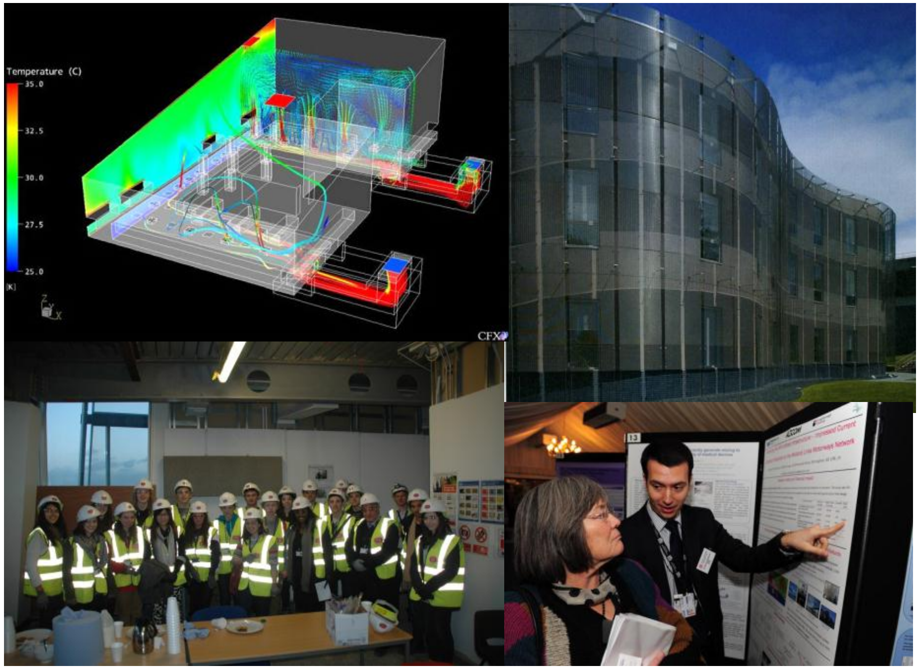
Dr Christina Hopfe, CEng FCIBSE FHEA CEPH
School of Architecture, Building & Civil Engineering
Loughborough University

School of Architecture, Building and Civil Engineering

- One of 10 Schools
- Over 100 years old
- 70 academic staff
- >150 researchers
- >1k students
- c.£20m research projects
- >250 industry partners



WHATUNI? STUDENT CHOICE Awards 2018 WINNER UNIVERSITY OF THE YEAR

THE STUDENT EXPERIENCE SURVEY 2017-18 FIRST PLACE

TEF Gold Teaching Excellence Framework

THE TIMES THE SUNDAY TIMES GOOD UNIVERSITY GUIDE 2019 UNIVERSITY OF THE YEAR

Tackling building energy performance measuring and modelling

- BERG: Building Energy Research Group
- London-Loughborough doctoral centre (LoLo)
- Six test houses
- Consultancy activity (DECC/BEIS/National Trust)

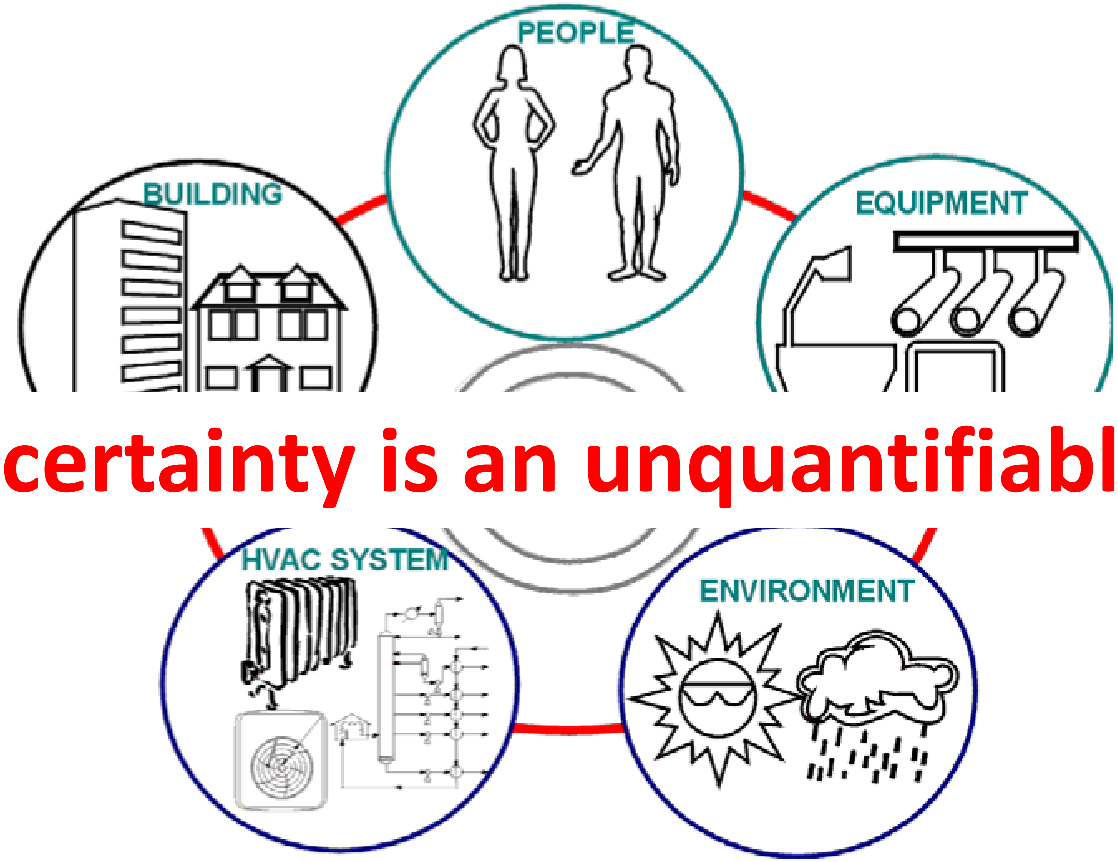
Addressing UNCERTAINTY in building performance simulation to enable informed decision making

Christina Hopfe
Reader in Low Energy Design
School of Architecture, Building and Civil Engineering
Loughborough University, UK

SIMUREX 2018 scientific school
15-19 October 2018
INES, Le Bourget du Lac &
Aussois, France

Source http://wordpress.com

Buildings are composed of interacting sub-systems



Uncertainty is an unquantifiable risk!

E. Djunaedy, J. Hensen, C. Hopfe, C. Struck, M. Trcka, and A. Yahiaoui, 2006. Notes on building performance simulation and the role of IBPSA

Problems

- Buildings underperform
- Performance gap not well understood
- How to separate losers from winners?

Source CIOB http://www.constructionmanagermagazine.com

SECTION 1

UNCERTAINTY BASICS

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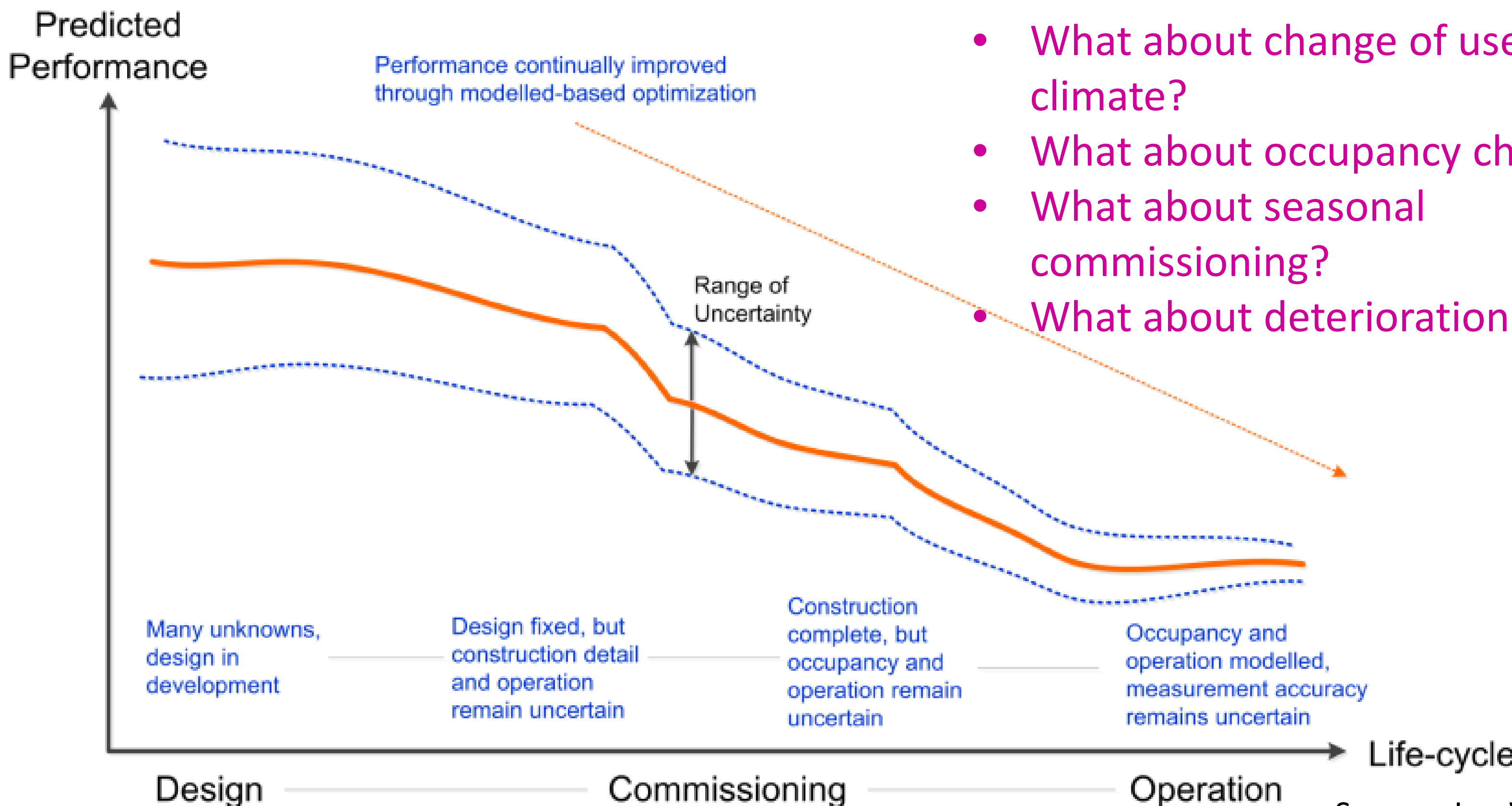
Design and uncertainty

