep2,Sep_i);

```

```

Oct2=cat(1,Oct2,Oct_i);
Nov2=cat(1,Nov2,Nov_i);
Dec2=cat(1,Dec2,Dec_i);
end

CDFdiff1=abs(Jan-Jan2);
CDFdiff2=abs(Feb-Feb2);
CDFdiff3=abs(Mar-Mar2);
CDFdiff4=abs(Apr-Apr2);
CDFdiff5=abs(May-May2);
CDFdiff6=abs(Jun-Jun2);
CDFdiff7=abs(Jul-Jul2);
CDFdiff8=abs(Aug-Aug2);
CDFdiff9=abs(Sep-Sep2);
CDFdiff10=abs(Oct-Oct2);
CDFdiff11=abs(Nov-Nov2);
CDFdiff12=abs(Dec-Dec2);
%
%FS(1,:)=sum(reshape(CDFdiff1,31,3000));
%FS(2,:)=sum(reshape(CDFdiff2,28,3000));
%FS(3,:)=sum(reshape(CDFdiff3,31,3000));
%FS(4,:)=sum(reshape(CDFdiff4,30,3000));
%FS(5,:)=sum(reshape(CDFdiff5,31,3000));
%FS(6,:)=sum(reshape(CDFdiff6,30,3000));
%FS(7,:)=sum(reshape(CDFdiff7,31,3000));
%FS(8,:)=sum(reshape(CDFdiff8,31,3000));
%FS(9,:)=sum(reshape(CDFdiff9,30,3000));
%FS(10,:)=sum(reshape(CDFdiff10,31,3000));
%FS(11,:)=sum(reshape(CDFdiff11,30,3000));
%FS(12,:)=sum(reshape(CDFdiff12,31,3000));
% ISO above
FS(1,:)=sum(reshape(CDFdiff1,31,3000))/31;

```

```

FS(2,:)=sum(reshape(CDFdiff2,28,3000))/28;
FS(3,:)=sum(reshape(CDFdiff3,31,3000))/31;
FS(4,:)=sum(reshape(CDFdiff4,30,3000))/30;
FS(5,:)=sum(reshape(CDFdiff5,31,3000))/31;
FS(6,:)=sum(reshape(CDFdiff6,30,3000))/30;
FS(7,:)=sum(reshape(CDFdiff7,31,3000))/31;
FS(8,:)=sum(reshape(CDFdiff8,31,3000))/31;
FS(9,:)=sum(reshape(CDFdiff9,30,3000))/30;
FS(10,:)=sum(reshape(CDFdiff10,31,3000))/31;
FS(11,:)=sum(reshape(CDFdiff11,30,3000))/30;
FS(12,:)=sum(reshape(CDFdiff12,31,3000))/31;

```

```

FS_temp=FS';
save FS_temp.mat FS_temp;

```

```

save CDFdiff_temp.mat CDFdiff1 CDFdiff2 CDFdiff3 CDFdiff4 CDFdiff5
CDFdiff6 CDFdiff7 CDFdiff8 CDFdiff9 CDFdiff10 CDFdiff11 CDFdiff12;

```

```

time=clock;
a2=time(4:6);
fprintf('\n Ending at  %4d hour %4d min %4.2f second', a2);
a=a2-a1;
fprintf('\n Time spent: %4d hour %4d min %4.2f second', a);
clear all;

```

```

% Step 3.1: Capture solar radiation data for each month in that year and in
whole 100 years
fprintf('\n Step 3.1: Capturing solar radiation for each month .....(Estimated
time: 1 min)')
load daily;

```

```

Tempdaily=pdaily(:,3); % capture solar radiation data from daily data
clear pdaily;
%Tempdaily=double(Tempdaily);
time=clock;
a1=time(4:6);
%fprintf('\n Starting at %4d hour %4d min %4.2f second', a1);

%capture daily average data from each month; format is Jand_i, such as
Jan3000_100
for i=1:100
    for d=3001:3030
        s01=['Jan' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',1,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',1,31)-1096093+10957*(i-
1))))]; %1096093=datenum(3000,12,31);10957=datenum(3030,12,31)-
datenum(3000,12,31)
        s02=['Feb' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',2,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',2,28)-1096093+10957*(i-
1))))];
        s03=['Mar' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',3,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',3,31)-1096093+10957*(i-
1))))];
        s04=['Apr' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',4,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',4,30)-1096093+10957*(i-
1))))];
        s05=['May' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',5,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',5,31)-1096093+10957*(i-
1))))];
        s06=['Jun' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',6,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',6,30)-1096093+10957*(i-
1))))];

```

```

        s07=['Jul' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',7,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',7,31)-1096093+10957*(i-
1))))'];

        s08=['Aug' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',8,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',8,31)-1096093+10957*(i-
1))))'];

        s09=['Sep' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',9,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',9,30)-1096093+10957*(i-
1))))'];

        s10=['Oct' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',10,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',10,31)-1096093+10957*(i-
1))))'];

        s11=['Nov' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',11,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',11,30)-1096093+10957*(i-
1))))'];

        s12=['Dec' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',12,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',12,31)-1096093+10957*(i-
1))))'];

        eval(s01);
        eval(s02);
        eval(s03);
        eval(s04);
        eval(s05);
        eval(s06);
        eval(s07);
        eval(s08);
        eval(s09);
        eval(s10);
        eval(s11);
        eval(s12);

    end
end

```



```
clear d s01 s02 s03 s04 s05 s06 s07 s08 s09 s10 s11 s12
```

```
%Generate matrix for a calendar month in the whole data set;
```

```
%size(Jan)=90000
```

```
Jan=[];
```

```
Feb=[];
```

```
Mar=[];
```

```
Apr=[];
```

```
May=[];
```

```
Jun=[];
```

```
Jul=[];
```

```
Aug=[];
```

```
Sep=[];
```

```
Oct=[];
```

```
Nov=[];
```

```
Dec=[];
```

```
for i=1:100
```

```
for d=3001:3030
```

```
s1=['Jan=[Jan;Jan' int2str(d) '_' int2str(i) '];'];
```

```
s2=['Feb=[Feb;Feb' int2str(d) '_' int2str(i) '];'];
```

```
s3=['Mar=[Mar;Mar' int2str(d) '_' int2str(i) '];'];
```

```
s4=['Apr=[Apr;Apr' int2str(d) '_' int2str(i) '];'];
```

```
s5=['May=[May;May' int2str(d) '_' int2str(i) '];'];
```

```
s6=['Jun=[Jun;Jun' int2str(d) '_' int2str(i) '];'];
```

```
s7=['Jul=[Jul;Jul' int2str(d) '_' int2str(i) '];'];
```

```
s8=['Aug=[Aug;Aug' int2str(d) '_' int2str(i) '];'];
```

```
s9=['Sep=[Sep;Sep' int2str(d) '_' int2str(i) '];'];
```

```
s10=['Oct=[Oct;Oct' int2str(d) '_' int2str(i) '];'];
```

```
s11=['Nov=[Nov;Nov' int2str(d) '_' int2str(i) '];'];
```

```
s12=['Dec=[Dec;Dec' int2str(d) '_' int2str(i) '];'];
```

```

eval(s1);
eval(s2);
eval(s3);
eval(s4);
eval(s5);
eval(s6);
eval(s7);
eval(s8);
eval(s9);
eval(s10);
eval(s11);
eval(s12);
end
end
clear d s1 s2 s3 s4 s5 s6 s7 s8 s9 s10 s11 s12
save radiation.mat;

time=clock;
a2=time(4:6);
%fprintf('\n Ending at  %4d hour %4d min %4.2f second', a2);
a=a2-a1;
fprintf('\n Time spent: %4d hour %4d min %4.2f second', a);
clear all;          %take 50 seconds

% Step 3.2: Calculating Cumulative Distribution of solar radiation
time=clock;
load radiation
fprintf('\n Step 3.2: Calculating Cumulative Distribution of solar
radiation...(Estimated time: 1 min)');
a1=time(4:6);
%fprintf('\n Starting at %4d hour %4d min %4.2f second', a1);

```

%Tie rank percentage of the ith value of each daily temperature data within that calender month in the whole data set

```
Jan=CDFiso(Jan);  
Feb=CDFiso(Feb);  
Mar=CDFiso(Mar);  
Apr=CDFiso(Apr);  
May=CDFiso(May);  
Jun=CDFiso(Jun);  
Jul=CDFiso(Jul);  
Aug=CDFiso(Aug);  
Sep=CDFiso(Sep);  
Oct=CDFiso(Oct);  
Nov=CDFiso(Nov);  
Dec=CDFiso(Dec);
```

%Tie rank percentage of the ith value of each daily temperature data within that month and that year

```
for i=1:100
```

```
for d=3001:3030
```

```
s1=['Jan' int2str(d) '_' int2str(i) '=CDFiso(Jan' int2str(d) '_' int2str(i) ');'];  
s2=['Feb' int2str(d) '_' int2str(i) '=CDFiso(Feb' int2str(d) '_' int2str(i) ');'];  
s3=['Mar' int2str(d) '_' int2str(i) '=CDFiso(Mar' int2str(d) '_' int2str(i) ');'];  
s4=['Apr' int2str(d) '_' int2str(i) '=CDFiso(Apr' int2str(d) '_' int2str(i) ');'];  
s5=['May' int2str(d) '_' int2str(i) '=CDFiso(May' int2str(d) '_' int2str(i) ');'];  
s6=['Jun' int2str(d) '_' int2str(i) '=CDFiso(Jun' int2str(d) '_' int2str(i) ');'];  
s7=['Jul' int2str(d) '_' int2str(i) '=CDFiso(Jul' int2str(d) '_' int2str(i) ');'];  
s8=['Aug' int2str(d) '_' int2str(i) '=CDFiso(Aug' int2str(d) '_' int2str(i) ');'];
```

```

s9=['Sep' int2str(d) '_' int2str(i) '=CDFiso(Sep' int2str(d) '_' int2str(i) ');'];
s10=['Oct' int2str(d) '_' int2str(i) '=CDFiso(Oct' int2str(d) '_' int2str(i) ');'];
s11=['Nov' int2str(d) '_' int2str(i) '=CDFiso(Nov' int2str(d) '_' int2str(i) ');'];
s12=['Dec' int2str(d) '_' int2str(i) '=CDFiso(Dec' int2str(d) '_' int2str(i) ');'];
eval(s1);
eval(s2);
eval(s3);
eval(s4);
eval(s5);
eval(s6);
eval(s7);
eval(s8);
eval(s9);
eval(s10);
eval(s11);
eval(s12);
end
end
clear d s1 s2 s3 s4 s5 s6 s7 s8 s9 s10 s11 s12

save month_rank_radiation.mat % save month value with rank order

time=clock;
a2=time(4:6);
fprintf('\n Ending at %4d hour %4d min %4.2f second', a2);
a=a2-a1;
fprintf('\n Time spent: %4d hour %4d min %4.2f second', a);
clear time a1 a2 a i; %take 50 seconds

% Step 3.3: Calculate Finkelstein-Schafer statistic of solar radiation for each
month

```

```
fprintf('\n Step 3.3: Calculating Finkelstein-Schafer statistic of solar  
radiation.....(Estimated time: 1 mins)')
```

```
time=clock;
```

```
a1=time(4:6);
```

```
%fprintf('\n Starting at %4d hour %4d min %4.2f second', a1);
```

```
Jan2=[];
```

```
Feb2=[];
```

```
Mar2=[];
```

```
Apr2=[];
```

```
May2=[];
```

```
Jun2=[];
```

```
Jul2=[];
```

```
Aug2=[];
```

```
Sep2=[];
```

```
Oct2=[];
```

```
Nov2=[];
```

```
Dec2=[];
```

```
for i=1:100
```

```
    Jan_i=[];
```

```
    Feb_i=[];
```

```
    Mar_i=[];
```

```
    Apr_i=[];
```

```
    May_i=[];
```

```
    Jun_i=[];
```

```
    Jul_i=[];
```

```
    Aug_i=[];
```

```
    Sep_i=[];
```

```
    Oct_i=[];
```

```
    Nov_i=[];
```

```

Dec_i=[];
for y=3001:3030
    s1=['Jan_y=Jan' int2str(y) '_' int2str(i) '(:,1)'];
    s2=['Feb_y=Feb' int2str(y) '_' int2str(i) '(:,1)'];
    s3=['Mar_y=Mar' int2str(y) '_' int2str(i) '(:,1)'];
    s4=['Apr_y=Apr' int2str(y) '_' int2str(i) '(:,1)'];
    s5=['May_y=May' int2str(y) '_' int2str(i) '(:,1)'];
    s6=['Jun_y=Jun' int2str(y) '_' int2str(i) '(:,1)'];
    s7=['Jul_y=Jul' int2str(y) '_' int2str(i) '(:,1)'];
    s8=['Aug_y=Aug' int2str(y) '_' int2str(i) '(:,1)'];
    s9=['Sep_y=Sep' int2str(y) '_' int2str(i) '(:,1)'];
    s10=['Oct_y=Oct' int2str(y) '_' int2str(i) '(:,1)'];
    s11=['Nov_y=Nov' int2str(y) '_' int2str(i) '(:,1)'];
    s12=['Dec_y=Dec' int2str(y) '_' int2str(i) '(:,1)'];
    eval(s1);
    eval(s2);
    eval(s3);
    eval(s4);
    eval(s5);
    eval(s6);
    eval(s7);
    eval(s8);
    eval(s9);
    eval(s10);
    eval(s11);
    eval(s12);
    Jan_i=cat(1,Jan_i,Jan_y);
    Feb_i=cat(1,Feb_i,Feb_y);
    Mar_i=cat(1,Mar_i,Mar_y);
    Apr_i=cat(1,Apr_i,Apr_y);
    May_i=cat(1,May_i,May_y);
    Jun_i=cat(1,Jun_i,Jun_y);

```

