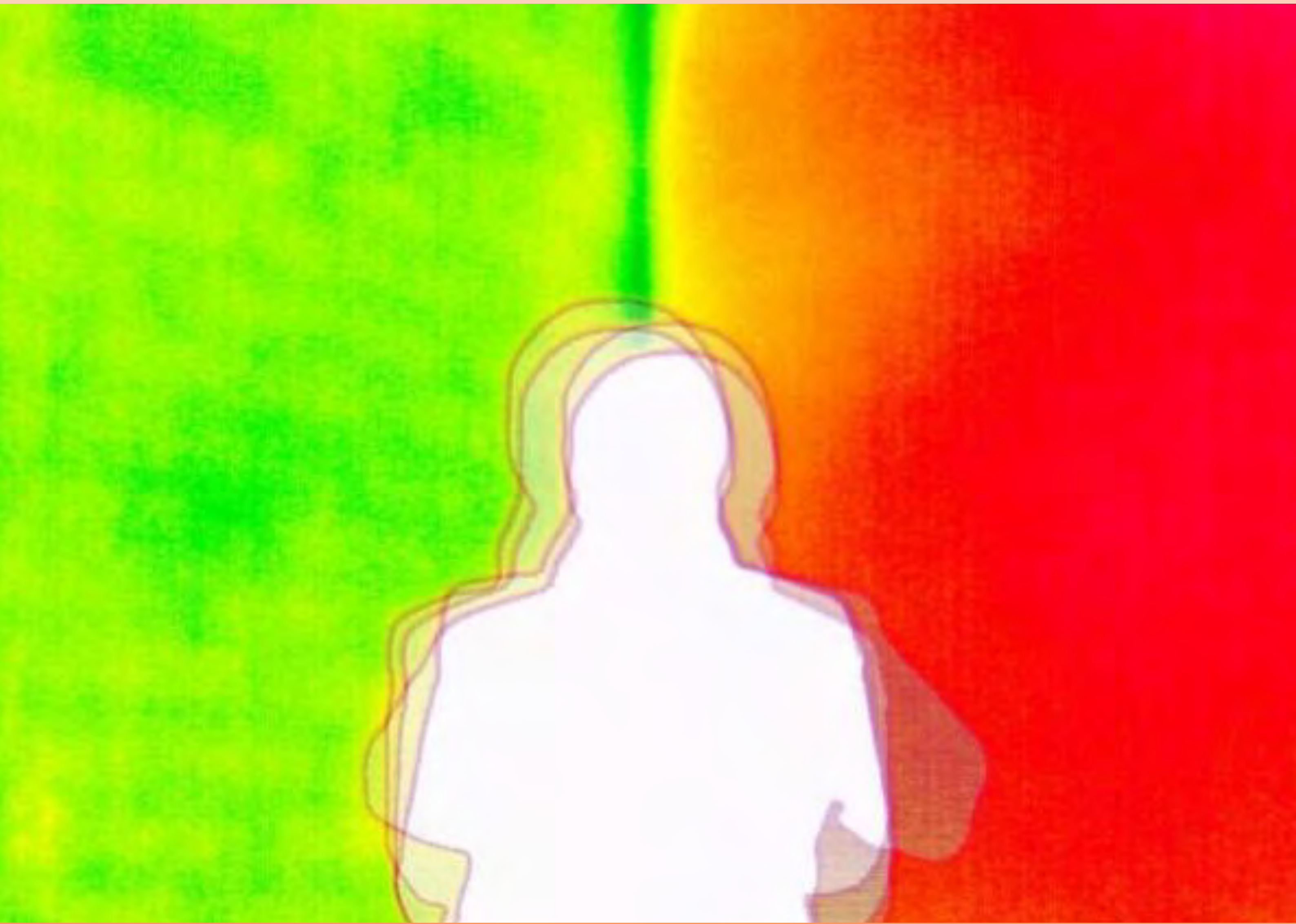
5th International Symposium on Occupant Behaviour

Annex 79

Southampton
20 - 23 April 2020



Symposium Presentation Programme

Organised by the
Energy and Climate Change Division
www.energy.soton.ac.uk
www.iea-annex.org

UNIVERSITY OF Southampton

Introduction

Headlines from the Chairs

The Energy and Climate Change Division (ECCD) and the Sustainable Energy Research Group (SERG) within the School of Engineering at the University of Southampton, UK, hosted the International Energy Agency's (IEA) Energy in Buildings and Communities (EBC) Programme Symposium and Task Group meetings addressing Occupant-Centric Building Design and Operation ('Annex 79') from 20-23 April 2020.

In light of the COVID-19 pandemic, the 4-day event took place virtually using a video and web conferencing platform. This was the first time the event was held online. The ease of attending virtually, facilitated by the Management Team, resulted in a record attendance of over 230 delegates from 25 countries and 82 institutions (Fig 1).

Map of IEA Annex 79 attendees
231 participants from 25 countries

Prof AbuBakr S. Bahaj
ICEC 2020 Chair
Head, Energy & Climate Change Division, UoS

Dr Stephanie Gauthier
ICEC 2020 Co-chair
Lecturer in Energy and Buildings, UoS

Leading academics, practitioners, policy-makers, manufacturers and students from the fields of engineering, architecture, psychology, sociology and marketing came together to exchange ideas and good practice. Creating and strengthening partnerships to integrate and implement occupancy and occupant behaviour into the design process of buildings and their operation, enhancing both energy performance and occupant comfort.

IEA Annex 79 attendance figures

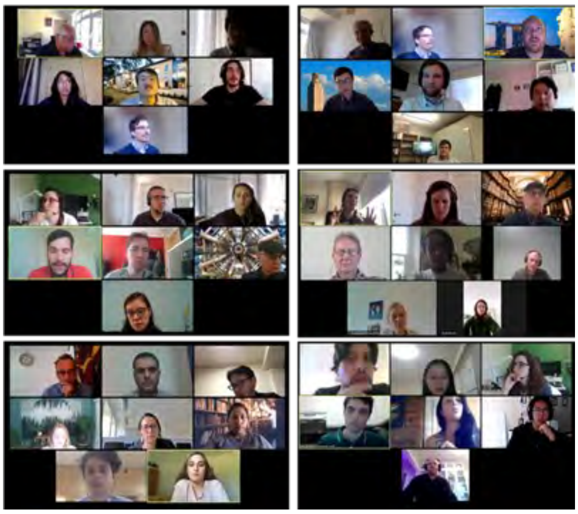
Topic	Attendees	Concurrent views
Symposium Session 1	155	125
Symposium Session 2	150	131
Symposium Session 3	144	121
Symposium Session 4	131	111
Symposium Session 5	136	118
Symposium Session 6	123	115
Expert Meeting Day 1	136	126
Expert Meeting Day 2	122	115

Summary

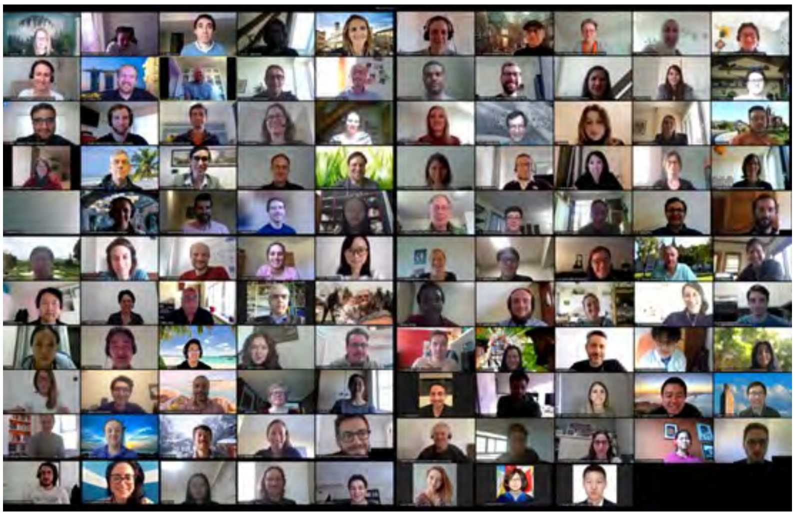
The first two days of virtual meetings (20-21 April) comprised the 5th International Symposium, and a full programme of the six sessions, chaired jointly by Stephanie Gauthier and AbuBakr Bahaj of ECCD (Fig 2). With the various presentations and question and answer sessions covering cutting-edge research from around the world, including topics as diverse as building simulation, teleworking, ‘big data’ modelling, nudges and behaviour change, introducing a range of case studies and academic approaches to the attendees.

The final two days (22-23 April) was dedicated to the 4th IEA EBC Annex 79 Expert Meeting (Fig 3). These experts meetings discussed, planning and pursuing research activities and initiatives for the five year Annex 79 across the four sub-tasks:

Subtask 1: Multi-aspect environmental exposure, building interfaces, and human behaviour.
Subtask 2: Data-driven occupant modelling strategies and digital tools.
Subtask 3: Applying occupant behaviour models in performance-based design process.
Subtask 4: Development and demonstrations of occupant-centric building controls.



IEA Annex 79 Symposium presenters



IEA Annex Expert Meeting group photo

These Subtask Meetings included an overview of activities within each subtask (plenary) and then three breakout sessions held as Breakout Rooms within the digital platform. The Rooms provided flexibility to allow participants to join appropriate sessions and move between the subtasks. The discussion that ensued in the various sessions covered how to implement innovations and the transfer of knowledge between researchers and practitioners in the best practice for occupant-centric building design and operation. With participants sharing, a post-meeting drink together in various time zones honouring Annex tradition.

The follow-up event will be held at the University of Southern Demark lead by Professor Mikkel Baun Kjærgaard see annex79.iea-ebc.org for further details.

More information about ECCD and SERG can be found in the ECCD research portfolio booklet.

Day 1 – programme

Monday, 20 April 2020

11:30	**Registration and log-in**	
11:45	**Welcome to Southampton** — AbuBakr Bahaj & Stephanie Gautheir, *Chairs*	
11:50	**Introducing Annex 79** — Liam O'Brien & Andreas Wagner, *Operating Agents of Annex 79*	

Personalised Comfort and Building Controls (Chair: AbuBakr Bahaj)

12:00	**Exploring Thermal Comfort in Immersive Virtual Environment** — Yimin Zhu, *Louisiana State University, USA*
12:10	**Extending the Fanger PMV Model to Include the Effect of Non-Thermal IEQ Conditions on Occupant's Thermal Comfort** — Sarah Crosby, *University of British Columbia, Canada*
12:20	**Are Comfortable Temperature Ranges Healthy?** — Simona D'Oca, *Huygen Engineers and Consultants, Netherlands*
12:30	**Energy Flexibility of Buildings: Understanding how Thermal Acceptability can Enable Demand-Response Strategies** — Matteo Favero, *Norwegian University of Science and Technology, Norway*
12:34	**Occupant-Centric Control with Personalized and Contextual Thermal Comfort Behaviour Dynamics Prediction** — Michael Kane, *Northeastern University, USA*
12:38	**On Multidimensional Comfort: Multi-Parametric Experimental Experiment Within a BIM Designed Virtual Environment** — Fillipo Vittori, *University of Perugia, Italy*
12:42	**Open Discussion**
13:10	**Refreshment Break**

Occupant-Centric Building Controls (Chair: Ben Anderson)

13:25	**Implementation of Occupancy-Based Predictive Controls for Outdoor Air Intake Dampers: Lessons Learned** — Brodie Hobson, *Carleton University, Canada*
13:35	**What do Occupants Want? Let's Ask Them Using Smart Watches and Cozie** — Clayton Miller, *National University of Singapore, Singapore*
13:45	**A Human-Centered Approach to Residential Buildings** — Philip Agee, *Virginia Tech, USA*

13:55	**Optimization of Solar Shading Control Strategies in Terms of User Behaviour, Energy Performance, Visual and Thermal Comfort** — Ghadeer Derbas, *Wuppertal University, Germany*
13:59	**A Reinforcement Learning for Occupant Centric Thermostat Control** — June Young Park, *University of Texas, USA*
14:03	**Monitoring Occupant Window Opening Behaviour in Buildings and Relevant Influential Parameters: A Critical Review** — Shen Wei, *University College London, UK*
14:07	**Preliminary Insights into Interviews with Building Energy Mangers Regarding Occupant Centric Control** — Michael Kane, *Northeastern University, USA*
14:10	**Open Discussion**
14:35	**Refreshment Break**

Modelling and Simulation, Session 1 (Chair: Victoria Aragon)

14:50	**Occupant Behaviour Profile Development based on Smart Meter Data** — Miklós Horváth, *Budapest University of Technology and Economics, Hungary*
15:00	**Analysing Smart Thermostat Data and Unregulated Loads to Support the Canadian Net Zero Energy Ready Code** — Mohamed Ouf, *Concordia University, Canada*
15:10	**Agent-Based Modelling of Building Occupants: Promise and Challenges** — Ardeshir Mahdavi, *Tu Wien, Austria*
15:20	**Inserting Occupant Behaviour Models Within the Workflow of Practitioners: A Practice-Based Perspective** — Clarice Bleil de Souza, *Welsh School of Architecture, Wales*
15:24	**Is a Zero-Net-Energy (ZNE) Home Really ZNE?** — Tianzhen Hong, *Lawrence Berkeley National Laboratory, USA*
15:28	**Demand Response Events in Residential Buildings: Not Noticeable at All?** — Marika Vellei, *La Rochelle Université, France*
15:32	**Occupant Behaviour and SAP: Integration of Stochastic Occupancy Modelling into Compliance Tools** — Benjamin Halls, *Loughborough University, UK*
15:35	**Open Discussion**

16:00	**Closing Remarks** — AbuBakr Bahaj & Stephanie Gautheir, *Chairs*

16:10	**End of day**

Day 2 – programme

Tuesday, 21 April 2020

11:30	**Registration and log-in**
11:50	**Welcome** — AbuBakr Bahaj & Stephanie Gauthier, *Chairs*

Modelling and Simulation, Session 2 (Chair: Patrick James)

12:00	**Generic vs. Occupant Specific Behaviour Modelling in Building Simulation and Building Automation** — Clara-Larissa Lorenz, *RWTH Aachen University, Germany*
12:10	**What Does a Zero Energy and Zero Carbon Tenant Look Like?** — Julia Day, *Washington State University, USA*
12:20	**Effectiveness of Feedforward Information System on Occupant's Behaviour** — Isabel Mino-Rodriguez, *Karlsruhe Institute of Technology, Germany*
12:30	**Quantifying the Impact of Occupant Presence on Building Energy Simulation with Real and Synthetic Data** — Adrian Chong, *National University of Singapore, Singapore*
12:34	**Prediction of Indoor Clothing Insulation Levels: A Comparison of Different Machine Learning Approaches** — Anooshmita Das, *University of Southern Denmark, Denmark*
12:38	**Analysis of Occupants Presence in Homes** — Alasdair Mann, *University of Southampton, UK*
12:42	**The Impact of Occupants' Distribution on Energy and Comfort in a Case study Office Building** — Tareq Abuimara, *Carleton University, Canada*
12:45	**Open Discussion**
13:10	**Refreshment Break**

Other Building Occupant-Related Research (Chair: Massimilianno Manfren)

13:25	**Does Teleworking Save Energy? A Critical Review of Quantitative Studies and their Research Methods** — Liam O'Brien, *Carleton University, Canada*
13:35	**A Systematic Approach to Preserve Privacy in Smart Buildings** — Alan Wang, *University of Virginia, USA*
13:45	**Understanding New Technology and their Impacts on Occupants** — Victoria Aragon, *University of Southampton, UK*

13:55	**Towards Low-Energy Housing in the Canadian North from an Occupant-Centric Perspective** — Louis Gosselin, *Université Laval, Canada*
13:59	**User Behaviour in Low-Environmental Impact Buildings in Tropical Climates** — Maareva Payet, *University of La Réunion, France*
14:03	**N-Gage: Sensing in-class Multidimensional Learning Engagement in the Wild** — Nan Gao, *Royal Melbourne Institute of Technology University, Australia*
14:07	**Open Discussion**
14:35	**Refreshment Break**

Case Studies of Occupant-Centric Modelling, Design and Operations
(Chair: Stephanie Gauthier)

14:50	**Introduction to PhD Thesis: Subjective Data-Streams for Indoor Climate Assessment in Buildings** — Niels Lassen, *Norwegian University of Science and Technology, Norway*
15:00	**Evaluating Acoustic Comfort in Multi-Unit Residential Buildings** — Marianne Touchie, *University of Toronto, Canada*
15:10	**Learning to Live in Low-Energy Dwellings: A Mixed-Methods Case Study** — Lucile Sarran, *Technical University of Denmark, Denmark*
15:20	**Capturing Real-Time Motivations Behind Human-Building Interactions: The OBdrive App** — Verena Barthelmes, *Ecole Polytechnique Fédérale de Lausanne, Switzerland*
15:24	**Evaluating Varying Comfort** — Gary Raw, *GRPS, UK*
15:28	**Case Study: Reasons of Office Occupant's Dissatisfaction with an Automated Lighting Control System** — Sarah Weiner, *Fraunhofer Institute, Germany*
15:32	**Impact of Visual and Auditory Factors on Perceived Thermal Comfort: A Case Study** — Ardeshir Mahdavi, *Tu Wien, Austria*
15:35	**Open Discussion**

Closing

16:00	**Invitation to IEA Annex 79 Expert Meeting** — Liam O'Brien & Andreas Wagner, Operating Agents of Annex 79
16:10	**Closing Remarks** — AbuBakr Bahaj & Stephanie Gauthier, Chairs
16:15	**End of day**

Presentations

Session 1 - First presenter

Zhu, Yimin &

Hong, Tianzhen

Louisiana State University, USA and Lawrence Berkeley National Laboratory, USA

Session 1

Day 1, 12:00

Exploring Thermal Comfort in Immersive Virtual Environment

Y. Zhu, T.Hong

Immersive virtual environment (IVE) has been increasingly applied to building design. Most applications utilize the strength of the technology to support visual and spatial modeling. However, such capability is not enough, because IVE alone cannot effectively provide thermal stimuli for thermal comfort-related studies. The project team examined the potential of augmented IVE, i.e., IVE plus a climate-controlled environment, to support thermal comfort-related studies. To this end, experiments were conducted comparing the thermal experience of participants (such as thermal sensation, thermal comfort, and thermal acceptability) between IVE and in-situ settings. Each experiment had a heating and a cooling sequence in both in-situ and IVE settings. The heating and cooling sequences were controlled at 65°F/18°C, 75°F/24°C, and 85°F/29°C with the relative humidity set at 55%. Thirty participants completed all experiment sessions. Thermal state votes, physiological responses (e.g., skin temperature and hear rate), and other demographic data were collected, cleaned, and processed for analysis. Statistical analysis was applied to testing the hypothesis that the thermal experience of participants was not significantly different between IVE and in-situ. The experience was measured using three parameters, the control temperature distribution over the thermal state scale, the thermal state vote distribution at a temperature step, and the physiological response. The sample-wide analysis suggests that participants' experience is not significantly different between IVE and in-situ settings, when experiment conditions are well-controlled.

Exploring Thermal Comfort in Immersive Virtual Environment

Yimin Zhu, Louisiana State University, Baton Rouge, LA

Tianzheng Hong, Lawrence Berkeley National Laboratory, Berkeley, CA

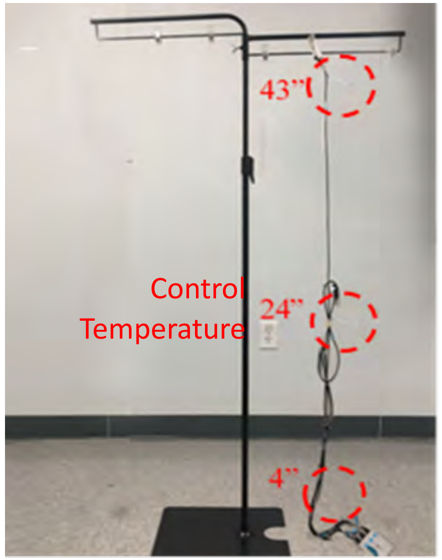
Background and Research Question

- Challenge
  - Observing thermally-driven human-building interactions for buildings under design
- Opportunity
  - Immersive virtual environment – providing contextual conditions and observing interactions
  - Climate chamber – providing and controlling thermal stimuli
- Question
  - Is participants' experience significantly different between IVE and *in-situ* settings?
  - Thermal state (sensation, comfort and acceptability), perceived temperature, and physiological response

Experiment Equipment and Devices

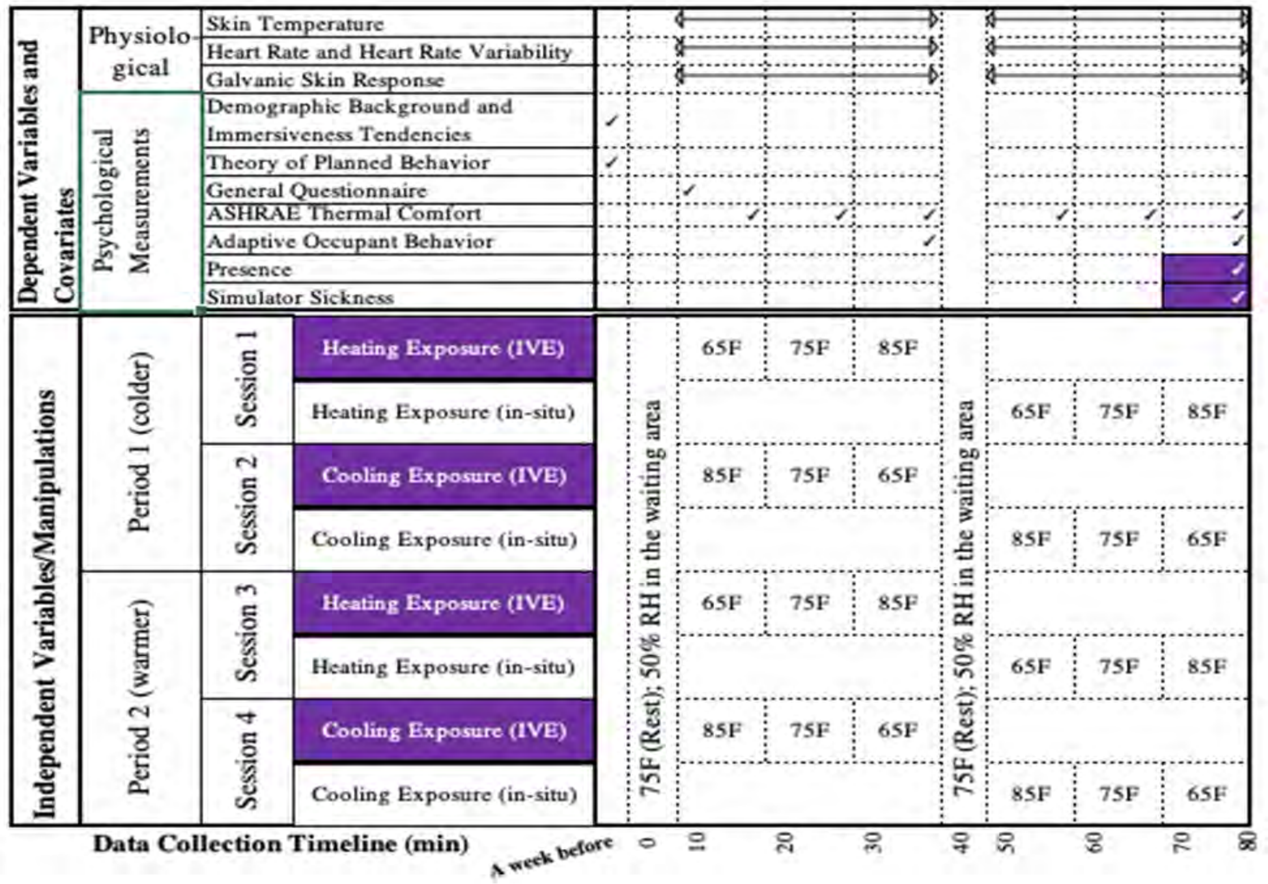
- Climate chamber
- Heart rate sensor
- Skin temperature sensors
- Head mounted display (HMD)
- Survey instruments
  - ASHARE thermal sensation 7-point scale
  - Customized 6-point comfort and acceptability scales
  - iGroup Presence Questionnaire (IPQ) and Simulator Sickness Questionnaire (SSQ)






Experiment Procedure

- Thermal exposure
  - Cooling vs. heating
  - Three steps: 65°F/18.3°C, 75°F/23.8°C, and 85°F/29.4°C
- Experiment environment
  - Immersive virtual environment (IVE) vs. *in-situ*
- Contrasting outdoor temperatures
  - Warmer vs. cooler
- Data cleaning
  - Control temperature between IVE and in-situ: $\pm$3°F [1]



[1] Darian-Smith, I., and Johnson, K. O. (1977). “Thermal sensibility and thermoreceptors.” *Journal of Investigative Dermatology*, 69(1).

Hypotheses

- H_0: $V_{temp} = V'_{temp}$; H_1: $V_{temp} \neq V'_{temp}$
    - V_{temp} and V': Sensation, comfort, and acceptability vote distribution in IVE and *in-situ* respectively; temp: temperature step - 65°F/18°C, 75°F/24°C, and 85°F/29°C
    - Fisher's exact test, 0.05 significance level
- H_0: $T_{level} = T'_{level}$; H_1: $T_{level} \neq T'_{level}$
    - T_{level} and T'_{level} : IVE and *in-situ* control temperature distribution respectively; level: sensation, comfort, or acceptability
    - Kolmogorov-Smirnov test, 0.05 significance level
- H_0: $PR_{temp} = PR'_{temp}$; H_1: $PR_{temp} \neq PR'_{temp}$
    - PR_{temp} and PR'_{temp}: the mean of T_{sk} at the eight sites at a certain temperature step in IVE and *in-situ* settings respectively; temp: temperature step - 65°F/18°C, 75°F/24°C, and 85°F/29°C
    - Two-tailed t-test (paired), 0.05 significance level

Participant Data

- Demographic data
  - 14 Female and 16 Male (n=30)
  - 30% (n=9) Caucasian
  - 26.66% (n=8) Middle Eastern
  - 26.66% (n=8) Asian
  - 16.66% from other race/ethnicities
- Overall virtual reality experience:
  - Presence: reported average - 38.16; this study - 48.97 and over
  - Cybersickness: reported SSQ total mean scores, 5.30 - 27.25; this study 20.25 and 18.43

Age	Mean	Highest level of Education	Count
Mean	26.9	Postgraduate degree	9
Std Dev	6.15	College graduate	8
Std Err Mean	2.29	Some college	10
Upper 95% Mean	29.2	High school graduate	3
Lower 95% Mean	24.6	Total	30

Example: Thermal State Vote Distribution

- H_0: $V_{temp} = V'_{temp}$; H_1: $V_{temp} \neq V'_{temp}$
  - Thermal sensation vote count
- Fisher's exact test, instead of Chi Square test.

	General Thermal Sensation		Vote Level	In-Situ N	IVE N	p-value
Period 1, Colder	Cooling	65 ºF/18.3 ºC	-3	3	4	0.87
			-2	15	16	
			-1	12	10	
		75 ºF/23.8 ºC	-2	4	5	0.882
			-1	11	12	
			0	14	12	
		85 ºF/29.4 ºC	0	3	4	0.806
			1	10	13	
			2	11	7	
			3	1	1	
	Heating	65 ºF/18.3 ºC	-3	2	3	1
			-2	12	12	
			-1	11	11	
			0	4	3	
		75 ºF/23.8 ºC	-1	2	4	0.799
			0	15	13	
			1	10	9	
			2	1	2	
		85 ºF/29.4 ºC	0	2	2	0.529
			1	8	13	
			2	15	10	
			3	2	2	

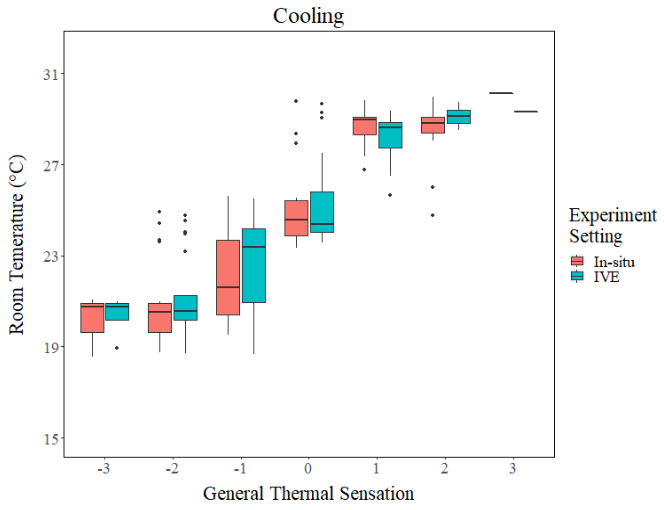
Analysis and Results

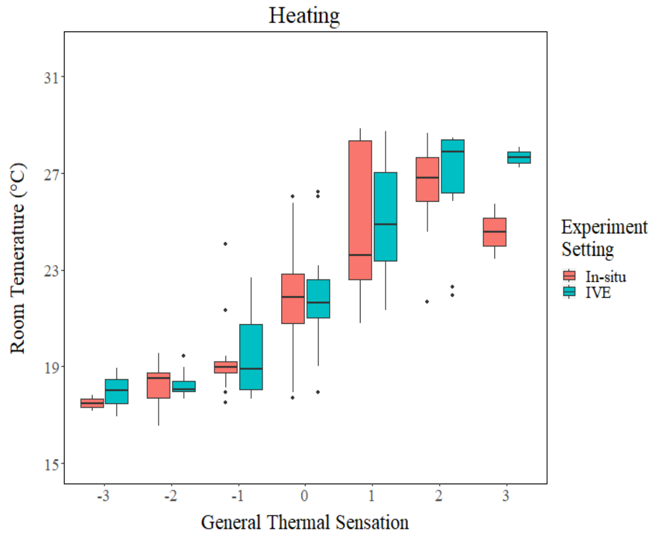
- None of the hypotheses were rejected.
- The thermal state vote distribution at a certain temperature step in the *in-situ* setting was not significantly different from that in the IVE setting.
- When participants voted for their thermal state in both *in-situ* and IVE settings, the thermal state vote distributions of the two settings were not significantly different regardless of the experiment period, the exposure type, and the temperature step.

Exmaple: Control Temperature Distribution

- H_0: $T_{level} = T'_{level}$; H_1: $T_{level} \neq T'_{level}$
  - General thermal sensation

Period	General Thermal Sensation Level		Control Temperature (in-situ) N	Control Temperature (in-situ) Mean (ºC)	Control Temperature (in-situ) St. Dev (ºC)	Control Temperature (IVE) N	Control Temperature (IVE) Mean (ºC)	Control Temperature (IVE) St. Dev (ºC)	K-S Test (p-value)
Period 1, Colder	Cooling	-3	3	20.12	1.38	4	20.34	0.96	1
		-2	19	20.82	1.91	21	21.16	1.81	
		-1	23	22.27	1.97	22	22.53	2.02	
		0	17	25.11	1.86	16	25.38	2.15	
		1	10	28.62	0.93	13	28.22	1.13	
		2	11	28.31	1.55	7	29.11	0.44	
		3	1	30.13	-	1	29.32	-	
	Heating	-3	2	17.48	0.45	3	17.96	0.99	0.937
		-2	12	18.27	0.8	12	18.26	0.51	
		-1	13	19.31	1.69	15	19.52	1.8	
		0	21	21.63	2.31	18	21.77	2.12	
		1	18	24.89	2.98	22	25.01	2.32	
		2	16	26.54	1.7	12	26.79	2.34	
		3	2	24.58	1.61	2	27.66	0.6	





Analysis and Results

- None of the hypotheses were rejected.
- The control temperature distribution over the thermal state scale in the *in-situ* setting was not significantly different from that in the IVE setting.
- When participants voted for their thermal state in both *in-situ* and IVE settings, the corresponding control temperature distributions in both settings were not significantly different, regardless of the exposure type (heating vs. cooling) and the experiment period (warmer vs. colder).

Exmaple: Physiological Responses

- H_0: $PR_{temp} = PR'_{temp}$; H_1: $PR_{temp} \neq PR'_{temp}$
  - Eight body sites at each temperature step, and HR
  - Only significant results

		Condition	Response Variable	In-Situ			IVE			DF	t	p-value
				N	Mean	St. Dev.	N	Mean	St. Dev.			
Period 1, Colder	Cooling	65 ºF/18.3 ºC	Forehead Skin Temperature (ºC)	30	34.32	0.85	30	35.75	1.18	29	-5.43	7.49E-06
		75 ºF/23.8 ºC	Forehead Skin Temperature (ºC)	29	34.96	0.53	29	35.76	0.63	28	-6.1	1.39E-06
	Heating	65 ºF/18.3 ºC	Forehead Skin Temperature (ºC)	29	33.67	0.95	29	34.49	0.63	28	-5.14	1.85E-05
		75 ºF/23.8 ºC	Forehead Skin Temperature (ºC)	28	34.16	0.92	28	35.17	0.69	27	-6.18	1.30E-06
		85 ºF/29.4 ºC	Forehead Skin Temperature (ºC)	27	35.1	0.77	27	35.94	0.51	26	-6.23	1.33E-06
		85 ºF/29.4 ºC	Neck Skin Temperature (ºC)	27	33.94	1.21	27	33.32	1.88	26	2.42	0.022

Analysis and Results

- H_0: $PR_{temp} = PR'_{temp}$; H_1: $PR_{temp} \neq PR'_{temp}$
  - Eight body sites at each temperature step, and HR
  - Only significant results

Period 2, Warmer	Condition		Response Variable	In-Situ			IVE			DF	t	p-value
				N	Mean	St. Dev.	N	Mean	St. Dev.			
Period 2, Warmer	Cooling	65 ºF/18.3 ºC	Forehead Skin Temperature (ºC)	28	34.39	0.64	28	35.94	1.05	27	-6.95	1.79E-07
	Cooling	75 ºF/23.8 ºC	Forehead Skin Temperature (ºC)	27	34.87	0.64	27	36.07	0.52	26	-8.05	1.56E-08
	Cooling	85 ºF/29.4 ºC	Forehead Skin Temperature (ºC)	29	35.16	0.89	29	35.94	0.5	28	-4.04	0.0003
	Heating	75 ºF/23.8 ºC	Upperback Skin Temperature (ºC)	27	33.26	0.99	27	33.63	1.03	26	-2.33	0.02
	Heating	85 ºF/29.4 ºC	Forehead Skin Temperature (ºC)	29	35.22	0.52	29	35.83	1.48	28	-2.41	0.02

Analysis and Results

- Significantly different responses - the skin temperature:
  - Forehead (both cooling and heating sequences at different temperature steps)
  - Neck at 85 ºF/29.4 ºC, heating
  - Upper-back at 75 ºF/23.8 ºC, heating
- Forehead: most likely caused by the use of the HMD
- Neck and upper-back: No obvious explanation

Summary and Future Studies

- When experiment conditions are well-controlled, the sample-wide analysis suggests that participants' experience is not significantly different between IVE and *in-situ* settings.
  - Significantly similar patterns between IVE and *in-situ (t*he control temperature distribution over the thermal state scale, and the thermal state vote distribution at a temperature step)
  - Limited differences in the skin temperature responses between IVE and *in-situ (m*ostly at forehead due to the use of HMD)
- Future studies should include:
  - Comparisons at each level of the thermal state scales,
  - Impact of contrasting seasons,
  - Investigation of behavioral factors,
  - Individual level analysis, and
  - Collaborative experiment and data sharing.

Acknowledgment

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- Project Team
  - Dr. Yimin Zhu (LSU), Dr. Tracey Rizzuto (LSU), Dr. Neil Johannsen (LSU), Dr. Tianzhen Hong (LBNL), and Dr. Jared Langevin (LBNL)
- Research Assistants
  - Dr. Sanaz Saeidi (Microsoft Corporation, former Ph.D. student), Ms. Samantha Chacon (LSU, MSc. student), Mr. Girish Rentala (LSU, Ph.D. student)

Questions

Presentations

Session 1 - Second presenter

Crosby, Sarah

University of British Columbia, Canada

Session 1

Day 1, 12:10

Extending the Fanger PMV Model to Include the Effect of Non-Thermal IEQ Conditions on Occupant's Thermal Comfort

S. Crosby

The judgment of thermal comfort is a cognitive process influenced by occupant's well-being and overall satisfaction. The potential implications of occupants' thermal dissatisfaction and its effect on overall satisfaction with the indoor environment have been the focus of many recent studies in the literature. Taking advantage of the emerging awareness of the interdependencies between perceived thermal comfort and overall IEQ, we have developed a novel methodology that considers the effect of non-thermal building environmental design conditions, such as indoor air quality and noise levels, on perceived thermal comfort. The methodology involves the use of Bayesian inference to relate occupant's thermal satisfaction not only to thermal conditions (i.e., parameters of the original Fanger model) but also to measurable non-thermal, "well-being"-type, metrics. In the first phase of this study, field data are drawn from a prior field study of about 800 offices throughout Canada and the US conducted by the National Research Council of Canada in early 2000s. The Bayesian inference analysis reveals that there exist statistically significant independent correlations between some non-thermal metrics of IEQ and thermal comfort, as perceived by occupants of open-plan offices. The most significant finding is that a modest increase in measured indoor CO_2 concentrations, from 500ppm to 900ppm, is found to be correlated with a decrease in perceived thermal satisfaction by 30%. Such observable correlations have revealed the need for developing an updated version of the data collected. A large IEQ field study of 150 offices carried out at the University of British Columbia across 2019/2020 is presented. This study seeks to update the recent findings while addressing the most prevailing research gap vis-à-vis thermal comfort models by proposing an extension to the Fanger model which consists of a more holistic evaluation method.

Extending the Fanger PMV model to include the effect of non-thermal IEQ conditions on occupant's thermal comfort

Sarah Crosby, Adam Rysanek

University of British Columbia, Canada

OB-20 Symposium

Southampton, UK

April 20, 2020

THE UNIVERSITY OF BRITISH COLUMBIA

Holistic Approach to Thermal Comfort

- ASHRAE defines **thermal comfort** as :"**the condition of the mind** in which satisfaction is expressed with the thermal environment".

- The judgment of thermal comfort is a **cognitive process** influenced by occupant's well-being.

- Considering **only <u>thermal</u> environmental design conditions** as a proxy for occupants' thermal comfort might not be the right approach.

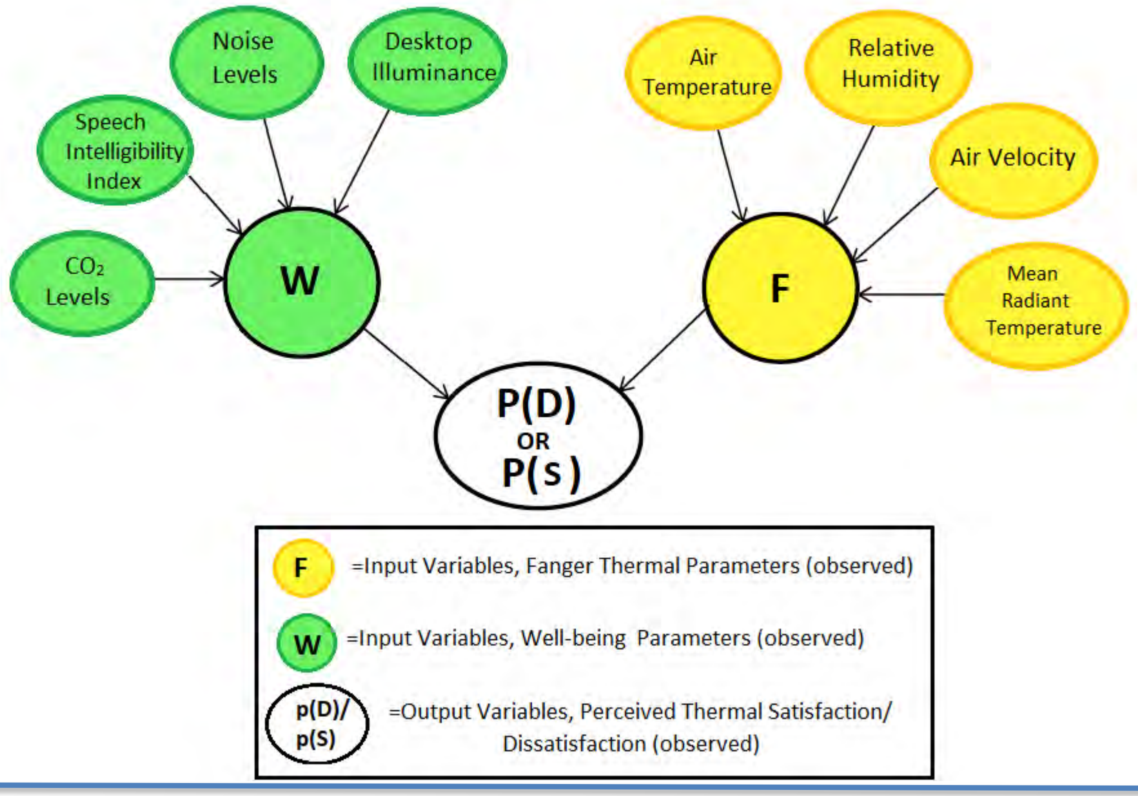
Thermal Comfort is Sensed by Your Body and Perceived by Your Brain

A Novel Thermal Comfort Evaluation Technique

- Current models have not always accurately predicted true thermal comfort observations in real-world setup and only consider thermal factors **despite the increasing awareness of the interdependencies between IEQ and perceived thermal comfort.**

- This research fills a **prevailing research gap** with respect to standard models of thermal comfort: **: the effect of well-being IEQ parameters**, such as air quality, visual comfort, acoustic performance, and biophilia accessibility, **on perceived thermal comfort.**

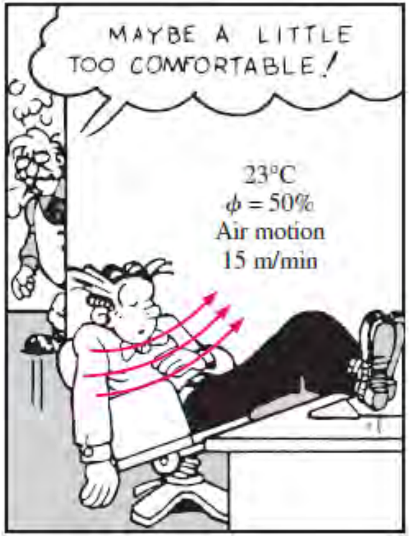
Hypothesis: Can we infer the likelihood of non-thermal parameters affecting perceived thermal comfort using Bayesian networks?



Two main research questions:

1- Do non-thermal parameters of IEQ have an effect on occupants' thermal satisfaction?

2- Does considering non-thermal parameters of IEQ improve predictions of thermal comfort?

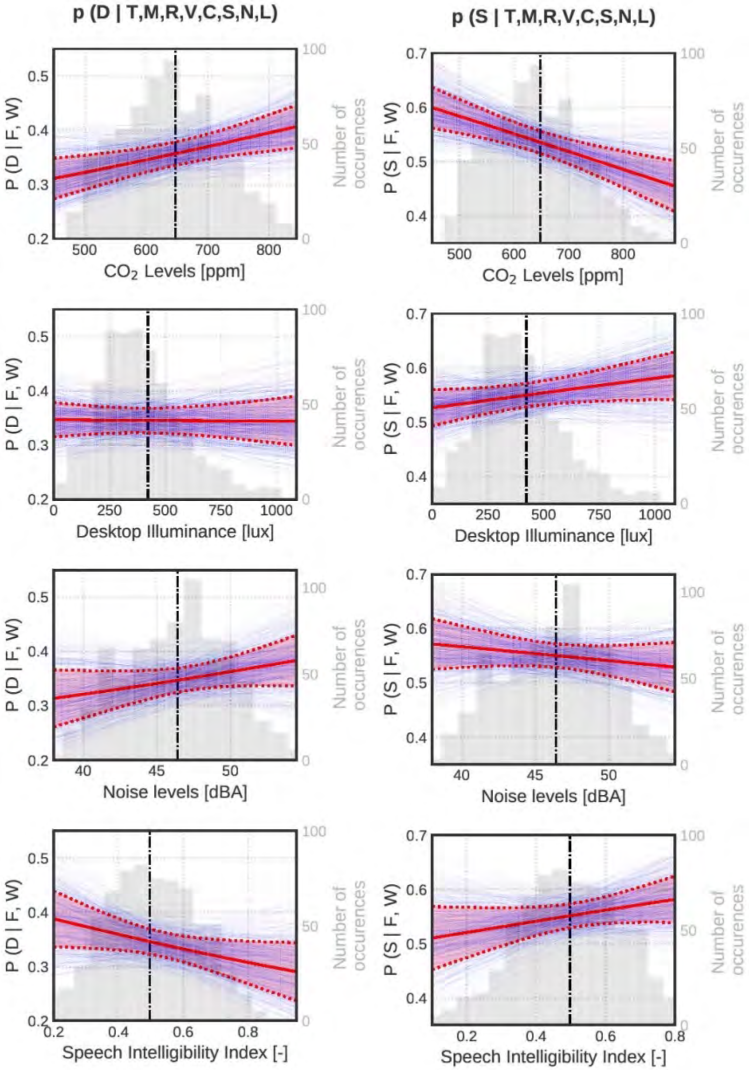


Field Data Sources: COPE Database (National Research Council – Canada)

The Cart + Chair System used to generate the COPE database (NRC)

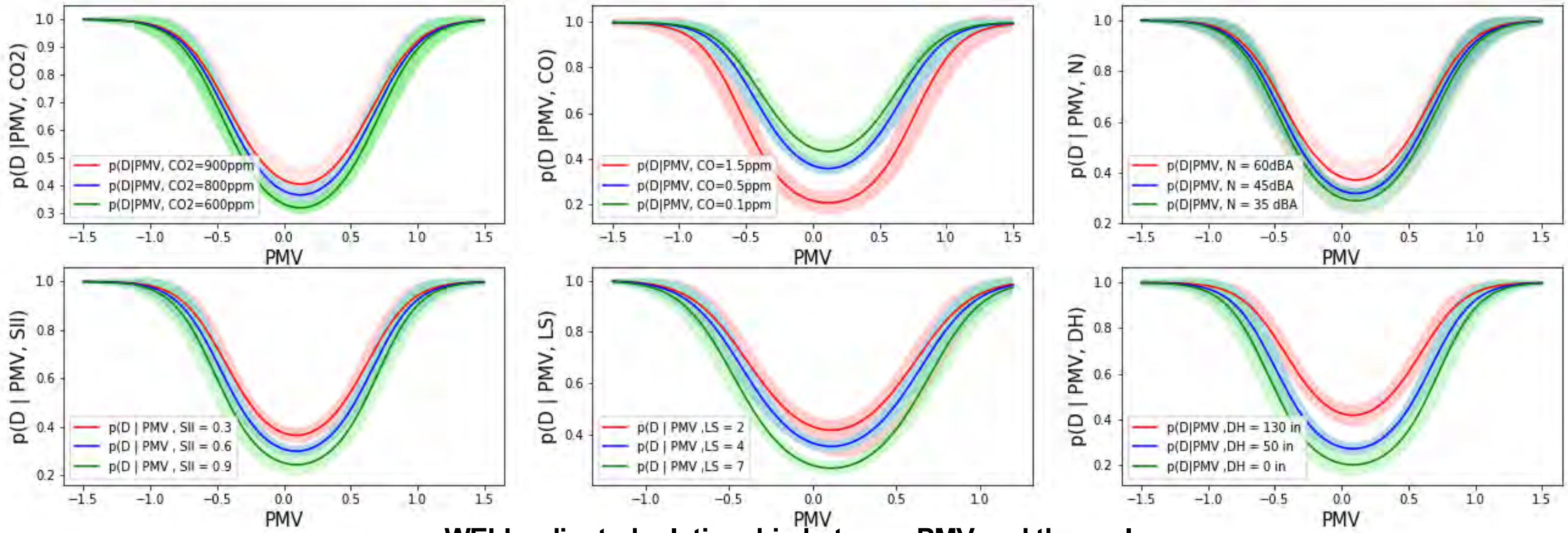
1st set of Bayesian Logistic Models:

I- The effect of non-thermal parameters of IEQ on occupant's thermal satisfaction and thermal dissatisfaction



Implications of results to standard thermal comfort models

II- WELL-adjusted relationship between PMV and thermal dissatisfaction p(D)



WELL-adjusted relationship between PMV and thermal dissatisfaction *p*(D)

Model Selection Results

Bayesian Model	WAIC Score	WAIC standard error	Bayes Factor
P(S|C)	1002.13	4.06	3.33
p(S| T,M,C)	999.65	4.26	3.13
P(S| C,S,N,L)	1002.82	5.29	1.57
p(S| T,M,L)	1002.14	3.35	1.34
P(S| T,M,R,V,C)	1000.27	4.79	1.27
P(S| T,M,N)	1002.25	3.66	1.09
P(S| T,M)	1004.38	3.06	1.00
P(S| T,M,R,C)	1002.15	4.285	0.61
P(S| T,M,R,V,L)	1002.43	3.89	0.45
P(S| T,M,R,V,S)	1003.38	4.42	0.41
P(S| T,M,R,V)	1003.14	3.57	0.4
P(S| T,M,R,V,C,S,N,L)	1003.03	5.35	0.32
P(S| T,M,R)	1004.07	3.12	0.29
P(S| T,M,R,V,N)	1004.32	4.04	0.2

WAIC Scores and Bayes Factors for the p(S) models, with Null hypothesis shown in red

2nd Phase of Research

Field IEQ Study Across UBC Offices

Meet ESTEBAN !

The "<u>E</u>xceptional <u>S</u>ensing <u>T</u>estbed for <u>E</u>nvironment, <u>B</u>iophilia, <u>A</u>ir-quality, and <u>N</u>ippiness"

Field IEQ Study across UBC's Offices

Measured IEQ parameters

CO

RH

NO

CO2

MRT

Temp

VOCs

Air Velocity

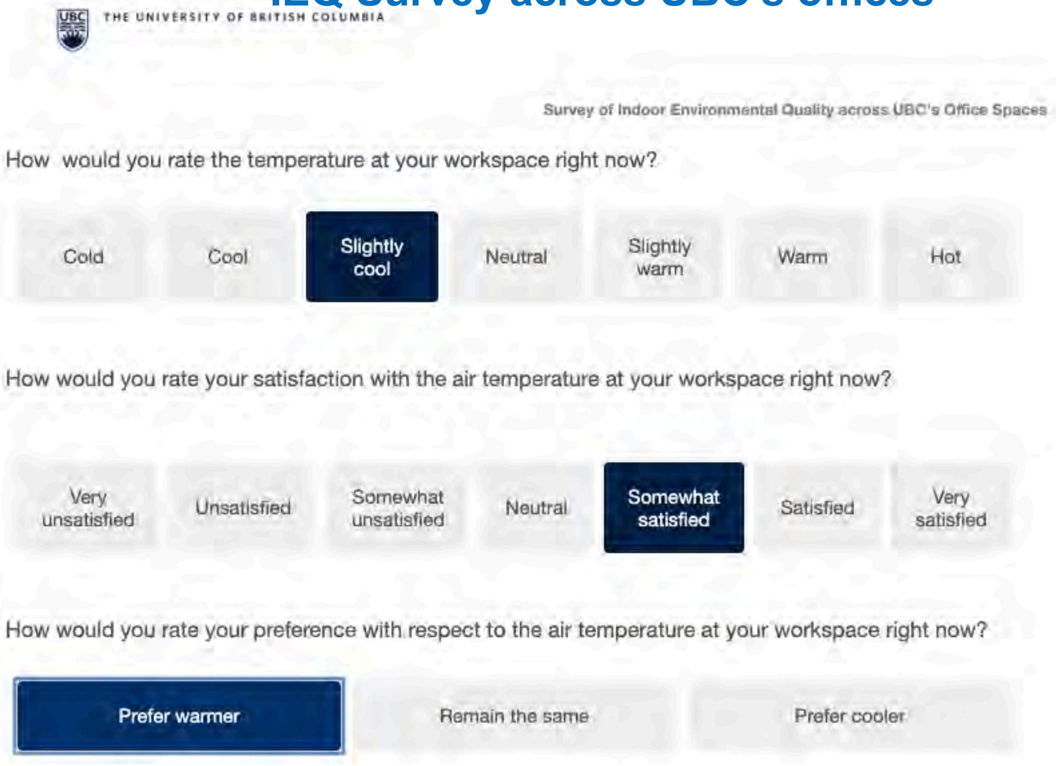
Noise levels

Light Intensity

Partition Height

%Greenery / Biophilia

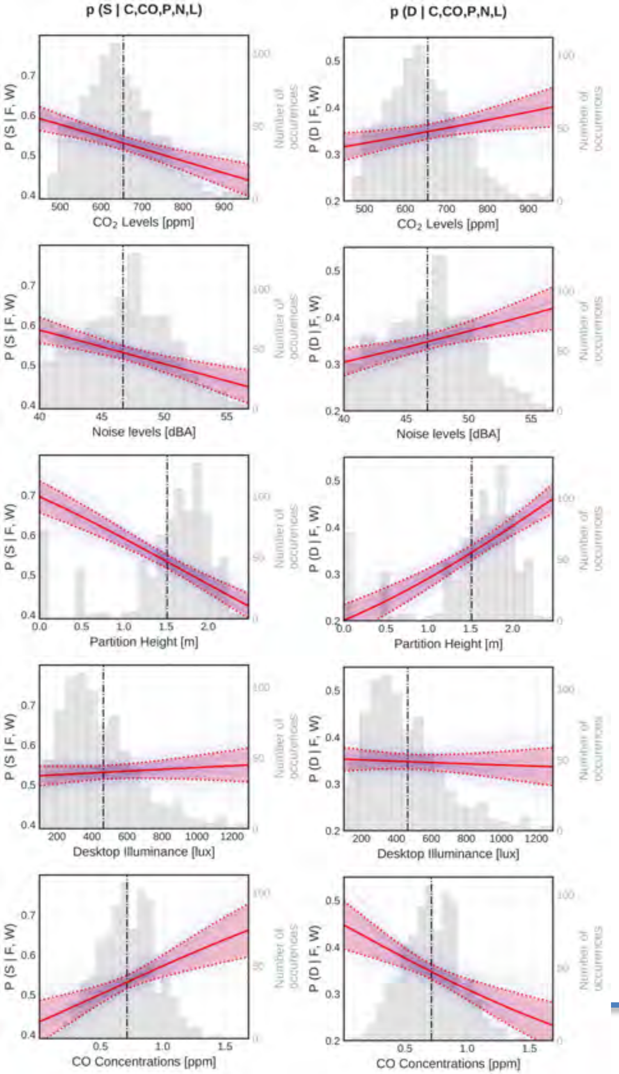
IEQ Survey across UBC's offices



UBC + COPE Datasets

Bayesian Model	WAIC Score	WAIC standard error	Bayes Factor
P(S| C,N,L,CO,P)	1182.0	10.12	13608.89
P(S| T,M,R,V,C,N,L,CO,P)	1184.46	10.6	1024.67
P(S| P)	1192.55	7.82	328.81
p(S| CO)	1199.2	5.67	13.76
P(S| C)	1201.97	4.92	4.55
P(S| T,M,C)	1200.65	5.38	3.8
P(S| C,N,L)	1202.69	5.46	2.77
P(S| T,M,R,V,C)	1201.25	6.21	1.15
P(S| T,M,R,V,C,N,L)	1200.93	6.79	1.08
P(S| T,M,R,C)	1201.63	5.65	1.01
P(S| T,M)	1204.48	4.19	1.00
P(S| T,M,N)	1204.51	4.64	0.89
P(S| T,M,L)	1205.69	4.26	0.51
P(S| T,M,R)	1205.11	4.76	0.35
P(S| T,M,R,V)	1205.37	5.02	0.31

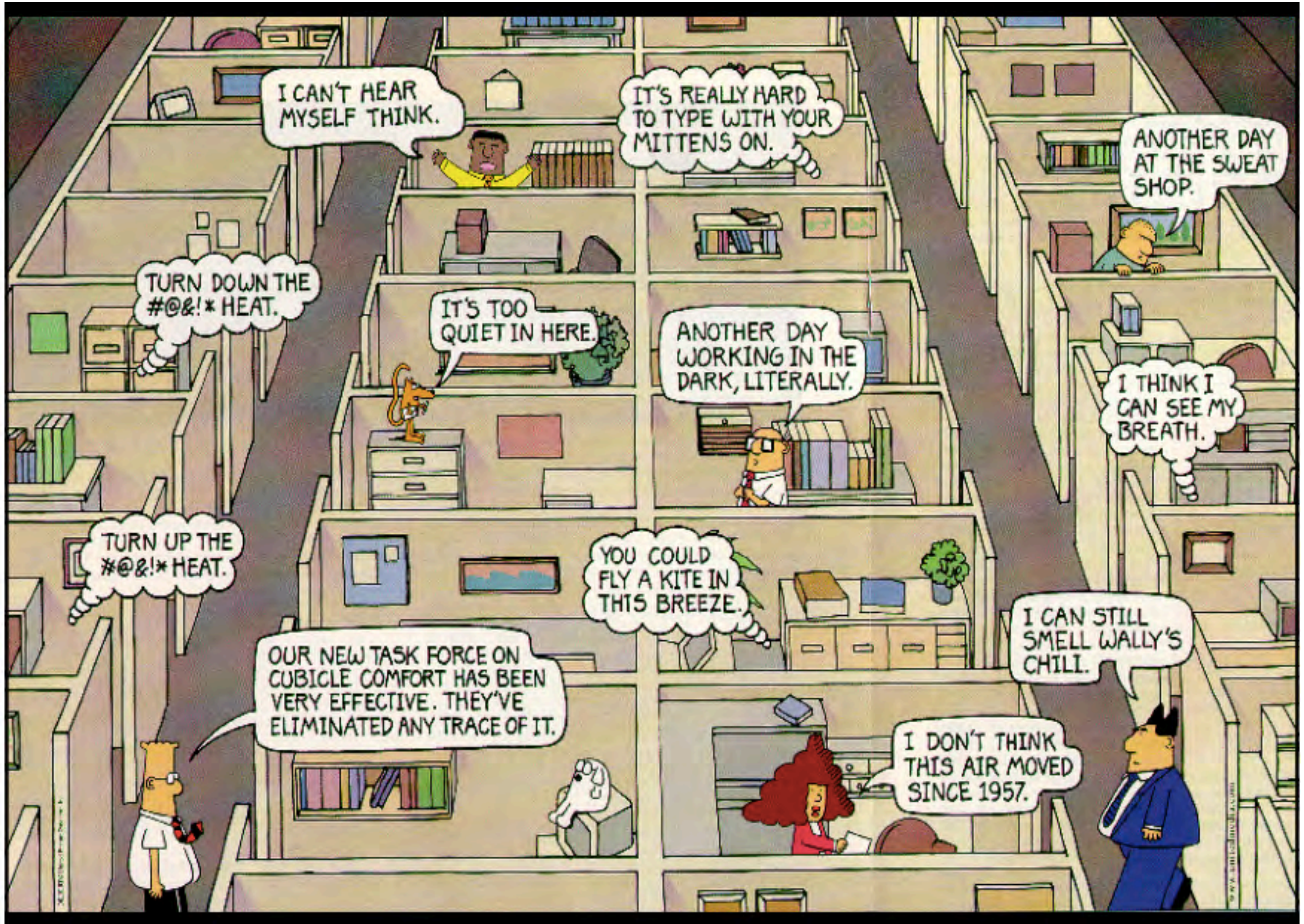
WAIC Scores and Bayes Factors generated for the p(S) models for the COPE + UBC datasets. The Null hypothesis shown in red



Conclusions

- This research advances a novel technique for improving thermal comfort models while filling a prevailing research gap.
- Having repeatable results from the recent field IEQ data indicates that the previous findings are robust and significant.
- This is the first known work to provide evidence that measured CO_2 concentrations might improve thermal satisfaction predictions in a significant manner, at least in open-plan offices.
- These findings suggest that, in the future, it might very well be possible to directly affect thermal satisfaction in indoor spaces through the improvement of non-thermal environmental conditions.

THANKS !


I CAN'T HEAR MYSELF THINK.
IT'S REALLY HARD TO TYPE WITH YOUR MITTENS ON.
ANOTHER DAY AT THE SWEAT SHOP.
TURN DOWN THE #@&!* HEAT.
IT'S TOO QUIET IN HERE.
ANOTHER DAY WORKING IN THE DARK, LITERALLY.
I THINK I CAN SEE MY BREATH.
TURN UP THE #@&!* HEAT.
YOU COULD FLY A KITE IN THIS BREEZE.
I CAN STILL SMELL WALLY'S CHILI.
OUR NEW TASK FORCE ON CUBICLE COMFORT HAS BEEN VERY EFFECTIVE. THEY'VE ELIMINATED ANY TRACE OF IT.
I DON'T THINK THIS AIR MOVED SINCE 1957.

Presentations

Session 1 - Third presenter

D'Oca,
Simon

Huygen Engineers and Consultants, Netherlands

Session 1

Day 1, 12:20

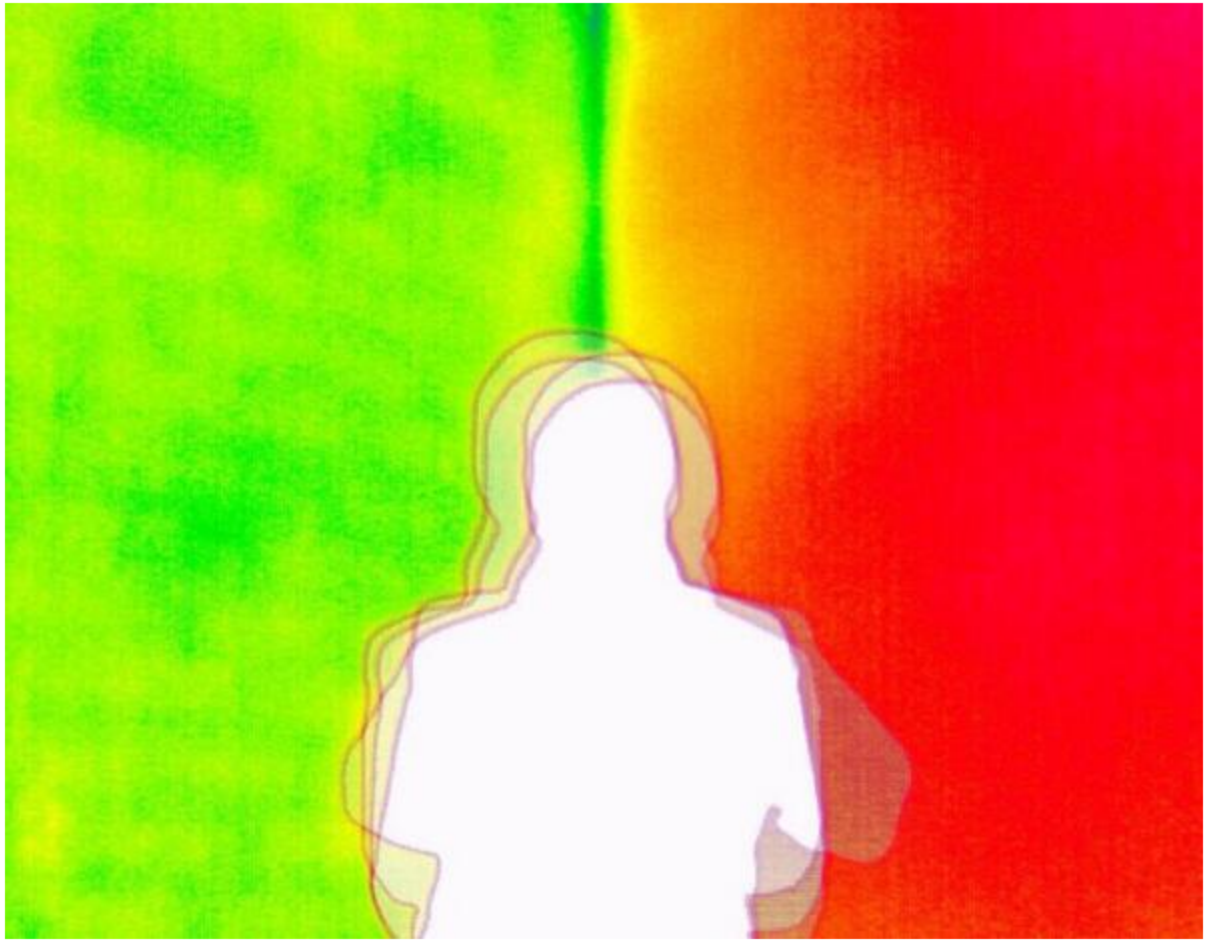
Are Comfortable Temperature Ranges Healthy?

S. D'Oca

Building occupants have often limited knowledge about the quality of the indoor climate they are working or living in. There is an overall lack of awareness of the influence of adaptive behaviors and indoor climate on overall building's performance, and even less on personal health. Experimental studies showed regular exposure to mild cold environment can increase energy expenditure in terms of human energy metabolism, resilience to thermal discomfort due to acclimation, and resistance to cardiovascular disease and insulin sensitivity. In the MOBISTYLE project, we are aiming to prove gradually cooler environment in winter and warmer in summer can lead to higher acceptance of comfort ranges in office settings. Dynamic temperature training can furthermore have a great effect on the productivity and well-being of the occupants, therefore optimizing operating (labor) costs of the building. Not only, significant reduction of final energy consumption (up to 16%) can be prompted by dynamic thermal environment, as well as reduction of CO_2 emissions. Dynamic open-office settings have been deployed in the Huygen offices (Netherlands) combining dynamic temperature profiles for improving health, comfort and saving energy, with dynamic lighting for increasing alertness and improving sleep-wake rhythm. Under these living-lab dynamic settings, the Office App is coupling the office BMS data, with data from wearables gathering information on workers well-being and physical health, as well feedback on perceived comfort and productivity.

Are comfortable temperature ranges healthy?

Dr. Simona D'Oca, PhD.



EBC

UNIVERSITY OF Southampton

Occupant Behaviour 2020 (OB-20)
5th International Symposium
IEA EBC Annex 79 "Occupant behavior-centric building design and operation".
20th April 2020, Southampton, UK

HUYGEN
INGENIEURS & ADVISEURS


Health is
todays'
wealth

H2020 MOBISTYLE Project

Motivating end-users behavioral change by combined ICT based tools and modular information services on energy use, indoor environment, health and lifestyle

HUYGEN INGENIEURS & ADVISEURS

EBC

UNIVERSITY OF Southampton

This project has received funding from the European Union’s H2020 framework programme for research and innovation under grant agreement no 723032.

H2020 MOBISTYLE Project

Motivating end-users behavioral change by combined ICT based tools and modular information services on energy use, indoor environment, health and lifestyle

Develop easy to use ICT-based tools which will make energy monitoring well-accepted and attractive

Transform measured data into understandable information for identified user profiles (from behavioral change to habit formation, routine).

Motivate long lasting behavioral change of end users by combined modular information on energy use, IEQ, health and lifestyle.

Deploy and validate the developed solutions for 5 demonstration cases featuring different building types and end user types.

Foster new business models and applications for employees in an office environment, residents in a social housing, students and staff in university buildings, residents living in a smart city, hotel guests

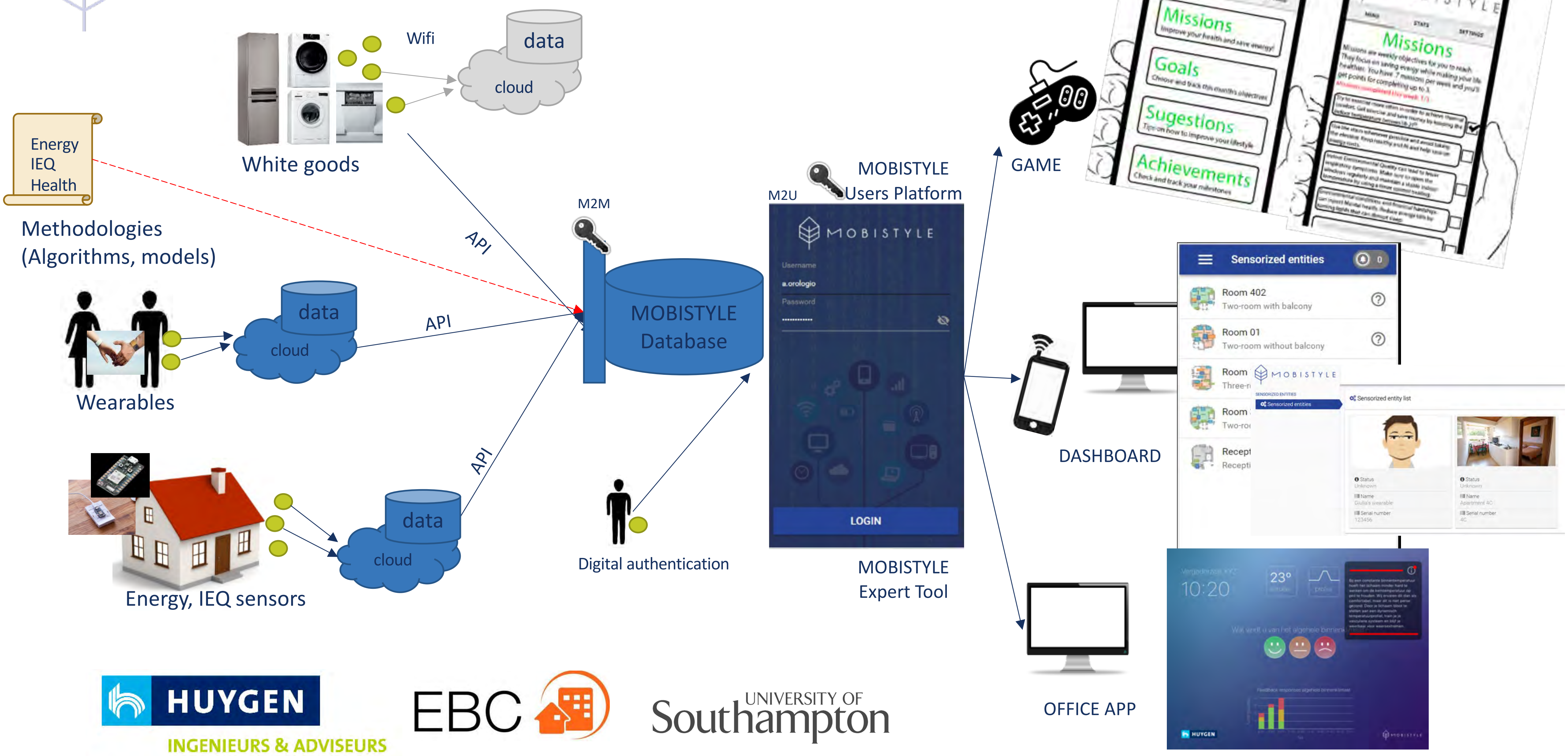
HUYGEN INGENIEURS & ADVISEURS

EBC

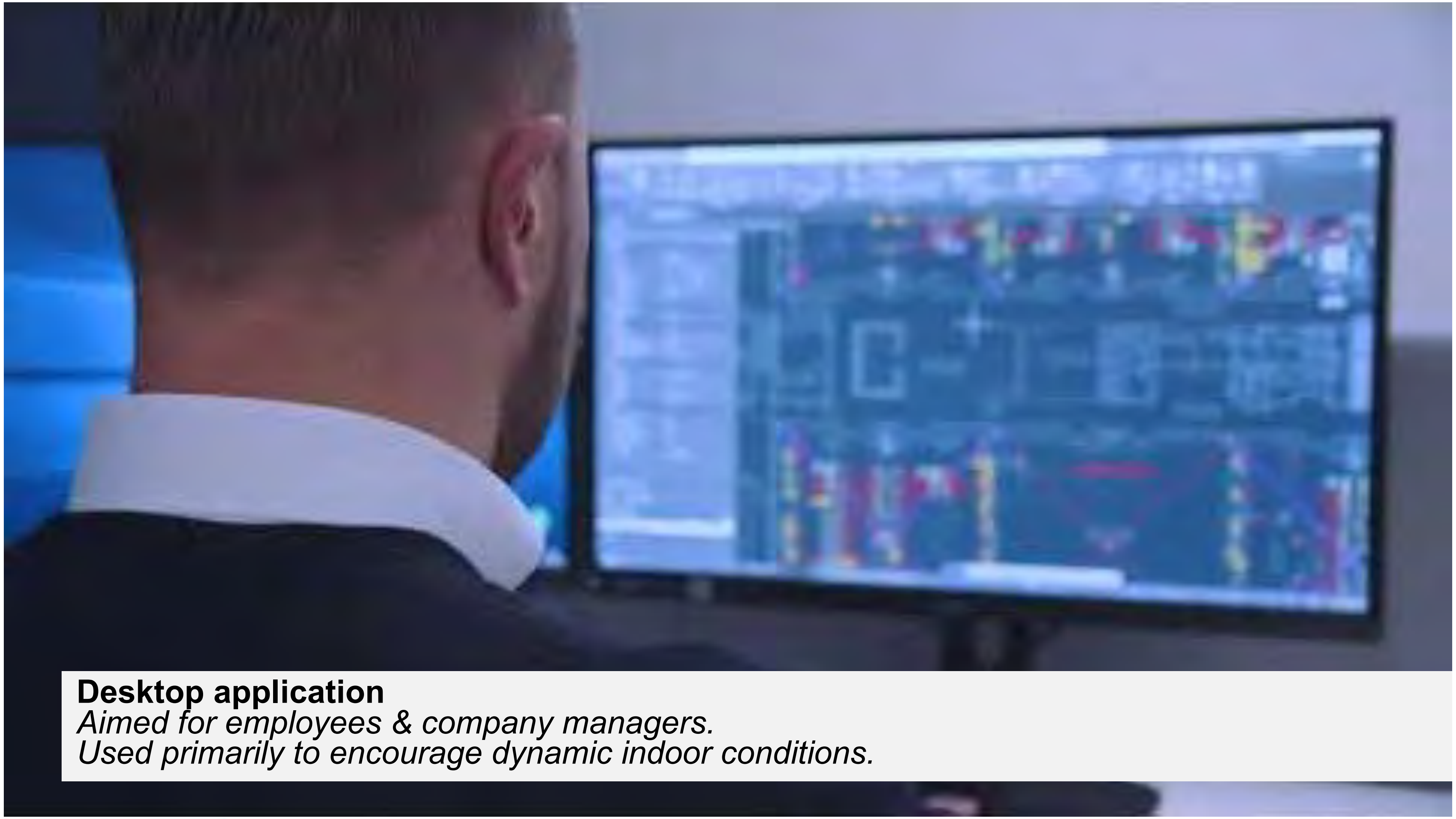
UNIVERSITY OF Southampton

This project has received funding from the European Union’s H2020 framework programme for research and innovation under grant agreement no 723032.

MOBISTYLE Architecture



MOBISTYLE Office App



Desktop application
Aimed for employees & company managers.
Used primarily to encourage dynamic indoor conditions.

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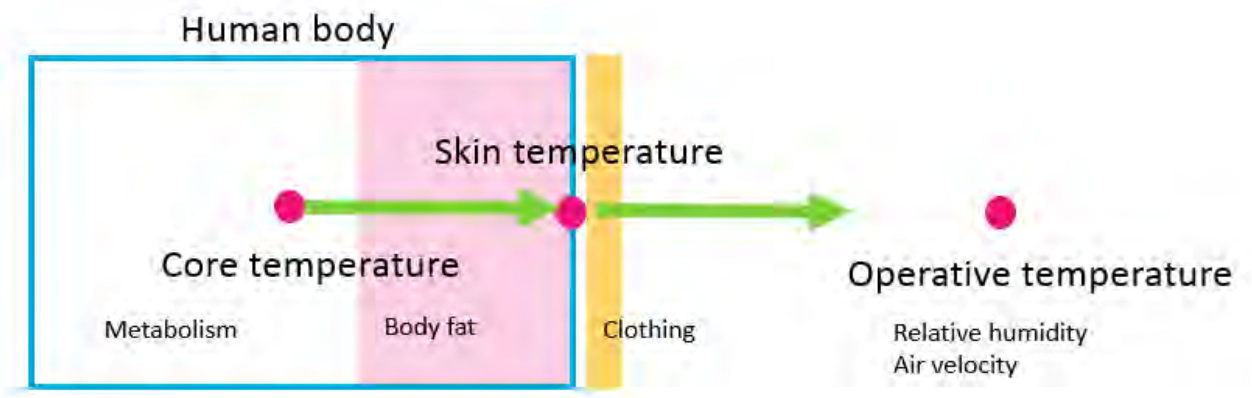
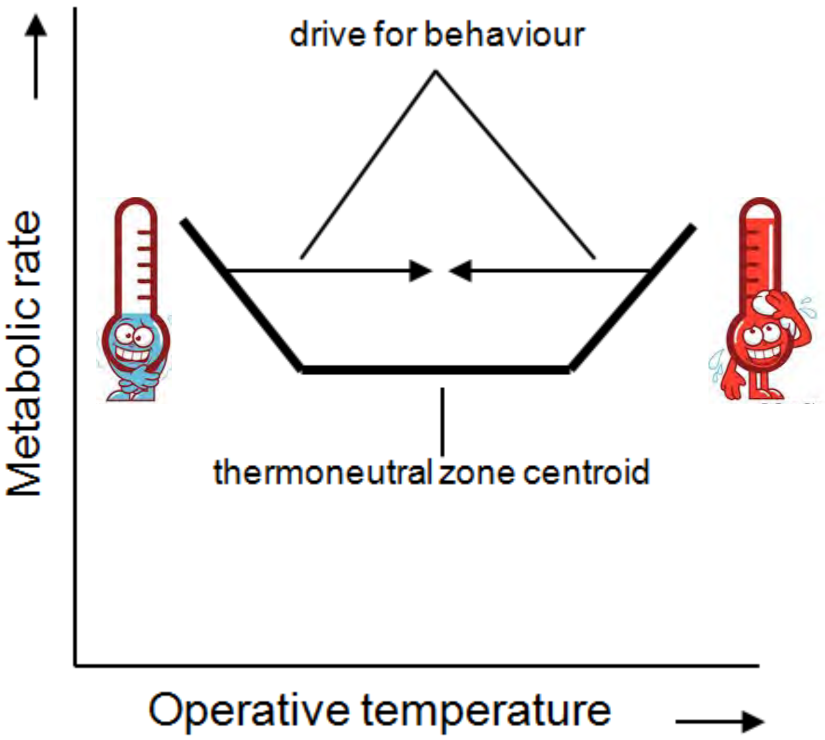
MOBISTYLE

Are comfortable temperatures healthy?

Physiological response → Psychological response →

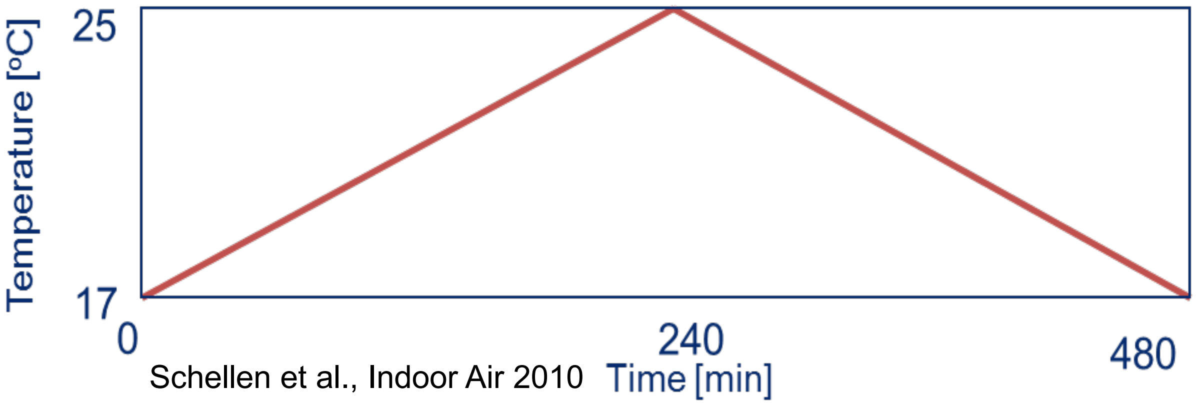


Maastricht University

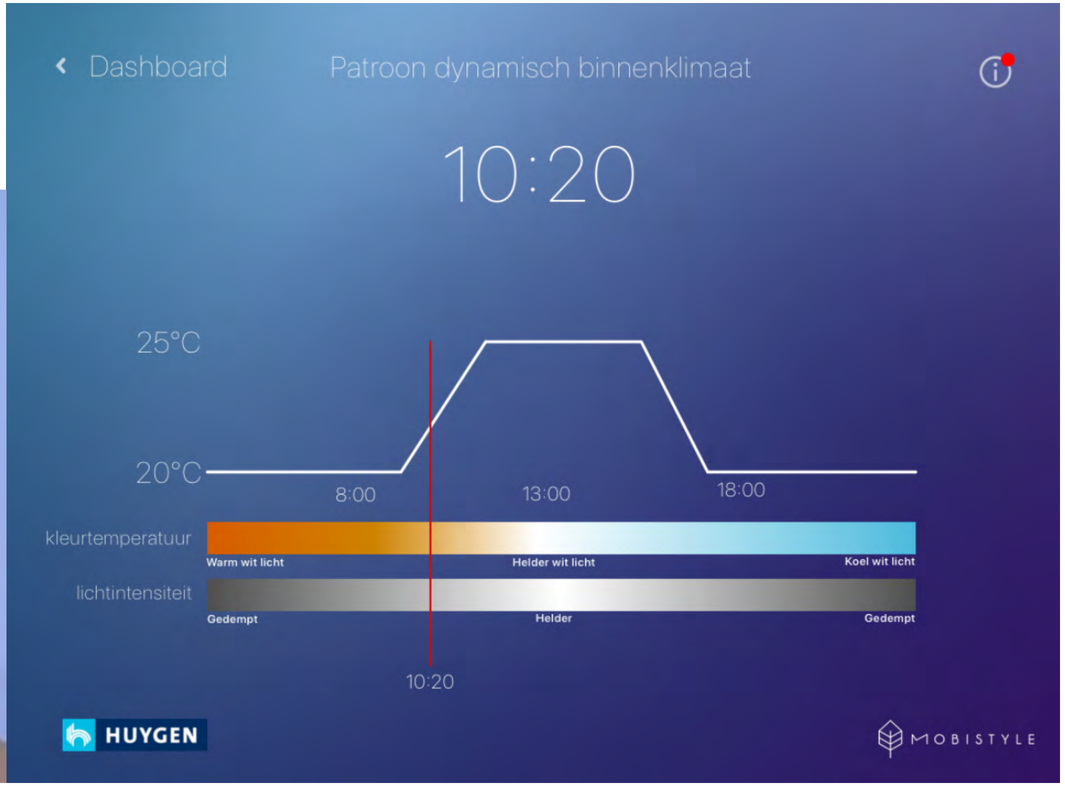


Van Marken Lichtenbelt, W.D., Kingma, B., Lans, A., Schellen, L. (2014). Cold exposure – an approach to increasing energy expenditure in humans.
Van Marken Lichtenbelt, W. D.; Hanssen, M.; Pallubinsky, H.; Kingma, B.; Schellen, L. Healthy excursions outside the thermal comfort zone, Building Research & Information, 2017.
Van der Lans, A. A.; Hoeks, J.; Brans, B.; Vijgen, G. H.; Visser, M. G.; Vosselman, M. J.; Hansen, J.; Jorgensen, J.A.; Wu, J.; Mottaghy, F. M.; Schrauwen, P.; van Marken Lichtenbelt, W. D.. Cold acclimation recruits human brown fat and increases non-shivering thermogenesis, The Journal of clinical investigation, 2013, 123, 3395-3403.

Dynamic indoor climate



Schellen et al., Indoor Air 2010



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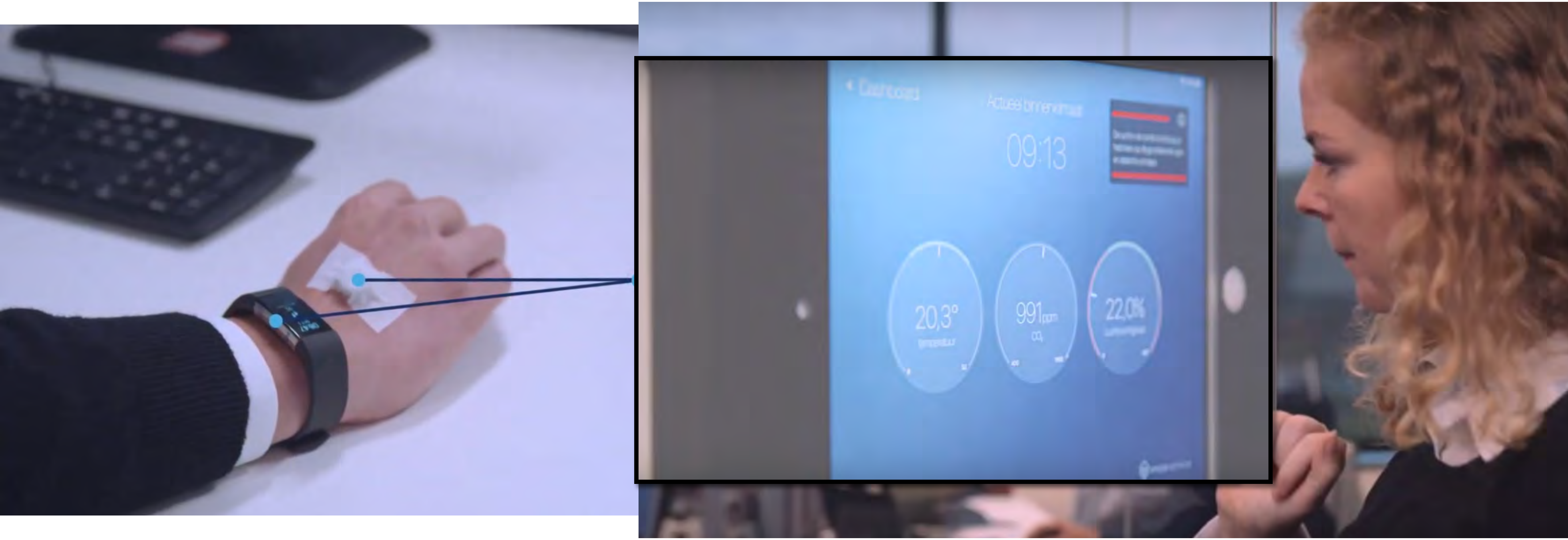
MOBISTYLE

Dynamic indoor lighting

HUYGEN INGENIEURS & ADVISEURS EBC UNIVERSITY OF Southampton MOBISTYLE

Wearables and feedback



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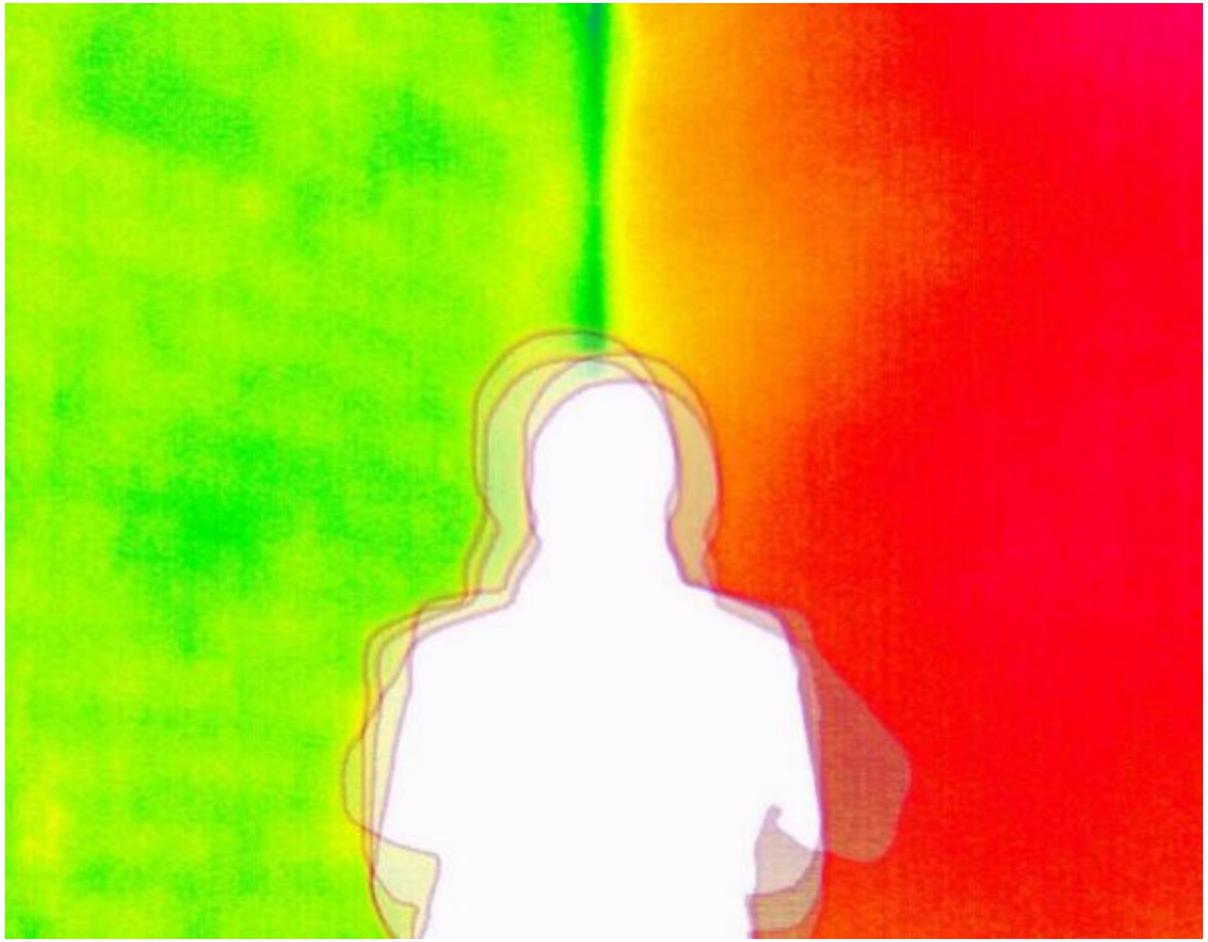
MOBISTYLE

Thanks for your attention

s.doca@huygen.net
a.tisov@huygen.net



EBC UNIVERSITY OF Southampton

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HUYGEN
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Presentations

Session 1 - Fourth presenter

Favero, Matteo &

Carlucci, Salvatore

Norwegian University of Science and Technology, Norway

Session 1

Day 1, 12:30

Energy Flexibility of Buildings: Understanding how Thermal Acceptability can Enable Demand-Response Strategies

M. Favero, S. Carlucci

Current research in building science aims at implementing strategies to exploit the energy flexibility of buildings. This consists in shifting energy use for given energy services in order to adapt the hour-by-hour energy consumption to what is optimal for the energy system. Energy uses for space heating and cooling are important terms of a building's energy balance and can be displaced by some hours, utilising building's thermal mass, without significantly affecting the thermal comfort of the occupants. However, this is an assumption that needs to be verified. Thus, to what extent it is possible to exploit building's energy flexibility without compromising thermal comfort experienced by their occupants remains an open research question. A dedicated experiment, executed in the ZEB Test Cell Lab in the NTNU premises, aims at understanding occupant's thermal acceptability in dynamic indoor conditions and how it compares with the ASHRAE 55-2017 limits on temperature cycles, ramps, and drifts. In this study, participants were asked to spend full or half days in the facility, furnished like a typical cellular office, and to evaluate the indoor environment through questionnaires while carrying out their everyday work activity. During the experiment, the air temperature was modified according to predefined thermal ramps (Fig. 1) while other environmental parameters, such as air velocity, relative humidity, CO2 concentration, and illuminance on the work surface were also recorded. Furthermore, the participants were asked to press a button as soon as they felt uncomfortable, where uncomfortable was defined as "take an action to restore a comfort condition" (e.g., if too warm environment, then regulate the thermostat or open the window). In this way, it will be possible, after the analysis of collected data, to understand the limits of the human thermal acceptability under different temperature variations, before voluntary adaptation mechanisms or actions are undertaken.