Performance optimization and uncertainty reduction and current practice

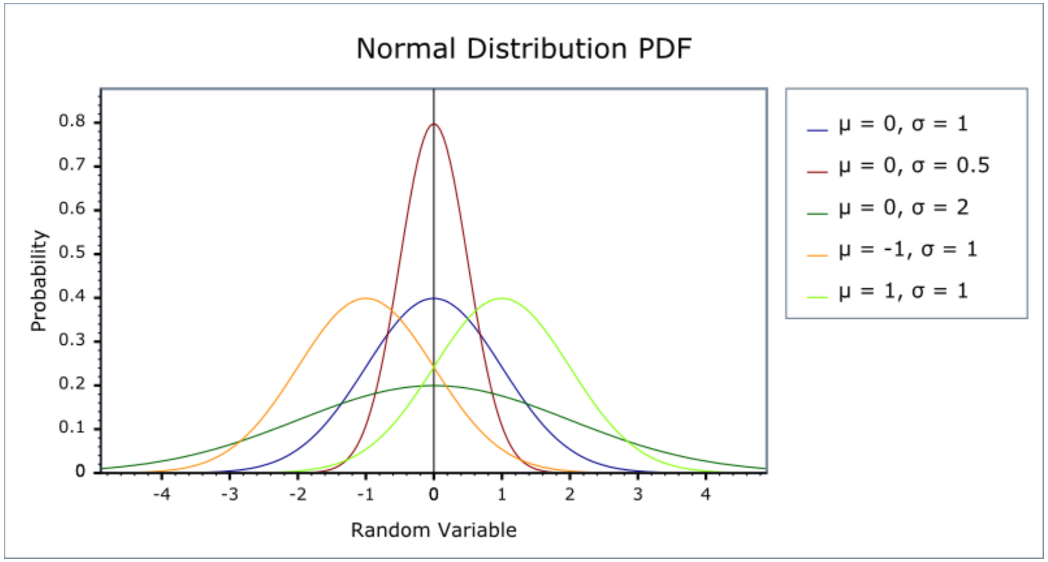


- What about change of use or climate?
- What about occupancy change?
- What about seasonal commissioning?
- What about deterioration?

Source: Jon Wright

Uncertainty analysis

- Sampling the range of an input parameter (statistical analysis)
- Quantify effect of modelling assumption (sometimes iteratively)
- Find "guess interval" in physical parameters (expert judgment study)
- Workmanship effects: inspection



But: case based!

- No generic uncertainty analysis exists
- Therefore: always case driven
- Difference between “incomplete knowledge” and “uncertainty”
- Incomplete knowledge can be replaced by scenarios

Source: wohnen.at

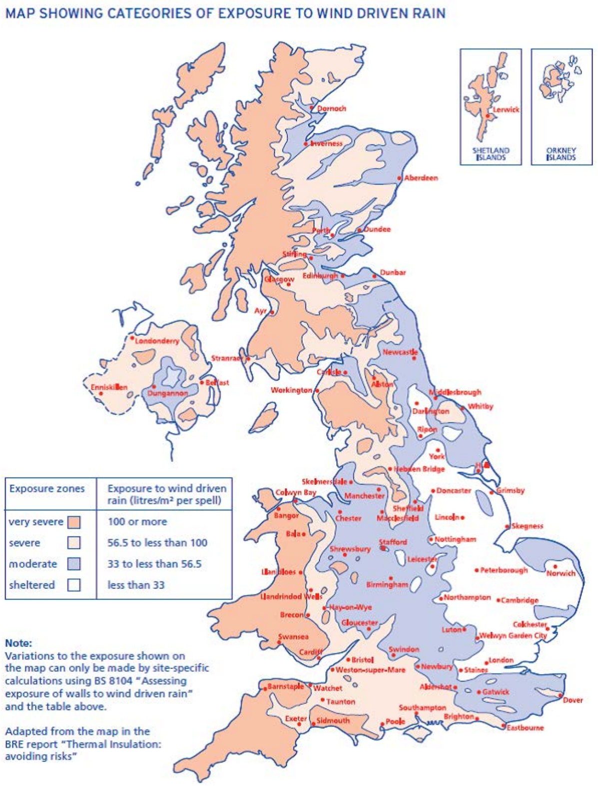
SECTION 2

CURRENT RESEARCH

What weather inputs are appropriate?

- WDR is a combination of wind and rain
- Different theories on co-occurrence wind and rain
  - High rainfall – high wind speed
  - High rainfall – low wind speed / low rainfall – high wind speed
- Large variability in geographic location
- WDR difficult to measure directly (incl. direction)
- Limited information of the influence of

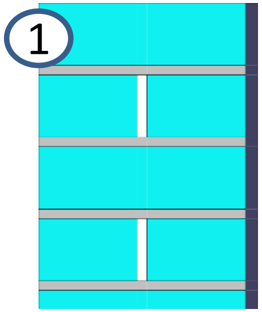
  climate change

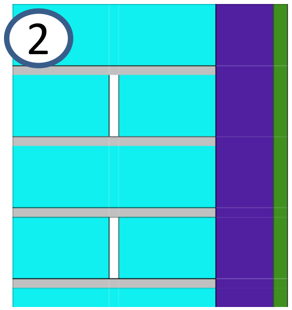


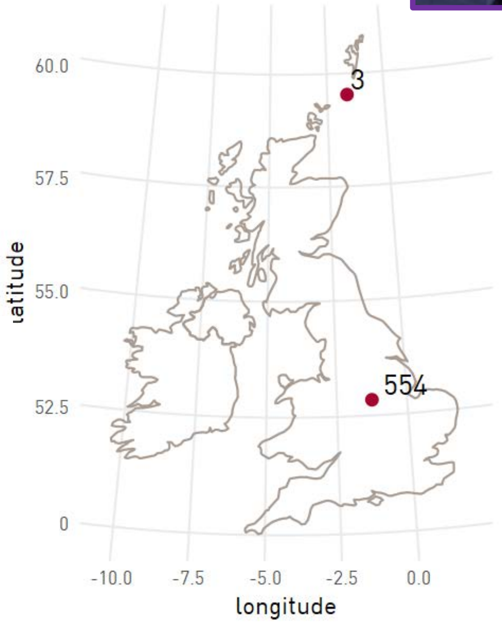
Project title of PhD: Risks and Uncertainties associated with Wind Driven Rain on Solid-wall Dwellings
Supervisors: Christina Hopfe & David Allinson

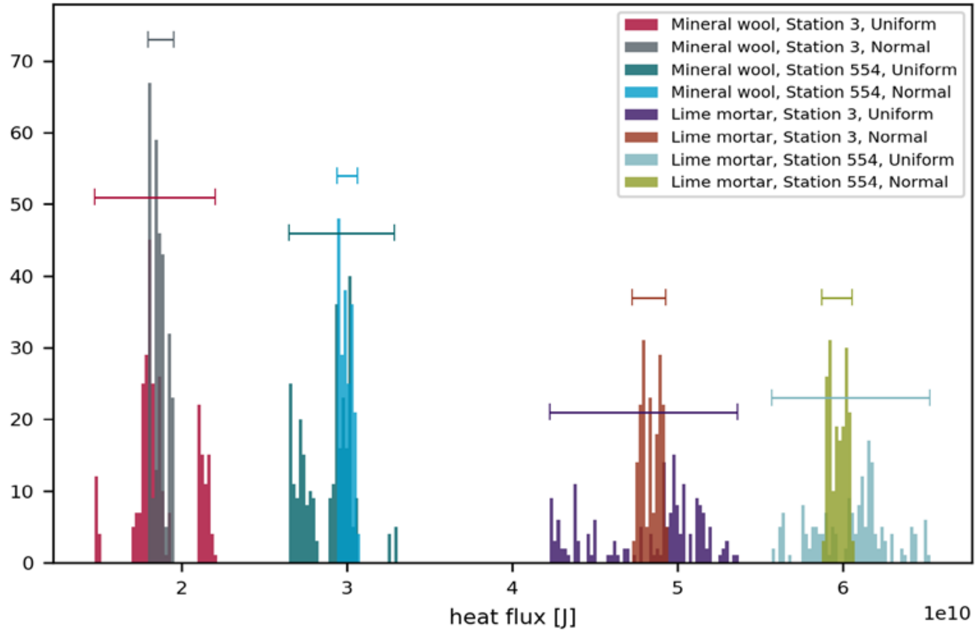
References:
- Building Research Establishment. *Thermal insulation–avoiding risks : a guide to good practice building construction.* Building Research Establishment, 1989.
- Shuzo Murakami, Yoshiteru Iwasa, Yasushige Morikawa, and Noriko Chino. Extreme wind speeds for various return periods during rainfall. *Journal of Wind Engineering and Industrial Aerodynamics*, 26:105–125, 1987.