```

    Jul_i=cat(1,Jul_i,Jul_y);
    Aug_i=cat(1,Aug_i,Aug_y);
    Sep_i=cat(1,Sep_i,Sep_y);
    Oct_i=cat(1,Oct_i,Oct_y);
    Nov_i=cat(1,Nov_i,Nov_y);
    Dec_i=cat(1,Dec_i,Dec_y);
end
Jan2=cat(1,Jan2,Jan_i);
Feb2=cat(1,Feb2,Feb_i);
Mar2=cat(1,Mar2,Mar_i);
Apr2=cat(1,Apr2,Apr_i);
May2=cat(1,May2,May_i);
Jun2=cat(1,Jun2,Jun_i);
Jul2=cat(1,Jul2,Jul_i);
Aug2=cat(1,Aug2,Aug_i);
Sep2=cat(1,Sep2,Sep_i);
Oct2=cat(1,Oct2,Oct_i);
Nov2=cat(1,Nov2,Nov_i);
Dec2=cat(1,Dec2,Dec_i);
end

CDFdiff1=abs(Jan-Jan2);
CDFdiff2=abs(Feb-Feb2);
CDFdiff3=abs(Mar-Mar2);
CDFdiff4=abs(Apr-Apr2);
CDFdiff5=abs(May-May2);
CDFdiff6=abs(Jun-Jun2);
CDFdiff7=abs(Jul-Jul2);
CDFdiff8=abs(Aug-Aug2);
CDFdiff9=abs(Sep-Sep2);
CDFdiff10=abs(Oct-Oct2);
CDFdiff11=abs(Nov-Nov2);

```

```

CDFdiff12=abs(Dec-Dec2);

%FS(1,:)=sum(reshape(CDFdiff1,31,3000));
%FS(2,:)=sum(reshape(CDFdiff2,28,3000));
%FS(3,:)=sum(reshape(CDFdiff3,31,3000));
%FS(4,:)=sum(reshape(CDFdiff4,30,3000));
%FS(5,:)=sum(reshape(CDFdiff5,31,3000));
%FS(6,:)=sum(reshape(CDFdiff6,30,3000));
%FS(7,:)=sum(reshape(CDFdiff7,31,3000));
%FS(8,:)=sum(reshape(CDFdiff8,31,3000));
%FS(9,:)=sum(reshape(CDFdiff9,30,3000));
%FS(10,:)=sum(reshape(CDFdiff10,31,3000));
%FS(11,:)=sum(reshape(CDFdiff11,30,3000));
%FS(12,:)=sum(reshape(CDFdiff12,31,3000));
% ISO above
FS(1,:)=sum(reshape(CDFdiff1,31,3000))/31;
FS(2,:)=sum(reshape(CDFdiff2,28,3000))/28;
FS(3,:)=sum(reshape(CDFdiff3,31,3000))/31;
FS(4,:)=sum(reshape(CDFdiff4,30,3000))/30;
FS(5,:)=sum(reshape(CDFdiff5,31,3000))/31;
FS(6,:)=sum(reshape(CDFdiff6,30,3000))/30;
FS(7,:)=sum(reshape(CDFdiff7,31,3000))/31;
FS(8,:)=sum(reshape(CDFdiff8,31,3000))/31;
FS(9,:)=sum(reshape(CDFdiff9,30,3000))/30;
FS(10,:)=sum(reshape(CDFdiff10,31,3000))/31;
FS(11,:)=sum(reshape(CDFdiff11,30,3000))/30;
FS(12,:)=sum(reshape(CDFdiff12,31,3000))/31;

FS_rad=FS';
save FS_rad.mat FS_rad;

```



```
save CDFdiff_rad.mat CDFdiff1 CDFdiff2 CDFdiff3 CDFdiff4 CDFdiff5 CDFdiff6
CDFdiff7 CDFdiff8 CDFdiff9 CDFdiff10 CDFdiff11 CDFdiff12;
```

```
time=clock;
a2=time(4:6);
%fprintf('\n Ending at %4d hour %4d min %4.2f second', a2);
a=a2-a1;
fprintf('\n Time spent: %4d hour %4d min %4.2f second', a);
clear all;
```

```
% Step 4.1: Capture solar relative humidity for each month in that year and in
whole 100 years
```

```
time=clock;
fprintf('\n Step 4.1: Capturing relative humidity for each month .....(Estimated
time: 1 min)')
load daily;
Tempdaily=pdaily(:,2); % capture relative humidity data from daily data
clear pdaily;
%Tempdaily=double(Tempdaily);
a1=time(4:6);
%fprintf('\n Starting at %4d hour %4d min %4.2f second', a1);
```

```
%capture daily average data from each month; format is Jand_i, such as
Jan3000_100
```

```
for i=1:100
```

```
    for d=3001:3030
```

```
        s01=['Jan' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',1,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',1,31)-1096093+10957*(i-
```

```

1))))]; %1096093=datenum(3000,12,31);10957=datenum(3030,12,31)-
datenum(3000,12,31)
s02=['Feb' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',2,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',2,28)-1096093+10957*(i-
1))))];
s03=['Mar' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',3,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',3,31)-1096093+10957*(i-
1))))];
s04=['Apr' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',4,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',4,30)-1096093+10957*(i-
1))))];
s05=['May' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',5,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',5,31)-1096093+10957*(i-
1))))];
s06=['Jun' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',6,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',6,30)-1096093+10957*(i-
1))))];
s07=['Jul' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',7,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',7,31)-1096093+10957*(i-
1))))];
s08=['Aug' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',8,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',8,31)-1096093+10957*(i-
1))))];
s09=['Sep' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',9,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',9,30)-1096093+10957*(i-
1))))];
s10=['Oct' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',10,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',10,31)-1096093+10957*(i-
1))))];
s11=['Nov' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',11,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',11,30)-1096093+10957*(i-
1))))];

```

```
s12=['Dec' int2str(d) '_' int2str(i) '=Tempdaily((datenum(' int2str(d)
',12,1)-1096093+10957*(i-1)):(datenum(' int2str(d) ',12,31)-1096093+10957*(i-
1)))'];
```

```
eval(s01);
```

```
eval(s02);
```

```
eval(s03);
```

```
eval(s04);
```

```
eval(s05);
```

```
eval(s06);
```

```
eval(s07);
```

```
eval(s08);
```

```
eval(s09);
```

```
eval(s10);
```

```
eval(s11);
```

```
eval(s12);
```

```
end
```

```
end
```

```
clear d s01 s02 s03 s04 s05 s06 s07 s08 s09 s10 s11 s12
```

```
%Generate matrix for a calendar month in the whole data set;
```

```
%size(Jan)=90000
```

```
Jan=[];
```

```
Feb=[];
```

```
Mar=[];
```

```
Apr=[];
```

```
May=[];
```

```
Jun=[];
```

```
Jul=[];
```

```
Aug=[];
```

```
Sep=[];
```

```
Oct=[];
```

```

Nov=[];
Dec=[];

for i=1:100
for d=3001:3030
s1=['Jan=[Jan;Jan' int2str(d) '_' int2str(i) '];'];
s2=['Feb=[Feb;Feb' int2str(d) '_' int2str(i) '];'];
s3=['Mar=[Mar;Mar' int2str(d) '_' int2str(i) '];'];
s4=['Apr=[Apr;Apr' int2str(d) '_' int2str(i) '];'];
s5=['May=[May;May' int2str(d) '_' int2str(i) '];'];
s6=['Jun=[Jun;Jun' int2str(d) '_' int2str(i) '];'];
s7=['Jul=[Jul;Jul' int2str(d) '_' int2str(i) '];'];
s8=['Aug=[Aug;Aug' int2str(d) '_' int2str(i) '];'];
s9=['Sep=[Sep;Sep' int2str(d) '_' int2str(i) '];'];
s10=['Oct=[Oct;Oct' int2str(d) '_' int2str(i) '];'];
s11=['Nov=[Nov;Nov' int2str(d) '_' int2str(i) '];'];
s12=['Dec=[Dec;Dec' int2str(d) '_' int2str(i) '];'];
eval(s1);
eval(s2);
eval(s3);
eval(s4);
eval(s5);
eval(s6);
eval(s7);
eval(s8);
eval(s9);
eval(s10);
eval(s11);
eval(s12);
end
end
clear d s1 s2 s3 s4 s5 s6 s7 s8 s9 s10 s11 s12

```

```

save humidity.mat;
time=clock;
a2=time(4:6);
%fprintf('\n Ending at  %4d hour %4d min %4.2f second', a2);
a=a2-a1;
fprintf('\n Time spent: %4d hour %4d min %4.2f second', a);
clear all;          %take 50 seconds

```

```

% Step 4.2: Calculating Cumulative Distribution of relative humidity
fprintf('\n Step 4.2: Calculating Cumulative Distribution of relative
humidity...(Estimated time: 1 min)')
time=clock;
a1=time(4:6);
%fprintf('\n Starting at %4d hour %4d min %4.2f second', a1);
load humidity
%Tie rank percentage of the ith value of each daily temperature data within that
calender month in the whole data set

```

```

Jan=CDFiso(Jan);
Feb=CDFiso(Feb);
Mar=CDFiso(Mar);
Apr=CDFiso(Apr);
May=CDFiso(May);
Jun=CDFiso(Jun);
Jul=CDFiso(Jul);
Aug=CDFiso(Aug);
Sep=CDFiso(Sep);
Oct=CDFiso(Oct);
Nov=CDFiso(Nov);
Dec=CDFiso(Dec);

```

```
%Tie rank percentage of the ith value of each daily temperature data within that month and that year
```

```
for i=1:100
```

```
for d=3001:3030
```

```
s1=['Jan' int2str(d) '_' int2str(i) '=CDFiso(Jan' int2str(d) '_' int2str(i) ');'];  
s2=['Feb' int2str(d) '_' int2str(i) '=CDFiso(Feb' int2str(d) '_' int2str(i) ');'];  
s3=['Mar' int2str(d) '_' int2str(i) '=CDFiso(Mar' int2str(d) '_' int2str(i) ');'];  
s4=['Apr' int2str(d) '_' int2str(i) '=CDFiso(Apr' int2str(d) '_' int2str(i) ');'];  
s5=['May' int2str(d) '_' int2str(i) '=CDFiso(May' int2str(d) '_' int2str(i) ');'];  
s6=['Jun' int2str(d) '_' int2str(i) '=CDFiso(Jun' int2str(d) '_' int2str(i) ');'];  
s7=['Jul' int2str(d) '_' int2str(i) '=CDFiso(Jul' int2str(d) '_' int2str(i) ');'];  
s8=['Aug' int2str(d) '_' int2str(i) '=CDFiso(Aug' int2str(d) '_' int2str(i) ');'];  
s9=['Sep' int2str(d) '_' int2str(i) '=CDFiso(Sep' int2str(d) '_' int2str(i) ');'];  
s10=['Oct' int2str(d) '_' int2str(i) '=CDFiso(Oct' int2str(d) '_' int2str(i) ');'];  
s11=['Nov' int2str(d) '_' int2str(i) '=CDFiso(Nov' int2str(d) '_' int2str(i) ');'];  
s12=['Dec' int2str(d) '_' int2str(i) '=CDFiso(Dec' int2str(d) '_' int2str(i) ');'];  
eval(s1);  
eval(s2);  
eval(s3);  
eval(s4);  
eval(s5);  
eval(s6);  
eval(s7);  
eval(s8);  
eval(s9);  
eval(s10);  
eval(s11);  
eval(s12);  
end
```

```

end
clear d s1 s2 s3 s4 s5 s6 s7 s8 s9 s10 s11 s12

save month_rank_relhum.mat % save month value with rank order

time=clock;
a2=time(4:6);
%fprintf('\n Ending at %4d hour %4d min %4.2f second', a2);
a=a2-a1;
fprintf('\n Time spent: %4d hour %4d min %4.2f second', a);
clear time a1 a2 a i; %take 50 seconds

% Step 4.3: Calculate Finkelstein-Schafer statistic of relative humidity for each
month
fprintf('\n Step 4.3: Calculating Finkelstein-Schafer statistic of relative humidity
...(Estimated time: 1 mins)')
time=clock;

a1=time(4:6);
%fprintf('\n Starting at %4d hour %4d min %4.2f second', a1);

Jan2=[];
Feb2=[];
Mar2=[];
Apr2=[];
May2=[];
Jun2=[];
Jul2=[];
Aug2=[];
Sep2=[];

```