NTNU | Norwegian University of Science and Technology

Energy flexibility of buildings: understanding how thermal acceptability can enable demand-response strategies

Matteo Favero, PhD candidate, NTNU
Salvatore Carlucci, Professor, The Cyprus Institute & NTNU

Definition

- **ISO 7730 (2005)***

  3.2 drift temperature. Passive monotonic, steady, non-cyclic change in the operative temperature of an enclosed space.

  3.3 ramp temperature. Actively controlled monotonic, steady, non-cyclic change in the operative temperature of an enclosed space.

  8.3 Temperature drifts or ramps. If the rate of temperature change for drifts or ramps is lower than 2.0 K/h, the methods for steady-state variation apply.

- **ASHRAE 55 (2017)****

  5.3.5.3 Drifts or Ramps. Monotonic, noncyclic changes in operative temperature t_0 and cyclic variations with a period greater than 15 minutes shall not exceed the most restrictive requirements from Table 5.3.5.3.

*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, Switzerland: International Organization for Standardization.

**ANSI/ASHRAE Standard 55. (2017). Thermal environmental conditions for human occupancy. Atlanta, GA: American Society of Heating, Refrigerating and Air-Conditioning Engineers.

Definition

Table 5.3.5.3 Limits on Temperature Drifts and Ramps*

Time period, h	0.25	0.5	1	2	4
Maximum Operative Temperature to Change Allowed, °C (°F)	1.1 (2.0)	1.7 (3.0)	2.2 (4.0)	2.8 (5.0)	3.3 (6.0)

Informative note: For example, the operative temperature shall not change more than 2.2°C (4.0°F) during a 1.0 h period and more than 1.1 °C (2.0°F) during any 0.25 h period within that 1.0 h period.

Translated to

Limits on Temperature Increment for Drifts and Ramps

Thermal ramp, °C/h (°F/h)	4.4 (8.0)	3.4 (6.0)	2.2 (4.0)	1.4 (2.5)	0.825 (1.5)

Focus of the experiment

(for both heating and cooling)

*ANSI/ASHRAE Standard 55. (2017). Thermal environmental conditions for human occupancy. Atlanta, GA: American Society of Heating, Refrigerating and Air-Conditioning Engineers.

Definition

Tab. A.5 – Example design criteria for spaces in various types of building*

Activity W/m²	Category	Operative temperature °C		Maximum mean air velocity [a] m/s	
		Summer (cooling season)	Winter (heating season)	Summer (cooling season)	Winter (heating season)
	A	24.5 ± 1.0	22.0 ± 1.0	0.12	0.10
70	B	24.5 ± 1.5	22.0 ± 2.0	0.19	0.16
	C	24.5 ± 2.5	22.0 ± 3.0	0.24	0.21 [b]

[a] The maximum net air velocity is based on a turbulence intensity of 40% and air temperature equal to the operative temperature according to 6.2 and Figure A.2 of the ISO 7730-2005. A relative humidity of 60% and 40% is used for summer and winter, respectively. For both summer and winter a lower temperature in the range is used to determine the maximum mean air velocity.

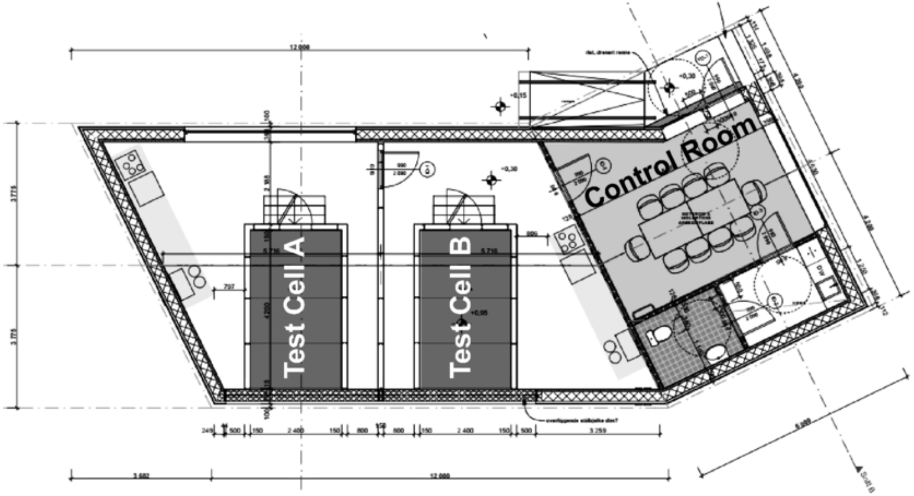
[b] Below 20°C limit (see Figure A.2 of ISO 7730-2005).

Focus of the experiment
(for both heating and cooling)

*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, Switzerland: International Organization for Standardization.

ZEB Test Cell Laboratory

View of south facade



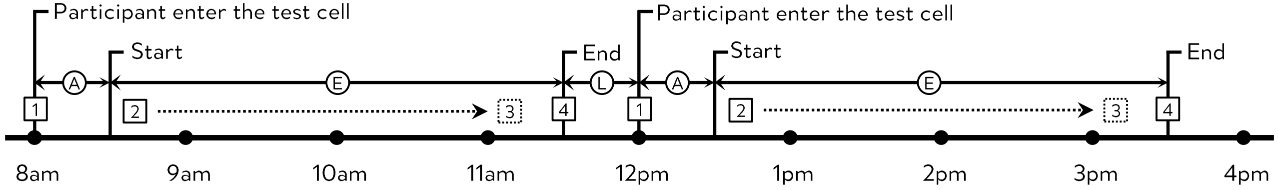
Plan of the building

Experiment description

- **Period:** from 3rd September 2019 to 9th January 2020, about 4 months
- **Participants:**

		Age (yr)		Weight (kg)		Height (cm)	
	number	Mean (SD)	Range	Mean (SD)	Range	Mean (SD)	Range
Male	10	29.2 (4.5)	23 - 37	79.3 (16.2)	63 - 114	176.2 (6.6)	167 - 185
Female	30	27.9 (7.1)	20 - 49	62.2 (8.4)	48 - 80	168.8 (6.4)	157 - 185

- **Participation:**
  - four full days/eight half-day (4 mornings + 4 afternoons) or,
  - two full days/four half-day (2 mornings + 2 afternoons)
- **Experiment schedule:**



A Acclimatisation period (30 min)
E Experiment (180 min)
L Lunch (30 min)
1 Questionnaire type 1
2 Questionnaire type 2
3 Questionnaire type 3
4 Questionnaire type 4

Questionnaire overview

- **Questionnaire 1 – Entry questionnaire**

  Gender, age, height, weight, time living in Norway, rank the three most important physical features that make workplace a pleasant one, clo-value, satisfaction with workplace (Likert scale).

- **Questionnaire 2 – Subjective judgement scale**

  Perception, evaluation, preference, personal acceptability (graphic categorical scale).

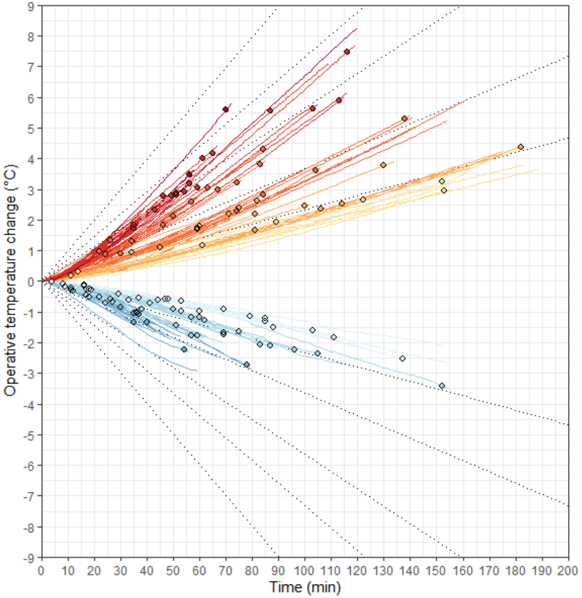
- **Questionnaire 3 – Subjective judgement scale + discomfort event**
  - Perception, evaluation, preference, personal acceptability (graphic categorical scale),
  - Source of discomfort, strategies to maintain/restore comfort.

- **Questionnaire 4 – Exit questionnaire**

  Satisfaction with workplace (Likert scale).

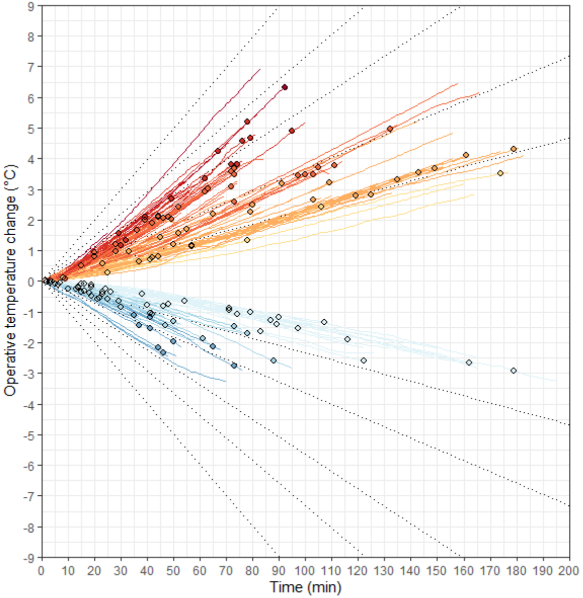
Thermal Ramps

Cell A



Total number of ramps: 172
With "thermal discomfort event": 117

Cell B



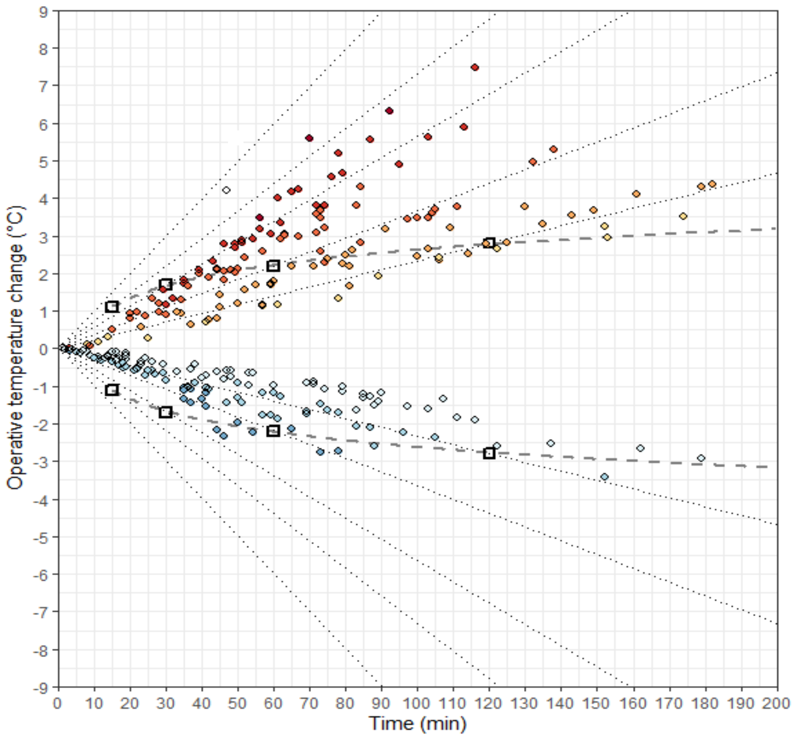
Total number of ramps: 181
With "thermal discomfort event": 136

Experimental condition

- 4.4°C/h < ramp ≤ 6.0°C/h
- 3.4°C/h < ramp ≤ 4.4°C/h
- 2.2°C/h < ramp ≤ 3.4°C/h
- 1.4°C/h < ramp ≤ 2.2°C/h
- 0.0°C/h < ramp ≤ 1.4°C/h
- 0.0°C/h > ramp ≥ -1.4°C/h
- -1.4°C/h > ramp ≥ -2.2°C/h
- -2.2°C/h > ramp ≥ -3.4°C/h
- -3.4°C/h > ramp ≥ -4.4°C/h
- -4.4°C/h > ramp ≥ -6.0°C/h)

Thermal discomfort event

Cell A and B



Experimental condition	Total Ramps	With "thermal discomfort event"
4.4°C/h < ramp ≤ 6.0°C/h	6	3
3.4°C/h < ramp ≤ 4.4°C/h	46	30
2.2°C/h < ramp ≤ 3.4°C/h	60	45
1.4°C/h < ramp ≤ 2.2°C/h	52	38
0.0°C/h < ramp ≤ 1.4°C/h	21	14
0.0°C/h > ramp ≥ -1.4°C/h	72	62
-1.4°C/h > ramp ≥ -2.2°C/h	63	44
-2.2°C/h > ramp ≥ -3.4°C/h	33	17
-3.4°C/h > ramp ≥ -4.4°C/h	0	0
-4.4°C/h > ramp ≥ -6.0°C/h)	0	0
	353	253

ASHARE comfort limit

Statistics Analysis (ongoing)

- **Multilevel linear modelling**
  – Participants' thermal sensation
- **Multilevel logistic modelling**
  – Participants' thermal acceptability
- **Survival Analysis**
  – Discomfort event (stop button)

Presentations

Session 1 - Fifth presenter

Kane, Michael

Northeastern University, USA

Session 1

Day 1, 12:34

Occupant-Centric Control with Personalized and Contextual Thermal Comfort Behaviour Dynamics Prediction

M. Kane

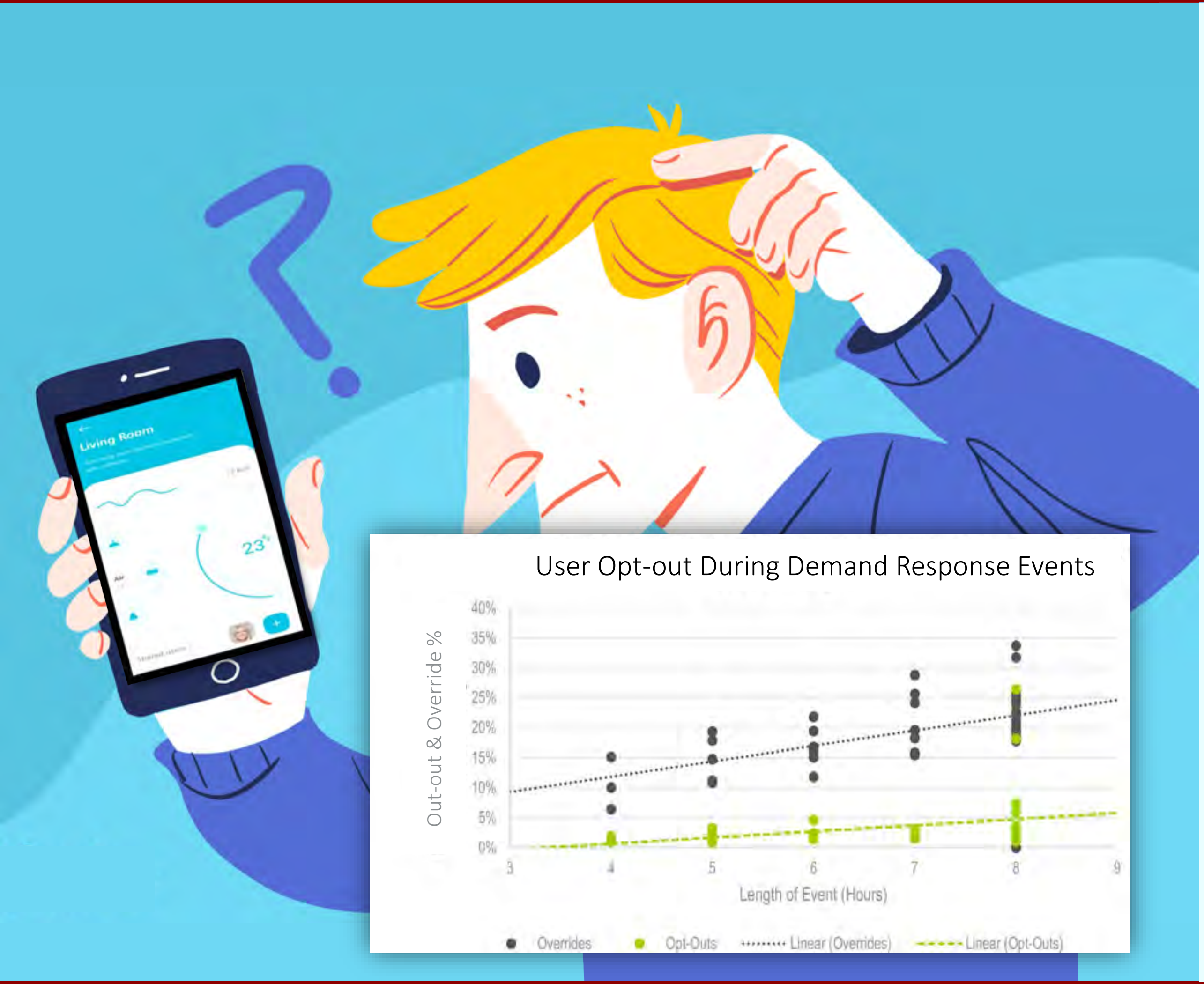
Demand response (DR) as a gear in the energy sector, works to curtail peak electricity demand to maintain high grid reliability and reduce costly transmission capacity. Conventional DR programs use emails, texts, and phone calls, with the latest automatic DR using direct load control. These methods lack fidelity to provide accurate load curtailment. Even with the advent of adoption smart devices, the same settings are implemented for all participants, irrespective of each person's thermal comfort zone, leading to reduced quality of service. Eventually, frustration tends to mount up and the result is an increase in occupant overrides, over 30% of 8-hour DR events in one study. The consumers as a result of this frustration lose trust, which further impacts demand response programs and utilities in the form of millions of dollars in penalties nationwide. This motivates the need to personalize thermal comfort and architect DR controls that consider contextual and personal factors. The goal the work to be presented is to develop personalized predictive models of manual thermostat overrides. Machine learning methods like decision trees and artificial neural network applied to the ecobee Donate Your Data dataset with ~1259 users and ~285 events per user. Based on these methods, the resulting personalized models are compared in terms of their accuracy, computational complexity, and outlier management. Interactions with ecobee thermostats were also analyzed to predict the impact of such personalized DR on overrides, energy curtailment magnitude, and reliability.

Occupant-Centric Control with Personalized and Contextual Prediction Thermal Comfort Behavior Dynamics

… Let's Make Automation Serve the People, not the Algorithms

Michael B Kane, PhD; Kunind Sharma
Assistant Prof., Civil and Environmental Engineering, Northeastern University

Motivation



Occupant Satisfaction

Electric Load Flexibility

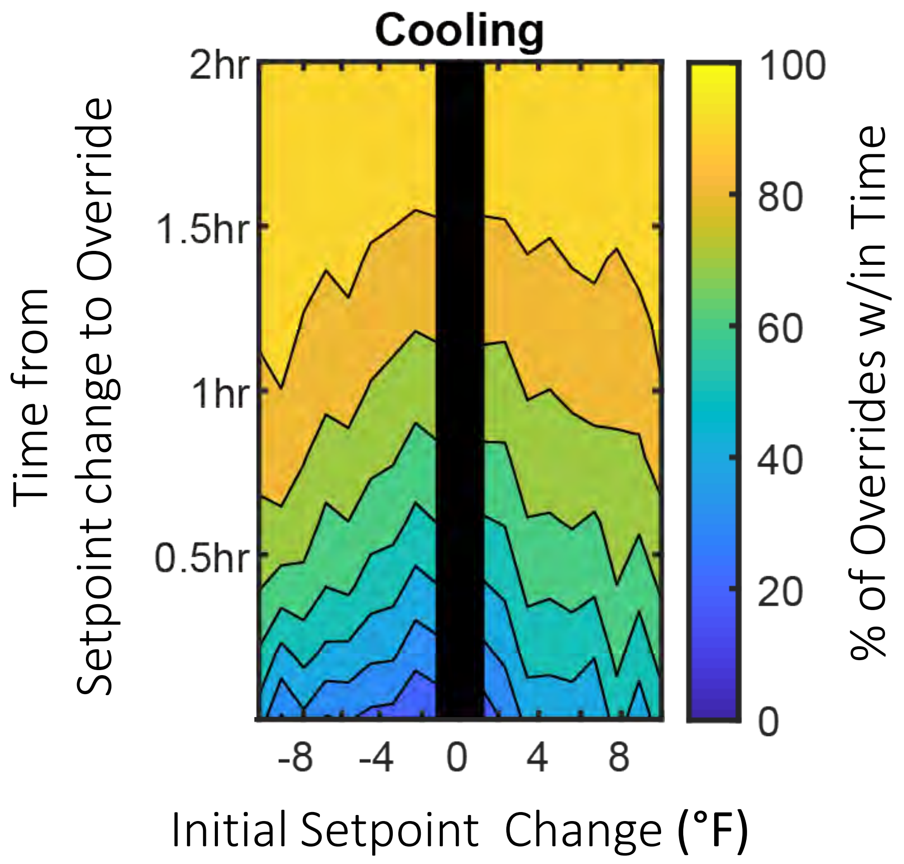
Overview

Contextual & Personal Predictions *of*

Occupant Thermal Comfort Behavior

and its impact on

Load Flexibility Capacity and Reliability



Overview

Contextual & Personal Predictions *of*

Occupant Thermal Comfort Behavior

and its impact on

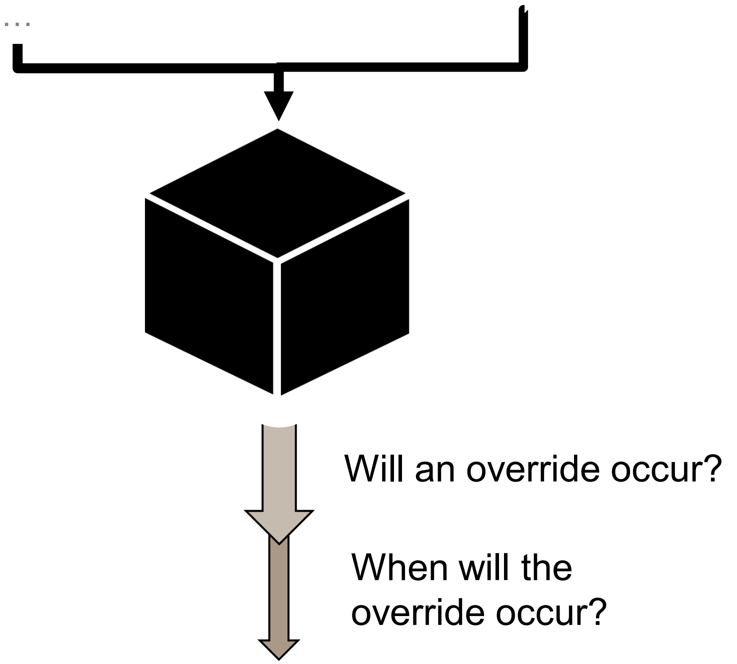
Load Flexibility Capacity and Reliability

Contextual

Relative Humidity
Previous setpoint
Outdoor Temp
Indoor Temp.
Occupied?
Setpoint
Season
Event
…

Personal

Day of week overrides (Avg.)
Time of day of override (Avg.)
% stp. ↑/↓ in a season (Avg.)
% stp ↑/↓ in a season (%)
Instance response (Avg.)
Override delay (Avg.)
Override mag. (Avg.)
…



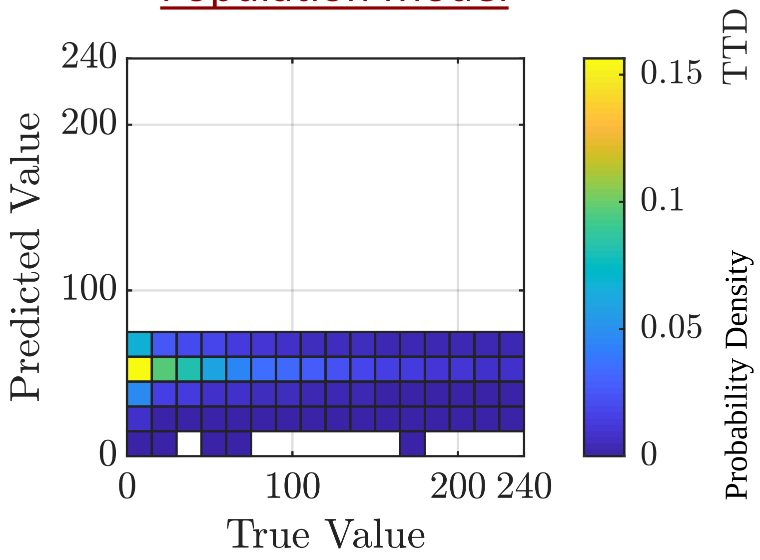
Will an Override Occur? Neural Net vs Decision Tree

		True Value				Row Summary	
		No Override		Override			
Predicted Value	No Override	50.4% *103,538*	45.9% *94,368*	15.5% *31,753*	13.9% *28,598*	76.5% 23.5% *135,291*	76.7% 23.3% *122,966*
		46.7% *96,036*	46.3% *95,198*	29.5% *60,658*	29.0% *59,678*	61.3% 38.7% *156,694*	61.5% 38.5% *154,876*
	Override	2.3% *4,774*	6.8% *13,944*	31.8% *65,399*	33.4% *68,554*	93.2% 6.8% *70,173*	83.1% 16.9% *82,498*
		6.0% *12,276*	6.4% *13,114*	17.8% *36,494*	18.2% *37,474*	74.8% 25.2% *48,770*	74.1% 25.9% *50,588*
Column Summary		95.6% 4.4% *108,312*	**99.8%** 0.2% *108,312*	67.3% 32.7% *97,152*	**70.6%** 29.4% *97,152*		
		88.7% 11.3% *108,312*	**88.0%** 12.0% *108,312*	37.6% 62.4% *97,152*	**38.6%** 61.4% *97,152*		

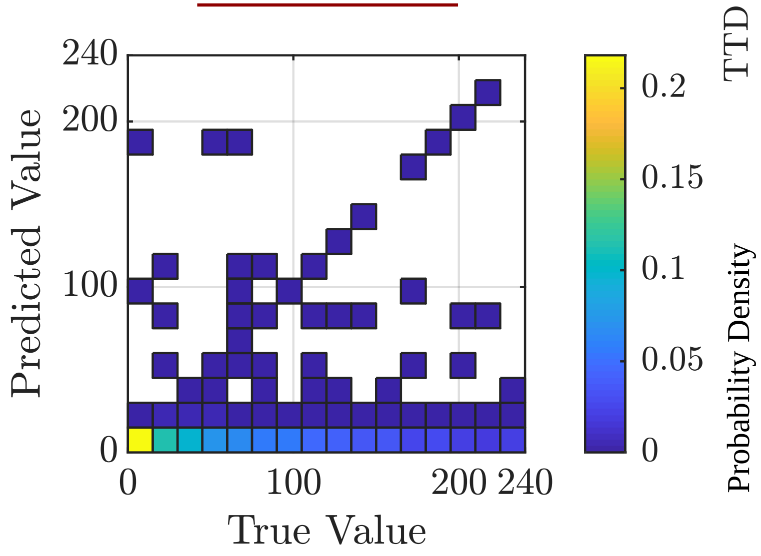
Northeastern University
College of Engineering

If so, When will the User Override?

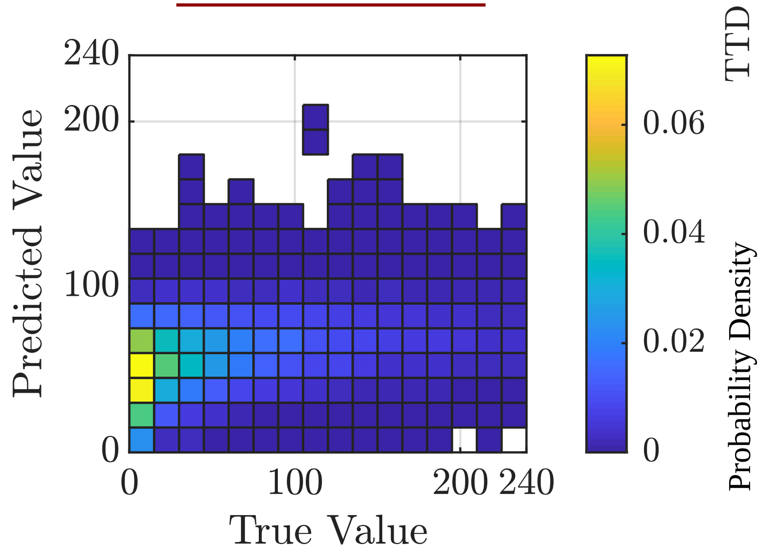
Population Model



Decision Tree



Neural Network



	Cooling RMSE	Heating RMSE		Cooling RMSE	Heating RMSE		Cooling RMSE	Heating RMSE
	150-min	152-min		201-min.	208-min.		108-min.	113-min.
				198-min.	209-min.		112-min.	112-min.

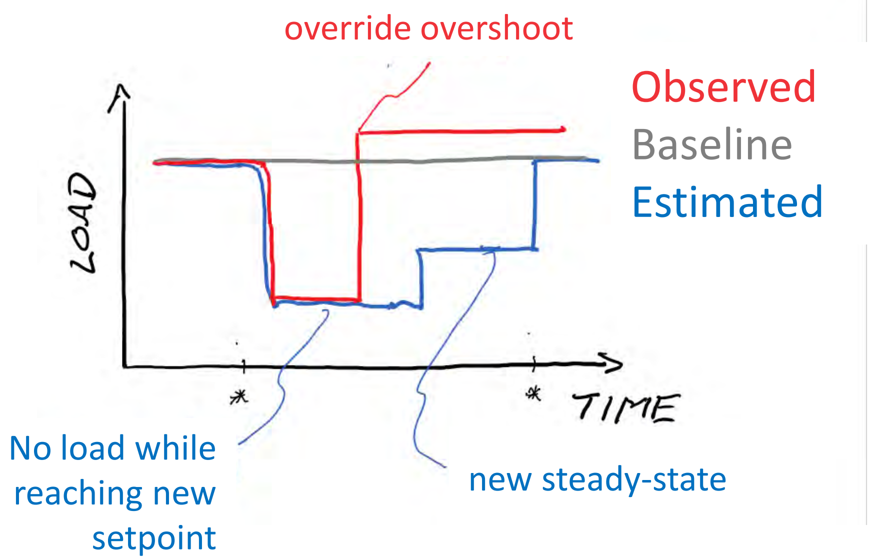
Overview

Contextual & Personal Predictions *of*

Occupant Thermal Comfort Behavior

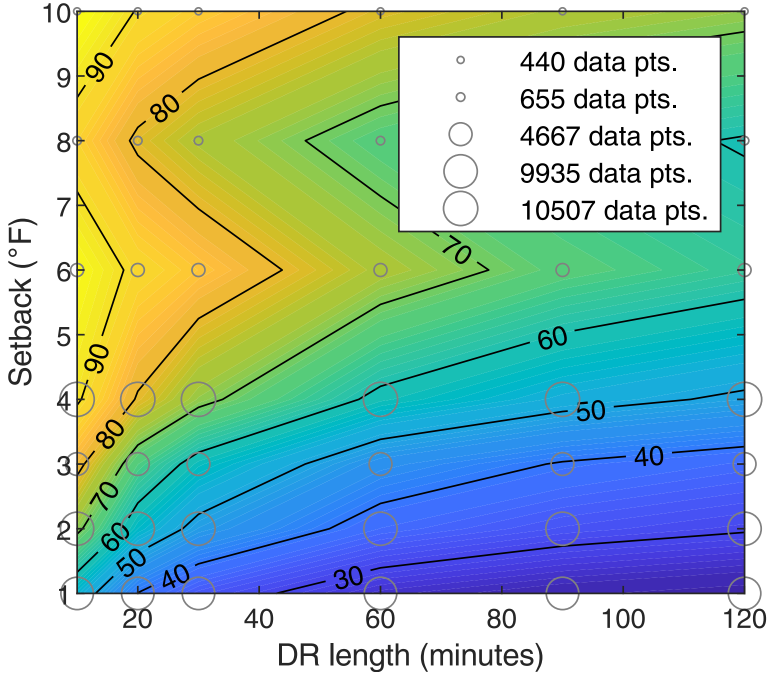
and its impact on

Load Flexibility Capacity and Reliability

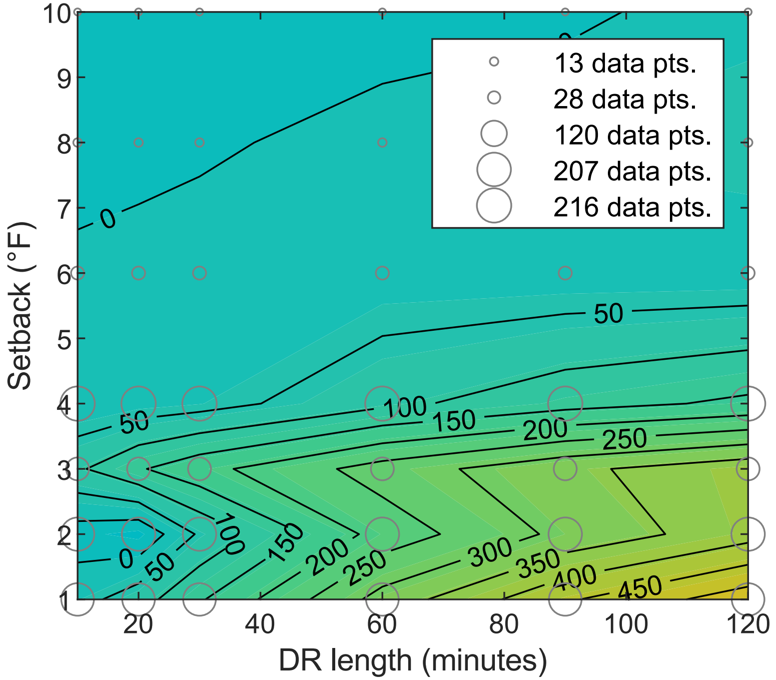


Overrides & Load Shedding Error

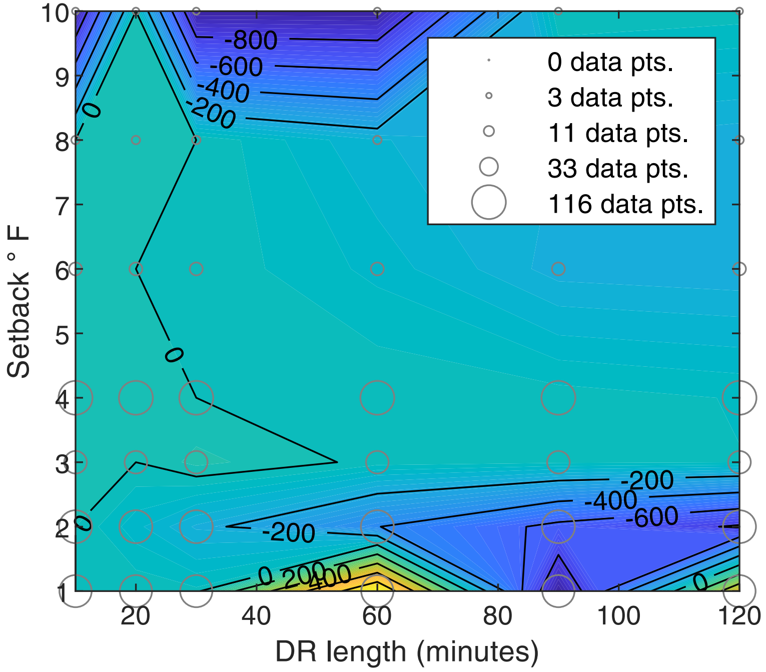
Curtailment *vs* Baseline without Overrides



Curtailment *Error* with Overrides



Curtail *Error with* Personalized Setback Duration



Thank You

Any Questions?

Presentations

Session 1 - Sixth presenter

Pisello, Anna,
Vittorj, Filippo &
Pigliautile, Ilaria

University of Perugia, Italy

Session 1

Day 1, 12:38

On Multidimensional Comfort: Multi-Parametric Experimental Experiment Within a BIM Designed Virtual Environment

A. Pisello, F. Vittori, I. Pigliautile

Architecture, Engineering, and Construction industry professionals, together with building physics scientists, agree about the key role played by building occupants in determining final energy needs imputable to their energy-related behaviors. Occupant behavior represents indeed a major variable affecting buildings' energy performance, but its impact is difficult to predict since the early design stage. That is the reason why this study proposes a new analysis framework and field test method aimed at better comprehending and monitoring people feelings and attitudes, while stimulated by means of virtual design stage variables and building energy efficiency parameters, assumed to produce non-negligible effect on people perception and related actions. Nevertheless, the same selection and construction of a proper test bench represents a key issue within this research framework, together with the selection of the affecting variables, for better predicting occupants' perception versus the indoor environmental quality. This work proposes to face this challenge by means of Virtual Reality (VR) strategies included in a workflow where immersive environments are modeled in a parametric platform, able to change the geometry and every necessary peculiarity of the future spaces, after verifying the immersive quality of the virtual context. The investigated methodology integrates Building Information Model (BIM) and VR in order to simulate the human factor in the built environment. A preliminary validation test is submitted to 50 people, with a result of 76% of tested subjects declaring a satisfactory sense of presence inside the virtual environment, showing promising possible development in the field of multidimensional comfort studies.

Annex 79-EBC by IEA

5th International Symposium on Occupant Behaviour

Filippo Vittori

Ilaria Pigliautile, Anna Laura Pisello

Southampton 20/23/2020

Università degli studi di Perugia

On Multidimensional Comfort: Multi-Parametric Experiment Within a BIM

VR simulation, field survey, and multi-physics monitoring through BIM

VR + BIM method

Target

Propose a methodology able to provide low-cost tools for the simulation of conditions influencing perceptions of indoor and outdoor comfort

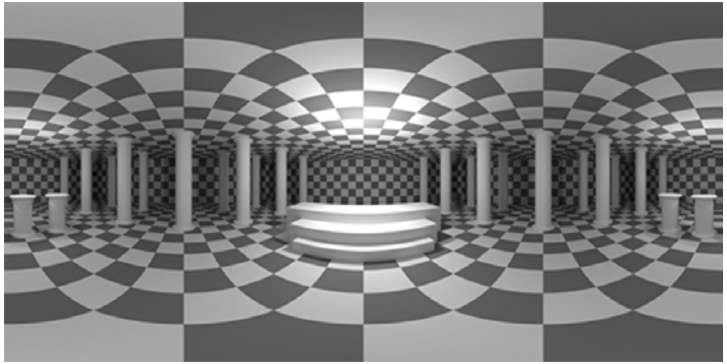
Procedure

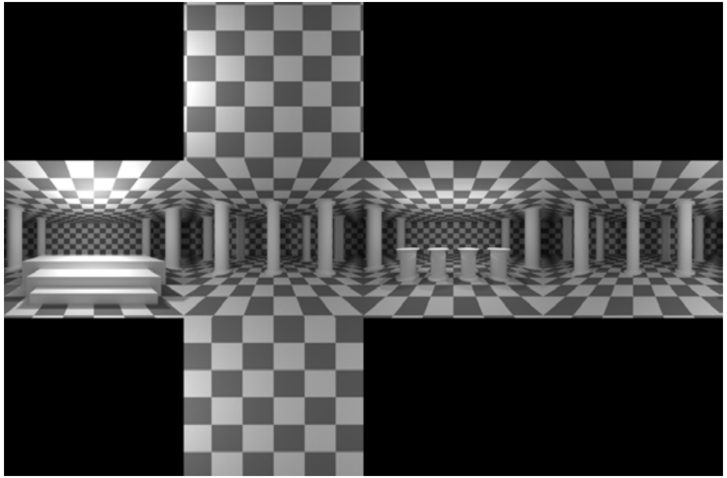
Phase 0 :	Phase 1 :	Phase 3:
concept	validation	experiment

concept

VR

- Immersivity
- Physical presence
- Simulation
- Inexpensiveness
- Easy to use





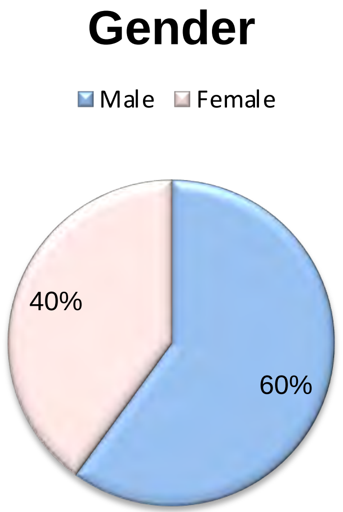
VR

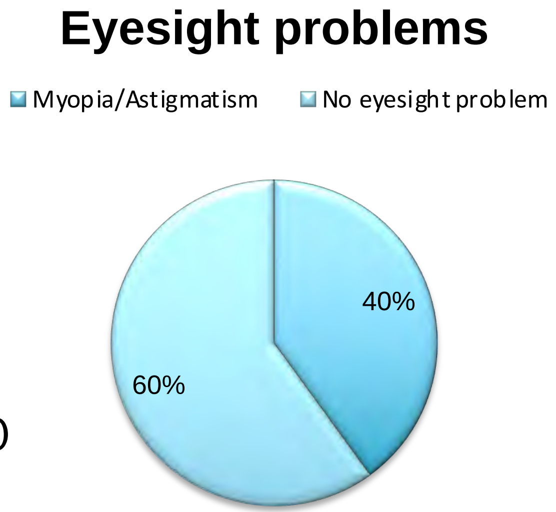
- Immersivity
- Physical presence
- Simulation
- Inexpensiveness
- Easy to use

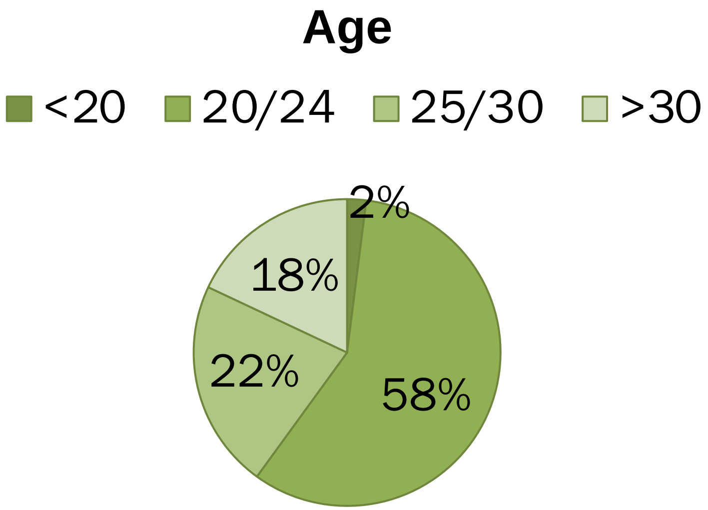
validation
50 people

sense of presence(1/5)

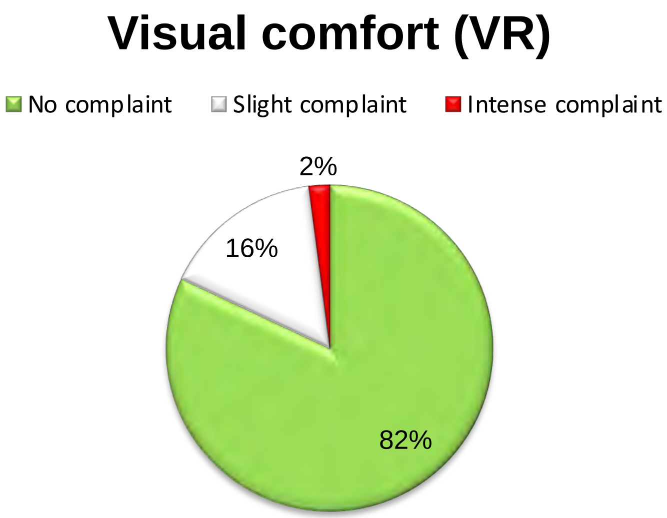
Sample

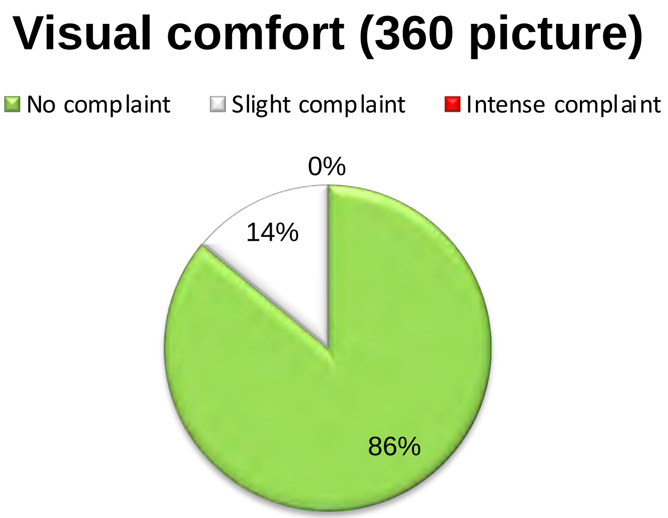

Gender
Male
Female
40%
60%


Eyesight problems
Myopia/Astigmatism
No eyesight problem
40%
60%

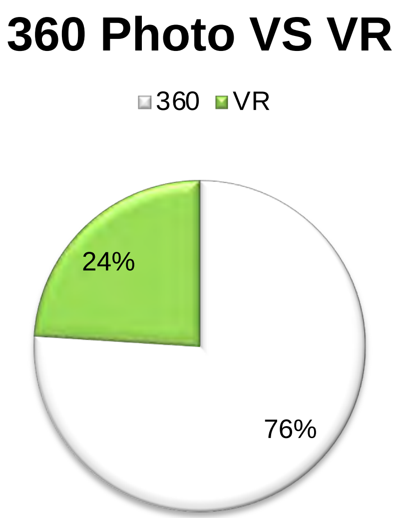

Age
<20
20/24
25/30
>30
2%
18%
22%
58%

Results

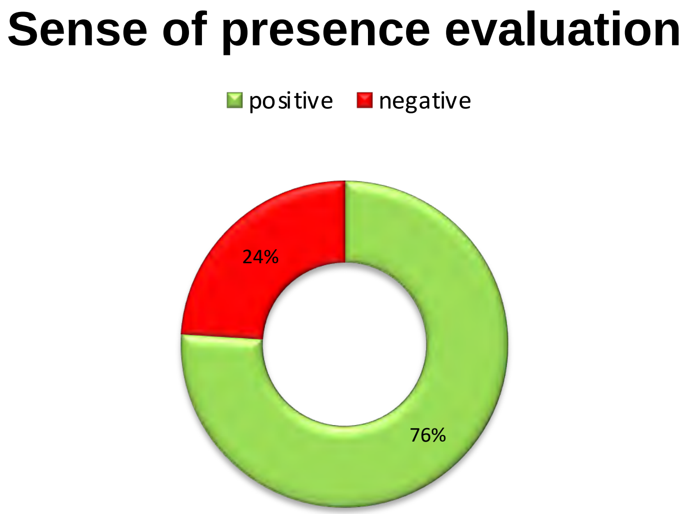

Visual comfort (VR)
No complaint
Slight complaint
Intense complaint
2%
16%
82%

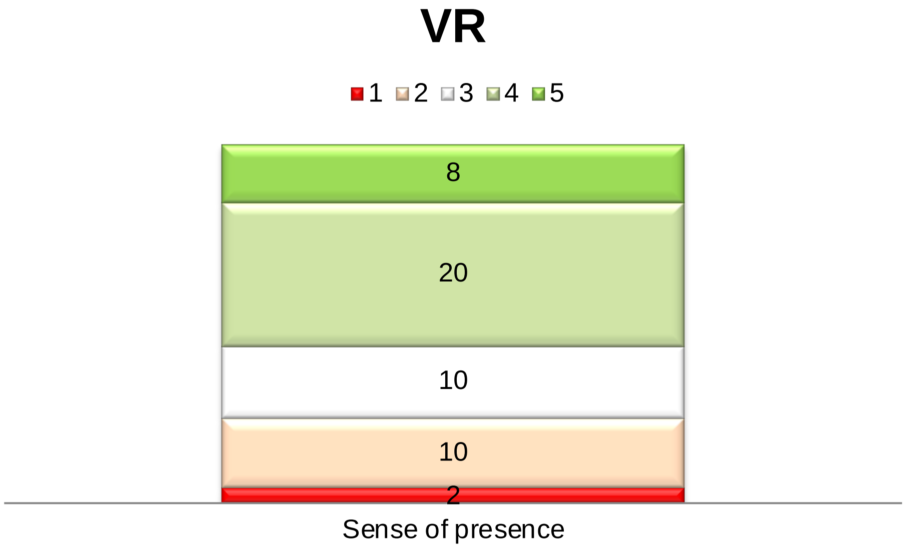

Visual comfort (360 picture)
No complaint
Slight complaint
Intense complaint
0%
14%
86%

Results



Results


Sense of presence evaluation
positive
negative
24%
76%


VR
1
2
3
4
5
8
20
10
10
2
Sense of presence

experiment
100 people

comfort (-2/+2)

3 parameters
4 blocks
12 scenes

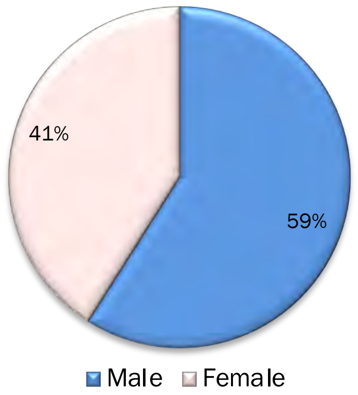
window aspect ratio

window coating

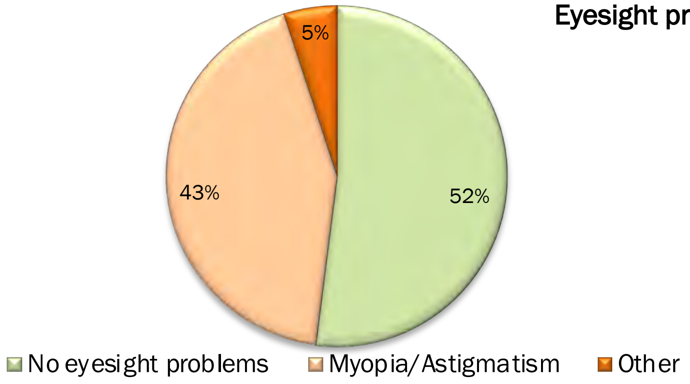
color temperature of lighting fixtures

Sample

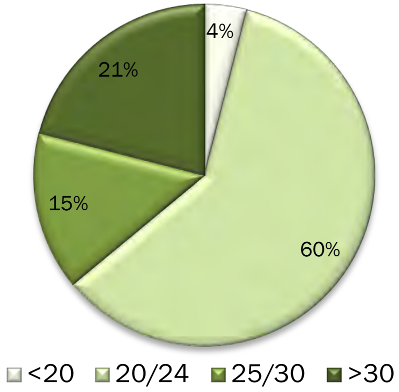
Gender



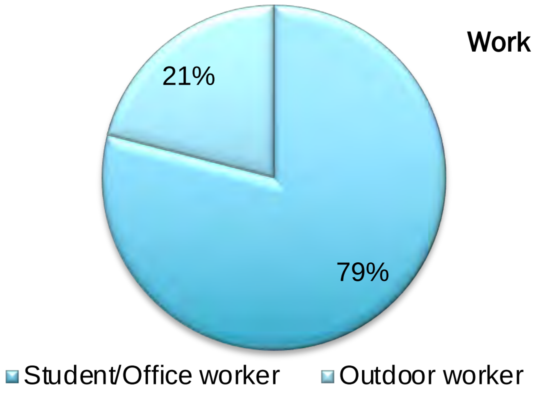
Eyesight problems



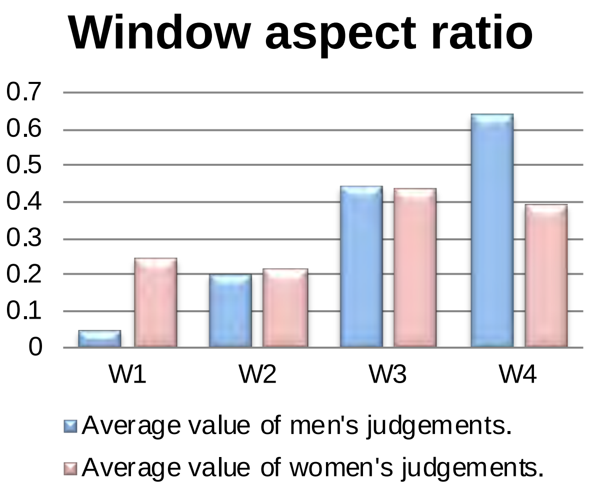
Age

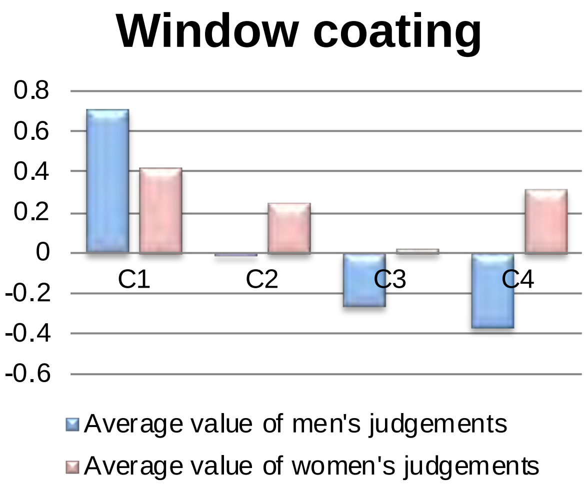


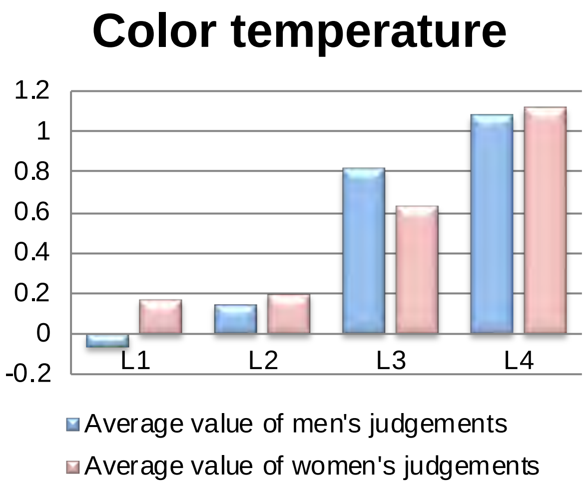
Work environment



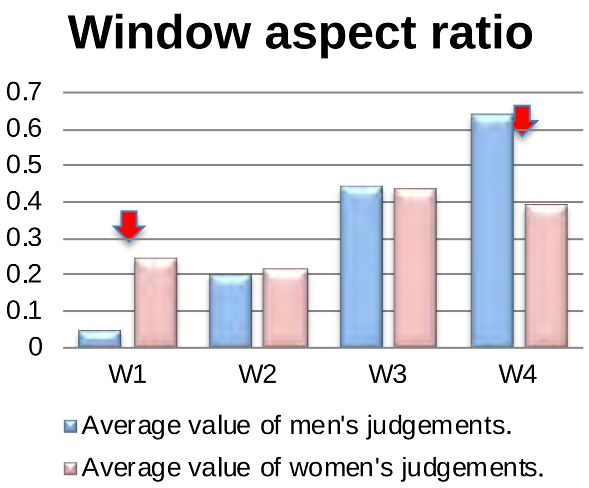
Results

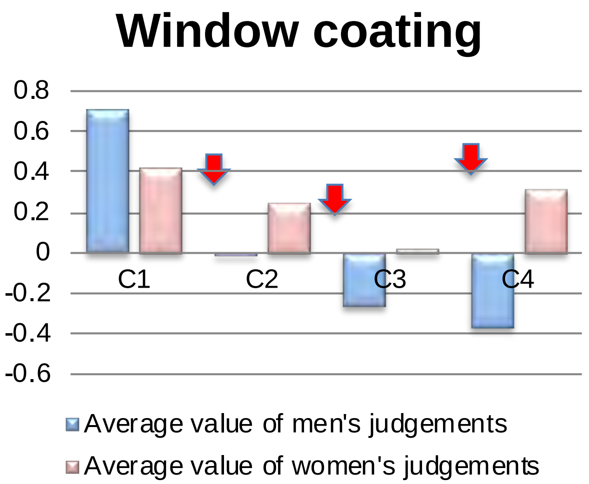

Window aspect ratio
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
W1
W2
W3
W4
Average value of men's judgements.
Average value of women's judgements.

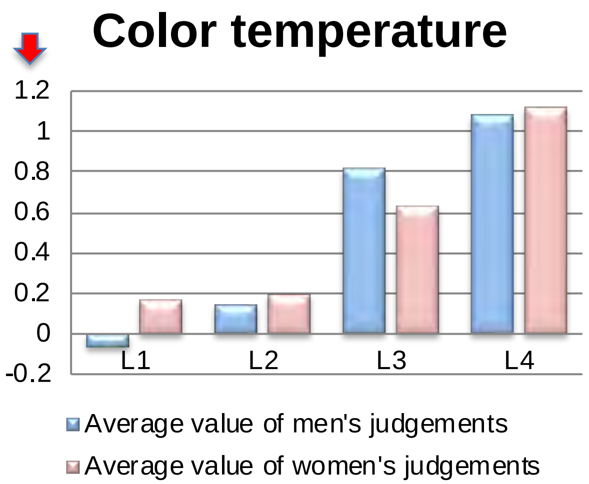

Window coating
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
C1
C2
C3
C4
Average value of men's judgements
Average value of women's judgements


Color temperature
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
L1
L2
L3
L4
Average value of men's judgements
Average value of women's judgements

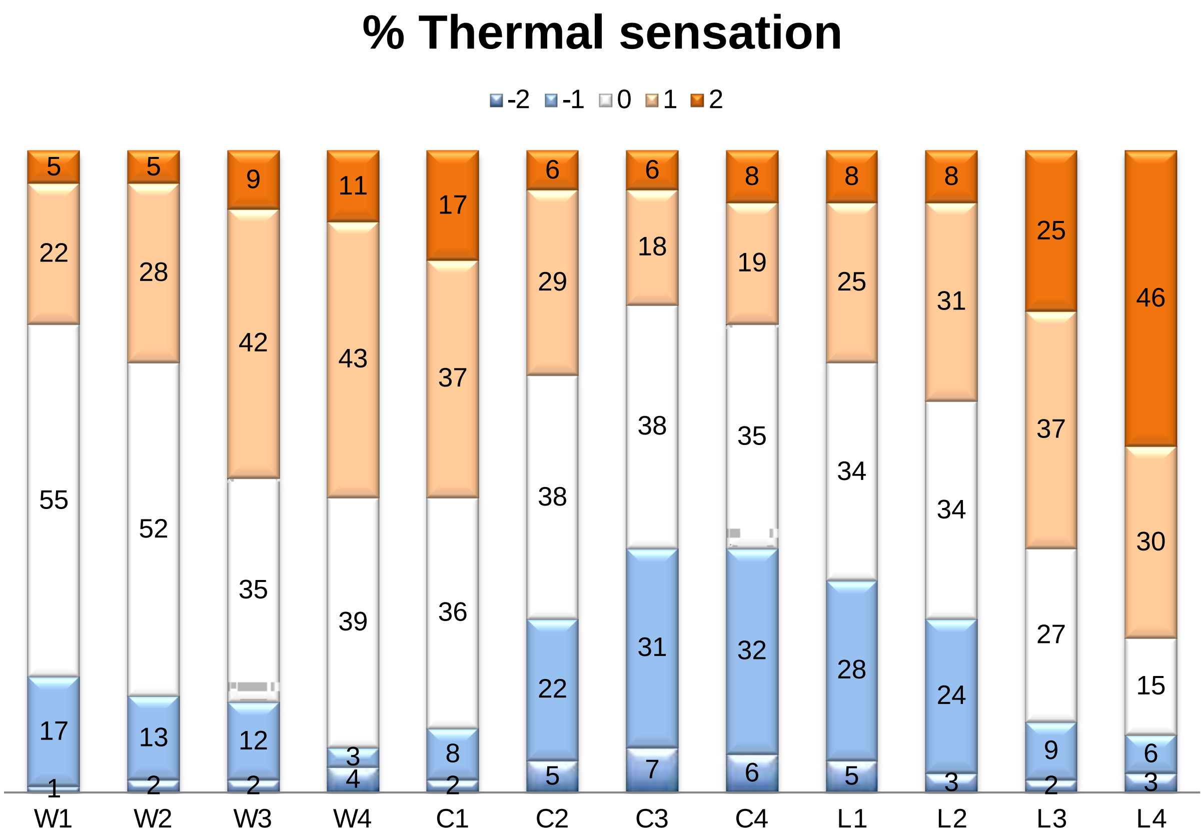
Results


Window aspect ratio
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
W1
W2
W3
W4
Average value of men's judgements.
Average value of women's judgements.


Window coating
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
C1
C2
C3
C4
Average value of men's judgements
Average value of women's judgements


Color temperature
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
L1
L2
L3
L4
Average value of men's judgements
Average value of women's judgements

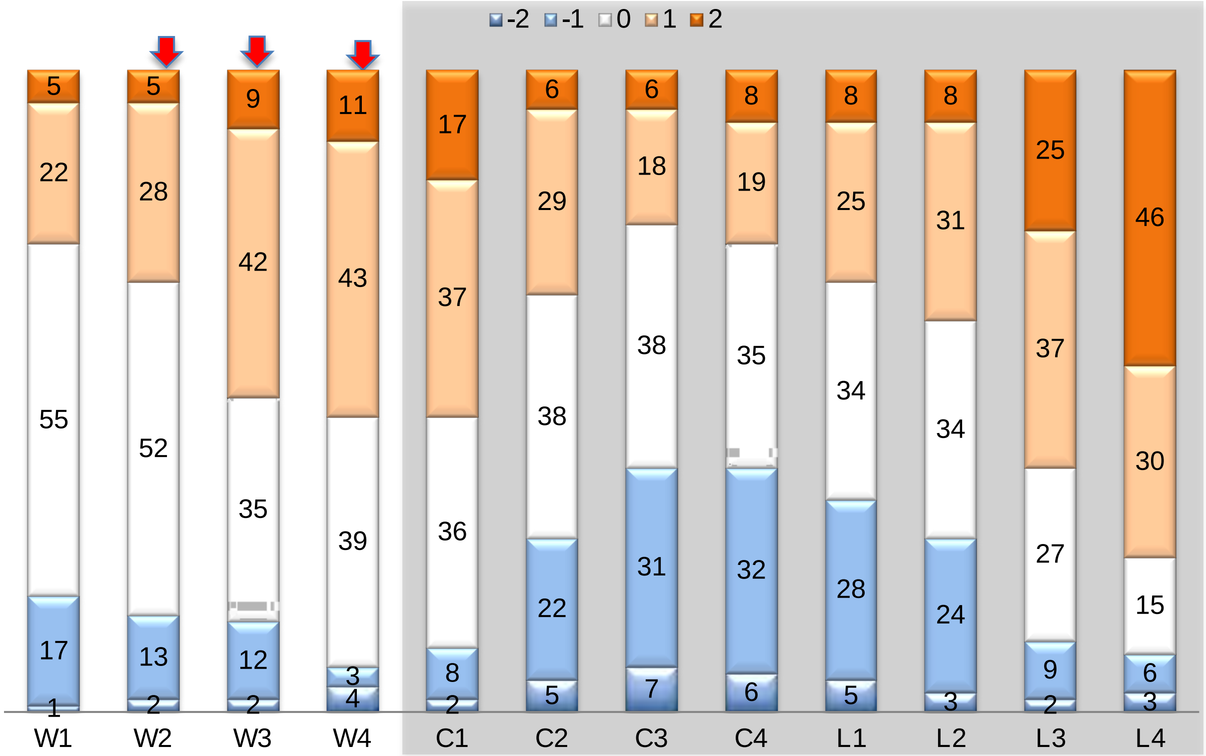
Results



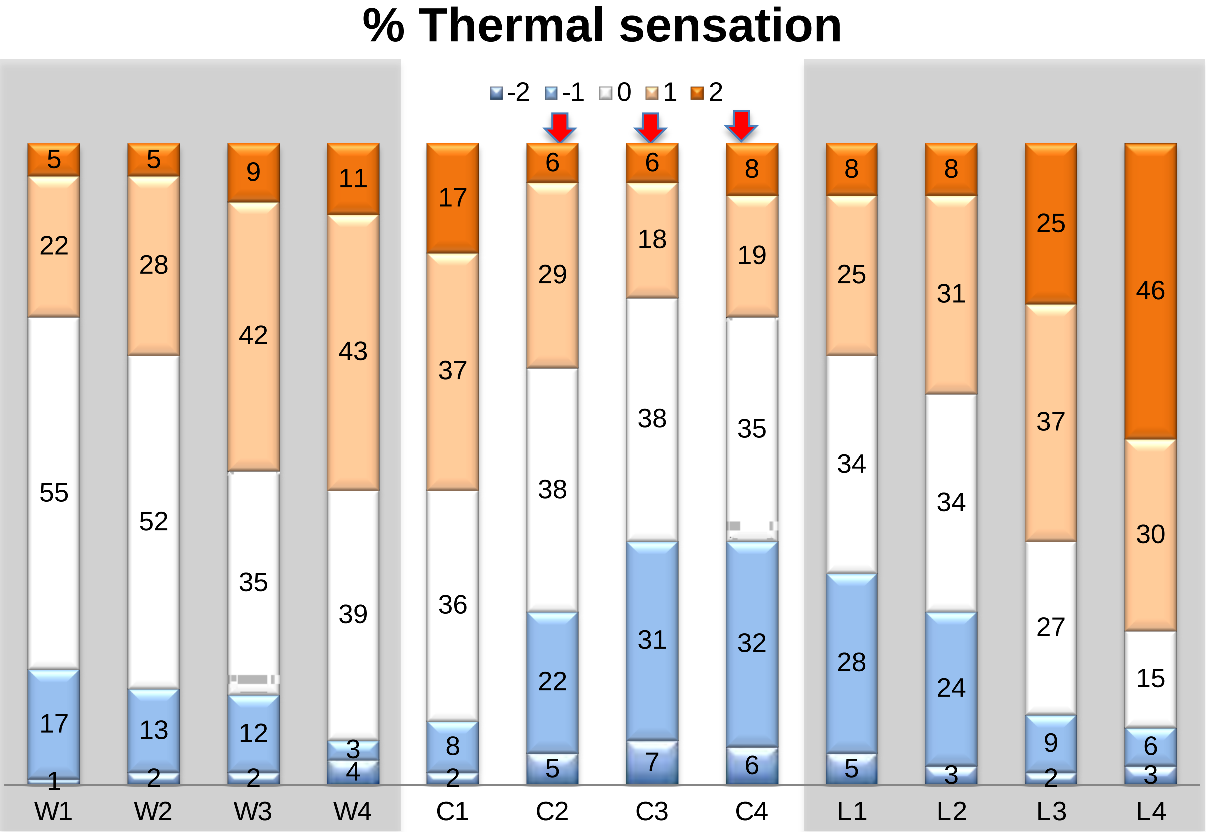
% Thermal sensation
-2 -1 0 1 2
W1: 1, 17, 55, 22, 5
W2: 2, 13, 52, 28, 5
W3: 2, 12, 35, 42, 9
W4: 4, 3, 39, 43, 11
C1: 2, 8, 36, 37, 17
C2: 5, 22, 38, 29, 6
C3: 7, 31, 38, 18, 6
C4: 6, 32, 35, 19, 8
L1: 5, 28, 34, 25, 8
L2: 3, 24, 34, 31, 8
L3: 2, 9, 27, 37, 25
L4: 3, 6, 15, 30, 46

Results

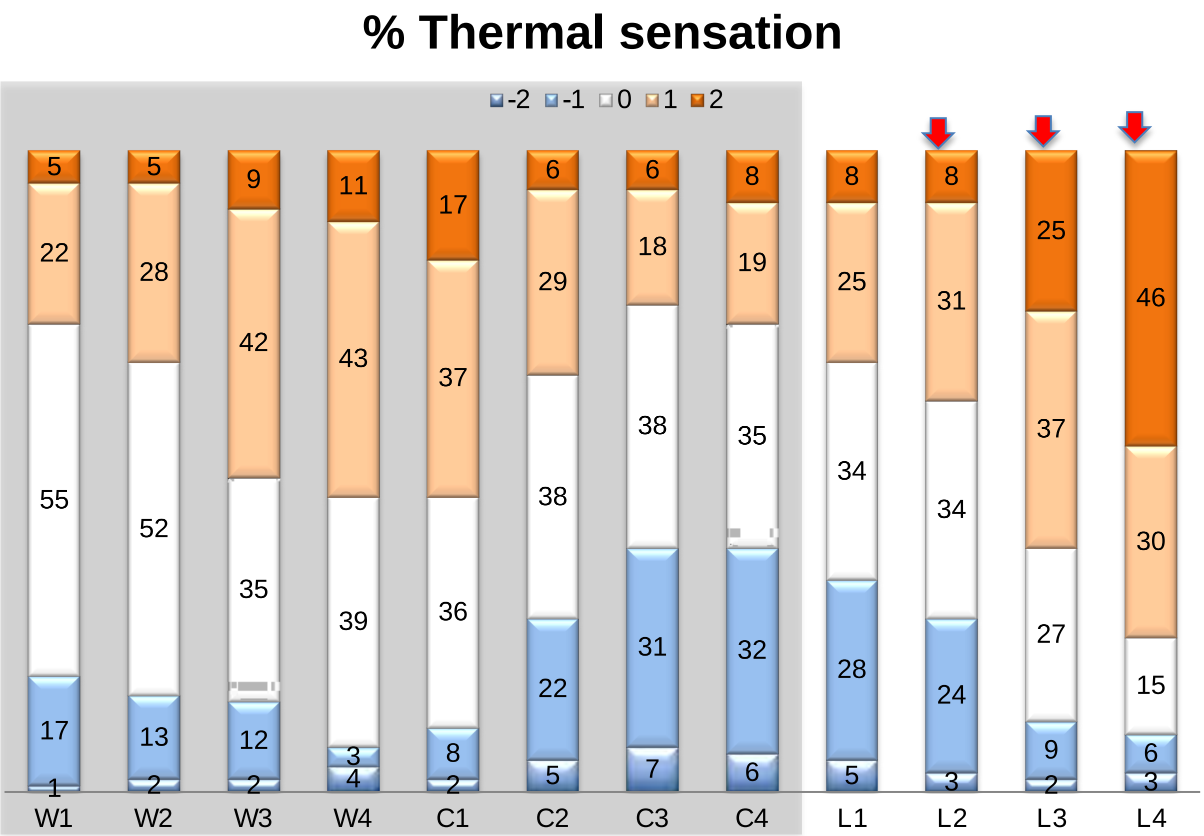
% Thermal sensation



Results


% Thermal sensation
-2 -1 0 1 2
W1: 1, 17, 55, 22, 5
W2: 2, 13, 52, 28, 5
W3: 2, 12, 35, 42, 9
W4: 4, 3, 39, 43, 11
C1: 2, 8, 36, 37, 17
C2: 5, 22, 38, 29, 6
C3: 7, 31, 38, 18, 6
C4: 6, 32, 35, 19, 8
L1: 5, 28, 34, 25, 8
L2: 3, 24, 34, 31, 8
L3: 2, 9, 27, 37, 25
L4: 3, 6, 15, 30, 46

Results


% Thermal sensation
-2 -1 0 1 2
W1: 1, 17, 55, 22, 5
W2: 2, 13, 52, 28, 5
W3: 2, 12, 35, 42, 9
W4: 4, 3, 39, 43, 11
C1: 2, 8, 36, 37, 17
C2: 5, 22, 38, 29, 6
C3: 7, 31, 38, 18, 6
C4: 6, 32, 35, 19, 8
L1: 5, 28, 34, 25, 8
L2: 3, 24, 34, 31, 8
L3: 2, 9, 27, 37, 25
L4: 3, 6, 15, 30, 46

further developments

Thank you for the attention

Presentations

Session 2 - First presenter

Hobson, Brodie

Carleton University, Canada

Session 2

Day 1, 13:25

Implementation of Occupancy-Based Predictive Controls for Outdoor Air Intake Dampers: Lessons Learned

B. Hobson

As modern workplaces begin to transition towards flexible work hours, commercial and institutional buildings are hosting a fraction of their maximum occupancy on typical workdays. Despite this, most HVAC systems operate on static pre-set schedules that assume the building is almost fully occupied during working hours, resulting in chronic overventilation. As conditioning outdoor air requires significant energy in heating dominated climates, there is a growing oppourtunity to reduce energy use and greenhouse gas emissions by providing HVAC services at an appropriate level for the actual occupancy of the building, without significantly impacting occupant comfort. However, reactive controls based on occupant-count estimates alone are insufficient for optimal operation of system-level equipment, such as air handling units. This is due to the transient nature of buildings' thermal and air quality conditions. Instead, forecasting occupancy levels can facilitate proactive and informed decisions about air handler operations. An occupancy-based predictive control program was implemented in a building automation system to control the outdoor air intake dampers of two air handling units. Clustering and motif identification were used to create a rules-based approach for occupancy forecasting by leveraging readily available electrical load data and historic Wi-Fi device count data. Three-parameter univariate changepoint models show that the program reduced building cooling and heating energy use by 10.3% and 38.4%, respectively, during a 24-week implementation period. The program had a negligible impact on indoor CO_2 concentrations and caused a 5.8% reduction in hours spent within ± 1°C of temperature setpoints. Challenges and relevant anecdotes from the implementation are also examined and discussed. This study highlights how occupancy data can improve building operational efficiency without the need for additional sensing or controls infrastructure.

Implementation of Occupancy-Based Predictive Controls for Modulation of Outdoor Air Dampers: Lessons Learned

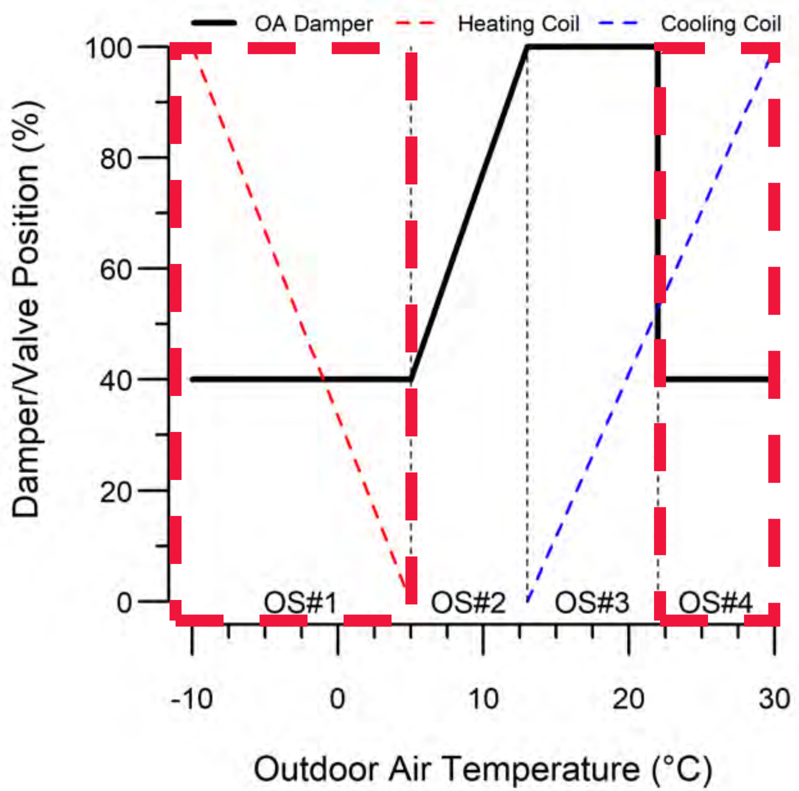
Brodie W. Hobson, EIT

Supervised by: Prof. H. Burak Gunay, PhD, PEng

Case Study Building

- Academic office building in Ottawa, Canada.
- Mix of private/semi-private offices, labs, classrooms.
- Served by two AHUs that provided 10,000 L/s (1000 persons) combined outdoor air at 30% and 40% minimum position.


West façade of building [1]



Operating State (OS)	Heating Valve (%)	Cooling Value (%)	OA Damper (%)
#1 Heating	0 < x < 100	0	40
#2 Free cooling	0	0	40 < x < 100
#3 Economizing + cooling	0	0 < x < 50	100
#4 Mechanical cooling	0	50 < x < 100	40

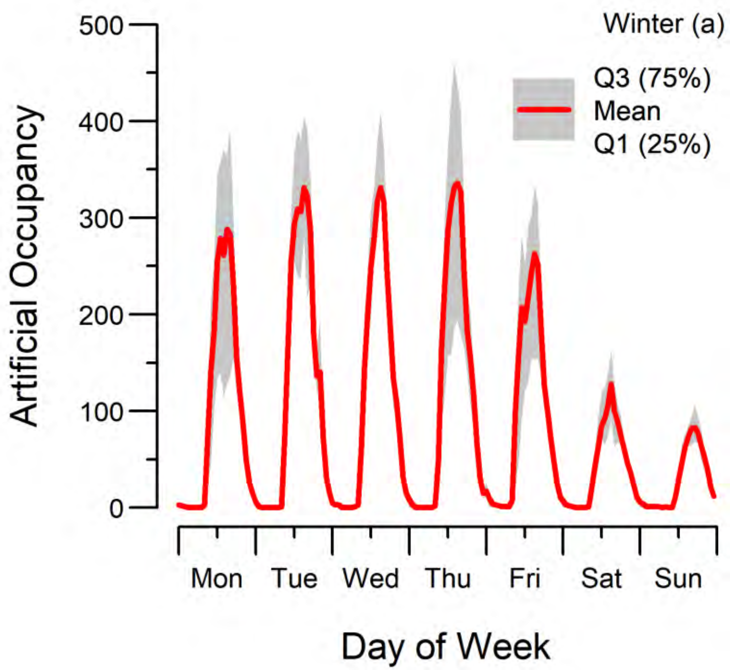
Adapted from *ASHRAE Guideline 36* [2]

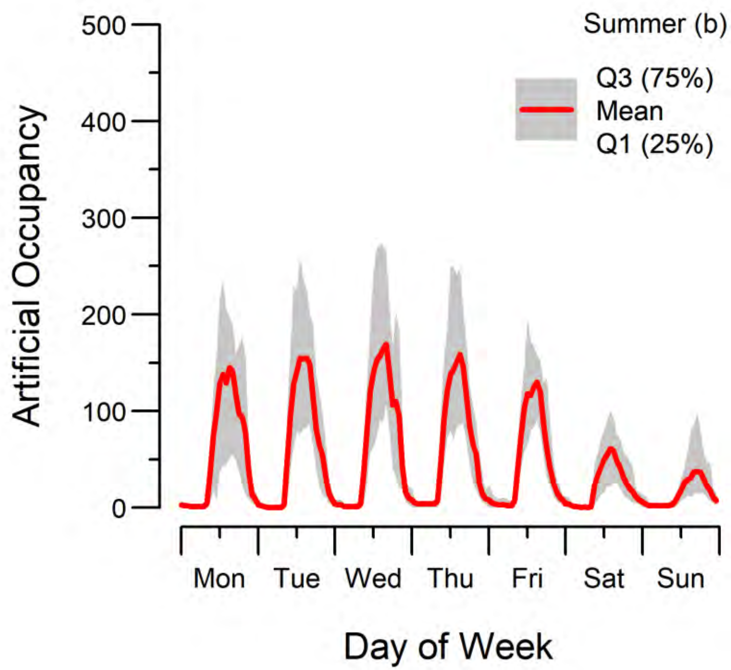
Overview

- Objective: **Predict** occupancy-levels in a case study building to make proactive decisions about reducing AHU outdoor air damper positions to meet the needs of the building occupants.
- Considerations:
  1. Implementation must be made with commercially available and already installed sensors and software.
  2. Maintain acceptable indoor air quality.
  3. Generate HVAC energy savings.

Occupancy Forecast

- Peak occupancy in the building estimated at approx. 500 persons with average weekday occupancy of approx. 250 persons (recall 1000 persons used for operation).



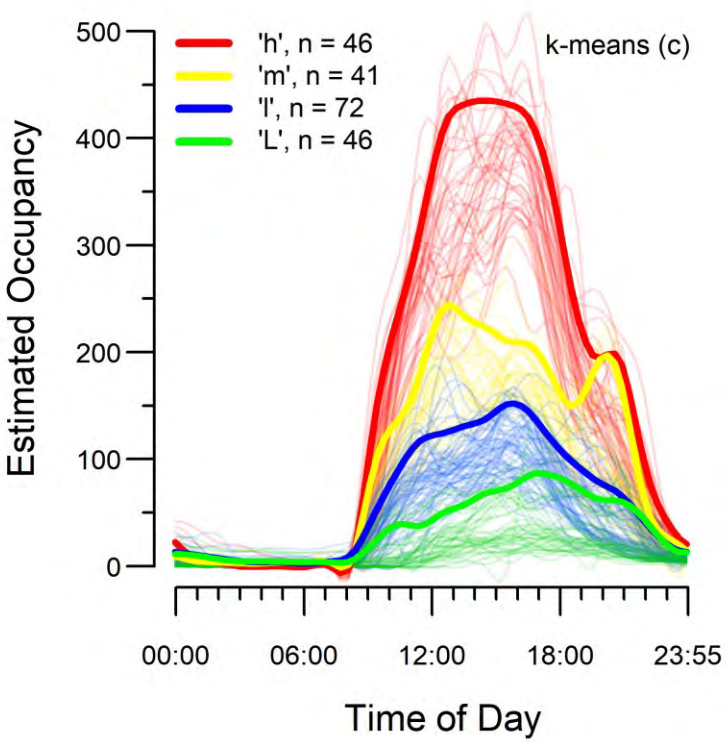


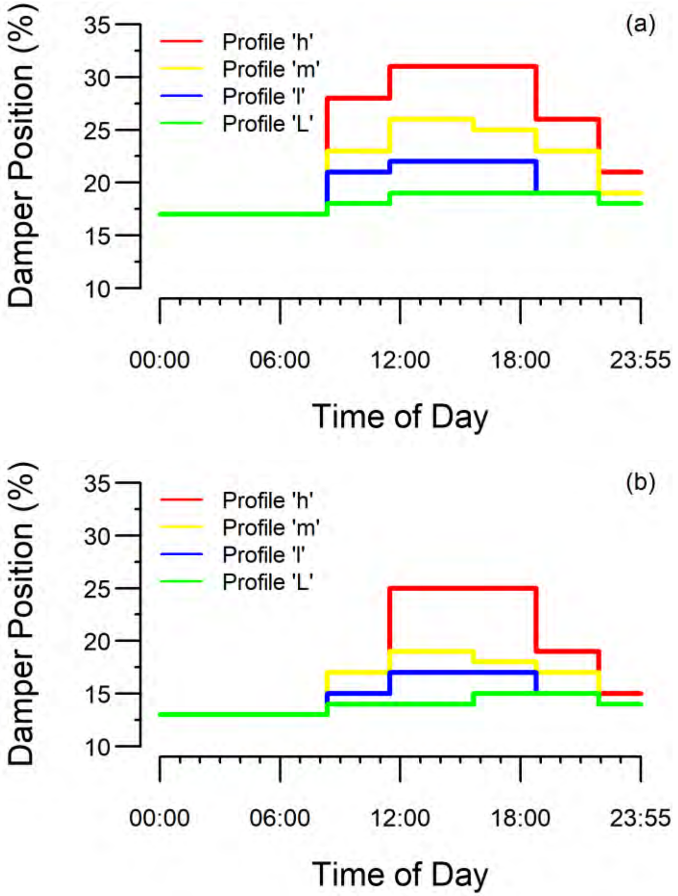
Occupancy Forecast

- Typical time-series forecasting techniques are either computationally expensive or require data isolated from the BAS.
- Instead, a rules-based forecast can be trained offline and implemented in the BAS without additional infrastructure.
- Three main components:
  1. Clustering
  2. Motif/discord identification
  3. Classification tree

Occupancy Forecast

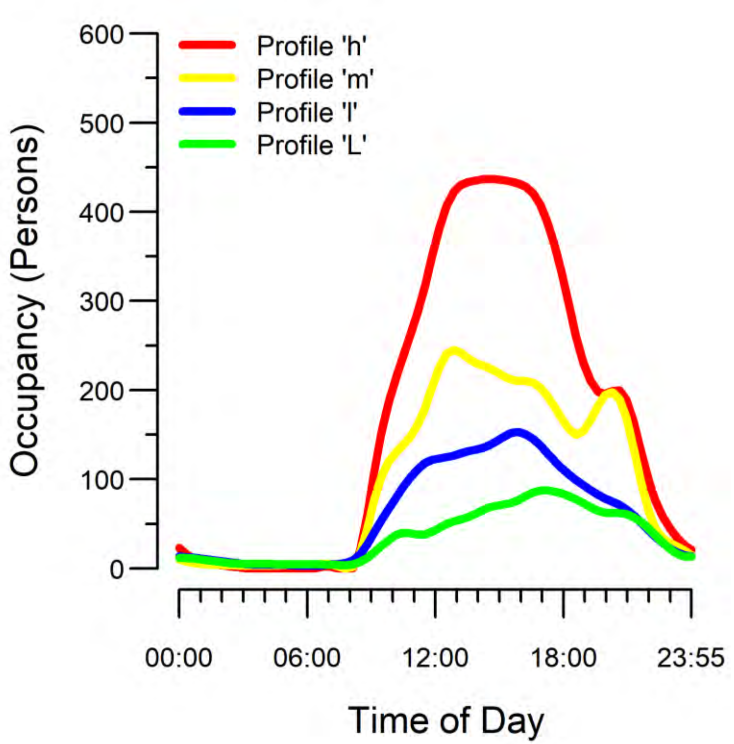
1. Clustering: Find a handful of representative daily profiles.