..and how is this effected by the choice of materials?









References: Tersteeg, Hopfe, Allinson, 2018. : Hygrothermal assessment of two solid-brick walls under varying internal and external parameter settings, Building Simulation and Optimization (BSO)18, Cambridge

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Simulation engine: how accurate is it?

Uncertainty due to weather models

- Weather file data
- Illuminance efficacy models
- Sky luminance distribution models

Uncertainty due to design assumptions

- Surface reflectances
- Fenestration systems optical properties

Uncertainty due to the modeller

- Simulation parameters
- Analysis grid settings

Uncertainty due to measurements (existing buildings)

- Window and room dimensions
- Reflectance / transmittance properties

DAYLIGHT SIMULATION SOFTWARE (*Radiance*-based for this research)

Illuminance values for the whole year (higher uncertainty)

CBDM metrics e.g. Daylight Autonomy (DA), Useful Daylight Illuminance (UDI) (lower uncertainty)

Project title of PhD: **Applicability of Climate-Based Daylight Modelling**

Supervisors: Prof J Mardaljevic, Dr C Hopfe, Dr F Anselmo

References: Brembilla, E., Mardaljevic, J. & Hopfe, C.J., 2015. Sensitivity Analysis studying the impact of reflectance values assigned in Climate-Based Daylight Modelling. In Proceedings of BS2015: 14th Conference of IBPSA. Hyderabad.

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Simulation engine: how accurate is it?

Analysis on the **reflectance values** assigned to the modelled main surfaces

5 surfaces

- External ground
- Floor
- Interior walls
- Ceiling
- Window frames

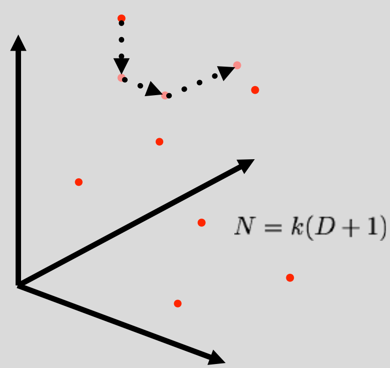
5 CBDM techniques

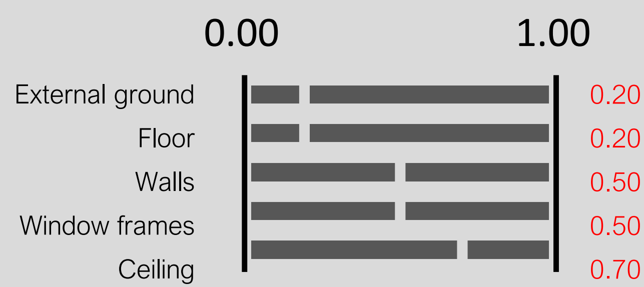
- 4-component method
- DAYSIM
- 2-phase method
- 3-phase method
- 5-phase method

3 CBDM annual metrics used to express the results

- Useful Daylight Illuminance (UDI)
- Daylight Autonomy (DA)
- Total Annual Illuminance (TAI)

Morris Method as sampling and Sensitivity Analysis (SA) strategy





References: Brembilla, E., Mardaljevic, J. & Hopfe, C.J., 2017. Sensitivity Analysis studying the impact of reflectance values assigned in Climate-Based Daylight Modelling. Journal of Building Performance Simulation

Simulation engine: how accurate is it?

Inter-model Comparison of Five Climate-Based Daylight Modelling Techniques: Redirecting Glazing/Shading Systems

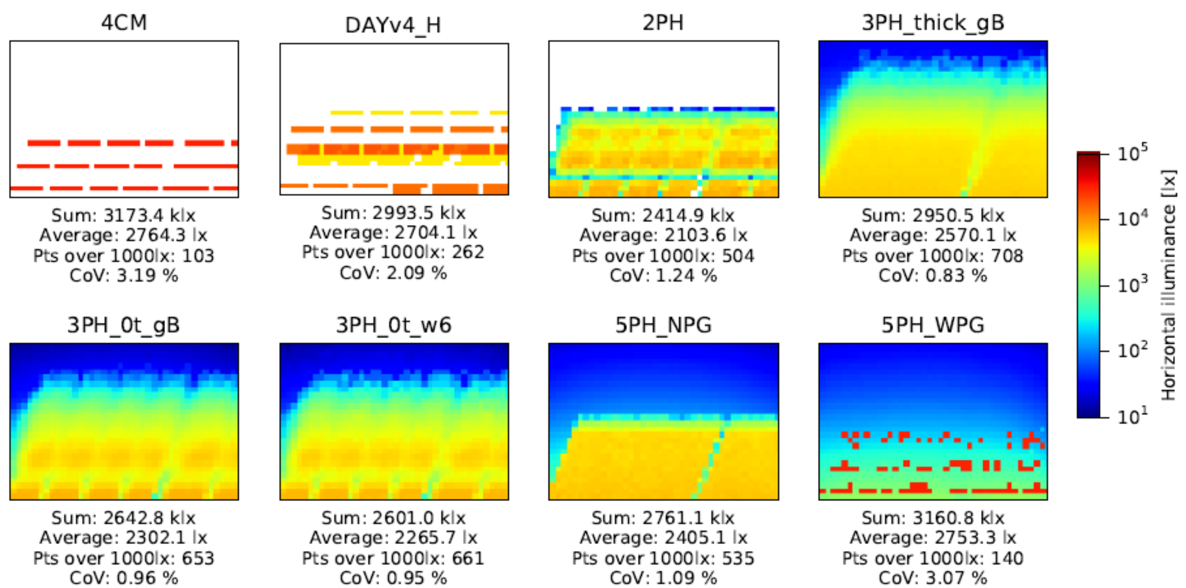


Figure 6: These plots show the direct illuminance for the 1st March at 13:00, for each of the analysed CBDM methods. This instant represents an instance in which the illuminance values obtained from the 4-component method are high (> 32.000 lx).

References: Brembilla, E., Mardaljevic, J. & Hopfe, C.J., 2017. Inter-model Comparison of Five Climate-Based Daylight Modelling Techniques. In Proceedings of BS2017: 15th Conference of IBPSA. San .

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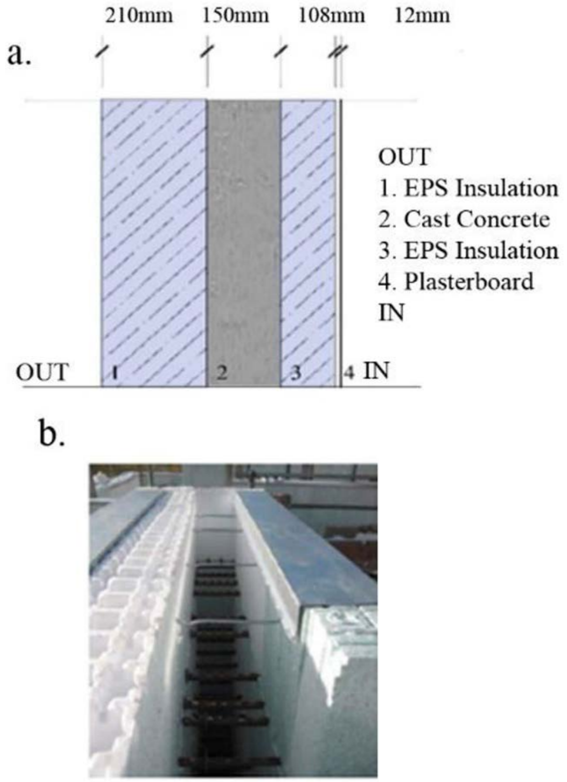
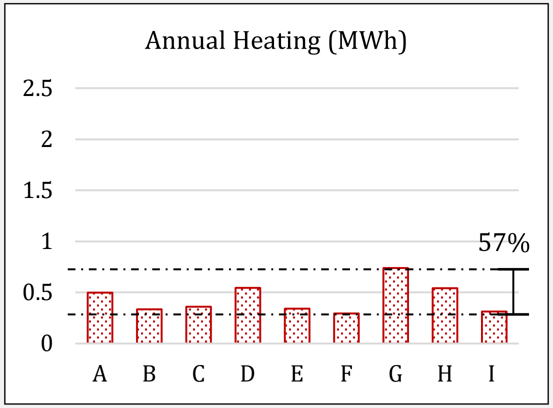
Simulation engine: how accurate is it?