```

Oct2=[];
Nov2=[];
Dec2=[];
for i=1:100
    Jan_i=[];
    Feb_i=[];
    Mar_i=[];
    Apr_i=[];
    May_i=[];
    Jun_i=[];
    Jul_i=[];
    Aug_i=[];
    Sep_i=[];
    Oct_i=[];
    Nov_i=[];
    Dec_i=[];
for y=3001:3030
    s1=['Jan_y=Jan' int2str(y) '_' int2str(i) '(:,1)'];
    s2=['Feb_y=Feb' int2str(y) '_' int2str(i) '(:,1)'];
    s3=['Mar_y=Mar' int2str(y) '_' int2str(i) '(:,1)'];
    s4=['Apr_y=Apr' int2str(y) '_' int2str(i) '(:,1)'];
    s5=['May_y=May' int2str(y) '_' int2str(i) '(:,1)'];
    s6=['Jun_y=Jun' int2str(y) '_' int2str(i) '(:,1)'];
    s7=['Jul_y=Jul' int2str(y) '_' int2str(i) '(:,1)'];
    s8=['Aug_y=Aug' int2str(y) '_' int2str(i) '(:,1)'];
    s9=['Sep_y=Sep' int2str(y) '_' int2str(i) '(:,1)'];
    s10=['Oct_y=Oct' int2str(y) '_' int2str(i) '(:,1)'];
    s11=['Nov_y=Nov' int2str(y) '_' int2str(i) '(:,1)'];
    s12=['Dec_y=Dec' int2str(y) '_' int2str(i) '(:,1)'];
    eval(s1);
    eval(s2);
    eval(s3);

```



```

eval(s4);
eval(s5);
eval(s6);
eval(s7);
eval(s8);
eval(s9);
eval(s10);
eval(s11);
eval(s12);
Jan_i=cat(1,Jan_i,Jan_y);
Feb_i=cat(1,Feb_i,Feb_y);
Mar_i=cat(1,Mar_i,Mar_y);
Apr_i=cat(1,Apr_i,Apr_y);
May_i=cat(1,May_i,May_y);
Jun_i=cat(1,Jun_i,Jun_y);
Jul_i=cat(1,Jul_i,Jul_y);
Aug_i=cat(1,Aug_i,Aug_y);
Sep_i=cat(1,Sep_i,Sep_y);
Oct_i=cat(1,Oct_i,Oct_y);
Nov_i=cat(1,Nov_i,Nov_y);
Dec_i=cat(1,Dec_i,Dec_y);
end
Jan2=cat(1,Jan2,Jan_i);
Feb2=cat(1,Feb2,Feb_i);
Mar2=cat(1,Mar2,Mar_i);
Apr2=cat(1,Apr2,Apr_i);
May2=cat(1,May2,May_i);
Jun2=cat(1,Jun2,Jun_i);
Jul2=cat(1,Jul2,Jul_i);
Aug2=cat(1,Aug2,Aug_i);
Sep2=cat(1,Sep2,Sep_i);
Oct2=cat(1,Oct2,Oct_i);

```

```

Nov2=cat(1,Nov2,Nov_i);
Dec2=cat(1,Dec2,Dec_i);
end

CDFdiff1=abs(Jan-Jan2);
CDFdiff2=abs(Feb-Feb2);
CDFdiff3=abs(Mar-Mar2);
CDFdiff4=abs(Apr-Apr2);
CDFdiff5=abs(May-May2);
CDFdiff6=abs(Jun-Jun2);
CDFdiff7=abs(Jul-Jul2);
CDFdiff8=abs(Aug-Aug2);
CDFdiff9=abs(Sep-Sep2);
CDFdiff10=abs(Oct-Oct2);
CDFdiff11=abs(Nov-Nov2);
CDFdiff12=abs(Dec-Dec2);
%
%FS(1,:)=sum(reshape(CDFdiff1,31,3000));
%FS(2,:)=sum(reshape(CDFdiff2,28,3000));
%FS(3,:)=sum(reshape(CDFdiff3,31,3000));
%FS(4,:)=sum(reshape(CDFdiff4,30,3000));
%FS(5,:)=sum(reshape(CDFdiff5,31,3000));
%FS(6,:)=sum(reshape(CDFdiff6,30,3000));
%FS(7,:)=sum(reshape(CDFdiff7,31,3000));
%FS(8,:)=sum(reshape(CDFdiff8,31,3000));
%FS(9,:)=sum(reshape(CDFdiff9,30,3000));
%FS(10,:)=sum(reshape(CDFdiff10,31,3000));
%FS(11,:)=sum(reshape(CDFdiff11,30,3000));
%FS(12,:)=sum(reshape(CDFdiff12,31,3000));
% ISO above
FS(1,:)=sum(reshape(CDFdiff1,31,3000))/31;
FS(2,:)=sum(reshape(CDFdiff2,28,3000))/28;

```

```

FS(3,:)=sum(reshape(CDFdiff3,31,3000))/31;
FS(4,:)=sum(reshape(CDFdiff4,30,3000))/30;
FS(5,:)=sum(reshape(CDFdiff5,31,3000))/31;
FS(6,:)=sum(reshape(CDFdiff6,30,3000))/30;
FS(7,:)=sum(reshape(CDFdiff7,31,3000))/31;
FS(8,:)=sum(reshape(CDFdiff8,31,3000))/31;
FS(9,:)=sum(reshape(CDFdiff9,30,3000))/30;
FS(10,:)=sum(reshape(CDFdiff10,31,3000))/31;
FS(11,:)=sum(reshape(CDFdiff11,30,3000))/30;
FS(12,:)=sum(reshape(CDFdiff12,31,3000))/31;

```

```

FS_relhum=FS';
save FS_relhum.mat FS_relhum;

```

```

save CDFdiff_relhum.mat CDFdiff1 CDFdiff2 CDFdiff3 CDFdiff4 CDFdiff5
CDFdiff6 CDFdiff7 CDFdiff8 CDFdiff9 CDFdiff10 CDFdiff11 CDFdiff12;

```

```

time=clock;
a2=time(4:6);
%fprintf('\n Ending at  %4d hour %4d min %4.2f second', a2);
a=a2-a1;
fprintf('\n Time spent: %4d hour %4d min %4.2f second', a);
clear all;

```

```

% Step 5: Selecting three months with the lowest FS ranking
fprintf('\n Step 5: Selecting three months with the lowest FS
ranking.....(Estimated time: 1 mins)');
load FS_relhum;
load FS_temp;

```

```

load FS_rad;
[~,a]=sort(FS_temp);
[~,XI_temp]=sort(a);
[~,a]=sort(FS_rad);
[~,XI_rad]=sort(a);
[~,a]=sort(FS_relhum);
[~,XI_relhum]=sort(a);

XI=XI_relhum+XI_rad+XI_temp; %sum order of three climate parameters

[~,a]=sort(XI);
n=zeros(3,12);y=zeros(3,12);
for o=1:12      %12 months
    for z=1:3   %first three low value
        n(z,o)=floor((a(z,o)-1)/30)+1; % n is set of data
        y(z,o)=a(z,o)-30*(n(z,o)-1)+3000; % y is year
    end
end
end

clear XI XI_rad XI_relhum XI_temp o z

save yearall.mat;
save year.mat n y;

% Step 6: Calculate daily wind speed
fprintf('\n Step 6: Calculate daily wind speed .....(Estimated time:
3 secs)');
%time=clock;
%a1=time(4:6);
%fprintf('\n Starting at %4d hour %4d min %4.2f second', a1);

```

```

load pday; % load raw daily data

JD=pday(:,1); %Day Number of the year
Tmax=pday(:,5)+273.16; %Tmax, K
Tmin=pday(:,4)+273.16; %Tmin, K
temp1=(pday(:,4)+pday(:,5))/2; %daily mean temperature
ss=pday(:,8); % sunshine hours day total

Rs=pday(:,9)+pday(:,10); % total incoming solar radiation, MJ/m2/d
PET=pday(:,11);

ea=pday(:,6)/10;
temp2(1,1)=temp1(size(temp1,1),1);%generate temperature for previous day
temp2(2:size(temp1,1),1)=temp1(1:size(temp1,1)-1,1);

%calculate DEC solar declination in radians
DEC=0.409*sin(2*pi/365*JD-1.39);

%DEC=(0.33281-22.984*cos(JD)+3.7872*sin(JD)-
0.3499*cos(2*JD)+0.03205*sin(2*JD)-
0.1398*cos(3*JD)+0.07187*sin(3*JD))*pi/180; %results in radians
% simplified DEC=0.409*sin(JD-1.39);

load latitude;
lat=latitude*pi/180;

Omega=acos(-tan(lat).*tan(DEC)); %calcuete sunset hour angle

dyln=7.64*Omega; %dyln, sunshine hour angle, from Richard Excel and
pet_penmon.f90

```

```

ssf=ss./dyln;
for i=1:size(ssf,1)
    if ssf(i,1)>1
        ssf(i,1)=1;
    end
end
JD=2*pi*JD/366; %Julian day in radians
dr=1+0.033*cos(JD); %inverse relative distance from Earth to sun
Gsc=0.0820; %solar constant, MJ/m2/min

Ra=1440/pi*Gsc.*dr.*(Omiga.*sin(lat).*sin(DEC)+cos(lat).*cos(DEC).*sin(Omiga
)); %extraterrestrial radiation, ML/m2/d
z=0; % station elevation, meter
Rso=(0.75+2e-5*z)*Ra; %daily clear sky solar radiation Rso at z meter,
ML/m2/d

Sigma=4.903e-9; %Stefan-Boltzmann constant, MJ/K4/m2/d

Rnl=Sigma*((Tmax.^4+Tmin.^4)/2).*(0.34-0.14*ea.^0.5).*(0.9*ssf+0.1);
%Rnl=Sigma*((Tmax.^4+Tmin.^4)/2).*(0.34-0.14*ea.^0.5).*(1.35*Rs./Rso-0.35);
% outgoing net longwave radiation, from Irmak's paper

alpha=0.23; %albedo or canopy reflection coefficient, 0.23 for a grass reference
crop surface
Rns=0.77*(0.25+0.5*ssf).*Ra; % incoming net shortwave raditaion, Rns,
balance between incoming and reflected solar radiation
%Rns=(1-alpha)*Rs, Irmak's paper

Rn=Rns-Rnl; %net radiation at the crop surface, MJ/m2/day

%calculate G, soil heat flux density, MJ/m2/day

```

```

G=0.38*(temp1-temp2);

%calculate lambda, latent heat of vaporization, MJ*kg-1
lambda=2.501-2.361e-3*temp1;
%calculate P, atmospheric pressure at elevation z, kPa
P=101.3;
%calculate r, psychrometric constant, kPa/K
r=0.00163*P./lambda;
%calculate es, saturated vapour pressure, kPa
es=(0.6108*exp((17.27*(Tmax-273.16))./(Tmax+237.3-
273.16))+0.6108*exp((17.27*(Tmin-273.16))./(Tmin-273.16+237.3)))/2;
%es=0.611*exp((17.27*temp1)./(temp1+237.3));%
%calculate delta, gradient of vapour pressure against temperature curve at
%temperature, kPa/K
delta=4098*es./((temp1+237.3).^2);

wind2=(PET.*delta+PET.*r-0.408*delta.*(Rn-G))./(900*r.*(es-
ea)./(temp1+2731.6)-0.34*PET.*r); %wind speed at 2m

wnf=log((2-0.08)/0.015)/log((10-0.08)/0.015); %convert wind speed at 2m to
10m
wind10=wind2/wnf; %wind speed at 10meter
windspeed=wind10;
index1=0;
index2=0;
for i=1:size(windspeed,1)
    if windspeed(i,1)<0
        windspeed(i,1)=-windspeed(i,1);
        index1=index1-1;
    end %delete negative values
    if windspeed(i,1)>21
        windspeed(i,1)=21;

```

```

        index2=index2+1;
        end %set 21 m/s as threshold, if the windspeed over 21, set to 21
end

if windspeed(1,1)>20 % for i=1
    windspeed(1,1)=(windspeed(size(windspeed,1),1)+windspeed(2,1))/2;
end

for i=2:(size(windspeed,1)-1)
    if windspeed(i,1)>20
        windspeed(i,1)=(windspeed(i-1,1)+windspeed(i+1,1))/2;
        end %if the windspeed over 20, set the windspeed to the average of
nearby values
end

if windspeed(size(windspeed,1),1)>20 % for i=size(windspeed,1)
    windspeed(size(windspeed,1),1)=(windspeed(size(windspeed,1)-
1,1)+windspeed(1,1))/2;
end

%time=clock;
%a2=time(4:6);
%fprintf('\n Ending at  %4d hour %4d min %4.2f second', a2);
%a=a2-a1;
%fprintf('\n Time spent: %4d hour %4d min %4.2f second', a);
%clear a1 a2 a
save windall.mat;
save wind.mat windspeed;
clear all