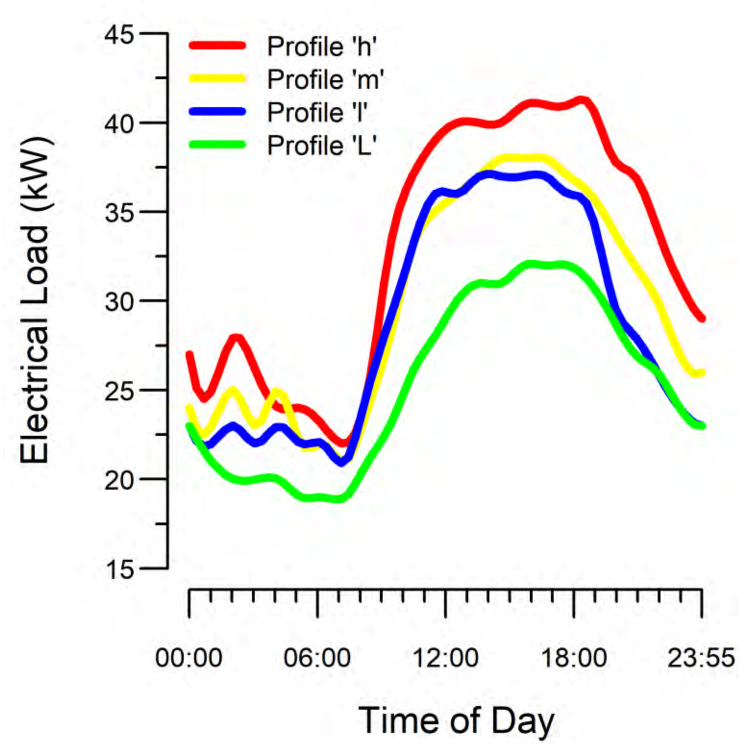




Occupancy Forecast

1. Clustering: Find a handful of representative daily profiles.





Occupancy Forecast

2. Motif identification: Find frequently repeated sequences of days (i.e., letters).

lLhhhhhlLhhhhhmLhhhhhlLlmmmmlLhhhhhlLhhhhhllhhhhhlLhhhh

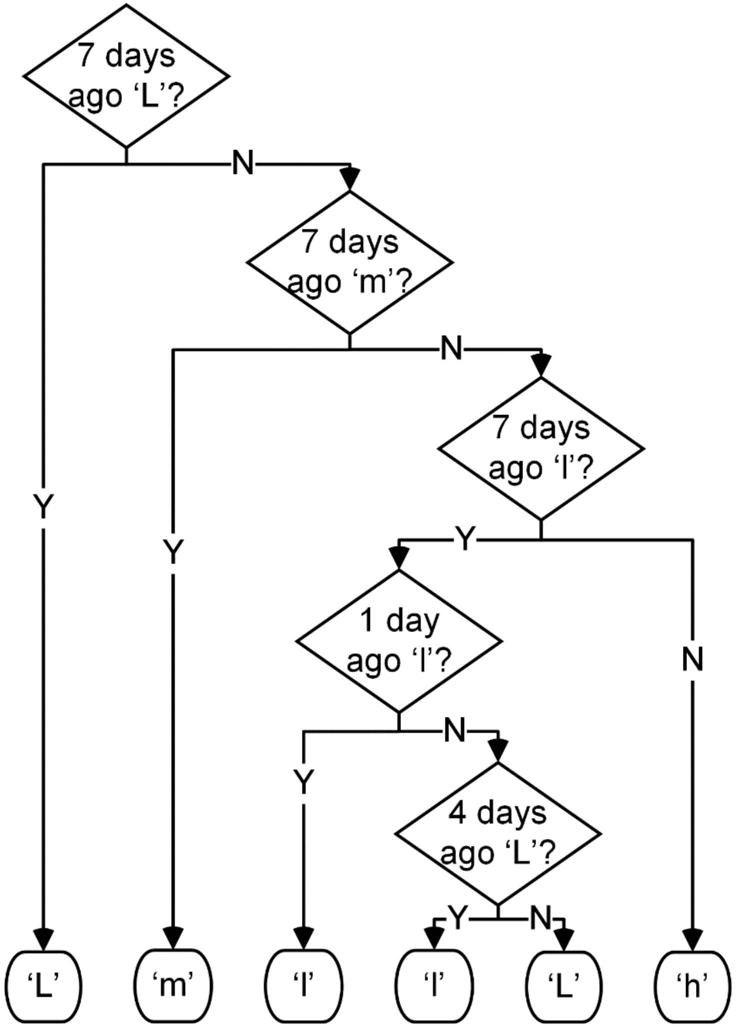
hmLhhhhlLLhhhhhlLmhhmmlllmlmllllmlllLlllllLLmmmLlLLmmmmlL

LLmmmmlLmmmmllLmmmmlLLmmmmllLmmlllLlllllLLLLmlLLmllll

Occupancy Forecast

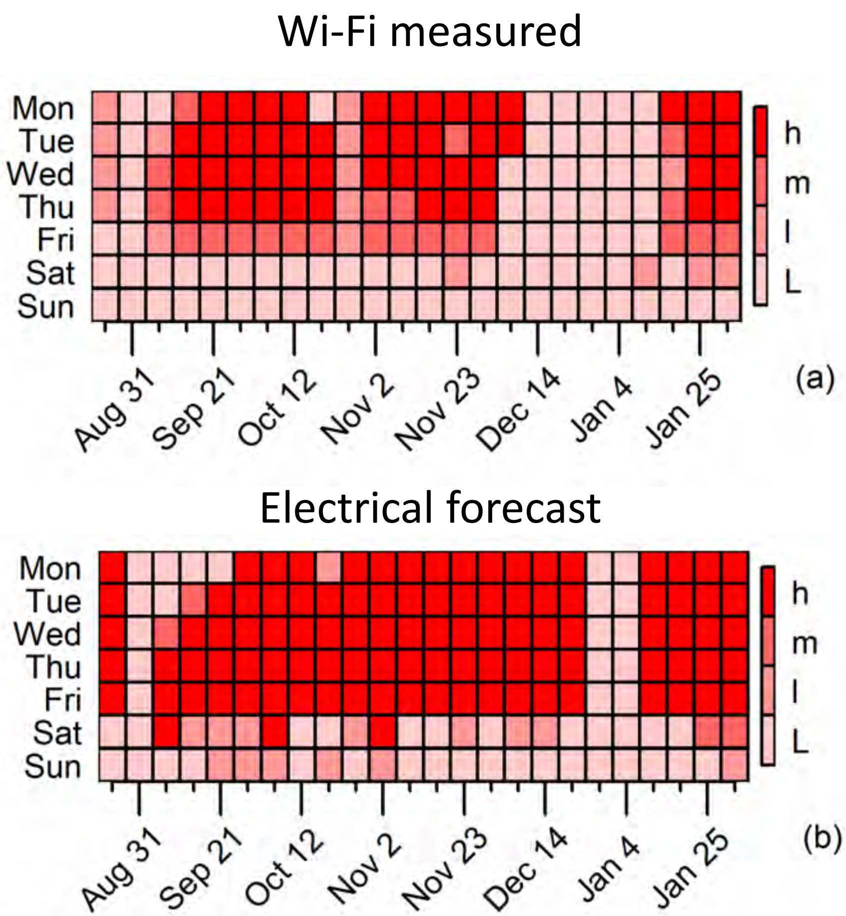
3. Classification tree: Determine what the character for the next day will be based on motif/discords.

- Prediction accuracy: 70.4%, but highly conservative.



Implementation Results

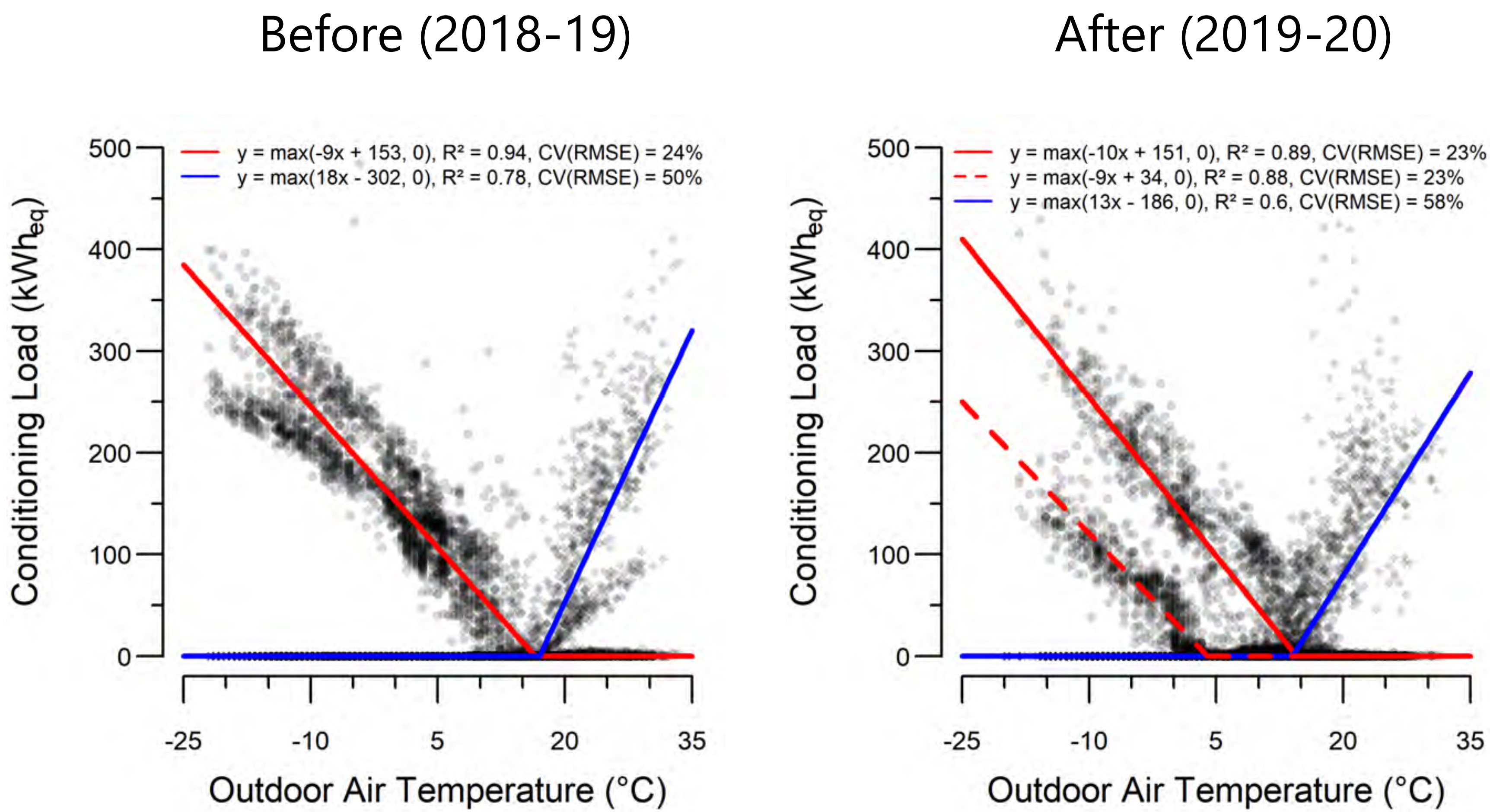
- Forecast accuracy: 58%, 97% classified correctly or overclassified.



Electrical forecast \ Wi-Fi measured	h	m	l	L
h	48	20	11	22
m	1	1	1	0
l	0	0	1	12
L	1	1	2	46

Implementation Results

Building Performance Research Centre
Carleton University

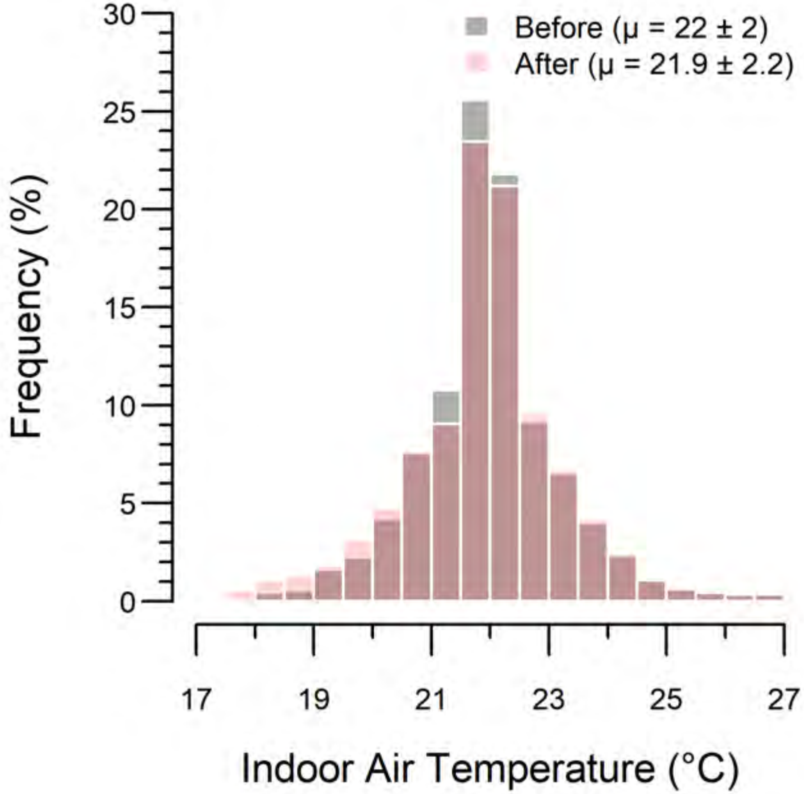


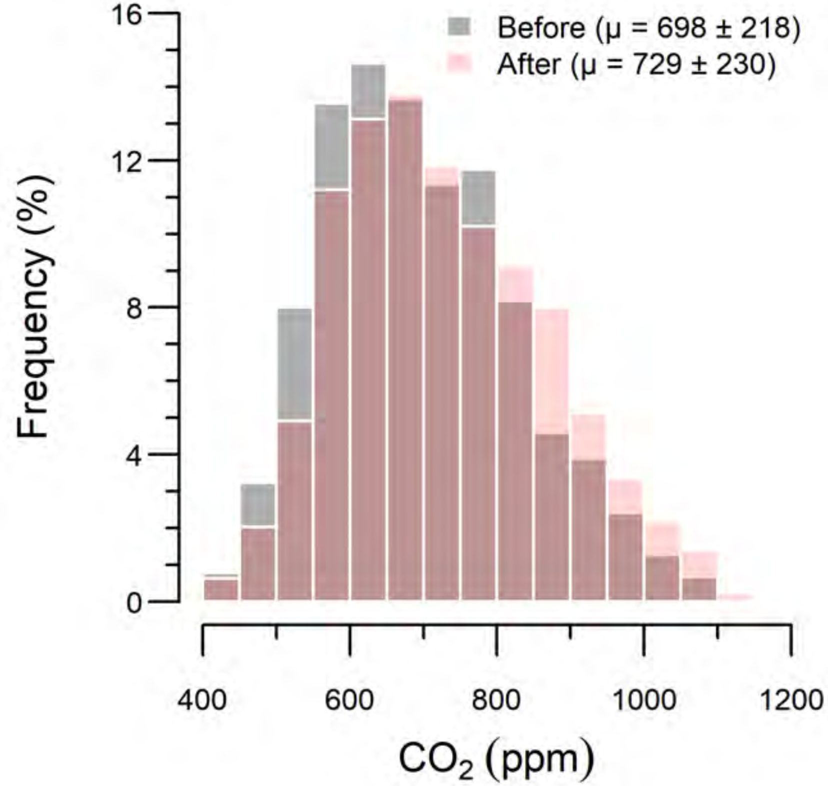
Implementation Results

Load	Before* (MWh_{eq})	After (MWh_{eq})	Est. Savings (%)
Heating	297	183	38.4
Cooling	85	76	10.3
Fan energy	71	70	2.8

*using baseline changepoint model on 2019-20 weather

Implementation Results





Lessons Learned

- Rules-based OCC can be implemented using available technology to generate HVAC energy savings.
- Faults in BAS should be identified and corrected before undertaking any OCC implementation.
- Airflow characteristics of dampers at low positions should be studied to determine OAF accurately in these low-flow regimes.
- Tweaks to zone-level equipment (i.e., VAVs) may help further eliminate any IAQ concerns.

Thank You

Questions?

brodie.hobson@carleton.ca

References

[1] R. Pilon, *Canal Building – Carleton University*. Photograph, 2014.

[2] ASHRAE. 2016. "ANSI/ASHRAE Standard 62.1-2016: Ventilation for Acceptable Indoor Air Quality." Atlanta, GA.

Presentations

Session 2 - Second presenter

Miller,
Clayton

National University of Singapore, Singapore

Session 2

Day 1, 13:35

What do Occupants Want? Let's Ask Them Using Smart Watches and Cozie
C. Miller

A large amount of focus is placed on the passive detection and characterization of occupancy using sensors and machine learning. These techniques have made significant progress in certain aspects of performance improvement, namely in energy conservation (turning things off when no one is there). However, when it comes to the thermal, aural, or visual preferences of the occupants, sometimes observation is not enough - we need to ask them what they like. This presentation will a set of experiments using wearables devices and an open-source platform called Cozie. The methodology showcased is Ecological Momentary Assessment (EMA), an ad-hoc method of collecting information from experimental participants in the field in a longitudinally-intensive way. We show the initial deployment of Cozie in several scenarios in Singapore and request collaboration for deployment in other research projects around the world. Issues are covered related to survey fatigue, sampling rate, and subtle integration into tools designed for uses other than feedback.

National University of Singapore

What do occupants want? Let's ask them using smart watches and Cozie

Clayton Miller, Ph.D.

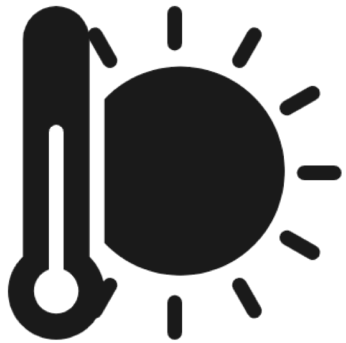
National University of Singapore

clayton@nus.edu.sg

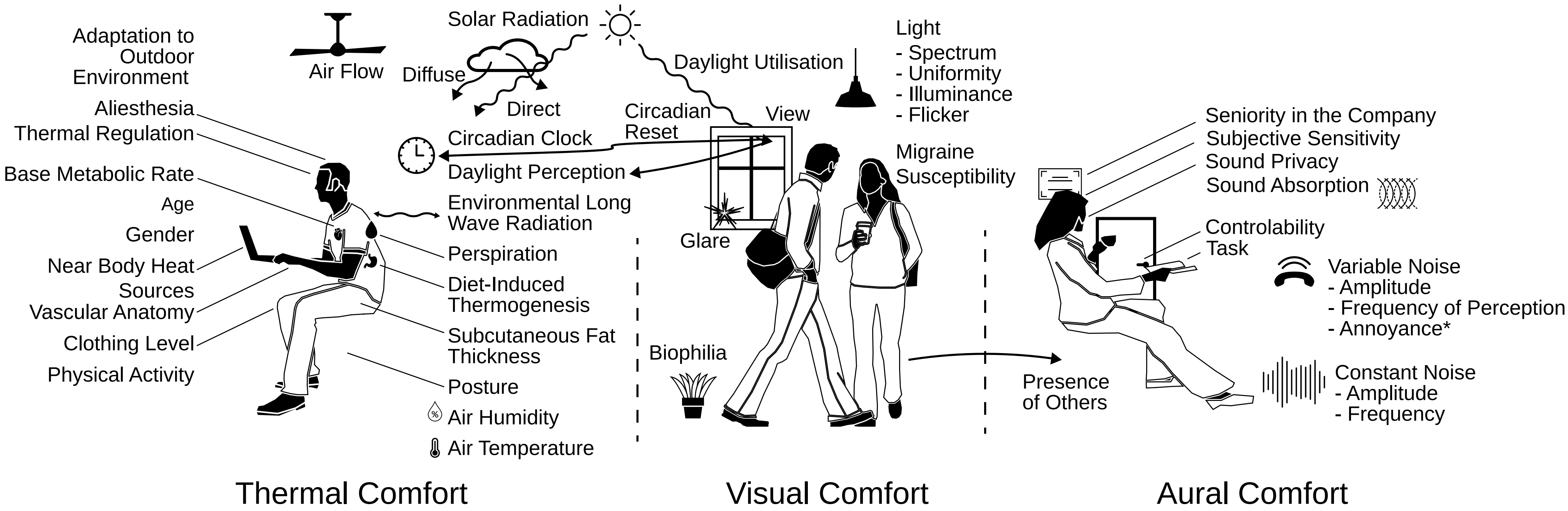
The Age Old Question in the Built Environment

What do occupants want?

How do we understand what influences preference in the indoor environment?



There are numerous factors that influence comfort and preference in the built environment



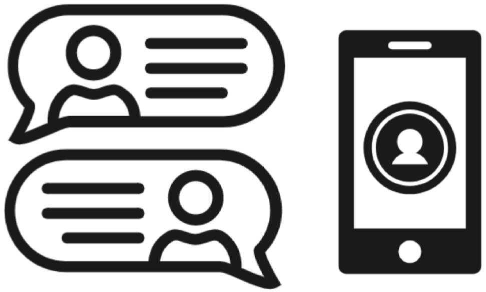
Do we need to measure all of these environmental, physiological, psychological, and behavioral attributes?

Or can we train models by collecting data from the best sensor of all (humans)? (Jayathissa et. al, 2020 Preprint)

Facebook, Google, Amazon, etc. collect human preference very successfully

Several large digital companies dominate the advertising and retail industries.

A large portion of this success is due to innovation in the way they collect information:



They create digital platforms that provide value to users

And harvest specific preference feedback in that context

How do make a “Like” button for buildings and spaces?

How do we get in-context preference data collection that is specific to objectives related to satisfaction with spaces?

The built environment has its own complexity due to the relevance of **temporal and spatial dimensions**

Cozie - Dynamically Spatial and Temporal Subjective Feedback

Introducing Cozie – a customizable, real-time occupant satisfaction preference data collection for buildings. Open source and free to use (Jayathissa et. al, 2019)

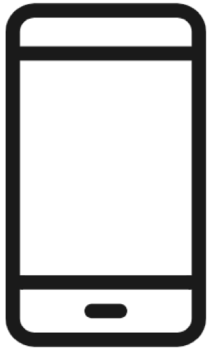
https://cozie.app/

Ecological Momentary Assessment and Experience Sampling Methodologies

Pioneered in medicine, psychology, and marketing, and advertising (Shiffman et. al, 2008, Intille et. al 2016):

Ecological

- Real-world environment and experience
- Ecological validity



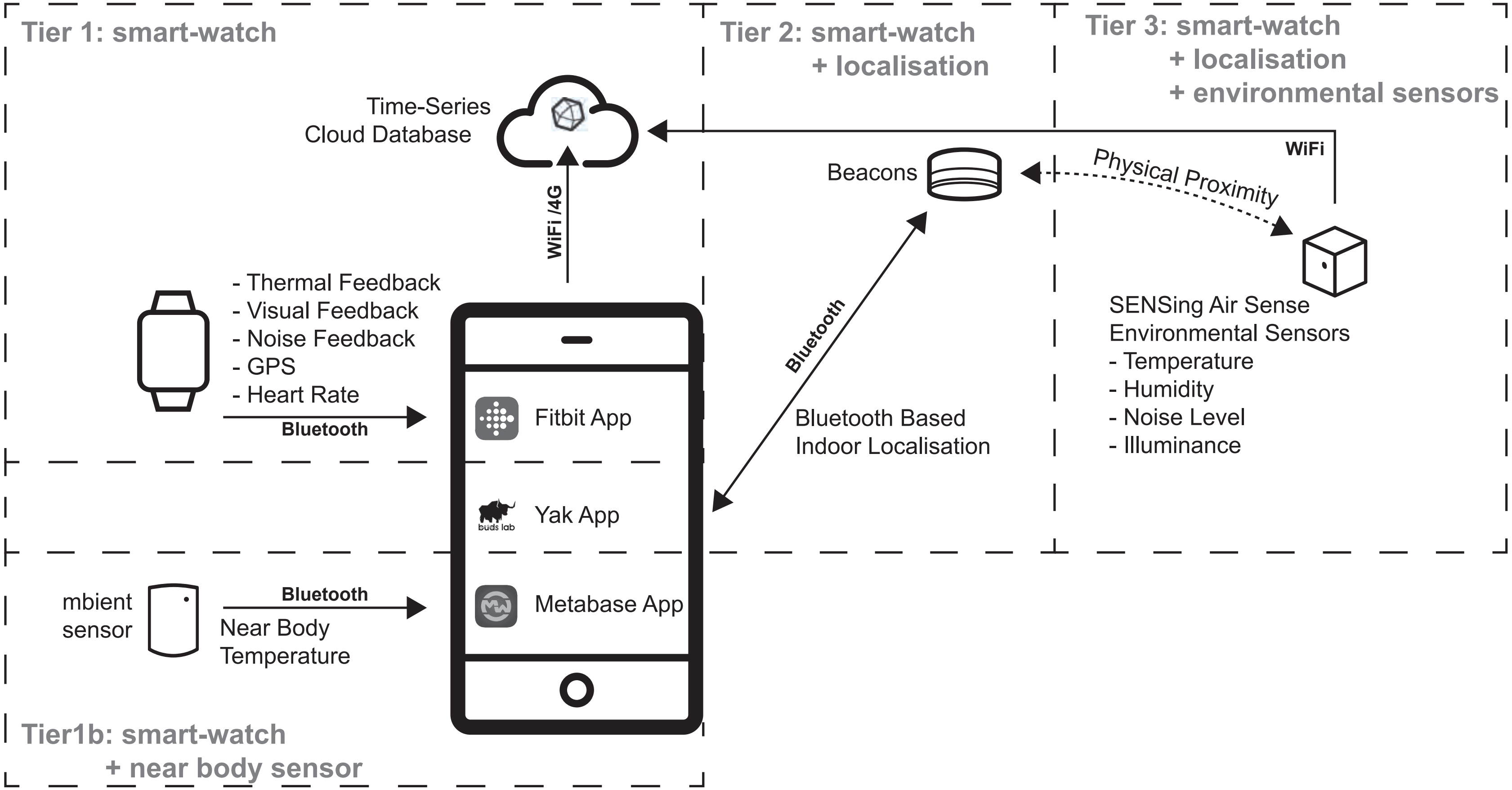
Momentary

- Real-time assessment and focus

Assessment

- Self-reported
- Repeated, intensive and longitudinal
- Allow analysis of process over time

Cozie Data Integration Infrastructure for Experiments at NUS

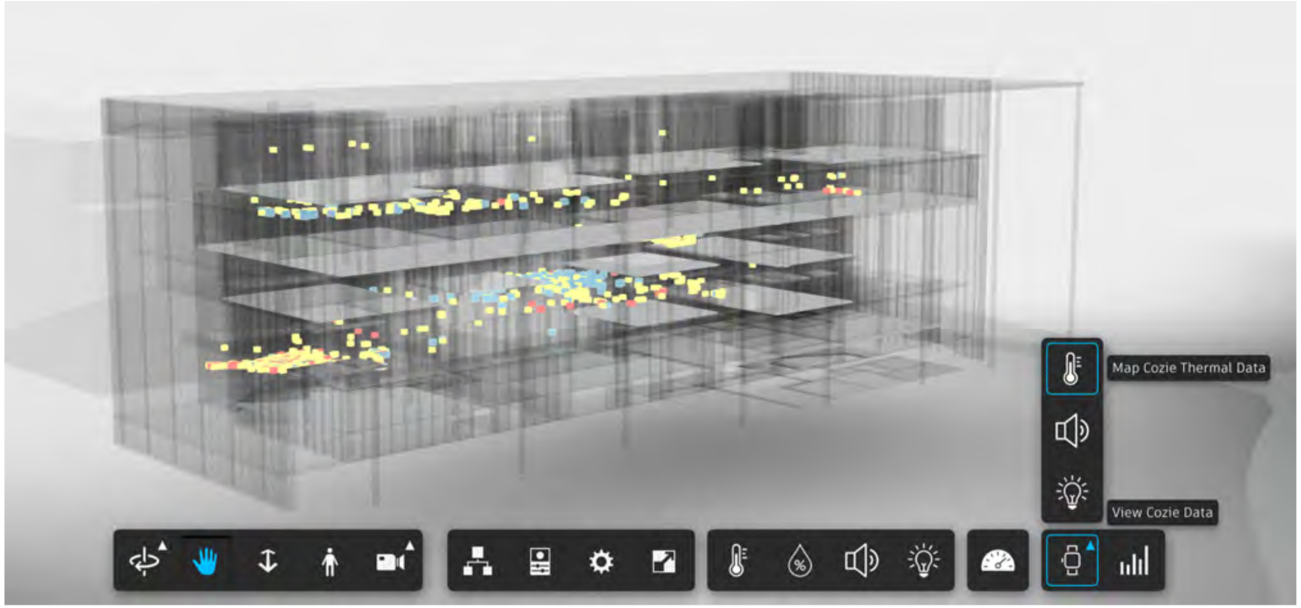


- Three tiers of data collection for different practical constraints and methodological objectives (Jayathissa et. al, 2020 Preprint)
- Subjective, Physiological, Environmental and Spatial data convergence

Cozie Experiment Subjective Feedback Questions

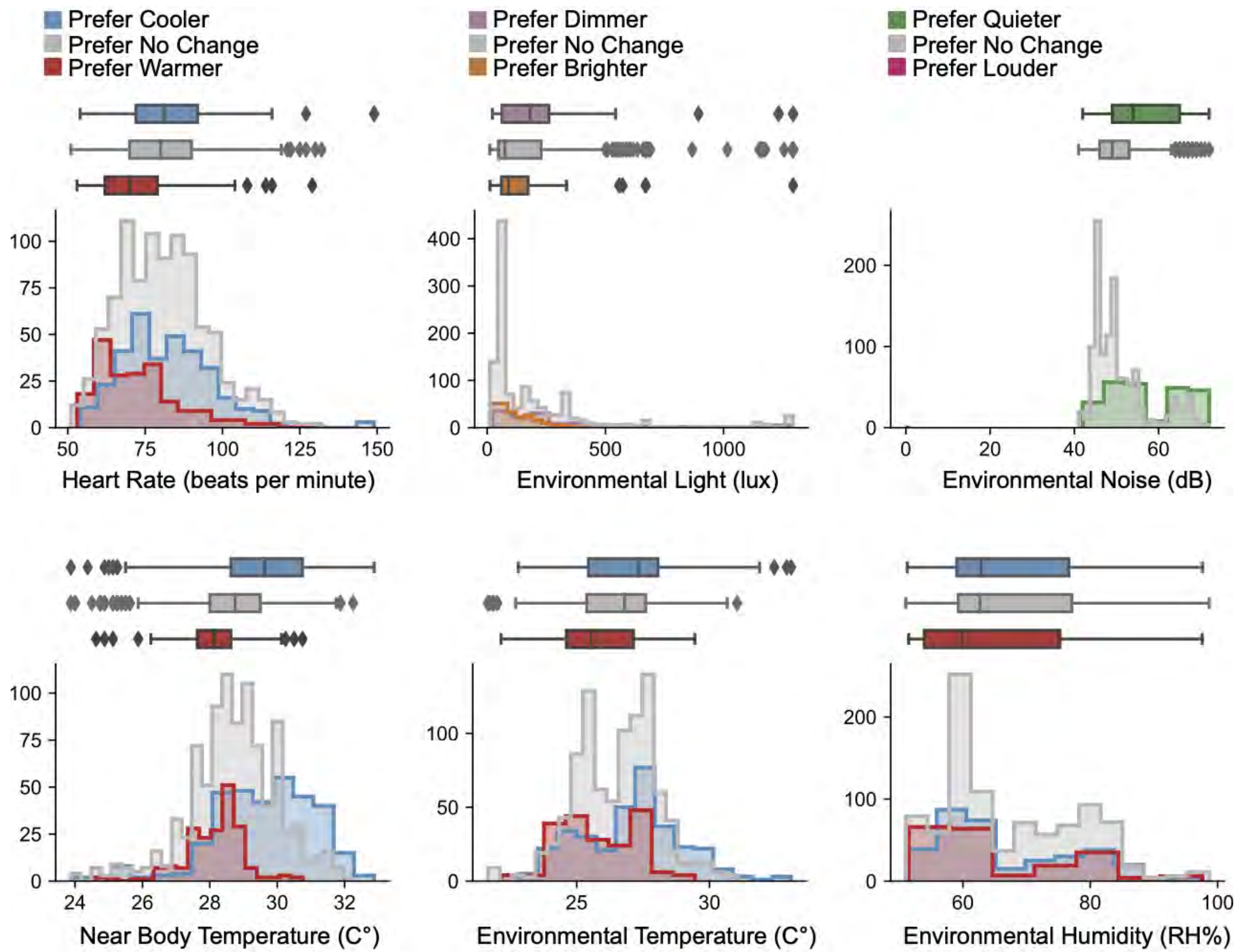
- Five times per day the subjects were requested to give feedback (Jayathissa et. al, 2020 Preprint)
- Questions asked three-point preference-based questions for Thermal, Visual, and Aural Feedback

Scalable Field-based Data Collection Experiments



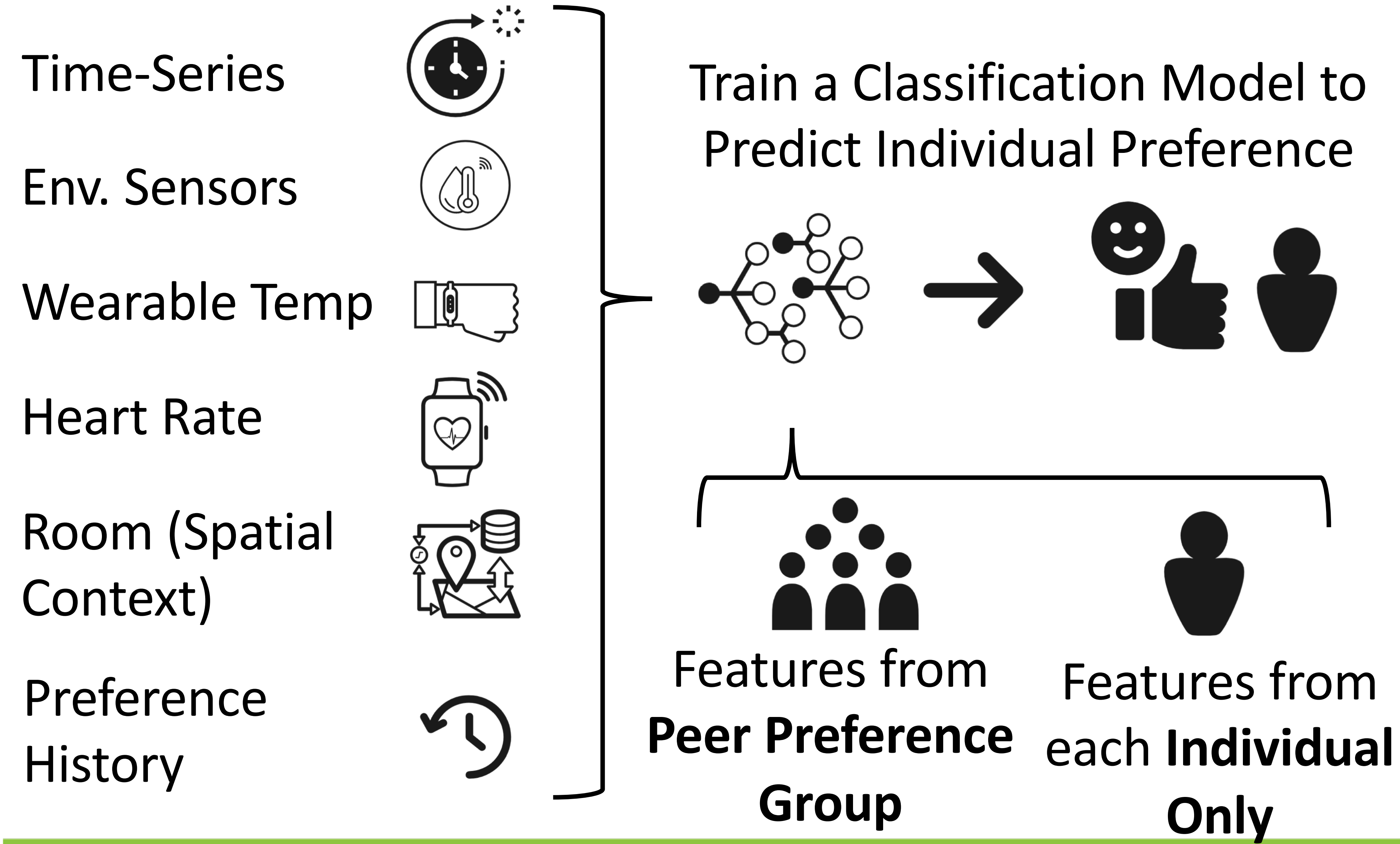
- Field-based deployment in the SDE4 Net Zero Energy Building at NUS
- Thirty participants were asked to give at least 100 feedback points in two weeks
- **4,378 total feedback data points were given for all three IEQ questions**

Environmental, Heart Rate, and Near-body Temperature IoT

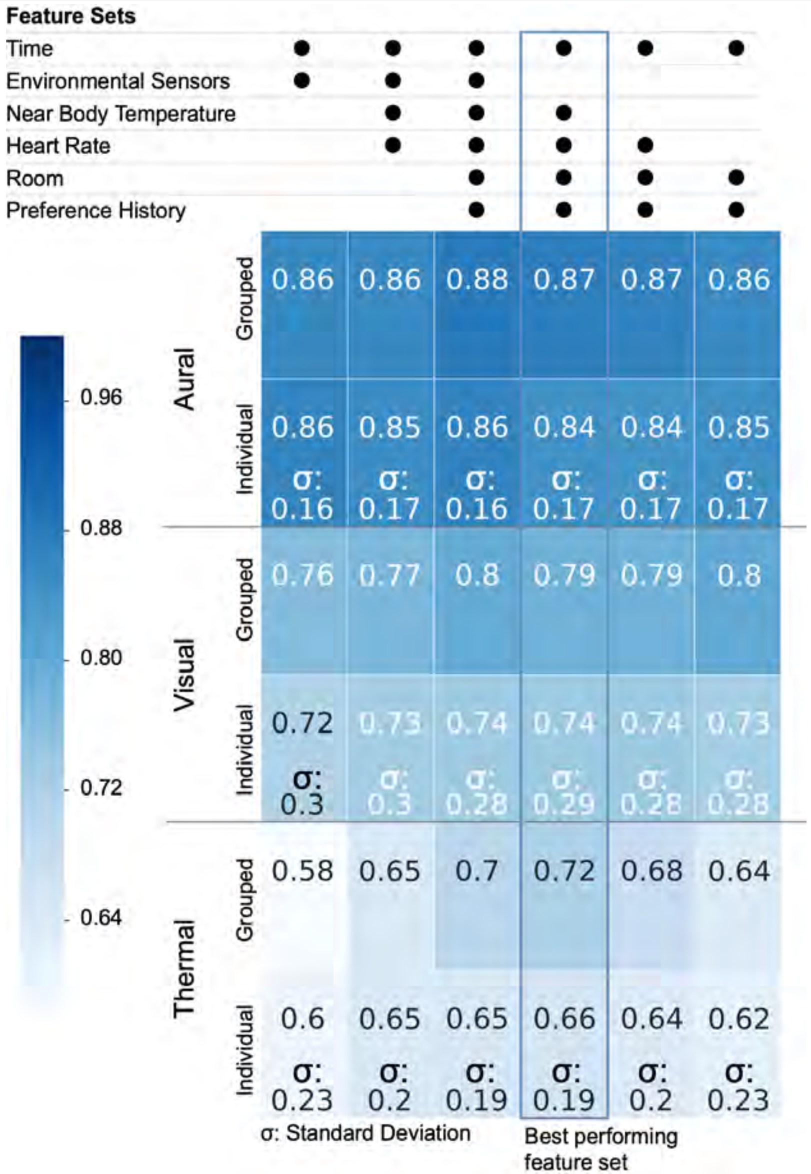


- Environmental, physiological and near-body variables (Jayathissa et. al, 2020 Preprint)
- There are indications of sensors can be meaningful, but are not capturing everything

Prototype Preference Modelling using Peer and Space Groups

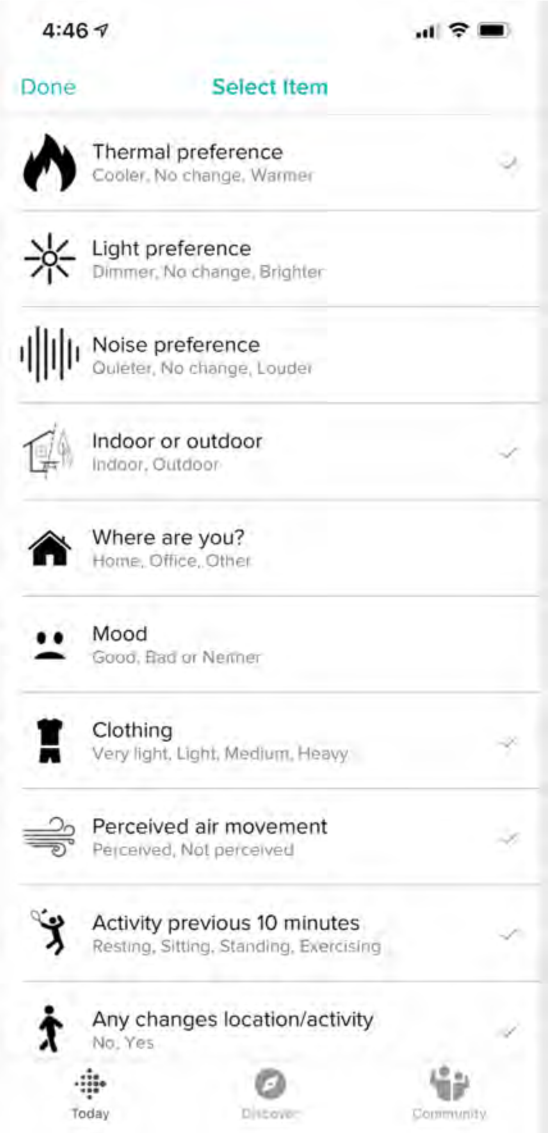


Initial Modeling Results



- The model accuracy was highest with Time, Near-body, HR, Room, and Preference History (Jayathissa et. al, 2020 Preprint)
- **Most accurate models didn't include environmental sensors**
- Grouped models consistently outperform individual models

In-Progress: Expansion of Survey Question Library



Current questions include:

- Thermal preference
- Light preference
- Noise preference
- Location
- Mood
- Clothing and activity
- Perceived air movement

Future question development for privacy, productivity, and even health/symptoms in progress

Get involved!

You can be a part of the Cozie project or use it on your methodology!

- You can install on your own Fitbit today
- Add to the question library
- Branch or fork the code and make something new
- *Urgent help needed: Cozie-Covid symptoms version testers and developers*

Cozie website: https://cozie.app/

Documentation: https://www.budslab.org/website-dev/docs/home

Open-sourced codebase: https://github.com/buds-lab/cozie

Questions/comments: clayton@nus.edu.sg

Thanks to the Cozie team: Prageeth Jayathissa, Federico Tartarini, Matias Quintana, Mahmoud Abdelrahman, Yi Ting Teo, Yuan Xuan Chua

References

Intille, Stephen, Caitlin Haynes, Dharam Maniar, Aditya Ponnada, and Justin Manjourides. 2016. "μEMA: Microinteraction-Based Ecological Momentary Assessment (EMA) Using a Smartwatch." *Proceedings of the ... ACM International Conference on Ubiquitous Computing. UbiComp (Conference)* 2016 (September): 1124–28.

Jayathissa, Prageeth, Matias Quintana, Mahmoud AbdelRahman, and Clayton Miller. n.d. "Indoor Comfort Personalities: Scalable Occupant Preference Capture Using Micro Ecological Momentary Assessments."

Jayathissa, Prageeth, Matias Quintana, Tapeesh Sood, Negin Nazarian, and Clayton Miller. 2019. "Is Your Clock-Face Cozie? A Smartwatch Methodology for the in-Situ Collection of Occupant Comfort Data." *Journal of Physics. Conference Series* 1343 (1): 012145.

Shiffman, Saul, Arthur A. Stone, and Michael R. Hufford. 2008. "Ecological Momentary Assessment." *Annual Review of Clinical Psychology* 4: 1–32.

Presentations

Session 2 - Third presenter

Agee, Philip

Virginia Tech, USA

Session 2

Day 1, 13:45

A Human-Centered Approach to Residential Buildings

P. Agee

Traditionally, the Architecture, Engineering, and Construction (AEC) industry has employed a linear design and delivery approach. As residential buildings race to zero energy performance, the AEC industry must adapt. To maximize human well-being and the operational performance of zero energy buildings, an iterative, human-centered approach must be employed. The omission of human factors in the design and delivery of residential building systems risks misalignment between occupant-user needs and the AEC industry's perception of occupant-user needs. This research proposes a human-centered approach to housing. The study employed a multiphased, mixed-methods research design. Data were collected from 309 high performance housing units in the United States. Longitudinal energy use data (simulated and measured), occupant surveys, and semi-structured interviews are the primary data inputs. Affinity diagramming was leveraged to categorize the qualitative data. The output of the affinity diagramming analysis led to the development of data-driven Personas that communicate user needs. While this data was gathered in the United States, researchers, practitioners, and policy makers can leverage the human-centered approach beyond residential buildings toward the design of a human-centered built environment.

PHILIP AGEE, PH.D.
Virginia Center for Housing Research
Virginia Tech
pragee@vt.edu

A Human-centered Approach to Residential Buildings

VIRGINIA TECH

WHY HUMAN-CENTERED RESIDENTIAL BUILDINGS?

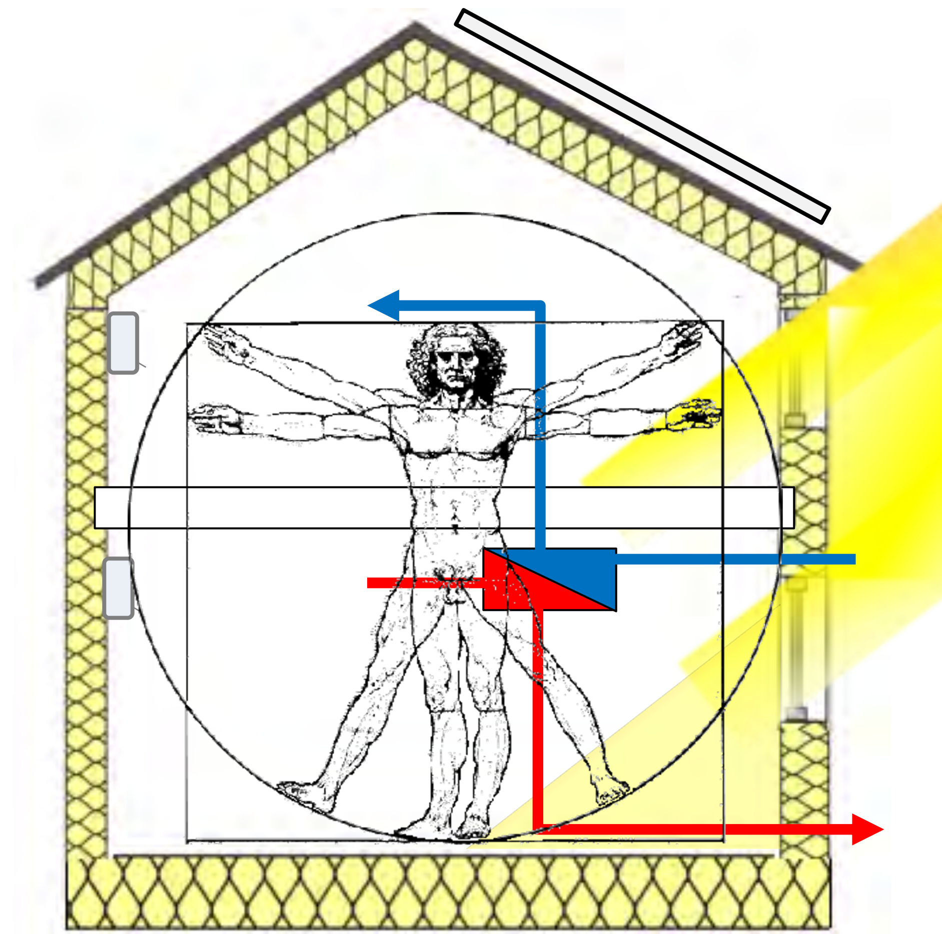
1. Housing is where commercial occupants behave before and after work;

2. Housing center = focus, data convivence;

3. Energy End-uses: shift from enclosure to human-centered end-uses.

NOT ONLY ABOUT TECHNOLOGY, ITS ABOUT

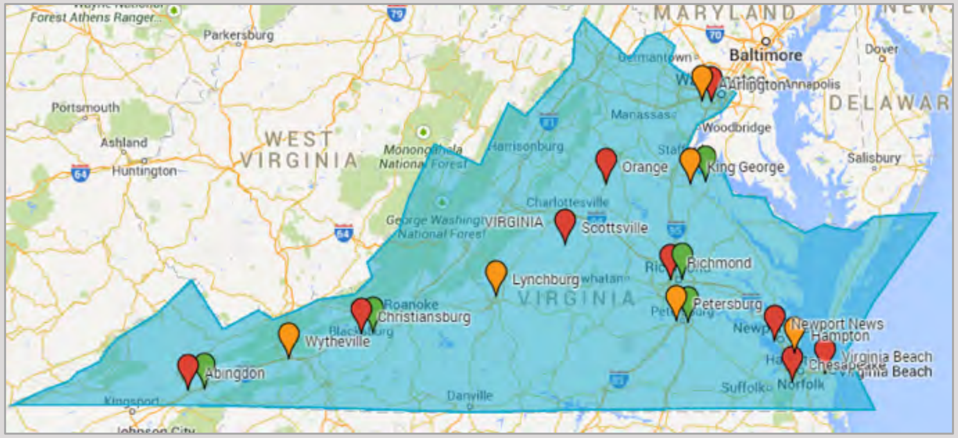
HUMAN-BUILDING INTERACTION



Research Overview

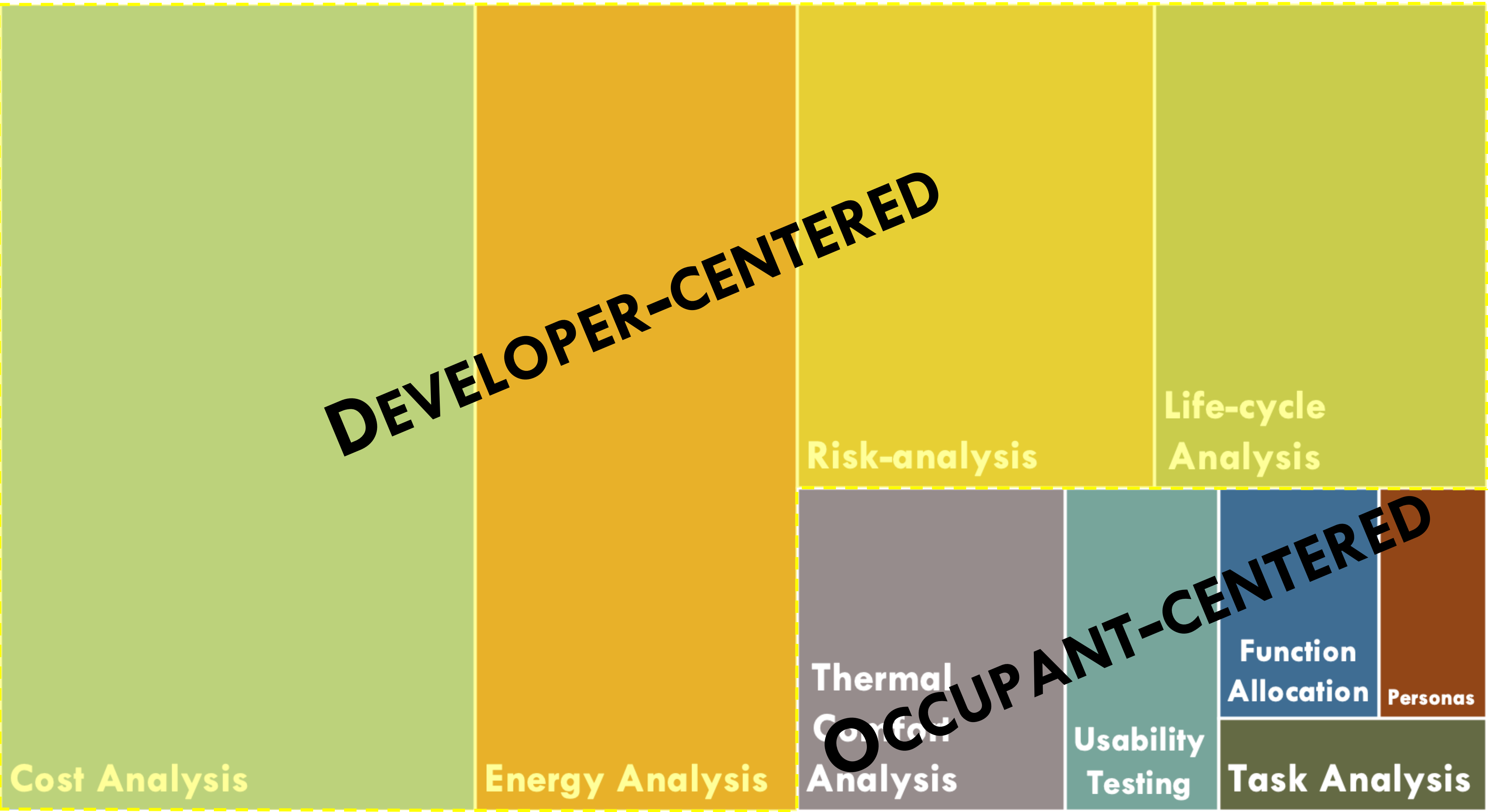
- ✓ **Sample:** 20 high performance multifamily developments in Virginia, USA;
- ✓ **Data:** Energy use (simulated + measured), user-surveys, interviews;
- ✓ **Methods:** focus on mixed-methods

2015	**Comparative Analysis** (simulated-measured energy use)
2016	**Interaction Effects** (energy use, behavior survey, technologies)
2017	**Education Intervention(s)** (video modules, EFDs, interviews)
2018	**Macroergonomics** (work system design, design methods)
2019	
2020	**Human-centered Design** (affinity diagramming, data-driven personas)



Sample: Senior, Non-senior, New, and Renovation

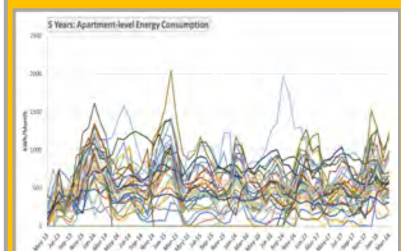
CURRENT DESIGN METHODS (n=38)



Design for People | Data-driven Personas

Step 1

Energy Analysis (n = 239)



Descriptive Statistics

- Energy Use Intensity (EUI)

Step 2

Behavioral Survey (n = 239)

Behaviors

- Thermostat set points
- Adaptive comfort behaviors
- Dishwasher use
- Shower length

Step 3

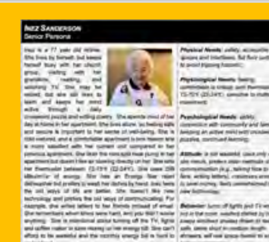
Semis-structured Interviews (n = 9)

Attitudes, Beliefs, Needs

- Energy efficiency
- Technology
- Comfort
- Physical, psychological needs

Step 4

Affinity Diagrams + Personas (n = 2)



Mixing of Steps 1, 2, 3

- Senior Persona
- Non-senior Persona

[Abbreviated] Results | Data-driven Personas

INEZ SANDERSON
Senior Persona

Physical Needs: *safety, accessible spaces and interfaces, flat floor surfaces to avoid tripping hazards;*

Physiological Needs: *feeling comfortable is critical, sets thermostat to 72-75°F (22-24°C), sensitive to drafts/air movement;*

Psychological Needs: *safety, connection with community and family, keeping an active mind with crossword puzzles, continued learning;*

Attitude: *is not wasteful, uses only what she needs, prefers older methods of communication (e.g., talking face to face, writing letters), conserves energy to save money, feels overwhelmed by new technology;*

Behavior: *turns off lights and TV when not in the room, washes dishes by hand, keeps windows shades drawn to feel safe, takes short to medium length showers, will use space heater to adapt indoor environment.*

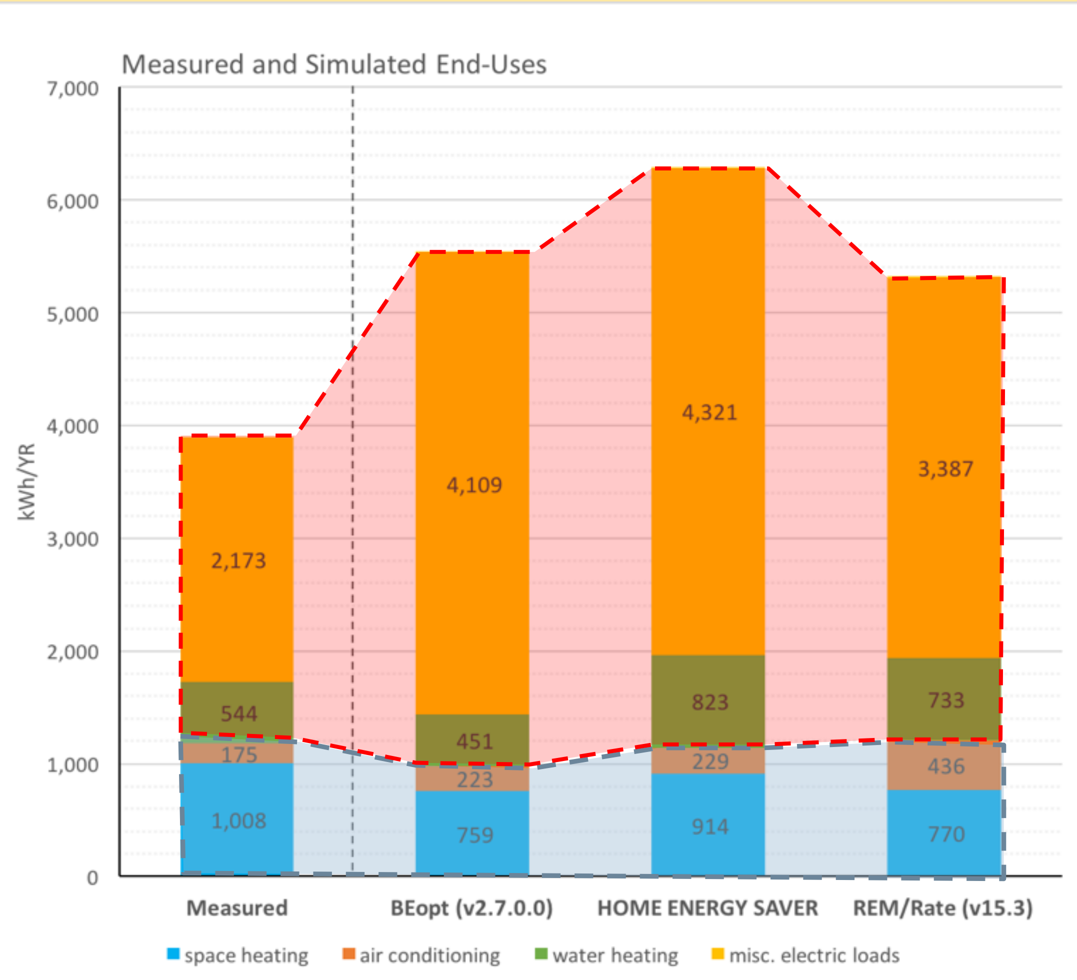
- ✓ Anchors design in user-needs;
- ✓ Data can be leveraged from multiple sources (e.g., benchmarking, interviews, surveys, contextual inquiry);
- ✓ As the built environment integrates interactive systems, AEC industry should look to lessons learned from Human-computer Interaction (HCI) literature and practice

ZERO ENERGY DUPLEXES

BLACKSBURG, VA, USA

CHARACTERISTICS	CS1
# of apartments	8
PV-system	30.2 m^2, south-facing, 3.78 kWp
Living area	966 ft^2 (90 m^2)
Building volume	7728 cf (218.8 m^3)
Heating system	Air-source heat pump 9 kBTUh, 10 HSPF
Cooling system	Air-source heat pump 9 kBTUh, 18 SEER
Distribution	Ducted air system
Water heating	Air-water heat pump heater (2.75 EF)
Ventilation	Exhaust-only system
Windows U-value	0.25 BTUh/ft^2/°F (0.78/W/m^2K)
SHGC (g-value)	0.27
Wall U-value	0.04 BTUh/ft^2/°F (0.13/W/m^2K)
Roof/Attic U-value	0.02 BTUh/ft^2/°F (0.05/W/m^2K)
Air tightness	2.0 ACH_{50}

Simulation Analysis



Measured:

- ✓ MELs and DWH
- ✓ Great enclosure = less HVAC load

Simulation(s):

Beopt:

- ✓ Overestimated MELs

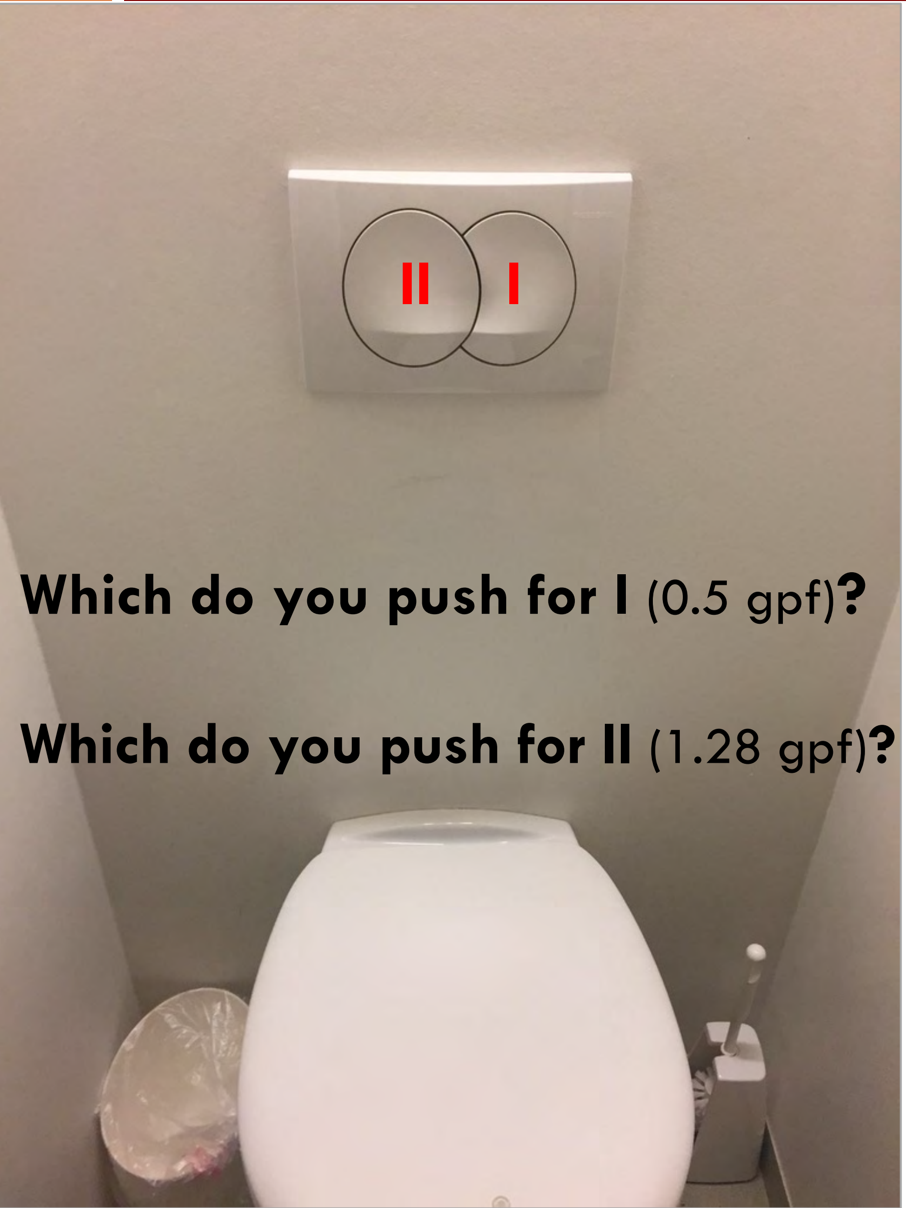
Home Energy Saver:

- ✓ Overestimated MELs, DWH

REM/Rate:

- ✓ Underestimated Heating
- ✓ Overestimated Cooling, MELs, DWH

Human-building Interaction



Human Factors:

✓ *Human Information Processing*

- Coding & affordances
- Visual acuity

Human-centered Methods:

✓ *Usability Testing*

- Task Analysis
- Think-aloud Protocol
- Eye-tracking

"All truth passes through three stages: First, it is ridiculed. Second, it is violently opposed. Third, it is accepted as self-evident." **- Arthur Schopenhauer**

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pragee@vt.edu (contact if interested in collaboration)

Presentations

Session 2 - Fourth presenter

Derbas, Ghadeer

Wuppertal University, Germany

Session 2

Day 1, 13:55

Optimization of Solar Shading Control Strategies in Terms of User Behaviour, Energy Performance, Visual and Thermal Comfort

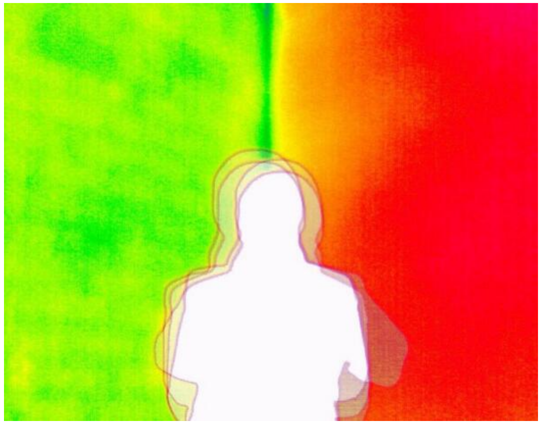
G. Debras

Automated shading systems represent a promising solution for improving the indoor environment and saving energy, particularly in highly glazed office buildings. Recent research reported that these systems are either deactivated or overrode by the occupants. For instance, some studies found conflicts between the commonly used metrics of automated shading and what occupants accepted. Moreover, the current study proposed that the accuracy of the shading control sensors could affect the user acceptance of the established metrics. Further research was needed to investigate the sensors' accuracy and user-shade interactions to find the optimal metrics of shade control with limited overrule actions. In this contribution, the current study presented an experimental field study on human interactions with automated shading systems in a full-scale test laboratory. The experiment was designed to (a) examine the accuracy of shade control sensors by testing two commercial devices and (b) investigate user interactions under three shade control strategies, then evaluate their satisfaction concerning thermal and visual comfort. Two simple strategies were used solar irradiance as triggering threshold, and an optimized control strategy was developed based on a combination of three control criteria: incident irradiance, indoor temperature and vertical illuminance. Shade deployments, indoor and outdoor physical parameters were recorded as well as a self-reported questionnaire. The current study found that the measurements of shading control sensors were statistically approved to be inaccurate with a high degree of error. Mean shade occlusion under the different control strategies was slightly different, whereas the optimized control strategy showed a significant impact on decreasing user shade lowering actions. Furthermore, glare and brightness were found to have more influence on shade adjustment than indoor thermal conditions. The current study was further expanded to simulate space design impact on shade control optimization in terms of energy performance, occupant behaviour and comfort.

The Fifth International Symposium on Occupant Behavior and Fourth Expert Meeting of IEA EBC Annex 79

University of Southampton, UK

20th to 23rd April, 2020



Optimization of Solar Shading Control Strategies in terms of User Behavior, Visual and Thermal Comfort

Doctoral researcher: Ghadeer Derbas, Forchungszentrum Juelich and Wuppertal University, Germany

Main supervisor: Prof. Dr.-Ing Karsten Voss, Wuppertal University, Germany

JÜLICH Forschungszentrum

RESEARCH MOTIVATION AND METHODS

MOTIVATION

Designers use “Perfect Controllers” of automated shading systems.

Conflict

Occupants accepted and preferred.

Occupants frequently override or disable the automated shading system.

OBJECTIVES

(a) Performance of commercial solar shading control devices

Investigating the quality and accuracy of two commercial shading control devices, by comparing with:

- Measurements of scientific instruments
- Simulation_based control algorithm

(b) Preferences of user behavior

Evaluating the performance of four solar shading control strategies, *in terms of:*

- User behavior
- Thermal comfort
- Visual comfort

JÜLICH Forschungszentrum

RESEARCH MOTIVATION AND METHODS

METHODS

- **Test facility:** Btga-box full-scale test laboratory, Wuppertal University, Germany.

- **Participants:** thirty-one test subjects, 15 males and 16 females , 68% German and 32% other, age range of 22-47 years.

- **Monitored variables:** Shading deployment, indoor environmental parameters and external weather conditions.

- Subjective web-based questionnaire (four times).

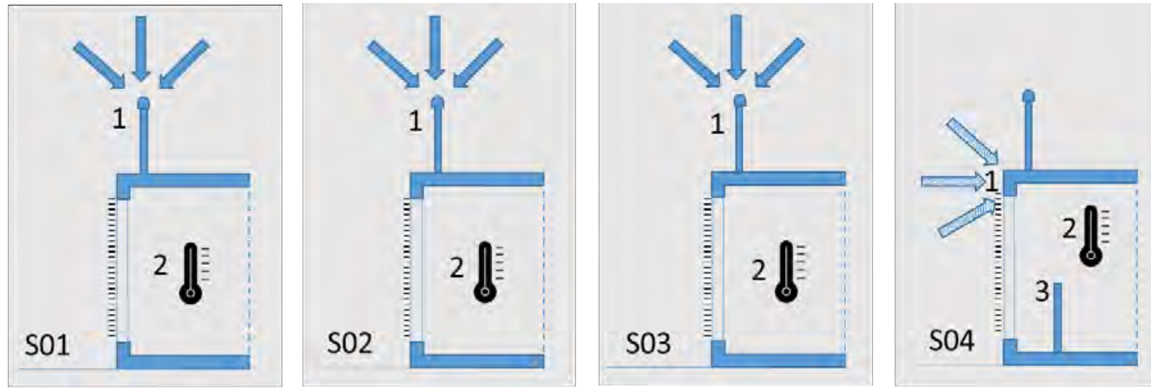
Btga-box test laboratory, Wuppertal University, Germany: (left) exterior view and (right) interior view.

JÜLICH Forschungszentrum

EXPERIMENT RESEARCH DESIGN

EXPERIMENT SESSIONS

- **S01:** Fully automated without user interface.
- **S02:** conventional algorithm (shade lowering when brightness threshold exceeded 35 Klux).
- **S03:** conventional algorithm (shade lowering when brightness threshold exceeded 50 Klux).
- **S04:** proposed algorithm based on three criteria.



(a) Fully automated (Low set points) Bench mark.

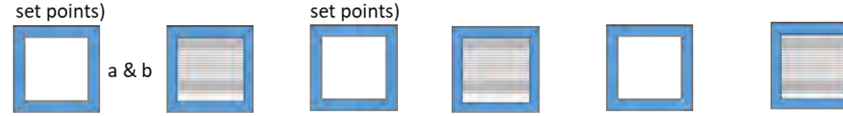
(b) Conventional algorithm with manual overridden (Low set points)

(c) Conventional algorithm with manual overridden (high set points)

(d) Proposed algorithm with manual overridden.

* According to lower and upper thresholds of the case studies.
** According to DIN EN ISO 13790:2008-09.
*** according to DIN EN 15251:2006.
**** According to Karlsen et al, 2015.
Ir: solar radiation.
T_{indoor} : indoor air temperature.

Ev : Vertical illuminance at the eye level.



[1] Ir < 15 [Klux]*. [2] T_{indoor} < 21.

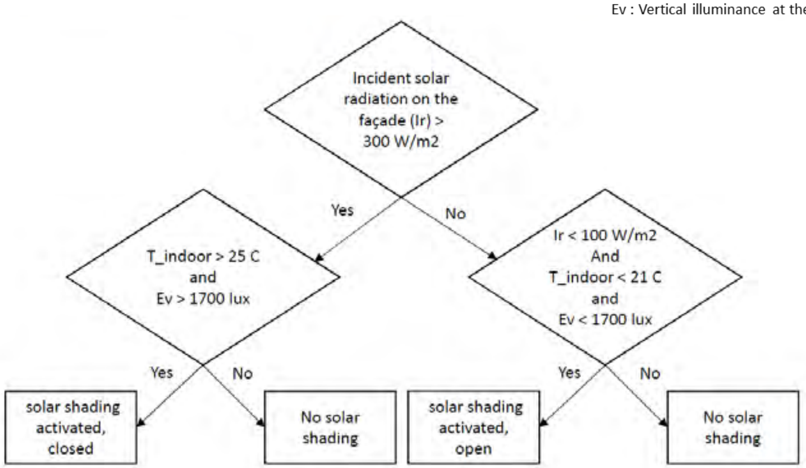
[1] Ir > 35 [Klux]*. [2] T_{indoor} > 25.

[1] Ir < 30 [Klux]* [2] T_{indoor} < 21.

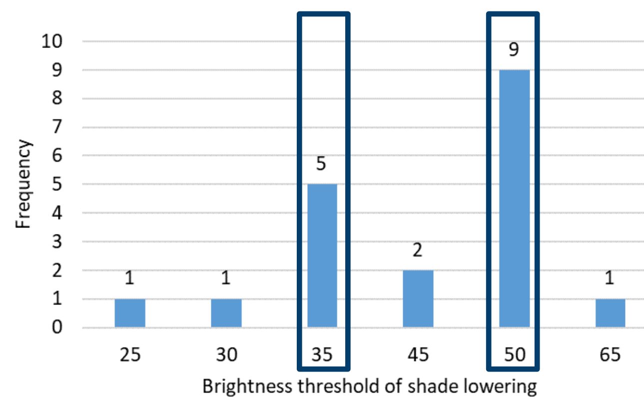
[1] Ir > 50 [Klux]*. [2] T_{indoor} > 25.

[1] Ir <11 Klux (100 W/m2)**. [2] T_{indoor} < 21***. [3] Ev < 1700 lux****.

[1] Ir > 33 Klux (300 W/m2). [2] T_{indoor} > 25. [3] Ev> 1700 lux.

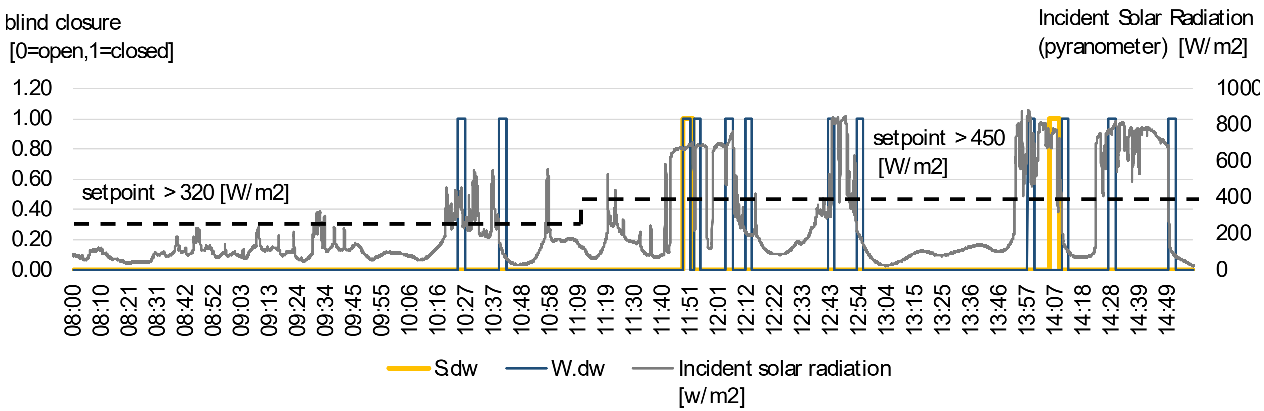


S04: proposed solar shading control strategy.



Survey results in 19 case studies office buildings: Frequency of shade lowering brightness thresholds

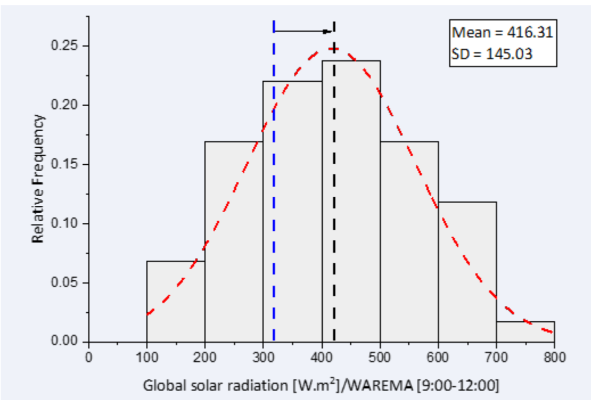
PERFORMANCE OF SOLAR SHADING CONTROL DEVICES

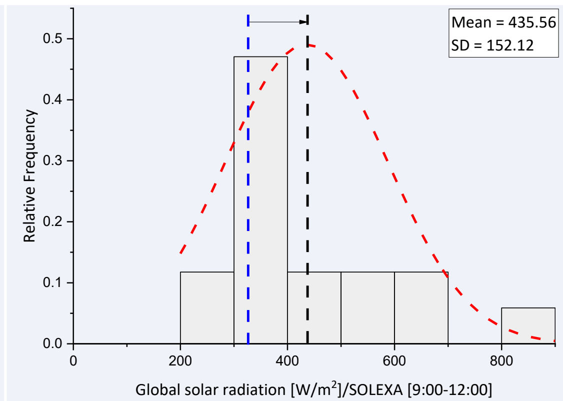


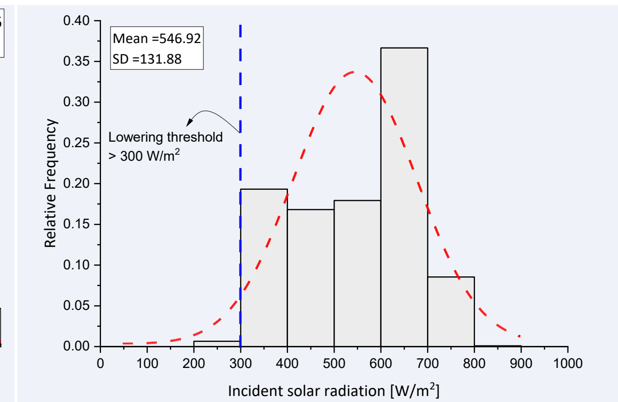
Behaviour comparison of SOLEXA and WAREMA control devices

Commercial shading control devices : SOLEXA (S) and WAREMA (W).

RESULTS







WAREMA shade lowering actions vs. Scientific instrument (weather station) One sample t-test (P-value = 0.00)	SOLEXA shade lowering actions vs. Scientific instrument (weather station) One sample t-test (P-value = 0.006)	Shade lowering actions of simulation-based control algorithm

CONCLUSIONS

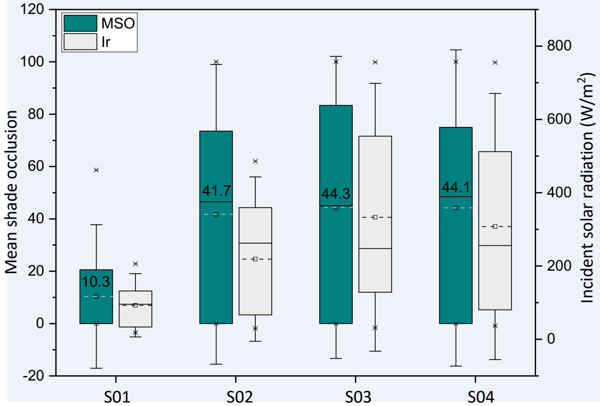
- Limitations are due to economic constraints and sensors’ inclinations.
- Limited accuracy and quality of commercial devices should be considered when developing optimal set points of shading control strategies.

JÜLICH Forschungszentrum

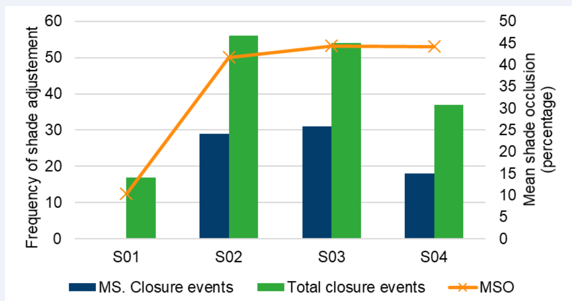
PERFORMANCE OF FOUR SOLAR SHADING CONTROL STRATEGIES

User overrule actions

Shade metric 01: Mean shade occlusion (MSO)

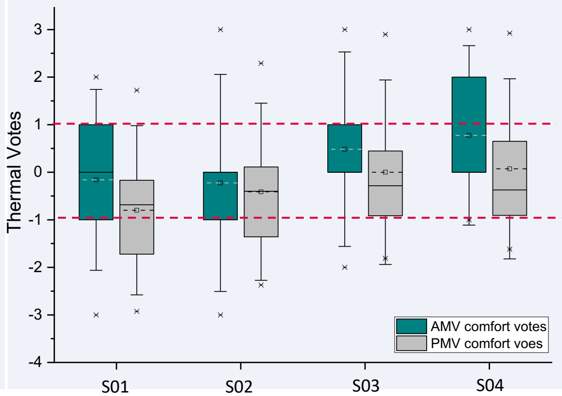


Shade metric 02: Frequency of shade adjustments

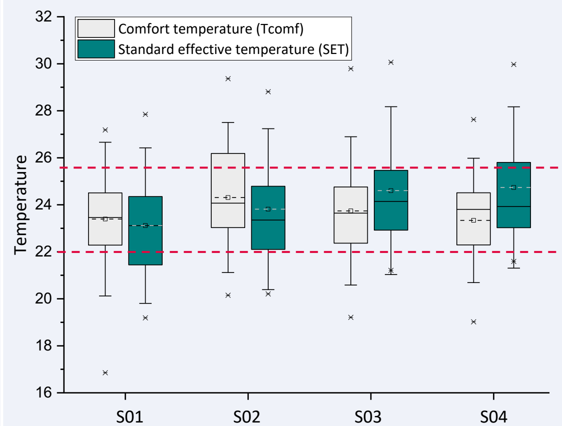


Thermal comfort

PI 01: Predicted mean vote (PMV) model

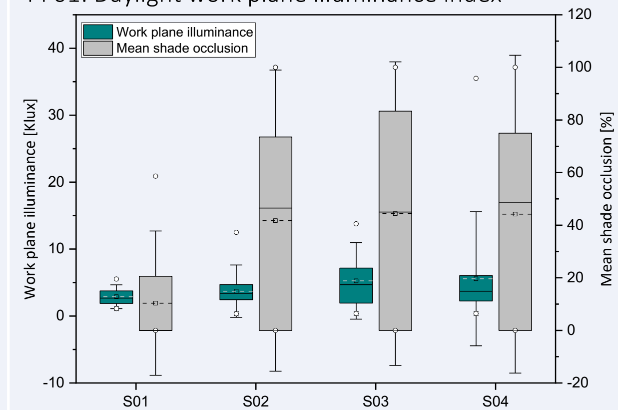


PI 02: Standard effective temperature (SET)

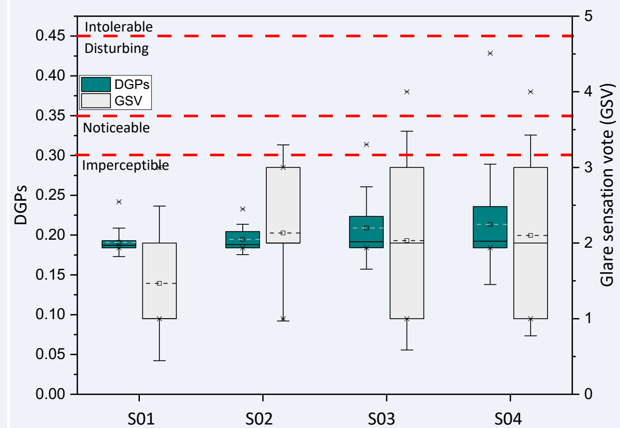


Visual comfort

PI 01: Daylight work plane illuminance index



PI 02: Simplified daylight glare probability (DGPs)



CONCLUSIONS

Con.1: Slight differences in MSO under S02, S03, S04.
Less overrule actions in S04 → more robust shading control strategy.

Con.2: no statistically significant difference → between S03 and S04.
All sessions except S01 → within the thermal comfort criteria (-1,+1).

Con.3: non-significant difference in light abundant between the four sessions, while slight differences in DGPs values.

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RESEARCH OUTLOOK

- The non-significant differences between the conventional and proposed shade control strategies might be explained due to the limited accuracy and quality of commercial shading control devices.
- The experiment will be conducted once more this summer considering all limitations.
- Any suggestion or feedback will be very helpful to the research progress.

Presentations

Session 2 - Fifth presenter

Park,
June

University of Texas, USA

Session 2

Day 1, 13:59

A Reinforcement Learning for Occupant Centric Thermostat Control

J. Park

Building systems need to control the indoor environment with the comfort range. With the rapid development of information and communication technology, building controllers have been developed with the goal of overall energy savings. However, conventional building control strategies typically use fixed threshold values and set-points for operation without considering the preference of the occupants. Therefore, we need an automatic adaptation to occupant comfort. In this paper, we propose a reinforcement learning (RL) based occupant centric controller (OCC) for learning the optimal thermostat set-points. The RL-OCC agent acquires data on the physical, indoor environment, which is interpreted as states for RL controller. Besides, data on the interaction between the occupant and the building systems, which is indicative of the comfort or, more often, the discomfort of the occupant, is also collected as rewards for RL controller. With this data, the agent can adapt to unique occupant behaviors and indoor environments over time and calculate the optimal control actions. We demonstrate our controller on an existing BAS system with facility managers in the loop. The case study is an academic office space and located on the campus of The University of Texas at Austin. Currently, this building is equipped with an active chilled beam system for heating and cooling, and the occupants have individual thermostats. We develop a low-cost hardware device (HVACLearn), which monitors indoor environmental quality as well as the feedback of the occupants. HVACLearn then calculates the optimal & personalized control actions, e.g., thermostat set-points, to balance between occupant comfort and energy efficiency. The optimized control action is updated with the facility manger’s confirmation to avoid malfunctions of the current system. We present system hardware, control algorithm, and the experimental results of 19 office spaces.