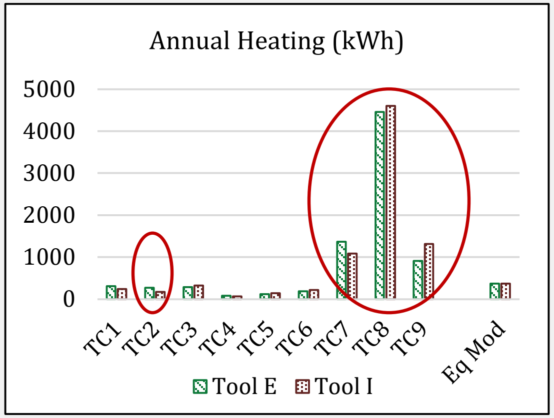
Step 1: Inter-Model Comparison **Default Algorithms**

- Significant inconsistencies in the simulation predictions provided by 9 BPS tools ~ 57% difference.



Step 2: Parametric Analysis on **Equivalent Models**

- Key factors affecting simulation results:
  - Internal surface convection coefficient
  - Infiltration
  - Variable natural ventilation
  - Thermal bridging calculation



<u>Project title of PhD</u>: A Computational and Empirical Evaluation of the Thermal Performance of Insulating Concrete Formwork

<u>Supervisors</u>: Prof Jacqui Glass, Dr Christina Hopfe, Prof Malcolm Cook

Mantesi, E., Hopfe, C. J, Cook, M. J., Glass, J. (2016). Investigating the impact of modelling uncertainty on the simulation of ICF for buildings. *Proceedings from BSO2016 Conference*. Newcastle, 12-14 September 2016, UK

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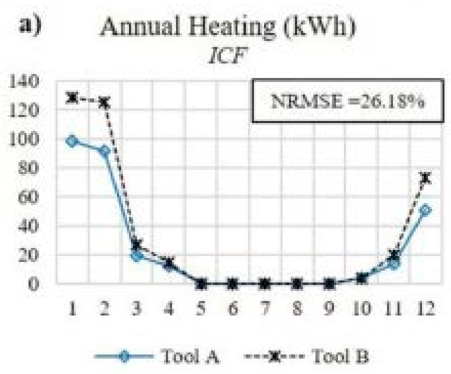
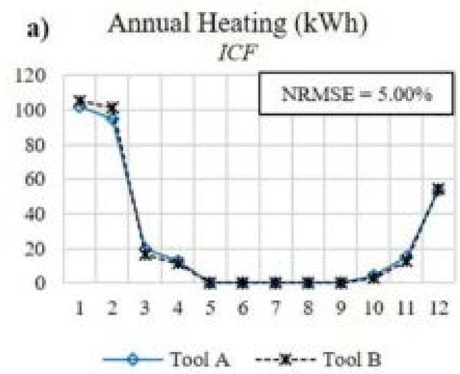
The modelling gap

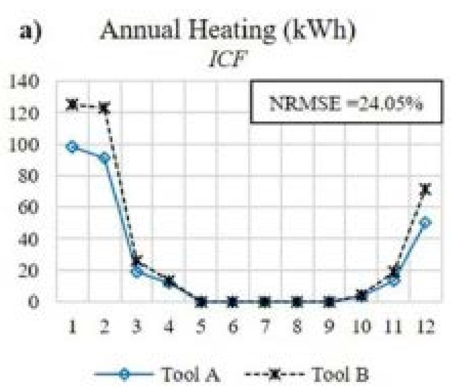
Step 1: Conduction Algorithm



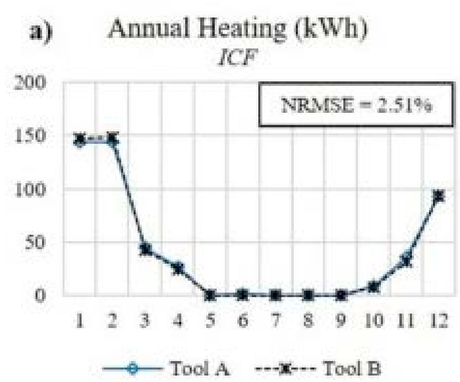
Step 3: Solar Distribution



Step 2: View Factors Calculation



Step 4: Convection Coefficient Calcu



Mantesi, E., Hopfe, C. J, Goodier, C., Glass, J., Cook, M. J. , Strachan, P. (2018). The modelling gap: Quantifying the discrepancy in the representation of thermal mass in building simulation

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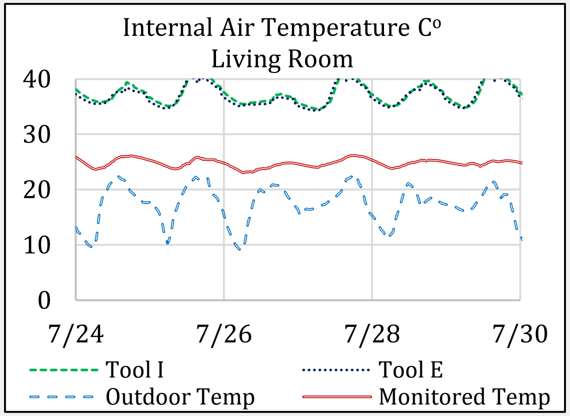
The modelling gap: what do we model?

Uncertainty in ICF Monitoring

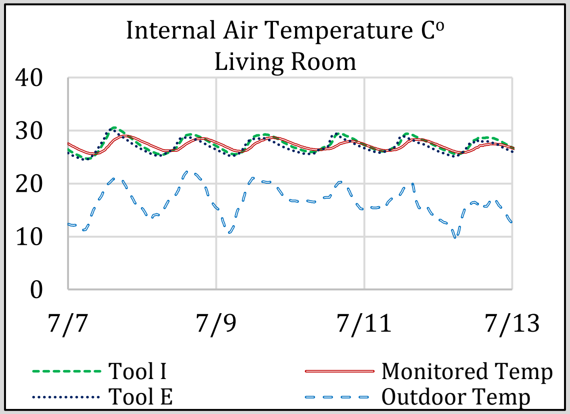
Step 1: Uncalibrated Models
Input data from NCM

- Good agreement in the simulation predictions provided by the two BPS tools.
- Significant divergence between simulation and monitoring results when models uncalibrated.



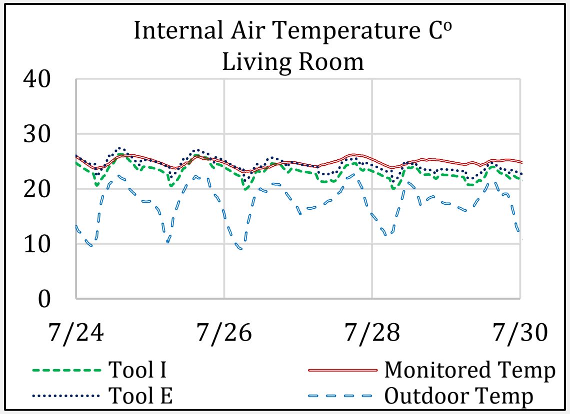
Step 2: Calibrated Models
Unoccupied Week

- Overall good consistency between simulation predictions from both BPS tools and between simulation and monitoring.
- The house is unoccupied – Scenario uncertainty excluded from the analysis.



Step 3: Calibrated Models
Occupied Week

- Higher inconsistency in the simulation results provided by the BPS tools.
- The divergence between simulation and monitoring results is also higher in the occupied period.



Mourkos, K., Mantesi, E., Hopfe, C. J, Goodier, C., Glass, J., Cook, M. J. (2017). The Role of Fabric Performance in the Seasonal Overheating of Dwellings. Building Simulation 2017.