% Step 7: Calculate monthly mean wind speed
load wind.mat

```



```

fprintf('\n Step 7: Calculate monthly mean wind speed.....(Estimated
time: 3 secs)');
WindDev=zeros(3000,12);
for i=1:100
    for d=3001:3030
        WindDev((i-1)*30+d-3000,1)=mean(windspeed((datenum(d,1,1)-
1096093+10957*(i-1)):(datenum(d,1,31)-1096093+10957*(i-1))));
        WindDev((i-1)*30+d-3000,2)=mean(windspeed((datenum(d,2,1)-
1096093+10957*(i-1)):(datenum(d,2,28)-1096093+10957*(i-1))));
        WindDev((i-1)*30+d-3000,3)=mean(windspeed((datenum(d,3,1)-
1096093+10957*(i-1)):(datenum(d,3,31)-1096093+10957*(i-1))));
        WindDev((i-1)*30+d-3000,4)=mean(windspeed((datenum(d,4,1)-
1096093+10957*(i-1)):(datenum(d,4,30)-1096093+10957*(i-1))));
        WindDev((i-1)*30+d-3000,5)=mean(windspeed((datenum(d,5,1)-
1096093+10957*(i-1)):(datenum(d,5,31)-1096093+10957*(i-1))));
        WindDev((i-1)*30+d-3000,6)=mean(windspeed((datenum(d,6,1)-
1096093+10957*(i-1)):(datenum(d,6,30)-1096093+10957*(i-1))));
        WindDev((i-1)*30+d-3000,7)=mean(windspeed((datenum(d,7,1)-
1096093+10957*(i-1)):(datenum(d,7,31)-1096093+10957*(i-1))));
        WindDev((i-1)*30+d-3000,8)=mean(windspeed((datenum(d,8,1)-
1096093+10957*(i-1)):(datenum(d,8,31)-1096093+10957*(i-1))));
        WindDev((i-1)*30+d-3000,9)=mean(windspeed((datenum(d,9,1)-
1096093+10957*(i-1)):(datenum(d,9,30)-1096093+10957*(i-1))));
        WindDev((i-1)*30+d-3000,10)=mean(windspeed((datenum(d,10,1)-
1096093+10957*(i-1)):(datenum(d,10,31)-1096093+10957*(i-1))));
        WindDev((i-1)*30+d-3000,11)=mean(windspeed((datenum(d,11,1)-
1096093+10957*(i-1)):(datenum(d,11,30)-1096093+10957*(i-1))));
        WindDev((i-1)*30+d-3000,12)=mean(windspeed((datenum(d,12,1)-
1096093+10957*(i-1)):(datenum(d,12,31)-1096093+10957*(i-1))));
        %1096093=datenum(3000,12,31);10957=datenum(3030,12,31)-
datenum(3000,12,31)
    end
end

```

```

end
clear d i windspeed;
save WindDev.mat WindDev;
clear all;

% Step 8: Calculate the deviation of the monthly mean wind speed from the
% corresponding multi-year calendar month mean
load WindDev;
fprintf('\n Step 8: Calculate monthly mean wind speed
deviation.....(Estimated time: 3 secs)');
load year.mat;
CalenderM=mean(WindDev);
Dev=zeros(3,12);
for i=1:12
    for o=1:3
        Dev(o,i)=WindDev((n(o,i)-1)*30+y(o,i)-3000,i)-CalenderM(i);
    end
end

end

[~,A]=sort(Dev);
year=zeros(2,12);
for i=1:12
    year(1,i)=y(A(1,i),i);
    year(2,i)=n(A(1,i),i);
end

save yearnumber.mat year;

fprintf('\n Selected 12 months for TRY:');
fprintf('\n Jan is from year %4d _ %2d th data set', year(:,1));

```

```

fprintf('\n Feb is from year %4d _ %2d th data set', year(:,2));
fprintf('\n Mar is from year %4d _ %2d th data set', year(:,3));
fprintf('\n Apr is from year %4d _ %2d th data set', year(:,4));
fprintf('\n May is from year %4d _ %2d th data set', year(:,5));
fprintf('\n Jun is from year %4d _ %2d th data set', year(:,6));
fprintf('\n Jul is from year %4d _ %2d th data set', year(:,7));
fprintf('\n Aug is from year %4d _ %2d th data set', year(:,8));
fprintf('\n Sep is from year %4d _ %2d th data set', year(:,9));
fprintf('\n Oct is from year %4d _ %2d th data set', year(:,10));
fprintf('\n Nov is from year %4d _ %2d th data set', year(:,11));
fprintf('\n Dec is from year %4d _ %2d th data set', year(:,12));

```

```

% Step 9: Generating TRY data(CIBSE format)

```

```

clear all;

```

```

fprintf('\n Step 9: Generating TRY data(CIBSE format).....(Estimated
time: 25 secs)');

```

```

load yearnumber;

```

```

DayNu=[31,28,31,30,31,30,31,31,30,31,30,31];

```

```

load txt;

```

```

a=1;

```

```

TRY=zeros(8760,11);

```

```

for i=1:12

```

```

    p0=dlmread(char(txt(year(2,i),1)),',', 'A1..K262968'); %1 control data

```

```

    %p0=dlmread(char(txt(year(2,i),2)),',', 'A1..K262968'); %2 senario data

```

```

    for m=1:262968

```

```

        if ((p0(m,1)==year(1,i)) && (p0(m,2)==i)&&(p0(m,3)==1)&&(p0(m,4)==0))

```

```

            TRY(a:(a+DayNu(i)*24-1,:)=p0(m:m+DayNu(i)*24-1,:);

```

```

        end

```

```

    end

```

```

    a=a+24*DayNu(i);

```

```

end
save TestReferenceYear.mat TRY
clear DayNu a i m p0 txt;

% Step 10: Adjusting the hourly value at the beginning and end of each
% month
fprintf('\n Step 10: Adjusting hourly value at beginning and end of each
month...(Estimated time: 25 secs)');
TRY_S=TRY;
for q=6:8 %column 6,7,8 are temp_hmean,vapourpressure_hmean and
relhum_hmean
% smooth beginning of Jan and end of Dec
y1=TRY(1:8,q);
y2=TRY(8760-7:8760,q);
y0=cat(1,y2,y1);
y(1)=y0(1);
y(5)=y0(16);
y(3)=mean(y0);
y(2)=mean(y2);
y(4)=mean(y1);
x=[1,4.75,8.5,13.25,16];
xx=1:16;
yy=spline(x,y,xx);
TRY_S(8760-7:8760,q)=yy(1:8)';
TRY_S(1:8,q)=yy(9:16)';
% smooth other months
for i=10:8760
    if (TRY(i,2)>TRY(i-1,2))
        y(1)=TRY(i-8,q);
        y(5)=TRY(i+7,q);
        y(3)=mean(TRY(i-8:i+7,q));
    end
end

```

```

    y(2)=mean(TRY(i-8:i-1,q));
    y(4)=mean(TRY(i:i+7,q));
    x=[1,4.75,8.5,13.25,16];
    xx=1:16;
    yy=spline(x,y,xx);
    TRY_S(i-8:i+7,q)=yy';
end
end
end
save TestReferenceYear_Smoothed.mat TRY_S;
clear y1 y2 y0 y x xx yy i q;

% Step 11: Caculate dew point temeperature, horizontal infrared and direct
normal radiation
fprintf('\n Step 11: Generating TRY data (EPW format):');
fprintf('\n Step 11.1: Calculating dew point temeperature.....(Estimated
time: 1 sec)');
r=17.271*TRY_S(:,6)./(237.7+TRY_S(:,6))+log(TRY_S(:,8));
TRY_S(:,12)=237.7*r./(17.271-r); %column 12, dew point temperature,

for i=1:8760
    if TRY_S(:,12)>TRY_S(:,6)
        TRY_S(:,12)=TRY_S(:,6);
    end
end

clear r

fprintf('\n Step 11.2: Calculating direct normal radiation.....(Estimated
time: 5 secs)');
%column 13, date number OF the year

```

```

TRY_S(1,13)=1; % first day number is 1
for i=2:8760
    if or(TRY_S(i,3)>TRY_S(i-1,3),TRY_S(i,2)>TRY_S(i-1,2))
        TRY_S(i,13)=TRY_S(i-1,13)+1;
    else
        TRY_S(i,13)=TRY_S(i-1,13);
    end
end
clear i;
%column 15, DEC, solar Declination (between the earth-sun line and the
equator plane) in radians
TRY_S(:,14)=2*pi*((TRY_S(:,13))/366); %N
TRY_S(:,15)=(0.33281-22.984*cos(TRY_S(:,14))+3.7872*sin(TRY_S(:,14))-
0.3499*cos(2*TRY_S(:,14))+0.03205*sin(2*TRY_S(:,14))-
0.1398*cos(3*TRY_S(:,14))+0.07187*sin(3*TRY_S(:,14)))*pi/180;
%column 16, HRA, hour angle from solar noon, 15 degree per hour, in radians
TRY_S(:,16)=15*(TRY_S(:,4)/100-11.5)*pi/180;
%LAT, geographical latitude (south negative), in radians
load latitude
LAT=latitude*pi/180;
%column 17, ALT, solar altitude(from horizontal max 90 zenith), in radians,
TRY_S(:,17)=asin(sin(TRY_S(:,15))*sin(LAT)+cos(LAT)*cos(TRY_S(:,16))).*cos(
TRY_S(:,15));
%column 18, direct normal=direct horizontal/sin(solar altitude),
TRY_S(:,18)=TRY_S(:,11)./sin(TRY_S(:,17));
a=0;
for i=2:8760
    if TRY_S(i,18)<0
        TRY_S(i,18)=0; %delete the negative value
    end
end
end

```

```
%delete unreasonable value at sunrise and sunset, (solar altitude <11 degree,  
direct normal>100)
```

```
TRY_S(:,19)=TRY_S(:,17)*180/pi; %column 19, solar altitude in degree
```

```
TRY_SS=TRY_S;
```

```
c=0;
```

```
for i=1:8760
```

```
    if and(TRY_S(i,19)<11,TRY_S(i,18)>200)
```

```
        TRY_SS(i,18)=200;
```

```
        c=c+1;
```

```
        A(c,1)=TRY_S(i,18);
```

```
        A(c,2)=TRY_S(i,19);
```

```
    end
```

```
end %when direct normal over 200, set to 200
```

```
c=0;
```

```
for i=1:8760
```

```
    if and(TRY_S(i,19)<11,TRY_S(i,18)>100)
```

```
        TRY_SS(i,18)=(TRY_SS(i-1,18)+TRY_SS(i+1,18))/2;
```

```
        c=c+1;
```

```
    end
```

```
end %re-run, when direct normal over 100, set to average of nearby values
```

```
fprintf('\n Step 11.3: Calculating cloud cover.....(Estimated time:  
2 secs)');
```

```
TRY_SS(:,20)=10*(1-TRY_SS(:,9)); %column 20, total sky cover in tenth
```

```
for i=1:8760
```

```
    if TRY_SS(i,9)==0
```

```
        TRY_SS(i,20)=0;
```

```
    end
```

```
end
```

```

% night cloud covers are equal to interpolation of cloud covers at sunrise and
sunset time
c1=0;
for i=2:8760
    if TRY_SS(i,19)*TRY_SS(i-1,19)<0
        c1=c1+1;
        Index(c1)=i;
    end %Identify night time
end

for i=1:(size(Index,2)-2)/2
    z(1)=TRY_SS(Index(i*2)-1,20);
    z(2)=TRY_SS(Index(i*2+1),20);
    TRY_SS(Index(i*2)-1:(Index(i*2+1)),20)=interp1(0:1,z,0:1/(Index(i*2+1)-
Index(i*2)+1):1);
end %liner interpolate cloud cover at night time

for i=1:8760
    TRY_SS(i,20)=round(TRY_SS(i,20));
end %integral function
%
fprintf('\n Step 11.4: Calculating horizontal infrared radiation
intensity...(Estimated time: 2 secs)');
TRY_SS(:,21)=round(TRY_SS(:,20)/2); %column 21, opaque sky cover,
assumed as half the value of total sky cover
SkyE=(0.787+0.764*log((TRY_SS(:,12)+273)/273)).*(1+0.0224*TRY_SS(:,21)+
0.0035*TRY_SS(:,21).^2+0.00028*TRY_SS(:,21).^3);
TRY_SS(:,22)=5.6697e-8*SkyE.*(TRY_SS(:,6)+273).^4; %column 22,
horizontal infrared radiation intensity

TRY_SS(:,23)=101300; %column 23, atmospheric pressure

```



```

TRY_SS(:,24)=TRY_SS(:,10)+TRY_SS(:,11); %column 24, global horizontal
radiation,
TRY_SS(:,8)=floor(100*TRY_SS(:,8)); %column 8, relative humidity, in
percentage
save TRY_EPW TRY_SS
dlmwrite('TRY.csv',TRY_SS);
fprintf('\n Congratulation!!! TRY is saved as "TRY.csv"');
clear;
%%
DRY99_Hu_Part_control; % to run script to generate DRY
DRY85_Hu_Part_control;
clear;
%PlotDRYTRY;
fprintf('\n Total ');
toc;

%column 1, year
%column 2, month
%column 3, date of the month
%column 4, hour
%column 5, precip htotal, mm/hour
%column 6, hourly temperature, degree C
%column 7, vapour pressure, hPa
%column 8, relative humidity, %
%column 9, sunshine hour, hours
%column 10, diffuse solar radiation, Wh/m2
%column 11, direct solar radiation in horizontal, Wh/m2
%column 12, dew point temperature, C
%column 13, date number of the year
%column 14, date number, in radians
%column 15, solar declination, in radians
%column 16, hour angle from solar noon

```

%column 17, solar altitude, in radians
%column 18, direct normal radiation, Wh/m²
%column 19, solar altitude, in degree
%column 20, total sky cover
%column 21, opaque sky cover
%column 22, horizontal infrared radiation intensity
%column 23, atmospheric pressure
%column 24, global horizontal radiation,