The University of Texas at Austin
Civil, Architectural and Environmental Engineering
Cockrell School of Engineering

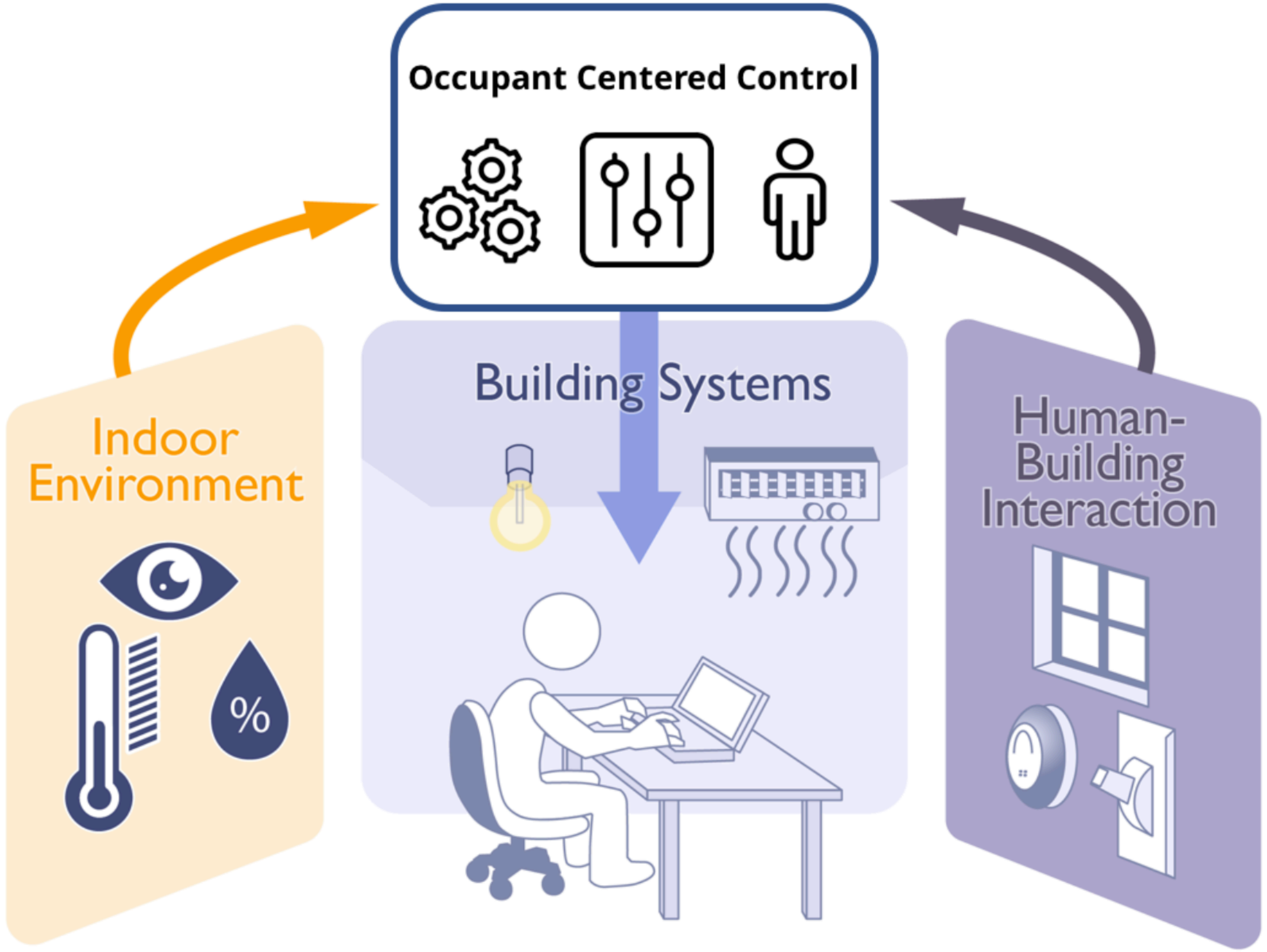
INTELLIGENT ENVIRONMENTS LABORATORY

HVACLearn: A Reinforcement learning based controller for occupant centric thermostat control

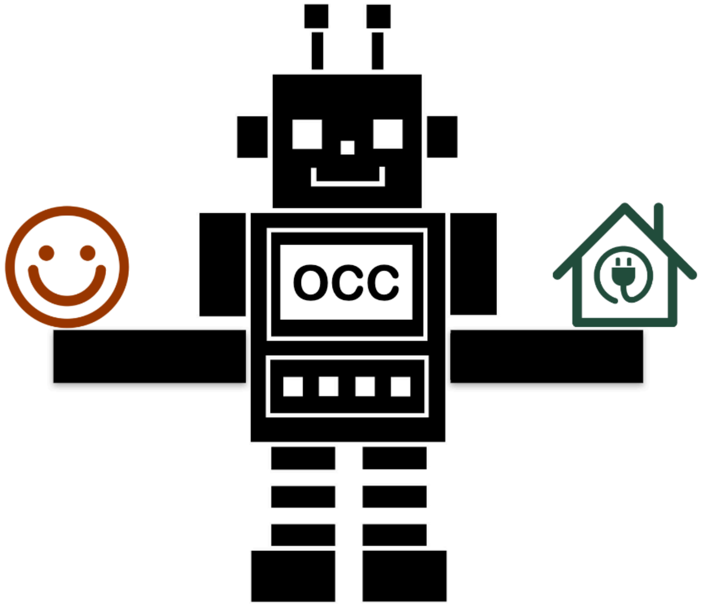
June Young Park
S. Bastami, K. Nweye, Z. Nagy

The University of Texas at Austin
WHAT STARTS HERE CHANGES THE WORLD

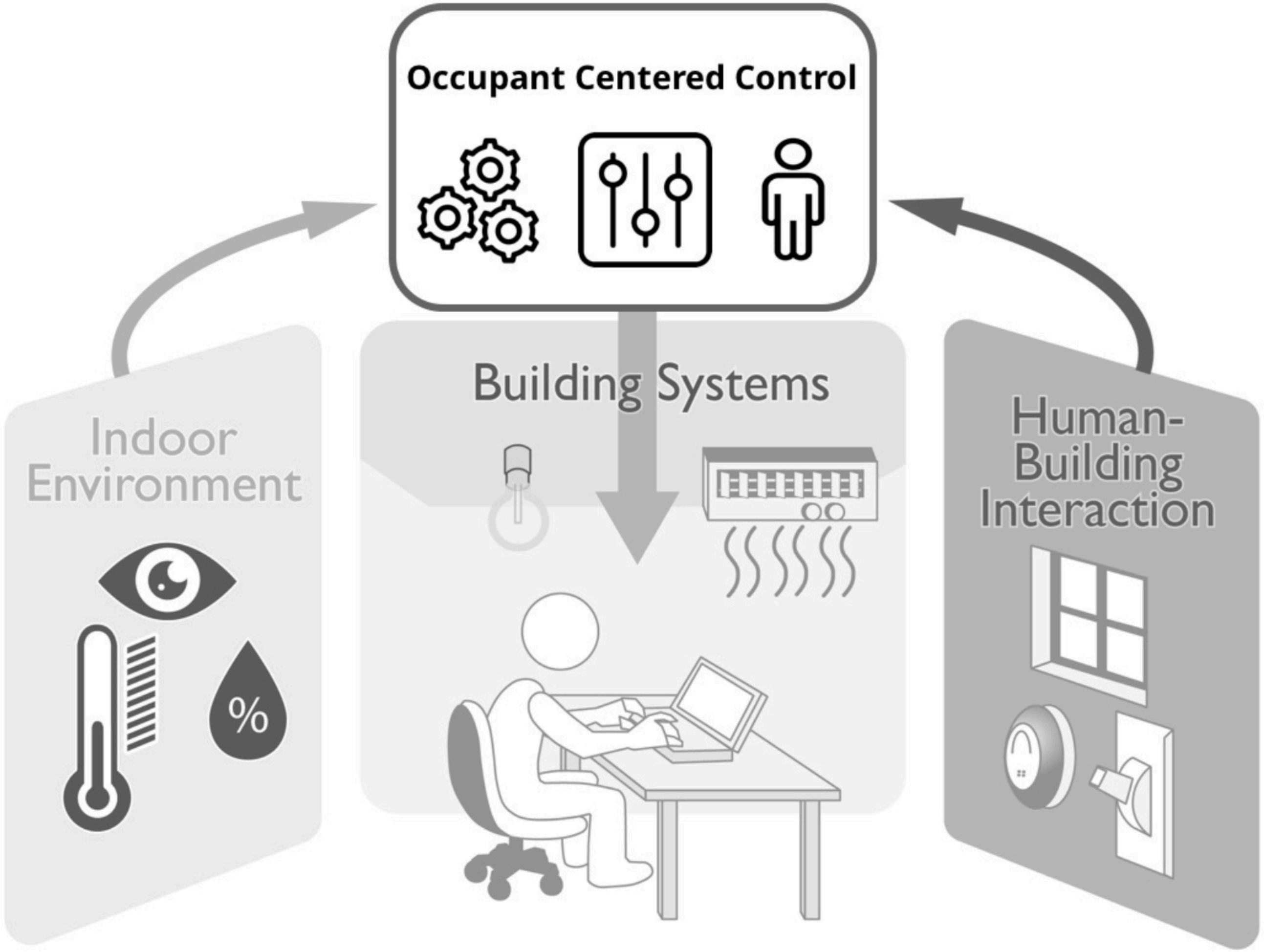
Occupant centric control for building systems

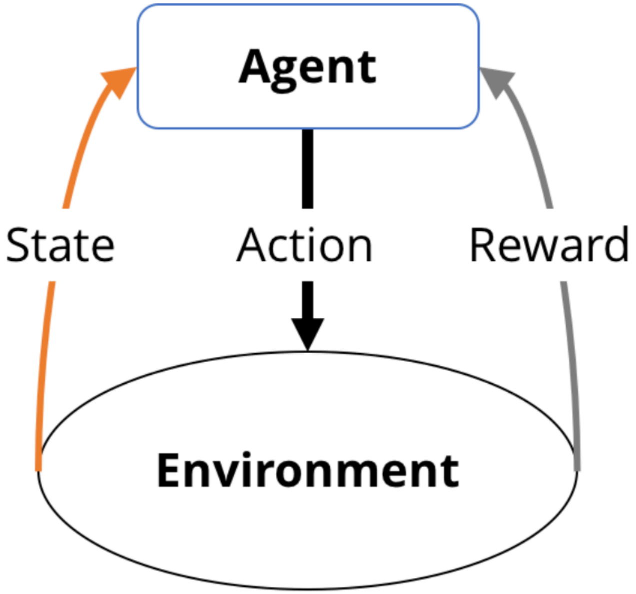


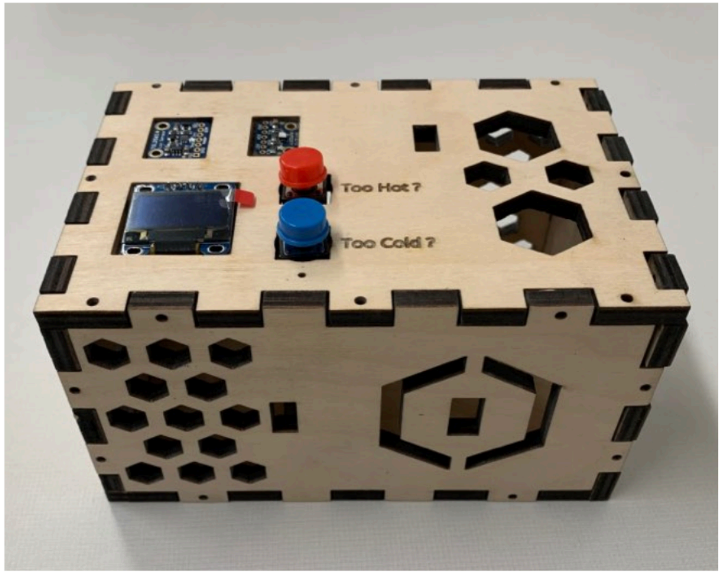
Balancing **occupant comfort** and **energy consumption**;



Reinforcement Learning

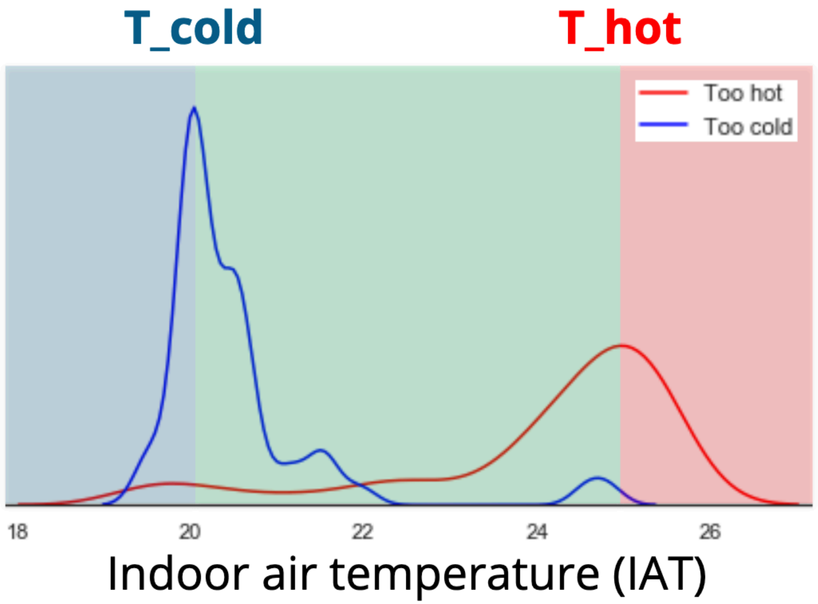






HVACLern operation

1. State reading



State

Cold

Neutral

Hot

HVACLern operation

1. State reading

2. Action selection

Action

Cooling setpoint	- 1	0	+ 1
Heating setpoint	- 1	0	+ 1

State

Cold

Neutral

Hot

Cooling_stpt

Heating_stpt

HVACLern operation

1. State reading
2. Action selection
3. Reward calculation

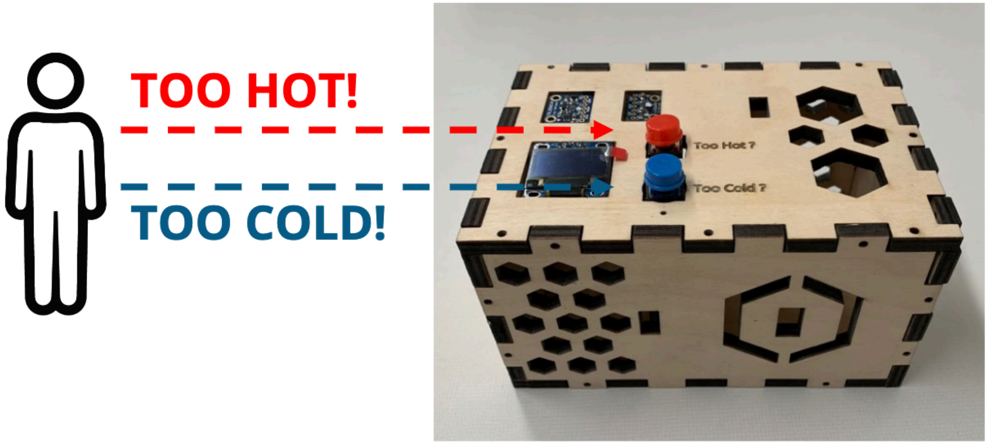
Action	Cooling setpoint	- 1	0	+ 1
	Heating setpoint	- 1	0	+ 1

State

Cold

Neutral

Hot



HVACLern operation

1. State reading
2. Action selection
3. Reward calculation
4. Update Q-value

old value

$$Q(s_t, a_t) \leftarrow (1 - lr) \cdot Q(s_t, a_t) + lr \cdot (reward + df \cdot \max_a Q(s_{t+1}, a))$$

learned value

Action	Cooling setpoint	- 1	0	+ 1
	Heating setpoint	- 1	0	+ 1
State	Cold	Q1	Q2	Q3
	Neutral	Q4	Q5	Q6
	Hot	Q7	Q8	Q9

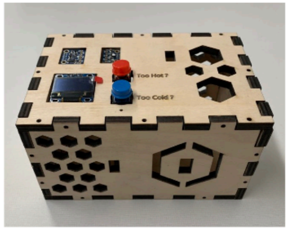
HVACLern operation

1. State reading
2. Action selection
3. Reward calculation
4. Update Q-value
5. Iterate #1-4 daily

Action				
	Cooling setpoint	- 1	0	+ 1
	Heating setpoint	- 1	0	+ 1

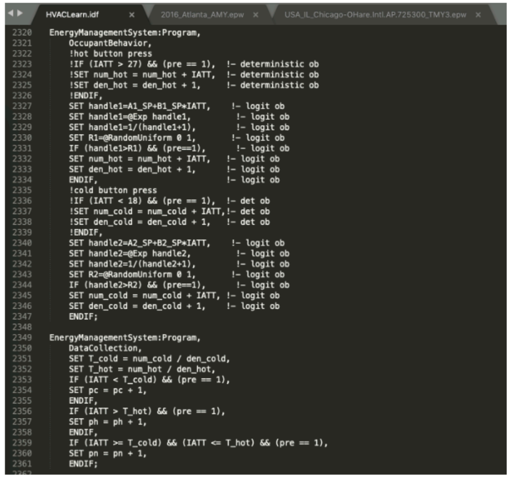
State				
	Cold	**Q1**	**Q2**	**Q3**
	Neutral	**Q4**	**Q5**	**Q6**
	Hot	**Q7**	**Q8**	**Q9**

Simulating *HVACLearn* operation



- HVACLearn Algorithm

- Occupancy: Wang et al. 2015
- Thermal vote: Ouf et al. 2020

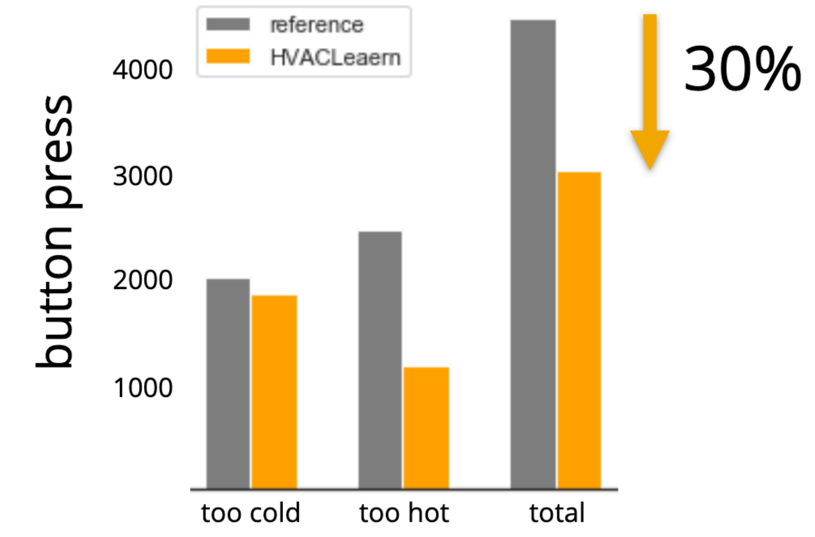


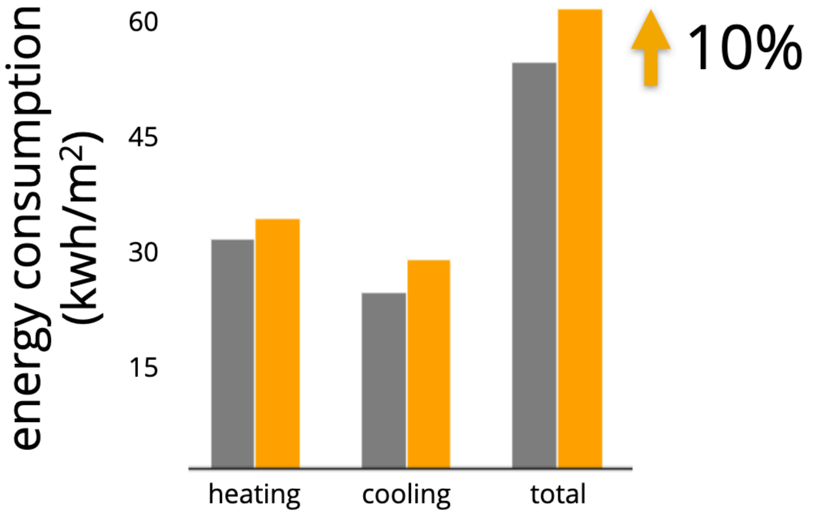

```
EnergyManagementSystem:Program,
    OccupantBehavior,
    !hot button press
    !IF (IATT > 27) && (pre == 1),  !- deterministic ob
    !SET num_hot = num_hot + IATT,  !- deterministic ob
    !SET den_hot = den_hot + 1,     !- deterministic ob
    !ENDIF,
    SET handle1=A1_SP+B1_SP*IATT,    !- logit ob
    SET handle1=@Exp handle1,         !- logit ob
    SET handle1=1/(handle1+1),        !- logit ob
    SET R1=@RandomUniform 0 1,       !- logit ob
    IF (handle1>R1) && (pre==1),      !- logit ob
    SET num_hot = num_hot + IATT,   !- logit ob
    SET den_hot = den_hot + 1,      !- logit ob
    ENDIF,                          !- logit ob
    !cold button press
    !IF (IATT < 18) && (pre == 1),  !- det ob
    !SET num_cold = num_cold + IATT,!- det ob
    !SET den_cold = den_cold + 1,   !- det ob
    !ENDIF,
    SET handle2=A2_SP+B2_SP*IATT,    !- logit ob
    SET handle2=@Exp handle2,         !- logit ob
    SET handle2=1/(handle2+1),        !- logit ob
    SET R2=@RandomUniform 0 1,       !- logit ob
    IF (handle2>R2) && (pre==1),      !- logit ob
    SET num_cold = num_cold + IATT, !- logit ob
    SET den_cold = den_cold + 1,    !- logit ob
    ENDIF;

EnergyManagementSystem:Program,
    DataCollection,
    SET T_cold = num_cold / den_cold,
    SET T_hot = num_hot / den_hot,
    IF (IATT < T_cold) && (pre == 1),
    SET pc = pc + 1,
    ENDIF,
    IF (IATT > T_hot) && (pre == 1),
    SET ph = ph + 1,
    ENDIF,
    IF (IATT >= T_cold) && (IATT <= T_hot) && (pre == 1),
    SET pn = pn + 1,
    ENDIF;
```

Energy Management System

EnergyPlus





Overall **30%** less button presses with **10%** more energy consumption

Tune **RL parameters** to balance between comfort and energy saving

Run **multiple simulations** with various locations & occupant behavior types to generalize RL-OCC performance

Presentations

Session 2 - Sixth presenter

Wei,
Shen

University College London, UK

Session 2

Day 1, 14:03

Monitoring Occupant Window Opening Behaviour in Buildings and Relevant Influential Parameters: a Critical Review

S. Wei

This paper introduces existing methods that have been used to measure/monitor occupant window opening behaviour in buildings, due to its significant impact on the building energy consumption. The review has identified five existing methods that have been used to monitor window usage (i.e. self-recording, electronic recording, observing by surveyors, self-estimating and camera images), and each method has its advantages and disadvantages in terms of feasible sample size, monitoring interval and duration, recognition of window states/opening angle, and the relative dynamic nature of behaviour. The aim has been to provide researchers with systematic criteria for selecting a suitable monitoring method for their specific research objectives. Additionally, the paper also demonstrates the need for a standard method for monitoring relevant influential factors, as these varied considerably between existing studies with respect to the accuracy, interval and location. Such variation clearly has the potential to influence the ability to perform cross-study comparisons.

5th International Symposium on Occupant Behaviour

Annex 79

Southampton

20 - 23 April 2020

Monitoring Occupant Window Opening Behaviour in Buildings and Relevant Influential Parameters: A Critical Review

Dr Shen Wei (Lecturer in Building Services Engineering)

The Bartlett School of Construction and Project Management

University College London (UCL), UK

shen.wei@ucl.ac.uk

20.04.2020

Methodology

- A Thorough Review on Studies in terms of Occupant Window Behaviour
  - Collected over 50 research articles
    - SCI impact journals (75%): Energy and Buildings, Building and Environment etc.
    - Key conferences (20%): ACEEE Summer Study Conference, Windsor Conference etc.
    - Academic technical reports or PhD thesis (5%)
  - Keywords: ‘occupant behaviour’, ‘adaptive behaviour’, ‘window behaviour’, ‘window control’ etc.

Capturing OB in Buildings

- Capturing Occupant Behaviour

Method 1: Self-recording by building occupants;

Method 2: Recording by electronic measuring devices;

Method 3: Observing by surveyors;

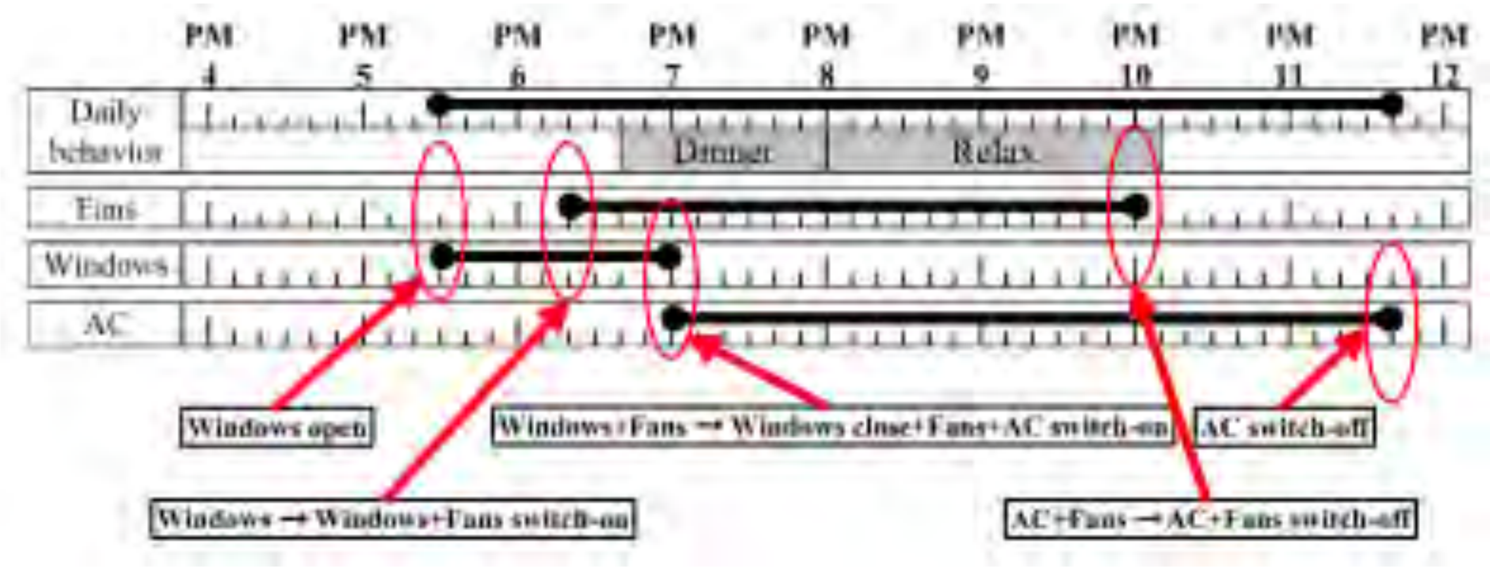
Method 4: Self-estimating by building occupants;

Method 5: Camera-based estimation

Capturing OB in Buildings

- Capturing Occupant Behaviour

Method 1: Self-recording by building occupants



(Nakaya et al. 2008)

Capturing OB in Buildings

- Capturing Occupant Behaviour

Method 2: Recording by electronic measuring devices

(Anderson et al. 2013)

Capturing OB in Buildings

- Capturing Occupant Behaviour

Method 3: Observing by surveyors

Visit	Time	Number of open windows per wall	Number of open doors (omit garage)	Floor location of openings (circle one)	Status of car door of attached garage	Likelihood of AC operation (circle one)	Likelihood of occupancy (circle one)	Evidence supporting occupancy rating	Precip. During last hour	Special conditions (write in)
A	______ am pm	39 Front__ 40 Right__ 41 Left__ 42 Back__ 43 Total__	44 Front__ 45 Right__ 46 Left__ 47 Back__ 48 Total__	49 None 50 Ground 51 Upper 52 Both	53 Closed 54 Open w/vehicle 55 Open w/o vehicle	56 100% 57 >50% 58 <50% 59 0% 60 Uncertain	61 100% 62 >50% 63 <50% 64 0% 65 Uncertain	Write in:	66 Yes 67 No 68 Uncertain	
B	______ am pm	69 Front__ 70 Right__ 71 Left__ 72 Back__ 73 Total__	74 Front__ 75 Right__ 76 Left__ 77 Back__ 78 Total__	79 None 80 Ground 81 Upper 82 Both	83 Closed 84 Open w/vehicle 85 Open w/o vehicle	86 100% 87 >50% 88 <50% 89 0% 90 Uncertain	91 100% 92 >50% 93 <50% 94 0% 95 Uncertain	Write in:	66 Yes 67 No 68 Uncertain	

(Johnson and Long, 2005)

- Capturing Occupant Behaviour

Method 4: Self-estimating by building occupants

Table 1
Survey information of opening windows.

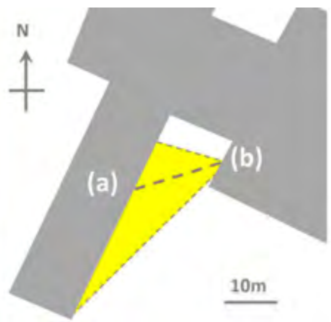
Category	Questions	Answers
Part I: Window opening habit	1. What's the frequency in the heating days?	A. scarcely B. not often C. often D. nearly every day
	2. What's the frequency in a day?	A. 1 B. 2 C. 3 D. more
	3. What's the continuous time each time?	A. 0–5 min B. 6–10 min C. 11–20 min D. more
	4. What's the opening size?	A. small B. moderate C. big D. fully open
	5. Single side ventilation or cross ventilation?	A. Single side ventilation B. cross ventilation
Part II: Potential related factors of opening window	1. What's the indoor thermal sensation?	A. cold B. a little cold C. moderate D. a little hot E. hot
	2. What's the house area?	A. 20–60 m^2 B. 61–100 m^2 C. 101–140 m^2 D.> 140 m^2
	3. What's the storey number?	A. $\leq$8 B. 9–16 C. more
	4. What's the total time at home in a day?	A. 8–11 h B. 12–16 h C. 17–19 h D. 20–24 h
	5. What's the household number?	A. 1 B. 2–3 C. 4–6 D. more than 6
	6. What's the feeling of IAQ?	A. good B. no feeling C. 3 bad
	7. How much do you care about personal health?	A. care a lot B. care a little C. don't care

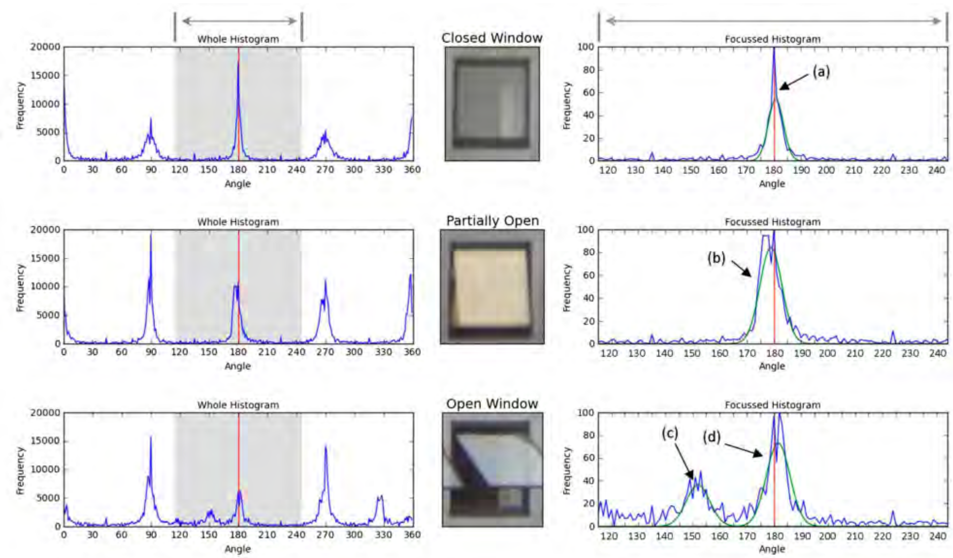
(Huang et al. 2014)

Capturing OB in Buildings

- Capturing Occupant Behaviour

Method 5: Camera-based estimation





(Bourikas et al. 2018)

Capturing OB in Buildings

- Method Comparison

	Advantages	Disadvantages
Method 1	1. Easy to use 2. Large sample size	1. Survey-fatigue 2. Accuracy
Method 2	1. Accurate 2. Continuous measurements 3. No human factor	1. Limited sample size (cost) 2. Malfunction of devices
Method 3	1. Easy to use 2. Large sample size 3. Accurate	1. Time involvement 2. Limited visit per object
Method 4	1. Easy to use 2. Large sample size	1. No real-time data 2. Do people do what they said?
Method 5	1. Large sample size 2. Accurate	1. Susceptible to certain limitations, e.g. daylight, glare and raindrops

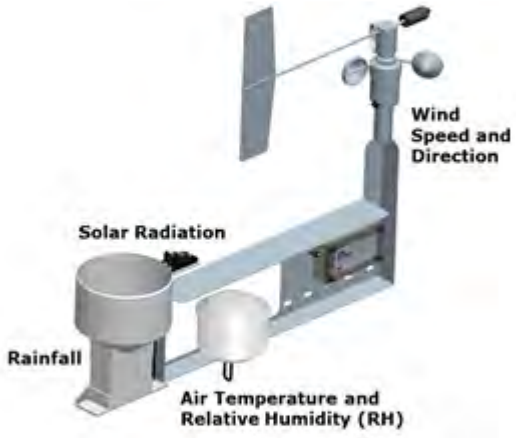
Capturing OB in Buildings

- Factors Affecting Occupant Window Behaviour

Outdoor Environmental Factors	Outdoor temperature, Wind speed, Solar radiation, Rain and Outdoor air pollution
Indoor Environmental Factors	Indoor temperature and CO_2 concentration
Building- and System-related Factors	Dwelling type, Room type, Room orientation, Ventilation type, Heating system, Window type, Floor level and Shared offices
Occupant-related Factors	Occupant age, Occupant gender, Ownership of the property and Smoking behaviour
Time-dependent Factors	Time of day and Season
Other Factors	Previous window state and room occupancy

Capturing OB in Buildings

- Outdoor Environmental Parameter Measurement
  - Located on the roof of the building under investigation
  - Nearby weather station (distance from 280m to 23miles)
  - Remote weather station handheld by the experimenters



Capturing OB in Buildings

- Indoor Environmental Parameter Measurement
  - Near participants' workstation (Haldi and Robinson, 2008; Zhang and Barret,2012; Yun et al. 2012)
  - Mounted on internal walls (Andersen et al. 2013; Herkel et al. 2008)
  - At the center of the zones (Nakaya et al. 2008; Iwashita and Akasaka, 1997)
  - Under participants' desks at the abdomen level (Wei et al. 2013)
  - Measured at four different heights or two different heights (Hellwig et al. 2008)
  - Averaging two values measured at different locations, i.e. one on the workstation and another on the book shelves (Yun and Steemers, 2008; 2010)

Capturing OB in Buildings

- Diversity in Data Collection Methodology
  - Different methods have been used to collect ***behavioural data*** from actual buildings, as discussed above. This brings diversity in sample size, resolution and accuracy.
  - Different methods have been used to collect ***outdoor environmental parameters*** (outdoor temperature, wind speed/direction and rainfall), from local weather stations located on the roof of the building, to remote measurement handheld by experimenters, or to public weather stations up to 23 miles away from the building under investigation.
  - Different methods have been used to collect ***indoor environmental parameters*** (indoor temperature, relative humidity and CO_2 concentrations), from under the participants' desks to shelves or walls, from a single measurement to average of two or more measurements.

5th International Symposium on Occupant Behaviour
Annex 79
Southampton
20 - 23 April 2020

How data can be COMPARABLE if they were collected using different methods???

Shen Wei (PhD, MSc, MEng, MASHRAE, FHEA)

The Bartlett School of Construction and Project Management

University College London (UCL), UK

shen.wei@ucl.ac.uk

20.04.2020

Presentations

Session 2 - Seventh presenter

Kane,
Michael

Northeastern University, USA

Session 2

Day 1, 14:07

Preliminary Insights into Interviews with Building Energy Mangers Regarding Occupant Centric Control

M. Kane

The presentation will provide an overview and preliminary results of the activity in Annex 79 – Subtask 4 on an "International survey on occupant sensing technologies and their usage". The goal of the project is to identify common occupant sensing technologies for energy management, determine how these technologies are used and supplemented with operator expertise, and define white-space for future R&D. The planned approach includes interviewing facility managers, energy managers, and building operators from across the world in multiple languages. This presentation covers preliminary insights into the initial surveys conducted in North America.

Preliminary Insights into Interviews with Building Energy Mangers regarding Occupant Centric Control

Activity of Annex 79 – Subtask 4.1

Michael B Kane, PhD
Asst. Prof., Northeastern University

Burak Gunay, PhD
Asst. Prof., Carleton University

GOAL:

Identify common **occupant sensing technologies** for energy management,

determine how these technologies are **used**

and **supplemented** with operator expertise, and

define **white-space** for future R&D.

The Interview

A 22-question semi-structured interview, taking less than 30-min., of

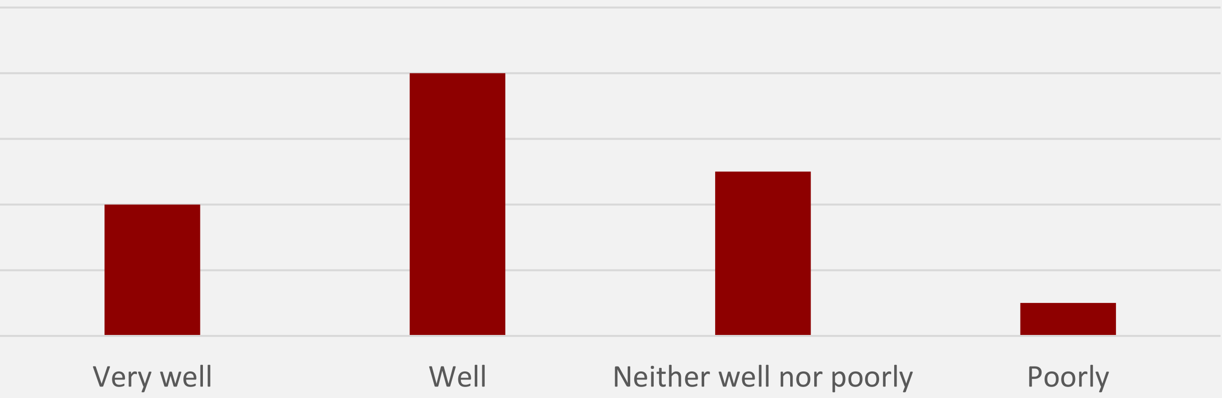
facility managers, energy managers, and building operators

Research Questions

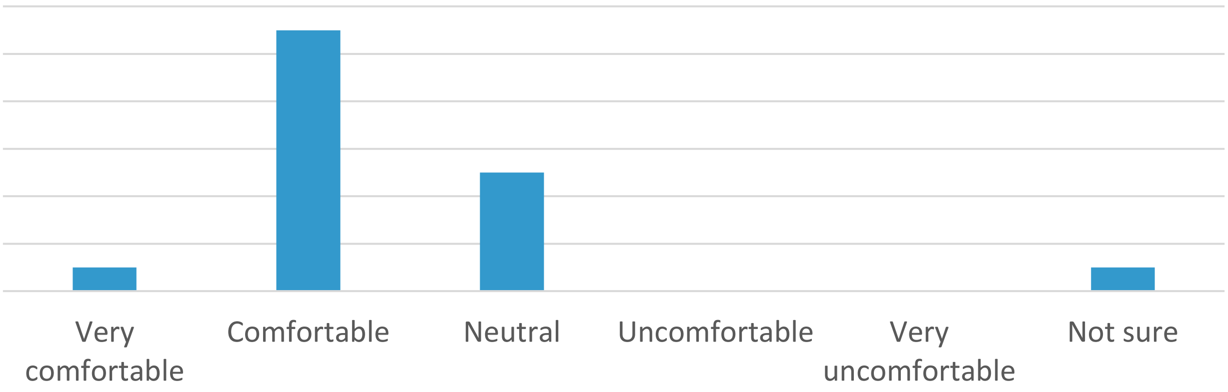
1. How common are various occupant **sensors and interfaces**, and how effective are they for operators?
2. In what ways do **operators' skills** affect occupant (dis)comfort and energy use?
3. In what ways do **operators' opinions** affect occupant (dis)comfort and energy use?
4. Do **operators trust** occupants to make adjustments without causing problems?
5. How do **occupants' needs and inputs** affect operator behavior?
6. What building **data and systems** are available, but operators don't know how to use?
7. In what ways can buildings be **improved** to adapt to occupants' needs?

Initial Results

How well do you feel that you understand the needs of building occupants?



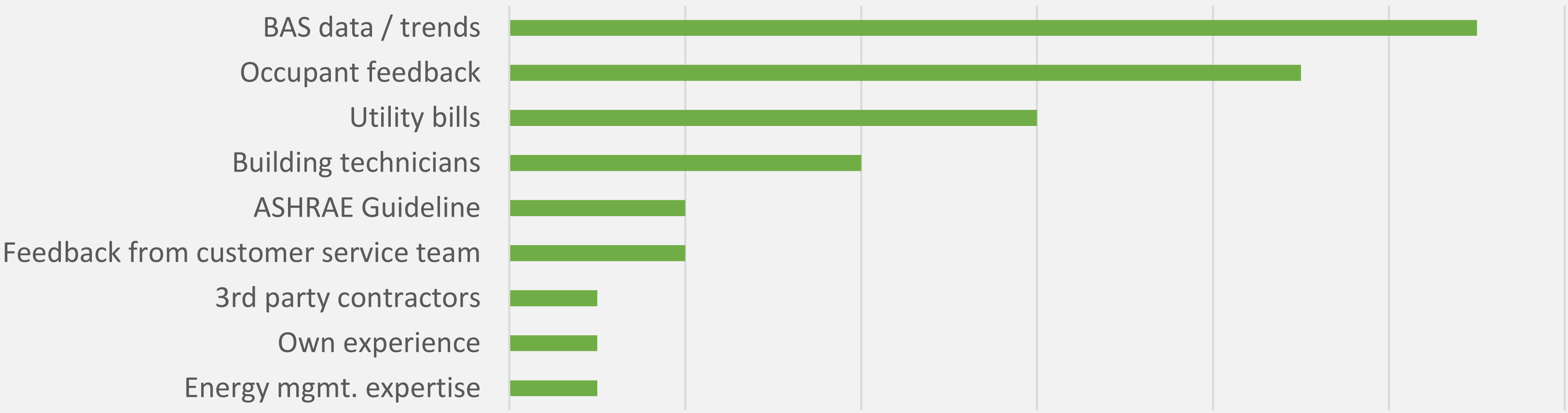
How comfortable do the building occupants seem to be?



What are the top 2 goals <u>that drive your operational decisions?</u>

Stand Operating Procedures
Energy Savings
GHG Reductions
Occupant Comfort
Ease of Operation
Reducing Equipment Cycling
Other

What two sources of information help you most in achieving these goals?



Thank You

Current

- Michael Kane – **Northeastern University (USA)**
  - *DOE Better Buildings Program*
- Burak Gunay, William O'Brien, Zakia Afroz, and Brodie Hobson – **Carlton University (Canada)**
- Giorgia Spigliantini – **Politecnico di Torino (Italy)**

Volunteers for Future Interviews

- Jakob Hahn – **Munich University of Applied Sciences (Germany)**
- Clayton Miller – **National University of Singapore (Singapore/USA)**
- Yuzhen Peng & Arno Schlueter – **ETH Zurich (Switzerland)**
- Zoltan Nagy – **UT Austin (USA)**
- Bing Dong – **Syracuse University (USA)**

- Conducting interviews internationally (Asia) and translating
- Expertise in qualitative analysis of interview transcripts
- Email: mi.kane@northeastern.edu

Thank You

Northeastern University
College of Engineering

Presentations

Session 3 - First presenter

Horváth, Miklós

Czetany, Laszio &

Vámos, Viktória

Budapest University of Technology and Economics, Hungary

Session 3

Day 1, 14:50

Occupant Behaviour Profile Development based on Smart Meter Data

M. Horváth, L. Czetany, V. Vámos

This presentation will cover the objectives and first results of the research project entitled “Large Scale Smart Meter Data Assessment for Energy Benchmarking and Occupant Behaviour Profile Development of Building Clusters,” conducted based on data from Hungary. The project seeks to utilize a new and unique opportunity for accessing and processing an enormous dataset collected by smart meters. Recently in Hungary, nearly 10 000 buildings have been equipped with smart meters within the "Central Smart Grid Pilot Project". By means of advanced data analysis techniques, consumption trends and motivations of building users are being investigated. The aims are to help building designers and engineers design more energy efficient buildings at lower investment costs by avoiding system oversizing and to obtain better knowledge about hourly, daily and monthly energy consumption trends. Furthermore, standard net demand values for normative energy calculations are being updated and specified more precisely since consumption habits change with time and depend on the region. In the first phase of the project, questionnaire surveys were conducted in public buildings both equipped and not equipped with smart meters. Attitude, knowledge and behavioural patterns of occupants were measured and then compared to smart meter datasets. Currently, the energy consumption profiles are being developed using different kind of clustering techniques. First, the classic K-Means and Fuzzy K-Means clustering methods are used but the research is going to be extended to the Hierarchical clustering method as well and the results will be compared. It was also investigated whether the commonly used data analysis techniques in electricity-based datasets can also be used for heat and natural gas consumption datasets of buildings.

OCCUPANT BEHAVIOUR PROFILE DEVELOPMENT BASED ON SMART METER DATA

MIKLÓS HORVÁTH[1], ZSÓFIA DEME BÉLAFI[1], VIKTÓRIA VÁMOS[1], LÁSZLÓ CZÉTÁNY[1], ZSUZSA SZALAY[2], TAMÁS CSOKNYAI[1]

[1] BUDAPEST UNIVERSITY OF TECHNOLOGY AND ECONOMICS, FACULTY OF MECHANICAL ENGINEERING, MUEGYETEM RKP. 3-9., 1111 BUDAPEST, HUNGARY

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MŰEGYETEM 1782

NATIONAL RESEARCH, DEVELOPMENT AND INNOVATION OFFICE HUNGARY

PROJECT FINANCED FROM THE NRDI FUND

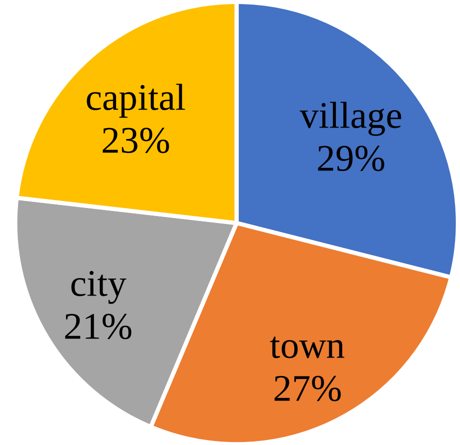
MOMENTUM OF INNOVATION

Smart meters in Hungary

- Central Smart Grid Pilot Project (KOM):
  - To assess the possibilities of a national smart monitoring system
  - 139 901 smart meters installed in 2016-2017
  - Residential, public, commercial and industrial buildings
  - Sampling time: 5 min – one week
- Large Scale Smart Meter Data Assessment for Energy Benchmarking and Occupant Behavior Profile Development of Building Clusters (2018-2021)
  - New research project to analyse the data
  - More precise picture on the energy consumption of the building stock
  - Comparative analysis of measured and modelled data
  - Establish user profiles and patterns

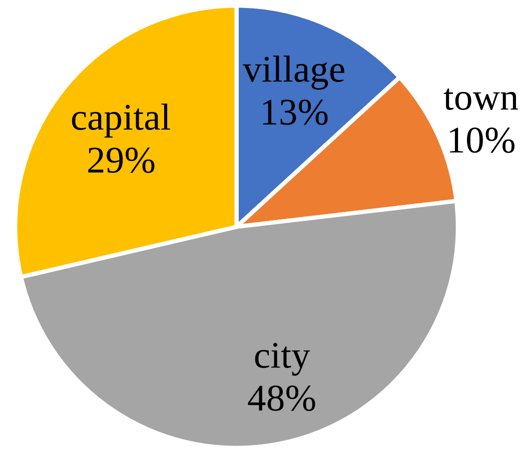
Objectives

- Occupant energy profile development for typical buildings, households
- Enhance current national building typology system
- Identify clusters of occupants based on their consumption and socio-demographic parameters
- Support national policy-making
- Compare results to international projects

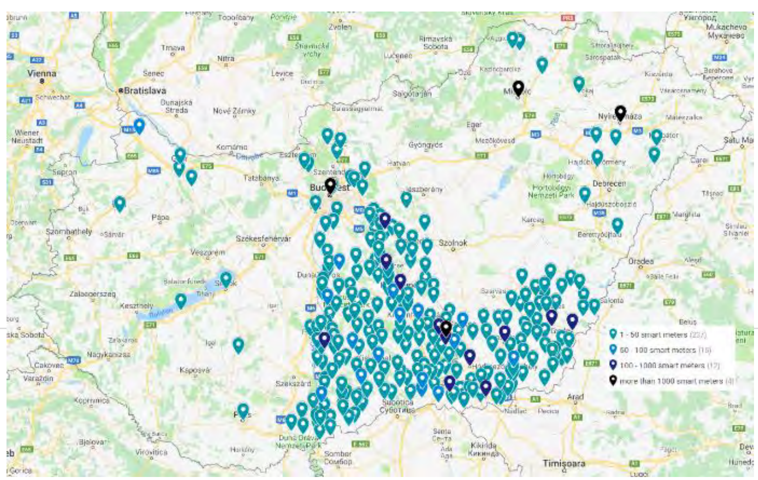


Methods – Smart meter datasets
Residential

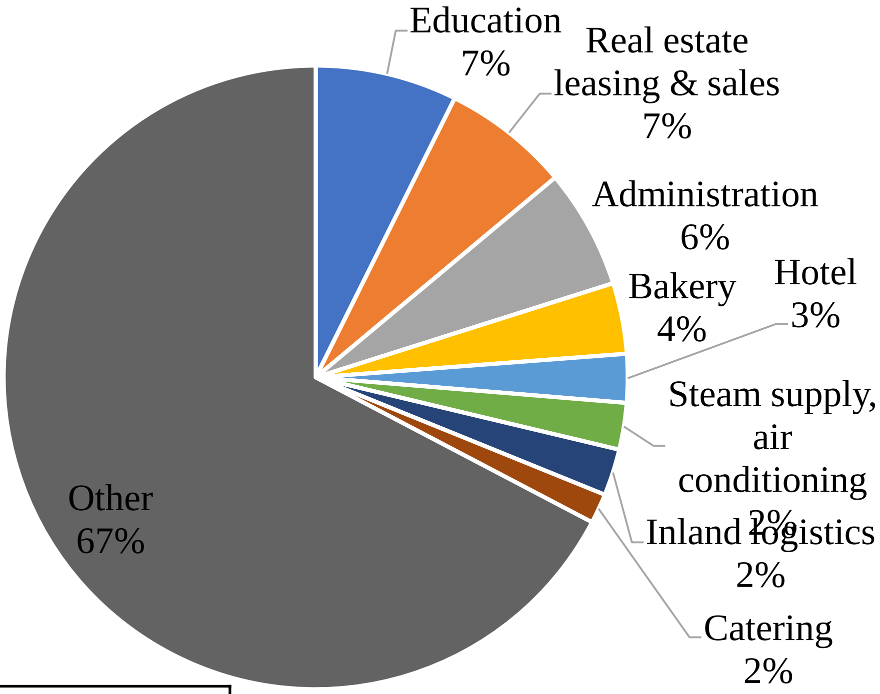
Consumption type	Residential			
	meters deployed	usable address	usable data	good meters with usable Google maps data
Natural gas	7368	6059	934	29
Heat	53432	53430	in progress	in progress
Electricity	24917	9237	4454	1282
Water	22231	22224	in progress	in progress
Σ	107948	90950	5388	1311



Distribution of residential buildings in Hungary (top) and the installed smart meters by settlement type (bottom)



Methods – Smart meter datasets
Non-residential



Consumption type	Non-residential			
	meters deployed	usable address	usable data	good meters with usable Google maps data
Natural gas	14711	in progress	1034	in progress
Heat	15	in progress	in progress	in progress
Electricity	4076	in progress	in progress	in progress
Water	1884	in progress	in progress	in progress
Σ	20686	in progress	1034	in progress

Methods – Qualitative Information Assigned to Smart Meter Data Points

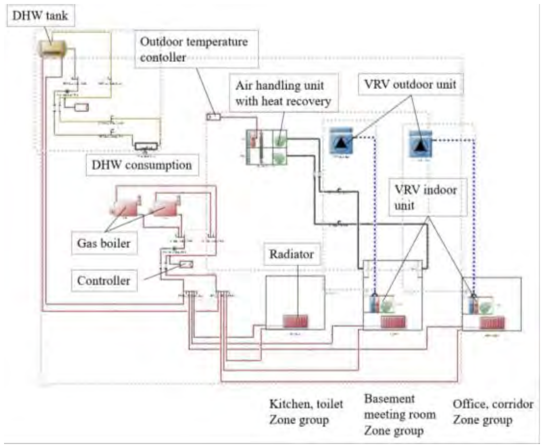
- Only address of the buildings is available
- Additional qualitative data is needed about the buildings
- Manual approach based on GIS mapping tool was chosen: compromise btw accuracy and time spent
- Parameters: building function, type, area, number of stories, condition of building, visible retrofit measures, type of roof, presence of solar panels/ collectors
- Subcategorization based on building archetypes
- Problems: streetview images not available in some villages, identification of building sometimes difficult, blocking by external obstacles

Methods – Time series analysis, clustering

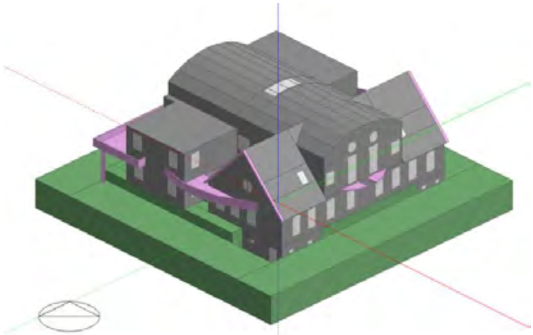
- Analysis of natural gas consumption and electricity
- Data filtering to discard unusable and false datasets
  - Manual analysis of some series to identify typical errors
  - Development of algorithms to automatically categorise the time series
  - Manual investigation kept to a minimum
- Clustering methods:
  - K-Means
  - Fuzzy K-Means
  - Hierarchical

Methods – Calibrated simulations for individual buildings analysed in detail

- Examined buildings:
  - Hegyvidék Office Building
  - Táltos Kindergarten
- Different models were developed:
  - Simple/detailed internal mass
  - Simple/detailed occupancy profile
  - Simple/detailed HVAC
- Results:
  - Models had to be adjusted to the measured data
  - The features of the HVAC system influence the energy consumption of the buildings largely



Circuit diagram for the detailed HVAC model in Hegyvidék Office Building – Helga Kovács



DesignBuilder model of Táltos Kindergarten

Methods – Questionnaires and Interviews

- Socio-demographic data is collected
- Independent variables from four models commonly used to determine social-psychological determinants of energy efficient technology acceptance were selected for surveys
- Three rounds of data collection:
  - Public buildings without SM
  - Public smart buildings
  - Households with SM

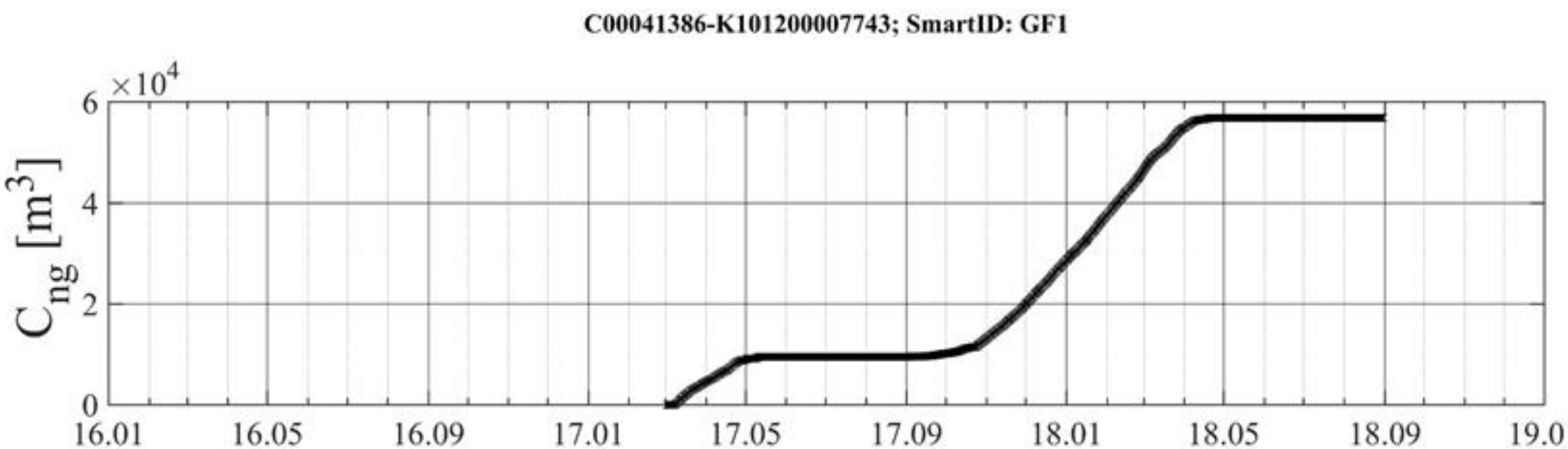
Model	Variables
Theory of Planned Behavior	**Attitude** towards the technology
Technology Acceptance Model	**Perceived usefulness** **Perceived ease of use**
Norm Activation Model	**Personal norms** (moral obligations)
Sustainable Energy Technology Acceptance (SETA)	**Trust in technology providers** **Knowledge** **Perceived risk to privacy** **Problem perception** (awareness of consequences)

+ dependent demographic variables (age, gender, occupation, education level, perceived material status and building characteristics and retrofit)

+ support for SM technology, etc.

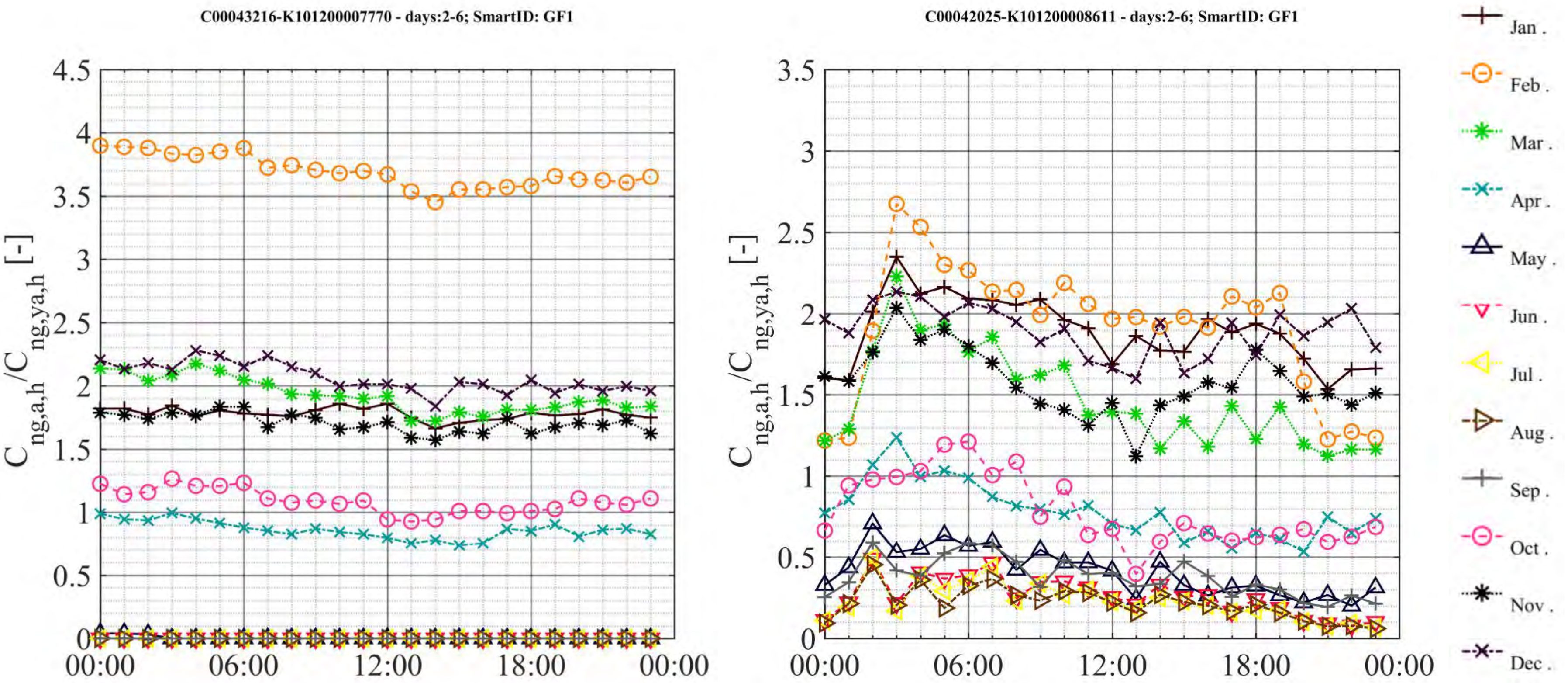
Preliminary results – data quality check

- Data filtering to discard unusable and false datasets
  - Manual analysis of some series to identify typical errors – based always on cummulative profiles created from the whole dataset available for the specific meter
  - Development of algorithms to to automatically categorise these cumulative profiles – a good cumulative natural gas consumption (C_{ng}) profile is shown below.



Preliminary results – Gas consumption profiles

Data filtering to discard find different usage patterns – for instance DHW consumption

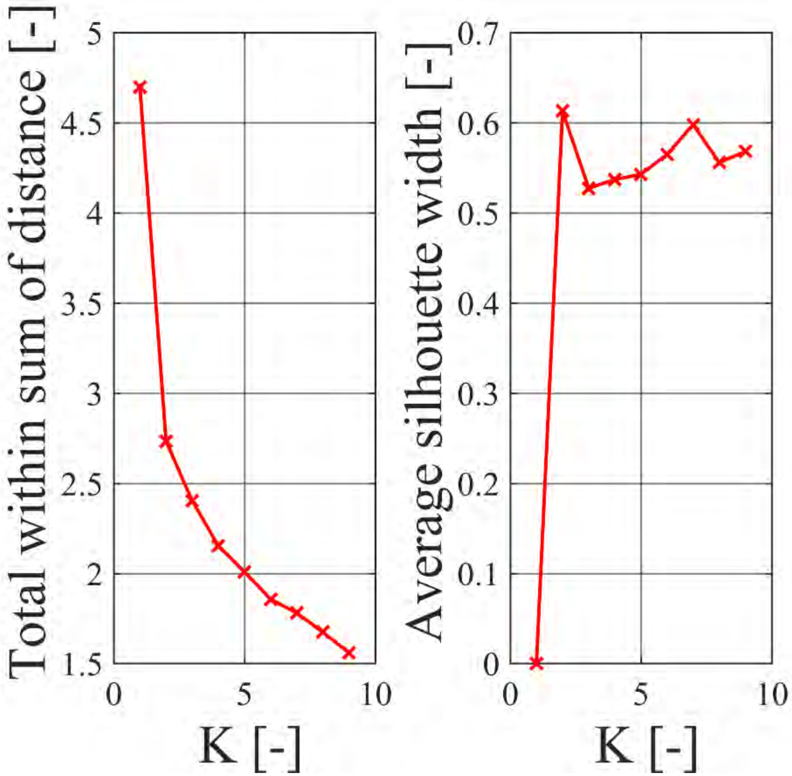


Preliminary results – Clustering

Data filtering to discard find different usage patterns – for instance DHW consumption.

Seasonal profiles were clustered for the summer months to find schools with DHW consumption.

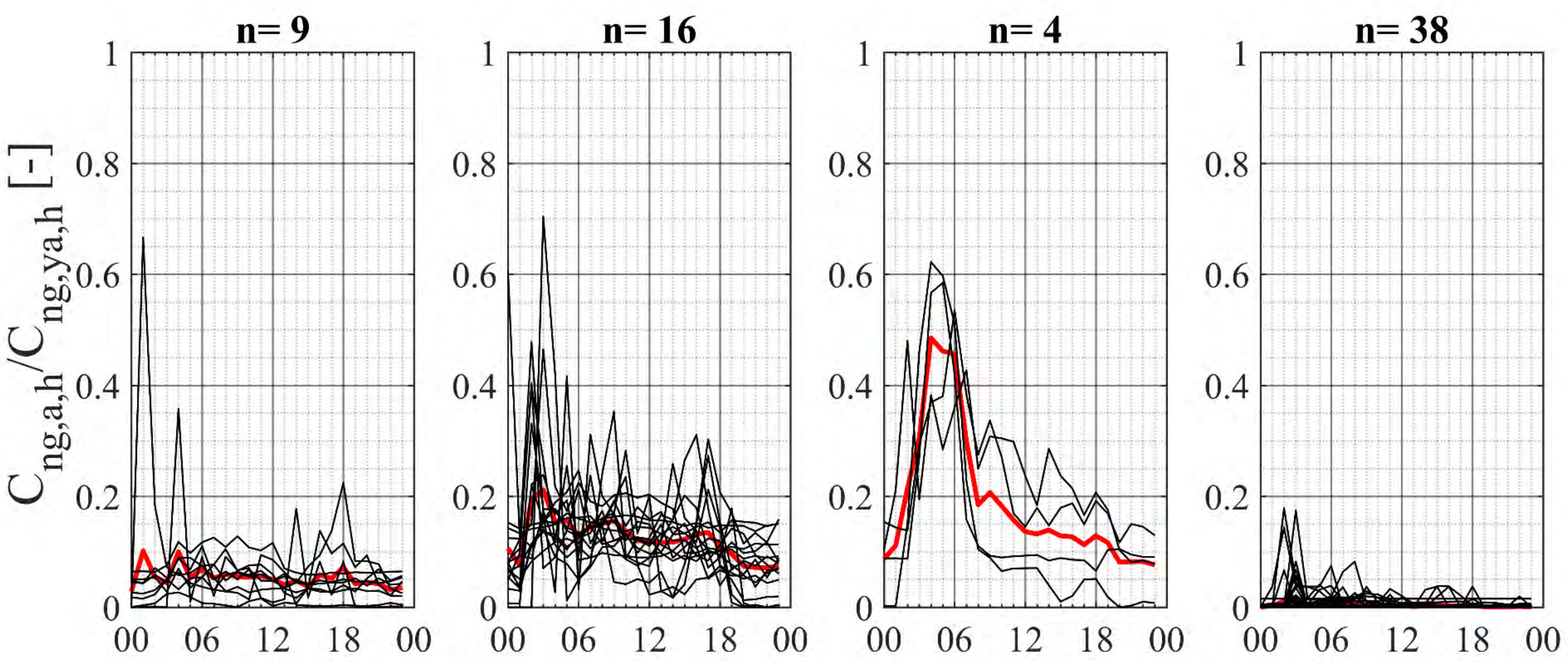
With the silhouette and elbow methods -> two clusters are adequate, but after checking the results -> four was chosen



Preliminary results – Clustering

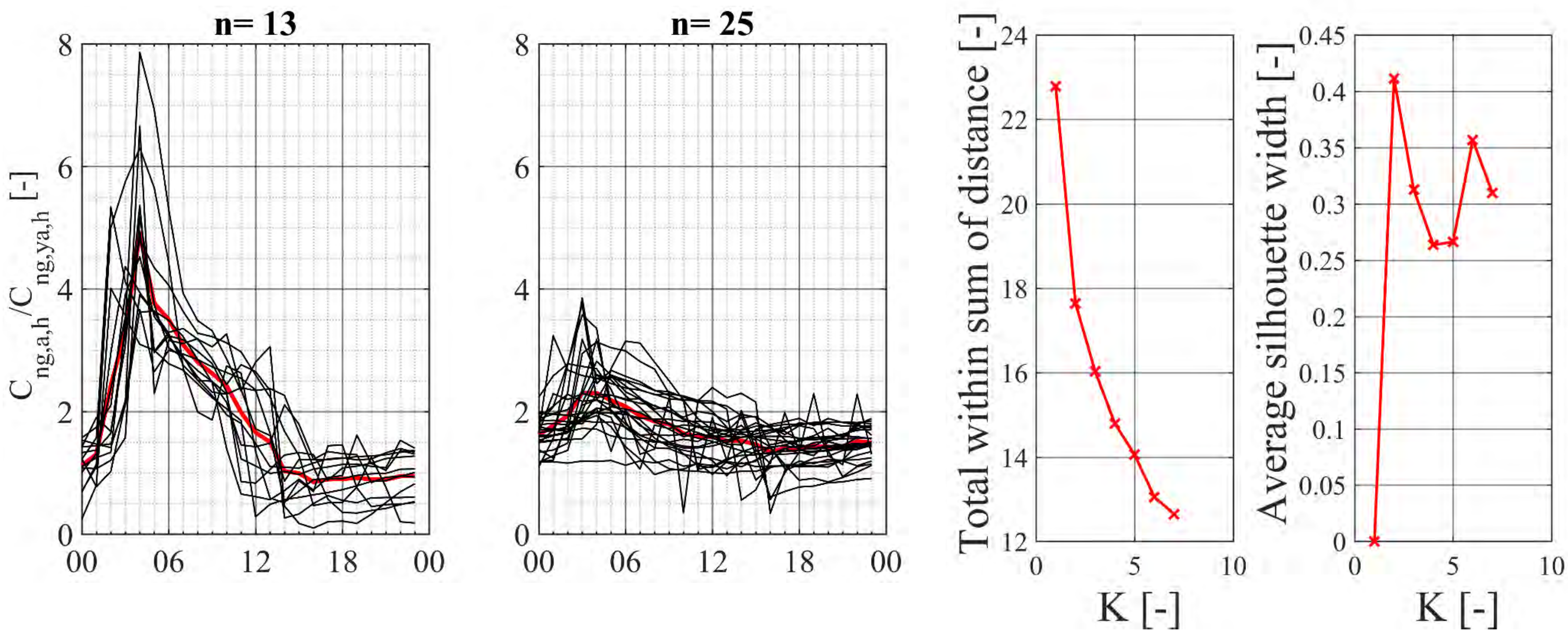
With the silhouette and elbow methods -> two clusters are adequate, but after checking the results -> four was chosen

In 38 schools there is no DHW consumption basically.



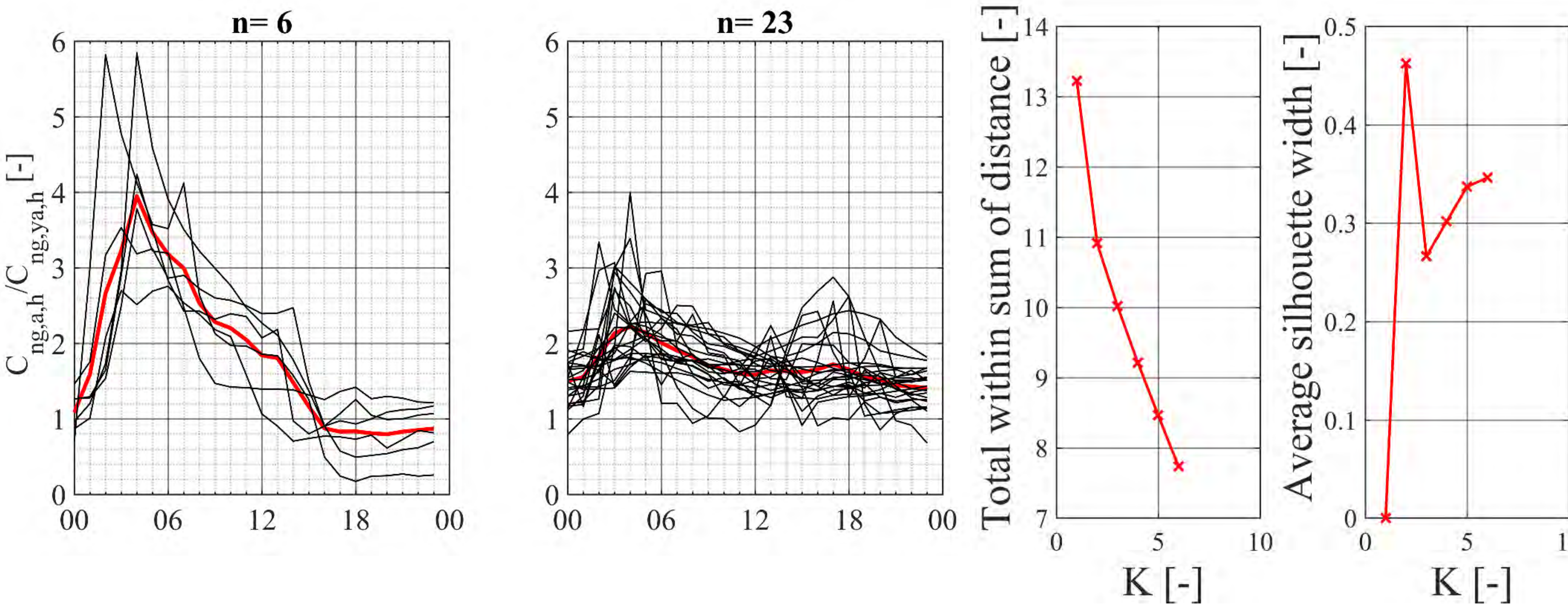
Preliminary results – Clustering

Schools with no DHW consumption for the heating season
With k-means 2 (or 6) clusters



Preliminary results – Clustering

Schools with suspected DHW consumption for the heating season
With k-means 2 clusters



Conclusions and future plans

- Representative results can be achieved for settlement categories and building types but not for geographical distribution
- GDPR makes it challenging to collect qualitative supplementary data for residential buildings
- Data quality issues
- Public buildings results analysed in more detail
- Residential building results
- Cluster analysis:
  - Examine other clustering methods
  - Determine the optimal number of clusters (Elbow method and Average silhouette method used before)
  - Determine the optimal fuzziness parameter for Fuzzy K-Means method

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MOMENTUM OF INNOVATION

Thank you for your attention!

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MOMENTUM OF INNOVATION

Acknowledgments

Results and the determined trends are being fine-tuned and extended for other building types with a geographic scope of Hungary in another research project entitled “Large Scale Smart Meter Data Assessment for Energy Benchmarking and Occupant Behavior Profile Development of Building Clusters“. Furthermore, methods and approaches developed in the current work are being further developed for large scale data analysis. The project (no. K 128199) has been implemented with the support provided from the National Research, Development and Innovation Fund of Hungary, financed under the K_18 funding scheme.

The monitoring data subject to analysis is being collected within the "Central Smart Grid Pilot Project" by KOM Smart Meter Ltd.

The research reported in this paper was also supported by the Higher Education Excellence Program of the Ministry of Human Capacities in the frame of Artificial intelligence research area of Budapest University of Technology and Economics (BME FIKP-MI).

The authors wish to acknowledge a Fulbright Visiting Student Researcher Award from the Fulbright Commission for Educational Exchange which enabled scientific exchange between Budapest University of Technology and Economics and University of Tennessee.

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MOMENTUM OF INNOVATION

Presentations

Session 3 - Second presenter

Ouf,
Mohamed

Concordia University, Canada

Session 3

Day 1, 15:00

Analysing Smart Thermostat Data and Unregulated Loads to Support the Canadian Net Zero Energy Ready Code

M. Ouf

Increasing efficiency requirements in energy codes typically focuses on adding more stringent provisions for HVAC and building envelope systems to decrease heating/cooling loads and associated energy use. However, reducing heating/cooling loads can increase the contribution of occupants to overall building energy consumption. Although previous studies demonstrated this effect, occupant-related assumptions, which are represented by schedules used in building simulations, remain treated with standard simplistic assumptions that do not match data from existing buildings. Since simulations are a principal mechanism for developing new code provisions, inappropriate input assumptions may lead to provisions with sub-optimal performance in practice. To this end, we re-evaluate occupant-related assumptions in the Canadian energy code using data from existing buildings. The research scope focuses on code provisions for unregulated loads (i.e., plug loads) and thermostat setpoint settings. To address unregulated load assumptions, published data on plug loads' usage in residential, commercial office and school buildings was analyzed. Two different approaches, namely scenario-based analysis and Monte-Carlo simulations were used to derive schedule inputs for building simulations and quantify the effect of plug load assumptions on energy use in 5 building archetypes across 5 Canadian climate zones. Results also compared the impact of unregulated load assumptions across 3 different versions of the Canadian energy code to demonstrate their relative effect. To address thermostat setpoint assumptions, anonymized, voluntarily shared smart thermostat data from 14,000 households across Canada were analyzed. This analysis identified unique setpoint profiles and investigated the effect of several factors such as house/household characteristics, seasonal variations and outdoor temperature. Using this dataset, novel approaches were also explored to characterize buildings' thermal properties using indoor and outdoor temperature measurements to identify the effect of changes in energy code requirements on the thermal behaviour of different homes.

Analyzing smart thermostat and unregulated loads data for the Canadian Net Zero Energy Ready Code

Mohamed Ouf, PhD, P.Eng
Assistant Professor
Department of Building, Civil and Environmental Engineering
Concordia University, Montreal, Canada

Overview

NRC Net Zero Energy Ready Project

Problem statement

- More efficient HVAC and building envelopes can increase the contribution of occupants to buildings' energy use

Goal

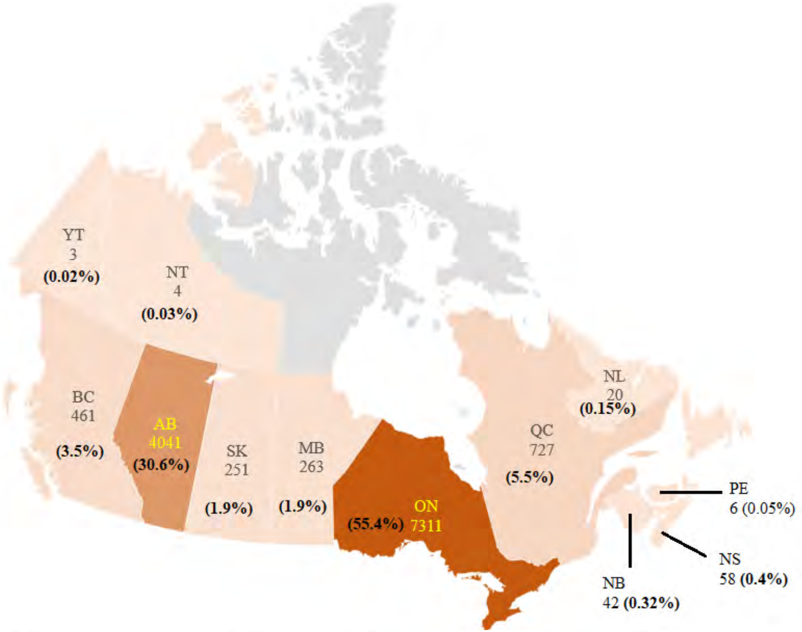
1. Evaluate occupant-related assumptions in the Canadian Energy Code against data from existing buildings
2. Evaluate the effect of previous code changes on buildings' thermal performance

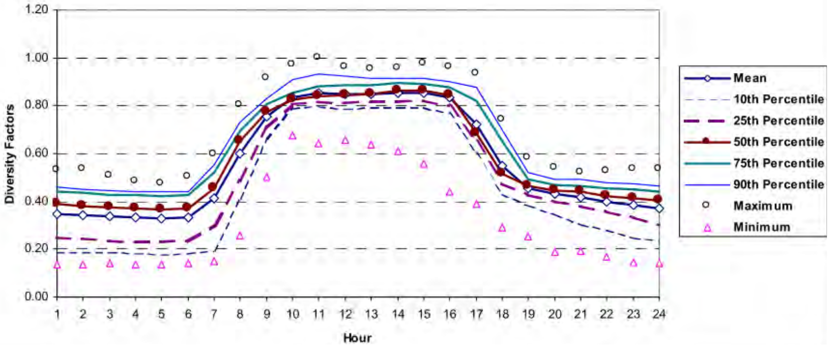
Approach

The analysis relied on TWO main sources

1. Ecobee smart thermostat data (~14,000 houses in Canada)
2. Previous literature data on plug loads' use in existing buildings

- Objectives
  - Investigate thermostat setpoint preferences across Canada
  - Identify heating/cooling setpoint profiles
  - Investigate the impact of plug loads assumptions on simulations





Inter-quartile analysis of plug loads in ASHRAE RP-1093 [1]

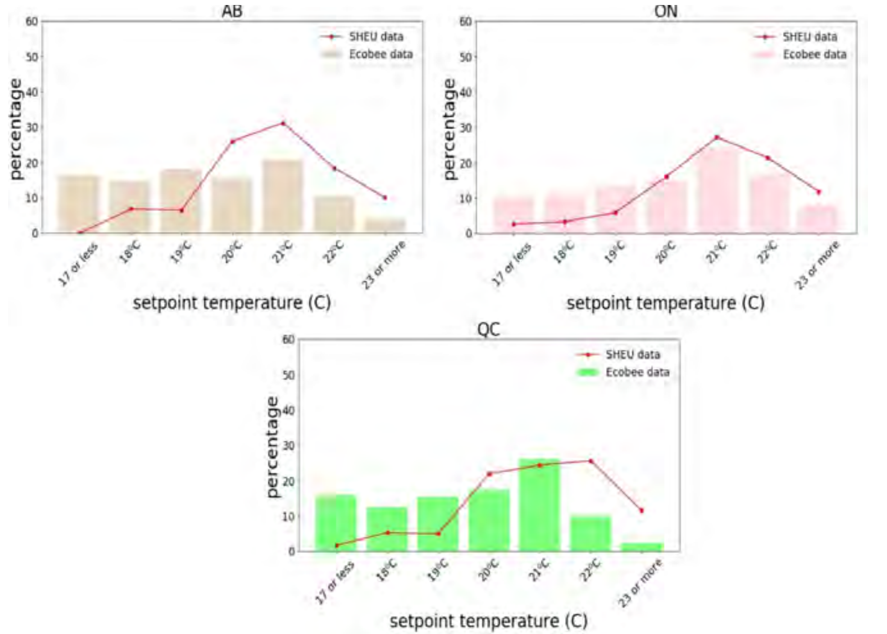
[1] Abushakra, Sreshthaputra, Haberl, David, and Claridge, "Compilation of diversity factors and schedules for energy and cooling load calculations ASHRAE Research Project 1093-RP Final Report,", 2001

Analysis of thermostat setpoint preferences

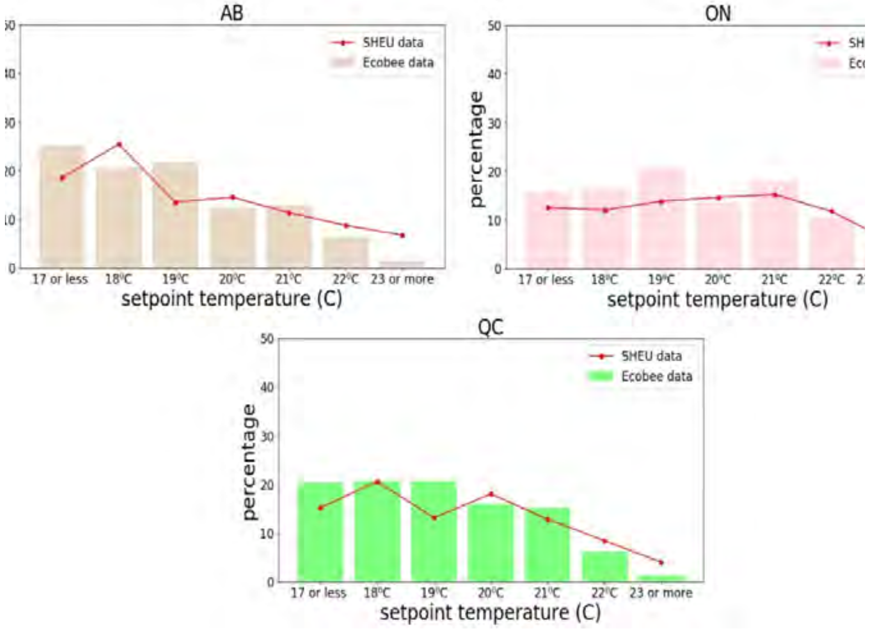
- A high-level analysis of average thermostat set-points
  - Dataset includes several types of events and schedules
    - Focused only on ‘*heating*’, ‘*cooling*’, schedules ‘*home*’, ‘*sleep*’
- Average 24-hr heating and cooling setpoints calculated for each house
- Potential Limitations
  - Not randomly sampled
  - Users likely represent higher-income brackets / tech-savvy
- To address these limitations
  - Analysis focused only on provinces with at least 500 thermostats
  - Results were compared with the Canadian Survey of Household Energy Use (SHEU)

Heating Setpoints

Daytime Setpoint (Home, "*when there and awake during the winter*")

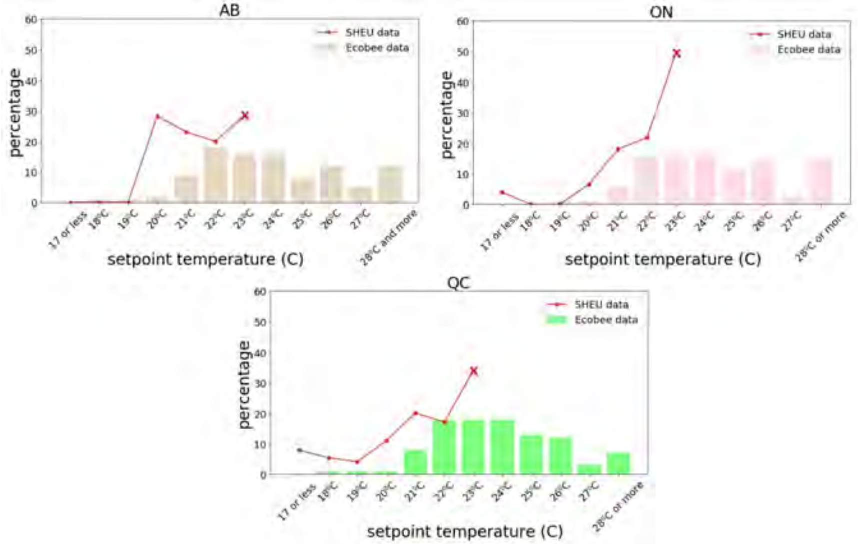


Nighttime Setpoint (Sleep, "*when asleep during the winter*")

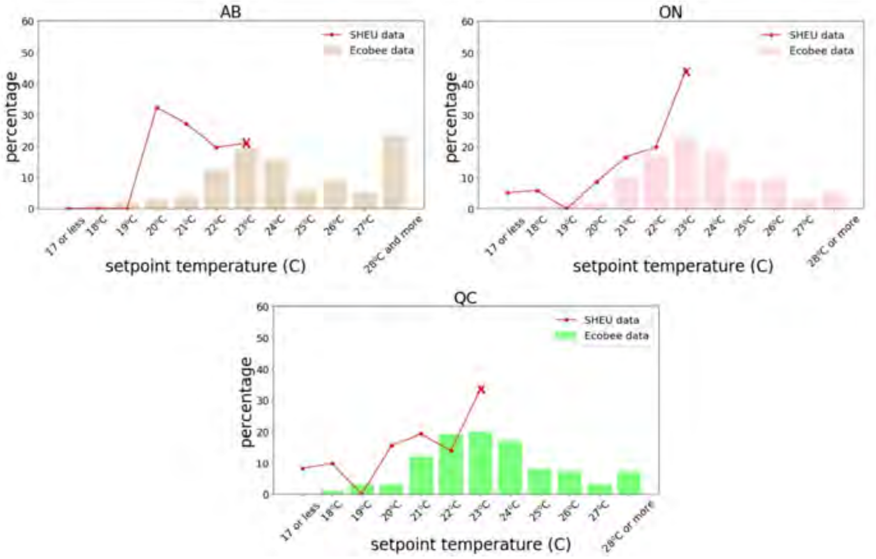


Cooling Setpoints

Daytime Setpoint (Home, “*when there and awake during the summer*”)

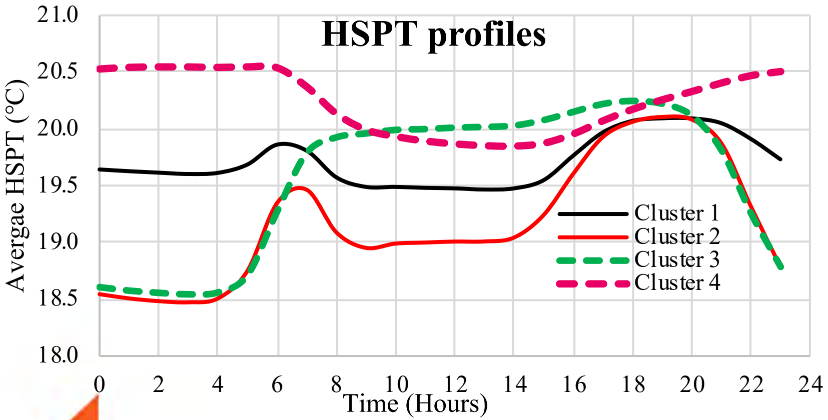


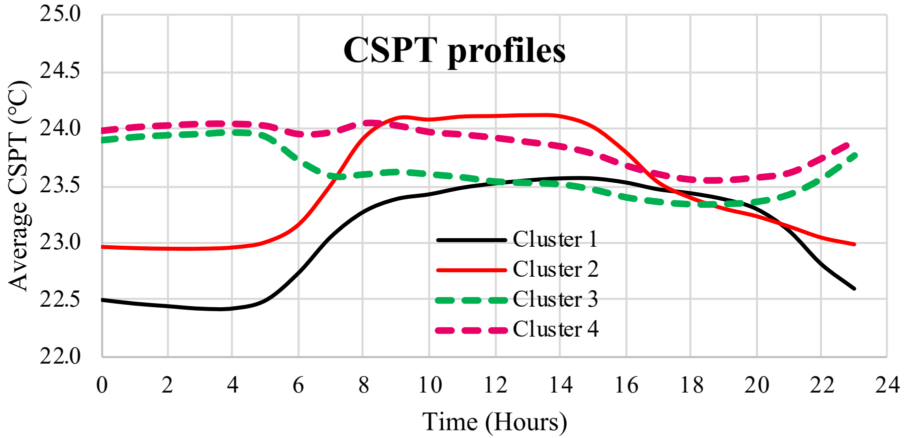
Nighttime Setpoint (Sleep, “*when asleep during the summer*”)



Analysis of thermostat setpoint preferences

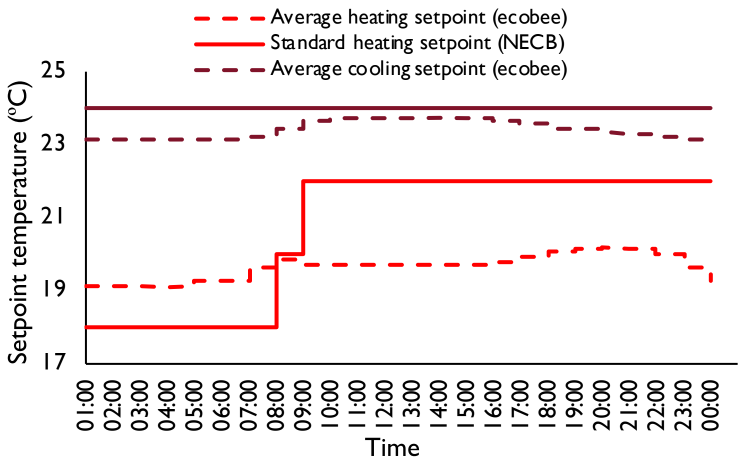
- K-shape clustering of average 24-hr heating / cooling profiles
- The highest Dunn index value was obtained with 4 clusters



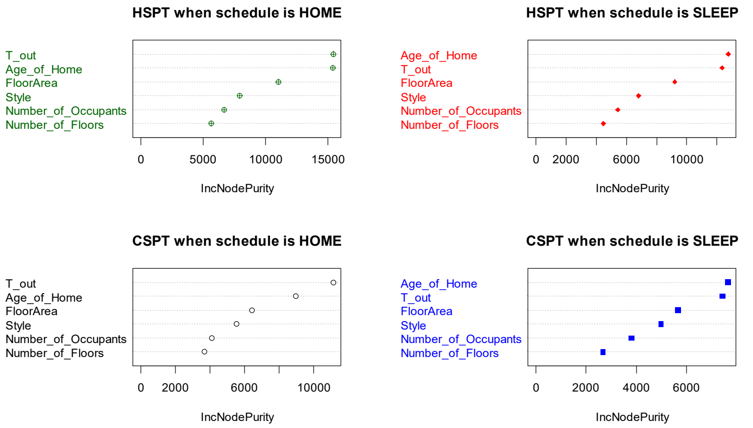


Analysis of thermostat setpoint preferences

- Ecobee data shows some level of agreement with statistically sampled data reported in SHEU
  - Data-driven heating / cooling setpoint profiles do not match Code assumptions



- Based on the results of a Random Forest analysis model
  - Average setpoint preferences are strongly influenced by outdoor temperature and building age
    - *which may represent thermal properties and envelope efficiency*

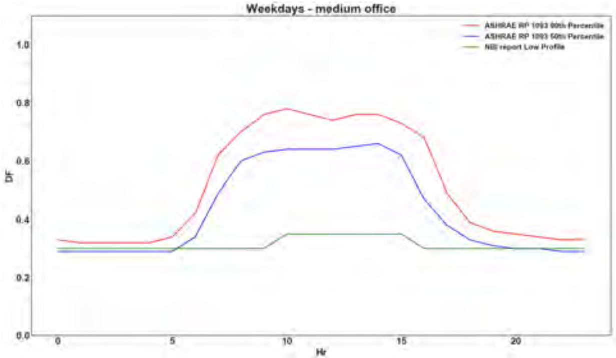


Analyzing the impact of plug loads on EUI

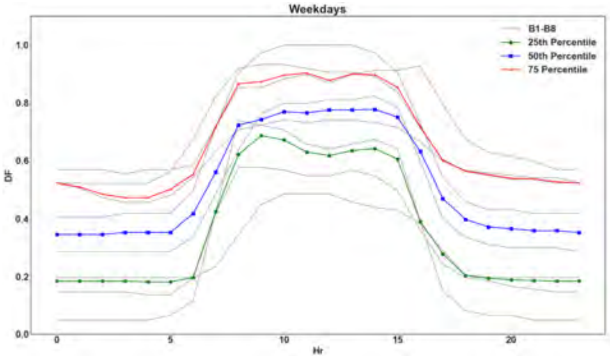
Reviewed the literature for studies that analyzed plug loads in existing buildings

- Focus on studies in which raw data was provided or a detailed hourly analysis was performed
- Three Building Types

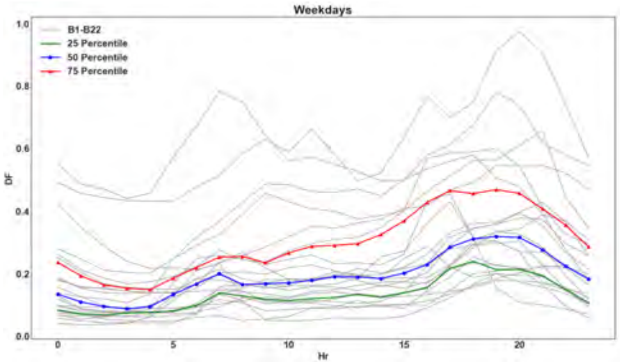
Offices



Schools



MURBs



[1] Abushakra, Sreshthaputra, Haberl, David, and Claridge, “Compilation of diversity factors and schedules for energy and cooling load calculations ASHRAE Research Project 1093-RP Final Report,”, 2001

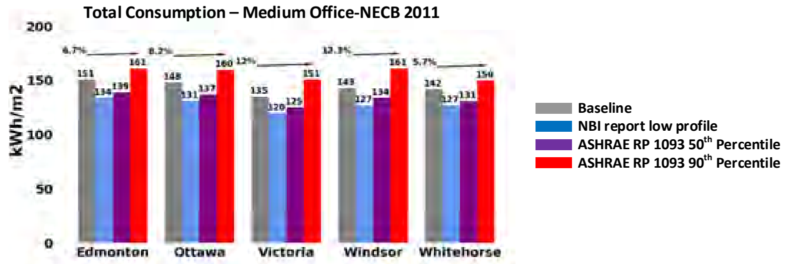
[2] R. S. Srinivasan, J. Lakshmanan, E. Santosa, and D. Srivastav, “Plug-load densities for energy analysis: K-12 schools,” Energy Build., vol. 43, no. 11, pp. 3289–3294, 2011.