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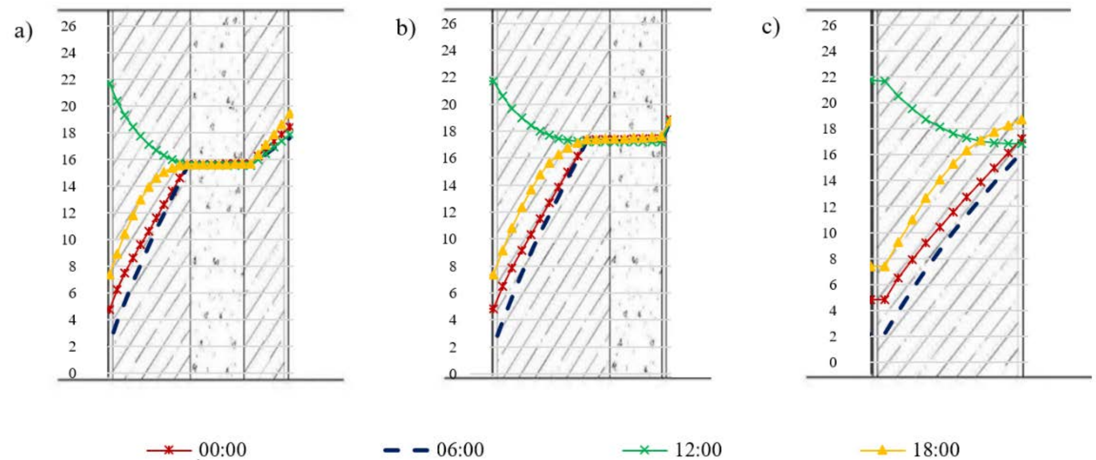
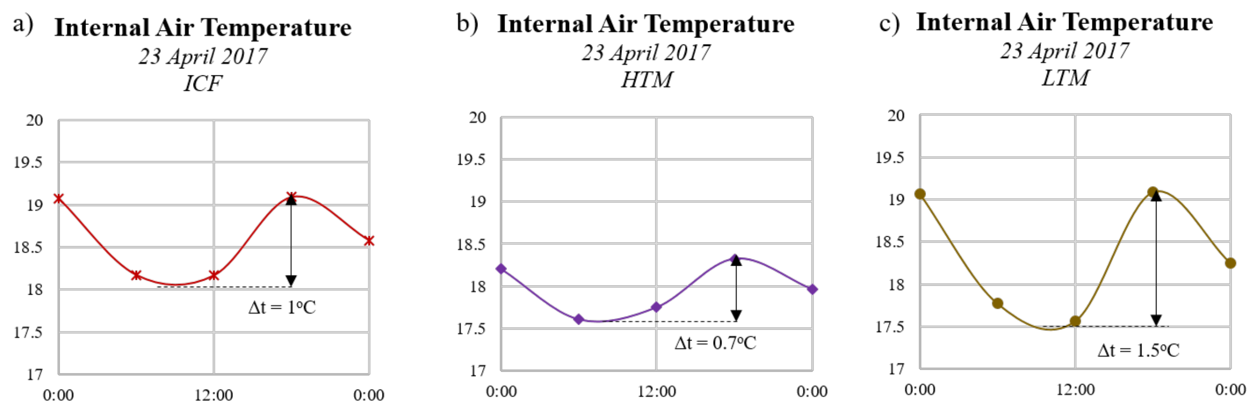
Is ICF thermally lightweight or heavyweight?





Mantesi, E., Hopfe, C. J, Glass, J., Cook, M. J. (2018). Accepted in Energy and Buildings. Empirical and Computational Evidence for Thermal Mass Assessment: The Example of Insulating Concrete Formwork

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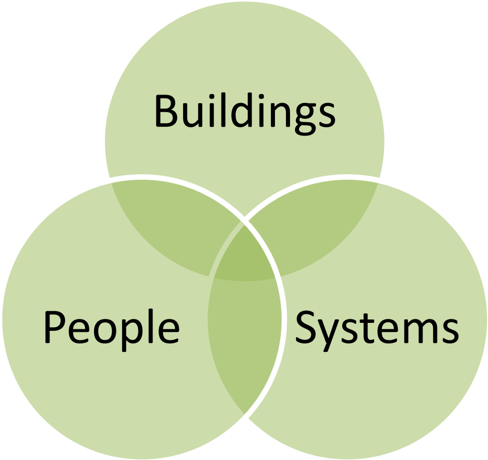
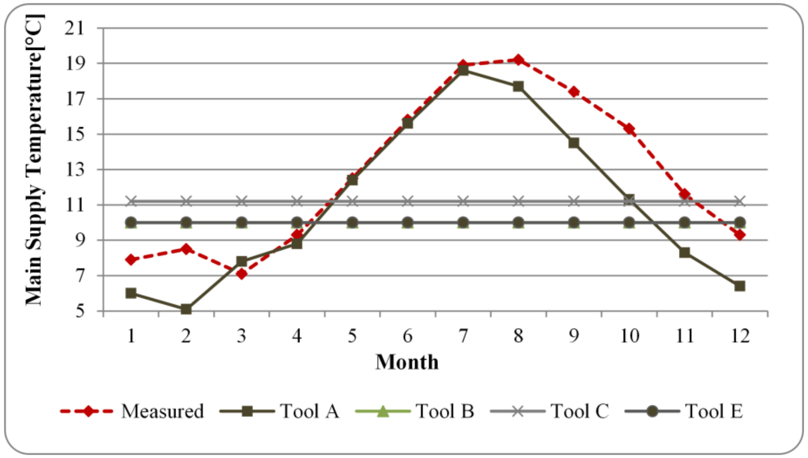
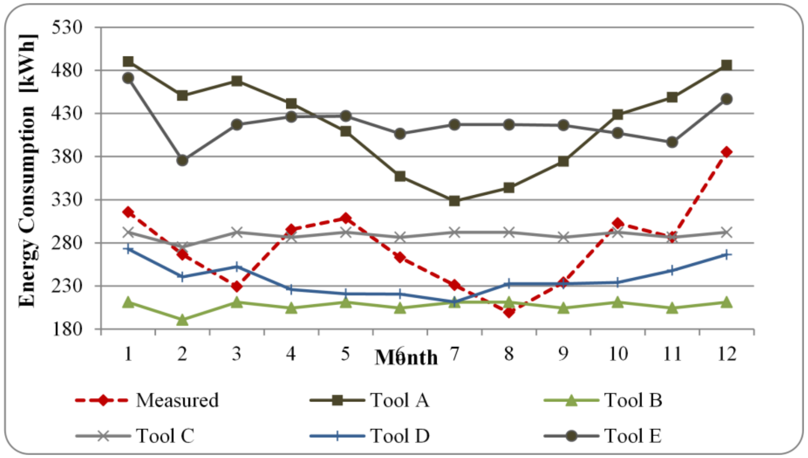
Simulation engine: how accurate is it?







Marini, D., Buswell, R., Hopfe CJ, 2015. *A critical software review- how hot water is modelled in current building simulation..* To be published at BS15

hothouse

Hot water provision in homes: consumption, storage and lifestyle

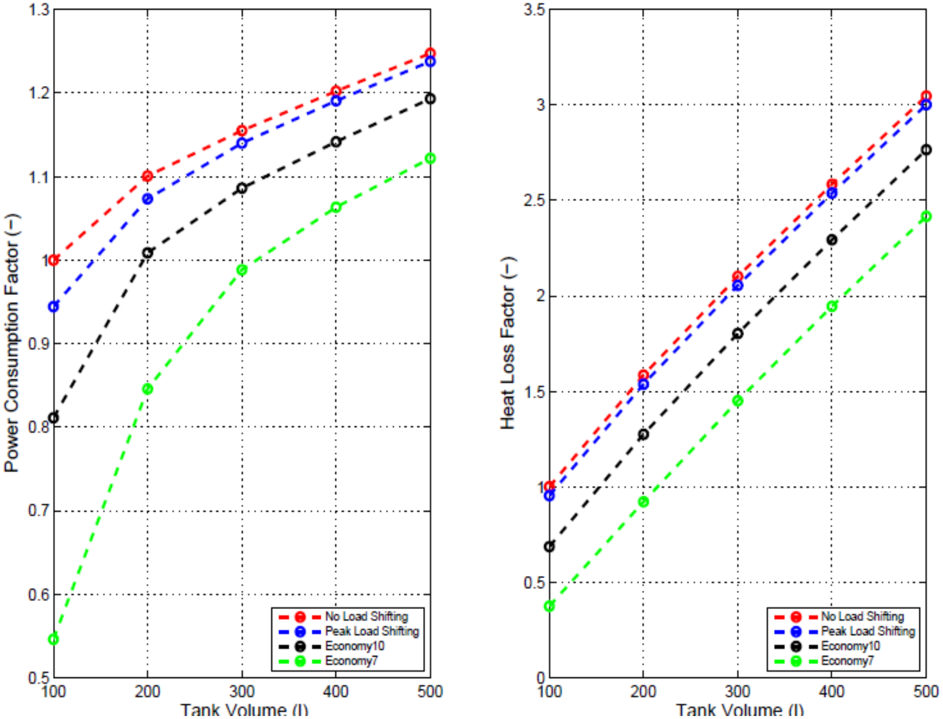
The role of the occupant

Potential cost reduction (%) when implementing: Peak Load Shifting; Economy10 and Economy7 opposed to no Load Shifting method.

Tank Size (l)	Load Shifting Method		
	Peak LSh*	Economy10	Economy7
100	-18.9	-19.2	-73.2
200	-15.7	-13.0	-62.3
300	-14.0	-12.3	-58.0
400	-14.4	-12.5	-56.6
500	-14.2	-12.7	-55.9

* *Peak Load Shifting*

Impact of tank size and load shifting on power consumption and heat loss.