```

%***** DRY85_Hu_Part_control.m *****
%% Step 12: Calculating monthly mean temperature for 3000 years
fprintf('\n Calculating DRY at 85 percentile...');
fprintf('\n Step 12: Calculating monthly mean temperature for 3000
years...(Estimated time: 1 min)')

load temperature;
save JanFebJunJulAug.mat Jan Feb Jun Jul Aug Dec;
SummerYearNumber=zeros(100,1);
m=0;
for i=1:100
    for d=3001:3030
        m=m+1;
        s1=['MonthMeanTemp(m,1)=mean(Jan' int2str(d) '_' int2str(i) ');'];
        s2=['MonthMeanTemp(m,2)=mean(Feb' int2str(d) '_' int2str(i) ');'];
        s3=['MonthMeanTemp(m,3)=mean(Mar' int2str(d) '_' int2str(i) ');'];
        s4=['MonthMeanTemp(m,4)=mean(Apr' int2str(d) '_' int2str(i) ');'];
        s5=['MonthMeanTemp(m,5)=mean(May' int2str(d) '_' int2str(i) ');'];
        s6=['MonthMeanTemp(m,6)=mean(Jun' int2str(d) '_' int2str(i) ');'];
        s7=['MonthMeanTemp(m,7)=mean(Jul' int2str(d) '_' int2str(i) ');'];
        s8=['MonthMeanTemp(m,8)=mean(Aug' int2str(d) '_' int2str(i) ');'];
        s9=['MonthMeanTemp(m,9)=mean(Sep' int2str(d) '_' int2str(i) ');'];
        s10=['MonthMeanTemp(m,10)=mean(Oct' int2str(d) '_' int2str(i) ');'];
        s11=['MonthMeanTemp(m,11)=mean(Nov' int2str(d) '_' int2str(i) ');'];
        s12=['MonthMeanTemp(m,12)=mean(Dec' int2str(d) '_' int2str(i) ');'];
        eval(s1);
        eval(s2);
        eval(s3);
        eval(s4);
        eval(s5);
        eval(s6);
        eval(s7);
    end
end

```

```

        eval(s8);
        eval(s9);
        eval(s10);
        eval(s11);
        eval(s12);
    end
end

MeanTemp(1)=mean(Jan);
MeanTemp(2)=mean(Feb);
MeanTemp(3)=mean(Mar);
MeanTemp(4)=mean(Apr);
MeanTemp(5)=mean(May);
MeanTemp(6)=mean(Jun);
MeanTemp(7)=mean(Jul);
MeanTemp(8)=mean(Aug);
MeanTemp(9)=mean(Sep);
MeanTemp(10)=mean(Oct);
MeanTemp(11)=mean(Nov);
MeanTemp(12)=mean(Dec);
save MonthMeanTemp.mat MonthMeanTemp MeanTemp

clear d s1 s2 s3 s4 s5 s6 s7 s8 s9 s10 s11 s12

clear;
%% Step 13: Selecting month for Design Reference Year
fprintf('\n Step 13: Selecting month for Design Reference
Year.....(Estimated time: 1 sec)')
load MonthMeanTemp
for i=1:12
    [RankedMeanTemp(:,i),X(:,i)]=sort(MonthMeanTemp(:,i));
end

```

% 99th percentile

```
YearJanFebJunJulAug(:,1)=X(451:480,1);  
YearJanFebJunJulAug(:,2)=X(451:480,2);  
YearJanFebJunJulAug(:,3)=X(2521:2550,6);  
YearJanFebJunJulAug(:,4)=X(2521:2550,7);  
YearJanFebJunJulAug(:,5)=X(2521:2550,8);  
YearJanFebJunJulAug(:,6)=X(451:480,12);
```

```
load JanFebJunJulAug;
```

```
Jan30=[];
```

```
Feb30=[];
```

```
Jun30=[];
```

```
Jul30=[];
```

```
Aug30=[];
```

```
Dec30=[];
```

```
for i=1:30
```

```
    yearnumberJan=YearJanFebJunJulAug(i,1);
```

```
    yearnumberFeb=YearJanFebJunJulAug(i,2);
```

```
    yearnumberJun=YearJanFebJunJulAug(i,3);
```

```
    yearnumberJul=YearJanFebJunJulAug(i,4);
```

```
    yearnumberAug=YearJanFebJunJulAug(i,5);
```

```
    yearnumberDec=YearJanFebJunJulAug(i,6);
```

```
    JanMonth=Jan((yearnumberJan-1)*31+1:(yearnumberJan-1)*31+31);
```

```
    FebMonth=Feb((yearnumberFeb-1)*28+1:(yearnumberFeb-1)*28+28);
```

```
    JunMonth=Jun((yearnumberJun-1)*30+1:(yearnumberJun-1)*30+30);
```

```
    JulMonth=Jul((yearnumberJul-1)*31+1:(yearnumberJul-1)*31+31);
```

```
    AugMonth=Aug((yearnumberAug-1)*31+1:(yearnumberAug-1)*31+31);
```

```
    DecMonth=Dec((yearnumberDec-1)*31+1:(yearnumberDec-1)*31+31);
```

```
    Jan30=cat(1,JanMonth,Jan30);
```

```
    Feb30=cat(1,FebMonth,Feb30);
```

```

Jun30=cat(1,JunMonth,Jun30);
Jul30=cat(1,JulMonth,Jul30);
Aug30=cat(1,AugMonth,Aug30);
Dec30=cat(1,DecMonth,Dec30);
end
Jan30Month=reshape(Jan30,31,30); % daily mean of selected 30 months
Feb30Month=reshape(Feb30,28,30);
Jun30Month=reshape(Jun30,30,30);
Jul30Month=reshape(Jul30,31,30);
Aug30Month=reshape(Aug30,31,30);
Dec30Month=reshape(Dec30,31,30);
% calculate FS-stat for selected 30 months
for i=1:30
    CDFJan(:,i)=CDFIso(Jan30Month(:,i));
    CDFFeb(:,i)=CDFIso(Feb30Month(:,i));
    CDFJun(:,i)=CDFIso(Jun30Month(:,i));
    CDFJul(:,i)=CDFIso(Jul30Month(:,i));
    CDFAug(:,i)=CDFIso(Aug30Month(:,i));
    CDFDec(:,i)=CDFIso(Dec30Month(:,i));
end
CDFJanAll=CDFIso(Jan30);
CDFFebAll=CDFIso(Feb30);
CDFJunAll=CDFIso(Jun30);
CDFJulAll=CDFIso(Jul30);
CDFAugAll=CDFIso(Aug30);
CDFDecAll=CDFIso(Dec30);

CDFJanA=reshape(CDFJanAll,31,30);
CDFFebA=reshape(CDFFebAll,28,30);
CDFJunA=reshape(CDFJunAll,30,30);
CDFJulA=reshape(CDFJulAll,31,30);
CDFAugA=reshape(CDFAugAll,31,30);

```

```
CDFDecA=reshape(CDFDecAll,31,30);
```

```
JanFS=sum(abs(CDFJanA-CDFJan));
```

```
FebFS=sum(abs(CDFFebA-CDFFeb));
```

```
JunFS=sum(abs(CDFJunA-CDFJun));
```

```
JulFS=sum(abs(CDFJulA-CDFJul));
```

```
AugFS=sum(abs(CDFAugA-CDFAug));
```

```
DecFS=sum(abs(CDFDecA-CDFDec));
```

```
[~,AJan]=sort(JanFS);
```

```
[~,AFeb]=sort(FebFS);
```

```
[~,AJun]=sort(JunFS);
```

```
[~,AJul]=sort(JulFS);
```

```
[~,AAug]=sort(AugFS);
```

```
[~,ADec]=sort(DecFS);
```

```
YearNumberDRY(1,1)=YearJanFebJunJulAug(AJan(1),1);
```

```
YearNumberDRY(2,1)=YearJanFebJunJulAug(AFeb(1),2);
```

```
YearNumberDRY(6,1)=YearJanFebJunJulAug(AJun(1),3);
```

```
YearNumberDRY(7,1)=YearJanFebJunJulAug(AJul(1),4);
```

```
YearNumberDRY(8,1)=YearJanFebJunJulAug(AAug(1),5);
```

```
YearNumberDRY(12,1)=YearJanFebJunJulAug(ADec(1),6);
```

```
YearNumberDRY(1,2)=YearJanFebJunJulAug(AJan(2),1);
```

```
YearNumberDRY(2,2)=YearJanFebJunJulAug(AFeb(2),2);
```

```
YearNumberDRY(6,2)=YearJanFebJunJulAug(AJun(2),3);
```

```
YearNumberDRY(7,2)=YearJanFebJunJulAug(AJul(2),4);
```

```
YearNumberDRY(8,2)=YearJanFebJunJulAug(AAug(2),5);
```

```
YearNumberDRY(12,2)=YearJanFebJunJulAug(ADec(2),6);
```

```
YearNumberDRY(1,3)=YearJanFebJunJulAug(AJan(3),1);
```

```
YearNumberDRY(2,3)=YearJanFebJunJulAug(AFeb(3),2);
```

```

YearNumberDRY(6,3)=YearJanFebJunJulAug(AJun(3),3);
YearNumberDRY(7,3)=YearJanFebJunJulAug(AJul(3),4);
YearNumberDRY(8,3)=YearJanFebJunJulAug(AAug(3),5);
YearNumberDRY(12,3)=YearJanFebJunJulAug(ADec(3),6);

```

```

YearNumberDRY(1,4)=YearJanFebJunJulAug(AJan(4),1);
YearNumberDRY(2,4)=YearJanFebJunJulAug(AFeb(4),2);
YearNumberDRY(6,4)=YearJanFebJunJulAug(AJun(4),3);
YearNumberDRY(7,4)=YearJanFebJunJulAug(AJul(4),4);
YearNumberDRY(8,4)=YearJanFebJunJulAug(AAug(4),5);
YearNumberDRY(12,4)=YearJanFebJunJulAug(ADec(4),6);

```

```

YearNumberDRY(1,5)=YearJanFebJunJulAug(AJan(5),1);
YearNumberDRY(2,5)=YearJanFebJunJulAug(AFeb(5),2);
YearNumberDRY(6,5)=YearJanFebJunJulAug(AJun(5),3);
YearNumberDRY(7,5)=YearJanFebJunJulAug(AJul(5),4);
YearNumberDRY(8,5)=YearJanFebJunJulAug(AAug(5),5);
YearNumberDRY(12,5)=YearJanFebJunJulAug(ADec(5),6);

```

```
save YearnumberDRY.mat YearNumberDRY
```

```
load radiation.mat
```

```
m=0;
```

```
for i=1:100
```

```
    for d=3001:3030
```

```
        m=m+1;
```

```
        s1=['MonthMeanRad(m,1)=mean(Jan' int2str(d) ' ' int2str(i) ');'];
```

```
        s2=['MonthMeanRad(m,2)=mean(Feb' int2str(d) ' ' int2str(i) ');'];
```

```
        s3=['MonthMeanRad(m,3)=mean(Mar' int2str(d) ' ' int2str(i) ');'];
```

```
        s4=['MonthMeanRad(m,4)=mean(Apr' int2str(d) ' ' int2str(i) ');'];
```

```
        s5=['MonthMeanRad(m,5)=mean(May' int2str(d) ' ' int2str(i) ');'];
```

```
        s6=['MonthMeanRad(m,6)=mean(Jun' int2str(d) ' ' int2str(i) ');'];
```

```
        s7=['MonthMeanRad(m,7)=mean(Jul' int2str(d) ' ' int2str(i) ');'];
```



```

s8=['MonthMeanRad(m,8)=mean(Aug' int2str(d) '_' int2str(i) ');'];
s9=['MonthMeanRad(m,9)=mean(Sep' int2str(d) '_' int2str(i) ');'];
s10=['MonthMeanRad(m,10)=mean(Oct' int2str(d) '_' int2str(i) ');'];
s11=['MonthMeanRad(m,11)=mean(Nov' int2str(d) '_' int2str(i) ');'];
s12=['MonthMeanRad(m,12)=mean(Dec' int2str(d) '_' int2str(i) ');'];
eval(s1);
eval(s2);
eval(s3);
eval(s4);
eval(s5);
eval(s6);
eval(s7);
eval(s8);
eval(s9);
eval(s10);
eval(s11);
eval(s12);
end
end
save MonthMeanRad.mat MonthMeanRad

FiveMonthRadMean(:,1)=MonthMeanRad(YearNumberDRY(1,:),1); %Selected
5 Jan mean radiation
FiveMonthRadMean(:,2)=MonthMeanRad(YearNumberDRY(2,:),1);
FiveMonthRadMean(:,3)=MonthMeanRad(YearNumberDRY(6,:),1);
FiveMonthRadMean(:,4)=MonthMeanRad(YearNumberDRY(7,:),1);
FiveMonthRadMean(:,5)=MonthMeanRad(YearNumberDRY(8,:),1);
FiveMonthRadMean(:,6)=MonthMeanRad(YearNumberDRY(12,:),1);

[~,XX]=sort(FiveMonthRadMean);
YearNumberDRYFinal(1)=YearNumberDRY(1,XX(1,1)); %Select the month
having lowest solar radiation

```

```

YearNumberDRYFinal(2)=YearNumberDRY(2,XX(1,2)); %Select the month
having lowest solar radiation
YearNumberDRYFinal(6)=YearNumberDRY(6,XX(5,3)); %Select the month
having highest solar radiation
YearNumberDRYFinal(7)=YearNumberDRY(7,XX(5,4)); %Select the month
having highest solar radiation
YearNumberDRYFinal(8)=YearNumberDRY(8,XX(5,5)); %Select the month
having highest solar radiation
YearNumberDRYFinal(12)=YearNumberDRY(12,XX(5,6)); %Select the month
having highest solar radiation
save YearNumberDRYFinal.mat YearNumberDRYFinal

```