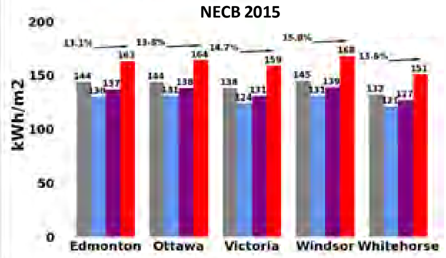
[3] D. Harris and C. Higgins, “Methodology for Reporting Commercial Office Plug Load Energy Use,” no. March, 2013

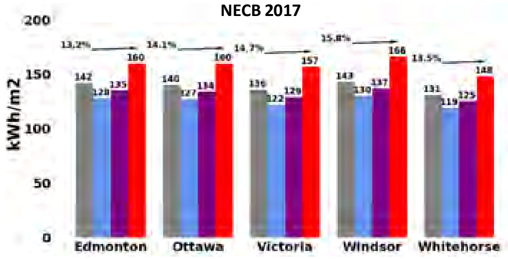
[4] N. Saldanha and I. Beausoleil-Morrison, “Measured end-use electric load profiles for 12 Canadian houses at high temporal resolution,” Energy Build., vol. 49, pp. 519–530, 2012.

Plug loads results

- Energy code assumptions (baseline) may be overestimating EUI
  - EUI is higher than plug loads assumptions of 25th and 50th percentiles
- The impact of plug-loads assumptions generally increases in newer Code versions
- Irrespective of Code version, a higher impact of plug loads assumptions is consistently observed in milder climates







Concordia

Thanks to a great team of researchers!

Aya Doma
MASc Student

Karthik Panchabikesan
Post-doctoral Researcher

Erin Gaucher-Loksts
MASc Student

CONCORDIA.CA

Presentations

Session 3 - Third presenter

Mahdavi, Ardeshir &

Berger, Christiane

TU Wien, Austria

Session 3

Day 1, 15:10

Agent-Based Modelling of Building Occupants: Promise and Challenges

A. Mahdavi, C. Berger

Building design, construction, and operation can benefit from utilization of digital technologies. In this context, Building Information Modeling (BIM) represents a well-known class of digital media geared toward supporting the building delivery process. More recently, efforts are made to extend BIM beyond static representation of buildings' constituent components: Utilizing numeric simulation, BIM could provide high-resolution dynamic representations and thus support a wide range of performance assessment services. Thereby, it is increasingly recognized that digital models of building must include representations of occupants. This is not only because occupants are the main recipients of the services buildings provide, but also because they influence buildings' performance. In this context, agent-based modelling (ABM) has been viewed as a promising instrument toward computational representation of processes associated with occupants' patterns of presence and behavior in buildings. In this context, the present contribution provides a general assessment of the state of the art regarding ABM deployment in the context of buildings' energy and indoor-environmental performance (e.g., energy demand, adaptive thermal comfort, visual comfort, acoustic comfort, indoor air quality, HVAC system design and operation). The investigation entailed in the present contribution suggests that the ABM-based incorporation of occupant behavior in simulation applications can increase their effectiveness. However, the contribution also reveals a number of shortcomings concerning the state of the art in this area. Thereby, a central drawback is the paucity of comprehensive empirical information concerning processes related to occupants' perception, evaluation, and behavior. ABM developments and platforms, no matter how elaborate they may be technically, must be supplied with detailed and reliable domain knowledge on human perception and behavior. Otherwise, they would fall short of providing useful insights toward building design and operation support.

Agent-based Modeling of Building Occupants: Promise and Challenges

Christiane Berger
Ardeshir Mahdavi

Department of Building Physics and Building Ecology
TU Wien, Austria

OB 2020 – IEA EBC Annex 79

Occupant behavior

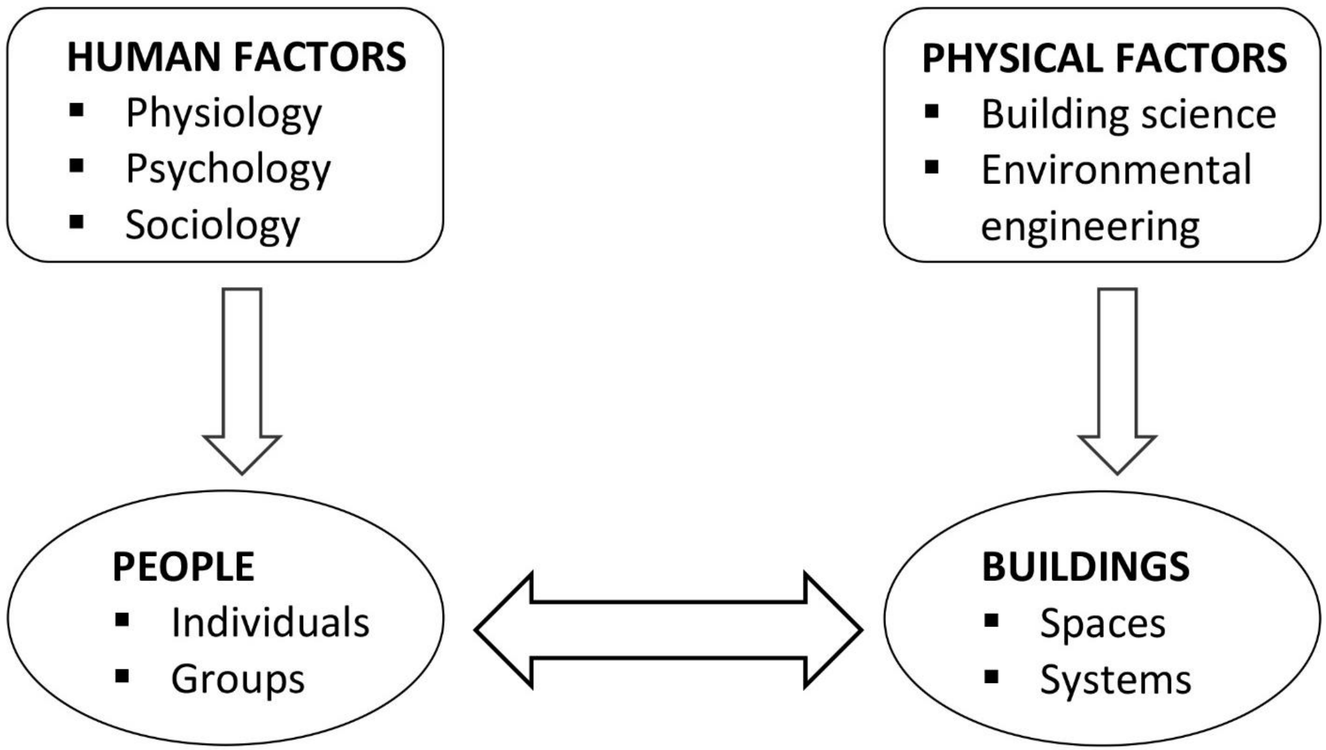
- Presence
- State of activity
- State of clothing
- Social environment
- Interactions with building systems
- ...

Agent-Based Modeling (ABM)

"ABM represents decision-making entities, called agents (i.e., building occupants) that individually assess their situation and make descision based on a set of rules"

(Bonabeau 2002)

Sources of domain knowledge in ABM applications



Systematic review effort

- Occupant-centric ABM for simulation of energy and indoor-environmental performance of buildings
- Publications between 2010 and 2018
- Multiple search engines and databases
- Different combinations of keywords
- 23 directly relevant publications

Systematic review effort

- Implementation purpose
- Representational approach
  (domain knowledge and relevant building type)
- Implementation tools
  (for both people's behavior and their environment)

Overview of selected publications

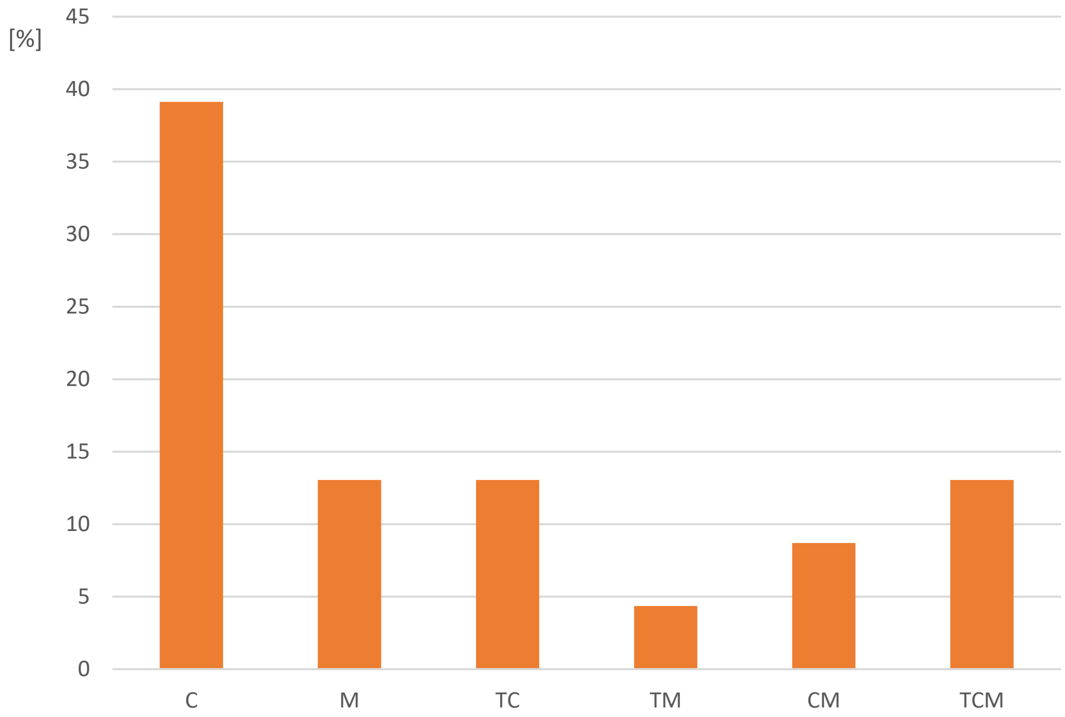
PUBLICATION	MODEL PURPOSE	PEOPLE		ENVIRONMENT	
		Domain knowledge	Implementation tools	Case study/ Domain knowledge	Implementation tools
Alfakara and Croxford [48]	To assess the impact of occupant behavior and occupants' interactions with building systems in response to overheating	agents' interaction with windows and the mechanical cooling system; two scenarios including a base-case behavioral scenario and an improved behavior scenario (occupants are assumed to be trained in view of energy conscious behavior) are simulated	Repast Symphony	case study in a residential setting, virtual model of a high-rise building	TAS
Andrews et al. [49]	To study the impact of occupant behavior and interactions with building systems (lighting) on building performance and occupant satisfaction	two decision-making theories, namely the Theory of Planned Behavior (TPB) and the Belief-Desire-Intention (BDI) framework are adopted to model decision-making processes; a survey in an office building was conducted to collect information about occupants	NetLogo	case study using a simplified five-zone single story commercial building layout with focus on different lighting systems and occupants' satisfaction of different lighting designs	Radiance
Azar and Menassa [50] Azar and Menassa [51]	To assess the impact of different energy use habits of occupants on energy consumption	three types of occupants (High Energy Consumers, Medium Energy Consumers, and Low Energy Consumers); energy consumption characteristics (usage of blinds, lighting, equipment, and hot water) are considered; "word of mouth" effect included	AnyLogic	case study in a student office in Madison-Wisconsin, US including 10 students	eQuest
Barakat and Khoury [53]	To study the impact of occupants' implications of provided comfort levels (thermal, visual, and acoustical comfort) on buildings' energy consumption	three different occupant types (green, neutral, and non-green); operation of doors, windows, shades, and lights assumed; thermal, visual, and acoustic comfort considered	AnyLogic	n.a.	n.a.
Chen et al. [54] Chen et al. [55] Luo et al. [56]	To assess the impact of occupancy behavior patterns on buidling's energy consumption	occupancy patterns are based on the OB XML schema that builts upon the OB DNAS theoretical framework	Occupancy Simulator	case study in an office building in Miami, US; occupancy data from an office building at Carnegie Mellon University was collected over a period of three months	EnergyPlus
Jia et al. [57] Jia et al. [58] Jia and Bharathy [59]	To study the impact of occupant behavior (considering thermal, visual, and air quality) and occupant interactions with building systems on building's energy consumption	occupants can operate windows, doors, and blinds; occupants react to uncomfortable ambient indoor environmental conditions (thermal, visual, and air quality comfort conditions); agents' decisions are based on values (as per GSP) and contexts (perceptions triggered by the indoor environmental conditions)	PMFserv	case study in an office building in Florida, US; indoor environmental data (including temperature, humidity, and illumination) was collected	EnergyPlus
Langevin et al. [60] Langevin et al. [61]	To simulate thermally adaptive behavior of office building occupants	agents are set up according to the Perceptual Control Theory (PCT); Five adaptive behaviors with regard to thermal comfort are considered (clothing adjustment, personal use of a heater or a fan, thermostat use, window opening/closing)	MATLAB	case study simulations for an office building in five different climate regions in the US; indoor-environmental data (i.e., temperature, humidity, air velocity) was measured over a period of one year	EnergyPlus
Lee [62] Lee and Malkawi [63]	To study the impact of occupants' behavior on buildings' energy use and occupants' thermal comfort	beliefs (including behavioral, control, and normative beliefs) associated with agents' behavior are adopted from the Reasoned Action Model; survey was conducted to obtain information of occupants	MATLAB	case study in an office building; model simulated also in different climate regions; different occupants' operations (e.g., windows, doors, blinds, fans, and heaters)	EnergyPlus
Linkola et al. [69]	To simulate occupants' water usage behavior in residential buildings	two decision-making theories: Theory of Planned Behavior (TPB) and the Belief-Desire-Intention (BDI) framework are adopted	NetLogo	case study in two residential settings in the US and the Netherlands; simulation model considers three different household scenarios (single, couple, family)	n.a.
Papadopoulos and Azar [64]	To assess the impact of occupants' behavior and interaction with building systems on buildings' energy consumption	three occupancy characteristics, namely preferences for cooling and heating thermostat set points, lighting energy use patterns, and plug loads energy use patterns are assumed	AnyLogic	case study in an office building in Abu Dhabi, UAE; both occupants and facility managers are considered	EnergyPlus
Azar and Papdopoulos [52]		six occupancy characteristics (lighting, equipment use patterns, and cooling and heating set points) are assumed	MATLAB	case study in a commercial prototype building including occupants and facility managers	

Common implementation tools

Implementation tools (Occupancy behavior)	Implementation tools (Environment)
NetLogo, AnyLogic, Repast Simphony, Unity 3D, Matlab, Occupancy Simulator	EnergyPlus, eQuest, Radiance, TAS

Main sources of domain knowledge

T Theory-based
C Codes, standards, guidelines
M Case-based original data



Promise

- Dynamic and detailed representation of occupants
- Enrichment of the analysis repertoire of simulation tools

Challenges

- Lack of comprehensive empirical information regarding occupants' perception, evaluation, and behavior
- Almost total absence of systematic model validation efforts

Future research

- Further technical enhancement of ABM tools and platforms
- Collaborative multi-disciplinary collection of observational data

Thank you for your attention!

Agent-based Modeling of Building Occupants:
Promise and Challenges

Christiane Berger
Ardeshir Mahdavi

Department of Building Physics and Building Ecology
TU Wien, Austria

OB 2020 – IEA EBC Annex 79

Presentations

Session 3 - Fourth presenter

Bleil de Souza, Clarice &

Tucker, Simon

Welsh School of Architecture, UK & Liverpool School of Art and Design, Liverpool John Moores University, UK

Session 3

Day 1, 15:20

Inserting Occupant Behaviour Models Within the Workflow of Practitioners: A Practice-Based Perspective

C. Bleil de Souza, S. Tucker

We invite the building performance simulation community to discuss how occupant behaviour models can be inserted or integrated within the workflow of practitioners. We propose a practice–based perspective, where the workflow of practitioners is rationalized from high level, considering how they make decisions, down to its lower level, when decisions are implemented in practice aided by simulation tools. This practice-based perspective was developed in previous work sponsored by EPSRC/UK, grounded on a mixed methods approach which included, Interaction Design, Participatory Action Research, a survey, interviews and discussions with practitioners. It explored the workflow of decision-making behind ill-defined problems, in which designers make decisions in a non-systematic way based on reflection in action as a result of 'what if' experiments. This is one of the most challenging types of decision making processes to be rationalised as building designers need information and ideas in order to understand better what is significant to the design challenge at hand and to inform design decisions based on evidence. Increasing the uptake of occupancy modelling by designers will require that inherently complex information is presented to practitioners in ways that support their design process. Therefore, this presentation is supposed to: 1. Briefly show the overarching framework of decision-making for ill-defined problems, providing an overview on how practitioners make decisions, including worked examples validated in practice. 2. Discuss how the framework can be translated into simulation workflows within the logic of object oriented programming, likewise commonly used in digital design tools. 3. Open a discussion on how catalogues of decisions, grounded on the identification of the different 'dimensions' of occupant modelling which are relevant to the design process, can be developed to insert and recall different types of occupant behaviour models within the decision-making workflow of practitioners.

Inserting occupant behavior models within the workflow of practitioners:

A practice-based perspective

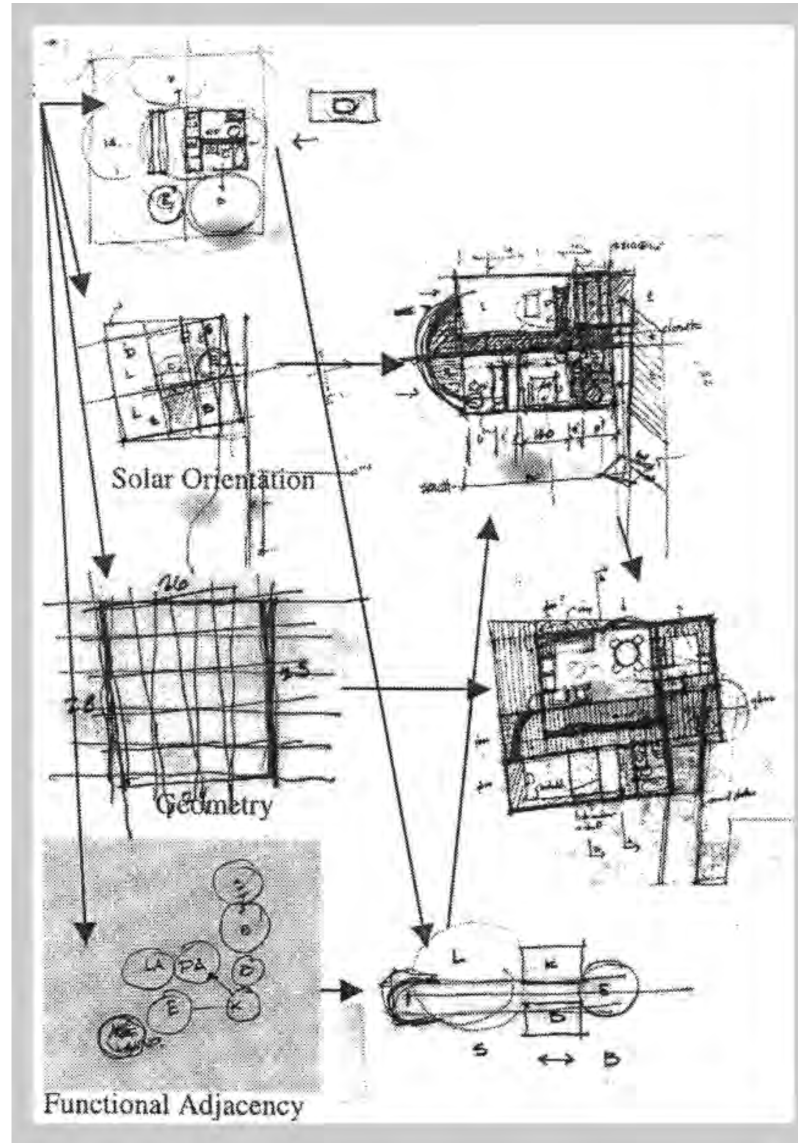
Clarice Bleil de Souza

Simon Tucker

The Framework: ill-defined problems

Designers need to make decisions with:

- **Incomplete information &**
- **Multiple goals (e.g.)**
  - **Aesthetic**
  - **Technical**
  - **Environmental performance**
  - **Financial**
  - **Personal and professional**
  - **Legislation**
  - **Imposed by client**



Besides:

Designers solve problems by 'reflecting in action' through 'a conversation with the materials of the situation' (Schon 1991)

Image:

Akin, O. 2001. "Variants in Design Cognition." In *Design Knowing and Learning: Cognition in Design Education*, edited by Eastman, C., M. McCracken, and W. Newstetter, 105–124. Atlanta: Elsevier.

The Framework: ill-defined problems

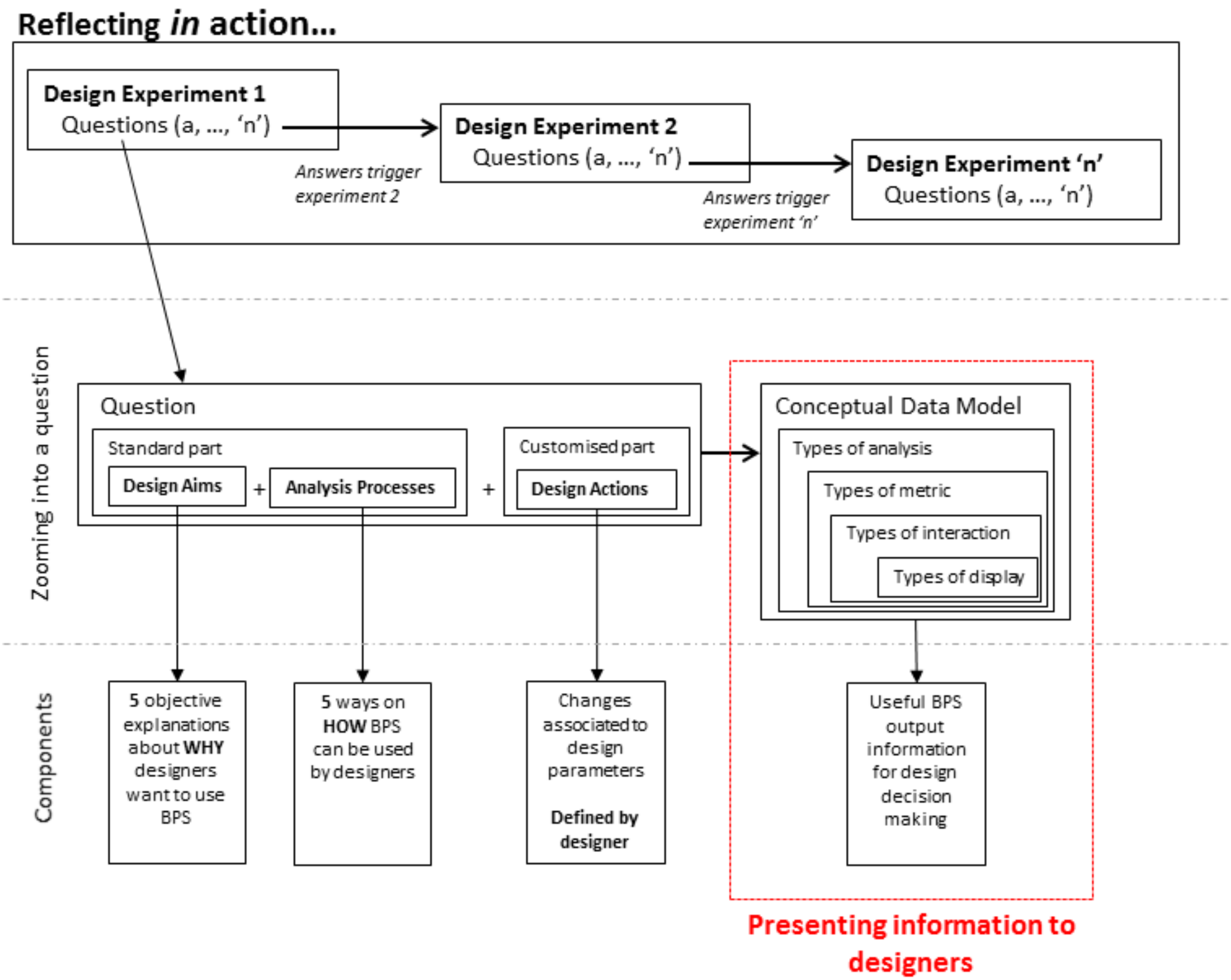
Framework

- Recognises that designers ***always ask questions*** about the building, how it performs, how it can be made better, what options the designer has for developing it, etc. (i.e. performance queries or design advice)

- Deconstructs and formalises *potential* questions such that they can be encoded in a database and recalled by the simulation user.

- The database contains all of the questions that one can ask about the building performance, and contains all of the knowledge ('the answers') on strategies for analysing and improving performance.

The Framework: ill-defined problems



'What if' scenarios

Driven by ***QUESTIONS***

Looking for:

- ***Performance queries***
- ***Design advice***

Image:
Bleil De Souza, C. and Tucker, S. 2015. Thermal simulation software outputs: a conceptual data model of information presentation for building design decision making. Journal of Building Performance Simulation 9(3), pp. 227-254.

Translation into simulation workflows

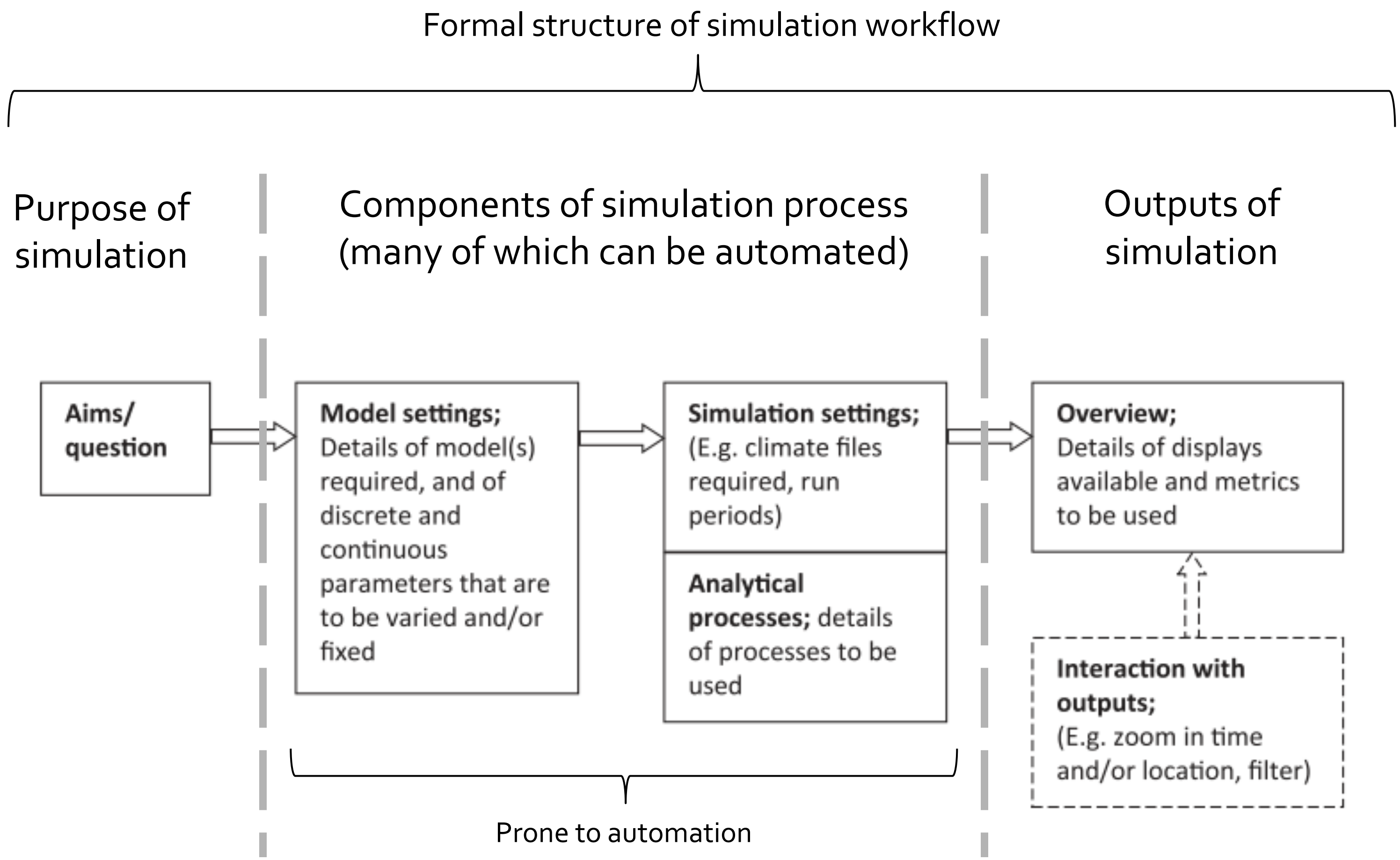


Image:
Modified from: Tucker, S. and Bleil De Souza, C. 2016. Thermal simulation outputs: exploring the concept of patterns in design decision-making. Journal of Building Performance Simulation 9(1), pp. 30-49.

Example – Iterative design of shading devices

List of 'standard' questions

E1
How does my building perform without any shading device?

E1
How does my building perform with these proposed shading devices?

U3b
How sensitive is the building to design parameters: Proportion and Area of shading device?

E2
What is the effect on performance if I change either type, position, proportion, or area of shading device ?

E3
What is the effect on performance if I change any combination of type, position, proportion, or area of shading device?

O1b
Optimize type, position, proportion, or area of shading device for minimum heating and cooling demands?

Question assemblages

E1
How does my building perform without any shading device?

E3
What is the effect on performance if I change any combination of type, position, proportion, or area of shading device?

O1b
Optimize type, position, proportion, or area of shading device for minimum heating and cooling demands?

An individual's design process should be supported by flexibility in the sequence in which information is requested and delivered

Example – Iterative design of shading devices

List of 'standard' questions

E1
How does my building perform without any shading device?

E1
How does my building perform with these proposed shading devices?

U3b
How sensitive is the building to design parameters: Proportion and Area of shading device?

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Optimize type, position, proportion, or area of shading device for minimum heating and cooling demands?

Question assemblages

E1
How does my building perform with these proposed shading devices?

↓

U3b
How sensitive is the building to design parameters: Proportion and Area of shading device?

↓

E2
What is the effect on performance if I change either type, position, proportion, or area of shading device ?

Translation into simulation workflows

Object-oriented structure:

- Useful sequences can be identified
- Recorded in databases

We refer to these as 'Patterns'

Table 2. Examples of patterns.

	Goal/question	Model settings	Simulation/analysis/ post-processing	Outputs (overview)	Interaction with outputs
1	Will the building meet BB101 overheating targets in 2020, 2050, 2080? What would the energy use be?[a]	1. Base case: As per drawings/ specifications. Settings follow recommendations.[b] 1a. Free-running 1b. With heat/cool system.	Descriptive analysis. Weather files:[c] 2020/H/90/DSY 2020/H/50/DSY 2050/H/90/DSY 2050/H/50/DSY 2080/H/90/DSY 2080/H/50/DSY	Text: BB101 PASS or FAIL. Table of BB101 figures. Bar chart: Annual heat and cool energy.[d]	Zoom: Location and time (produces Bar chart: Heat and cool energy).[e] Bar chart: Heat and cool energy.
2	Will the fixed shading as designed be sufficient until 2050, or should it be made adjustable or extendable?[f]	1. Base case. 2. No shading. 3.100% efficient shading.[g] *Each model simulated with:* 3 * ventilation values (1, 3, 5 ac/hr). 2 * internal gains values (low & standard).	Comparative analysis Weather files; 2050/H/90/DSY 2050/H/50/DSY	Text: BB101 PASS or FAIL. Table of BB101 figures. Bar chart: Annual heat and cool energy.	Zoom: Location and time (produces Bar chart: Heat and cool energy) Bar chart: Heat and cool energy.[e]

<u>Image:</u>
Tucker, S. and Bleil De Souza, C. 2016. Thermal simulation outputs: exploring the concept of patterns in design decision-making. Journal of Building Performance Simulation 9(1), pp. 30-49.

Patterns: Object-oriented Structure

Types of pattern: high level planning, building related, detailed modelling

Table 3. Proposed hierarchy of patterns.

Level	Type/purpose	Modelling details/notes
High-level, planning related	Site analysis, guidance on climatic strategies, passive and low-energy strategies and renewable energy systems potential	Simple models (from a library) could be used to test concepts (e.g. heavy – lightweight, insulation levels, glazing for solar gains) and explore site and overarching design strategy
Mid-level, building related	Exploring building form, glazing ratios, insulation of building elements, preliminary calculations on renewable energy systems integration and site specific 'rules-of-thumb'	Models (user generated) tend to have many defaults ascribed
Low-level, detailed modelling	Effect on performance of building parameters, plant efficiencies and effect of occupants	User-detailed model is constructed to carry out detailed building performance experiments

Building occupant behaviour patterns?

Patterns could be based on (Including ***dimensions*** taken from Annex 66 final report pp.57):

- Phase in the delivery process (from early design to policy making)
- Climate / Culture
- Building type (School, House, Office, etc.)
- Environmental ambition (Zero Carbon, naturally ventilated, etc.)
- Modelling domain (e.g. layout, lighting, thermal, acoustic, safety design, HVAC, structure, etc.)
- Type of occupant interaction (e.g. intelligent systems, manual controls)

The construction of well focussed patterns can also help to identify where further research is needed.

A catalogue of patterns?

We could start from your case studies

References & Acknowledgements

This work is based on an EPSRC research project with the following outputs:

Bleil De Souza, C. and Tucker, S. 2016. Placing user needs at the center of building performance simulation (BPS) tool development: using 'designer personas' to assess existing BPS tools. Presented at: Building Simulation and Optimization, Newcastle, UK, 12-14 September 2016.

Tucker, S. and Bleil De Souza, C. 2016. Placing user needs at the centre of building performance simulation: transfering knowledge from human computer interaction. Presented at: Building Simulation and Optimization, Newcastle, UK, 12-14 September 2016.

Tucker, S. and Bleil De Souza, C. 2016. Thermal simulation outputs: exploring the concept of patterns in design decision-making. Journal of Building Performance Simulation 9(1), pp. 30-49. (10.1080/19401493.2014.991755)

Bleil De Souza, C. and Tucker, S. 2015. Thermal simulation software outputs: a conceptual data model of information presentation for building design decision making. Journal of Building Performance Simulation 9(3), pp. 227-254. (10.1080/19401493.2015.1030450)

Bleil De Souza, C. and Tucker, S. 2014. Thermal simulation software outputs: a framework to produce meaningful information for design decision-making. Journal of Building Performance Simulation (10.1080/19401493.2013.872191)

Bleil De Souza, C. and Tucker, S. 2013. Thermal simulation software outputs: what do building designers propose?. Presented at: Building Simulation 2013 (BS2013): *Proceedings of BS2013: 13th Conference of International Building Performance Simulation Association, Chambéry, France, August 26-28*. International Building Performance Simulation Association pp. 468-475.

Tucker, S. and Bleil De Souza, C. 2013. Thermal simulation software outputs: patterns for decision making. Presented at: Building Simulation 2013 (BS2013): *Proceedings of BS2013: 13th Conference of International Building Performance Simulation Association, Chambéry, France, August 26-28*. International Building Performance Simulation Association pp. 394-401.

Presentations

Session 3 - Fifth presenter

Hong, Tianzhen

Lawrence Berkeley National Laboratory, USA

Session 3

Day 1, 15:24

Is a Zero-Net-Energy (ZNE) Home Really ZNE?

T. Hong

California, as a U.S. state, requires new residential buildings to be zero-net energy (ZNE) starting 2020 by its building energy efficiency standards, aka Title 24. The zero-net energy metric is on an annual basis, i.e., a residential building (either single or multi-family) produces enough energy on-site to meet its energy demand during a whole-year period. ZNE homes are designed with a package of technologies based on the optimized cost balancing energy efficiency measures and on-site renewable energy generation (e.g., from PV). However, the actual operating performance of ZNE homes would vary significantly due to actual weather conditions and more importantly, the energy use behaviours of the occupants in those ZNE homes. In the energy modelling and analysis that derives the ZNE home design, typical meteorological year (TMY) weather data in 16 Californian climate zones and static and homogeneous occupant profiles are used. There lacks quantification of the variability of performance of ZNE homes. This presentation introduces research and energy modelling conducted to characterize and quantify the influence of weather and occupant behaviour on the performance of ZNE homes, which helps address the question – when does a ZNE home become energy positive or negative, and by how much? The findings suggest scenarios of weather data and occupant behaviours should be developed and considered in the energy modelling process that supports the Title 24 development so that variations of ZNE home performance are quantified and ZNE home technologies can be optimized to ensure robust ZNE target.

OB-20 International Symposium

Is a ZNE Home Really ZNE?

Tianzhen Hong, Theo Picard

Building Technology and Urban Systems Division

April 20-21, 2020

Background

A zero-net energy building (ZNE) is an energy-efficient building where, on the basis of **annual source energy**, the delivered energy is less than or equal to the on-site generated renewable energy.

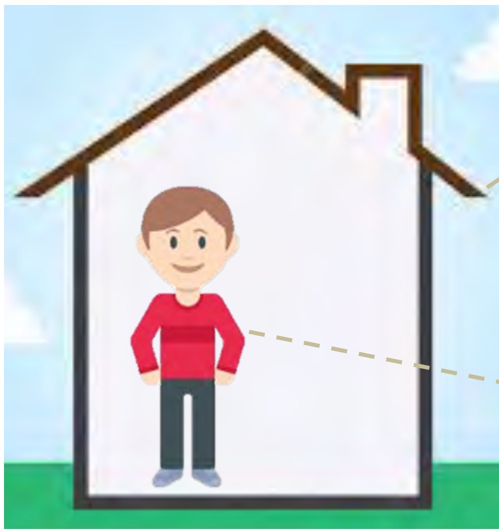
The California Energy Efficiency Strategic Plan:

- All new residential construction is required to ZNE starting Jan 2020.
- All new commercial construction will be ZNE by 2030

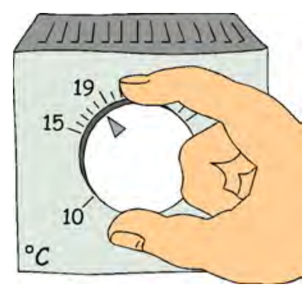
The problem:

- Will a ZNE designed home achieve ZNE performance in reality?
- Buildings are designed using static weather data. What is the impact of weather variability and climate change on the performance of ZNE homes?
- Static average occupant behaviors are used in building design. What is the impact of OB on the performance of ZNE homes?

Occupant behavior is a key factor influencing building performance

Buildings	Main Components	Energy Conservation measures
	Envelope	Technology
	 Equipment	Technology and operation
	Occupants	Behavioral change

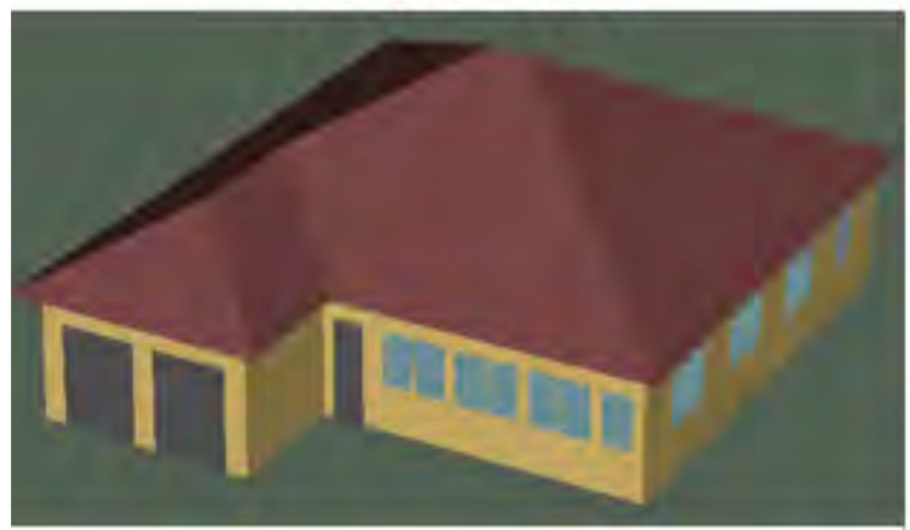
Occupant behaviors



Approach

◆ Use ZNE home energy models to simulate the impacts on weather and OB on performance of ZNE homes in 3 typical Californian climates.

- CZ3 San Francisco
- CZ10 Fresno
- CZ13 Riverside



Single Family Home, 2100sf (195 m²)

Approach

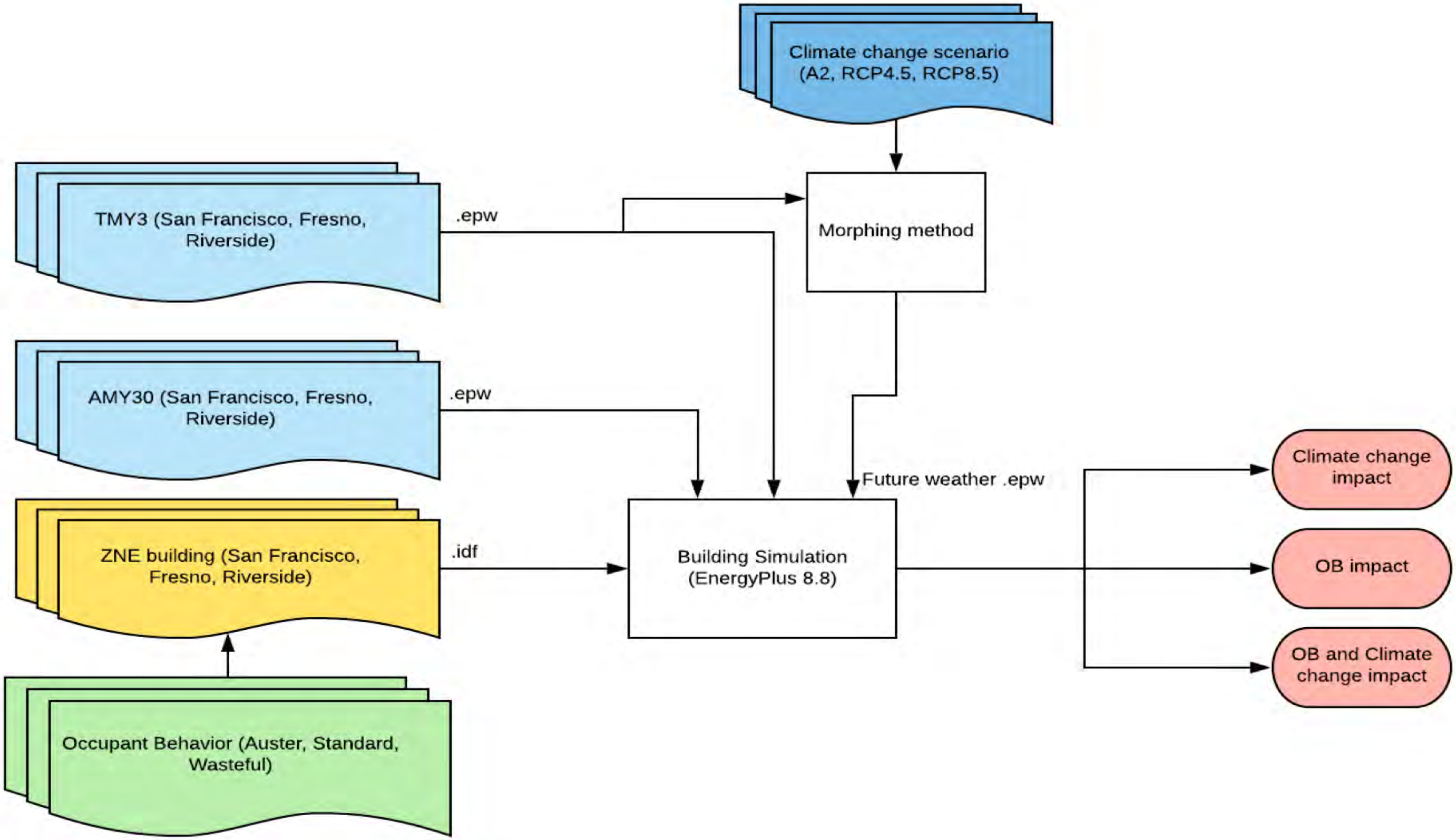

Climate change scenario
(A2, RCP4.5, RCP8.5)
TMY3 (San Francisco, Fresno, Riverside)
.epw
Morphing method
AMY30 (San Francisco, Fresno, Riverside)
.epw
Future weather .epw
ZNE building (San Francisco, Fresno, Riverside)
.idf
Building Simulation
(EnergyPlus 8.8)
Climate change impact
OB impact
OB and Climate change impact
Occupant Behavior (Auster, Standard, Wasteful)

Table 1 Key Characteristics of the ZNE Single Family Home in California Climate Zone 13 (Fresno)

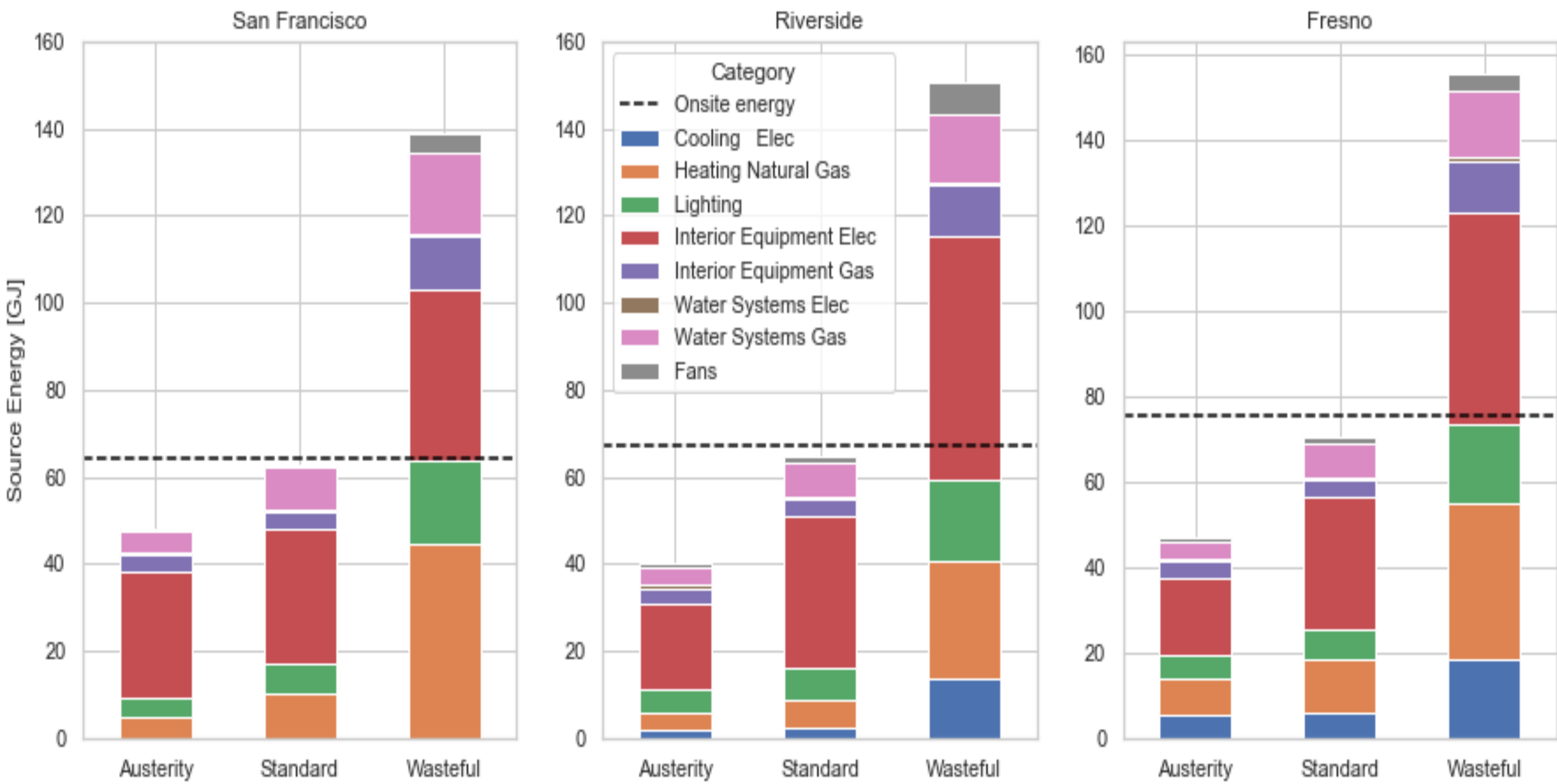
Technology		ZNE Efficiency Measures
Walls	Wood Stud	R-21 Fiberglass Batt, Grade-1
	Wall Sheathing	R-5 Expanded Polystyrene Insulation
	Exterior Finish	Stucco, Medium/Dark
Ceilings/Roofs	Unfinished Attic	Ceiling R-38 + Roof R-19 Grade-1, Vented
	Roof Material	2019 Title-24 Steep Slope Cool Roof
Windows & Doors	Windows	U value 0.30, SHGC 0.23
	Doors	Fiberglass
Airflow	Natural Ventilation	Available for Ventilation and Cooling Load Reduction
	Air Leakage	5 ACH under 50Pa
	Mechanical Ventilation	Exhaust Fan Meeting 2016 ASHRAE 62.2
Space Conditioning	Air Conditioner	SEER 16 EER 13.5 2-speed
	Furnace	Gas Furnace, 92.5% Annual Efficiency
	Ducts	In Finished Space
Space Conditioning Schedules	Heating Setpoint	CBECC RES Heating Thermostat Setpoint
	Cooling Setpoint	CBECC RES Cooling Thermostat Setpoint
Water Heating	Water Heater	Gas Tankless Water Heater
	Distribution	R-5, Trunk Branch, PEX, Demand
Lighting	Lighting Power	CEC Prototype using LED Lights, 676 kWh/year
Appliances & Fixtures	Refrigerator	Bottom freezer, Energy Factor 15.9
	Cooking Range	Optimized Burner Gas Cooktop / Gas Self-Cleaning Oven Forced Convection
	Dishwasher	DOE Standard Efficiency Dishwasher
	Clothes Washer	Standard Top-loading Baseline 2018 DOE Standard
	Clothes Dryer	Vented Gas with DOE Efficiency Level 2
	Plug Loads	Advanced Power Strips with Infrared and Occupancy Sensor
Power Generation	PV System	3.4 kW
	PV Azimuth	South
	PV Tilt	Roof Pitch Tilt

Note that U value is in Btu/h·ft2·F and R value is in h·ft2·F/Btu

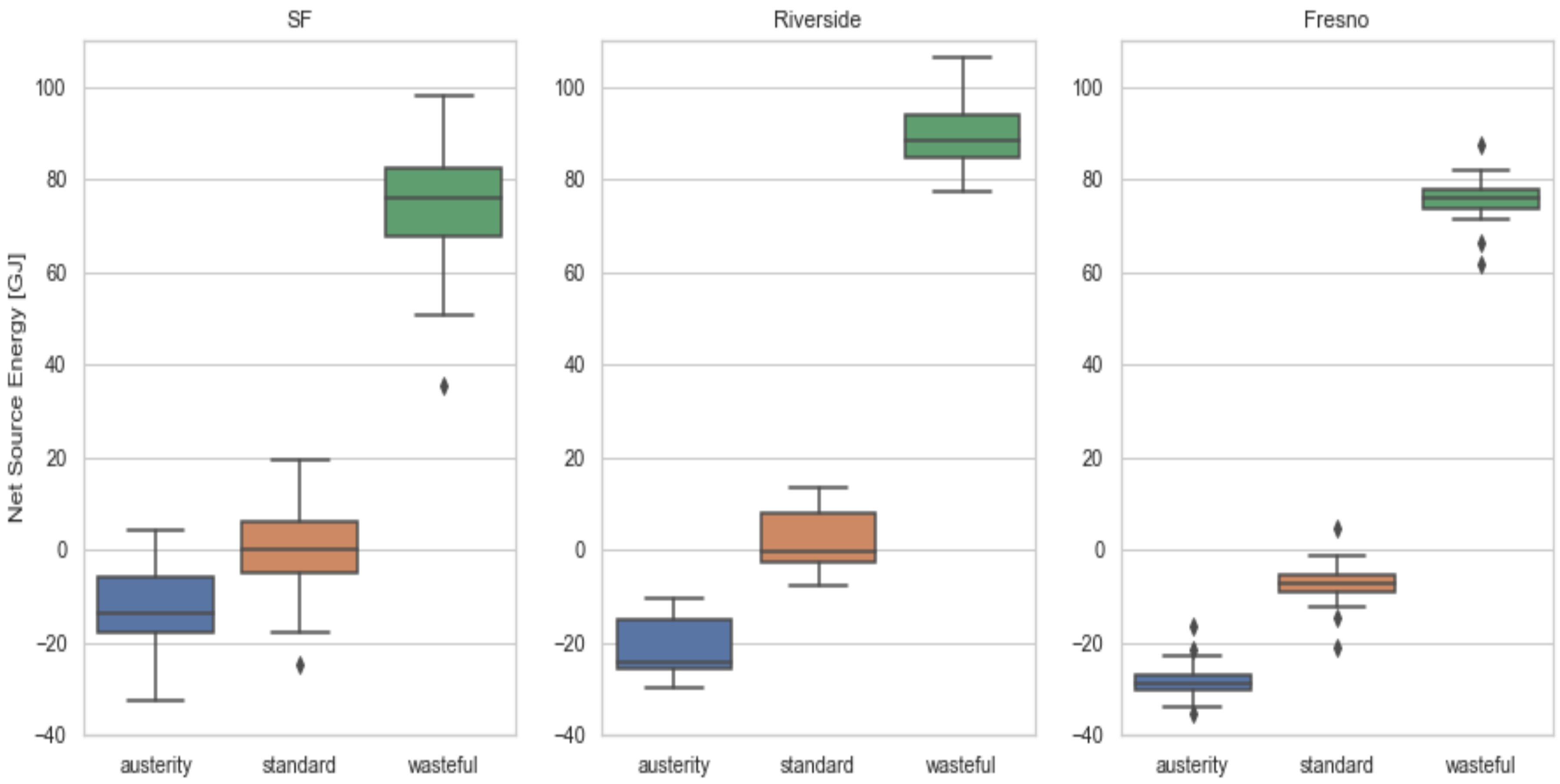
Table 1 – Summary of key assumptions of three occupant behavior scenarios

	Baseline	Energy Austerity	Energy Wasteful
Cooling thermostat setpoint (°C)	24.4 always	26	23
Heating thermostat setpoint (°C)	21.1	18	23
HVAC operation	Scheduled	On only if occupied	Always on
Appliances	Scheduled	On if use, off if not use	Always on
Lighting	Scheduled	On if occupied and if illuminance in the room < 300 lux	Always on
Hot water use / bath	Scheduled	Water use is reduced by half	Water use is doubled

Impact of OB on ZNE Performance



Impact of AMY on ZNE Performance

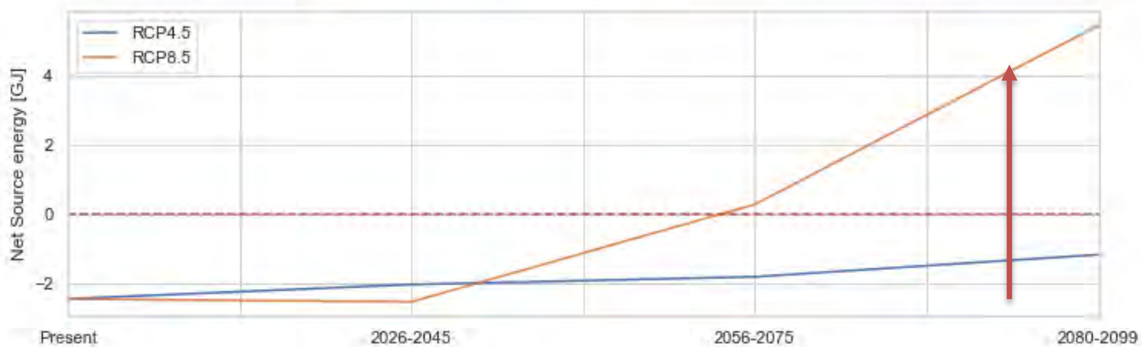


Impact of Future Climate

San Francisco

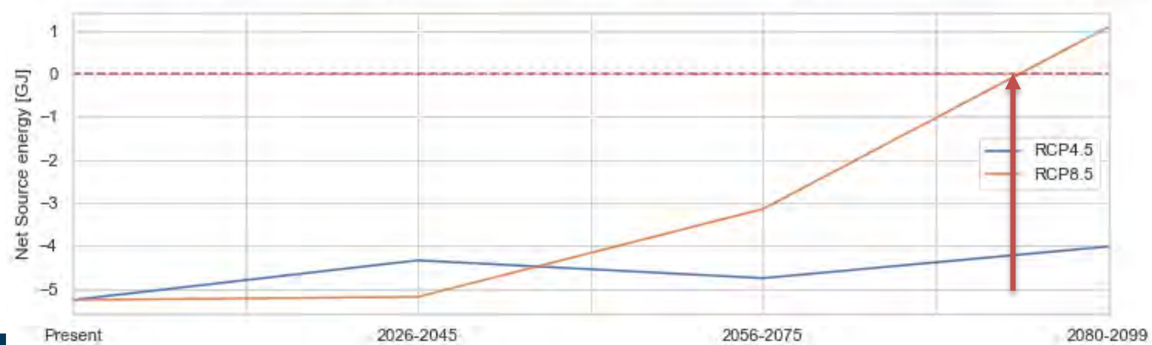
Performance improved

Riverside



Performance deteriorated

Fresno



Performance deteriorated

Findings

Simulation results of the ZNE homes in annual source energy show:

(1) A decrease of 23-38% for occupants with energy austerity behavior and an increase of 120-130% for occupants with energy wasteful behavior, compared with the baseline assumption of normal occupants;

(2) A variation range of –15% to +14% for the results using 30-year AMY weather data compared with the baseline TMY3 results;

(3) An increase of 10-13% with future weather in Fresno and Riverside and a decrease of 15% in San Francisco.

(4) Recommend to consider various OB scenarios and AMY and future climate in evaluation and design of ZNE homes.

A ZNE home may not be ZNE in reality!

Presentations

Session 3 - Sixth presenter

Vellei,
Marika

La Rochelle Université, France

Session 3

Day 1, 15:28

Demand Response Events in Residential Buildings: Not Noticeable at All?

M. Vellei

Demand Response (DR)-activated smart thermostats can be used to exploit the flexibility of residential electric heating and/or cooling systems. Their acceptance depends on how occupants' thermal comfort is affected by the dynamic thermal conditions induced during DR events. In residential settings, occupants can engage in activities other than sedentary ones and, thus, their thermal conditions can be dynamic due to the time-varying metabolic rates. If the dynamic thermal comfort conditions induced by changes in metabolic rates are comparable with the dynamic conditions induced during DR events, these events could remain unnoticed to the occupants, who are already accustomed to behaviourally adjust, e.g. by adapting their clothing, to such transient thermal conditions. To evaluate the impact of DR events, we therefore compare differently induced dynamic conditions by simulating both occupants' stochastic activity levels and DR events in two case study buildings, which represent typical archetypes of old and new single-family houses in France. The dynamic thermal simulations are carried out within the simulation platform DIMOSIM (DIstrict MOdeller and SIMulator), which use a R7C4 mono-zone building model. Occupants' activity levels and, thus, the time-varying metabolic rates are simulated with a stochastic activity model, while for evaluating the transient thermal conditions we adopt a novel dynamic thermal comfort model. This comprises a thermo-physiological model able to predict the body core and mean skin temperatures and a dynamic thermal perception model, which uses the simulated temperatures to predict thermal sensation and thermal comfort. The used thermo-physiological model is an updated version of the classical Gagge's two-node model, while the dynamic thermal perception model is elaborated from Fiala's Dynamic Thermal Sensation (DTS) model and Fanger's Predicted Percentage of Dissatisfied (PPD) indices.

ANR
CLEF
(2018-2021)

EQL'ORE
(2019-2021)

DEMAND RESPONSE EVENTS IN RESIDENTIAL BUILDINGS: NOT NOTICEABLE AT ALL?

MARIKA VELLEI

POST-DOC, LA ROCHELLE UNIVERSITÉ

OB-20 Symposium
20th April 2020

CONTEXT

Demand Response (DR) is *"a concept describing an incentivizing of customers by costs, ecological information or others in order to initiate a change in their consumption or feed-in pattern"*

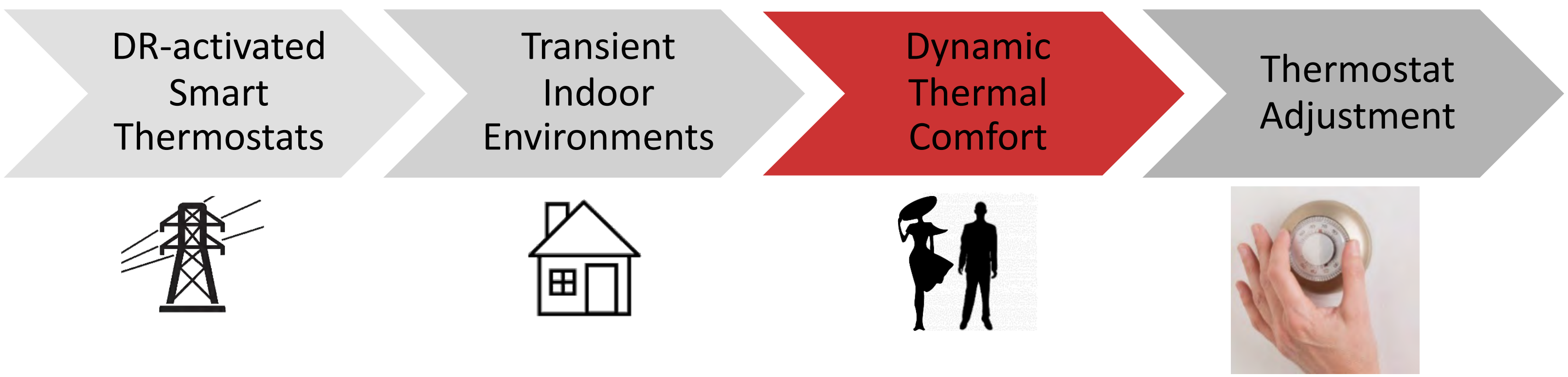
Smart thermostats are likely to become the first residential appliance to offer significant DR capacity worldwide

In France, ≈75% of all the electric thermal systems (space heating) are expected to be flexible by 2050

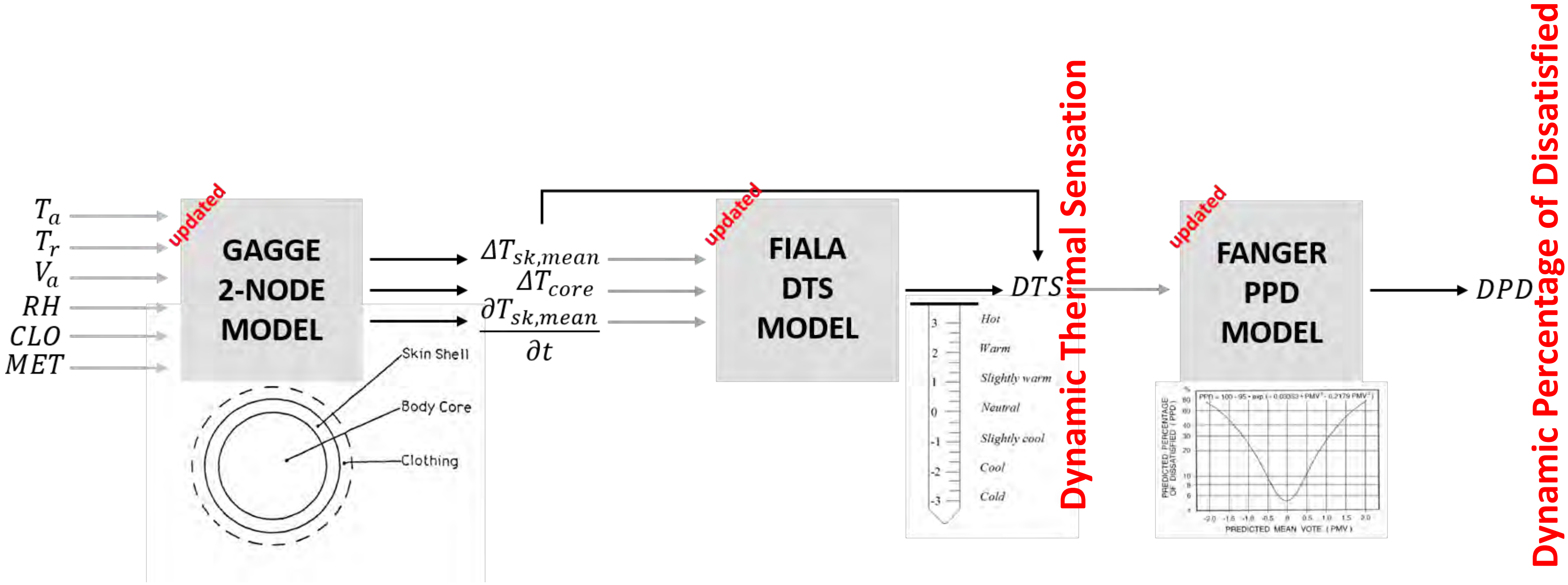
PROBLEM

The acceptance of DR-activated smart thermostats depends on how occupants' thermal comfort is affected by the **transient thermal conditions** induced during DR events

Understanding and modelling occupants' **dynamic thermal comfort response** and **thermostat adjustment behaviour** is, thus, crucial for the design, assessment and control of DR strategies



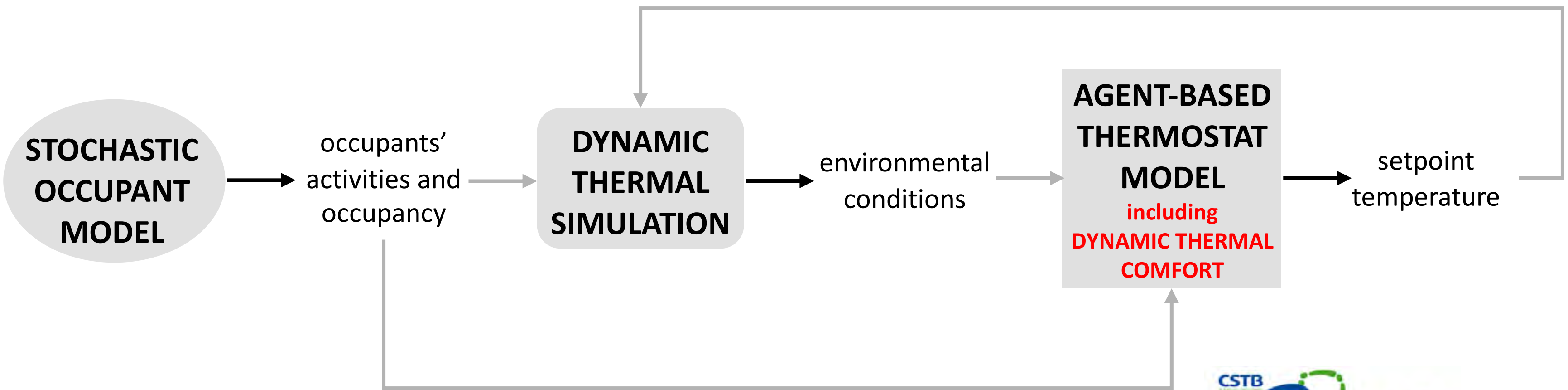
A NOVEL DYNAMIC THERMAL COMFORT MODEL



References:

Marika Vellei & Jérôme Le Dréau, On the prediction of dynamic thermal comfort under uniform environments, Proceedings of the 2020 Windsor Conference: Resilient Comfort, Windsor, UK.

PART OF A NOVEL MODELLING FRAMEWORK



References:

P. Riederer, V. Partenay, N. Perez, C. Nocito, R. Trigance, T. Guiot, Development of a Simulation Platform for the Evaluation of District Energy System Performances, in: BS2015 14th Conf. Int. Build. Perform. Simul. Assoc., Hyderabad (IN), 2015.

M. Vellei, J. Le Dréau, S.Y. Abdelouadoud, Predicting the demand flexibility of wet appliances at national level: The case of France, Energy Build. 214 (2020) 109900. doi:10.1016/j.enbuild.2020.109900.

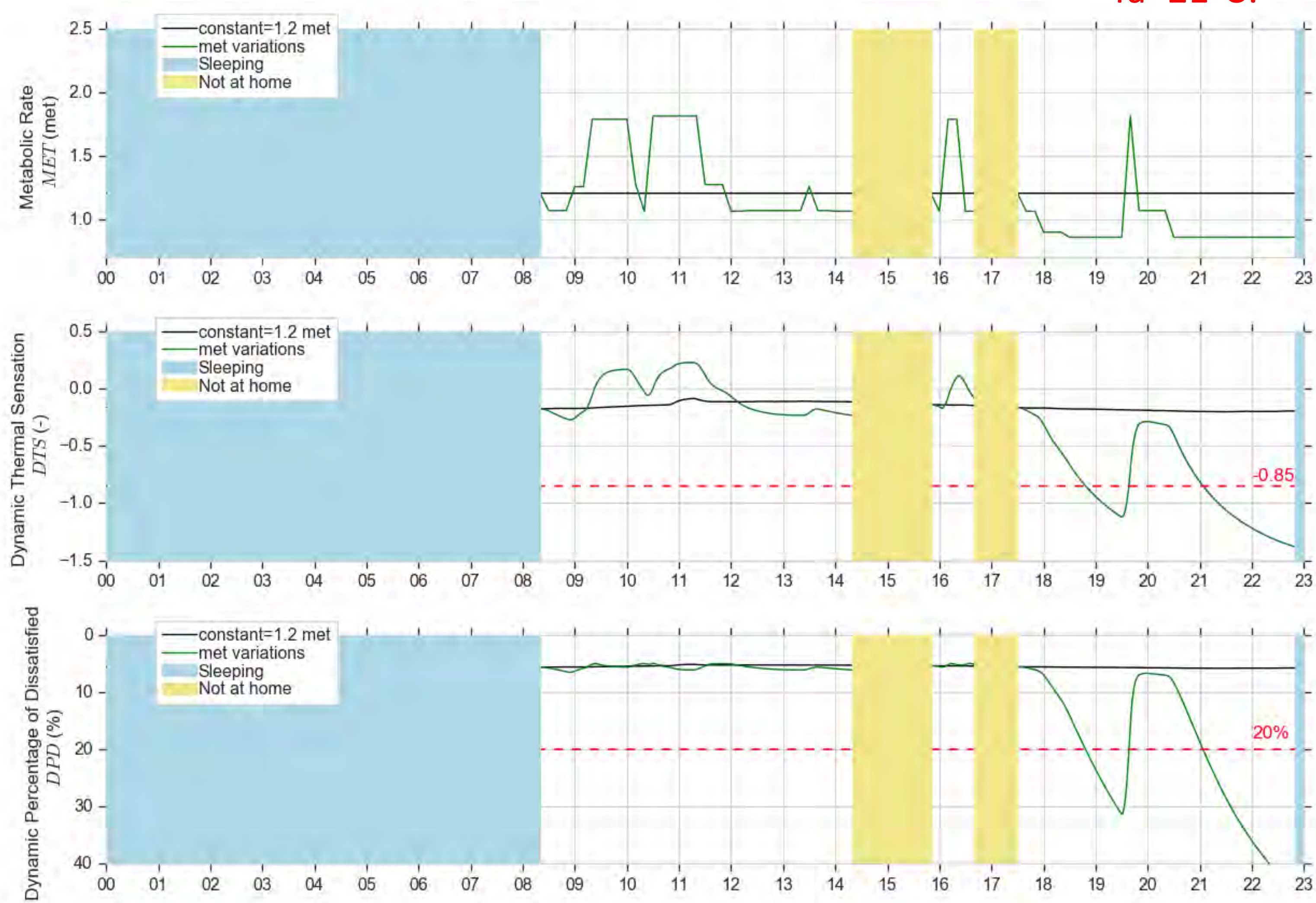
TODAY’S RESEARCH QUESTION

Are the dynamic thermal comfort conditions induced by changes in **MET** of lower magnitude than the dynamic conditions produced by changes in **Ta** during **DR events**?

- If this is true, we can assume that DR events remain relatively unnoticed to the occupants, who are already accustomed to behaviourally adjust, e.g. by adapting their clothing, to such transient thermal conditions-

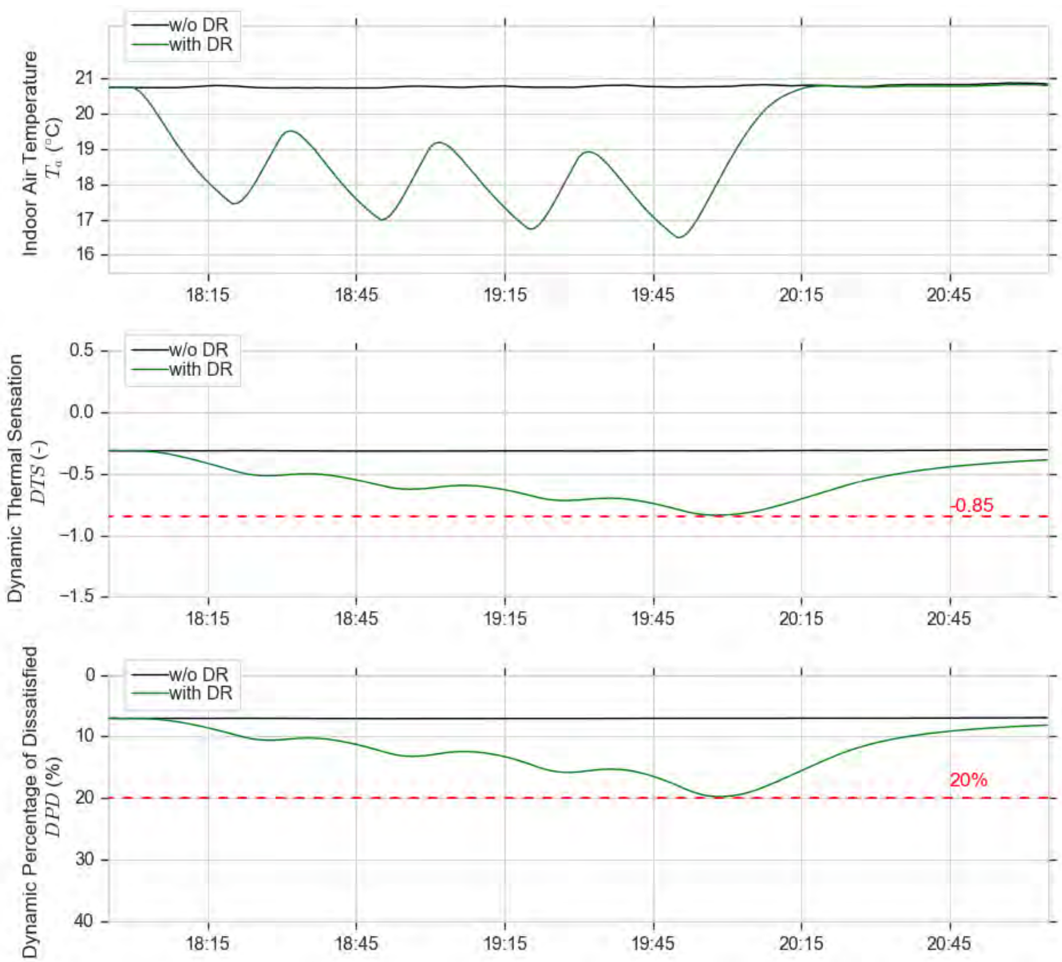
SOME RESULTS ON THE THERMAL COMFORT EFFECT OF MET VARIATIONS

at constant Ta=21°C!



SOME RESULTS ON
THE THERMAL COMFORT EFFECT OF TEMPERATURE VARIATIONS

at constant MET=1.2met!



MERCI DE VOTRE ATTENTION !

Contacts : Marika VELLEI (marika.vellei@univ-lr.fr)

Jérôme LE DRÉAU (jledreau@univ-lr.fr)

Web sites : *http://lasie.univ-larochelle.fr/2018-2021-CLEF-ANR*

https://www.researchgate.net/project/ANR-CLEF-Control-strategies-for-Large-scale-aggregation-of-Energy-Flexible-buildings

https://gitlab.univ-lr.fr/jledreau

The novel thermal comfort models coded in Python are available to download at :

https://gitlab.univ-lr.fr/jledreau/dynamic-thermal-comfort

Presentations

Session 3 - Seventh presenter

Halls, Benjamin

Loughborough University, UK

Session 3

Day 1, 15:32

Occupant Behaviour and SAP: Integration of Stochastic Occupancy Modelling into Compliance Tools

B. Halls

This study will address the topic of 'Integrate occupant modelling into building design process'. Occupant behaviour has a significant impact on the energy demand of buildings. However, representation of occupant behaviour within building simulation tools and building regulations is often simplified, leading to discrepancies between predicted and actual energy demand of buildings. The UK standard assessment procedure (SAP) is used to measure the energy performance of buildings for compliance and regulation. SAP is used to produce Energy performance certificates (EPCs), rating buildings on their energy efficiency. However, SAP uses standard assumptions for occupant behaviour, resulting in large variances between predicted and actual energy demand of buildings. A better representation of occupant behaviour in SAP and compliance tools will aid in low energy building design.

This study aims to integrate occupant behaviour into compliance such as SAP, to investigate the potential benefit, applications and impact of including stochastic occupant behaviour within energy demand predictions for domestic buildings. The integration of occupant behaviour will provide a better representation of how and when occupants use energy in UK dwellings, by including the variation in energy demand across households within the SAP calculations. Integration of heating, lighting, appliance use, and occupancy presence distributions will be examined in SAP.

A literature review which outlines the research gap and highlights the potential for improvement has been developed along with an initial Markov model. Further work will consider alternative modelling techniques such as agent-based modelling and logistic regression to test the performance of more detailed modelling approaches in SAP for domestic buildings. Time use survey datasets such as Energy follow up survey, household electricity survey and UK time use survey will be used for the development of the models.