Marini, D., Buswell, R., Hopfe, CJ., Improving domestic hot water system performance and load shifting through optimal sizing and control methods, Building Simulation 2017

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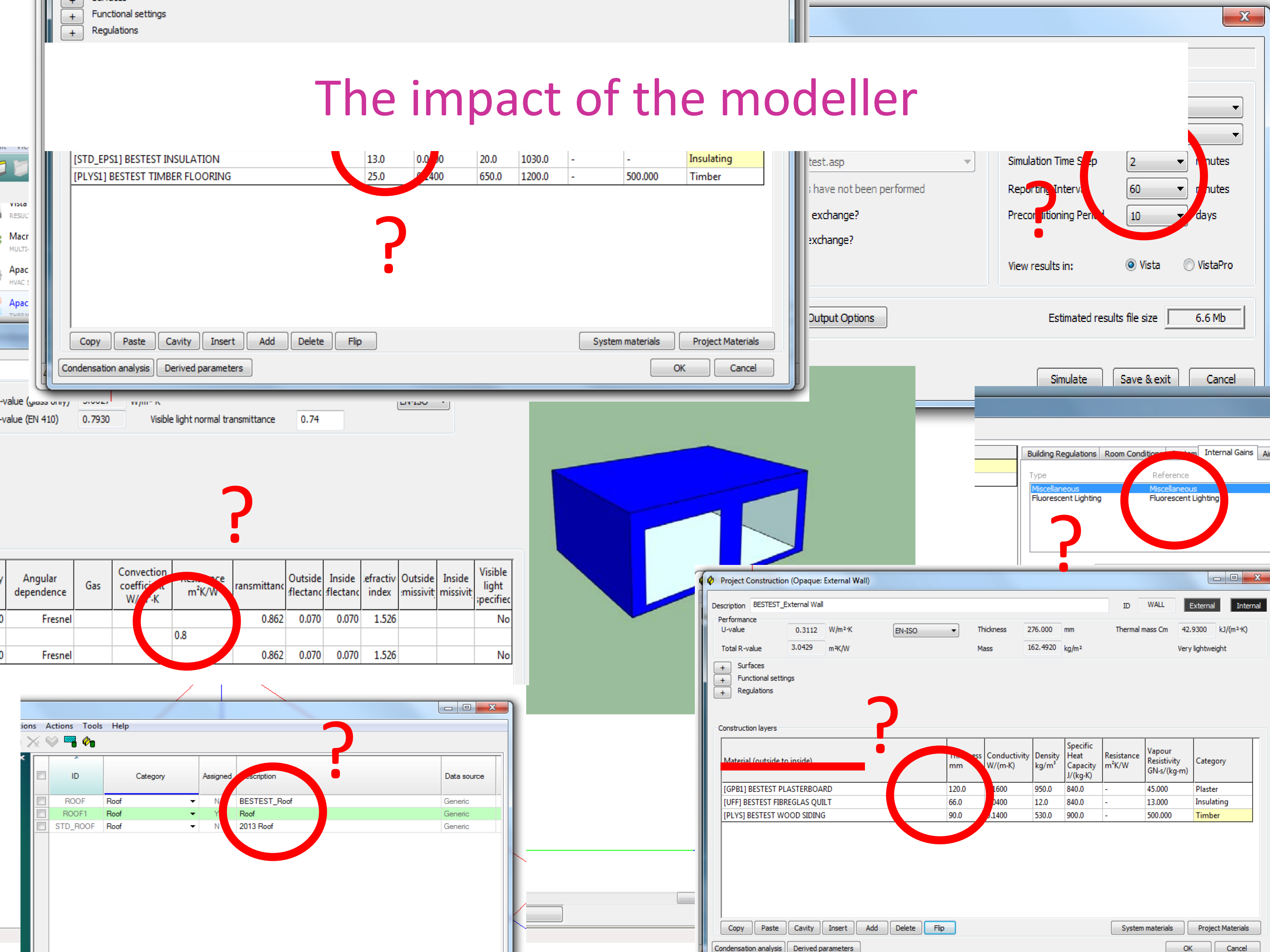
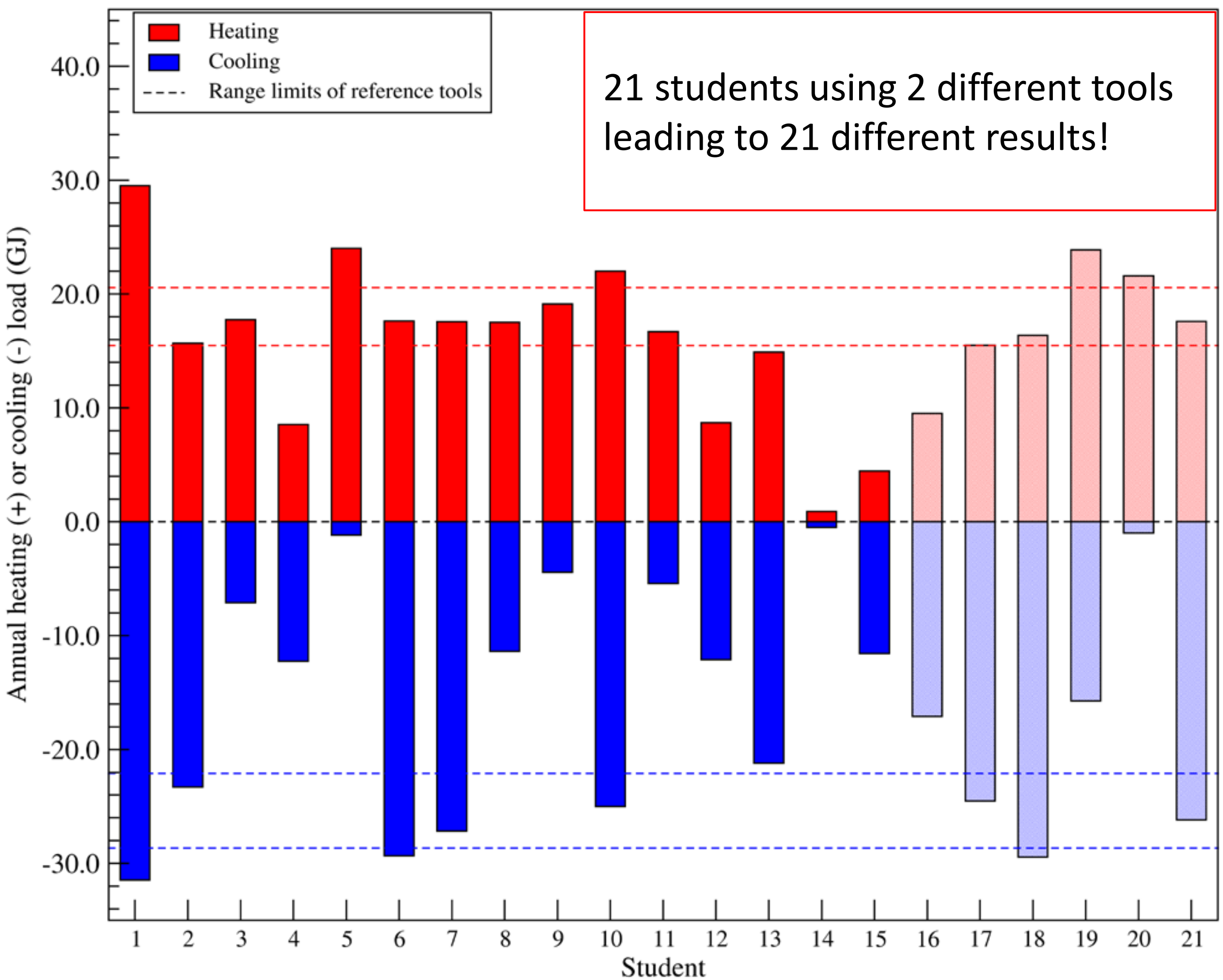
The impact of the modeller



Active experimentation – on students!



I Beausoleil-Morrison, CJ Hopfe, 2015 Teaching building performance simulation through a continuous learning cycle, BS 2015

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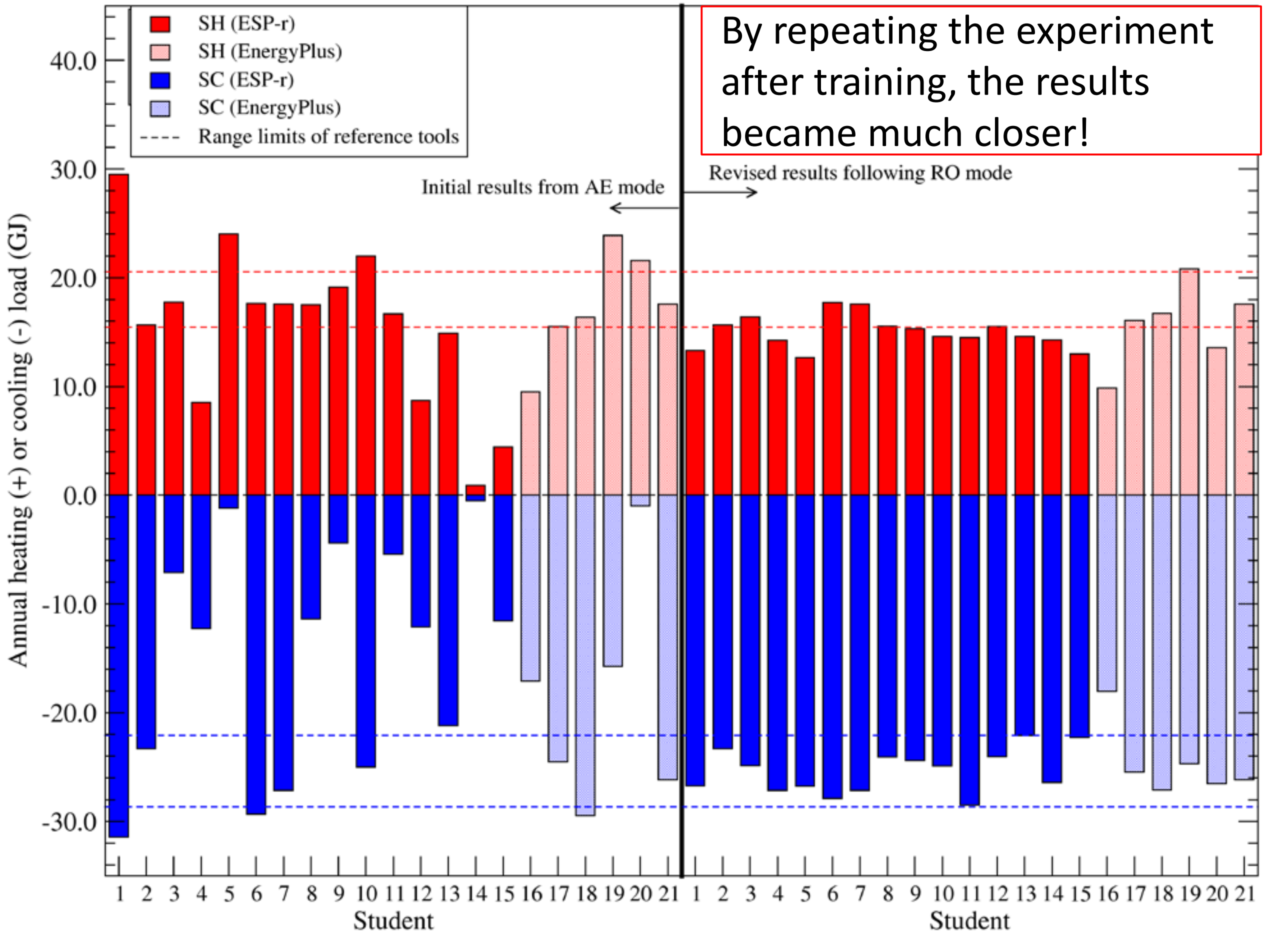
Reflective observation – does it help?