```

n=zeros(1,12);y=zeros(1,12);
a=YearNumberDRYFinal;
for o=1:12          %12 months
    n(o)=floor((a(o)-1)/30)+1; % n is set of data
    y(o)=a(o)-30*(n(o)-1)+3000; % y is year
end

```

```

load YearNumber
y0=year(1,:);
n0=year(2,:);
n(3:5)=n0(3:5);
y(3:5)=y0(3:5);
n(9:11)=n0(9:11);
y(9:11)=y0(9:11);

```

```

year(1,:)=y;
year(2,:)=n;

```

```

fprintf('\n Selected 5 months for DRY:');

```

```

fprintf('\n Jan is from year %4d _ %2d th data set', year(:,1));
fprintf('\n Feb is from year %4d _ %2d th data set', year(:,2));
fprintf('\n Jun is from year %4d _ %2d th data set', year(:,6));
fprintf('\n Jul is from year %4d _ %2d th data set', year(:,7));
fprintf('\n Aug is from year %4d _ %2d th data set', year(:,8));
fprintf('\n Dec is from year %4d _ %2d th data set', year(:,12));
save yearDRY.mat n y;
clear all;

```

%% Step 14: Generating DSY data(CIBSE format)

```

fprintf('\n Step 14: Generating DSY data(CIBSE format).....(Estimated
time: 25 secs)');
load yearDRY;
load txt;
year(1,:)=y;
year(2,:)=n;

```

```

DayNu=[31,28,31,30,31,30,31,31,30,31,30,31];
a=1;
DRY=zeros(8760,11);
for i=1:12
    p0=dlmread(char(txt(year(2,i),1)),',', 'A1..K262968'); %1 control data
    %p0=dlmread(char(txt(year(2,i),2)),',', 'A1..K262968'); %2 senario data
    for m=1:262968
        if ((p0(m,1)==year(1,i)) && (p0(m,2)==i)&&(p0(m,3)==1)&&(p0(m,4)==0))
            DRY(a:(a+DayNu(i)*24-1),:)=p0(m:m+DayNu(i)*24-1,:);
        end
    end
    a=a+24*DayNu(i);
end
save DesignReferenceYear.mat DRY
clear;

```

```

% Step 15: Adjusting the hourly value at the beginning and end of each
% month
fprintf('\n Step 15: Adjusting hourly value at beginning and end of each
month...(Estimated time: 25 secs)');
load DesignReferenceYear
DRY_S=DRY;
for q=6:8 %column 6,7,8 are temp_hmean,vapourpressure_hmean and
relhum_hmean
% smooth beginning of Jan and end of Dec
y1=DRY(1:8,q);
y2=DRY(8760-7:8760,q);
y0=cat(1,y2,y1);
y(1)=y0(1);
y(5)=y0(16);
y(3)=mean(y0);
y(2)=mean(y2);
y(4)=mean(y1);
x=[1,4.75,8.5,13.25,16];
xx=1:16;
yy=spline(x,y,xx);
DRY_S(8760-7:8760,q)=yy(1:8)';
DRY_S(1:8,q)=yy(9:16)';
% smooth other months
for i=10:8760
    if (DRY(i,2)>DRY(i-1,2))
        y(1)=DRY(i-8,q);
        y(5)=DRY(i+7,q);
        y(3)=mean(DRY(i-8:i+7,q));
        y(2)=mean(DRY(i-8:i-1,q));
        y(4)=mean(DRY(i:i+7,q));
        x=[1,4.75,8.5,13.25,16];
    end
end

```

```

        xx=1:16;
        yy=spline(x,y,xx);
        DRY_S(i-8:i+7,q)=yy';
    end
end
end
save DesignReferenceYear_Smoothed.mat DRY_S;
clear y1 y2 y0 y x xx yy i q;

% Step 16: Caculate dew point temeprature, horizontal infrared and direct
normal radiation
fprintf('\n Step 16: Caculating parameters for EPW format!');
fprintf('\n Step 16.1: Caculating dew point temeprature.....(Estimated
time: 1 secs)');
r=17.271*DRY_S(:,6)./(237.7+DRY_S(:,6))+log(DRY_S(:,8));
DRY_S(:,12)=237.7*r./(17.271-r); %column 12, dew point temperature,

for i=1:8760
    if DRY_S(:,12)>DRY_S(:,6)
        DRY_S(:,12)=DRY_S(:,6);
    end
end

clear r

fprintf('\n Step 16.2: Caculating direct normal radiation.....(Estimated
time: 5 secs)');
%column 13, date number OF the year
DRY_S(1,13)=1; % first day number is 1
for i=2:8760
    if or(DRY_S(i,3)>DRY_S(i-1,3),DRY_S(i,2)>DRY_S(i-1,2))

```

```

        DRY_S(i,13)=DRY_S(i-1,13)+1;
    else
        DRY_S(i,13)=DRY_S(i-1,13);
    end
end
clear i;
%column 15, DEC, solar Declination (between the earth-sun line and the
equator plane) in radians
DRY_S(:,14)=2*pi*((DRY_S(:,13))/366); %N
DRY_S(:,15)=(0.33281-22.984*cos(DRY_S(:,14))+3.7872*sin(DRY_S(:,14))-
0.3499*cos(2*DRY_S(:,14))+0.03205*sin(2*DRY_S(:,14))-
0.1398*cos(3*DRY_S(:,14))+0.07187*sin(3*DRY_S(:,14)))*pi/180;
%column 16, HRA, hour angle from solar noon, 15 degree per hour, in radians
DRY_S(:,16)=15*(DRY_S(:,4)/100-11.5)*pi/180;
%LAT, geographical latitude (south negative), in radians
load latitude
LAT=latitude*pi/180;
%column 17, ALT, solar altitude(from horizontal max 90 zenith), in radians,
DRY_S(:,17)=asin(sin(DRY_S(:,15))*sin(LAT)+cos(LAT)*cos(DRY_S(:,16)).*cos
(DRY_S(:,15)));
%column 18, direct normal=direct horizontal/sin(solar altitude),
DRY_S(:,18)=DRY_S(:,11)./sin(DRY_S(:,17));
a=0;
for i=2:8760
    if DRY_S(i,18)<0
        DRY_S(i,18)=0; %delect the negative value
    end
end
end

%delete unreasonable value at sunrise and sunset, (solar altitude <11 degree,
direct normal>100)
DRY_S(:,19)=DRY_S(:,17)*180/pi; %column 19, solar altitude in degree

```

```

DRY_SS=DRY_S;
c=0;
for i=1:8760
    if and(DRY_S(i,19)<11,DRY_S(i,18)>200)
        DRY_SS(i,18)=200;
        c=c+1;
        A(c,1)=DRY_S(i,18);
        A(c,2)=DRY_S(i,19);
    end
end %when direct normal over 200, set to 200

c=0;
for i=1:8760
    if and(DRY_S(i,19)<11,DRY_S(i,18)>100)
        DRY_SS(i,18)=(DRY_SS(i-1,18)+DRY_SS(i+1,18))/2;
        c=c+1;
    end
end %re-run, when direct normal over 100, set to average of nearby values

fprintf('\n Step 16.3: Calculating cloud cover.....(Estimated time:
2 secs)');
DRY_SS(:,20)=10*(1-DRY_SS(:,9)); %column 20, total sky cover in tenth
for i=1:8760
    if DRY_SS(i,9)==0
        DRY_SS(i,20)=0;
    end
end

% night cloud covers are equal to interpolation of cloud covers at sunrise and
sunset time

```

```

c1=0;
for i=2:8760
    if DRY_SS(i,19)*DRY_SS(i-1,19)<0
        c1=c1+1;
        Index(c1)=i;
    end %Identify night time
end

for i=1:(size(Index,2)-2)/2
    z(1)=DRY_SS(Index(i*2)-1,20);
    z(2)=DRY_SS(Index(i*2+1),20);
    DRY_SS(Index(i*2)-1:(Index(i*2+1)),20)=interp1(0:1,z,0:1/(Index(i*2+1)-
Index(i*2)+1):1);
end %liner interpolate cloud cover at night time

for i=1:8760
    DRY_SS(i,20)=round(DRY_SS(i,20));
end %integral function
%
fprintf('\n Step 16.4: Caculating horizontal infrared radiation intensty...(Estimated
time: 2 secs)');
DRY_SS(:,21)=round(DRY_SS(:,20)/2); %column 21, opaque sky cover,
assumed as half the value of total sky cover
SkyE=(0.787+0.764*log((DRY_SS(:,12)+273)/273)).*(1+0.0224*DRY_SS(:,21)+
0.0035*DRY_SS(:,21).^2+0.00028*DRY_SS(:,21).^3);
DRY_SS(:,22)=5.6697e-8*SkyE.*(DRY_SS(:,6)+273).^4; %column 22,
horizontal infrared radiation intensty

DRY_SS(:,23)=101300; %column 23, atmospheric pressure
DRY_SS(:,24)=DRY_SS(:,10)+DRY_SS(:,11); %column 24, global horizontal
radiation,

```



```

DRY_SS(:,8)=floor(100*DRY_SS(:,8)); %column 8, relative humidity, in
percentage
DRY85_SS=DRY_SS;
save DRY85_EPW.mat DRY85_SS
dlmwrite('DRY85.csv',DRY85_SS);
fprintf("\n Congratulation!!! DRY at 85 centile is saved as "DRY85.csv");

```

```

%column 1, year
%column 2, month
%column 3, date of the month
%column 4, hour
%column 5, precip httotal, mm/hour
%column 6, hourly temperature, degree C
%column 7, vapour pressure, hPa
%column 8, relative humidity, %
%column 9, sunshine hour, hours
%column 10, diffuse solar radiation, Wh/m2
%column 11, direct solar radiation in horizontal, Wh/m2
%column 12, dew point temperature, C
%column 13, date number of the year
%column 14, date number, in radians
%column 15, solar declination, in radians
%column 16, hour angle from solar noon
%column 17, solar altitude, in radians
%column 18, direct normal radiation, Wh/m2
%column 19, solar altitude, in degree
%column 20, total sky cover
%column 21, opaque sky cover
%column 22, horizontal infrared radiation intensty
%column 23, atmospheric pressure
%column 24, global horizontal radiation,

```



```

%***** DRY99_Hu_Part_control.m *****
%% Step 12: Calculating monthly mean temperature for 3000 years
fprintf('\n Calculating DRY at 99 percentile...');
fprintf('\n Step 12: Calculating monthly mean temperature for 3000
years...(Estimated time: 1 min)')

load temperature;
save JanFebJunJulAug.mat Jan Feb Jun Jul Aug Dec;
SummerYearNumber=zeros(100,1);
m=0;
for i=1:100
    for d=3001:3030
        m=m+1;
        s1=['MonthMeanTemp(m,1)=mean(Jan' int2str(d) '_' int2str(i) ');'];
        s2=['MonthMeanTemp(m,2)=mean(Feb' int2str(d) '_' int2str(i) ');'];
        s3=['MonthMeanTemp(m,3)=mean(Mar' int2str(d) '_' int2str(i) ');'];
        s4=['MonthMeanTemp(m,4)=mean(Apr' int2str(d) '_' int2str(i) ');'];
        s5=['MonthMeanTemp(m,5)=mean(May' int2str(d) '_' int2str(i) ');'];
        s6=['MonthMeanTemp(m,6)=mean(Jun' int2str(d) '_' int2str(i) ');'];
        s7=['MonthMeanTemp(m,7)=mean(Jul' int2str(d) '_' int2str(i) ');'];
        s8=['MonthMeanTemp(m,8)=mean(Aug' int2str(d) '_' int2str(i) ');'];
        s9=['MonthMeanTemp(m,9)=mean(Sep' int2str(d) '_' int2str(i) ');'];
        s10=['MonthMeanTemp(m,10)=mean(Oct' int2str(d) '_' int2str(i) ');'];
        s11=['MonthMeanTemp(m,11)=mean(Nov' int2str(d) '_' int2str(i) ');'];
        s12=['MonthMeanTemp(m,12)=mean(Dec' int2str(d) '_' int2str(i) ');'];
        eval(s1);
        eval(s2);
        eval(s3);
        eval(s4);
        eval(s5);
        eval(s6);
        eval(s7);
    end
end

```

```

        eval(s8);
        eval(s9);
        eval(s10);
        eval(s11);
        eval(s12);
    end
end

```

```

MeanTemp(1)=mean(Jan);
MeanTemp(2)=mean(Feb);
MeanTemp(3)=mean(Mar);
MeanTemp(4)=mean(Apr);
MeanTemp(5)=mean(May);
MeanTemp(6)=mean(Jun);
MeanTemp(7)=mean(Jul);
MeanTemp(8)=mean(Aug);
MeanTemp(9)=mean(Sep);
MeanTemp(10)=mean(Oct);
MeanTemp(11)=mean(Nov);
MeanTemp(12)=mean(Dec);
save MonthMeanTemp.mat MonthMeanTemp MeanTemp

```

```

clear d s1 s2 s3 s4 s5 s6 s7 s8 s9 s10 s11 s12
clear;
%% Step 13: Selecting month for Design Reference Year
fprintf('\n Step 13: Selecting month for Design Reference
Year.....(Estimated time: 1 sec)')

load MonthMeanTemp
for i=1:12
    [RankedMeanTemp(:,i),X(:,i)]=sort(MonthMeanTemp(:,i));
end

```

% 99th percentile