Occupant Behaviour and SAP: Integration of Stochastic Occupancy Modelling into Compliance Tools

Ben Halls

Introduction

- 1st year PhD student at Loughborough University
- Supervised by Dr Steven Firth and Prof Kevin Lomas
- Student of LoLo CDT – Energy demand in the built environment
- MRes title – 'Occupant Behaviour: A Data Driven Markov Model for Occupancy Presence in Residential Buildings'

Aims & Objectives

Aim:

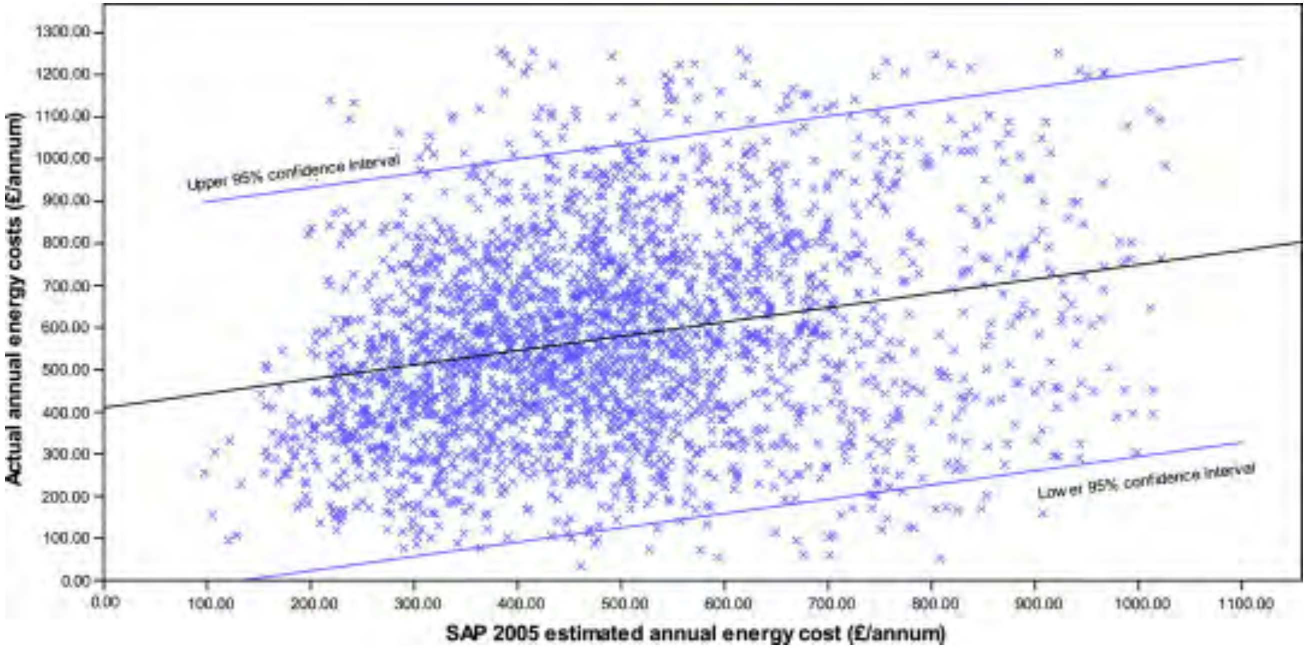
- Explore the integration of occupant behaviour modelling in SAP and evaluate the benefit and applications of including stochastic occupant representation in compliance tools

Objectives:

- Evaluate how sensitive SAP is to occupant behaviour
- Identify and develop stochastic modelling techniques suitable for SAP
- Evaluate the potential applications of stochastic representation of occupant behaviour in SAP

PhD Introduction-SAP

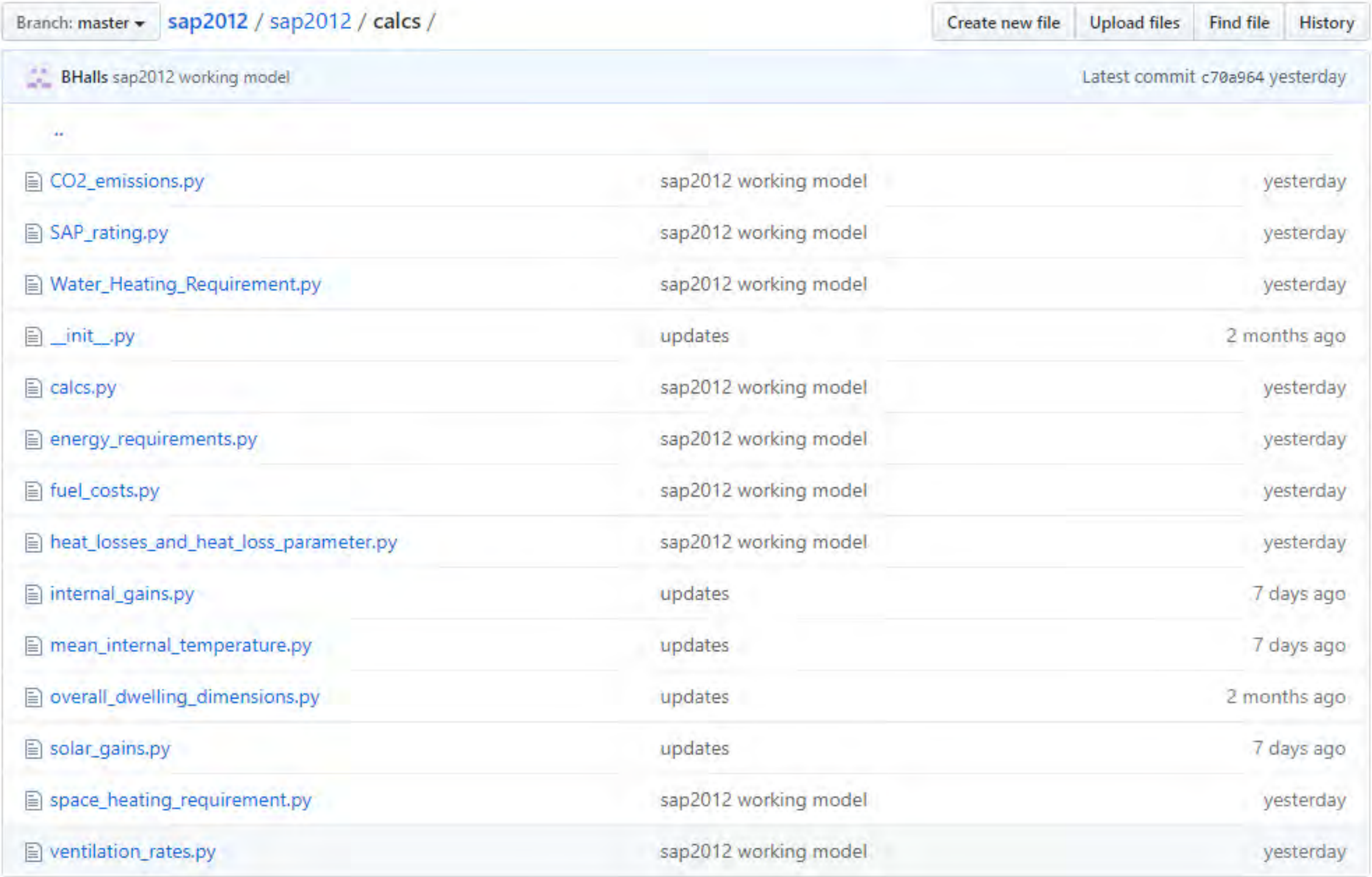
- Standard Assessment Procedure (SAP) is the UK compliance testing tool for building regulations
- Produces Energy Performance Certificates (EPCs) and assesses building energy efficiency
- SAP model has large variance between estimated and actual energy demand
- Reasons for variation can include poor workmanship, changes between design and construction and occupant behaviour



Kelly et al, (2012). Building performance evaluation and certification in the UK: Is SAP fit for purpose?
DOI: https://doi.org/10.1016/j.rser.2012.07.018

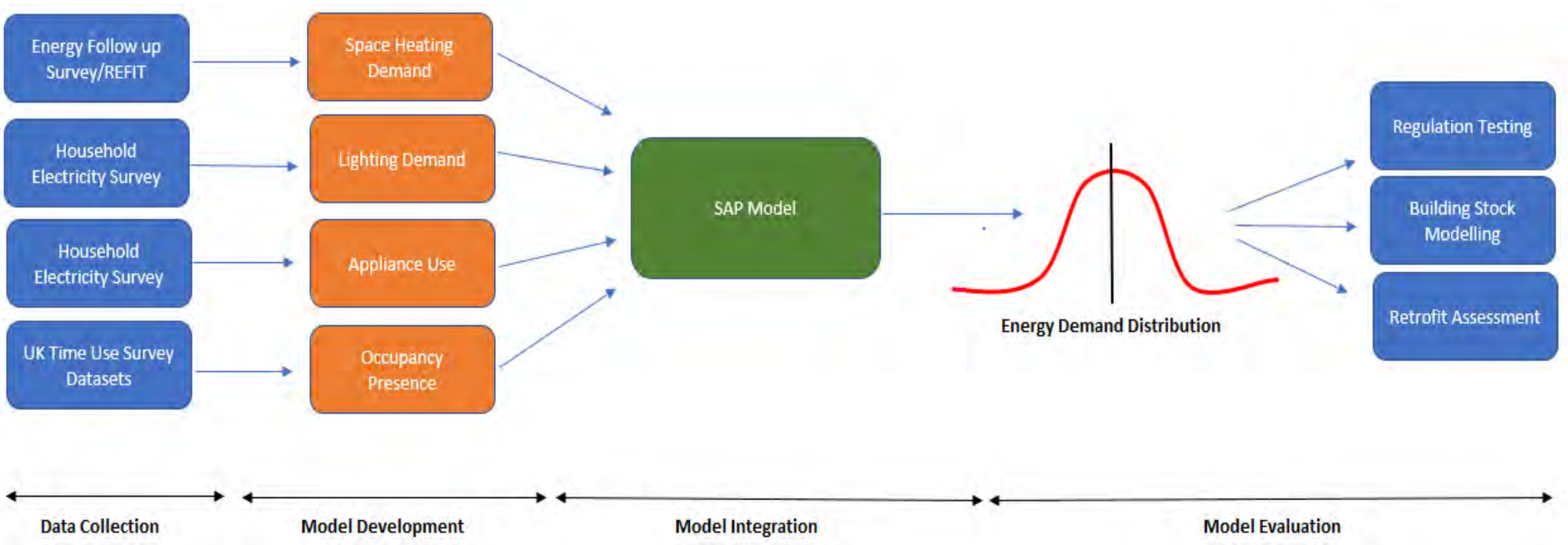
PhD Introduction-SAP Model

- Developed in Python and available on GitHub
- Open-sourced model, available to use at a later date
- SAP Model includes all calculations required to estimate annual energy demand of a dwelling



https://github.com/building-energy/sap2012

PhD Introduction-Methodology



Conclusion

- SAP is a compliance tool used within UK building regulations
- SAP predictions can vary significantly from actual energy demand
- Greater representation of occupant behaviour will be achieved with stochastic modelling techniques
- Introducing uncertainty levels will represent the variation in energy demand as a result of occupant behaviour

Presentations

Session 4 - First presenter

Lorenz, Clara-Larissa & **Syndicus**, Marc

RWTH Aachen University, Germany

Session 4

Day 2, 12:00

Generic vs. Occupant Specific Behaviour Modelling in Building Simulation and Building Automation

C. Lorenz, M. Syndicus

Machine Learning and Deep Learning are promising methods to model occupant behaviour (OB). OB models are particularly meaningful for 1) building simulation, to accurately simulate building energy consumption, and 2) building automation, where control strategies can be optimised based on predicted occupant interactions with the building. The requirements to OB models may however differ between use-cases. In the case of window-opening models, reliable results have so far only been obtained for use in building simulation. For example, Markovic et al. (2018) reliably predicted current window states via a generic model. As the model generalises occupancy types, the method points to difficulty when trying to predict and adjust to a specific occupants' future behaviour in building automation. It is further unknown how interfering in the current state changes the trajectory of a future prediction (e.g. when reducing output power for heating and ventilation based on a predicted upcoming window-opening event, the event may be delayed or not occur anymore). Hence, prognosis-based system adjustments in building automation require counterfactual reasoning and analysis, i.e. if change had been imposed (in system control), would OB patterns have remained the same and could energy savings have been achieved? We critically discuss these and other topics arising from implementations of Machine-and Deep Learning-based OB models. Specifically, we structure the discussion such, that we address the question as to what underlies the high accuracy of OB models for building simulation. We further inquire about the requirements that need to be met so that this success can similarly be acquired in building automation. With this work, we hope to provide clarity on the topic and help realise the innate potential of Machine- and Deep Learning methods in building automation.

Generic vs. Occupant Specific Behaviour Modeling in Simulation and Building Automation

Lorenz, Clara-Larissa Ph.D. Candidate
Syndicus, Marc Ph.D.

5th International Symposium on Occupant Behaviour
Institute of Sustainability and Sustainable Building | April 21st, 2020

e3D | RWTH AACHEN UNIVERSITY

Deep learning-based occupant generic and occupant specific behaviour modeling

Deep learning-based OB models in Building Simulation and Building Automation

- Recurrent Neural Networks with Short-Long-Term Memory architecture may find predictor in the past
  - Events such as occupant arrivals may trigger occupant interactions with the building (Yun & Steemers 2008)
  - Interactions may be more likely at certain day times
  - Outdoor climate and outside noise levels may determine the opening duration (Hoffmann et al. 2018)
  - Changes in indoor climate and overall thermal comfort – adaptive triggers (Stazi et al. 2017)
- Representation of OB patterns based on big data with generic model applicability in building simulation
  - Clustering of occupant behavior types followed by the selection of data from representative types to develop a generic model (Markovic et al. 2018)
- Model generalisation may point to difficulty when trying to predict and adjust to a specific occupant' future behaviour in building automation 
  - E.g. in occupant-centric control strategies, heating, ventilation or temperature set-points may need to be regulated office-wise. In that case, one prediction may not be applicable for all occupants.

Yun, G. Y. & Steemers, K. (2008). Time-dependent occupant behavior models of window control in summer. Building and Environment, 43-9, 1471-1482.
Hoffmann, C. et al. (2018) Fensterlüfter in Wohngebäuden (Sanierung und Neubau) – Die Sichtweise der Nutzer. 20. Status-Seminar 'Forschen für den Bau im Kontext von Energie und Umwelt', 6-7.9.2018. ETH Zürich. Switzerland.
Stazi, F. et al. (2017). A literature review on driving factors and contextual events influencing occupants' behaviours in buildings. Building and Environment. 118, 40-66.
Markovic et al. (2018). Window opening model using deep learning methods. Building and Environment. 145, 319-329.

Deep learning-based occupant generic and occupant specific behaviour modeling

Generalization in building simulation and building automation

Occupant 1
.
.
.
.
.
.
Occupant X

Occupant behaviour profile A

Occupant behaviour profile B

Occupant behaviour profile C

Patterns

Generic model

Scalability in building simulation

Same prediction for occupant 1 to occupant X

Limited flexibility adjusting prognosis-based systems to occupant specific behavior in building automation

Deep learning-based occupant generic and occupant specific behaviour modeling

Deep learning-based OB models in Building Simulation and Building Automation

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- Model generalisation may point to difficulty when trying to predict and adjust to a specific occupant' future behaviour in building automation 
  - E.g. in occupant-centric control strategies, heating, ventilation or temperature set-points may need to be regulated office-wise. In that case, one prediction may not be applicable for all occupants.
  - Requirements to OB modelling may therefore differ between use-cases

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Hoffmann, C. et al. (2018) Fensterlüfter in Wohngebäuden (Sanierung und Neubau) – Die Sichtweise der Nutzer. 20. Status-Seminar 'Forschen für den Bau im Kontext von Energie und Umwelt', 6-7.9.2018. ETH Zürich. Switzerland.
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Applications of occupant behaviour models in building simulation

Estimated vs. measured energy savings

- In order to achieve ambitious national energy saving targets, OB plays a crucial role
- Estimates for energy saving potential range from 5%−30% for commercial buildings and 10%−25% for non-commercial buildings (Zhang et al., 2018)
- Due to human peculiarities, the simulated or estimated saving potentials are seldom exploited. Aspects that prevent the full realization saving potentials are, among others,
  - Technical problems and faulty equipment
  - reactance, fears towards monitoring technology
  - General peculiarities of human behaviour, such as moods

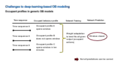
Model Predictive Control (MPC)

- By applying a receding horizon control scheme, MPC conducts simulations runs to find an optimal control solution by taking conflicting goals (energy saving vs. user comfort) as well as disturbances (occupancy or solar radiation) into account (Killina & Kozek, 2016)
- Although MPC has been utilized for Building energy management Systems, the incorporation of OB is still a challenge (white box vs. black box modelling)

Killian, M., & Kozek, M. (2016). Ten questions concerning model predictive control for energy efficient buildings. Building and Environment, 105, 403-412.
Zhang, Y., Bai, X., Mills, F. P., & Pezzey, J. C. (2018). Rethinking the role of occupant behavior in building energy performance: A review. Energy and Buildings, 172, 279-294.

Challenges to deep-learning-based OB modeling

Difficulty in predicting future interactions of occupants with the building

- Limitations are placed by the data used to develop the OB model
  - Recorded data/ predictor variables are incomplete, but may be measurable (distance to a control interface, outside noise levels as in Schweiker et al. 2020)
  - Predictor Variables may be difficult to measure (clothing, personal schedule, gender, weight etc.); possible violation of data protection acts
  - Predictor Variables may not be measurable (mood, fatigue, psychological factors, coincidental circumstances as in Kent et al. 2015, Fabi et al. 2012)
- Occupant behavior types – User profiles
  - Differences in number of interactions and interaction durations
  - More passive or active in nature (Bourgeois et al. 2006, Moghadam et al. 2015)
  - Classification of occupant behavior (Liiesberg et al. 2016) 

Schweiker, M. et al. (2020). Review of multi-domain approaches to indoor environmental perception and behavior. Building and Environment. 176.
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Moghadam, S. T. (2015). Simulating Window Behaviour of Passive and Active Users. 78, 621-626.
Liisberg, J. et al. (2016). Hidden Markov Models for indirect classification of occupant behaviour. Sustainable Cities and Society. 27, 83-98.

Challenges to deep-learning-based OB modeling

Occupant profiles in generic OB models

Time sequence	Occupant behaviour profile	Network Training	Network Prediction
Time sequence A	Occupant profile A opens window	Weight adaptation to best fits all given output (occupant actions)	Window closed
Time sequence A	Occupant profile B does not opens window		
Time sequence A	Occupant profile C opens window in ten minutes		

➡ Not all predictions can be correct

Challenges to deep-learning-based OB modeling

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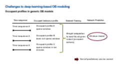
  - Classification of occupant behavior (Liiesberg et al. 2016) 
- Different choices of one and the same occupant for same or similar indoor climate sequences
- Trade-off between TPR and TNR 

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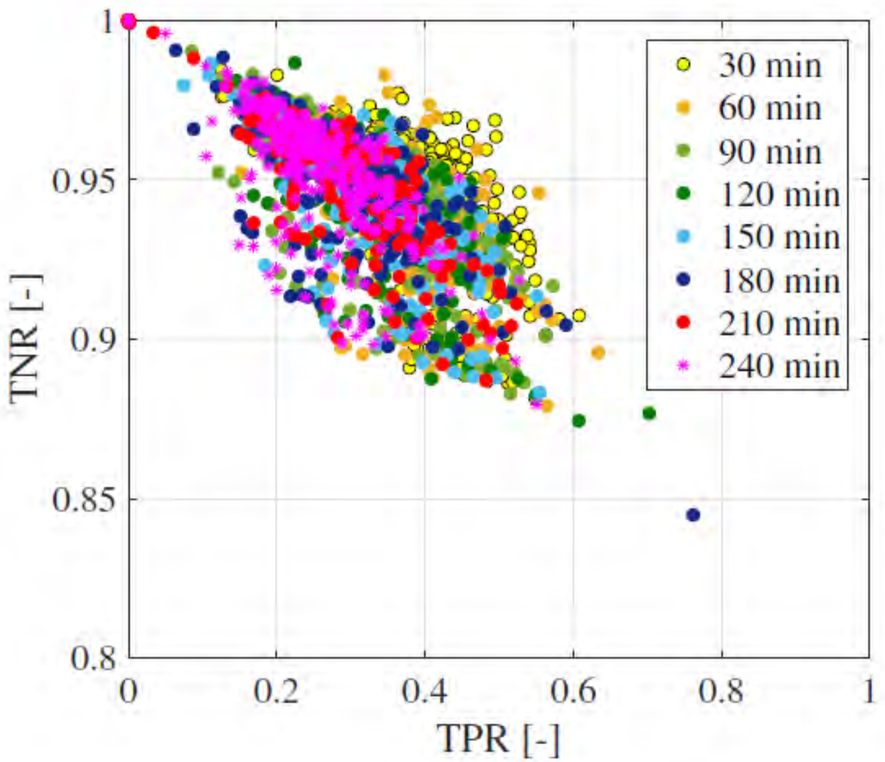
Challenges to deep-learning-based OB modeling

Difficulty in predicting future interactions of occupants with the building

- Trade-off between True Negative Rate and True Positive Ratio



TNR plotted over TPR for investigated cases of input sequence (Markovic et al. 2019)

Model result will vary depending on data imbalance, or adjustment to data imbalance via oversampling or applied unequal misclassification costs

Markovic, R. et al. (2019). Learning short-term past as predictor of window opening-related human behavior in commercial buildings. Energy & Buildings. 185, 1-11.

Challenges to deep-learning-based OB modeling

Difficulty in predicting future interactions of occupants with the building

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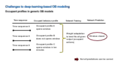
  - Classification of occupant behavior (Liiesberg et al. 2016) 
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Liisberg, J. et al. (2016). Hidden Markov Models for indirect classification of occupant behaviour. Sustainable Cities and Society. 27, 83-98.

Counterfactuality

How does interfering in a current state change the tragectory of a future prediction?

- Philosophical concept which breaks down to „What if“- questions, e.g.:
  If the building control did not raise the temperature according to its prediction, would the occupant still have changed it / used the thermostat? 

Counterfactuals: Goodman, N. (1947). The problem of counterfactual conditions. The Journal of Philosophy, 44, 113-128.

Counterfactuality

Challenges for building management prognosis systems in building automation

Scenario 1

Time t, t+1, t+2 ... | implement building control strategy A | …t+i Predicted window opening

reduce heating and ventilation performance in order to reduce energy consumption

Q: If heating was reduced, would the predicted opening still take place or be delayed?

Scenario 2

Time t, t+1, t+2 ... | implement building control strategy B | …t+i Predicted window opening

Improve occupant comfort in order to prevent the predicted window opening, reduce heat losses and therefore energy consumption

Q: If occupant comfort were improved, could the predicted event be avoided?

Counterfactuality

How does interfering in a current state change the tragectory of a future prediction?

- Philosophical concept which breaks down to „What if“- questions, e.g.:
  If the building control did not raise the temperature according to its prediction, would the occupant still have changed it / used the thermostat? 
- Appears to be relevant when continuously learning ML models are used, with these implications
  - Since human behaviour is inherently difficult (impossible) to predict deterministically, a continuous learning and adaption process appears more appropriate and “natural”
  - Human behaviour may be altered in presence of an algorithmic building control, e.g. in order to trick the system or to avoid certain actions of the system
  - As a consequence, the situation becomes interdependent and the learning algorithm potentially adapts to the altered behaviour of the occupant
- Potential solutions could involve experimental design approaches, e.g.
  - Comparison with Control groups that exert their behaviour without algorithm-based building control
  - Interrupted time series designs, where learning algorithms pause
  - Feedforward-backward-based approaches with occupants embedded in the ML training adaptation process

Counterfactuals: Goodman, N. (1947). The problem of counterfactual conditions. The Journal of Philosophy, 44, 113-128.

Presentations

Session 4 - Second presenter

Day, Julia,

Schwabe, Alison &

Ruiz, Shelby,

Washington State University & McKinstry PowerEd, USA

Session 4

Day 2, 12:10

What Does a Zero Energy and Zero Carbon Tenant Look Like?

J. Day, A. Schwabe, S. Ruiz

Occupancy patterns are necessary to estimate energy demand and evaluate thermal comfort in households. Because of this, many European countries are developing representative domestic schedules to replace outdated criteria. This paper evaluates the state of knowledge of UK domestic occupancy patterns and develops new domestic occupancy profiles for England. The presented research (1) characterizes methods for collecting occupancy data and inferring patterns; (2) identifies and assesses the quality of categories of occupancy patterns used in building simulation; and (3) develops updated occupancy profiles. A systematic scoping review identified social and monitoring surveys as the most deployed data-collection methods. A systematic literature review also established that the occupancy categories most frequently used in UK building simulation are (a) a family with dependent children where the parents work full time; and (b) a retired elderly couple who spend most of their time indoors. The interview sample from the English Housing Survey 2014–15 was used to map household typologies. Results show that categories (a) and (b) combined amount to only 19% of England's households, which suggest models are over-reliant on these groups. Considering this result, the paper develops occupancy patterns for England derived from 2015 UK Time Use Survey diaries for each household typology previously identified.

Submitted Title: ”What Does a Zero Energy and Zero Carbon Tenant Look Like?"

New Title: ”How does a Zero Energy and Zero Carbon Tenant Behave?"

5th International Symposium on Occupant Behavior (OB-20) – 21 April, 2020

Julia K. Day, Washington State University

Alison Schwabe, McKinstry PowerEd

Shelby Ruiz, Washington State University

Catalyst Building

The Catalyst Building is part of the first phase of a Spokane, WA, USA re-development project and city-wide sustainability initiative.

Catalyst Building

This pioneering project, expected to be completed in May 2020, will be the first net-zero energy and zero carbon building in Eastern Washington state.

Catalyst Building

The important role of the building occupant…

The owners realize that building occupants play a critical role in achieving aggressive energy goals…

Tenant Engagement

The authors have been tasked with the development of a tenant engagement and education program for the multi-tenanted Catalyst building to promote energy efficiency, health and community within the South Landing development.

Catalyst Building

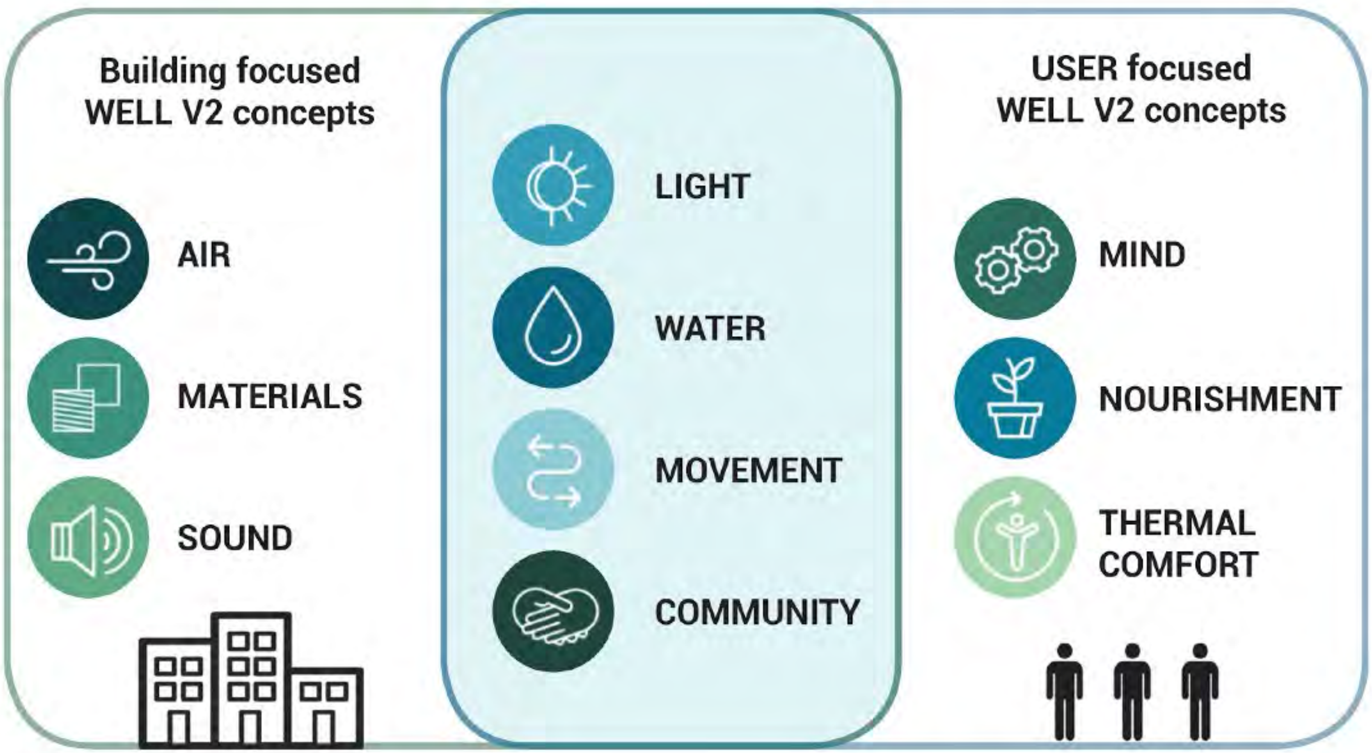
In the first phase, the team compiled case studies and literature to inform the tenant engagement campaign. Highlights will be presented.

The literature review included the following topics:

1. Principles within WELL and other “sustainability programs” to embed in engagement program
2. Occupant engagement strategies in multi-tenant, green/high performance facilities
   - *2.1. Current social science behavioral theories*
   - *2.2. Gamification*
   - *2.3. Effective communications strategies*
   - *2.4. Rewards and recognition*
3. Technology to engage occupants - apps, etc.
4. Occupant engagement strategies in multi-tenant, green/high performance facilities: Case studies
5. Green Leases

❶ Review of Sustainability Standards

Similar to the WELL Building Standard, we have taken a large view of the structure of many sustainability systems, and dissected each to discover relevant themes, and how they are implemented. This process helped to inform important tenant engagement strategies, goals, and focus points.



❶ Review of Sustainability Standards

Common Themes Related to Occupant Engagement:

- Education and Training of operators and users on multiple levels / multiple times
- Feedback of behavior, usage, and overall building data (visibility)
- Purchasing materials and outfitting of tenant improvement spaces
- specifying products and cleaners without harmful chemicals, not inhibiting daylit design or thermal setpoints
- Real time displays and feedback in public spaces and personally through dashboards
- Multiple ways to benefit user health and well-being

❷ Occupant Engagement Strategies

Environmental and energy use feedback combined with social interaction strategies create a gamified tenant engagement experience for the users of the Catalyst building. Original ID+CL Image.

❸ Technology to Engage Occupants

Based on our review, the following concepts are recommended for inclusion in a tenant engagement application:

1. Feedback
2. Peak-Time Management
3. User-centered Experience
4. Onboarding
5. User Profiles
6. Translated Energy Use Metrics
7. Occupant Training / Education
8. Energy Forecasting
9. Daily/Weekly Surveys
10. User-Focused Building Maps

❹ Occupant Engagement: Case studies

Lombardo Welcome Center, Millersville University, PA.

- Use of energy dashboard in person and online
- Host competitions to reduce energy usage through tenants
- Host educational energy-focused sustainability seminars

Brock Center, Chesapeake Bay Foundation, Virginia Beach, VA.

Online energy dashboard w/ kiosks
Onboarding training
Visitor tours of facility
Sustainability education classes

Bullitt Center, Bullitt Foundation Seattle, WA.

- Living Building certified
- Central energy kiosk and information plaques to guide experience
- N-Zero water and energy
- “Irresistible” stair to encourage activity
- Onboarding training and visitor tours
- Visible building systems to show operation
- Bicycle parking and local markets

❺ Green Leases

"Tenant shall cooperate with Landlord's efforts to implement and shall comply with the requirements and guidelines of the tenant engagement and management program. Tenant acknowledges that the tenant engagement and management programs are living documents that will be maintained separately from this lease and will be transferred to all subleases."

- Built to compliment primary lease and encourage tenants to participate in outlined activities
- Outlines benefits, responsibilities, and expectations of all parties
- Includes: Plug and leased space energy budgets, limited hours of operation, participation in activities and advocate groups, ongoing reviews, environmental and waste standards, annual reporting, and access to data to meet all sustainability goals
- Execution plan to ensure each activity is successful will be developed in next phase of development

Next Steps

The literature review process has guided the development of a robust tenant engagement program for the South Landing District to maximize net zero energy and zero carbon goals.

Stay tuned!!

QUESTIONS?

CONTACT: JULIA DAY: JULIA_DAY@WSU.EDU

Presentations

Session 4 - Third presenter

Mino-Rodriguez, Isabel

Karlsruhe Institute of Technology, Germany

Session 4

Day 2, 12:20

Effectiveness of Feedforward Information System on Occupant's Behaviour

I. Mino-Rodriguez

Feedforward is the strategic flow of information that forecasts patterns in anticipation of changing environmental conditions, intended to activate and direct coping responses of occupants in reaction to their perceived conditions. The scope of a feedforward information system is transferring energy-related data which enable occupants to learn, understand, and engage in and with buildings to achieve their desired outcomes such as comfort and energy targets. The effectiveness of feedforward information relies on the quality of communication between system and occupant and the level of persuasion among other factors. Thus, an appropriate design of a feedforward interface as a tool to convey energy information to occupants aiming to direct or modify attitudes or behaviour is of utmost importance. This study aims on understanding the key components to be considered in the design of feedforward interfaces and the potential effect of a well-structured feedback on modifying or redirecting occupant's behaviour. The study provides a review on four of the main basic components in feedforward processes that are (a) what is communicated, (b) when is the information revealed, (c) how is the information presented and, (d) where is the information shown. The study explores the feedback collected from 76 participants in a naturalistic office environment after interacting with a visual interface of an occupant assistance system. The analysis explores positive and negative feedback on two alternative interfaces that provide the predicted course of comfort levels on energy consumption of four cooling strategies (removing a piece of clothing, opening the window, switching on the ceiling fan, or switching on the air-conditioning). In addition, the analysis focuses on the relationship between (positive and negative) interface feedback and the effectivity of the feedforward interface in modifying occupant's behaviour. The study will draw conclusions on key elements to be considered for effective feedforward design.

Effectiveness of feedforward information system on occupant's behaviour

Isabel Mino-Rodriguez
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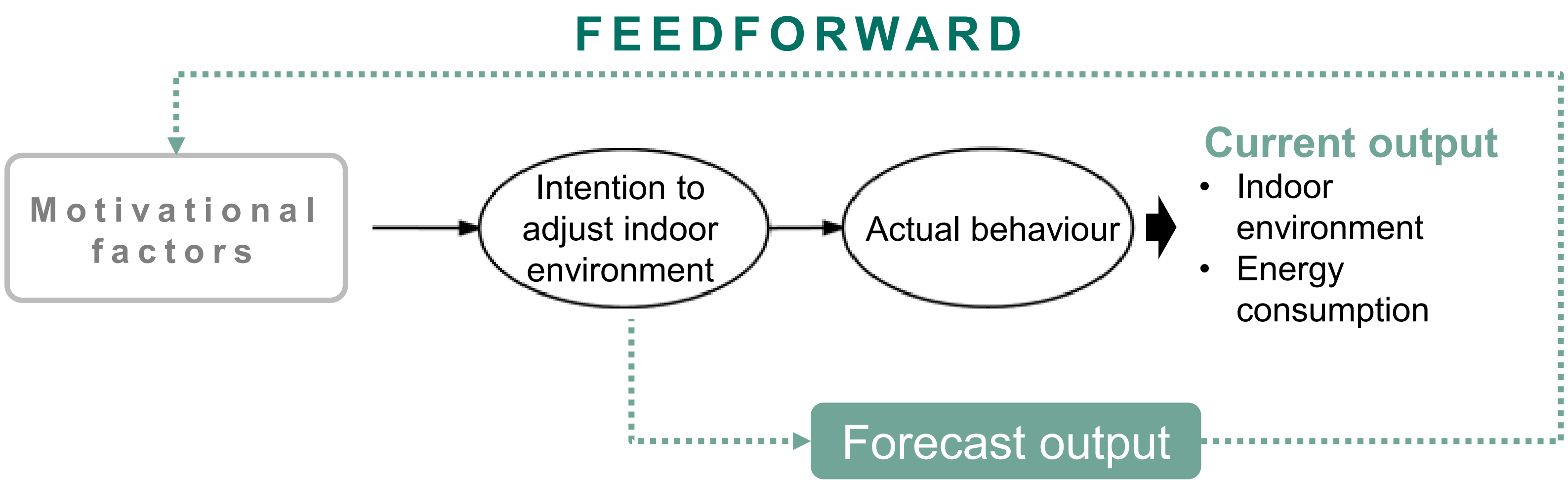
Feedforward

The strategic flow of information that **forecast patterns** the change of environmental conditions intended to **activate and direction** coping **responses of occupants** as they react to the perceived conditions.



Theory of planned behaviour

Feedforward interface

- Granularity of information
  (Actual, historical comparison)
- Content
- Target audience

- Format
  Visual, auditory
- Means
  Digital interfaces

What is informed?

How is presented?

Information

Where is displayed?

When is revealed?

- Access
- Context or dynamic

- Point in time
- Latency
- Frequency
- Duration

Feedforward interface

Comfort energy balance

What is informed?

How is presented?

Information

Where is displayed?

When is revealed?

Feedforward interface

- Granularity

Actual (controlled conditions)

- Content

Comfort level

Energy use

Remove a piece of clothing

Opening the window

Switching on ceiling fan

Switching on air-conditioning

What is informed?

How is presented?

Information

Where is displayed?

When is revealed?

- Access

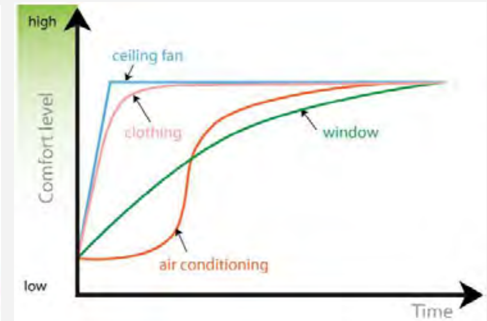
Individual (n=76)

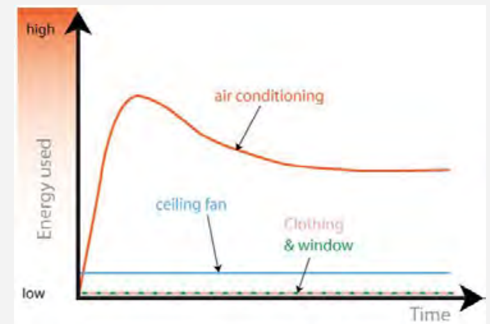
- Context

Screen on PC

Feedforward interface

Option 1





Option 2

What is informed?

How is presented?

Information

Where is displayed?

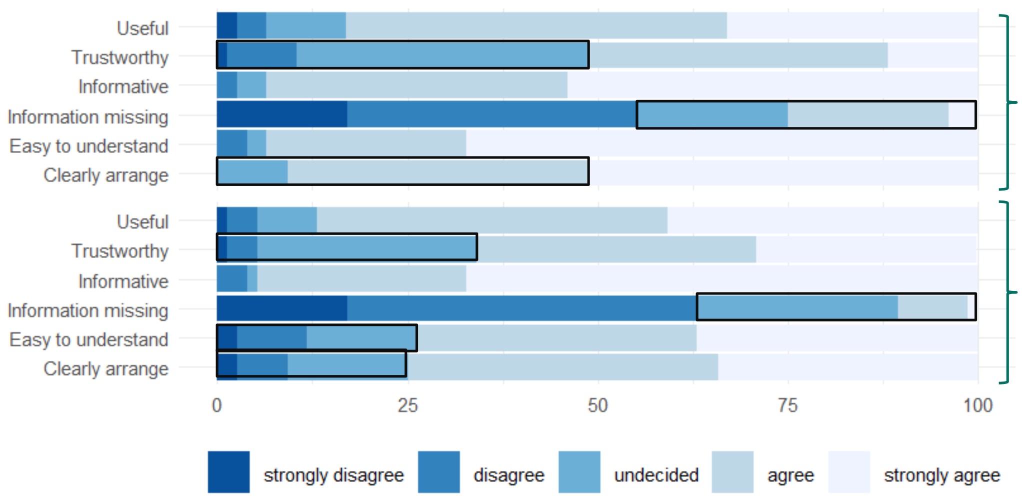
When is revealed?

- Point in time — Once
- Latency
- Frequency
- Duration

Karlsruher Institut für Technologie

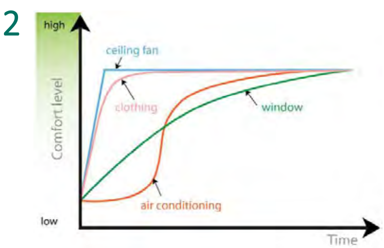
Assessment of interface

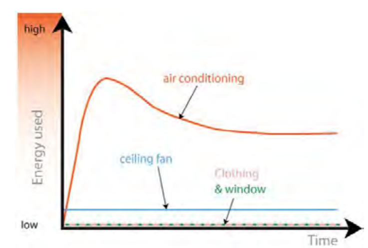
1. Rate the following statements :



Option 1

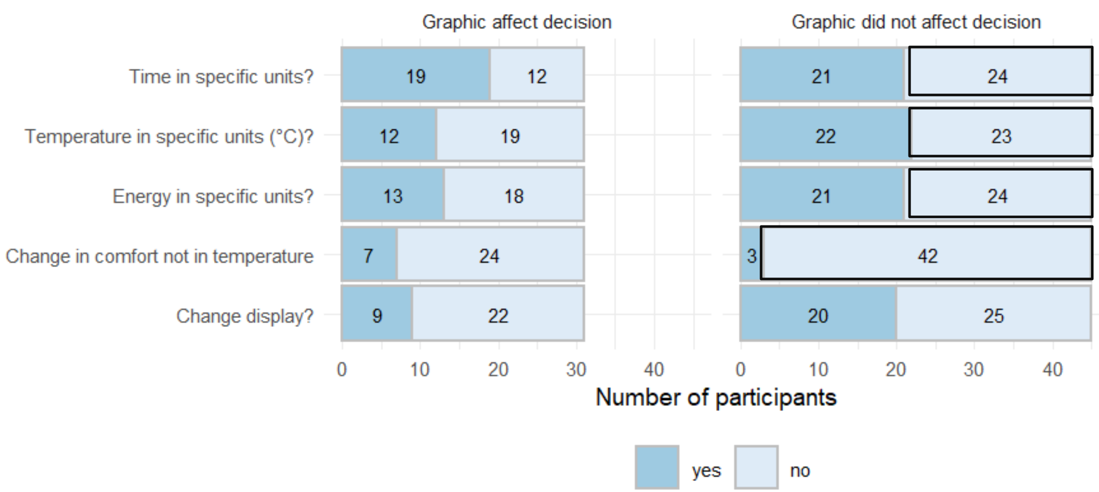
Option 2





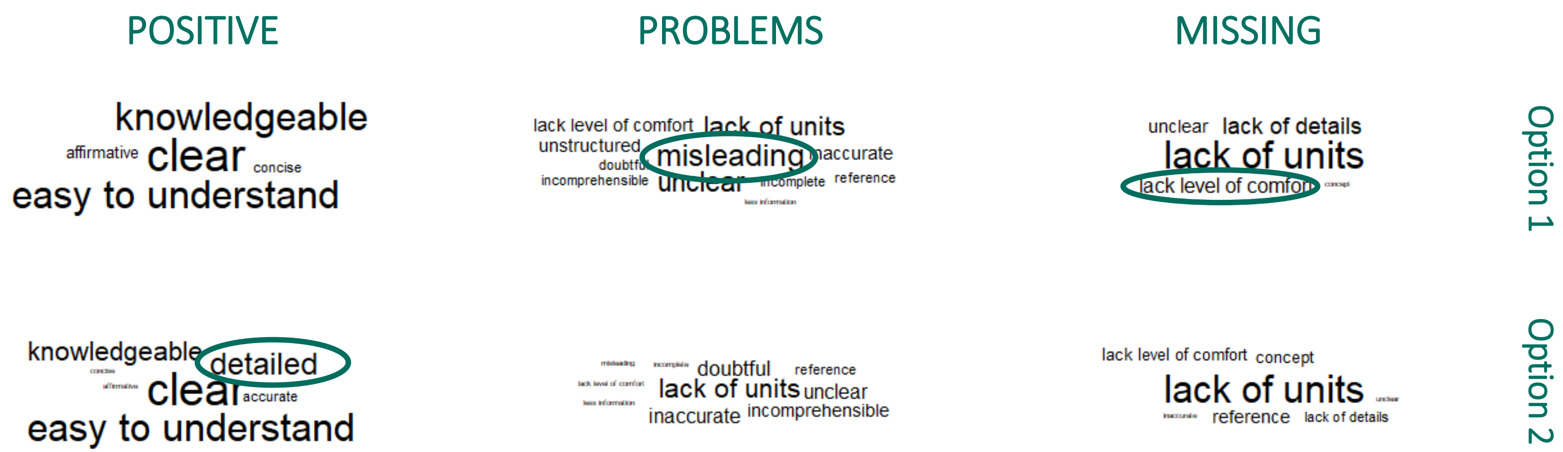
Assessment of interface

2. Did the graphics affect your decision?
3. Preference on info presentation…



Assessment of interface

4. Any positive, problem or missing information:
Categorisation – Open questions



Feedback - Feedforward interface

- Granularity

Actual /
long-term comfort

- Content
  - Alternative strategies
  - Concept (Comfort/energy consumption)
  - References or source
  - Trustworthy?
  - Temperature over comfort info

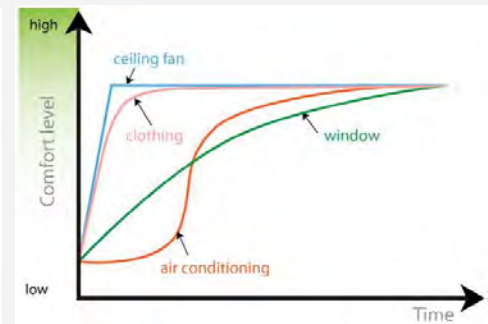
- Units

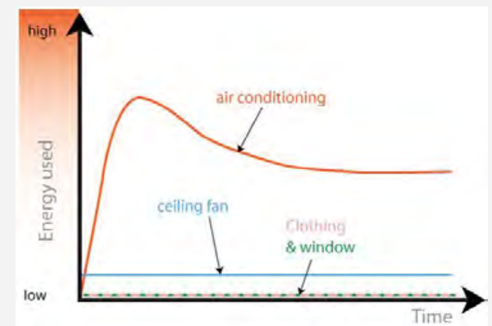
Specific units in known concepts (time) but probable not for energy.

Option 1

- Careful using different shapes of colours
Unclear/misleading

Option 2





What is informed?

How is presented?

Information

Thanks…

Questions or comments

Effectiveness of feedforward information system on occupant's behaviour

Isabel Mino-Rodriguez
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Presentations

Session 4 - Fourth presenter

Chong, Adrian

National University of Singapore, Singapore

Session 4

Day 2, 12:30

Quantifying the Impact of Occupant Presence on Building Energy Simulation with Real and Synthetic Data

A. Chong

Occupants have been recognized as a source of uncertainty with a significant impact on building energy simulation. To date, occupant behavior related inputs have typically been treated as an uncertain parameter to be calibrated. With advancements in occupant sensing, occupant information is becoming increasingly available and more easily accessible, providing an opportunity to model occupant information as an observed model input instead of a calibration parameter. This research aims to answer the question, "what is the lowest spatial resolution of occupant count needed for reducing the gap between simulated and measured energy use in buildings given an adequate calibration procedure." Thirteen case studies were defined to evaluate the impact of different levels of occupant presence on the calibration efficacy of building energy simulation. Different levels of spatial resolutions (building, level, and zone) were investigated. Of the thirteen, seven were derived from synthetic data using the DOE commercial large office reference building and an agent-based occupancy simulator. The remaining six case studies were derived from a real mixed-use building located at the National University of Singapore in Singapore, using WIFI data as a proxy for occupancy count. Synthetic data are useful because we know the true values of the calibration parameters that can be used for a quantitative evaluation of the effect of occupant presence. The real dataset is then used to verify the results and test the hypothesis using energy models of actual buildings, under real-life operating conditions.

Quantifying the impact of occupant presence on Building Energy Simulation

Adrian Chong

Assistant Professor

Department of Building | School of Design and Environment

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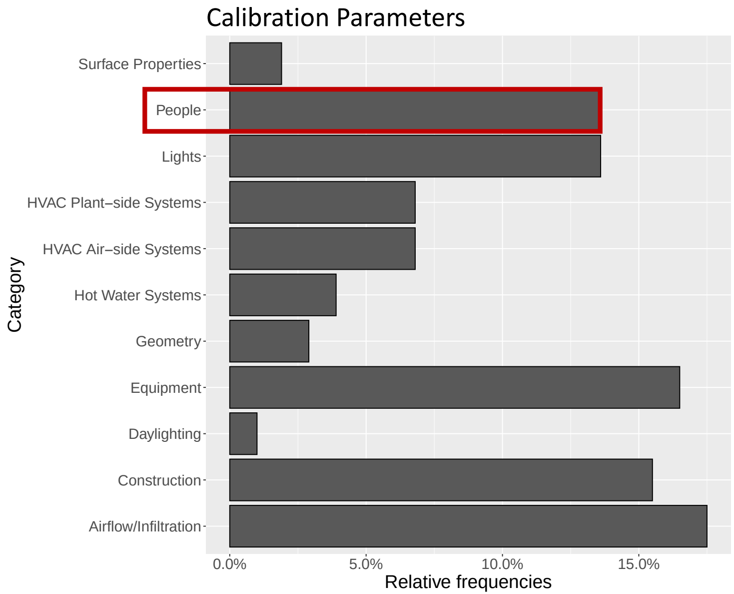
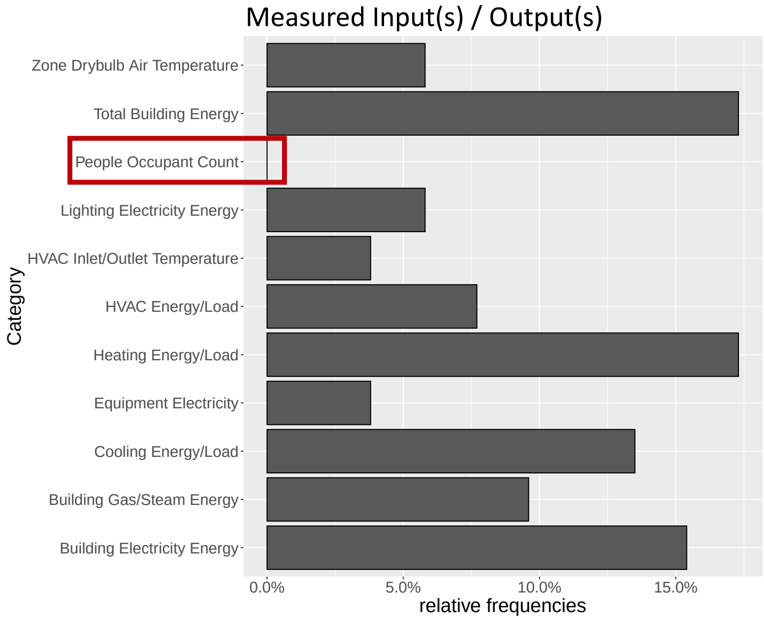
Background



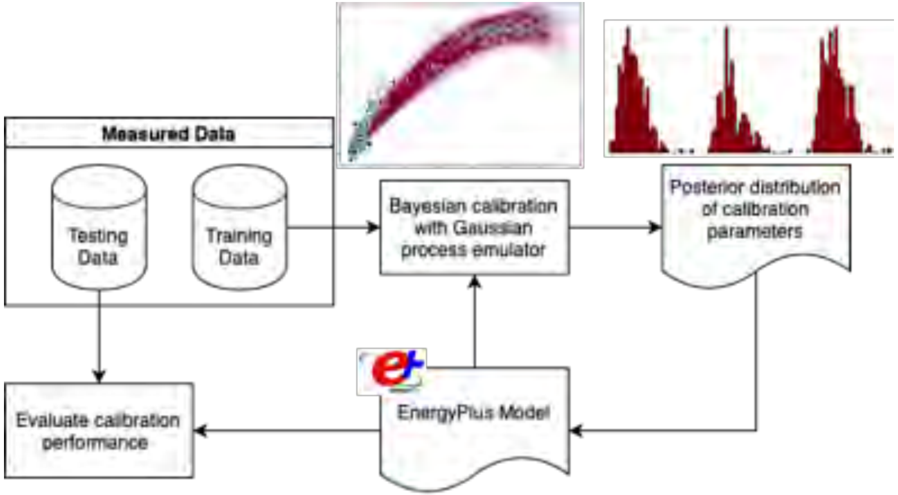


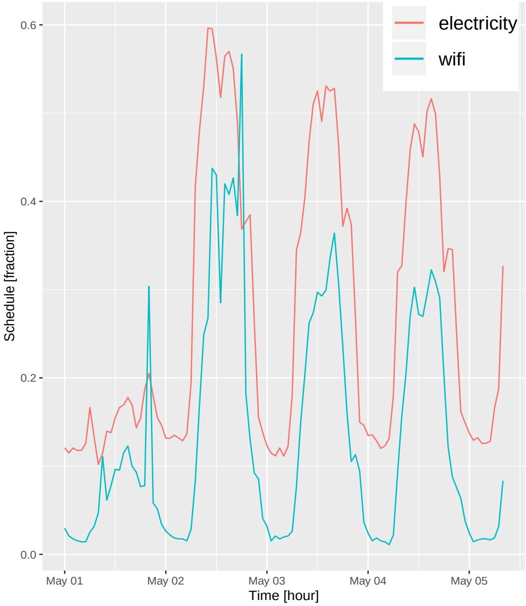
- Occupant presence and behavior often modeled as uncertain (i.e., as a calibration parameter)
- Increasing data availability with advancements in occupant sensing and data acquisition

Research Question

What is the impact of occupant count information on reducing the gap between simulated and measured energy use in buildings given an adequate calibration procedure

Method

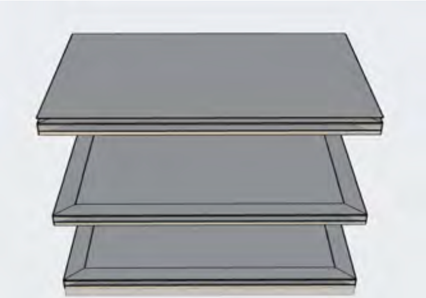




- Bayesian approach to calibration to more robustly quantify its impact on bridging the model performance gap

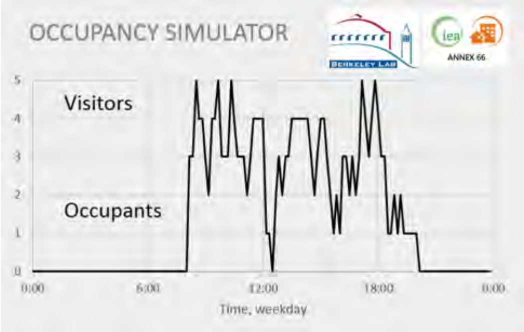
- However, using occupant presence directly might result in erroneous modeling of peak and base loads
- Model base and peak loads as random variables

Case Studies - Synthetic Data

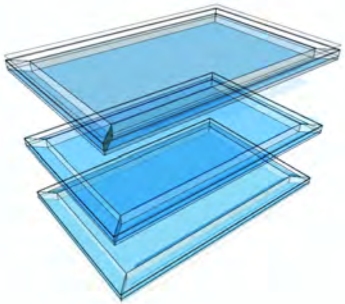


Reference Building Large Office

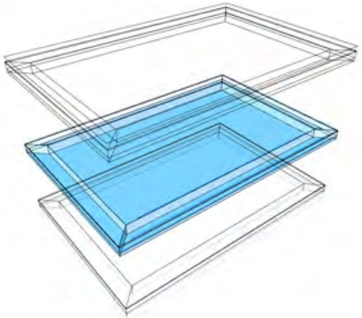
+



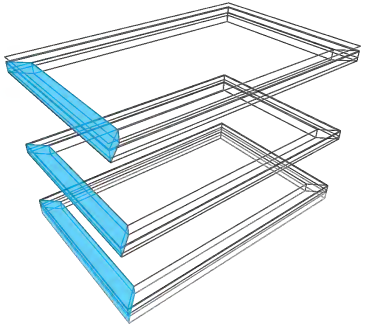
No occupant data (Baseline)



Total number of occupant known

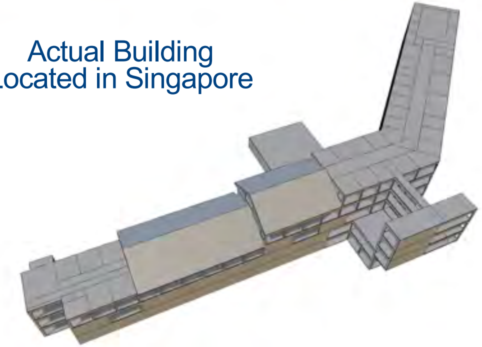


Total number of occupant per floor known



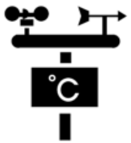
Total number of occupant aggregated by space function known

Case Studies - Real Data

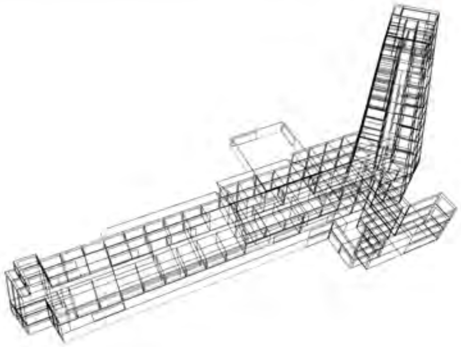


Actual Building
Located in Singapore

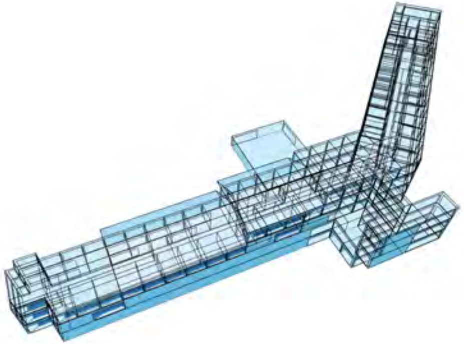
1 year of total building electricity energy consumption data



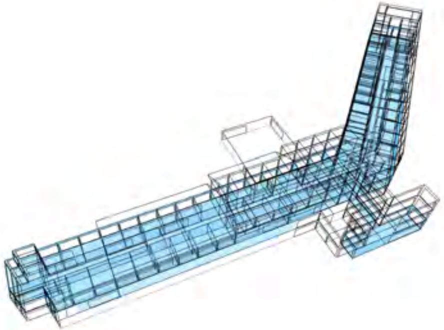
AMY Weather file from nearest weather station



No occupant data (Baseline)

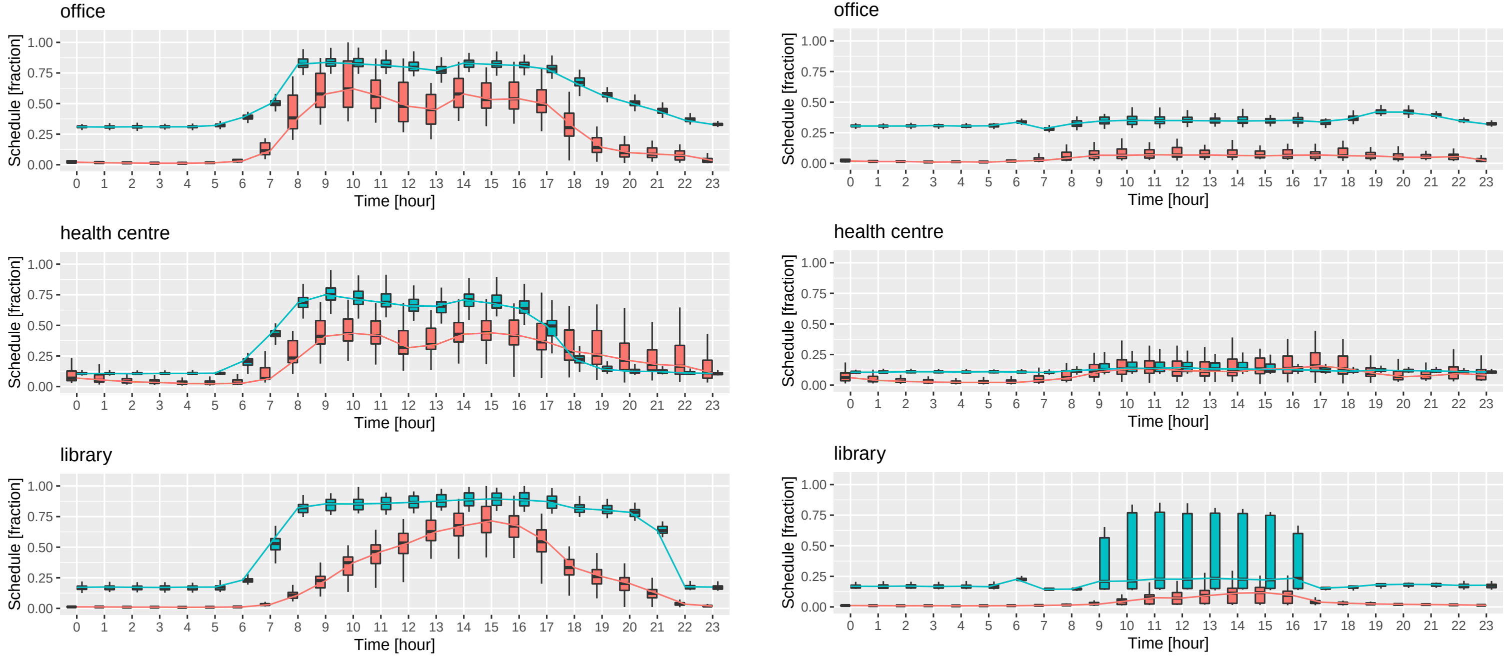


Wi-Fi data for whole building available



Wi-Fi data for each floor available

Wi-Fi as an Implicit Measure of Occupancy



- Wi-Fi data provides an implicit measure of occupancy and requires no modification to existing systems and have been shown to be suitable for use to create profiles to model hour to hour variations in internal loads

Performance Evaluation

4 evaluation metrics to evaluate different aspects of model performance

$$PICP = \frac{1}{n_{test}} \sum_{i=1}^{n_{test}} c_i$$

$$c_i = \begin{cases} 1, & t_i \in [L_i, U_i] \\ 0, & t_i \notin [L_i, U_i] \end{cases}$$

Number of measured values within prediction intervals

$$PI(NRMSW) = \frac{1}{R} \sqrt{\frac{1}{n_{test}} \sum_{i=1}^{n_{test}} (U_i^{(\alpha)} - L_i^{(\alpha)})^2}$$

Range of prediction intervals

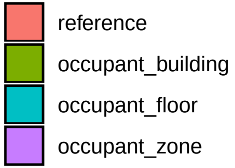
$$CVRMSE = \frac{\sqrt{\sum_{i=1}^{n_{test}} (y_i - \hat{y}_i)/(n_{test} - 1)}}{\bar{y}}$$

How well predictions matches measured values

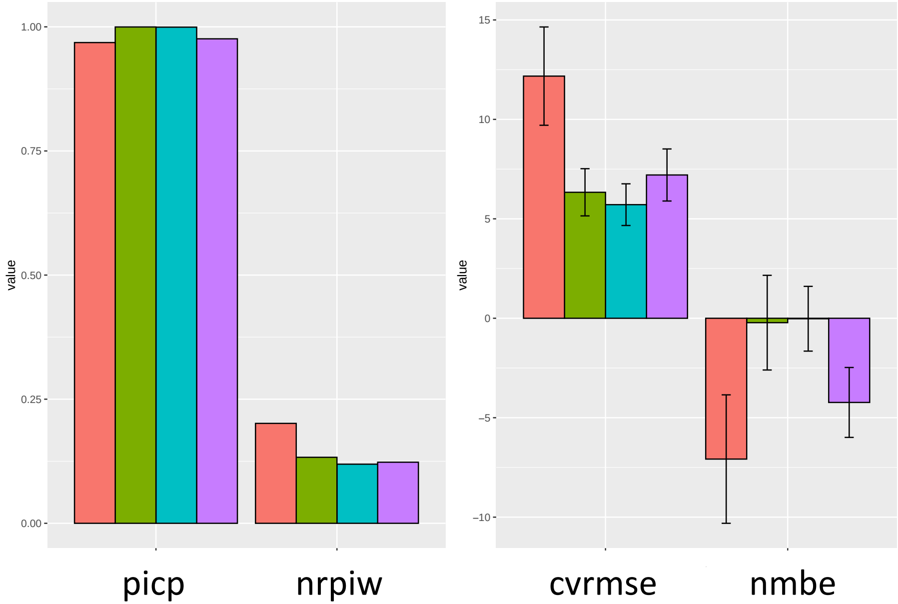
$$NMBE = 100 \times \frac{\sum_{i=1}^{n_{test}} (y_i - \hat{y}_i)}{(n_{test} - 1) \times \bar{y}}$$

Measure of over- or under-estimation

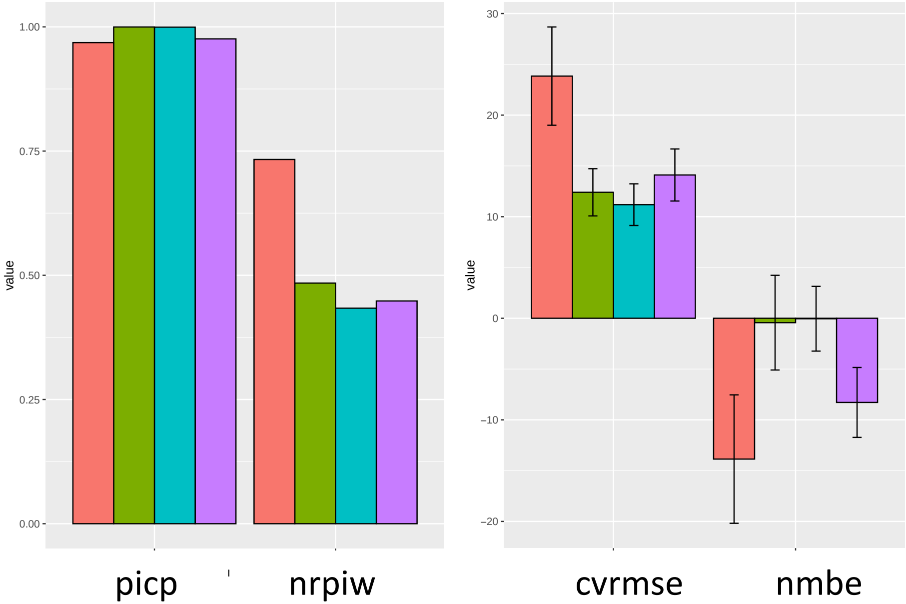
Results



Building Electricity

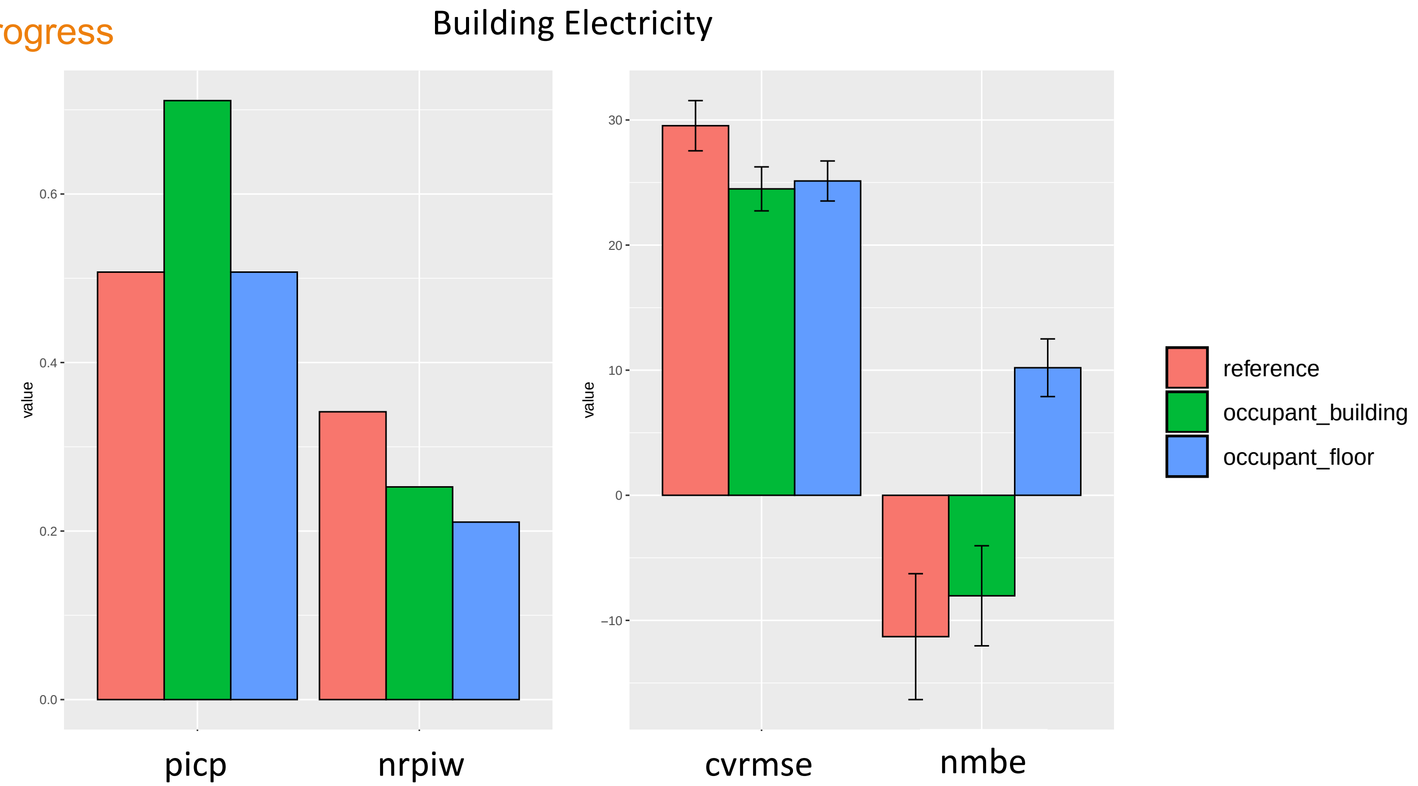


Interior Equipment Electricity



Results

Work in Progress



Conclusion

- Occupant information improves calibration performance but there is no convincing improvement in calibration performance with increased spatial resolution of occupancy information when the calibration is carried out at a whole building level
- Reference schedules can provide reasonable accuracy when the peak and base loads are reflective of actual conditions

Next

- Evaluate the subsequent impact on a specific purpose (e.g. retrofit analysis).
- Do these improvements in accuracy affect decision making
- Test approach on more case study buildings

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THANK YOU

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Presentations

Session 4 - Fifth presenter

Das,
Anooshmita

University of Southern Denmark, Denmark

Session 4

Day 2, 12:34

Prediction of Indoor Clothing Insulation Levels: A Comparison of Different Machine Learning Approaches

A. Das

Accurate prediction of clothing insulation levels is imperative for reducing building energy consumption. Clothing insulation is a critical parameter in the prediction of occupant thermal comfort. Lack of this information may result in miscalculations in the comfort conditions required, which may result in poorly sized heating, ventilation, and air conditioning (HVAC) systems. Predicting thermal comfort via clothing insulation levels of occupants in indoor settings using machine learning (ML) is a hot research topic. The advances in ML opens new opportunities for occupant thermal comfort prediction to mitigate the challenges encountered by existing models. Diverse algorithms and data preprocessing methods get applied to predict thermal comfort indices in heterogeneous contexts. But limited studies have systematically analyzed how different algorithms and data processing methods can have repercussions on the prediction accuracy. We experimentally study the perspectives of predicted comfort indices, algorithms implemented, different input features, data sources, sample-size, training and test set proportion, and predicting accuracy. For the data collection, a Microsoft Kinect camera is deployed and created a database with different clothing patterns, see Figure 1 (a). Ground-truth labels were collected with a second camera to validate the data annotations on clothing patterns for the classification task. We have applied four ML algorithms (K-Nearest Neighbor, Catboost, Gradient Boosting, XGBoost) for the Clo-value estimation. We also investigated the clothing patterns in natural and dark light settings. The relationship between clothing and gender was also meticulously analyzed and came up with interesting conclusions. The results in Figure 1 (b) highlight that the KNN has the best performance among the tested algorithms with an accuracy of 84.50% in dark light setting and 91.68% or the natural light setting.

Prediction of indoor clothing insulation levels: A comparison of different Machine Learning approaches

Anooshmita Das, University of Southern Denmark, SDU;

Jakub Dziedzic, Norwegian University of Science and Technology,NTNU

Mikkel Baun Kjærgaard, University of Southern Denmark, SDU;

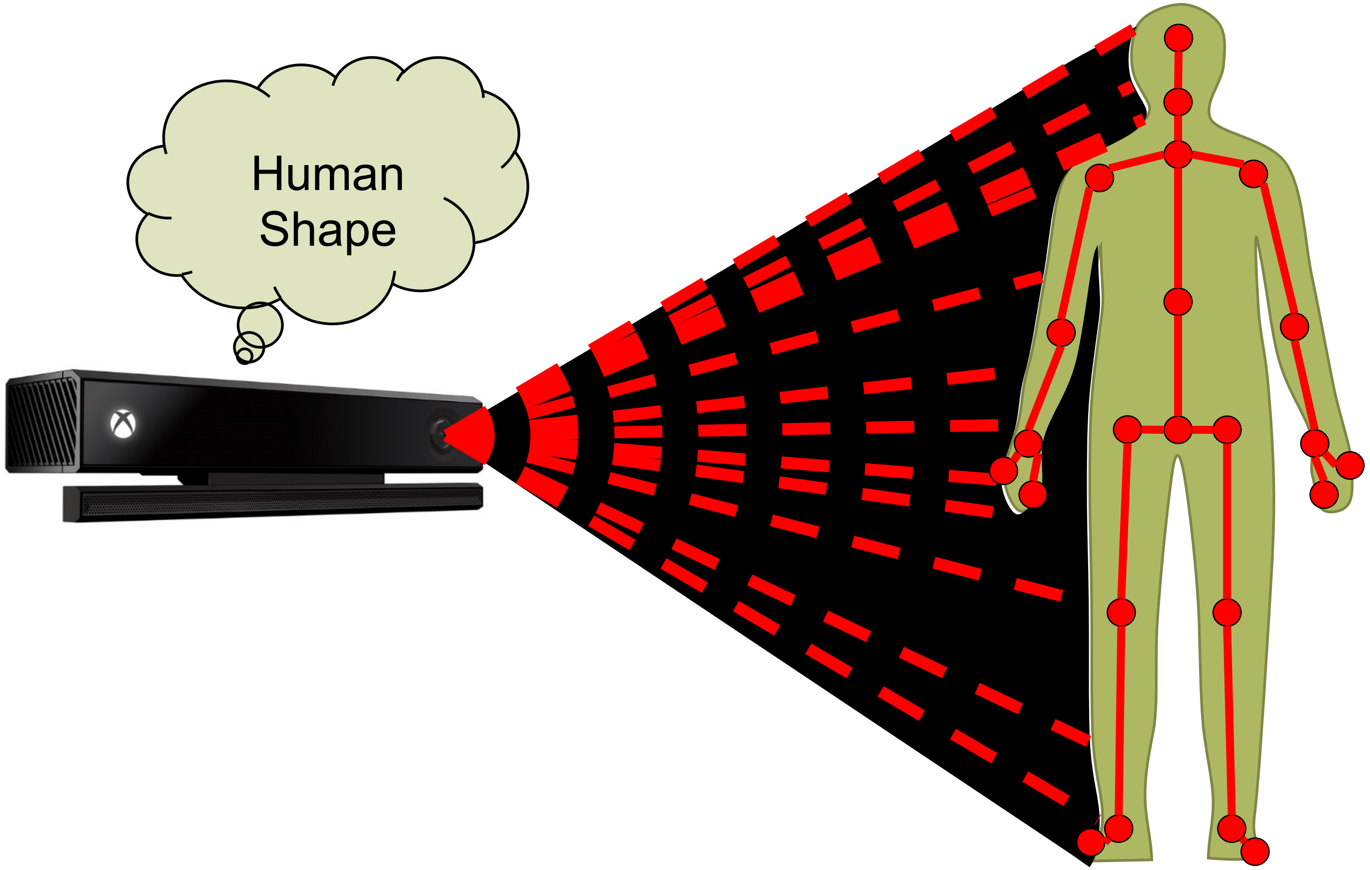
GOAL: Prediction of indoor clothing insulation levels

Clothing insulation is a critical parameter in the prediction of occupant thermal comfort.

Typical values of clothing insulation can be found in ASHRAE Standard 55 and ASHRAE Fundamentals.

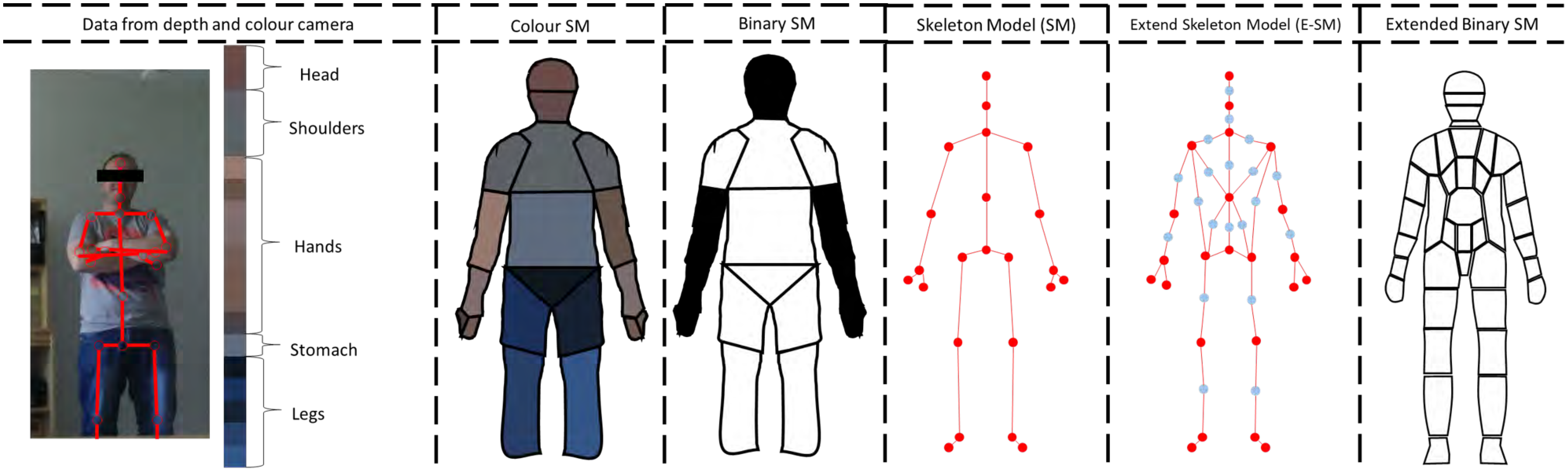
Lack of this information may result in … ?

Using Xbox Kinect in OB Research

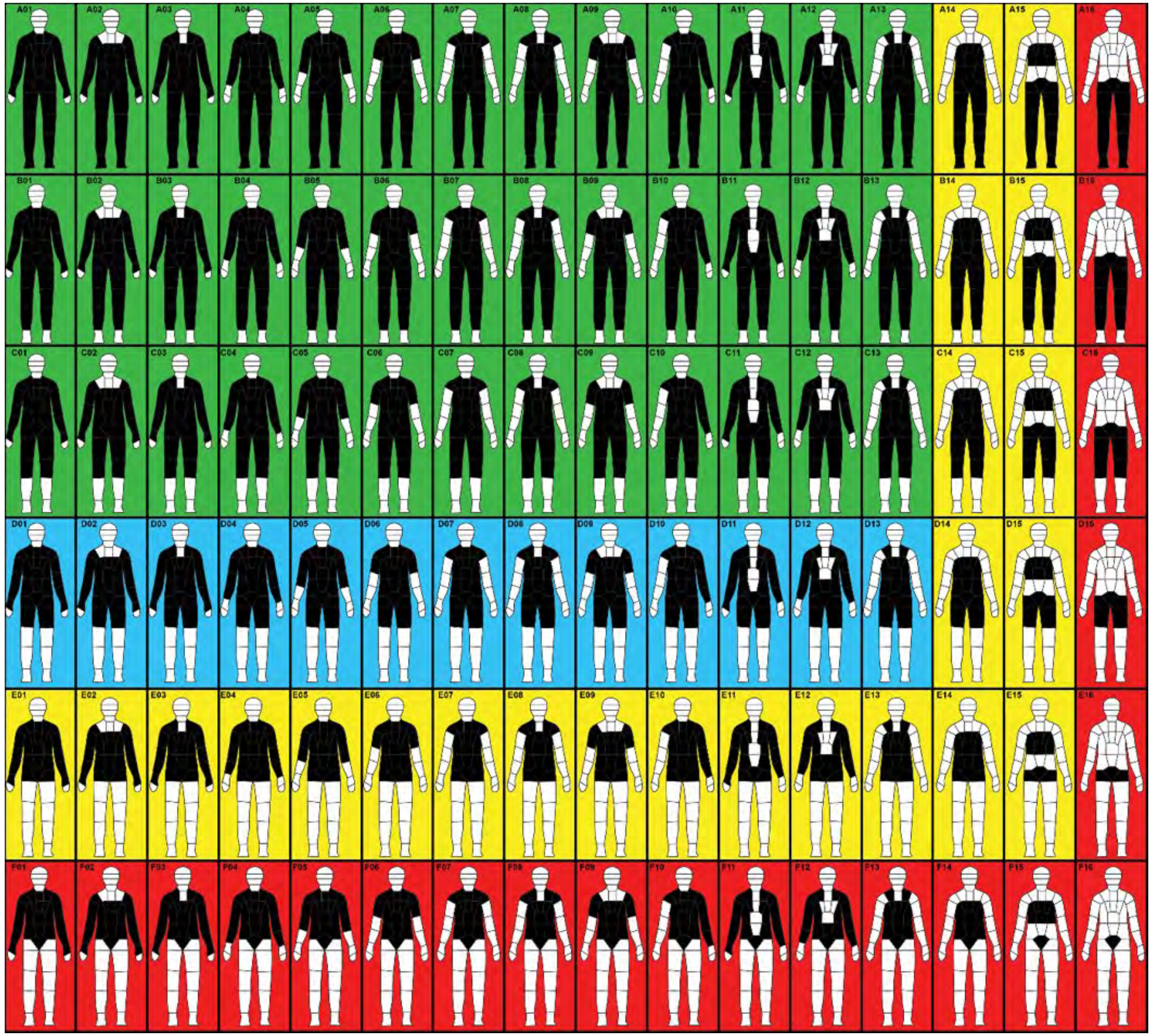


	X [m]	Y [m]	Z [m]
SpineBase = 1;	0.1066	-0.2272	2.3211
SpineMid = 2;	0.0990	0.0792	2.3576
Neck = 3;	0.0903	0.3762	2.3800
Head = 4;	0.0832	0.5278	2.3588
ShoulderLeft = 5;	-0.0939	0.2785	2.3739
ElbowLeft = 6;	-0.2182	0.0450	2.3635
WristLeft = 7;	-0.3324	-0.1487	2.3171
HandLeft = 8;	-0.3879	-0.1982	2.2953
ShoulderRight = 9;	0.2749	0.2756	2.3563
ElbowRight = 10;	0.4278	0.0628	2.3095
WristRight = 11;	0.5774	-0.0988	2.2356
HandRight = 12;	0.6207	-0.1409	2.2146
HipLeft = 13;	0.0210	-0.2271	2.2906
KneeLeft = 14;	-0.0017	-0.5919	2.2254
AnkleLeft = 15;	-0.0485	-0.8850	2.1211
FootLeft = 16;	-0.0264	-0.7374	2.1179
HipRight = 17;	0.1888	-0.2196	2.2758
KneeRight = 18;	0.2266	-0.5835	2.2297
AnkleRight = 19;	0.2552	-0.8882	2.1656
FootRight = 20;	0.2160	-0.7434	2.1606
SpineShoulder = 21;	0.0926	0.3032	2.3768
HandTipLeft = 22;	-0.4402	-0.2368	2.2771
ThumbLeft = 23;	-0.3892	-0.1488	2.2181
HandTipRight = 24;	0.6720	-0.1895	2.1962
ThumbRight = 25;	0.6357	-0.0864	2.1534

Using Xbox Kinect for CLO classification



CLO Multi-class classification patterns



Microsoft Kinect camera is deployed and created a database with different clothing patterns.

Figure 1 - Classification Table for Different Clothing Patterns (Green indicates clothing behavior patterns in public and office buildings (socially accepted) and has 39 classes. However data on blue, yellow and red could not be collected due to privacy reasons).

Approach

Predicting thermal comfort via clothing insulation levels of occupants in indoor settings using machine learning (ML) is a hot research topic.

The dataset is split into training (70 %), testing(20%) and validation sets(10%).
We have applied four ML classifiers (**K-Nearest Neighbor, Cat boost, Gradient Boosting, XGBoost)** for the classification task.

We investigated the clothing patterns in **natural and dark light settings**.

Ground-truth labels were collected with a second camera to validate the data annotations on clothing patterns for the classification task.

Result

Table 1: Full Data

ML Classifier / Evaluation Metrices	RGB			HSL		
	Accuracy	F1Score	Mis-classification Rate	Accuracy	F1Score	Mis-classification Rate
KNN	81.23 %	81.38 %	18.77 %	86.78 %	86.86 %	13.22 %
CatBoost	72.84 %	72.94 %	27.16 %	76.58 %	76.65 %	23.42 %
Gradient Boosting	62.73 %	62.84 %	37.27 %	64.91 %	64.98 %	35.02 %
XGBoost	56.58 %	56.70 %	43.42 %	58.17 %	58.20 %	41.83 %

Result

Table 2: Dark Light Settings

ML Classifier / Evaluation Metrices	RGB			HSL		
	Accuracy	F1Score	Mis-classification Rate	Accuracy	F1Score	Mis-classification Rate
KNN	80.41 %	80.59 %	19.59 %	84.50 %	84.70 %	15.5 %
CatBoost	74.62 %	74.60 %	25.38 %	77.51 %	77.53 %	22.49 %
Gradient Boosting	66.79 %	66.75 %	33.25 %	68.66 %	68.62 %	31.38 %
XGBoost	61.44 %	61.43 %	38.56 %	63.22 %	63.21 %	36.78 %

Table 3: Natural Light Settings

ML Classifier / Evaluation Metrices	RGB			HSL		
	Accuracy	F1Score	Mis-classification Rate	Accuracy	F1Score	Mis-classification Rate
KNN	86.05 %	86.01 %	13.95 %	91.68 %	91.69 %	8.32 %
CatBoost	83.68 %	83.68 %	16.32 %	87.79 %	87.80 %	12.21 %
Gradient Boosting	77.7 %	77.80 %	22.3 %	80.91 %	80.92 %	19.09 %
XGBoost	71.87 %	71.93 %	28.13 %	76.36 %	76.33 %	23.64 %

Presentations

Session 4 - Sixth presenter

Mann, Alasdair

University of Southampton, UK

Session 4

Day 2, 12:38

Analysis of Occupants Presence in Homes

A. Mann, S. Gauthier

Forecasting occupant behaviour will enable people in need of social care to intelligently manage their informal and formal care network, reducing the individual burden on carers. Creating these forecasts can be difficult since the occupant's schedule can change unexpectedly. Furthermore, the same methods might not be repeatable since occupants each have their own lifestyle. This means that models are prone to overfitting. This study explores how different amounts of features, lag times, and training instances affect the performance of traditional supervised machine learning regressors in forecasting occupants' presence (frequency and length of time within one hour). A key finding is that there is a threshold of around 72 hours for the number of useful lag times and training instances. After this threshold, depending on the occupant, the model's performance would plateau or decrease. Minor exceptions can be observed in some occupants with a weekly schedule where a model will suddenly improve if fed a week of lag times. This means that feature selection should be done carefully for predicting occupant behaviour.