Building Performance Simulation: User as the greatest source of uncertainty

I Beausoleil-Morrison, CJ Hopfe, 2016 Ever done an autopsy?, Building Simulation & Optimization, Newcastle, 2018

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Understanding the Uncertainty Across Energy Model Stages

Design uncertainty

Related to the availability of design information that changes within the design process!

Design process | Operation

Conceptual → Early → Detailed

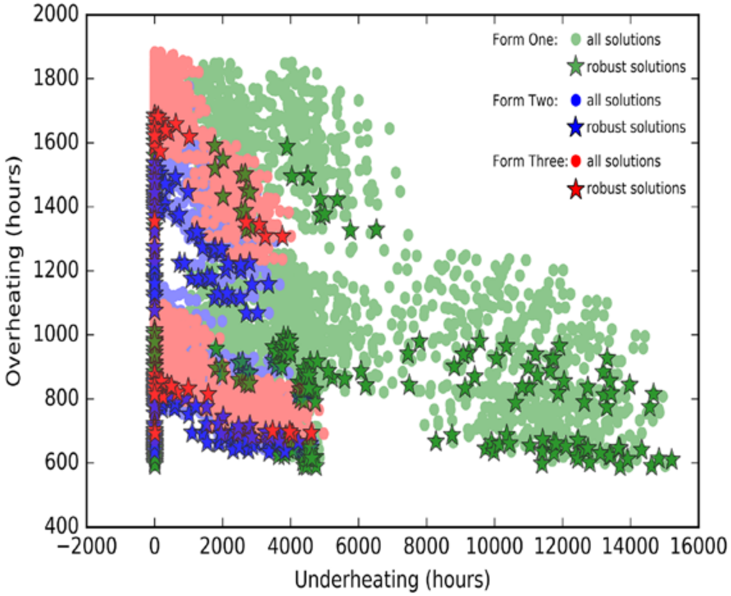
Geometry

Construction

Energy systems

Control strategies

Change in design parameters and uncertainty



The trade-off between the design objectives at the early design stage of the case-study building.

Project title of PhD: **Building Performance Modelling and Optimization for Design Support**

Supervisors: Prof. Jonathan Wright and Dr. Christina J. Hopfe

Nikolaidou, JA Wright, CJ Hopfe, 2017. Robust building scheme design optimization for uncertain performance prediction, Building Simulation 2017

E Nikolaidou, JA Wright, CJ Hopfe, 2015. Early and detailed design stage modelling using Passivhaus design; what is the difference in predicted building performance? Building Simulation 2015

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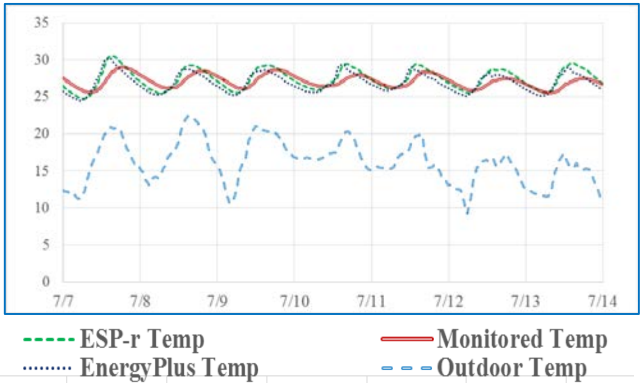
Closing the ‘overheating’ performance gap

Indoor air temperatures °C in the first floor living room



Uncertainty in predicting overheating

- One unoccupied week was analysed utilising actual weather data
- Both BPS tools overestimated peak temperatures; this may be due to the optical properties assigned to the windows (physical uncertainty) and the algorithm employed to predict solar gains (model inadequacy)

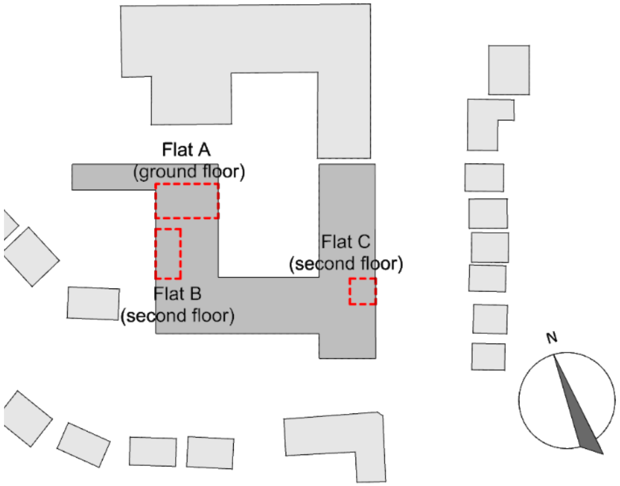
Project title of PhD: **Measuring and modelling overheating in domestic buildings**
Supervisors: Dr. Christina Hopfe, Dr. Chris Goodier, Dr Rob McLeod, Dr. Mich Swainson (BRE)

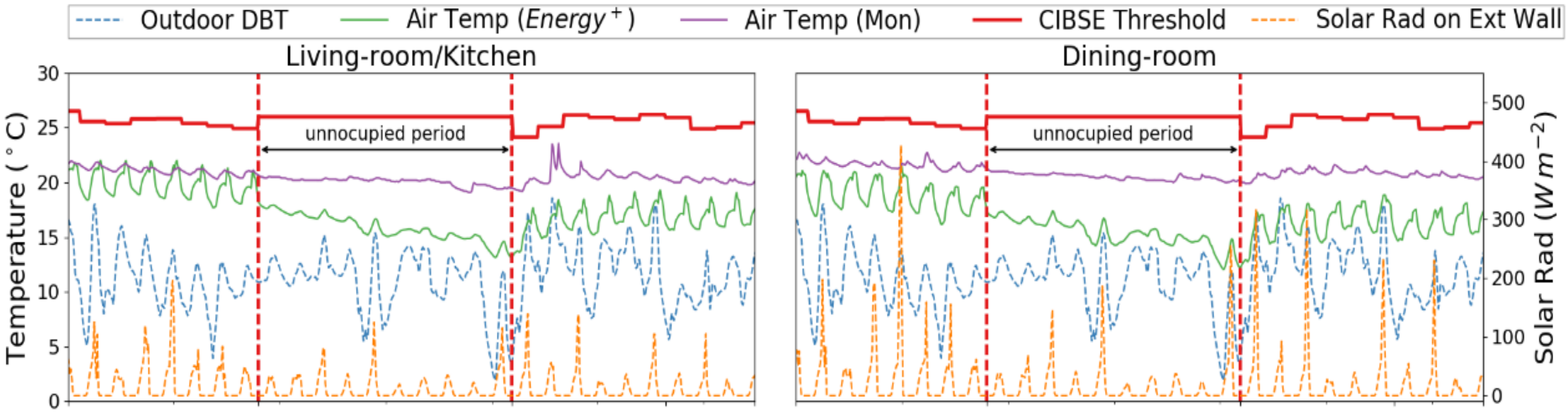
Mourkos, K., Mantesi, E., Hopfe, C. J, Goodier, C., Glass, J., Cook, M. J. (2016). The Role of Fabric Performance in the Seasonal Overheating of Dwellings. Manuscript submitted for publication.