```
YearJanFebJunJulAug(:,1)=X(31:60,1);  
YearJanFebJunJulAug(:,2)=X(31:60,2);  
YearJanFebJunJulAug(:,3)=X(2941:2970,6);  
YearJanFebJunJulAug(:,4)=X(2941:2970,7);  
YearJanFebJunJulAug(:,5)=X(2941:2970,8);  
YearJanFebJunJulAug(:,6)=X(31:60,12);
```

```
load JanFebJunJulAug;
```

```
Jan30=[];
```

```
Feb30=[];
```

```
Jun30=[];
```

```
Jul30=[];
```

```
Aug30=[];
```

```
Dec30=[];
```

```
for i=1:30
```

```
    yearnumberJan=YearJanFebJunJulAug(i,1);
```

```
    yearnumberFeb=YearJanFebJunJulAug(i,2);
```

```
    yearnumberJun=YearJanFebJunJulAug(i,3);
```

```
    yearnumberJul=YearJanFebJunJulAug(i,4);
```

```
    yearnumberAug=YearJanFebJunJulAug(i,5);
```

```
    yearnumberDec=YearJanFebJunJulAug(i,6);
```

```
    JanMonth=Jan((yearnumberJan-1)*31+1:(yearnumberJan-1)*31+31);
```

```
    FebMonth=Feb((yearnumberFeb-1)*28+1:(yearnumberFeb-1)*28+28);
```

```
    JunMonth=Jun((yearnumberJun-1)*30+1:(yearnumberJun-1)*30+30);
```

```
    JulMonth=Jul((yearnumberJul-1)*31+1:(yearnumberJul-1)*31+31);
```

```
    AugMonth=Aug((yearnumberAug-1)*31+1:(yearnumberAug-1)*31+31);
```

```
    DecMonth=Dec((yearnumberDec-1)*31+1:(yearnumberDec-1)*31+31);
```

```
    Jan30=cat(1,JanMonth,Jan30);
```

```
    Feb30=cat(1,FebMonth,Feb30);
```

```

Jun30=cat(1,JunMonth,Jun30);
Jul30=cat(1,JulMonth,Jul30);
Aug30=cat(1,AugMonth,Aug30);
Dec30=cat(1,DecMonth,Dec30);
end
Jan30Month=reshape(Jan30,31,30); % daily mean of selected 30 months
Feb30Month=reshape(Feb30,28,30);
Jun30Month=reshape(Jun30,30,30);
Jul30Month=reshape(Jul30,31,30);
Aug30Month=reshape(Aug30,31,30);
Dec30Month=reshape(Dec30,31,30);
% calculate FS-stat for selected 30 months
for i=1:30
    CDFJan(:,i)=CDFIso(Jan30Month(:,i));
    CDFFeb(:,i)=CDFIso(Feb30Month(:,i));
    CDFJun(:,i)=CDFIso(Jun30Month(:,i));
    CDFJul(:,i)=CDFIso(Jul30Month(:,i));
    CDFAug(:,i)=CDFIso(Aug30Month(:,i));
    CDFDec(:,i)=CDFIso(Dec30Month(:,i));
end
CDFJanAll=CDFIso(Jan30);
CDFFebAll=CDFIso(Feb30);
CDFJunAll=CDFIso(Jun30);
CDFJulAll=CDFIso(Jul30);
CDFAugAll=CDFIso(Aug30);
CDFDecAll=CDFIso(Dec30);

CDFJanA=reshape(CDFJanAll,31,30);
CDFFebA=reshape(CDFFebAll,28,30);
CDFJunA=reshape(CDFJunAll,30,30);
CDFJulA=reshape(CDFJulAll,31,30);
CDFAugA=reshape(CDFAugAll,31,30);

```

```
CDFDecA=reshape(CDFDecAll,31,30);
```

```
JanFS=sum(abs(CDFJanA-CDFJan));
```

```
FebFS=sum(abs(CDFFebA-CDFFeb));
```

```
JunFS=sum(abs(CDFJunA-CDFJun));
```

```
JulFS=sum(abs(CDFJulA-CDFJul));
```

```
AugFS=sum(abs(CDFAugA-CDFAug));
```

```
DecFS=sum(abs(CDFDecA-CDFDec));
```

```
[~,AJan]=sort(JanFS);
```

```
[~,AFeb]=sort(FebFS);
```

```
[~,AJun]=sort(JunFS);
```

```
[~,AJul]=sort(JulFS);
```

```
[~,AAug]=sort(AugFS);
```

```
[~,ADec]=sort(DecFS);
```

```
YearNumberDRY(1,1)=YearJanFebJunJulAug(AJan(1),1);
```

```
YearNumberDRY(2,1)=YearJanFebJunJulAug(AFeb(1),2);
```

```
YearNumberDRY(6,1)=YearJanFebJunJulAug(AJun(1),3);
```

```
YearNumberDRY(7,1)=YearJanFebJunJulAug(AJul(1),4);
```

```
YearNumberDRY(8,1)=YearJanFebJunJulAug(AAug(1),5);
```

```
YearNumberDRY(12,1)=YearJanFebJunJulAug(ADec(1),6);
```

```
YearNumberDRY(1,2)=YearJanFebJunJulAug(AJan(2),1);
```

```
YearNumberDRY(2,2)=YearJanFebJunJulAug(AFeb(2),2);
```

```
YearNumberDRY(6,2)=YearJanFebJunJulAug(AJun(2),3);
```

```
YearNumberDRY(7,2)=YearJanFebJunJulAug(AJul(2),4);
```

```
YearNumberDRY(8,2)=YearJanFebJunJulAug(AAug(2),5);
```

```
YearNumberDRY(12,2)=YearJanFebJunJulAug(ADec(2),6);
```

```
YearNumberDRY(1,3)=YearJanFebJunJulAug(AJan(3),1);
```

```
YearNumberDRY(2,3)=YearJanFebJunJulAug(AFeb(3),2);
```

```

YearNumberDRY(6,3)=YearJanFebJunJulAug(AJun(3),3);
YearNumberDRY(7,3)=YearJanFebJunJulAug(AJul(3),4);
YearNumberDRY(8,3)=YearJanFebJunJulAug(AAug(3),5);
YearNumberDRY(12,3)=YearJanFebJunJulAug(ADec(3),6);

```

```

YearNumberDRY(1,4)=YearJanFebJunJulAug(AJan(4),1);
YearNumberDRY(2,4)=YearJanFebJunJulAug(AFeb(4),2);
YearNumberDRY(6,4)=YearJanFebJunJulAug(AJun(4),3);
YearNumberDRY(7,4)=YearJanFebJunJulAug(AJul(4),4);
YearNumberDRY(8,4)=YearJanFebJunJulAug(AAug(4),5);
YearNumberDRY(12,4)=YearJanFebJunJulAug(ADec(4),6);

```

```

YearNumberDRY(1,5)=YearJanFebJunJulAug(AJan(5),1);
YearNumberDRY(2,5)=YearJanFebJunJulAug(AFeb(5),2);
YearNumberDRY(6,5)=YearJanFebJunJulAug(AJun(5),3);
YearNumberDRY(7,5)=YearJanFebJunJulAug(AJul(5),4);
YearNumberDRY(8,5)=YearJanFebJunJulAug(AAug(5),5);
YearNumberDRY(12,5)=YearJanFebJunJulAug(ADec(5),6);

```

```
save YearnumberDRY.mat YearNumberDRY
```

```
load radiation.mat
```

```
m=0;
```

```
for i=1:100
```

```
    for d=3001:3030
```

```
        m=m+1;
```

```
        s1=['MonthMeanRad(m,1)=mean(Jan' int2str(d) ' ' int2str(i) ');'];
```

```
        s2=['MonthMeanRad(m,2)=mean(Feb' int2str(d) ' ' int2str(i) ');'];
```

```
        s3=['MonthMeanRad(m,3)=mean(Mar' int2str(d) ' ' int2str(i) ');'];
```

```
        s4=['MonthMeanRad(m,4)=mean(Apr' int2str(d) ' ' int2str(i) ');'];
```

```
        s5=['MonthMeanRad(m,5)=mean(May' int2str(d) ' ' int2str(i) ');'];
```

```
        s6=['MonthMeanRad(m,6)=mean(Jun' int2str(d) ' ' int2str(i) ');'];
```

```
        s7=['MonthMeanRad(m,7)=mean(Jul' int2str(d) ' ' int2str(i) ');'];
```



```

s8=['MonthMeanRad(m,8)=mean(Aug' int2str(d) '_' int2str(i) ');'];
s9=['MonthMeanRad(m,9)=mean(Sep' int2str(d) '_' int2str(i) ');'];
s10=['MonthMeanRad(m,10)=mean(Oct' int2str(d) '_' int2str(i) ');'];
s11=['MonthMeanRad(m,11)=mean(Nov' int2str(d) '_' int2str(i) ');'];
s12=['MonthMeanRad(m,12)=mean(Dec' int2str(d) '_' int2str(i) ');'];
eval(s1);
eval(s2);
eval(s3);
eval(s4);
eval(s5);
eval(s6);
eval(s7);
eval(s8);
eval(s9);
eval(s10);
eval(s11);
eval(s12);
end
end
save MonthMeanRad.mat MonthMeanRad

```

```

FiveMonthRadMean(:,1)=MonthMeanRad(YearNumberDRY(1,:),1); %Selected
5 Jan mean radiation
FiveMonthRadMean(:,2)=MonthMeanRad(YearNumberDRY(2,:),1);
FiveMonthRadMean(:,3)=MonthMeanRad(YearNumberDRY(6,:),1);
FiveMonthRadMean(:,4)=MonthMeanRad(YearNumberDRY(7,:),1);
FiveMonthRadMean(:,5)=MonthMeanRad(YearNumberDRY(8,:),1);
FiveMonthRadMean(:,6)=MonthMeanRad(YearNumberDRY(12,:),1);

[~,XX]=sort(FiveMonthRadMean);
YearNumberDRYFinal(1)=YearNumberDRY(1,XX(1,1)); %Select the month
having lowest solar radiation

```

```

YearNumberDRYFinal(2)=YearNumberDRY(2,XX(1,2)); %Select the month
having lowest solar radiation
YearNumberDRYFinal(6)=YearNumberDRY(6,XX(5,3)); %Select the month
having highest solar radiation
YearNumberDRYFinal(7)=YearNumberDRY(7,XX(5,4)); %Select the month
having highest solar radiation
YearNumberDRYFinal(8)=YearNumberDRY(8,XX(5,5)); %Select the month
having highest solar radiation
YearNumberDRYFinal(12)=YearNumberDRY(12,XX(5,6)); %Select the month
having highest solar radiation
save YearNumberDRYFinal.mat YearNumberDRYFinal

```

```

n=zeros(1,12);y=zeros(1,12);
a=YearNumberDRYFinal;
for o=1:12          %12 months
    n(o)=floor((a(o)-1)/30)+1; % n is set of data
    y(o)=a(o)-30*(n(o)-1)+3000; % y is year
end

```

```

load YearNumber
y0=year(1,:);
n0=year(2,:);
n(3:5)=n0(3:5);
y(3:5)=y0(3:5);
n(9:11)=n0(9:11);
y(9:11)=y0(9:11);

```

```

year(1,:)=y;
year(2,:)=n;

```

```

fprintf('\n Selected 6 months for DRY:');

```

```

fprintf('\n  Jan is from year %4d _ %2d th data set', year(:,1));
fprintf('\n  Feb is from year %4d _ %2d th data set', year(:,2));
fprintf('\n  Jun is from year %4d _ %2d th data set', year(:,6));
fprintf('\n  Jul is from year %4d _ %2d th data set', year(:,7));
fprintf('\n  Aug is from year %4d _ %2d th data set', year(:,8));
fprintf('\n  Dec is from year %4d _ %2d th data set', year(:,12));
save yearDRY.mat n y;

clear all;

%% Step 14: Generating DSY data(CIBSE format)
fprintf('\n Step 14: Generating DSY data(CIBSE format).....(Estimated
time: 25 secs)');
load yearDRY;
load txt;
year(1,:)=y;
year(2,:)=n;

DayNu=[31,28,31,30,31,30,31,31,30,31,30,31];
a=1;
DRY=zeros(8760,11);
for i=1:12
    p0=dlmread(char(txt(year(2,i),1)),',', 'A1..K262968'); %1 control data
    %p0=dlmread(char(txt(year(2,i),2)),',', 'A1..K262968'); %2 senario data
    for m=1:262968
        if ((p0(m,1)==year(1,i)) && (p0(m,2)==i)&&(p0(m,3)==1)&&(p0(m,4)==0))
            DRY(a:(a+DayNu(i)*24-1),:)=p0(m:m+DayNu(i)*24-1,:);
        end
    end
    a=a+24*DayNu(i);
end
save DesignReferenceYear.mat DRY

```

```

clear;