UNIVERSITY OF Southampton

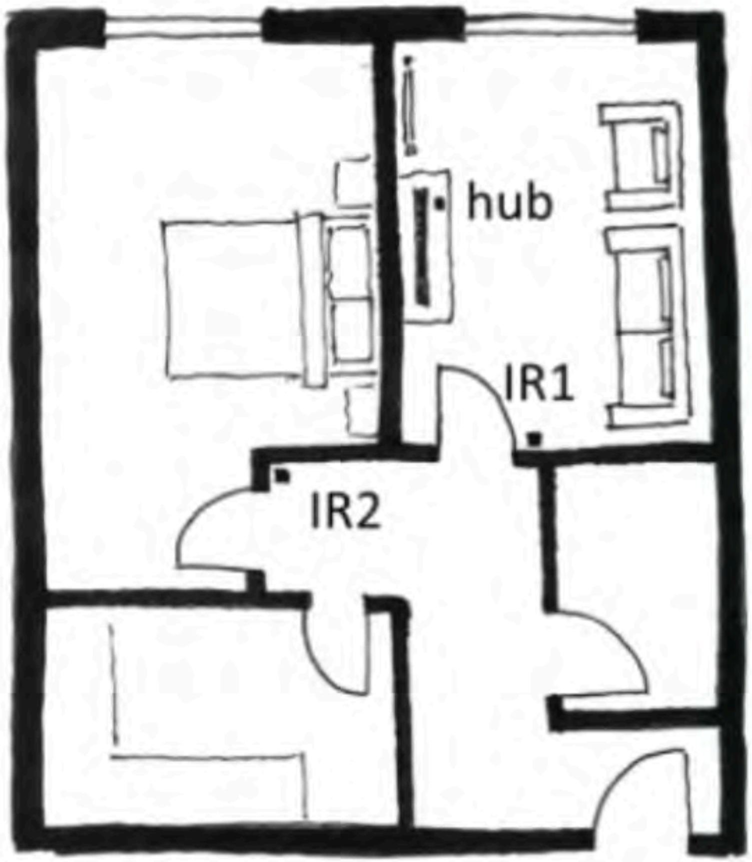
Analysis of Occupancy Data

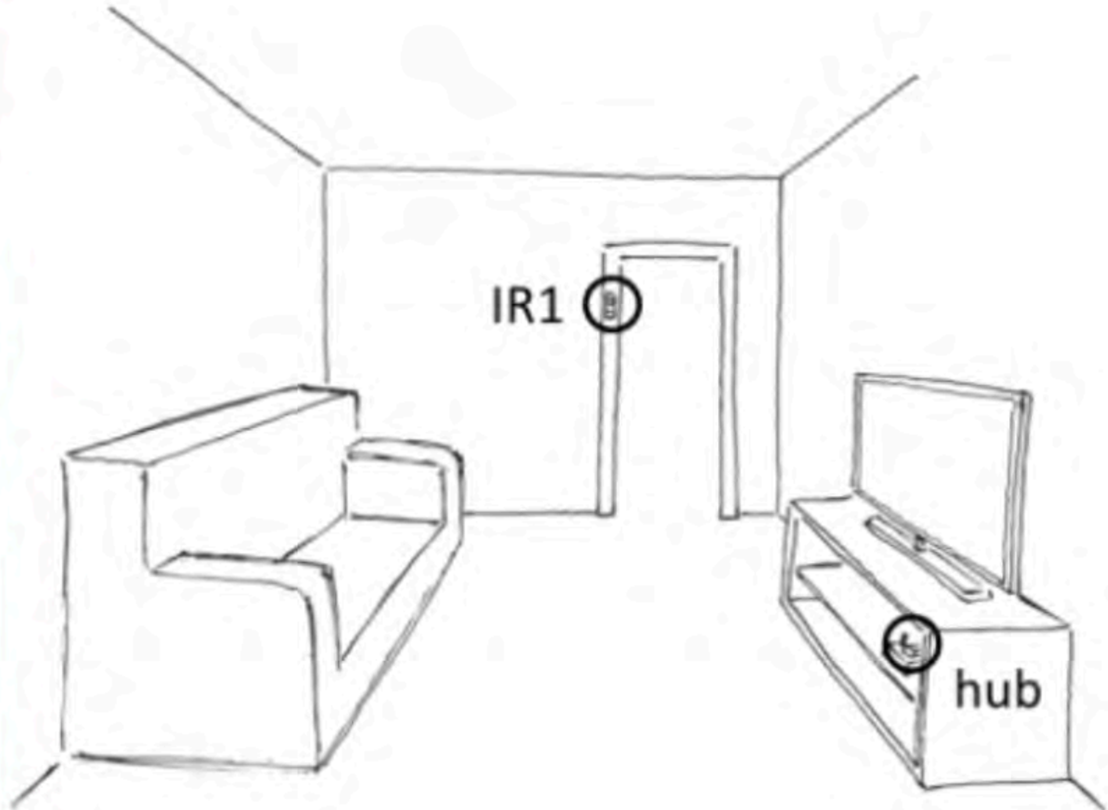
Alasdair Mann

21 April 2020

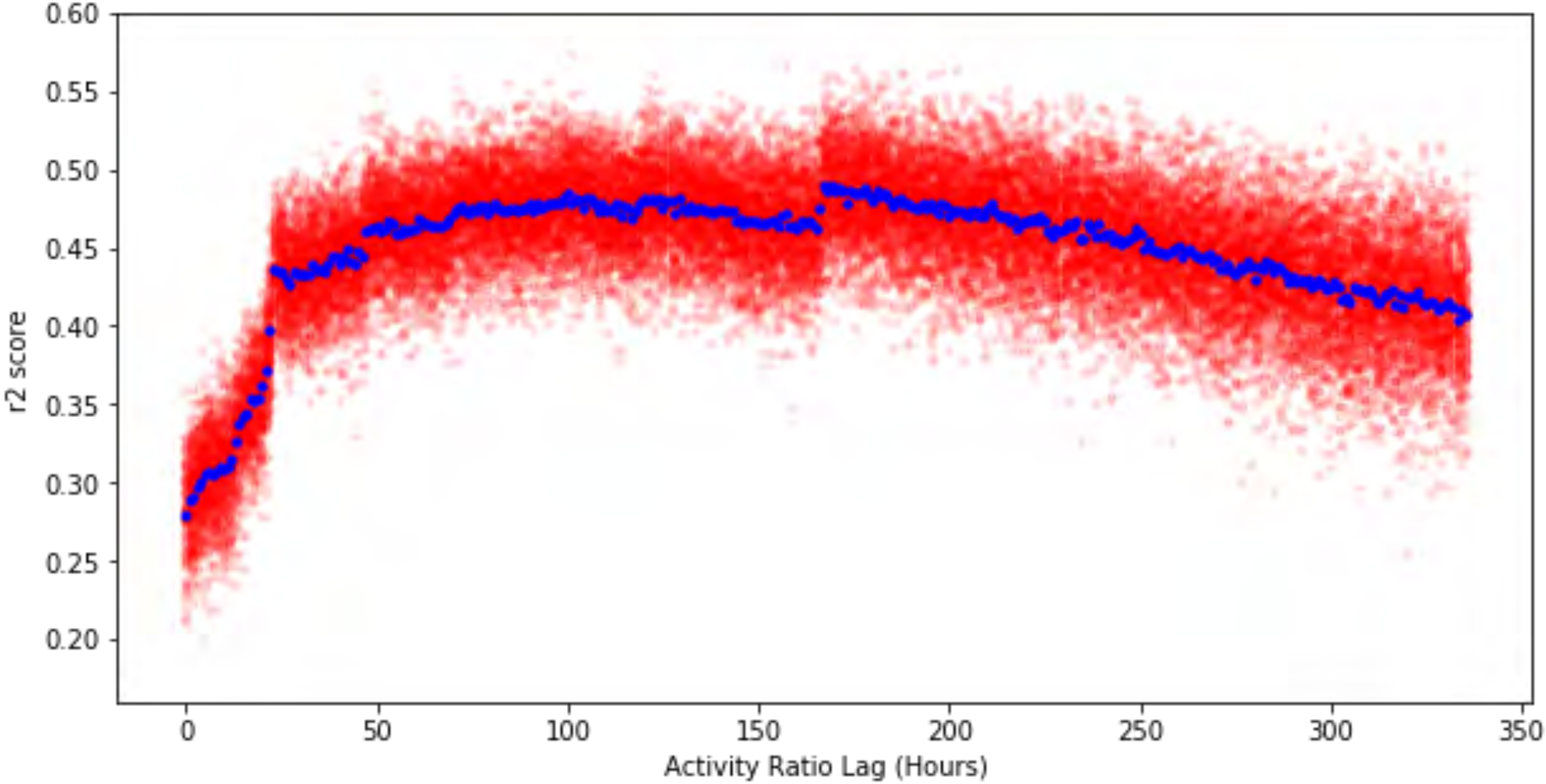
Predicting Occupancy in Social Care

The Dataset and Predictors

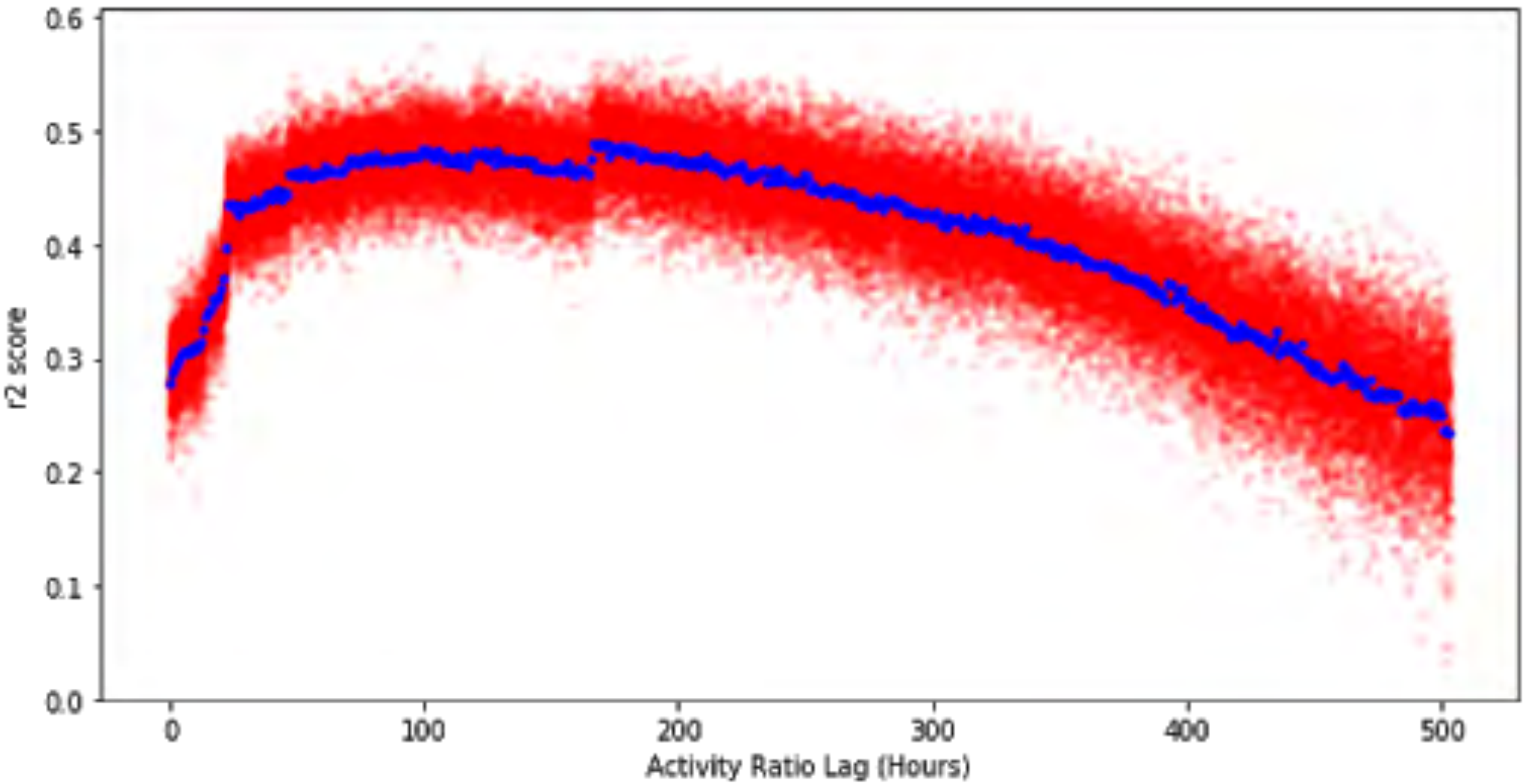




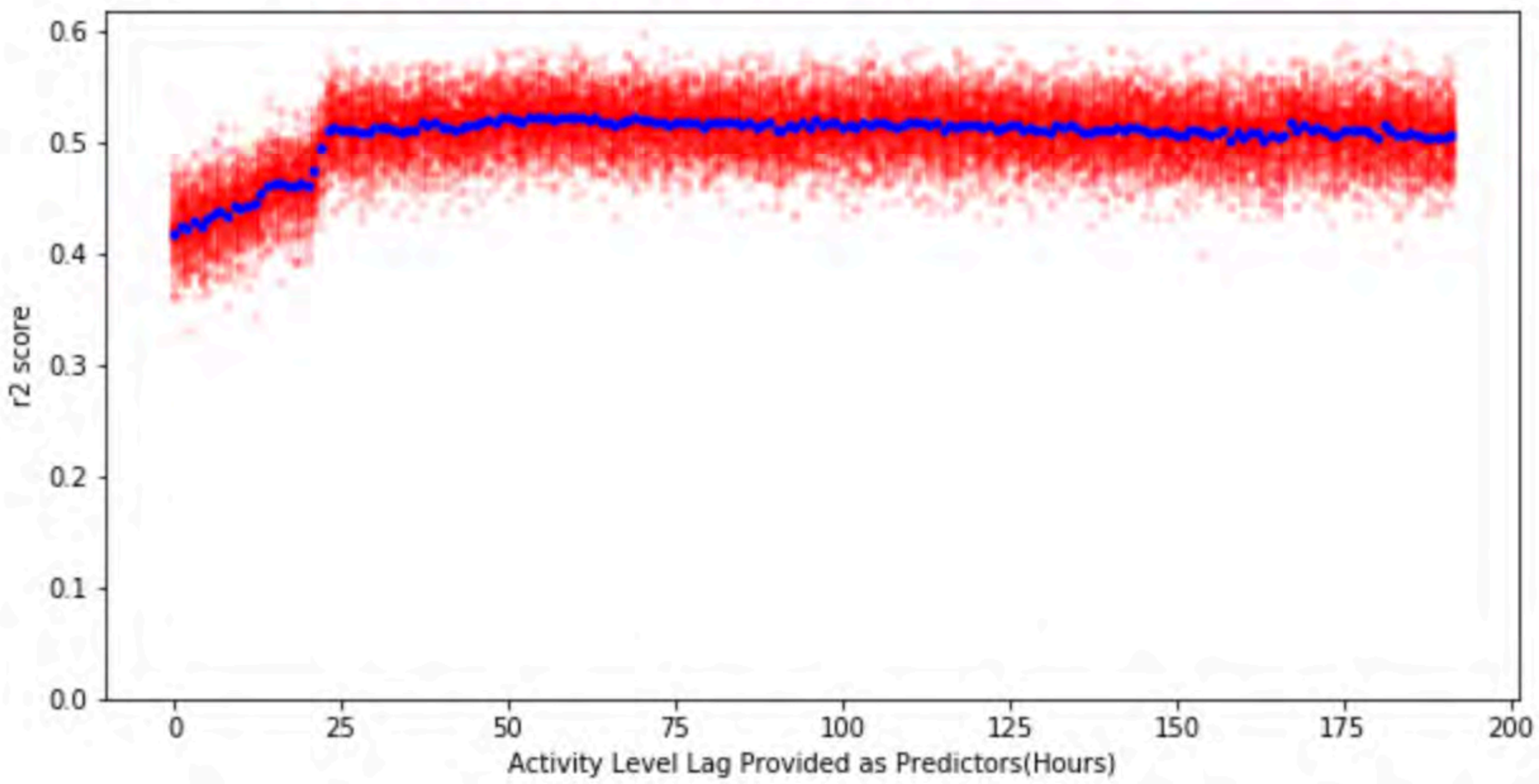
Effect of Increasing Lag on Model Performance



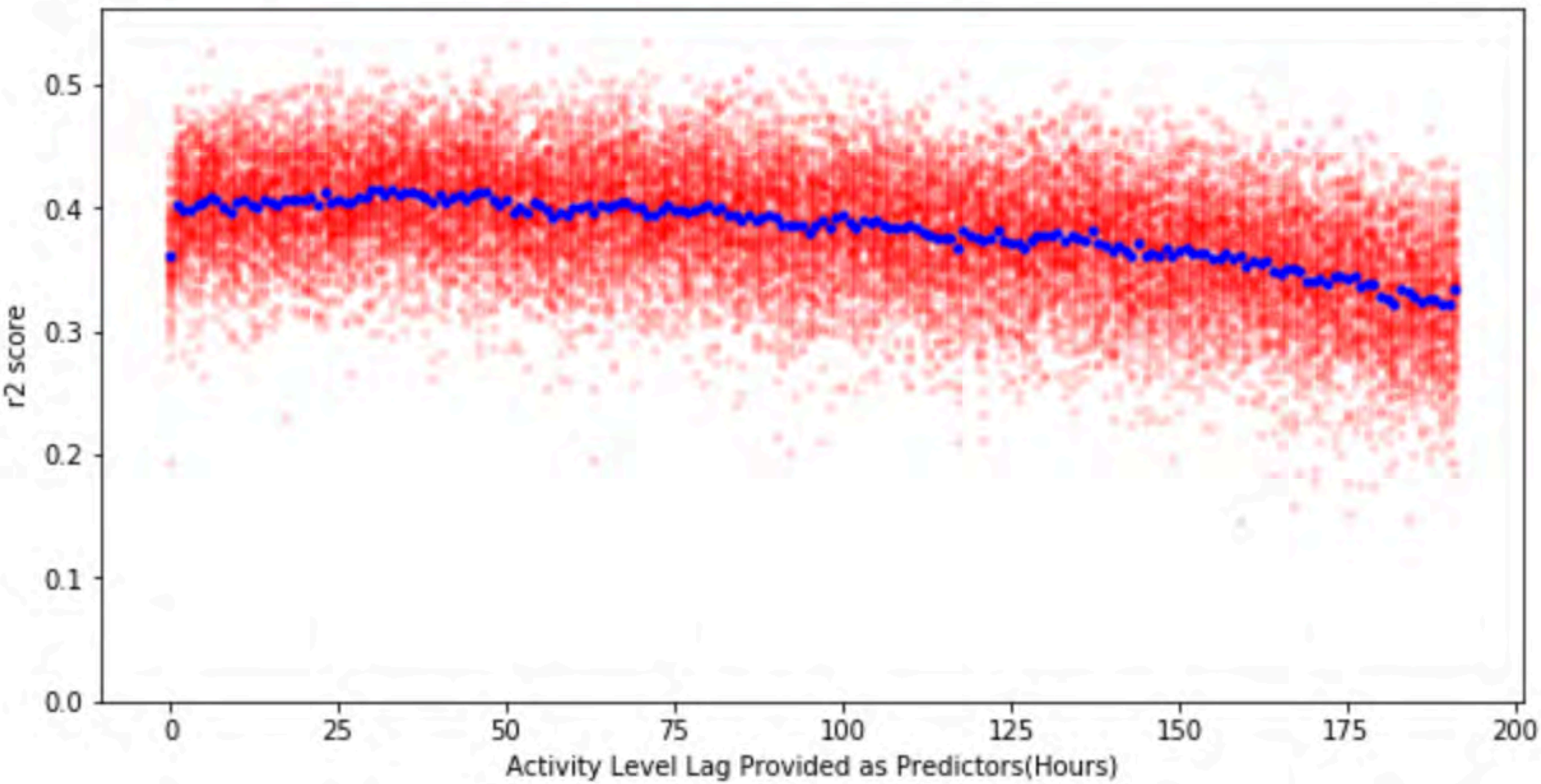
Further Increasing the Amount of Lag



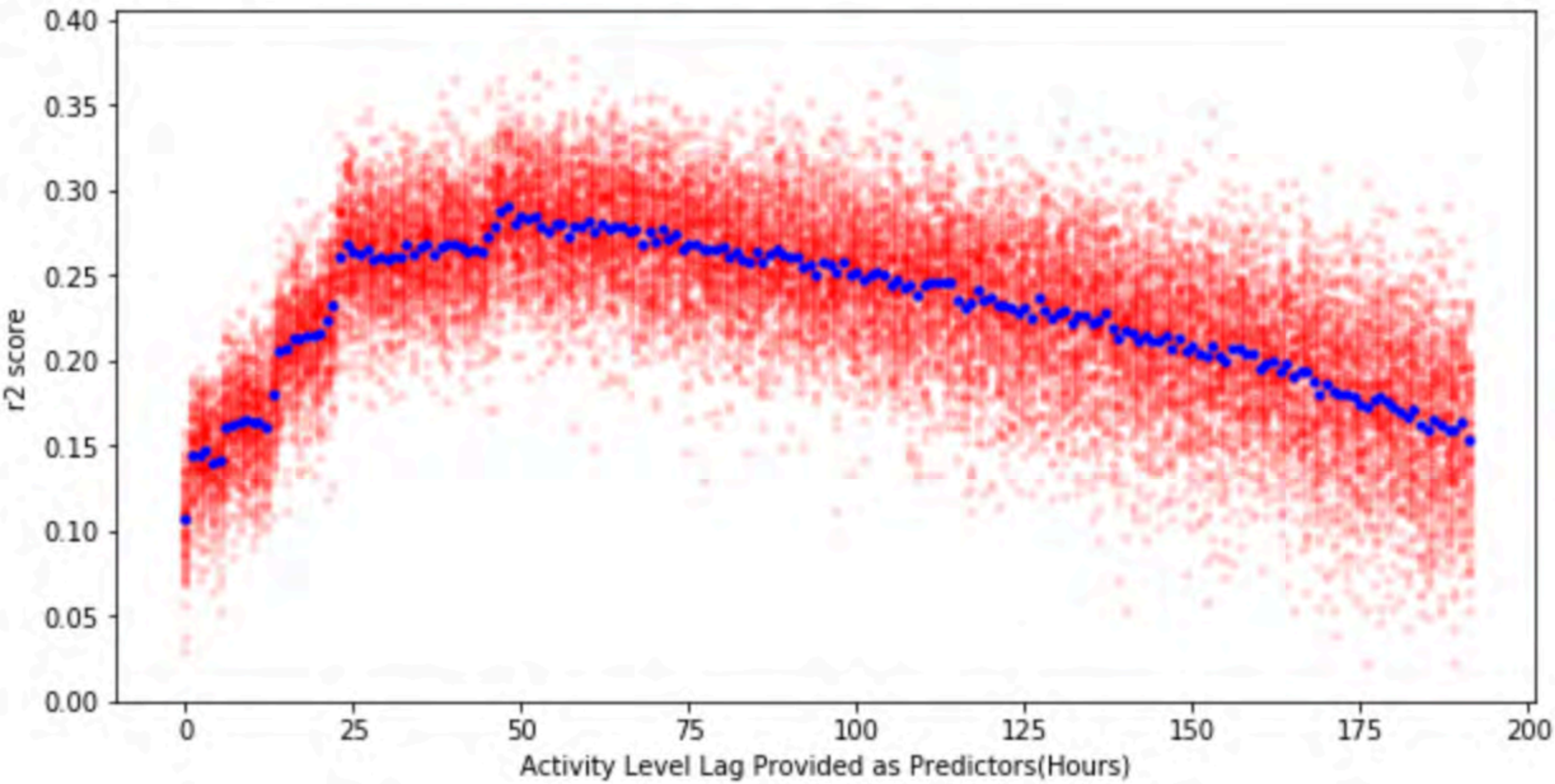
Results with Other Occupants



Results with Other Occupants



Results with Other Occupants



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Summary

- Data was collected for a social care context
- Specific lag times improve performance
- Adding more data is only beneficial up to a point
- Analysis limited by R^2 metric

University of Southampton

Alasdair Mann

am6u17@soton.ac.uk

21 April 2020

Presentations

Session 4 - Seventh presenter

Abuimara, Tareq

Carleton University, Canada

Session 4

Day 2, 12:42

The Impact of Occupants' Distribution on Energy and Comfort in a Case study Office Building

T. Abuimara

Observing the current occupant modelling approaches during simulation-aided building design reveals that energy modellers and designers assume that occupants are evenly distributed within areas of a given type (e.g. office space). Designers typically assume uniform occupant density (i.e. number of people/m2) to perform design tasks which is usually specified by building codes and standards. However, this assumption does not necessarily reflect reality, as occupants are often distributed heterogeneously in buildings due to several factors such as inter-tenant diversity in office buildings. To this end, this study examines the impact of occupants' distribution on energy and comfort performance of an office building model located in Toronto, Canada. A 15-zone model was simulated using EnergyPlus simulation tool under 33 different randomly generated occupants' distribution scenarios. The energy performance was assessed based on the energy use intensity (EUI) while a metric called discomfort occupant hours (DOH) was developed to assess comfort levels. DOH is calculated by summing the multiplication of the discomfort hours (i.e. indoor temperature not within acceptable range) by the number of people present at that hour in the zone. In addition, the traditional ASHRAE Standard 90.1 unmet hours, where the building is considered to have an unmet hour when a single zone of the building has an unmet hour, were reported. The results of the study indicate that occupant distribution scenarios can have significant impact on occupants' comfort as overpopulated zones had a significantly higher DOH compared to the DOH of standard distribution used in typical design processes. On the other hand, the change in occupants' distribution had moderate impact on energy performance as the highest difference in EUI was observed to be 9 kWh/m2 given that model HVAC were hard sized for all simulations.

IEA EBC Annex 79

Energy in Buildings and Communities Programme

5th International Symposium on Occupant Behaviour

The Impact of Occupants' Distribution on Energy and Comfort in a Case study Office Building

Tareq Abuimara ; William O'Brien; Burak Gunay

Carleton University
Ottawa, Canada

Carleton University

BPRC Building Performance Research Centre Carleton University

Hbi Human-Building Interaction Laboratory

DBOM Data-driven Building Operation and Maintenance Carleton University

Objectives

- Evaluating the impact of inter-tenant diversity on energy and comfort.

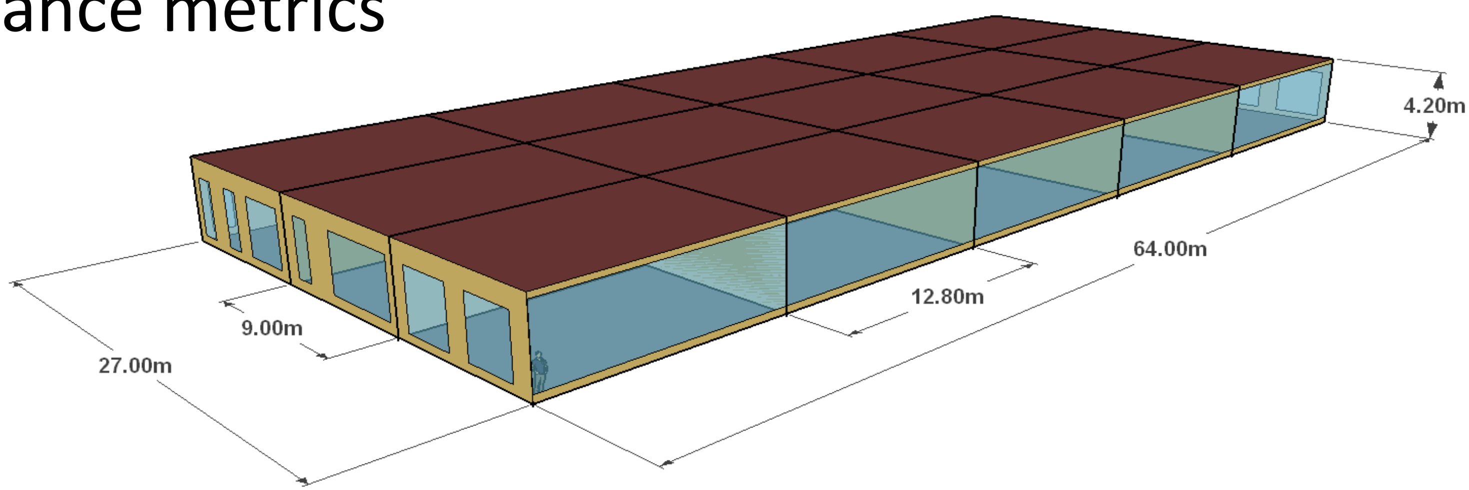
Methods

- Create base model

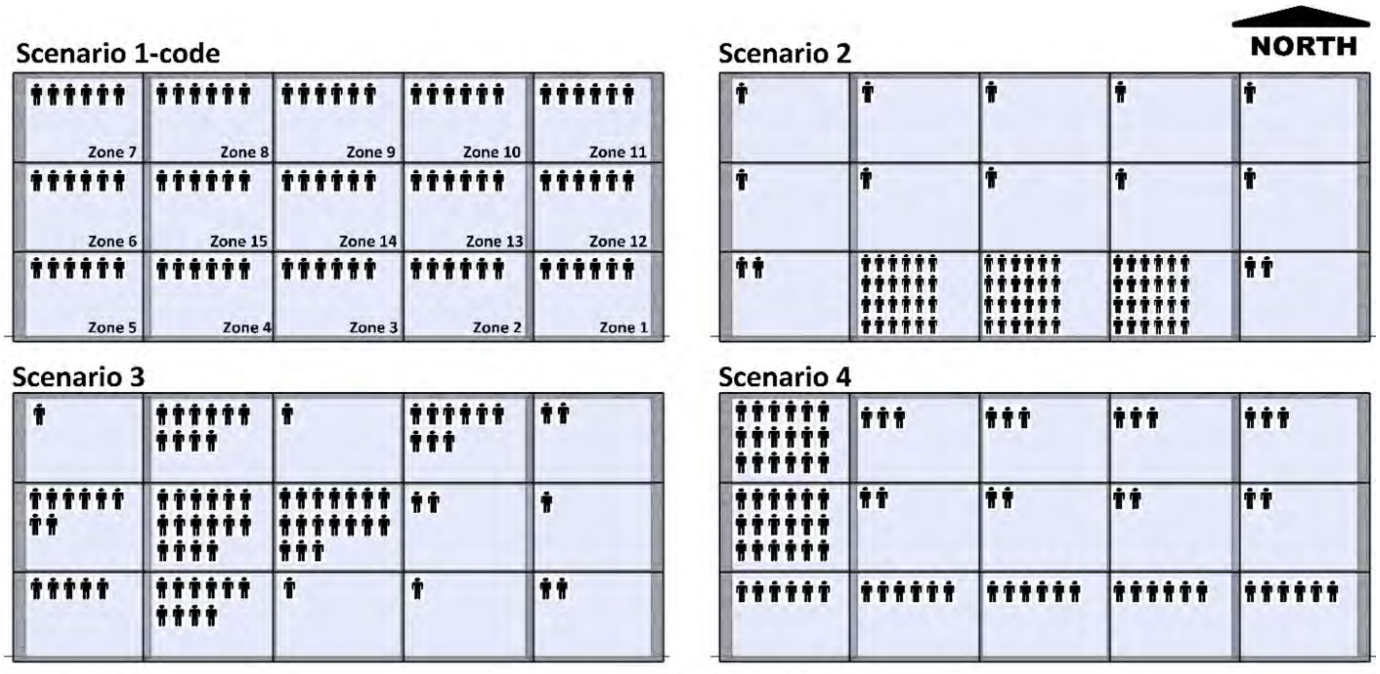
- Generate occupants' distributions scenarios

- Performance metrics

- Located in Toronto, Canada
- Office building typical floor
- 15 thermal zones



Occupants' distributions scenarios



Performance metrics

Energy

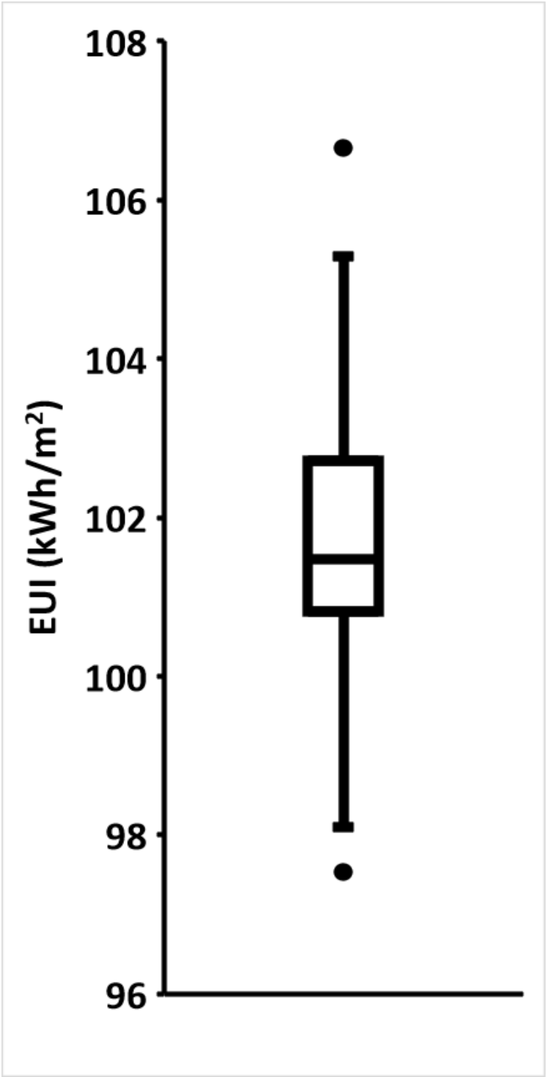
- EUI

Comfort

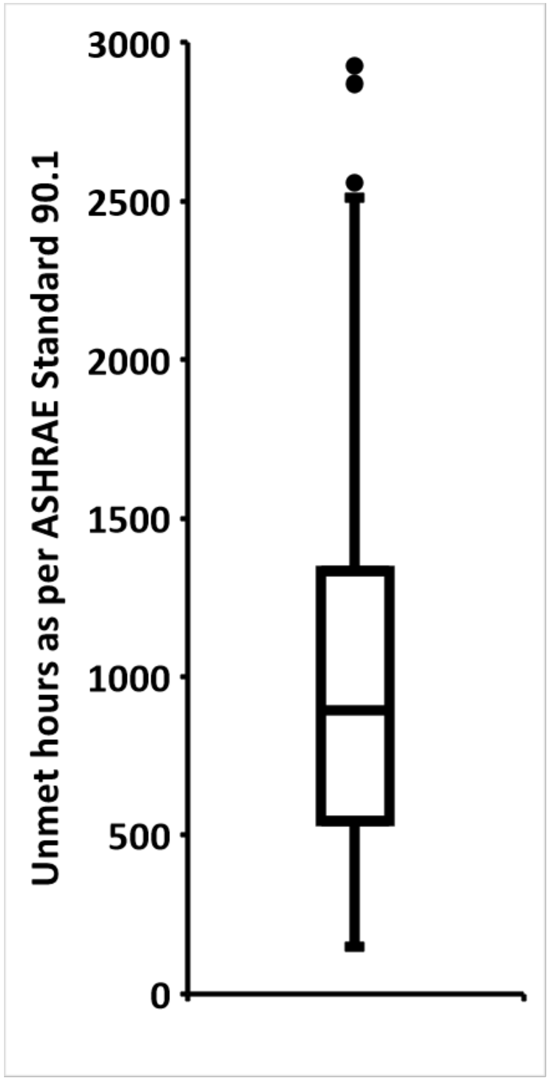
- Unmet hours as per ASHRAE Standard 90.1
- ODH

Results

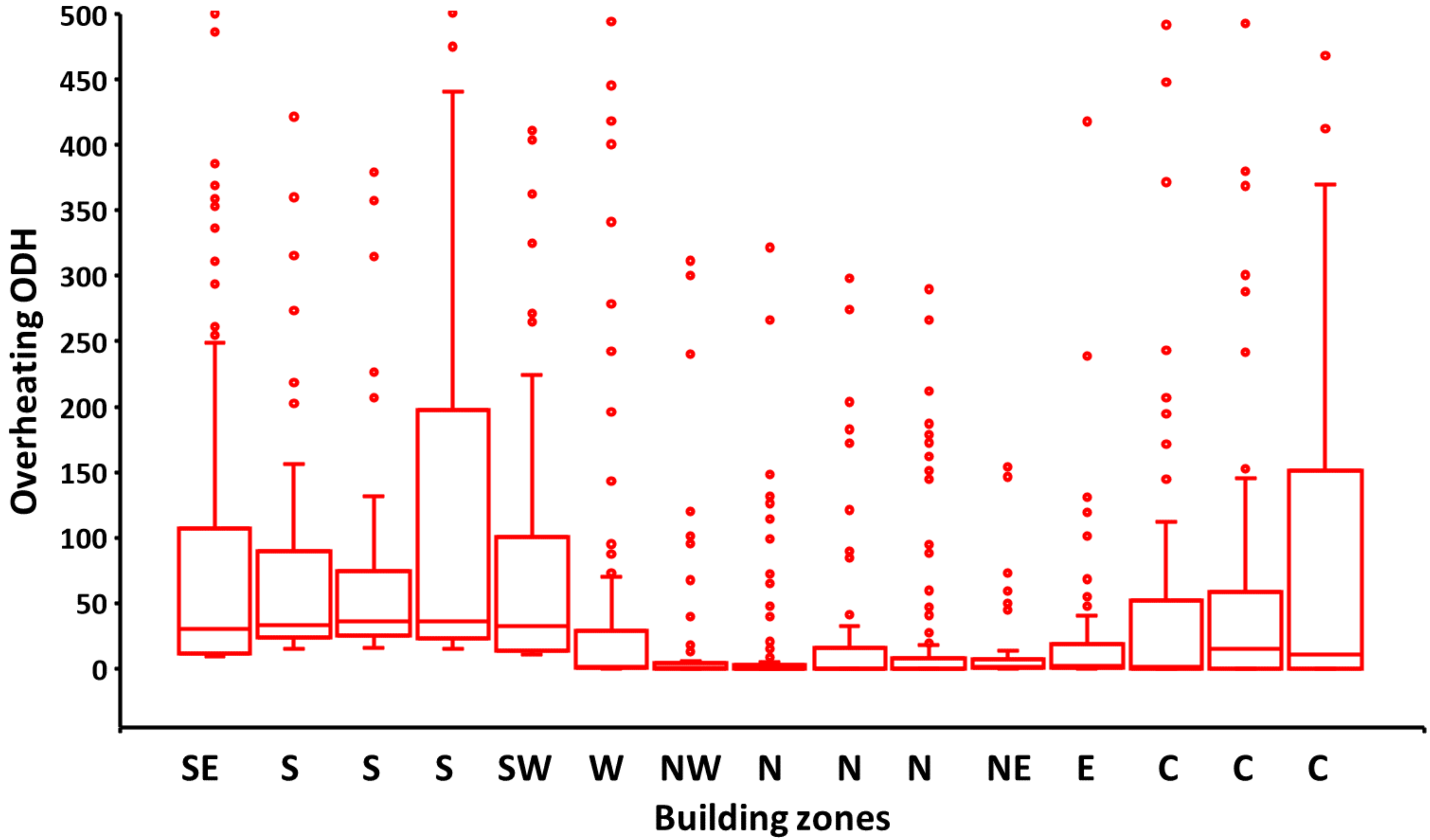
Energy performance



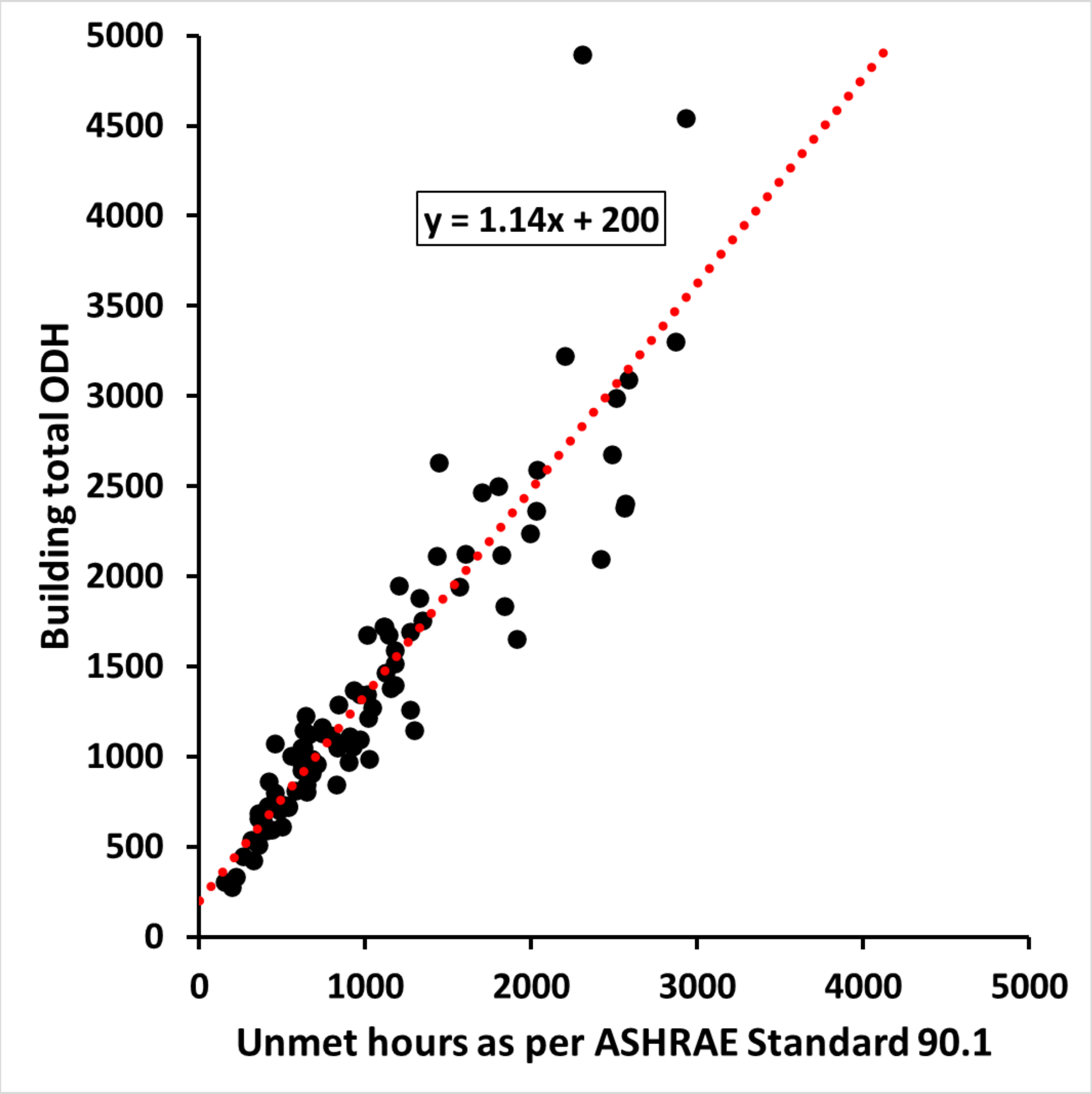
Thermal Comfort performance



Occupant discomfort hours (ODH)



Correlation between the unmet hours as per ASHRAE Standard 90.1 and the total ODH



Conclusions and recommendations

Conclusions

- Modest impact on energy
- Substantial impact on thermal comfort

Recommendations

- Consider spatial variation of occupancy in design
- Use different metrics to evaluate comfort

Thank You

Questions?

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Presentations

Session 5 - First presenter

O'Brien, Liam

Carleton University, Canada

Session 5

Day 2, 13:25

Does Teleworking Save Energy? A Critical Review of Quantitative Studies and their Research Methods

L. O'Brien

Teleworking has been widely perceived as a more sustainable mode of working for office workers compared to the status quo because of its reduced dependency on transportation and centralized office space. However, the situation is far more complex than would appear on the surface, when the scope is expanded to include home office energy use, the Internet, long-term consumer choices, and other so-called rebound effects are considered. Though telecommuting has been researched for the past four decades, few studies have quantified home, office, transportation, and communications energy or GHG emissions implications of telecommuting simultaneously. Moreover, the lack of data about workers' behaviors and purchasing decisions has led to researchers making simplistic assumptions. To make progress in answering the question of whether telecommuting results in less energy use than conventional centralized office working, this paper reviews research methods and results of primarily quantitative studies of any and all four domains that consider operating energy and/or greenhouse gas emissions. The results ultimately show that this problem is much more complex than most of the literature would suggest and indicate that current datasets and methods are inadequate for fully answering the research question.

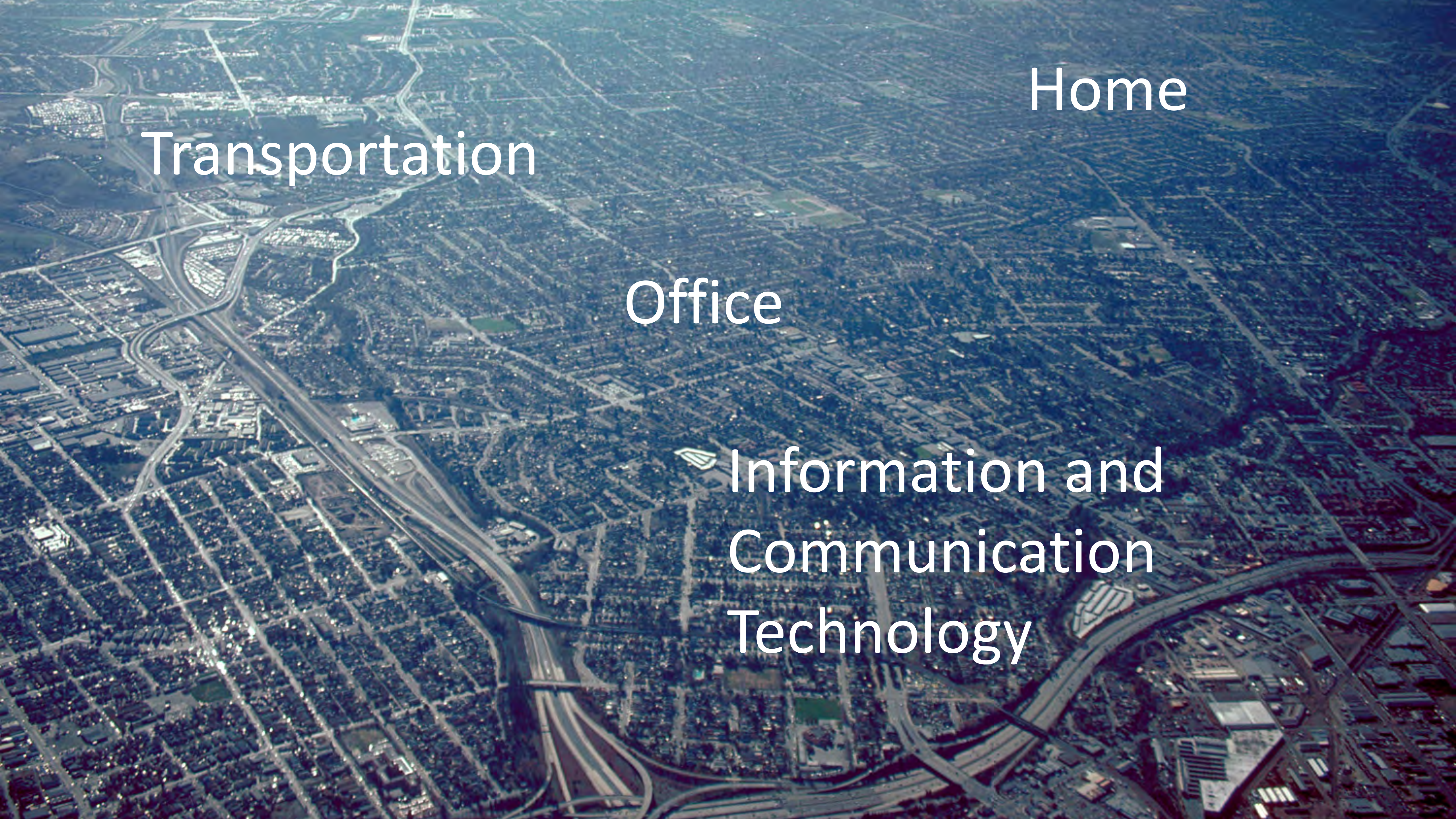
Does Teleworking Save Energy?

A Critical Review of Quantitative Studies and their Research Methods

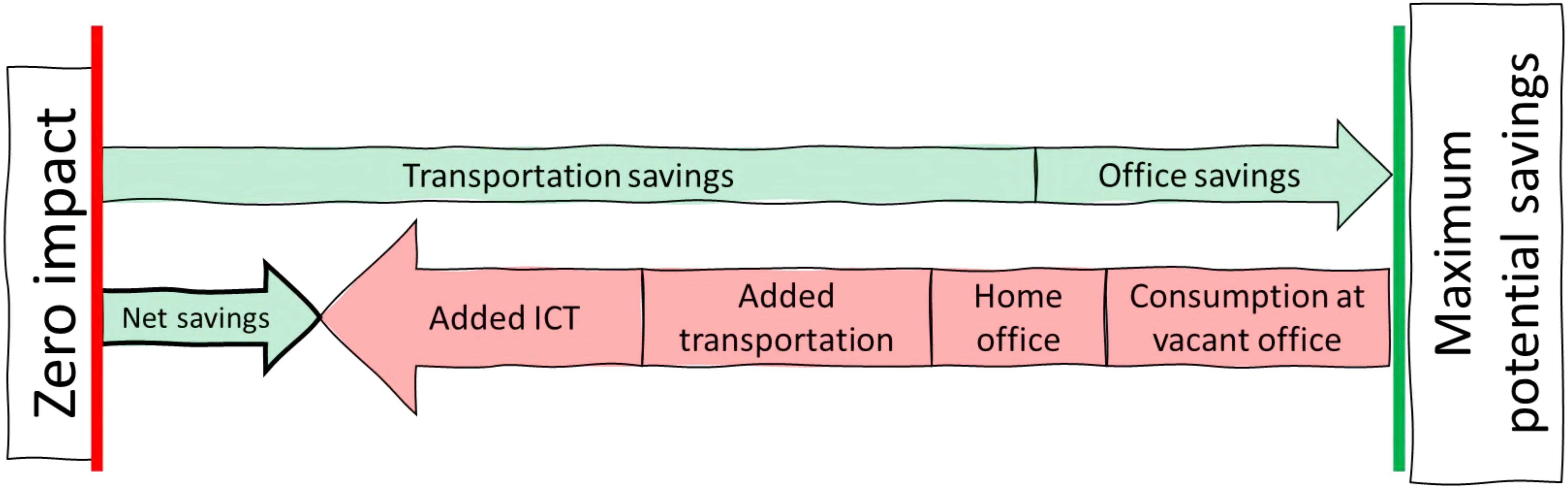
Liam O'Brien, PhD, P.Eng.

Associate Professor

Carleton University

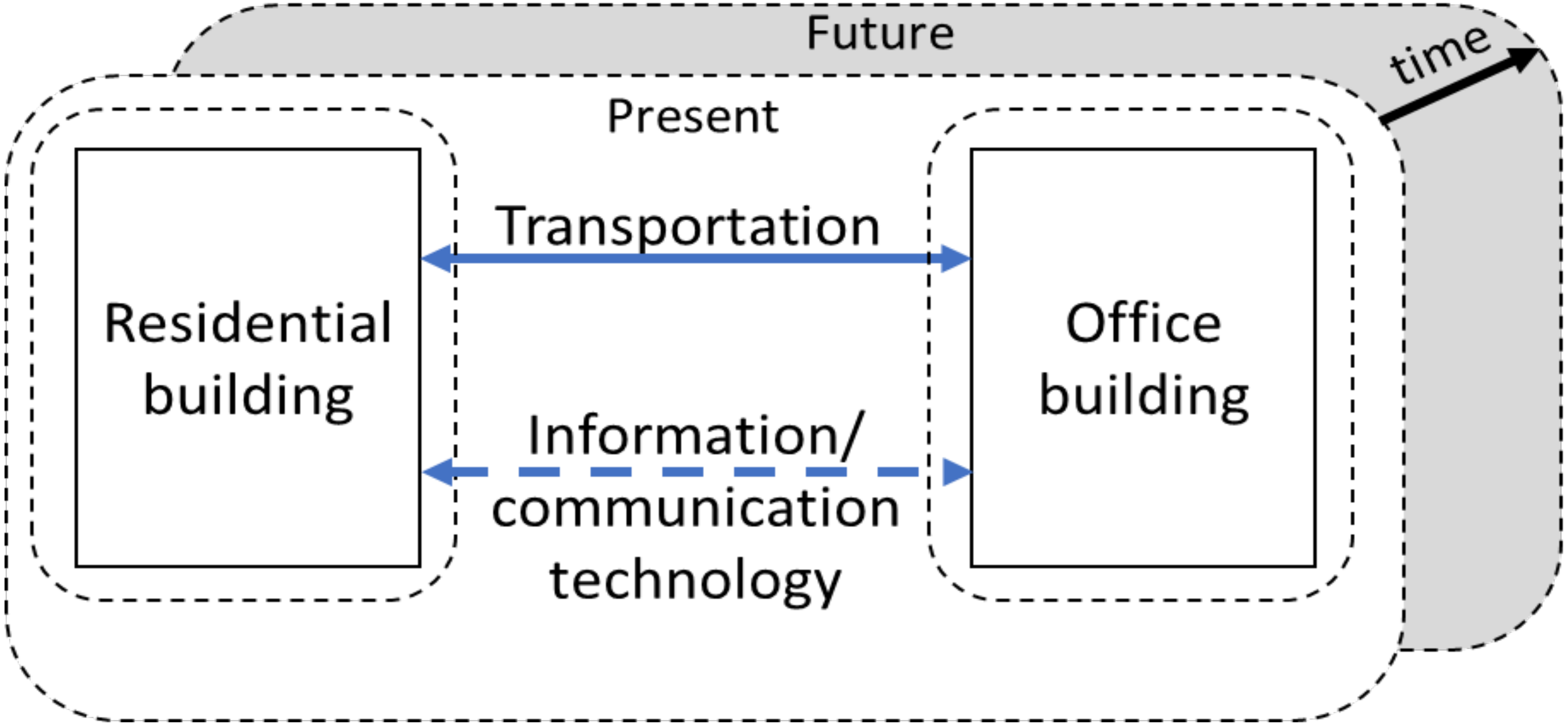

Home
Transportation
Office
Information and
Communication
Technology

Does teleworking save energy?



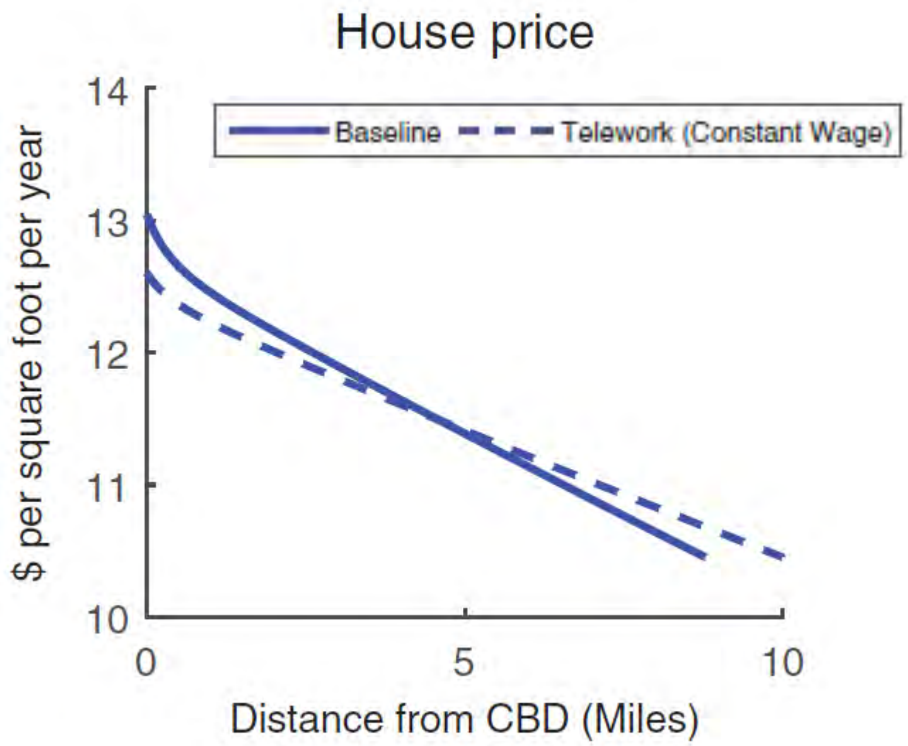
24 studies have looked at one or more domains; none have captured all.

Temporal and spatial scopes



Transportation

- Probably the biggest energy-saving opportunity
- BUT, 3 of 21 studies reported an increase
- Major rebound effects:
  - Poorer trip-chaining
  - Family now has car to use
  - Bigger/more cars
  - Suburban sprawl
  - Less traffic → more driving by others
- Unclear what comes first:
  - Teleworkers move farther
  - Suburbanites start teleworking more



Office

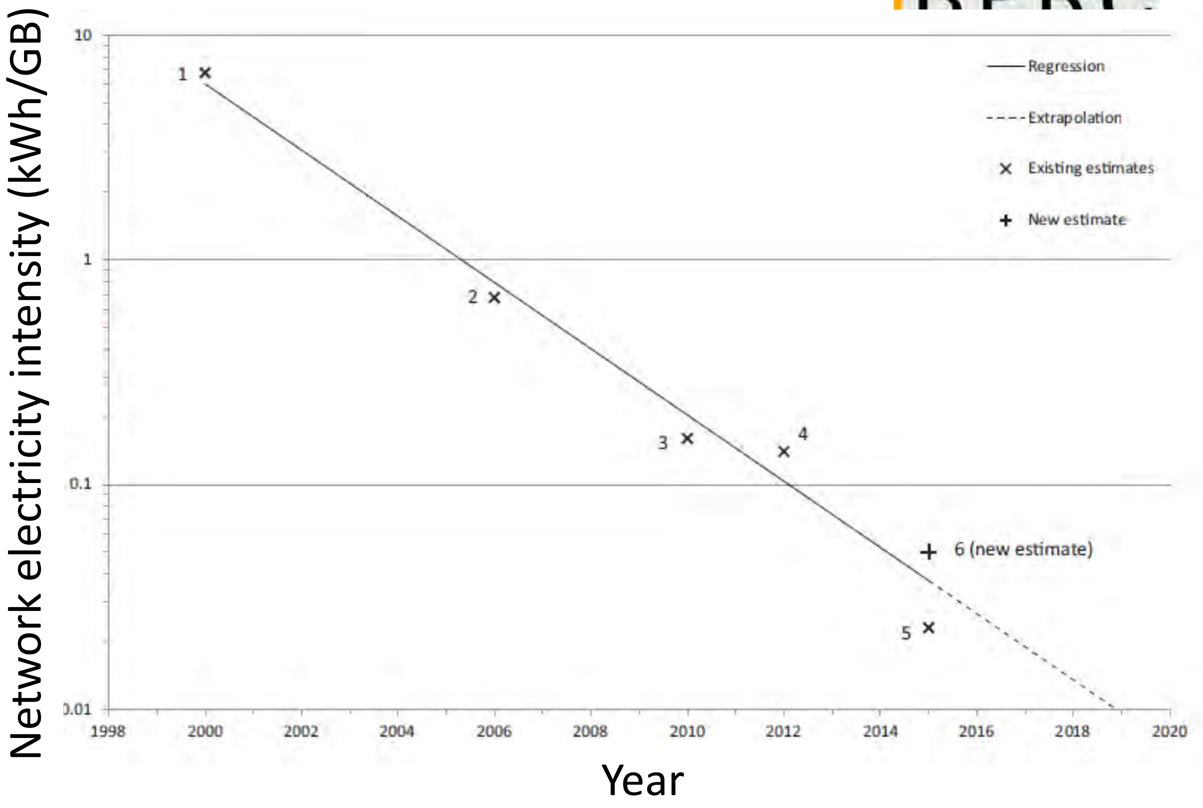
- Minor positive benefit
- Highly dependent on adaptability
  - Demand-controlled ventilation (DCV)
  - Occupancy-based lighting control
  - Sleep mode on electronics
  - Hotelling/hot-desking

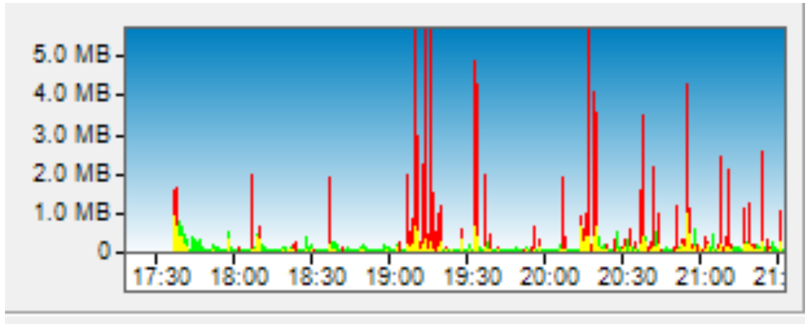
Home

- Negative effect
  - Estimates range from 0.1 to 20 kWh/teleworked day
- Highly dependent on operations
  - Zoned heating/cooling/lighting
  - Optimally-scheduled setpoints with vacancy setback
  - Laundry, baking, etc. shift peak loads
- Bigger home to accommodate office?
  - 4% larger (Nilles, 1990)

Information and Communications Technology (ICT)

- Negative effect, but enabler of teleworking
- Internet uses 5-10% of total electricity use – expected to double in a decade
- Major uncertainty about energy-intensity and data *actually* used for work
- 1 kWh = 100 GB (4 days of Netflix)
- 1 kWh = 15 km electric vehicle





Research methods and their limitations

BPRC
Building Performance Research Centre
Carleton University

Surveys/interviews/ diaries

- Measure the unmeasurable
- Understand causal directionality
- Measure decision-making logic
- Family/household issues

- Self-reporting error and bias
- Focused on individual scale

Modelling/simulation

- Many scenarios
- Multi-scale: time and space

- Difficult to capture complex decision-making processes
- Only as good as available theory/data
- May lack credibility

Secondary data analysis

- Based on reality
- Large sample

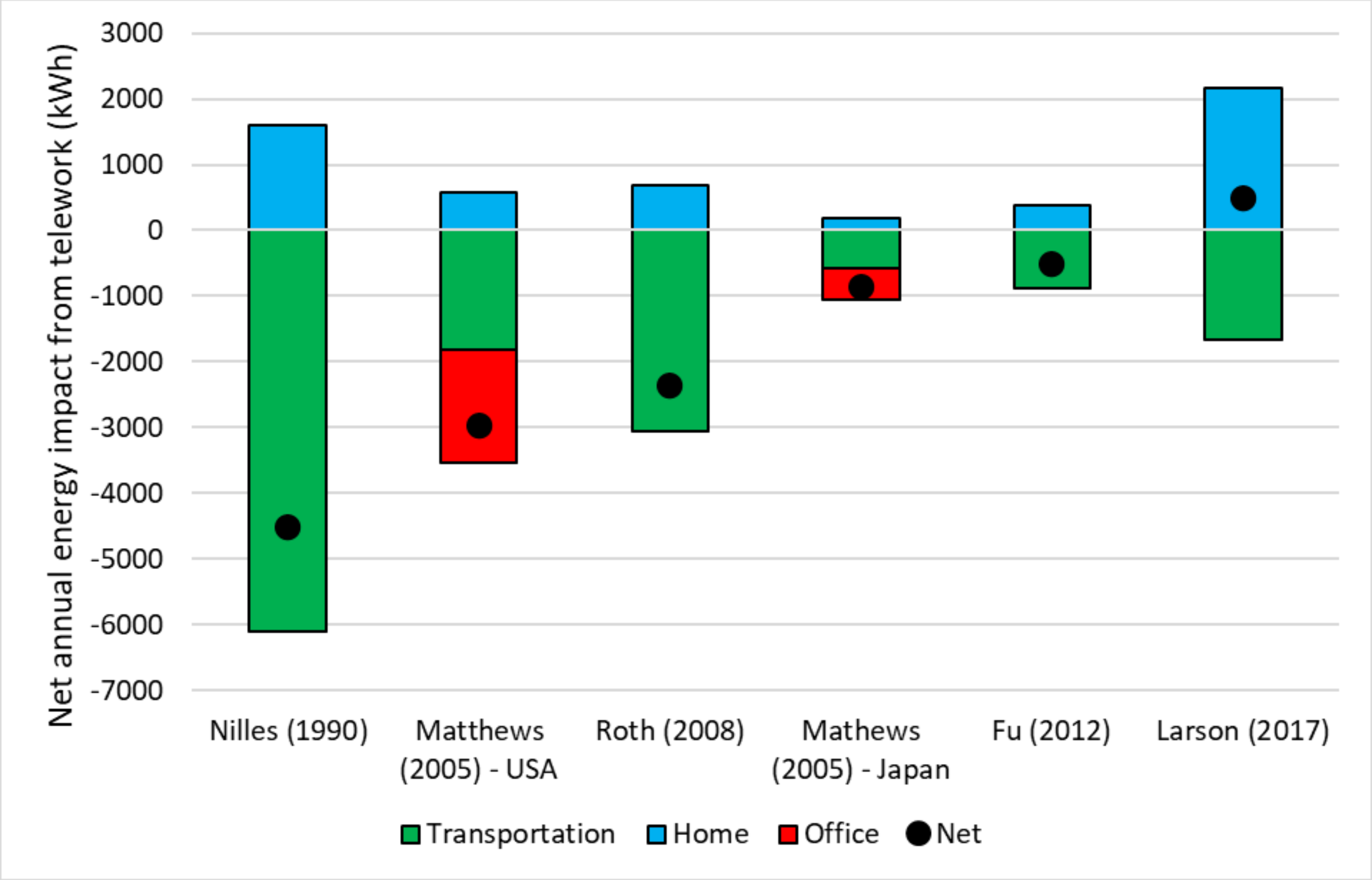
- Original data may be broad/aggregate
- Definition of telework is elusive
- Difficult to separate correlation from causation

Field study

- Detailed/direct measurement

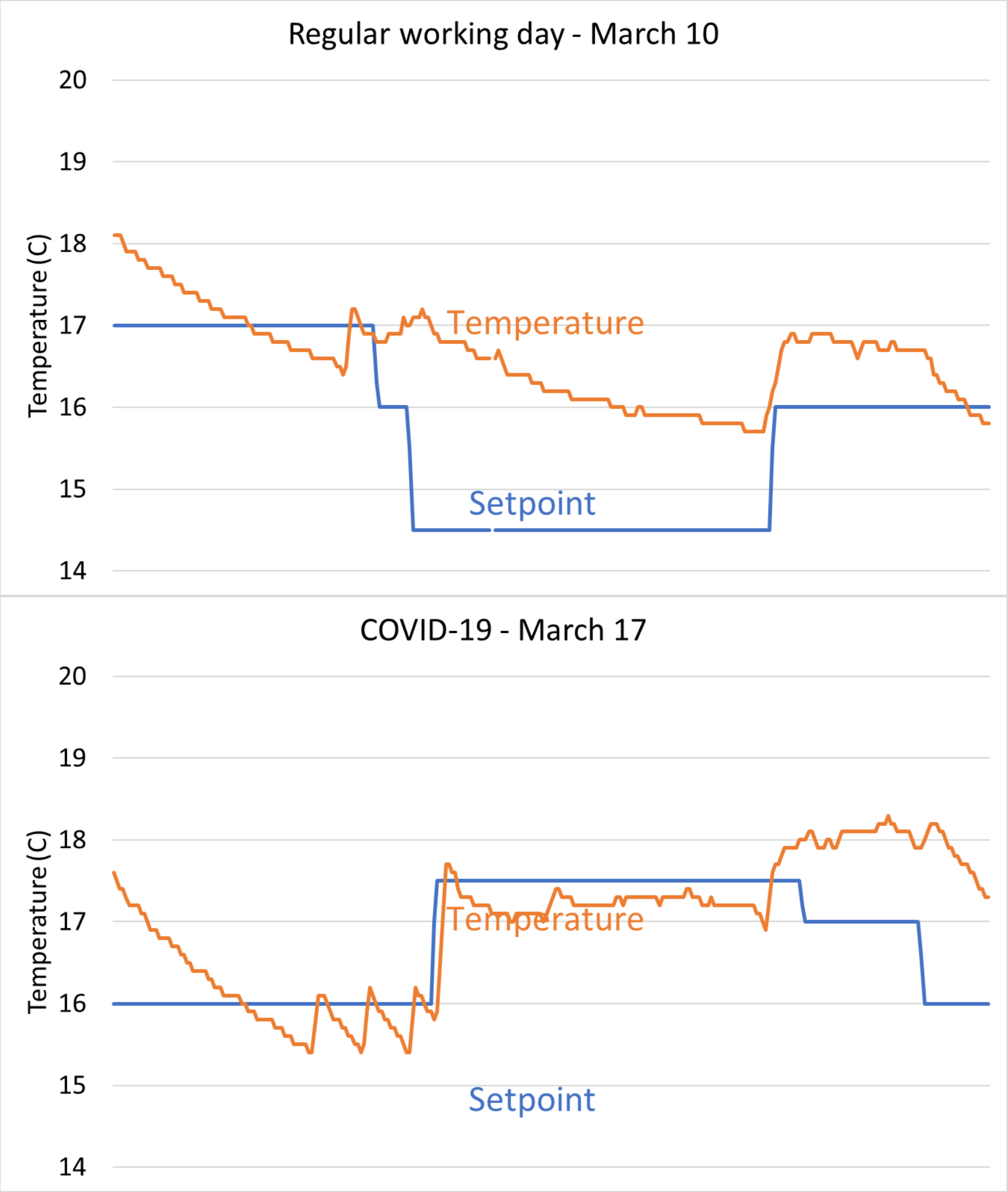
- Costly
- Labour-intensive

The verdict


Net annual energy impact from telework (kWh)
3000
2000
1000
0
-1000
-2000
-3000
-4000
-5000
-6000
-7000
Nilles (1990)
Matthews (2005) - USA
Roth (2008)
Mathews (2005) - Japan
Fu (2012)
Larson (2017)
Transportation
Home
Office
Net

Closing thoughts

- Clearly telework is growing in importance – especially now.
- New expertise needed in field – field is dominated by transportation researchers without building expertise
- Many new data sources (e.g., Google location data, building automation system) that has not been touched in the field



Thank You

Questions?

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Presentations

Session 5 - Second presenter

Wang, Alan &

Heydarian, Arsaian

University of Virginia, USA

Session 5

Day 2, 13:35

A Systematic Approach to Preserve Privacy in Smart Buildings

A. Wang, A. Heydarian

Longitudinal studies for naturalistic occupant behavior implicitly carry privacy risks. Longer duration studies divulge more information about trends that might not have been easily visible in shorter studies. Furthermore, discovering the long term patterns in occupant behavior can lead to improved building energy efficiency, occupant well-being, and work productivity. However, increasing the modalities of data collected exposes users to contextual privacy concerns. In this work, we propose a framework to track and adopt longitudinally to users' privacy settings and increase their perceived trust in the system. In our system, at first, we define data access between a device and a user. Making each user a subscriber to the device groups allows for effective ontological management of scenarios common in a research setting. For example, in the case of environmental sensors (e.g. temperature and humidity sensor) in an open office setting, one device normally covers more than one occupant. We then define the data access relation between two users based on their hierarchical relationship (e.g., employee and supervisor). Users with any vertical hierarchical relationship above (e.g. supervisor) that of another user (employee) are defined by default to never have access to the lower user's data unless the user opts-in. Lastly, since actuating one device to one user relationships are trivial, we describe the behavior for actuating the privacy-related settings between multiple users. By default, the system utilizes the principle of least privilege. For example, when controlling the frame rate of a camera resource that might cover two users, the user with the smallest frame rate is what the camera would collect. For our future work, we look towards adopting real-time edge computing paradigms that reduce the risk of user exposure, allowing the system to pre-process the data and remove sensitive information before pushing it onto the database.

UVA ENGINEERING
LINK LAB

A Systematic Approach to Preserve Privacy in Smart Buildings

Alan Wang[1]

Arsalan Heydarian[2]

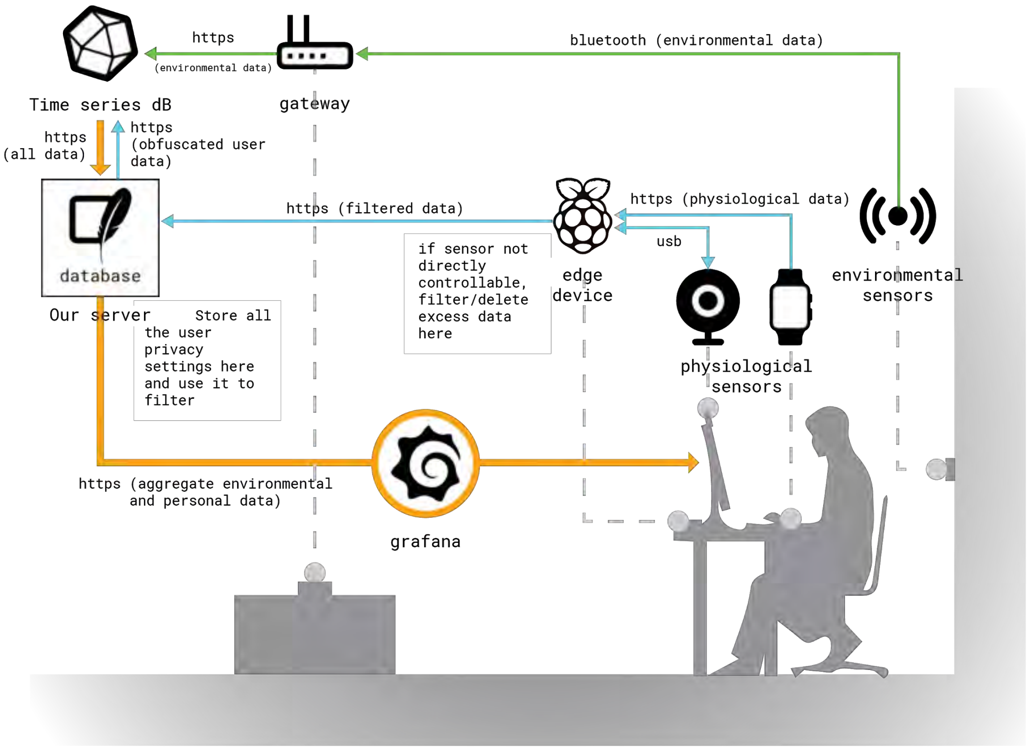
1. Ph.D. Student, University of Virginia, alanwang@virginia.edu
2. Assistant Professor, University of Virginia, ah6rx@virginia.edu

Behavioral Responsive and Automated Intelligence (BRAIn) Laboratory

Motivation and Background

- Occupant behavior is important (Wagner et al., 2018)
- **Longitudinal tracking** helps uncover adaptive interactions between occupant and surrounding environment (Lagevin, 2019)
- New methods required to **protect human research participants** in the age of **big data** (Fiske and Hauser, 2014)

Cyber-Physical Framework



Environmental Sensing


Occupancy
(DTMS)

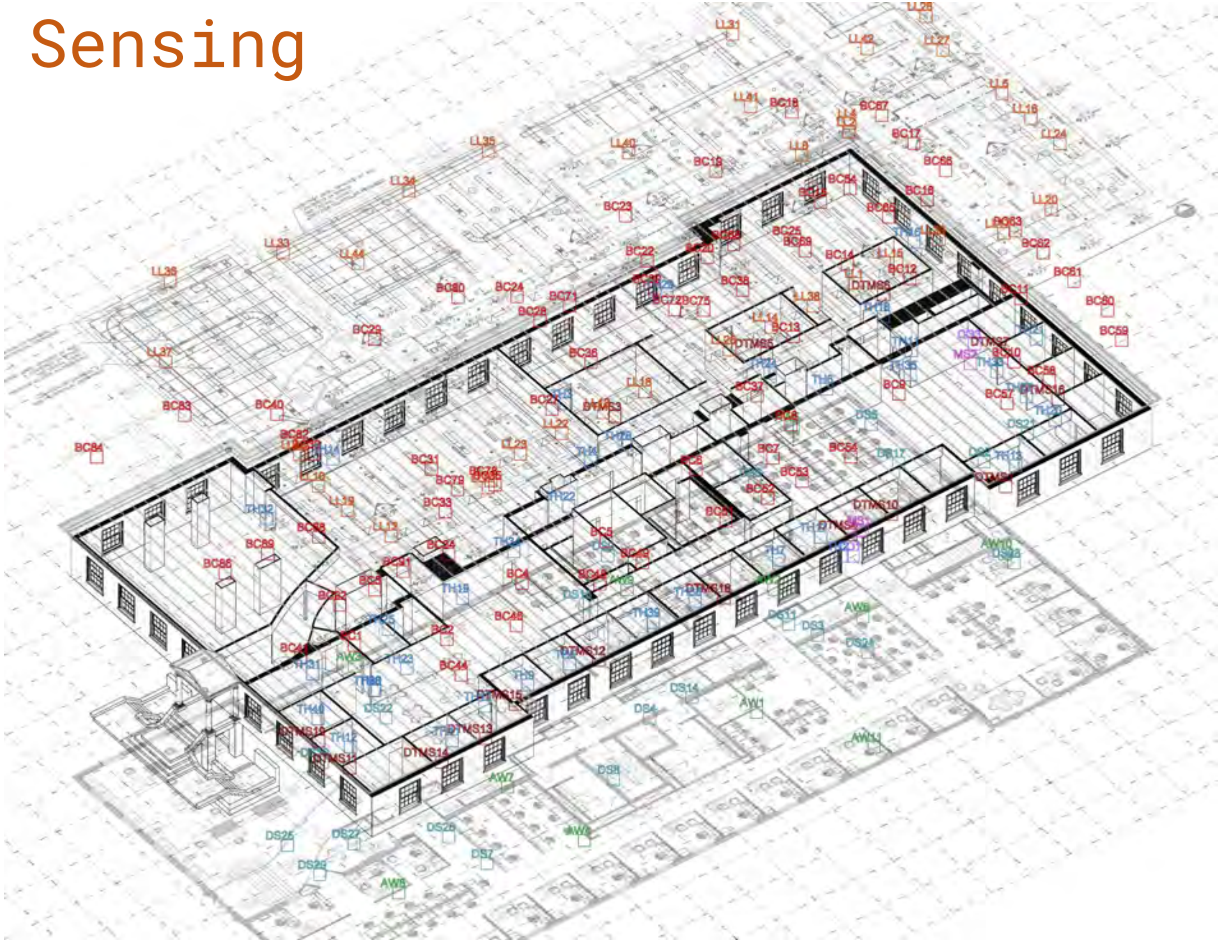

Power Blade
(PB)


Air Quality (AW)


Temperature
and Humidity
(TH)


Contact (DS)


Light Level (LL)



Behavioral Responsive and Automated Intelligence (BRAIn) Laboratory

Human Sensing

Wearable – Physiological Monitoring

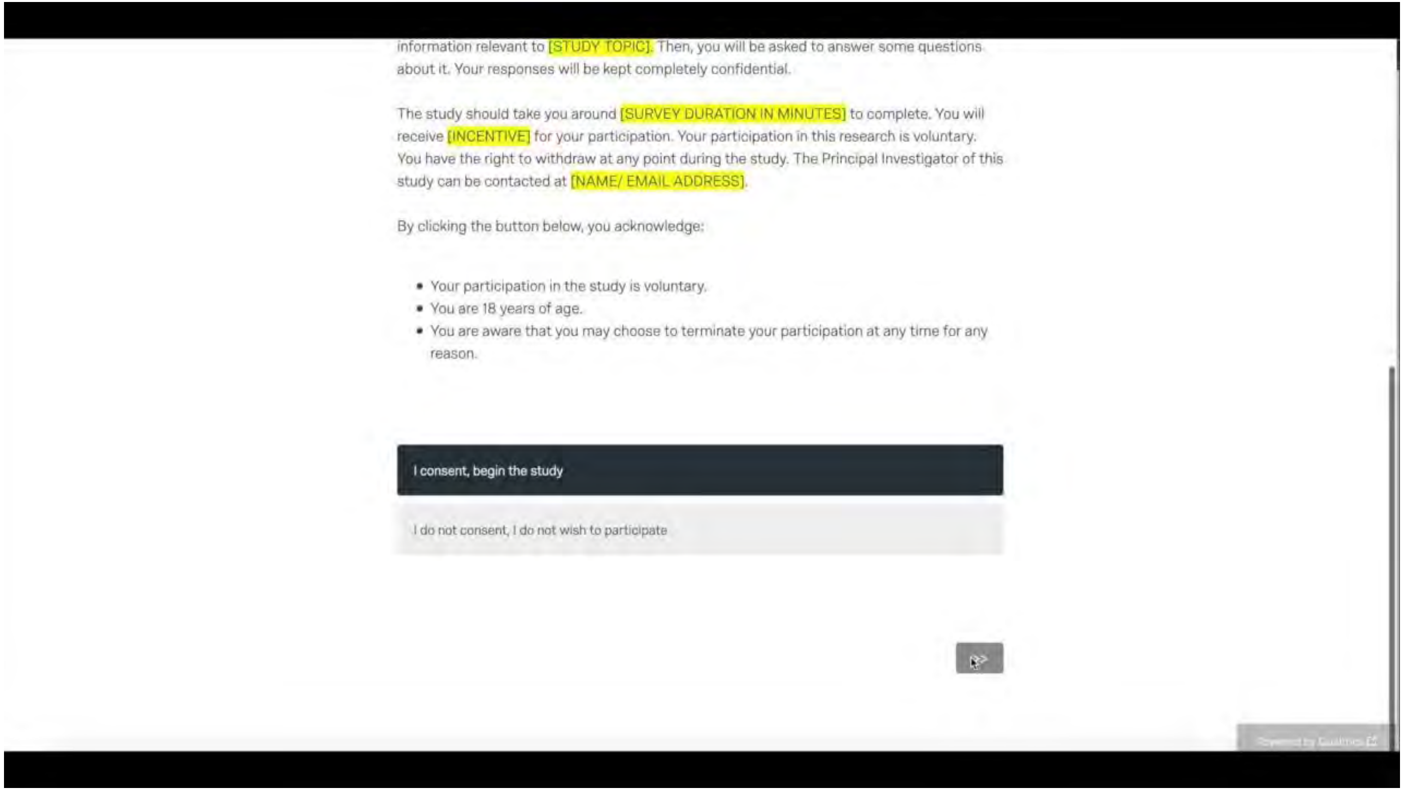
Camera

+ affectiva

Emotion Recognition

Indoor Localization

User Interface System

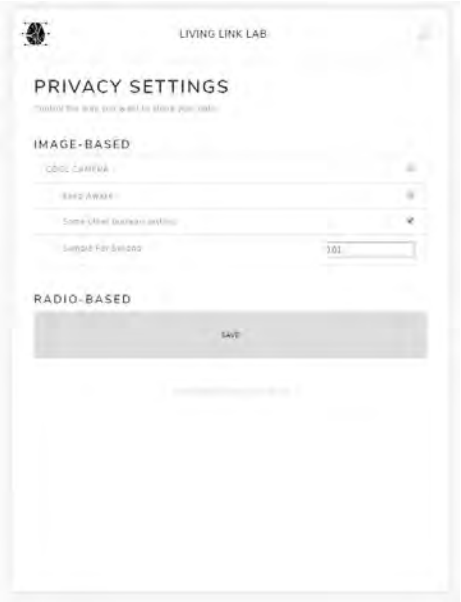


Behavioral Responsive and Automated Intelligence (BRAIn) Laboratory

Occupant Privacy

Edge computing to increase occupant-privacy

How does people's privacy preferences change over time and in response to personalized feedback (e.g., emotions)?

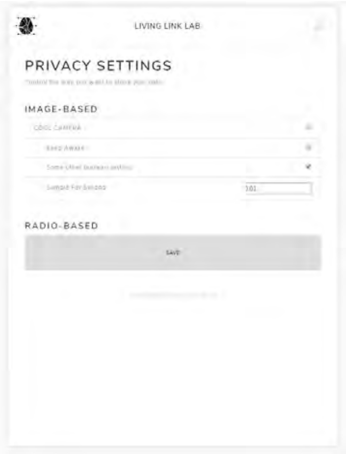


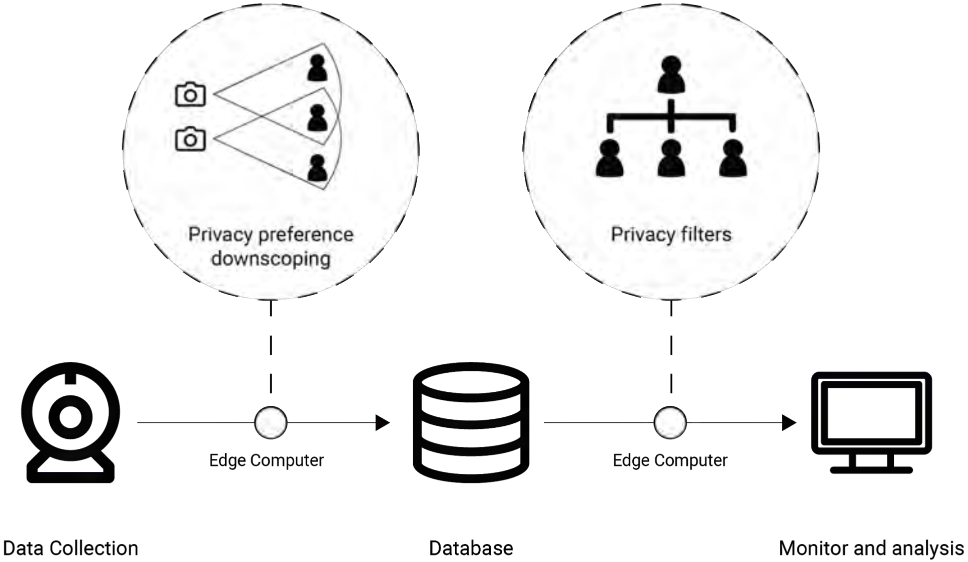
Users are able to set-up their own privacy settings (e.g. provide only specific data from smartwatch)

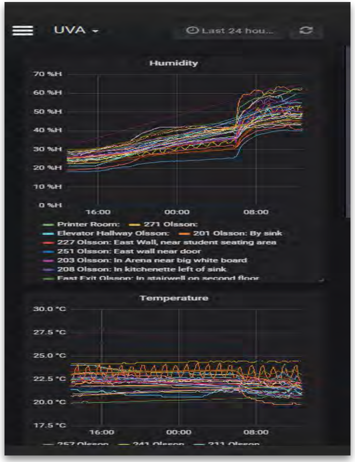
Research Question / Objective

- What are things we can do to **protect the privacy of the user** in a longitudinal system tracking occupant behavior?
- How might we put the **burden on the system** to preserve the privacy for the user?

Methodology



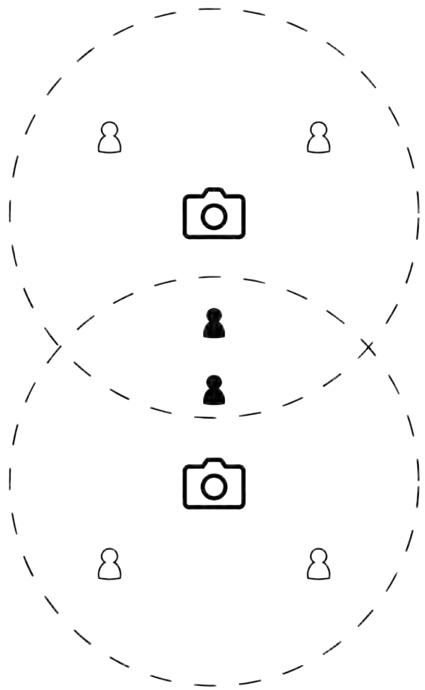




Passive privacy control

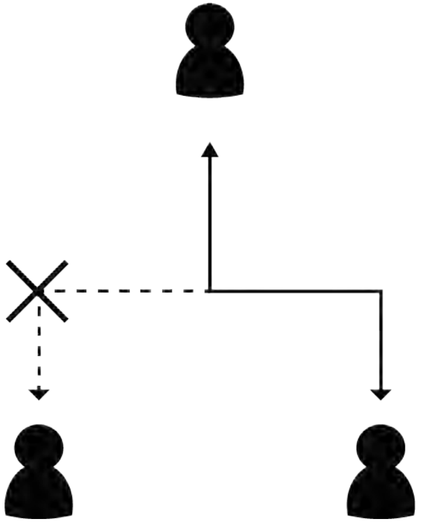
Privacy Preference Downscoping

- Each device can **only identify** the users **associated** to the device
- If all users within the view are
  - Identified - default to the **combined most private setting** in the group
  - Unidentified - default to **most private settings** (all off)



Privacy Filters

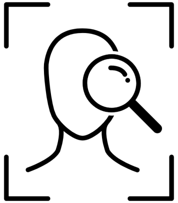
- **Hierarchical** filtering
  - Default not have access to people's information lower on that hierarchy
- **Research-oriented** data resolution filtering
  - Energy consumption pattern studies might not need very detailed user information
  - Impact of emotions on productivity - then you need much detailed user data



Behavioral Responsive and Automated Intelligence (BRAIn) Laboratory

Detailed Privacy Layers

- Find ways to encode **user identifiers**
- Assess the **difference** in data collected with and without these **passive privacy control**
- Impact of different **modalities** of data
  - Combination of information to reduce total information needed?
  - Most efficient times to collect data?
- **Preferences** of people for privacy
  - Different groups (socio-economic, culture, nationality) might have different privacy preferences



Future Works

- **Reducing information collected** while maintaining system efficiency
- Identifying the user trust based on:
  - The **amount of data collected**
  - **Where** their data is being used
  - Based on the **rewards** they receive - e.g. monetary, goal-oriented

Thank you!

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UNIVERSITY of VIRGINIA

Presentations

Session 5 - Third presenter

Aragon,
Victoria

University of Southampton, UK

Session 5

Day 2, 13:45

Understanding New Technology and their Impacts on Occupants

V. Aragon, S. Gauthier, P. James, A. Bahaj

In a domestic environment, the success of a certain technology will depend both on the effectiveness of its system and interface, and how users perceive and interact with it. This work examines the impact of Smart Thermostatic Valves (STVs) in the energy demand and user behaviour in a care home in the United Kingdom, as well as the technology's suitability to the type of residents. The analysis is based in energy and indoor monitoring (temperature and relative humidity) on site for more than two years. As part of Thermoss, an EU funded project on retrofitting heating systems across the EU, the heating system of the entire building was upgraded from manual valves to STVs in all radiators. A preliminary analysis on technology readiness and user acceptance predicts that there is a possible mismatch between the valves interface and elderly residents. Results show that : (i) residents adaptation was very difficult, requiring help from staff and intervention from researches to add visual aids, (ii) there was a change in the correlation between indoor and outdoor temperatures, (iii) several flats showed a reduction in the daily temperature range in Lounges. These results highlight the importance of understanding users comfort needs and how they interact with technology when selecting technology. Future work will focus on the usage of valves and control patterns before and after the upgrade.

2020 Occupant Behaviour Symposium

Understanding New Technology and their Impacts on Occupants

Victoria Aragon, Stephanie Gauthier, Patrick A.B. James, A.B.Bahaj

E-mail: V.Aragon@soton.ac.uk

THERMOSS

UNIVERSITY OF Southampton

Overview

UNIVERSITY OF Southampton

Care Home
South East, UK

Smart Thermostatic Valves

THERMOSS

Impact

Technology efficiency?

User behaviour?