Overheating – current definitions (homes)

Standard	Design criteria
CIBSE TM59: *Design methodology for the assessment of overheating risk in homes* *(**Criterion 1**)* - *adaptive*	*For <u>living rooms</u>, <u>kitchens</u> and <u>bedrooms</u>*: the number of **hours during which Δ*T* is greater than or equal to one degree (K) above the 'target temperature'** during the period May to September inclusive shall not be more than **3 per cent of occupied hours**. (CIBSE TM52 Criterion 1: *Hours of exceedance*).
CIBSE TM59: *Design methodology for the assessment of overheating risk in homes* *(**Criterion 2**)* - *deterministic*	*For <u>bedrooms</u> only*: to guarantee comfort during the sleeping hours the operative temperature in the bedroom from 10 pm to 7 am shall **not exceed 26 °C for more than 1% of annual hours**. (*Note*: 1% of the annual hours between 22:00 and 07:00 for bedrooms is 32.85 hours, so 33 or more hours above 26 °C will be recorded as a fail).
CIBSE TM59: *Design methodology for the assessment of overheating risk in homes (**Criteria for mech vented**)*	For homes with restricted window openings, <u>or</u> mech vented the CIBSE A fixed temperature test must be followed, i.e. **<u>all occupied rooms</u> should not exceed an operative temperature of 26 ˚C for more than 3%** of the annual occupied annual hours (CIBSE Guide A (2015a).

How to handle incomplete information





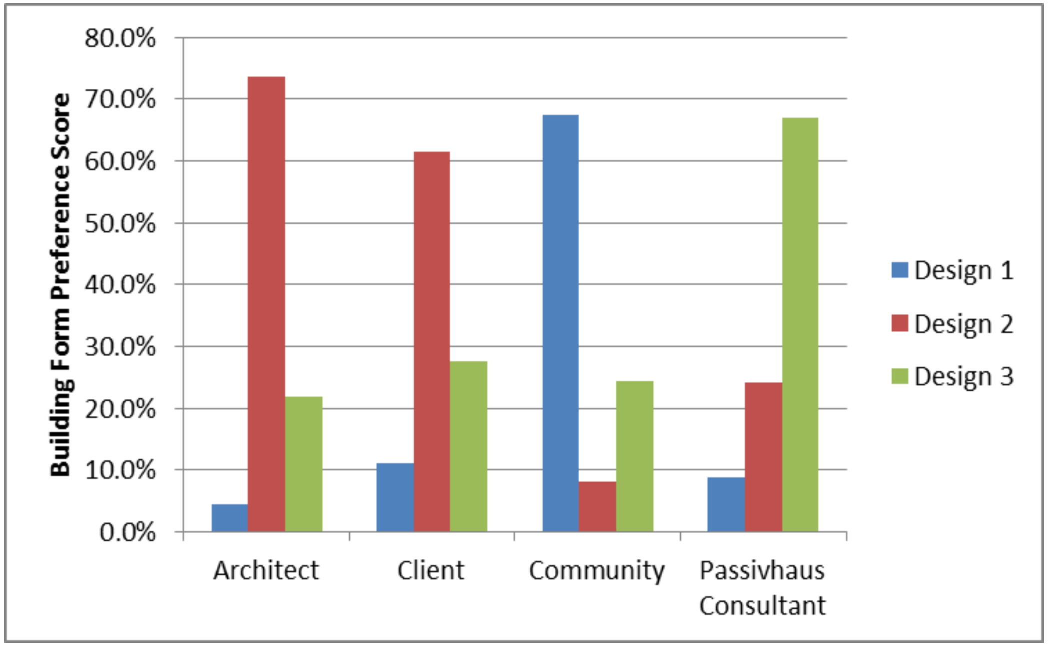
Mourkos, K., Hopfe, CJ, Goodier, C., McLeod, RS, Swainson, M., 2018. Modelling overheating in urban environments using CIBSE TM59 – does it work?

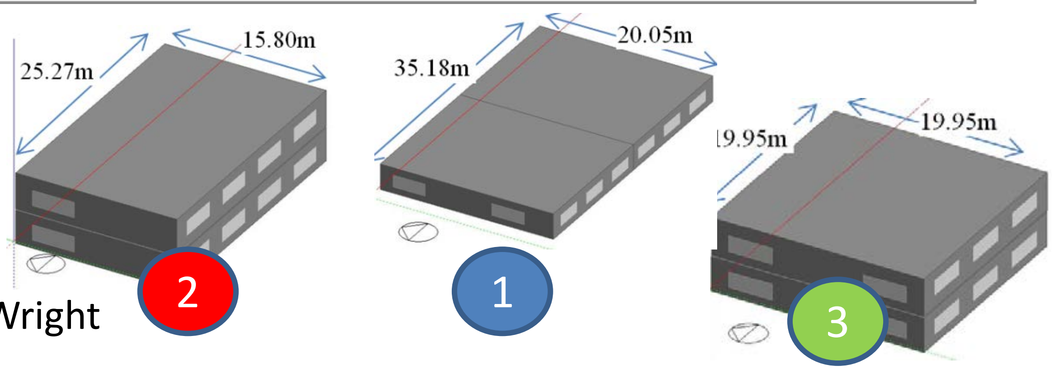
What do we want/ or know?

Uncertainty in stakeholder decision making

- Study into consideration of subjective views of multiple stakeholders alongside numeric measures of building performance

- Care important in interpreting results: preliminary sensitivity analysis indicates that small changes in the preference of a key stakeholder can change the outcome sufficiently that a different decision is made.





Project title of PhD: Decision support
Supervisors: Dr Christina Hopfe, Prof Jon Wright

E Robinson, CJ Hopfe, J Wright, 2016 Investigating the Potential Impact of Stakeholder Preferences in Passivhaus Design, BSO
E Robinson, CJ Hopfe, J Wright, 2016. Stakeholder decision making in Passivhaus design. SimAUD

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SECTION 3

CHALLENGES AND FINAL REMARKS

Challenges

- Decision makers can barely work with deterministic data - let alone probabilistic data
- User education and understanding of uncertainty and limitations
- Trade-off: Robustness vs computational efficiency
- Expensive/ perceived value

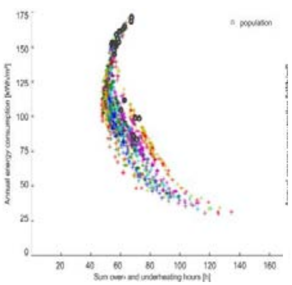
Solutions?

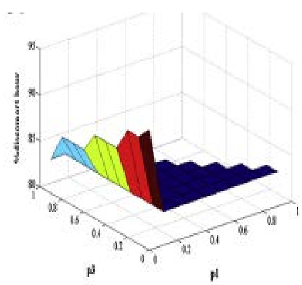
- Decision frameworks and benchmarking environments
- Better integration of uncertainty in conceptual design and across the design stages
- The analysis and presentation including uncertainty and sensitivity analysis; presented in a way that supports robust solutions
- Improved visualisation and analysis of optimized results: one single solution?

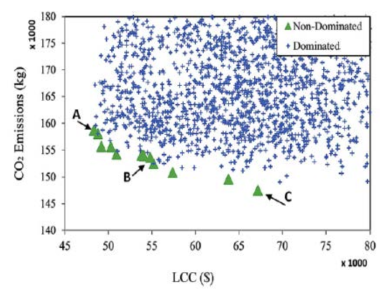
Is simulation or ‘computational optimization’ the answer?

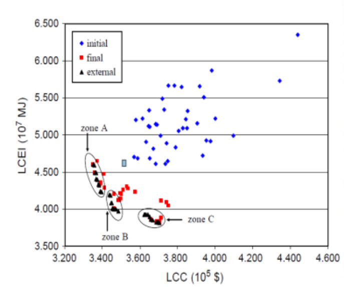
1. Requirement of high expertise: Necessary input parameters (e.g. number of design variables, number of objective function evaluations, population size) can already be too complex.

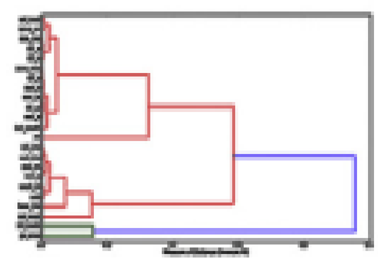
2. Low confidence in the results: The user has no impact on the outcomes, and his/her preferences are not taken into account. Optimal solutions with respect to a limited number of objectives may be rejected, as they are not compromised solutions.











We need to build resilient buildings

- **Toughness**; the capacity to recover quickly from difficulties
- Strategies incorporating both **robustness** and other attributes such as '**redundancy**' (or spare capacity) and **adaptability** are considered increasingly important even on the micro-scale.
- at a micro-scale robustness-based design approaches dominate the objective of achieving resilience.

>>instead of achieving resilience (whereby the building is able to withstand a number of different impacts) only single or multi-objective optimization (e.g. is the building carbon neutral) are actually typically considered

Source: earthshare.com

Hopfe, CJ, McLeod, RS, Rollason, T. 2017 Opening the black box: Enhancing community design and decision making processes with building performance simulation, BS 2017

Reflections for the audience

With knowledge of uncertainty…

- How do we define and re-present the likely or possible performance of the building?
- How are we able to guarantee performance to a client?
- How can we design (or define) zero or low energy buildings?
- How will we be able to detect faults in buildings?

Absolute certainty may not be achievable - but a better knowledge of uncertainty and risk is certainly possible!

Building Simulation Student Modelling Competition

BS 2019 2-4 SEPT ROME

Simulation, design and optimization of an historical building energy retrofit

http://buildingsimulation2019.org/competitions/

Thank you!

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