% Step 15: Adjusting the hourly value at the beginning and end of each
% month
fprintf('\n Step 15: Adjusting hourly value at beginning and end of each
month...(Estimated time: 25 secs)');
load DesignReferenceYear
DRY_S=DRY;
for q=6:8 %column 6,7,8 are temp_hmean,vapourpressure_hmean and
relhum_hmean
% smooth beginning of Jan and end of Dec
y1=DRY(1:8,q);
y2=DRY(8760-7:8760,q);
y0=cat(1,y2,y1);
y(1)=y0(1);
y(5)=y0(16);
y(3)=mean(y0);
y(2)=mean(y2);
y(4)=mean(y1);
x=[1,4.75,8.5,13.25,16];
xx=1:16;
yy=spline(x,y,xx);
DRY_S(8760-7:8760,q)=yy(1:8)';
DRY_S(1:8,q)=yy(9:16)';
% smooth other months
for i=10:8760
    if (DRY(i,2)>DRY(i-1,2))
        y(1)=DRY(i-8,q);
        y(5)=DRY(i+7,q);
        y(3)=mean(DRY(i-8:i+7,q));
        y(2)=mean(DRY(i-8:i-1,q));
        y(4)=mean(DRY(i:i+7,q));
    end
end

```

```

        x=[1,4.75,8.5,13.25,16];
        xx=1:16;
        yy=spline(x,y,xx);
        DRY_S(i-8:i+7,q)=yy';
    end
end
end
save DesignReferenceYear_Smoothed.mat DRY_S;
clear y1 y2 y0 y x xx yy i q;

% Step 16: Caculate dew point temeperature, horizontal infrared and direct
normal radiation
fprintf('\n Step 16: Caculating parameters for EPW format:');
fprintf('\n Step 16.1: Caculating dew point temeperature.....(Estimated
time: 1 secs)');
r=17.271*DRY_S(:,6)./(237.7+DRY_S(:,6))+log(DRY_S(:,8));
DRY_S(:,12)=237.7*r./(17.271-r); %column 12, dew point temperature,

for i=1:8760
    if DRY_S(:,12)>DRY_S(:,6)
        DRY_S(:,12)=DRY_S(:,6);
    end
end

clear r

fprintf('\n Step 16.2: Caculating direct normal radiation.....(Estimated
time: 5 secs)');
%column 13, date number OF the year
DRY_S(1,13)=1; % first day number is 1
for i=2:8760

```

```

    if or(DRY_S(i,3)>DRY_S(i-1,3),DRY_S(i,2)>DRY_S(i-1,2))
        DRY_S(i,13)=DRY_S(i-1,13)+1;
    else
        DRY_S(i,13)=DRY_S(i-1,13);
    end
end
clear i;
%column 15, DEC, solar Declination (between the earth-sun line and the
equator plane) in radians
DRY_S(:,14)=2*pi*((DRY_S(:,13))/366); %N
DRY_S(:,15)=(0.33281-22.984*cos(DRY_S(:,14))+3.7872*sin(DRY_S(:,14))-
0.3499*cos(2*DRY_S(:,14))+0.03205*sin(2*DRY_S(:,14))-
0.1398*cos(3*DRY_S(:,14))+0.07187*sin(3*DRY_S(:,14)))*pi/180;
%column 16, HRA, hour angle from solar noon, 15 degree per hour, in radians
DRY_S(:,16)=15*(DRY_S(:,4)/100-11.5)*pi/180;
%LAT, geographical latitude (south negative), in radians
load latitude
LAT=latitude*pi/180;
%column 17, ALT, solar altitude(from horizontal max 90 zenith), in radians,
DRY_S(:,17)=asin(sin(DRY_S(:,15))*sin(LAT)+cos(LAT)*cos(DRY_S(:,16))).*cos
(DRY_S(:,15));
%column 18, direct normal=direct horizontal/sin(solar altitude),
DRY_S(:,18)=DRY_S(:,11)./sin(DRY_S(:,17));
a=0;
for i=2:8760
    if DRY_S(i,18)<0
        DRY_S(i,18)=0; %delect the negative value
    end
end
end

%delete unreasonable value at sunrise and sunset, (solar altitude <11 degree,
direct normal>100)

```

```
DRY_S(:,19)=DRY_S(:,17)*180/pi; %column 19, solar altitude in degree
```

```
DRY_SS=DRY_S;
```

```
c=0;
```

```
for i=1:8760
```

```
    if and(DRY_S(i,19)<11,DRY_S(i,18)>200)
```

```
        DRY_SS(i,18)=200;
```

```
        c=c+1;
```

```
        A(c,1)=DRY_S(i,18);
```

```
        A(c,2)=DRY_S(i,19);
```

```
    end
```

```
end %when direct normal over 200, set to 200
```

```
c=0;
```

```
for i=1:8760
```

```
    if and(DRY_S(i,19)<11,DRY_S(i,18)>100)
```

```
        DRY_SS(i,18)=(DRY_SS(i-1,18)+DRY_SS(i+1,18))/2;
```

```
        c=c+1;
```

```
    end
```

```
end %re-run, when direct normal over 100, set to avearge of nearby values
```

```
fprintf('\n Step 16.3: Caculating cloud cover.....(Estimated time:  
2 secs)');
```

```
DRY_SS(:,20)=10*(1-DRY_SS(:,9)); %column 20, total sky cover in tenth
```

```
for i=1:8760
```

```
    if DRY_SS(i,9)==0
```

```
        DRY_SS(i,20)=0;
```

```
    end
```

```
end
```

```

% night cloud covers are equal to interpolation of cloud covers at sunrise and
sunset time
c1=0;
for i=2:8760
    if DRY_SS(i,19)*DRY_SS(i-1,19)<0
        c1=c1+1;
        Index(c1)=i;
    end %Identify night time
end

for i=1:(size(Index,2)-2)/2
    z(1)=DRY_SS(Index(i*2)-1,20);
    z(2)=DRY_SS(Index(i*2+1),20);
    DRY_SS(Index(i*2)-1:(Index(i*2+1)),20)=interp1(0:1,z,0:1/(Index(i*2+1)-
Index(i*2)+1):1);
end %liner interpolate cloud cover at night time

for i=1:8760
    DRY_SS(i,20)=round(DRY_SS(i,20));
end %integral function
%
fprintf('\n Step 16.4: Caculating horizontal infrared radiation intensty...(Estimated
time: 2 secs)');
DRY_SS(:,21)=round(DRY_SS(:,20)/2); %column 21, opaque sky cover,
assumed as half the value of total sky cover
SkyE=(0.787+0.764*log((DRY_SS(:,12)+273)/273)).*(1+0.0224*DRY_SS(:,21)+
0.0035*DRY_SS(:,21).^2+0.00028*DRY_SS(:,21).^3);
DRY_SS(:,22)=5.6697e-8*SkyE.*(DRY_SS(:,6)+273).^4; %column 22,
horizontal infrared radiation intensty

DRY_SS(:,23)=101300; %column 23, atmospheric pressure

```



```
DRY_SS(:,24)=DRY_SS(:,10)+DRY_SS(:,11); %column 24, global horizontal radiation,
```

```
DRY_SS(:,8)=floor(100*DRY_SS(:,8)); %column 8, relative humidity, in percentage
```

```
save DRY_EPW.mat DRY_SS
```

```
dlmwrite('DRY99.csv',DRY_SS);
```

```
fprintf("\n Congratulation!!! DRY at 99 centile is saved as "DRY99.csv");
```

```
%column 1, year
```

```
%column 2, month
```

```
%column 3, date of the month
```

```
%column 4, hour
```

```
%column 5, precip httotal, mm/hour
```

```
%column 6, hourly temperature, degree C
```

```
%column 7, vapour pressure, hPa
```

```
%column 8, relative humidity, %
```

```
%column 9, sunshine hour, hours
```

```
%column 10, diffuse solar radiation, Wh/m2
```

```
%column 11, direct solar radiation in horizontal, Wh/m2
```

```
%column 12, dew point temperature, C
```

```
%column 13, date number of the year
```

```
%column 14, date number, in radians
```

```
%column 15, solar declination, in radians
```

```
%column 16, hour angle from solar noon
```

```
%column 17, solar altitude, in radians
```

```
%column 18, direct normal radiation, Wh/m2
```

```
%column 19, solar altitude, in degree
```

```
%column 20, total sky cover
```

```
%column 21, opaque sky cover
```

```
%column 22, horizontal infrared radiation intensty
```

%column 23, atmospheric pressure

%column 24, global horizontal radiation,

```

%***** rankt.m *****
function ranks = rankt(V,direction)

if (nargin < 1) || (nargin > 2)
    error('RANKT:incorrectarguments', ...
        'Improper number of arguments. 1 or 2 arguments are required.')
end

if ~isvector(V)
    error('RANKT:incorrectarguments', ...
        'V must be a row or column vector.')
end
Vsize = size(V);
V = V(:);

% default and error check for direction
if (nargin < 2) || isempty(direction)
    direction = 'ascend';
elseif ~ischar(direction)
    error('RANKT:incorrectarguments', ...
        'direction must be either "ascend" or "descend" if supplied.')
else
    valid = {'ascend' 'descend'};

    ind = strmatch(lower(direction),lower(valid));
    if isempty(ind)
        % No hit found
        error('RANKT:incorrectarguments', ...
            'direction must be either "ascend" or "descend" if supplied, or a valid
shortening thereof.')
    else

```

```

    direction = valid{ind};
end
end

% unique will do the sort, plus allow us to know if there are reps
[VS,I,J] = unique(V); %#ok

% count the replicate elements to deal with ties
Vcount = accumarray(J,1);
cumulativeVcount = cumsum(Vcount);
ranks = cumulativeVcount(J) - (Vcount(J) - 1)/2;

% ensure that V ranks is the same orientation as was V
ranks = reshape(ranks,Vsize);

% Are these supposed to be increasing ranks or decreasing?
if direction(1) == 'd'
    % descending, so swap order
    ranks = (numel(V) + 1) - ranks;
end
end

```

```

%***** CDFiso.m *****
function CumulativeDistribution = CDFiso(V,OutputIndicator)
% This function is used for calculating Cumulative Distribution, the equation is in
section 5.3.1.b of EN ISO 15927-4:2005 standard
if (nargin < 1) || (nargin > 2)
    error('CDFiso:incorrectarguments', ...
        'Improper number of arguments. 1 or 2 arguments are required.')
end
[a,b]=size(V);
if and(a~=1, b~=1)
    error('RANKT:incorrectarguments', ...
        'Worry size of argument V. V should be one column vector.')
end
if a==1
    V=V';
end
% default and error check for direction
Vsize = size(V);

% unique will do the sort in increasing order, plus allow us to know if there are
reps
[~,~,J] = unique(V);

% count the replicate elements to deal with ties
Vcount = accumarray(J,1);
cumulativeVcount = cumsum(Vcount);
ranks = cumulativeVcount(J) - (Vcount(J) - 1)/2;

% ensure that V ranks is the same orientation as was V
ranks = reshape(ranks,Vsize);

```

```
% calculate Cumulative Distribution
CumulativeDistribution=ranks./(1+size(V,1));

if nargin ==2
    CumulativeDistribution=cat(2,V,ranks,CumulativeDistribution);
end
% If there is a OutputIndicator, output original data in column 3, and ranks in
column 2;
end
```

```

%***** GenDef.m *****
%location='Belfast';
%WMOcode=0;
%latitude=54.66;
%longitude=-6.22;
%elevation=63;
%UKCP09Grid=1300540;
%year=2080;
%senario='H';

function GenDef(location, WMOcode, latitude, longitude, elevation,
UKCP09Grid, year,senario)
fid = fopen('TRY.def', 'w'); % open the file with write permission
fprintf(fid, '&location');
fprintf(fid, '\r\nCity="%s"', location);
fprintf(fid, '\r\nCountry="GB"');
fprintf(fid, '\r\nWMO="%i"', WMOcode);
fprintf(fid, '\r\nLat=%2.2f', latitude);
fprintf(fid, '\r\nLong=%2.2f', longitude);
fprintf(fid, '\r\nElev=%i', elevation);
fprintf(fid, '\r\nTime=0');
fprintf(fid, '\r\n/');
fprintf(fid, '\r\n&miscdata');
fprintf(fid, '\r\nComments1="UKCP09 G%i S1547 %i%s %s,
Hu"',UKCP09Grid,year,senario,location);
fprintf(fid, '\r\n/');
fprintf(fid, '\r\n&wthdata');
fprintf(fid, '\r\nNumInHour=1');
fprintf(fid, '\r\nInputFileType="CUSTOM"');
fprintf(fid, '\r\nInFormat="DELIMITED"');
fprintf(fid,
\r\nDataElements=Year,Month,Day,Hour,rain,DryBulb,Ignore,Relative_Humidity

```

```

,Ignore,DifHorzRad,Ignore,DewPoint,Ignore,Ignore,Ignore,Ignore,Ignore,dirnorz
rad,Ignore,totskycvr,opaqskycvr,horzirsky,atmos pressure,glohorzrad');
fprintf(fid,
'\r\nDataUnits=x,x,x,x,"mm","C",x,"%%",x,"Wh/m2",x,"C",x,x,x,x,x,"Wh/m2",x,x,
x,"Wh/m2","Pa","Wh/m2");
fprintf(fid,
'\r\nDataConversionFactors=1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1');
fprintf(fid, '\r\nDelimiterChar="");
fprintf(fid, '\r\n/');
fprintf(fid, '\r\n&datacontrol');
fprintf(fid, '\r\nNumRecordsToSkip=0');
fprintf(fid, '\r\nMaxNumRecordsToRead=8760');
fprintf(fid, '\r\n/');
fclose(fid);
save latitude.mat latitude;
end

```