Monitoring

✓ Gas & Electricity demand	Monthly records from 2012
✓ Indoor temperature & RH ✓ Thermal comfort surveys	**10 flats** ~ 600 days

Setpoint T	**80 flats +** common areas ~ 300 days

Technology readiness & acceptance

Easy of use
- Relies on visual
- No mechanical min/max feedback
- Interface is different to previous valves

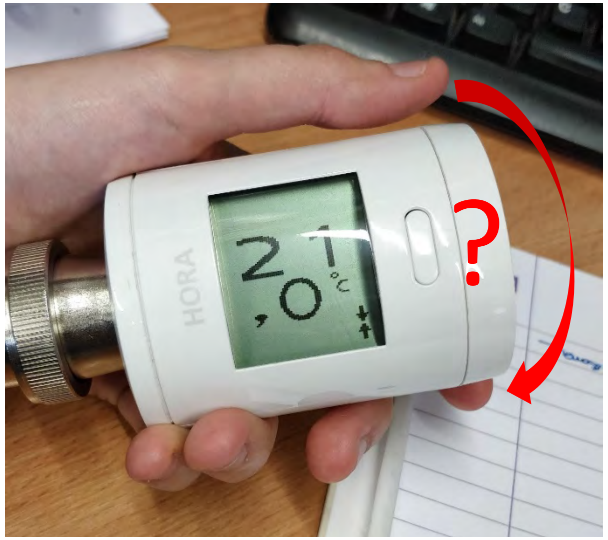
Usefulness
- Allows selecting ambient temperature

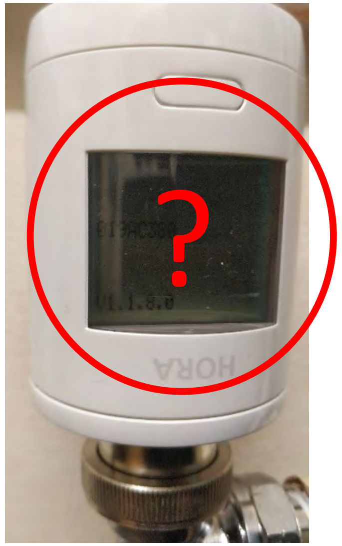
Demographic
- Elderly
- Visual / cognitive impairment (rely on carers for managing heating)

Innovativeness & Optimism
- Used to old system
- Did not choose to have new TRVs

Insecurity & Discomfort
- Do not trust new technology
- Rely on surface temperature to "test" the radiators

Technology readiness & acceptance



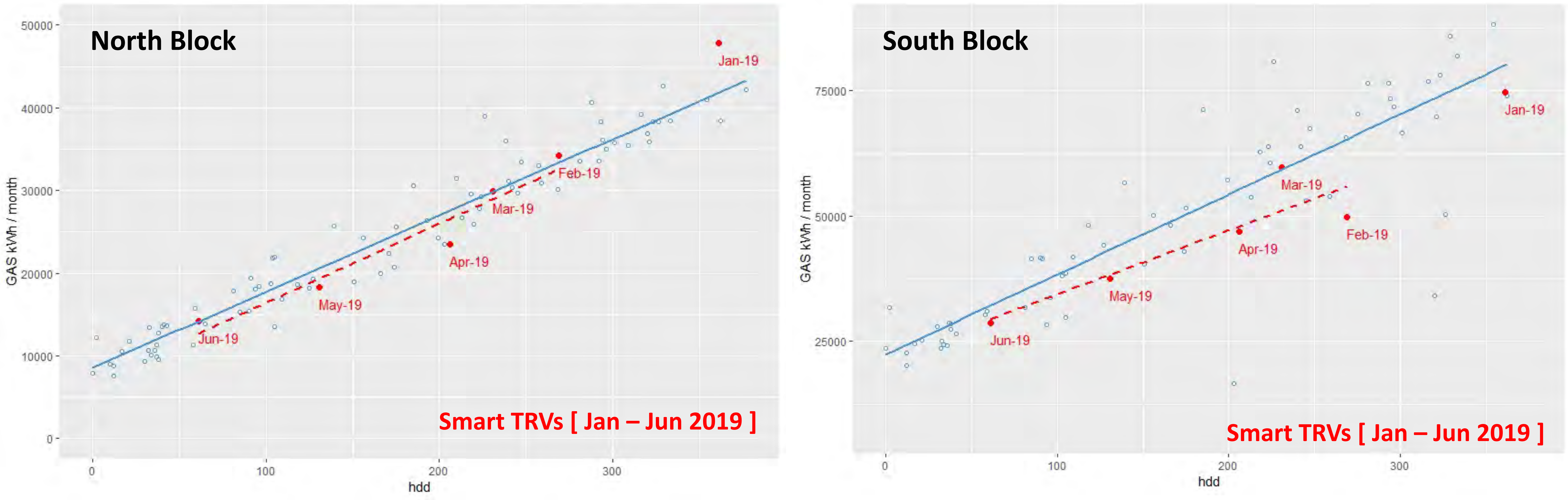




Impact: Energy demand

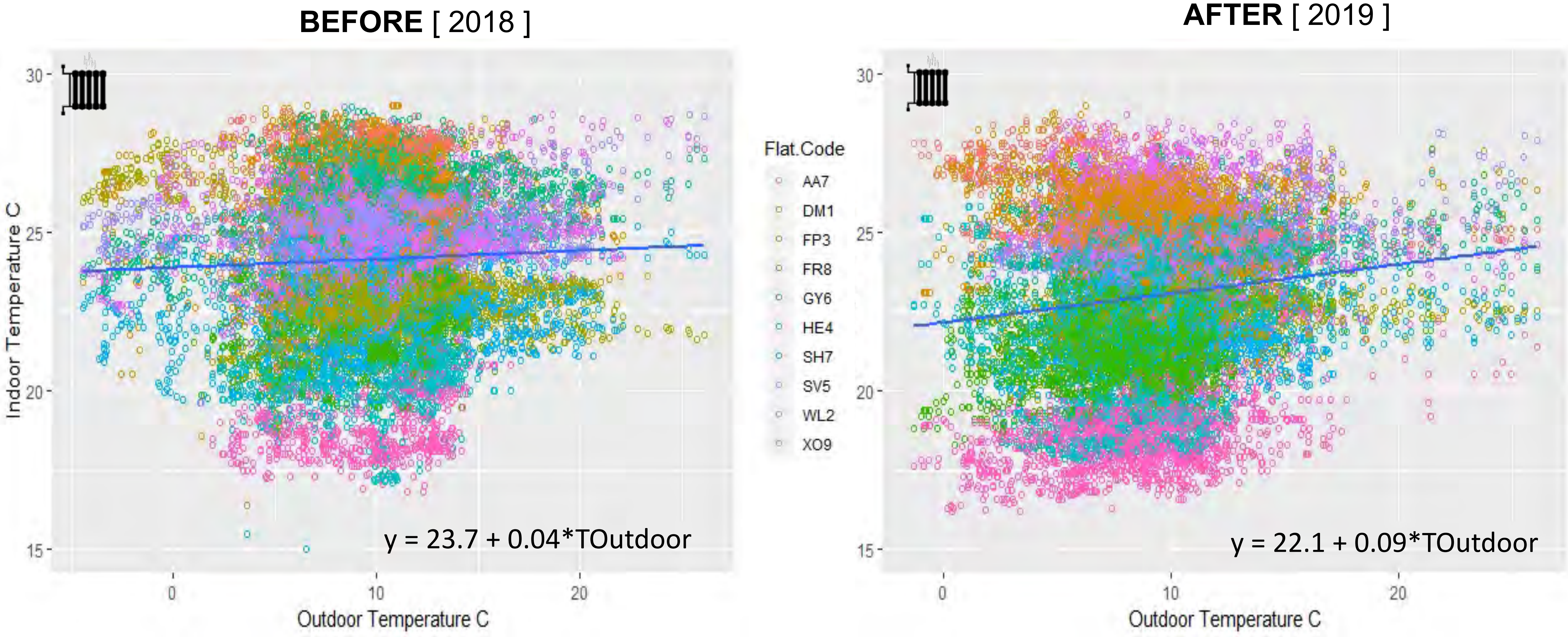
UNIVERSITY OF Southampton

Monthly gas usage vs Heating Degree Days



Impact: Occupant behaviour

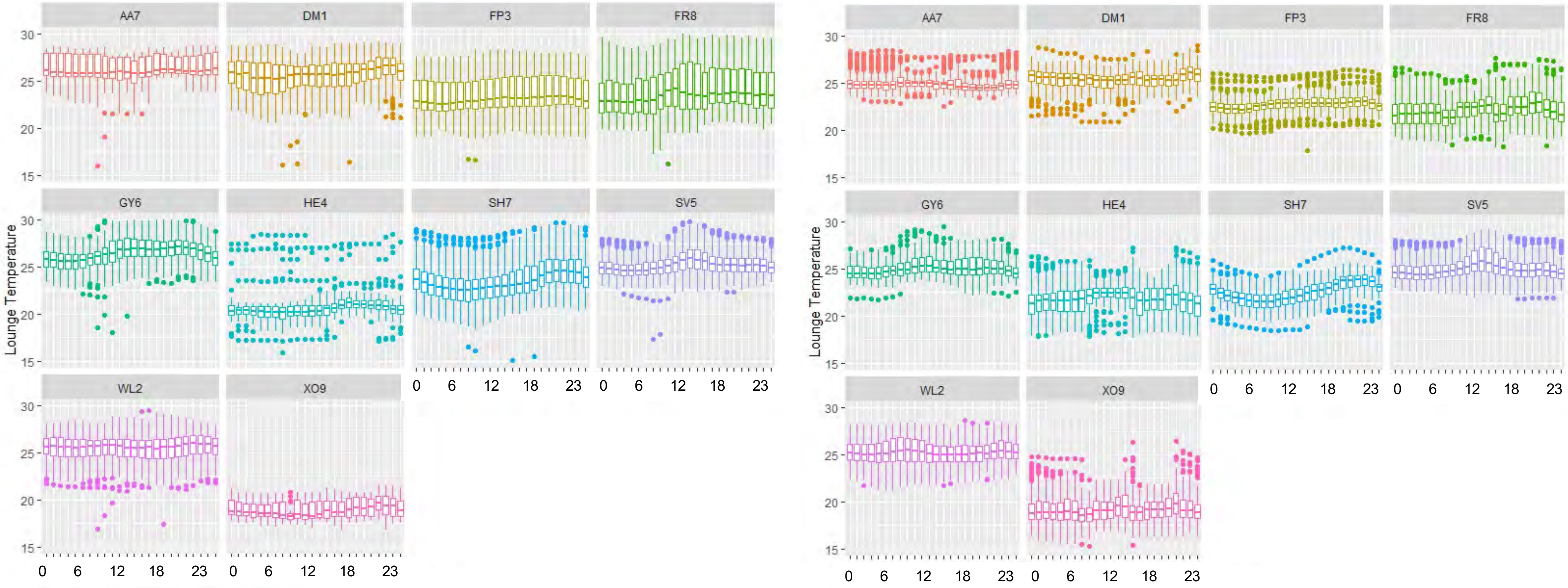
Lounge Temperature, Oct to Apr



Impact: Occupant behaviour

Lounge Temperature, Oct to Apr

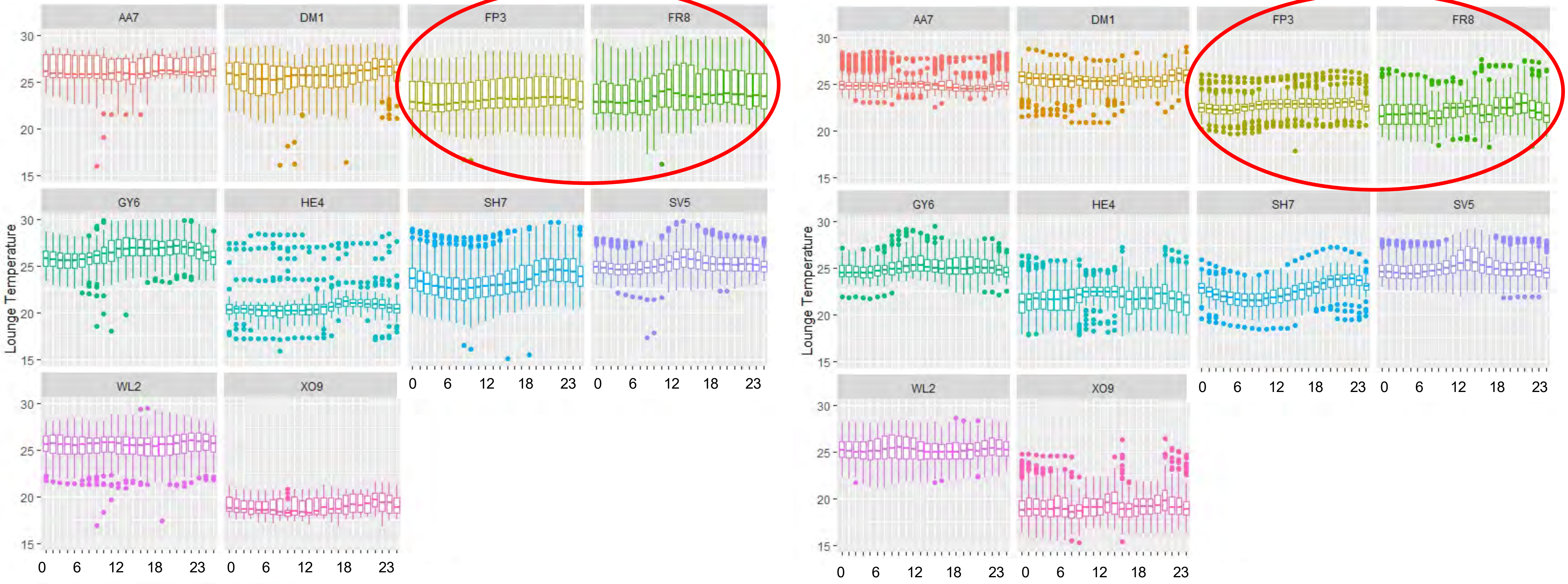
BEFORE [2018] **AFTER** [2019]



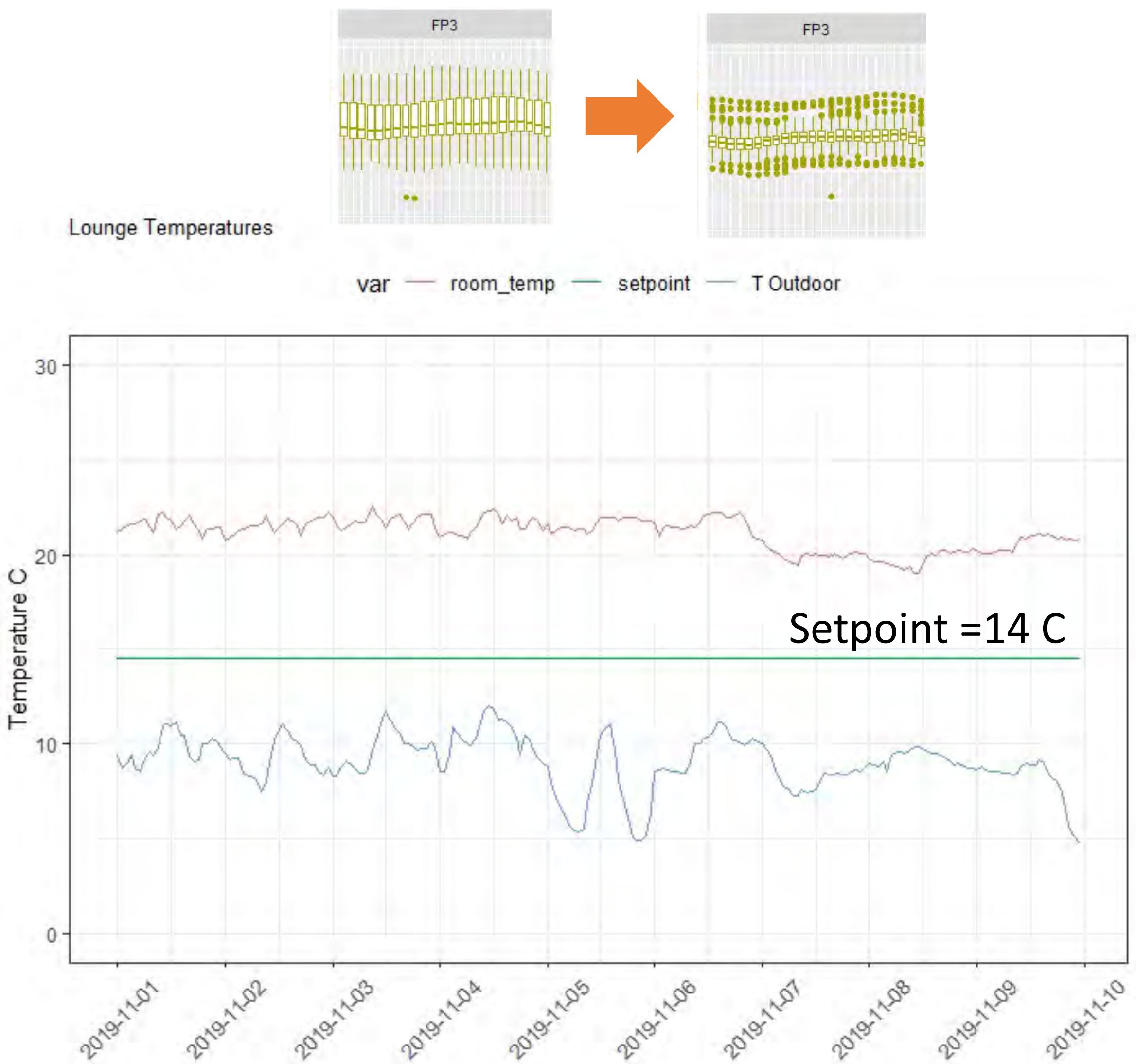
Impact: Occupant behaviour

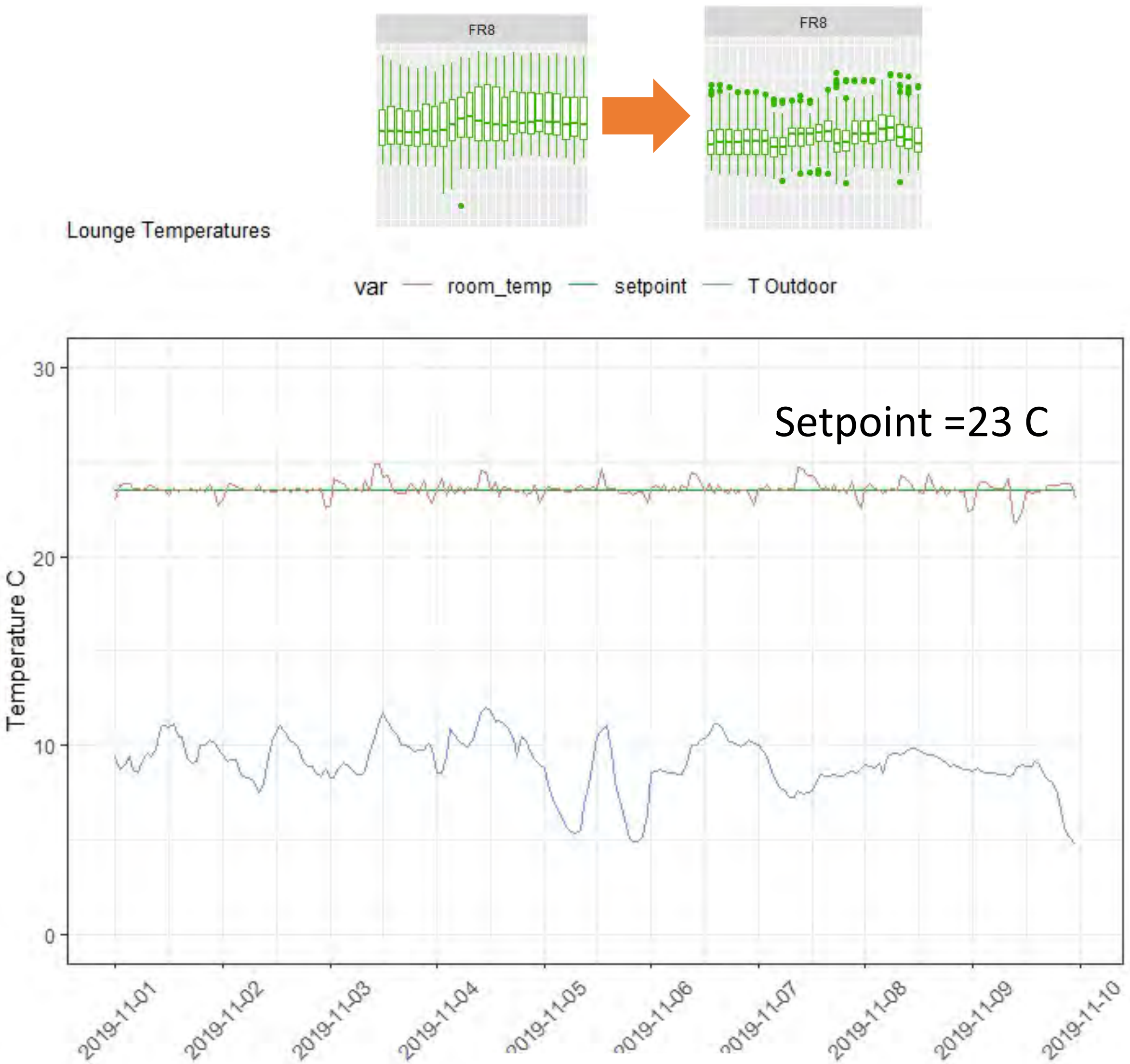
Lounge Temperature, Oct to Apr

BEFORE [2018] **AFTER** [2019]



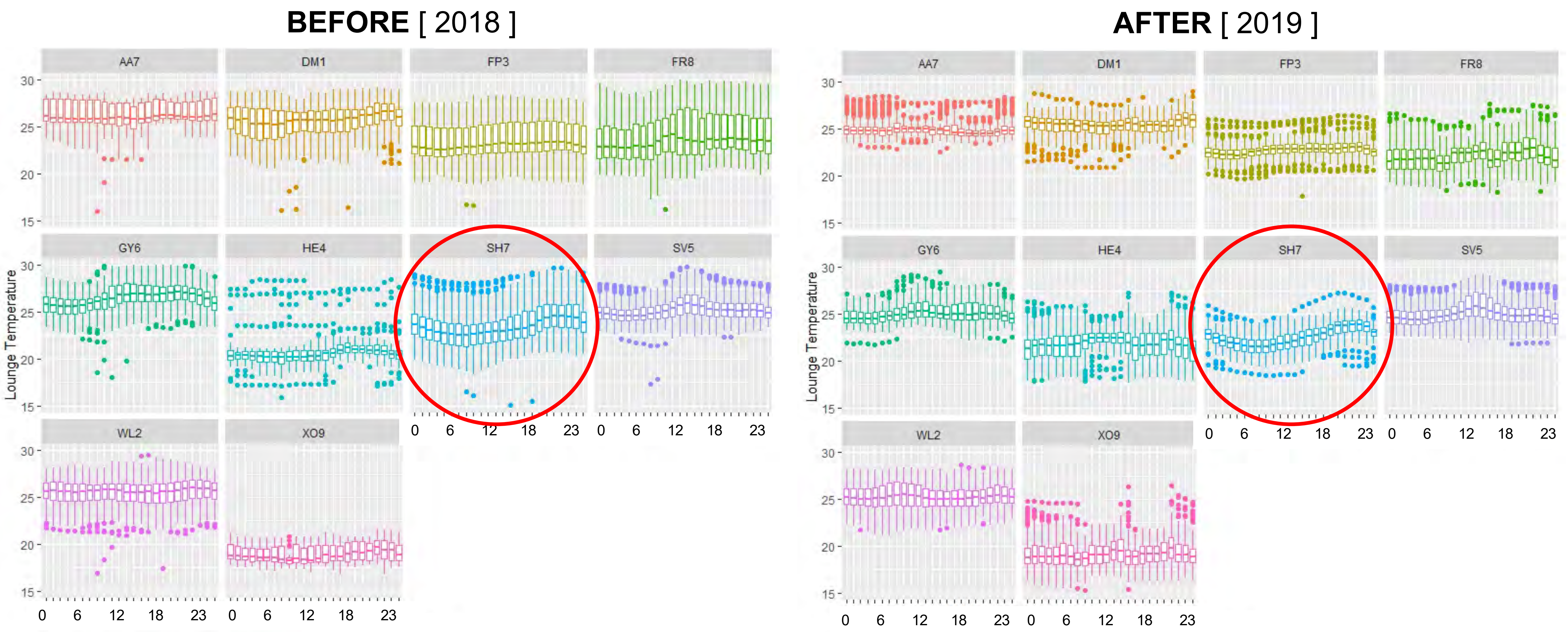
Impact: Occupant behaviour



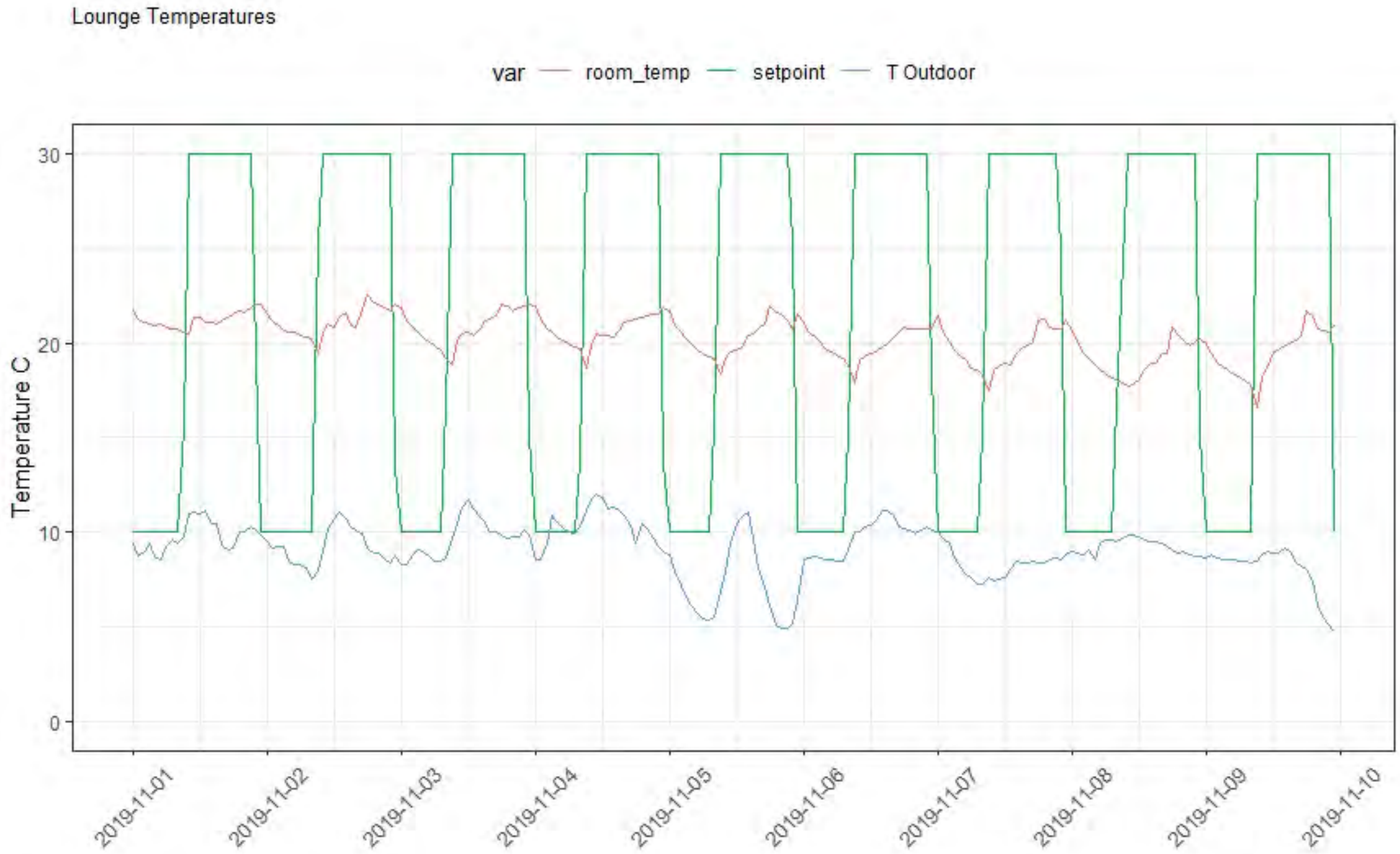


Impact: Occupant behaviour

Lounge Temperature, Oct to Apr



Impact: Occupant behaviour



Setpoint

Max = 30 C

Min = 10 C

Preliminary Conclusions & Future Work

UNIVERSITY OF Southampton

Smart Thermostatic Valves

- Very difficult adaptation to technology
- Most residents found the STVs difficult to understand
- Acceptance based on understanding, not technology performance ?

Occupant behavior

- Impact observed on Indoor Temperatures in Lounges
- More options == more comfort?
- Does behavior remain or change with different technology?

Future Work

- Level of Interaction with TRVs & setpoints in all building
- Before & After labels

Thank you! Any questions?

V.Aragon@soton.ac.uk

Presentations

Session 5 - Fourth presenter

Gosselin, Louis &

Rouleau, Jean

Université Laval, Canada

Session 5

Day 2, 13:55

Towards Low-Energy Housing in the Canadian North from an Occupant-Centric Perspective

L. Gosselin, J. Rouleau

Nunavik is the northern region of the Province of Québec (Canada). It has a population of around 14,000, most of which being Inuit (90%). They live in 14 villages along the coast. Due to their remoteness, these communities are off-grid. A diesel power plant in each village provides electricity, while space heating is obtained from fuel oil. Due to the cold climate, the typical heating need exceeds 300 kWh/m2. The environmental footprint of fossil fuels and their cost are among serious issues in that region. Additionally, the lack of dwellings and their unfitness to meet local needs have been recurrent problems related to housing in the North. Historically, Inuit were nomadic; they gradually transitioned to sedentary only in the 1950s. At that time, the government provided matchbox houses, which proved to be unfit for their needs. Today, stakeholders are aiming in the direction of designing, building and operating highly energy-efficient dwellings that are also culturally and socially adapted. With this target in mind, an occupant-centric perspective appears to be crucial. The analysis of building operational data, the development of models, and interviews and co-design with Inuit can help to better understand how occupants use energy in Nunavik's houses, what can be done to reduce that consumption and increase comfort, and what solutions are adapted to the people. During the talk, we will present current research projects on that topic and share some preliminary results.

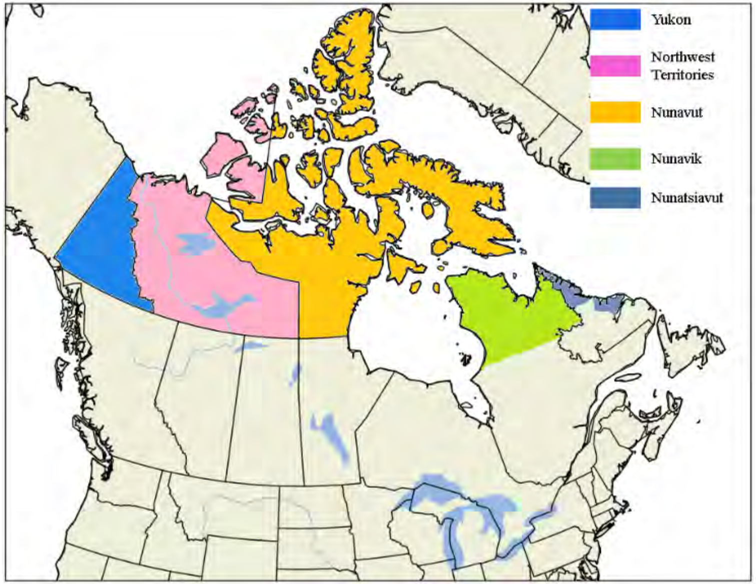
Towards low-energy housing in the Canadian North from an Occupant-centric perspective

OB-20 Session 5 – Other Building Occupant-Related Research

Jean Rouleau and Louis Gosselin

Université Laval, Canada

Nunavik



- Nunavik has a population of 14,000, most of which are Inuit (90%).
- Typical heating demand of 300 kWh/m^2.
- Communities are off-grid.
  - ➢ Space heating: Fuel oil
  - ➢ Electricity: Diesel power plant

	Heating degree days
Quaqtaq (58° N)	10,379
Oslo (59° N)	4,850
Tromsø (69° N)	6,292

Research projects

- Monitoring of occupant behaviour in residential buildings (12 dwellings).
    - Indoor temperature and relative humidity;
    - Use of heating and electricity;
    - DHW consumption;
    - Control of windows and mechanical ventilation;
- Interviews/workshops with Inuit.
- Comparison of occupant behaviour observed in Nunavik and occupant behaviour observed in the South of Canada.
- Energy simulation of monitored buildings.

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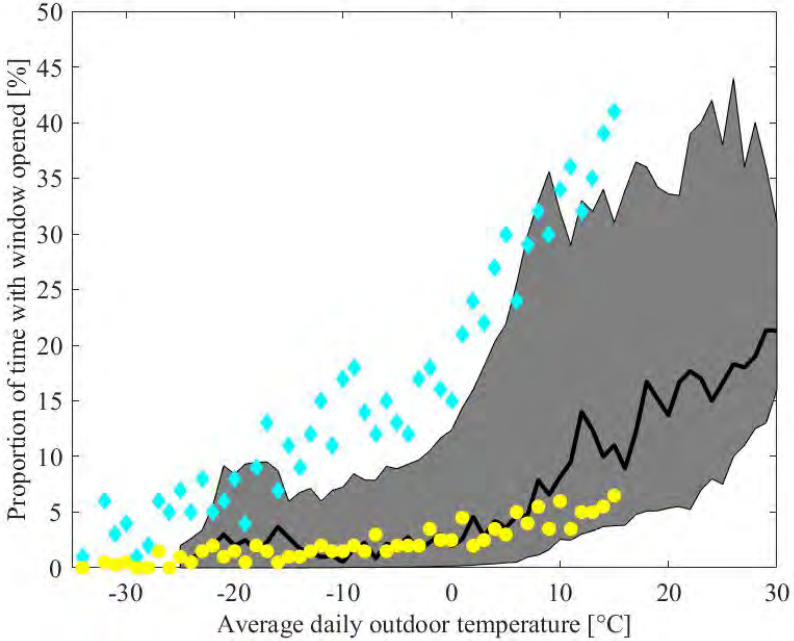
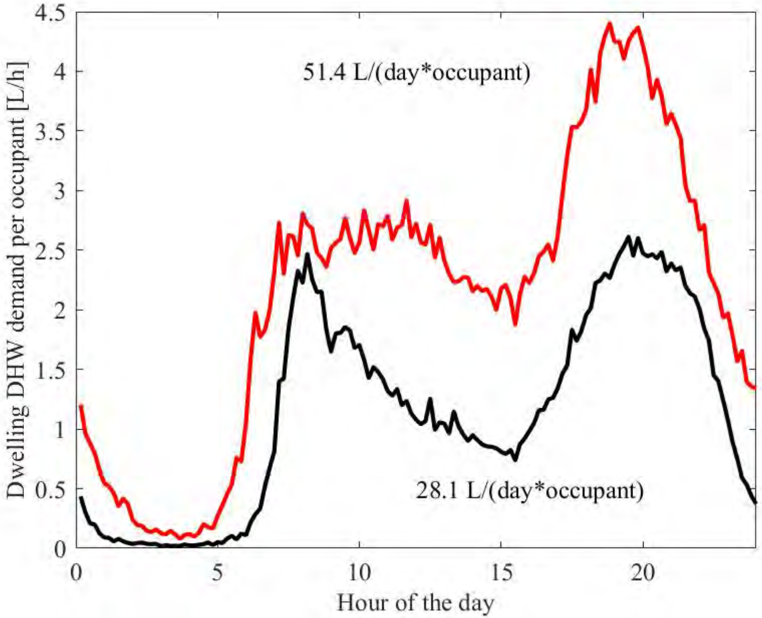
Preliminary results (2 dwellings)

Window opening behaviour



Dwelling 1 Dwelling 2 Quebec city (average) Quebec city (range of behaviour)

DHW consumption



Quaqtaq Quebec city

Presentations

Session 5 - Fifth presenter

Payet, Maareva

University of La Réunion, France

Session 5

Day 2, 13:59

User Behaviour in Low-Environmental Impact Buildings in Tropical Climates

M. Payet

Efforts are currently made to reduce the impact of the building sector. However, studies have shown that the impact of user behaviour on energy consumption is poorly estimated by designers. As a result, there are discrepancies between the energy performance predicted by simulation software and the actual one. Tropical climate characteristics allow the development of bioclimatic buildings, which use passive solutions, and where air handling uses are different from current temperate climates. These include the use of natural ventilation, sometimes combined with the use of fans, and the addition of air conditioning during the hottest periods, currently the main source of energy in the building sector. Except some recent post occupancy evaluation, which showed different behavioural patterns between air-conditioned and naturally ventilated environments, there is little feedback on user behaviour in naturally ventilated buildings in tropical climates. The aim of our research work is to analyse when users will switch from natural ventilation, by acting on windows, to the use of fans and air conditioning, and thus better predict consumptions. Data collection is in progress on 2 tertiary buildings in Reunion Island. We measure simultaneously the environmental parameters (indoor and outdoor weather), and the action parameters through the real time consumption monitored by end-use (air-cooling, fans) and by the level of opening of the windows. A statistical regression is applied to the first data, to detect which factors influence actions. The next step will be to use probabilistic models to model behaviours, preliminary step to the integration in simulation software. The originality of this study is its tropical character which determines particular uses of natural ventilation and air treatment. This issue could concern more geographic areas in the coming years that will be confronted with summer problems due to global warming.

User behavior in low-environmental impact buildings in tropical climates

5TH INTERNATIONAL SYMPOSIUM ON OCCUPANT BEHAVIOR

MAAREVA PAYET[1,2], MATHIEU DAVID[1], PHILIPPE LAURET[1], FRANÇOIS GARDE[1]

UNIVERSITÉ DE LA RÉUNION

1 LAB PIMENT PHYSIQUE ET INGÉNIERIE MATHÉMATIQUE POUR l'ÉNERGIE, l'ENVIRONNEMENT ET LE BÂTIMENT

2 LEU REUNION

Context

Tropical climate (Köppen Classification : Aw)

Season	Tmin	Tmean	Tmax
Summer	23°C	27°C	31°C
Winter	17°C	21°C	24,5°C

[PERENE, 2009]

Global warming issues

50% of the world population will live in the tropics by 2030

[https://worldpopulationreview.com/countries/tropical-countries, 2020]

"Summer" issues will concern more geographic areas in the coming years due to global warming

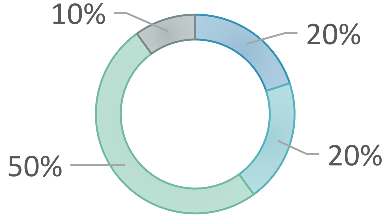
Issues

- To complete the poor knowledge about the user behavior in tropical climates
- To model the user behavior on air handling systems of bioclimatic/mixed-mode buildings in tropical climates

1 *Traditional design*

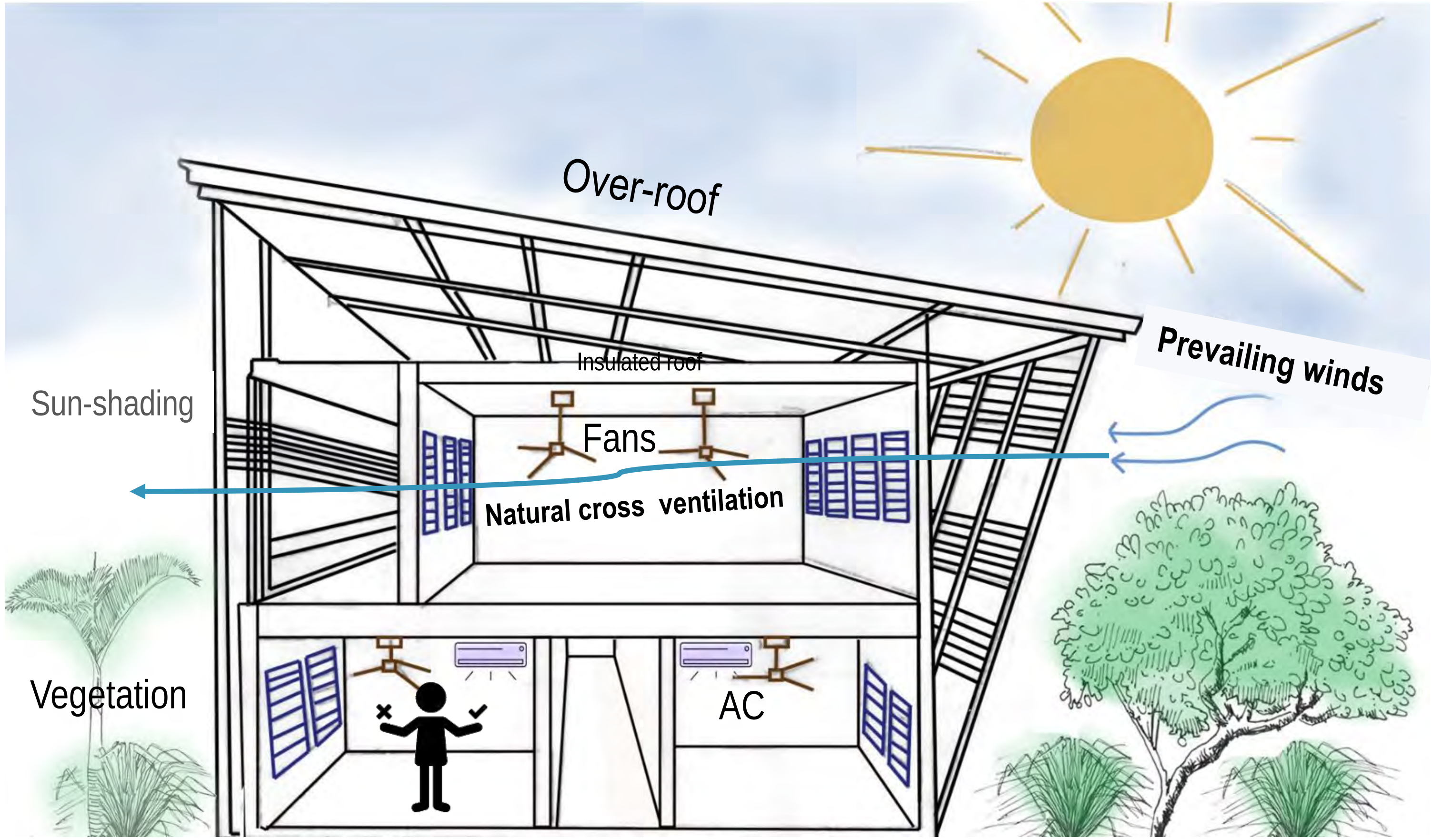
2 *On-going*

Non res. building consumption
≈ 100 kWh/m^2_{UA}.year

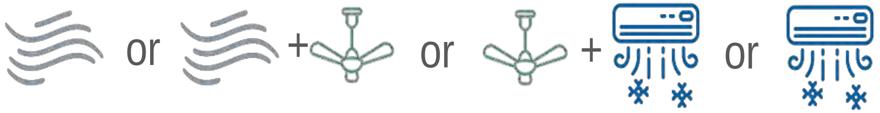


Lighting
Electrical outlets
Air conditionning
Others

Passive and energy-efficient solutions to reduce building energy demand by 50%



3 *Mixed-mode building to achieve comfort*



Scientific questions

How to define new user profiles for mixed-mode buildings with the particular use of NV with/without ceiling fans and/or air-conditioning?

When will the users switch between the different operating modes ?

Methodology and further developments

- Description of the data by statistical analysis,

- *Identification of key variables impacting the actions*
- *Development of stochastic modelling techniques*

- Occupancy modeling with Markov Chains [Vorger, E., 2014]

Modeling of window operation, fan use and air conditioning use with Bayesian networks [Ploix, S. et al.]

DATA COLLECTION

Input	Measured variables
Building inputs	Consumption of ceilling fans
	Consumption of air-conditioning
	Total consumption
	Indoor air temperature
	Indoor Relative Humidity
User inputs	State of Louvers
	State of celling Fans
	Occupation
Environmental inputs	Outdoor air temperature
	Outdoor Relative Humidity
	Wind speed
	Horizontal solar radiation

Ilet du Centre : Office building

Enerpos : Academic building

CONCLUSION AND FUTURE WORK

To establish user profiles and patterns for bioclimatic building in tropical climate

To identify the key factors impacting the behavior

To create a database of more tropical buildings to better predict consumptions at the design stage

To be an active user in a passive building

Thank you for your attention

maareva.payet@univ-reunion.fr

Presentations

Session 5 - Sixth presenter

Gao, Nan

Royal Melbourne Institute of Technology University, Australia

Session 5

Day 2, 14:03

N-Gage: Sensing in-class Multidimensional Learning Engagement in the Wild

N. Gao

The study of student engagement has attracted growing interests to address problems such as low academic performance, disaffection and high dropout rates. Existing approaches to measuring student engagement typically rely on survey-based instruments. While effective, those approaches are time-consuming and labour-intensive. Meanwhile, both the response rate and quality of the survey are usually poor. As an alternative, in this paper, we investigate whether we can infer and predict engagement at multiple dimensions just using sensors. We hypothesize that student multidimensional engagement level can be translated into physiological responses and activity changes during the class, and also be affected by the environmental changes. Therefore, we aim to explore the following questions: Can we measure the multiple dimensions of student's learning engagement including emotional, behavioural and cognitive engagement in high school classrooms with sensing data in the wild? Can we derive the activity, physiological, and environmental factors contributing to the different dimensions of student learning engagement? If yes, which sensors are the most useful in differentiating each dimension of the learning engagement? Then, we conduct an in-situ study in a high school from 23 students and 6 teachers in 144 classes over 11 courses for 4 weeks. We present the n-Gage, a student engagement sensing system using a combination of sensors from wearables and environments to automatically detect student in-class multidimensional learning engagement. Extensive experiment results show that n-Gage can accurately predict student multidimensional engagement in real-world scenarios with an average mean absolute error (MAE) of 0.794 and root mean square error (RMSE) of 0.977 using all the sensors. We also show a set of interesting findings of how different factors (e.g., combinations of sensors, school subjects, CO_2 level) affect each dimension of the student learning engagement in high school.

N-Gage: Sensing in-class Multidimensional Learning Engagement in the Wild

Nan Gao (PhD Candidate)

Supervisor: A/Prof Flora Salim, Dr Wei Shao, Dr. Mohammad Saiedur Rahaman

The research is funded by ARC linkage program (No. LP150100246) 'Swarming: micro-flight data capture and analysis in architectural design' by Prof J Burry, Prof S Watkins, A/Prof F Salim, RMIT University. Industry Partner of this research is Aurecon.

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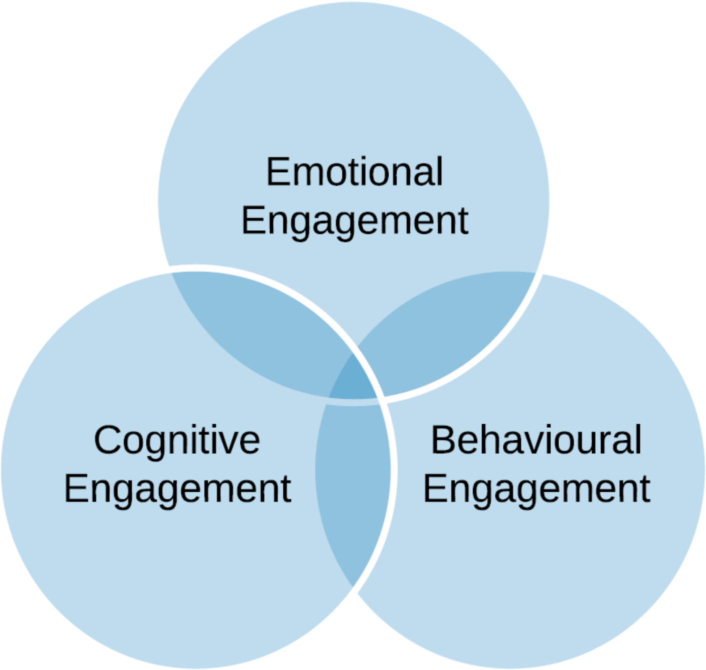
Student engagement



As many as 40-60% of high school students are disengaged

- Low academic performance
- Low disaffection
- High dropout rates

Research Questions

- Can we measure the multiple dimensions of student’s learning engagement including emotional, behavioural and cognitive engagement in high schools with sensing data in the wild?

- Can we derive the activity, physiological, and environmental factors contributing to the different dimensions of student learning engagement? If yes, which sensors are the most useful in differentiating each dimension of the learning engagement?

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Data Collection

- Time: 4 week in 2019
- Location: a private high school in Melbourne
- Participants: 23 Year 10 students, 6 teachers, 4 classrooms
- Collected data:
  - ✓ Wearables: ACC, PPG, EDA, Skin Temperature sensors
  - ✓ Weather station: temperature, humidity, noise, CO_2 sensors
  - ✓ Daily survey: multi-dimensional engagement, thermal comfort, etc.

(a) Empatica E4wristbands

(b) Netamo indoor weather station

(c) Classroom for Year 10 students

Extracted features

Table 5. Description of the features computed for different sensors

Sensors	*Feature Name*	*Description of features*
EDA	eda/tonic/phasic_avg	Average value for the raw, tonic, phasic data
	eda/tonic/phasic_std	Standard deviation for the raw, tonic, phasic data
	eda/tonic/phasic_n_p	Number of peaks for the raw, tonic, phasic data
	eda/tonic/phasic_a_p	Mean of peak amplitude for the raw, tonic, phasic data
	eda/tonic/phasic_auc	Area under the curve of the raw, tonic, phasic data
	num_arouse	Number of arousing moments during the class
	ratio_arouse	Ratio of arousing and unarousing moments
	$level_k$	Ratio of the number of $level_k$ and the length of S_k
	eda/tonic/phasic_pcct	Pearson correlation coefficient with teacher
	eda/tonic/phasic_pccs*	Pearson correlation coefficient with average value of students
	eda/tonic/phasic_dtwt	Dynamic time wraping distance with teacher
	eda/tonic/phasic_dtws*	Dynamic time wraping distance with average value of students
PPG	hrv_bpm	Average beats per minutes
	hrv_meani	Overall mean of RR intervals (Meani)
	hrv_sdnn	Standard deviation of intervals (SDNN)
	hrv_lf_power	Absolute power of the low-frequency band (0.04–0.15 Hz)
	hrv_hf_power	Absolute power of the high-frequency band (0.15–0.4 Hz)
	hrv_ratio_lf_hf	Ratio of LF-to-HF power
	hrv_rmssd	Root mean square of successive RR interval differences
	hrv_sdsd	Standard deviation of successive RR interval differences
	hrv_pnn50	Percentage of successive interval pairs that differ >50 ms
	hrv_pnn20	Percentage of successive interval pairs that differ >20 ms
ACC	acc_avg	Average physical activity intensity during the class
	acc_std	Standard deviation of physical activity intensity in class
	acc_dtw_t	Dynamic time wraping distance with teacher
	acc_dtw_s*	Dynamic time wraping distance with average value of students
	acc_pcc_t	Pearson correlation coefficient with teacher
	acc_pcc_s*	Pearson correlation coefficient with average value of students
ST	sktemp_avg/max/min	Average/maximum/minimum value of skin temperature
CO2	mean/max/min_co2	Average/maximum/minimum value of CO2
TEMP	mean/max/min_temp	Average/maximum/minimum value of indoor temperature
HUMID	mean/max/min_co2	Average/maximum/minimum value of humidity
SOUND	mean/max/min_temp	Average/maximum/minimum value of sound

Engagement distribution

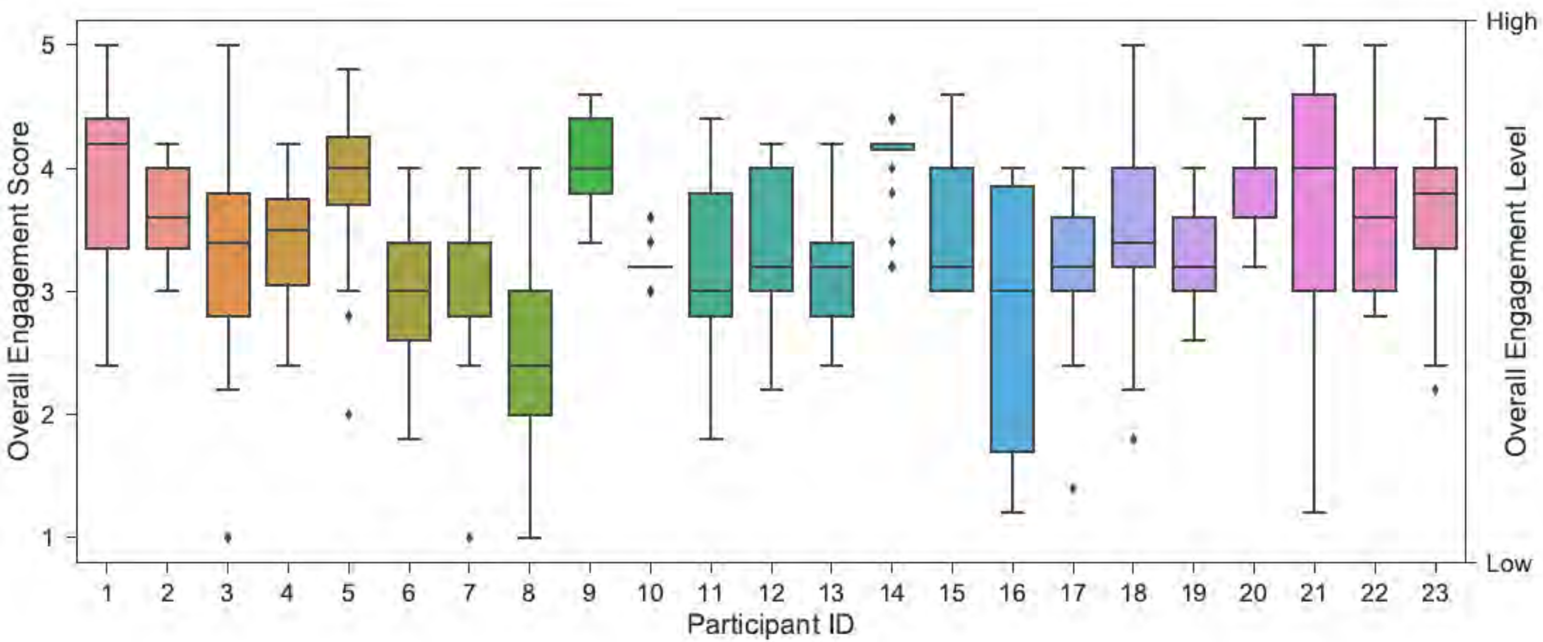

Fig. 5. Box plot of the general engagement scores for 23 student participants during 4-week data collection.

General Prediction performance

Table 6. Prediction performance for emotional, cognitive, behavioural, and overall engagement with all sensing data

Dimension	*MAE*			*RMSE*		
	Proposed	Baseline (avg.)	Baseline (rand.)	Proposed	Baseline (avg.)	Baseline (rand.)
Emotional	**0.675**	0.746	0.998	**0.856**	0.928	1.285
Cognitive	**0.928**	0.979	1.173	**1.122**	1.180	1.557
Behavioural	**0.779**	0.862	1.236	**0.953**	1.027	1.537
Overall	**0.603**	0.644	0.907	**0.757**	0.798	1.134

Most influential features

Table 7. The most influential features on multidimensional engagement.

Engagement	*Association*	*Most influential features*
Emotional Engagement	(+)	acc_pcc_s, tonic_a_p, eda_pcc_s
	(-)	**acc_avg***, **sktemp_avg***, eda_dtw_t
Cognitive Engagement	(+)	**intemp_min***, level_1, hrv_ratio_lf_hf
	(-)	**acc_pcc_s***, co2_max, acc_std
Behavioural Engagement	(+)	acc_std, acc_pcc_s, eda_pcc_avg
	(-)	**sktemp_avg***, **acc_pcc_t***, acc_dtw_t
Overall Engagement	(+)	level_1, tonic_a_p, intemp_max
	(-)	**acc_dtw_t***, sktemp_avg, acc_avg

* indicates p-value < 0.01.

Impact of different sensor combinations

Table 8. Summary of the Prediction performance of multidimensional engagement using different data sources. $\mathcal{X}_1$ indicates all the wearable data including EDA, HRV, ACC and ST data, and $\mathcal{X}_2$ means the indoor environmental data including CO_2 and temperature data.

Data source	*MAE/RMSE*			
	Emotional	*Cognitive*	*Behavioural*	*Overall*
EDA	0.699/0.879	0.962/1.157	0.854/1.028	0.639//0.803
HRV	0.715/0.900	0.952/1.146	0.836/1.006	0.658/0.808
EDA+HRV	0.701/0.877	0.963/1.159	0.845/0.993	0.623/0.786
EDA+ACC	0.677/0.856	0.932/1.137	0.813/0.982	0.625/0.784
HRV+ACC	0.689/0.871	0.930/1.131	0.810/0.980	0.642/0.800
EDA+HRV+ACC	0.679/0.859	0.929/1.132	0.804/0.964	0.621/0.781
$\mathcal{X}_1$ *	**0.674**/0.858	0.930/1.124	0.813/0.983	0.621/0.778
$\mathcal{X}_1 + \mathcal{X}_2$ * *(all)*	0.675/0.856	**0.928/1.122**	**0.779/0.953**	**0.603/0.757**

* indicates the proposed combination of features for engagement prediction.

Impact of class subjects

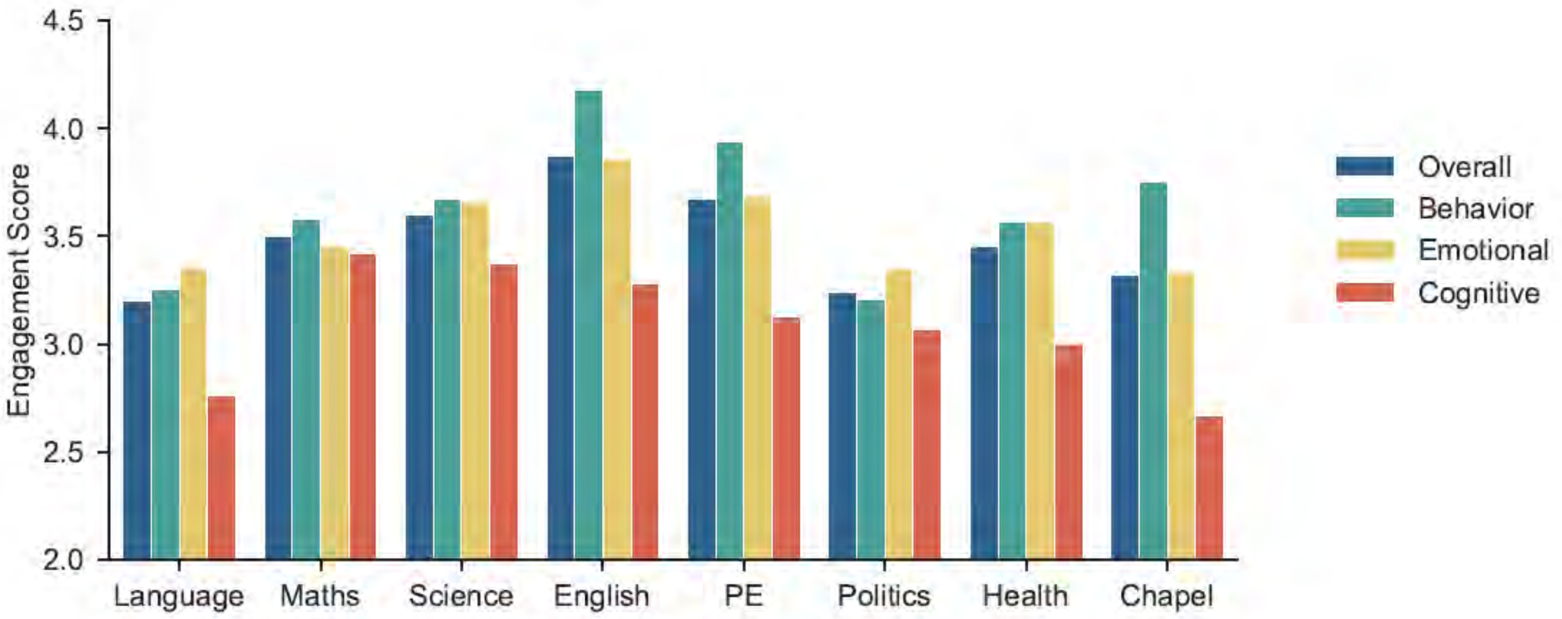

Fig. 7. Engagement scores on different subjects

Result

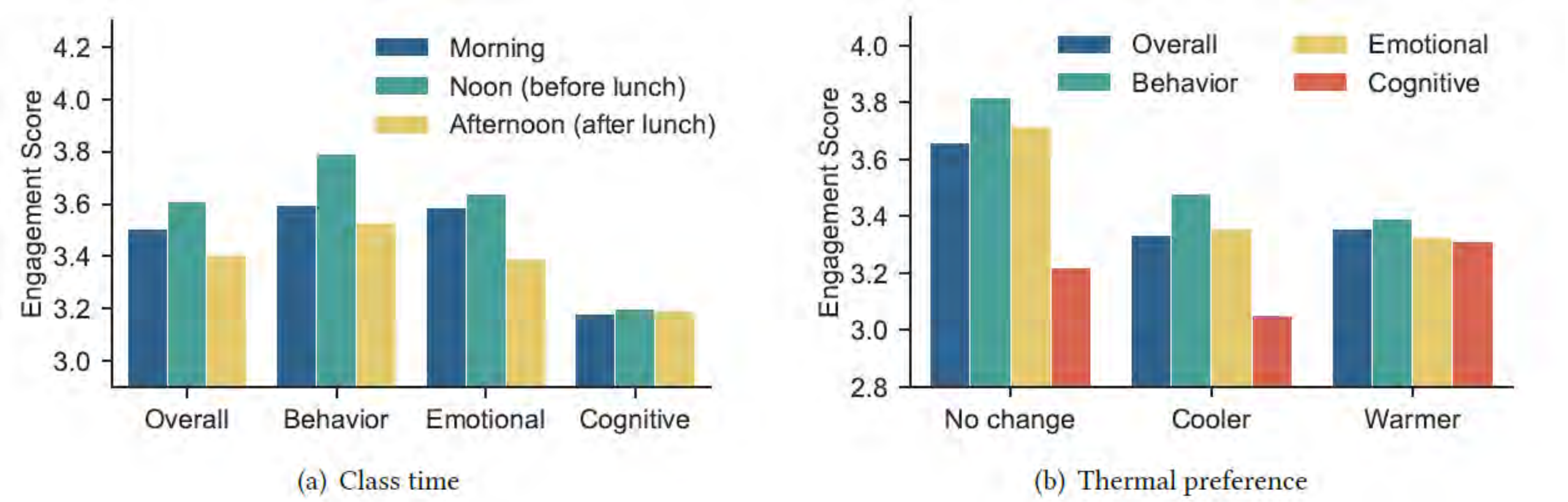

Fig. 8. Engagement scores with different class time and thermal comfort

Any Questions?

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Presentations

Session 6 - First presenter

Lassen, Niels

Norwegian University of Science and Technology, Norway

Session 6

Day 2, 14:50

Introduction to PhD Thesis: Subjective Data-Streams for Indoor Climate Assessment in Buildings

N. Lassen

A general presentation of background, research questions, experimental activities and preliminary findings in an ongoing PhD thesis. The aim of the thesis has been to understand the potential, functioning and validity of methods for continuous subjective occupant feedback for indoor climate in buildings and answer the question «Can continuous, non-intrusive collection of subjective data from occupants outperform traditional deterministic comfort models and POE's and can they bring added value to building benchmarking, tuning, control and design?». The research activities range from literature studies, development of a framework for classifying subjective information sources, and field experiments of occupants in 6 separate office spaces in Norway and Berkeley, USA. Field tests have focused on the validation of information gathered through a public smiley face poling station placed in the office environment, as well as occupants' use of personal heaters. Collected field data has been compared to results from occupant surveys and measurements of the physical climate during normal operation and during temperature interventions. All field tests have been performed on un-informed subjects performing regular office activities. Preliminary results indicate that real-time non-intrusive occupant feedback can outperform traditional predicting models and was able to capture occupant dissatisfaction in cases where physical measurements and comfort models were proven incapable.

SKANSKA

Introduction to PhD thesis: “Subjective data-streams for indoor climate assessment in buildings”

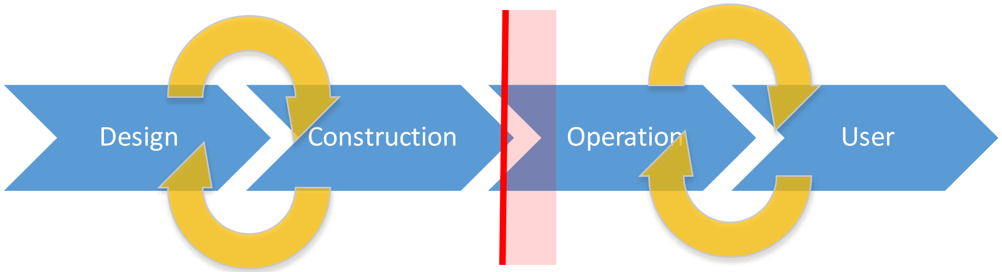
Niels Lassen

Senior advisor, PhD student IEQ & Smart Buildings

Skanska Norway / NTNU

Background

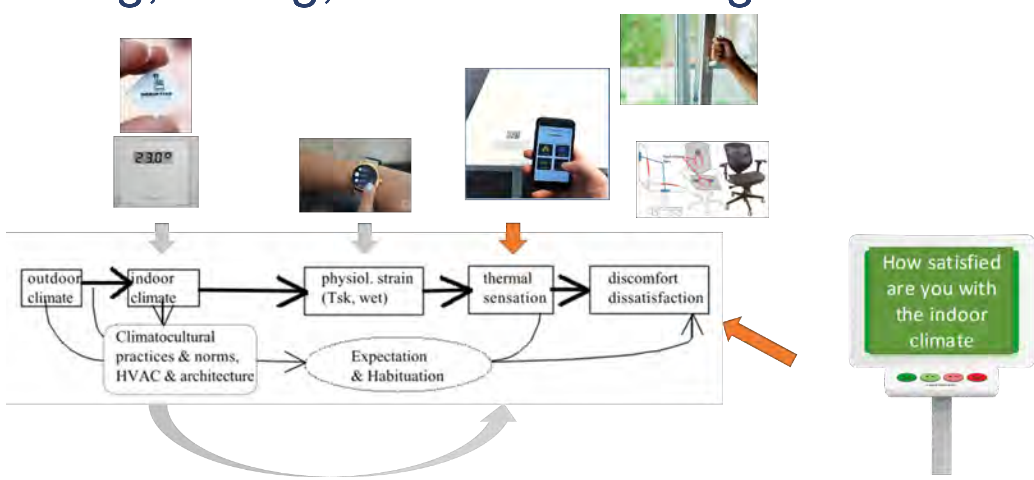
- Discipline specific performance criteria lead to sub-optimal solutions in holisticly designed ZEB's
- There exists a performance gap for occupant satisfaction and energy performance
- Can we use subjective occupant feedback to learn and support more holistic design choices?



Aim and research question

- Aim: Understand the potential, functioning and validity of methods for continuous subjective occupant feedback for indoor climate in buildings
- RQ: Can continuous, non-intrusive collection of subjective data from occupants outperform traditional deterministic comfort models and POE's and can they bring added value to building benchmarking, tuning, control and design?

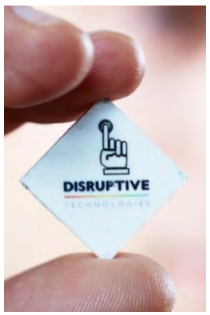
Which data can we collect without intruding on occupants?



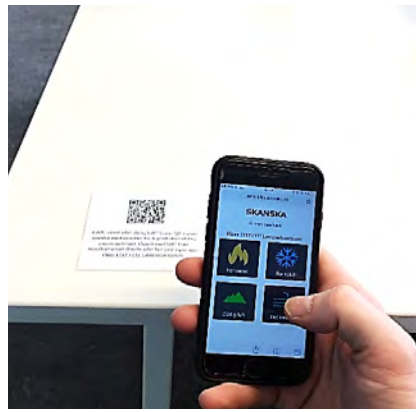
Psychological feedback loop from De Dear, Brager, Cooper (1998)

System design

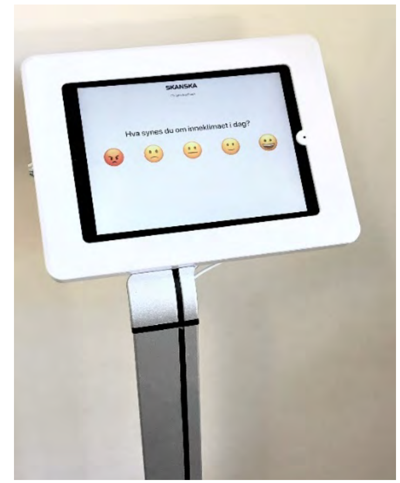
Physical environment	Sensations / Complaints / Control actions	Total user satisfaction



Physical measurements of Temp and Co2 from building BS and/or external sensors



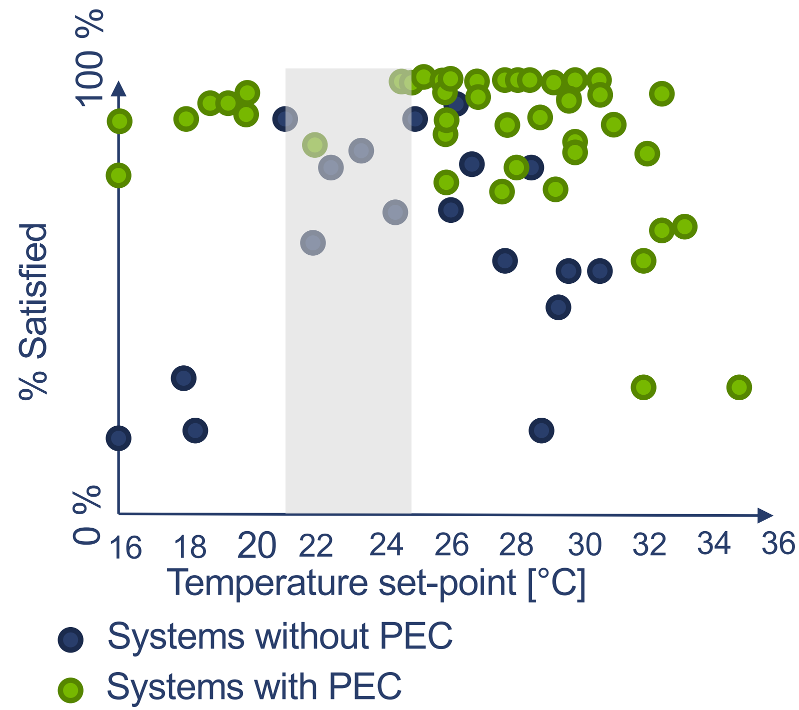
QR codes on each workdesk + personal heaters.



Public satisfaction polling station (SPS) near exits.

Theoretical study

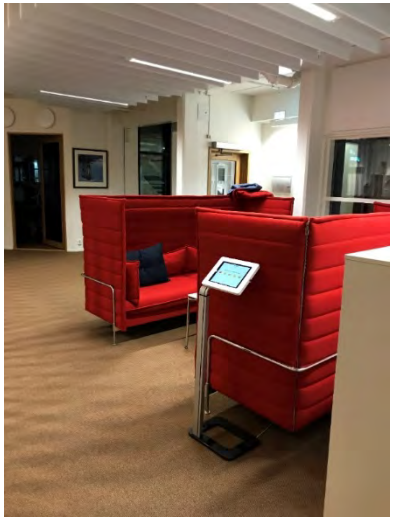
- Review of studies on subjective occupant feedback
- Thermal comfort theory – *Gap between expected and actual satisfaction*
- Psychology and Neuroscience of subjective occupant evaluations – *Senses are combined into perceptions*
- Market psychology – *Occupant as consumer of indoor climate*

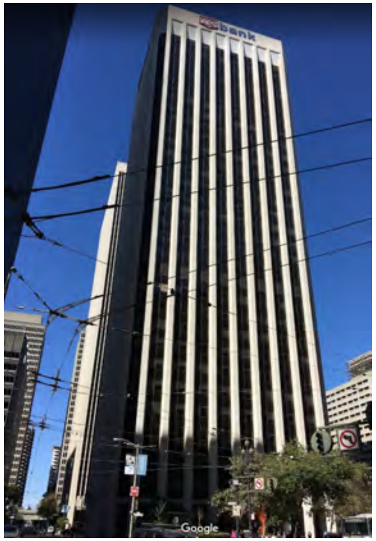


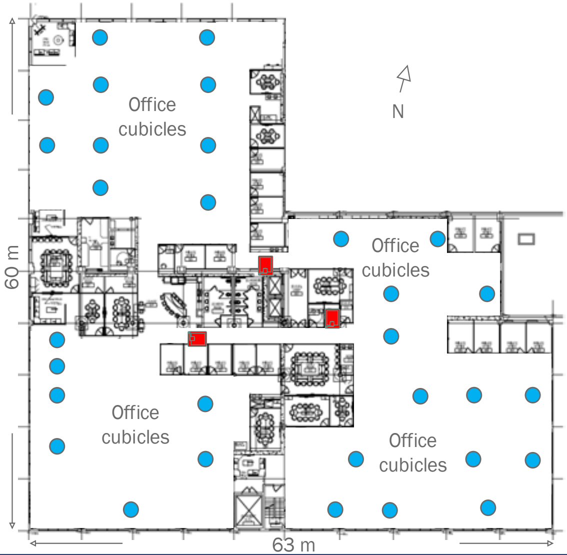
After Hoyt, Arens & Zhang, 2014

Experiments

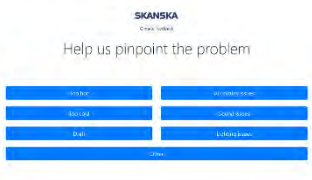
- 6 field studies in office buildings (Norway and California)
- Collected data from system & performed occupant surveys
- Temperature interventions
- Un-informed subjects

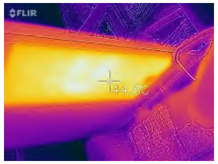






Collected data

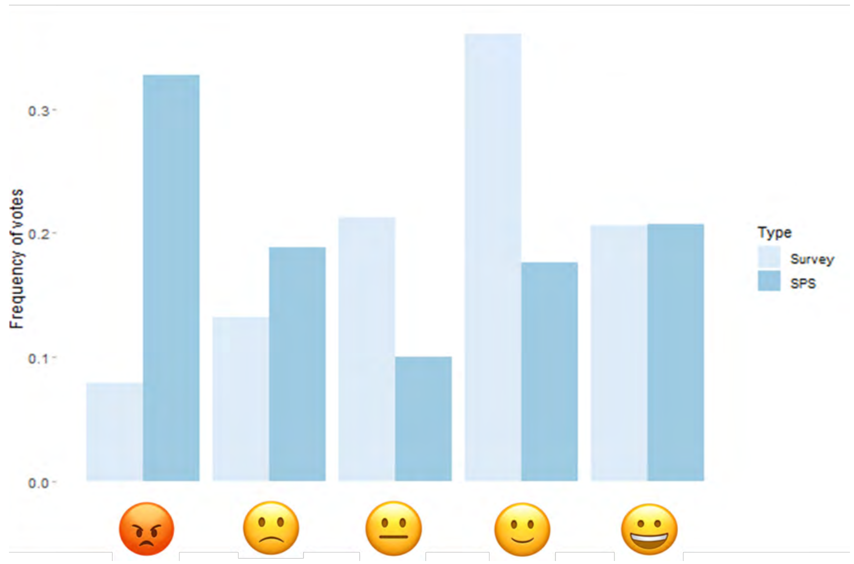


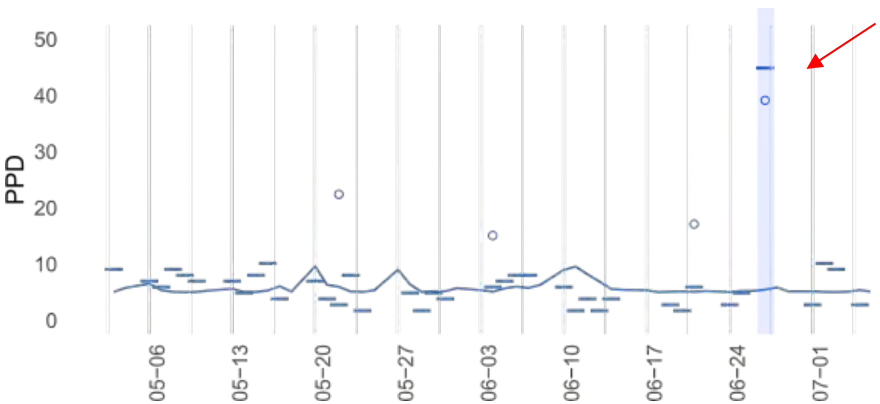


		Building 1	Building 2	Building 3	Building 4	Building 5	Building 6	Total
	Population	*14*	*26*	*12*	*25*	*95*	*25*	*205*
SPS	Length of study (days)	90	88	42	37	80	60	587
	Number of entries	612	97	124	90	1252	534	2882
	Number of entries on survey days	33	16	14	34	233	73	**403**
SPS Complaints	Length of study (days)	-	-	-	25	80	60	165
	Number of entries	-	-	-	41	519	137	697
	Number of entries on survey days	-	-	-	20	112	11	**143**
QR Feedback	Length of study (days)	90	15	14	-	-	-	309
	Number of entries	8	10	5	-	-	-	29
	Number of entries on survey days	1	1	0	-	-	-	**2**
Heater	Days in use	30	40	22	14	-	-	106
	Number of responses	20	978	54	445	-	-	1497
	Number of responses on survey days	4	270	0	131	-	-	**405**
Survey	Days	2	3	1	5	5	5	21
	Number of responses	11	40	7	97	413	60	**628**

Findings – Satisfaction polling station (SPS)

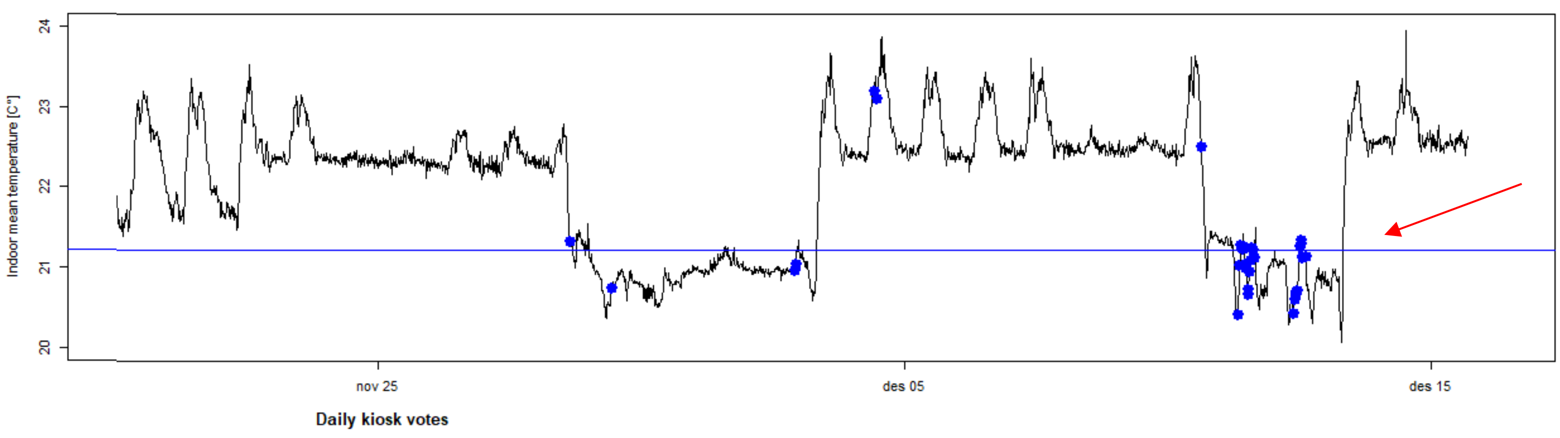
- Daily votes 20-40% of building population
- Large and variable Non-response bias, dissatisfied voters vote more often in some buildings
- High correlation between thermal complaints in SPS and Survey, outperforming PMV-PPD model
  (with temperature interventions)





Findings – Occupant feedback and control actions

- QR codes were not used frequently by users
- Personal heaters with manual control were used very frequently by approximately 20% of users. They were very satified with them.
- *Analysis of heater usage is not yet completed.*



Findings – Classification of feedback data

- We have different data sources from building occupants which are linked to different levels of physiological and cognitive processes within the user
  - Satisfaction or comfort ratings
    (cognitive & affective evaluation, subjective, conscious)
  - Complaints
    (cognitive evaluation & action, subjective, conscious)
  - Control actions
    (cognitive action, subjective, conscious)
  - Physiological reactions
    (objective, conscious or subconscious)
- They are not directly comparable, but there does not exist a framework to arrange them
- Unfortunately outside of PhD scope..

Summary

- Easy to make a working system which is taken into use by un-informed occupants
- The information collected has value for building tuning, control and design
  (is correlated with temperature changes and survey responses)
- It may also be usable for benchmarking, but must correct for the non-response bias which varies between buildings.
- There are differences between user groups in how they respond (demography, how communicated, attitude)
- We are missing a framework to classify what subjective data we are collecting

Presentations

Session 6 - Third presenter

Sarran, Lucile

Technical University of Denmark, Denmark

Session 6

Day 2, 15:10

Learning to Live in Low-Energy Dwellings: A Mixed-Methods Case Study

L. Sarran

Occupants' routines and practices around the use of the building services in their home may lead to energy performance gaps and indoor environmental issues, in particular when the building services are unknown. This work aims at documenting the successes and difficulties encountered by occupants while getting acquainted with new building services (heating and mechanical ventilation systems) after moving in a low-energy dwelling. Explanatory mixed methods were adopted. A questionnaire survey was first carried out in a social housing complex of 2007 recently retrofitted and non-retrofitted single-family houses in Denmark. The questionnaire investigated occupants' satisfaction with the indoor environment in their homes as well as their experience with using the building services. In a second phase, semi-structured interviews were carried out. The interviews set to ask the "why" questions and elucidate occupants' use and understanding of the building services. 23 interviews were carried out in the same social housing complex followed by 14 supplementary interviews in three newly built multi-family residential buildings. The questionnaire was answered by 344 residents (response rate: 17.1%). Occupants were in majority able to achieve a satisfactory indoor environment in their homes. In particular, stable temperature and pleasant air quality were largely appreciated. The usability of building services was however more of a concern, with occupants expressing difficulties to understand and operate them. Reasons for these issues were dysfunctional systems, lack of information and knowledge, and lack of personal control. Automation was mainly perceived as detrimental to comfort and user satisfaction when the building services were not functioning as intended. In order to avoid frustration and discomfort among occupants, the increasing complexity and automation in residential building services must go hand in hand with an increased product quality and a better exchange of information with the residents.

Lucile Sarran, Christian A. Hviid, Carsten Rode

Learning to Live in Low-Energy Dwellings

A Mixed-Methods Case Study

Introduction

- **Perceived personal control** has an influence on **perceived comfort**
- Personal control on comfort is often assumed to be high in **private dwellings**
- New and retrofitted dwellings are increasingly fitted with new, **complex**, **automated** building services
- Several POE show **usability** concerns with building services in low-energy dwellings

Usability:

"The extent to which a product can be used by specified users to **achieve specified goals** with **effectiveness**, **efficiency** and **satisfaction** in a specified context of use." (ISO 9241-11)

How do occupants experience indoor environmental quality after moving in a low-energy dwelling?

What is their experience with the usability of the building services (space heating and mechanical ventilation) and how do they learn to use them?

Is there a link between indoor environmental quality and occupants' perceived usability of building services?

Methodology

A mixed-methods case study

QUESTIONNAIRE

<u>Reported satisfaction with:</u>

I – Thermal comfort

II – Indoor air quality

III – Usability and control of heating systems

IV – Usability and control of mechanical ventilation systems

<u>Analysis:</u>

1 Variable **aggregation**:

26 individual questions → *Reliability tests: Factor Analysis + Cronbach's Alpha* → 9 aggregated latent variables

2 Analysis of the variables' **distribution**

3 **Correlation** study

SEMI-STRUCTURED INTERVIEWS

<u>Deeper explanation and description:</u>

- Reasons for satisfaction or dissatisfaction
- Evaluation of occupants' understanding of HVAC systems
- New routines
- Expectations towards low-energy dwellings

<u>Analysis:</u>

1 Recording

2 Transcription

3 **Thematic coding** + occupants' **stories**

The case buildings

Case 1: Social housing (2007 houses)

Case 2: Owned new apartments (14)

	Case 1				Case 2
	Type A	Type B	Type C	Type D	
Geometry	Row houses	Semi-detached	Semi-detached	Semi-detached	Apartments and row houses
Status	Retrofitted	Retrofitted	Retrofitted	Original from 1965	Newly built
Building standard	BR10	BR10	BR15	None	BR10 class 2020 DGNB Gold
Move-in date	2014-2015	2016-2018	2017-2018	Various	2015-2017
Water-based radiators + thermostatic valve	Bedrooms	X	X	X	
Water-based floor heating + programmable thermostat	Living room				X
CAV balanced mechanical ventilation with heat recovery	X	X	X		X
Ventilation supply diffuser location	High on wall	Under radiators	High on wall		High on wall
Turbo mode	Manual + moisture-controlled		Moisture-controlled		Manual

Questionnaire statistics	Type A	Type B	Type C	Type D
Number of houses	552	495	258	702
Number of valid responses	69	78	94	103
Response rate (%)	12.5	15.8	36.4	14.7

Number of interviews	7	6	10	6	14

Thermal comfort and heating

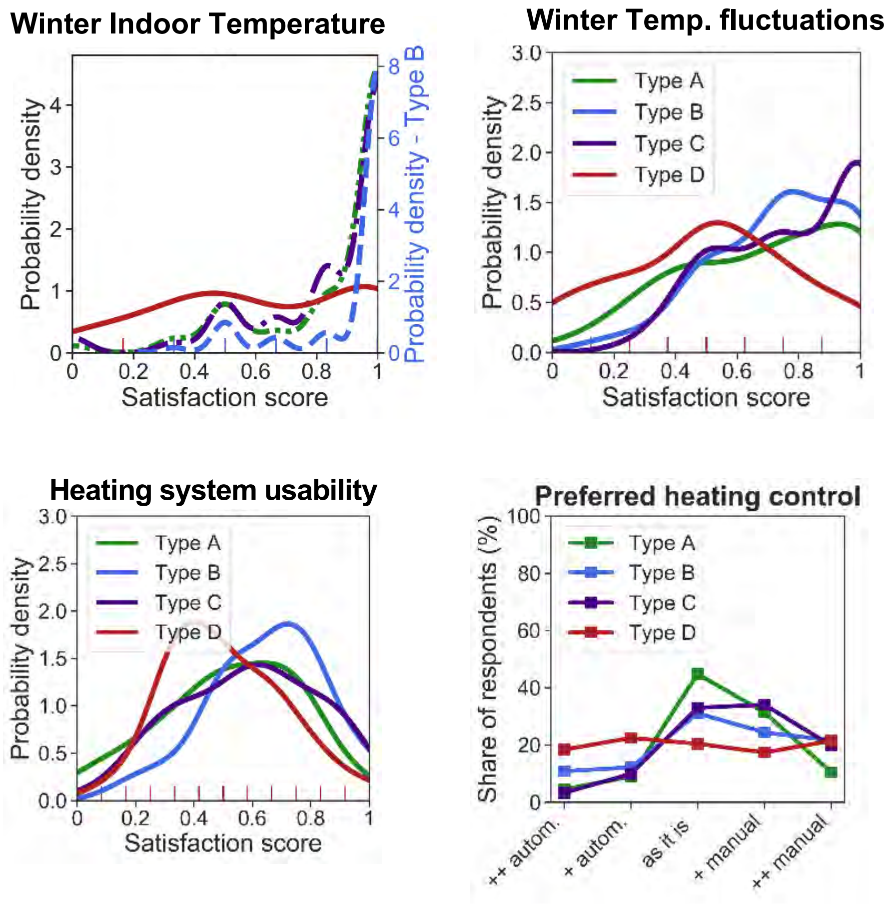
QUESTIONNAIRE

Type A: Floor heating with programmable thermostat

Type B: Standard radiators

Type C: Standard radiators

Type D: Non-retrofitted house with standard radiators

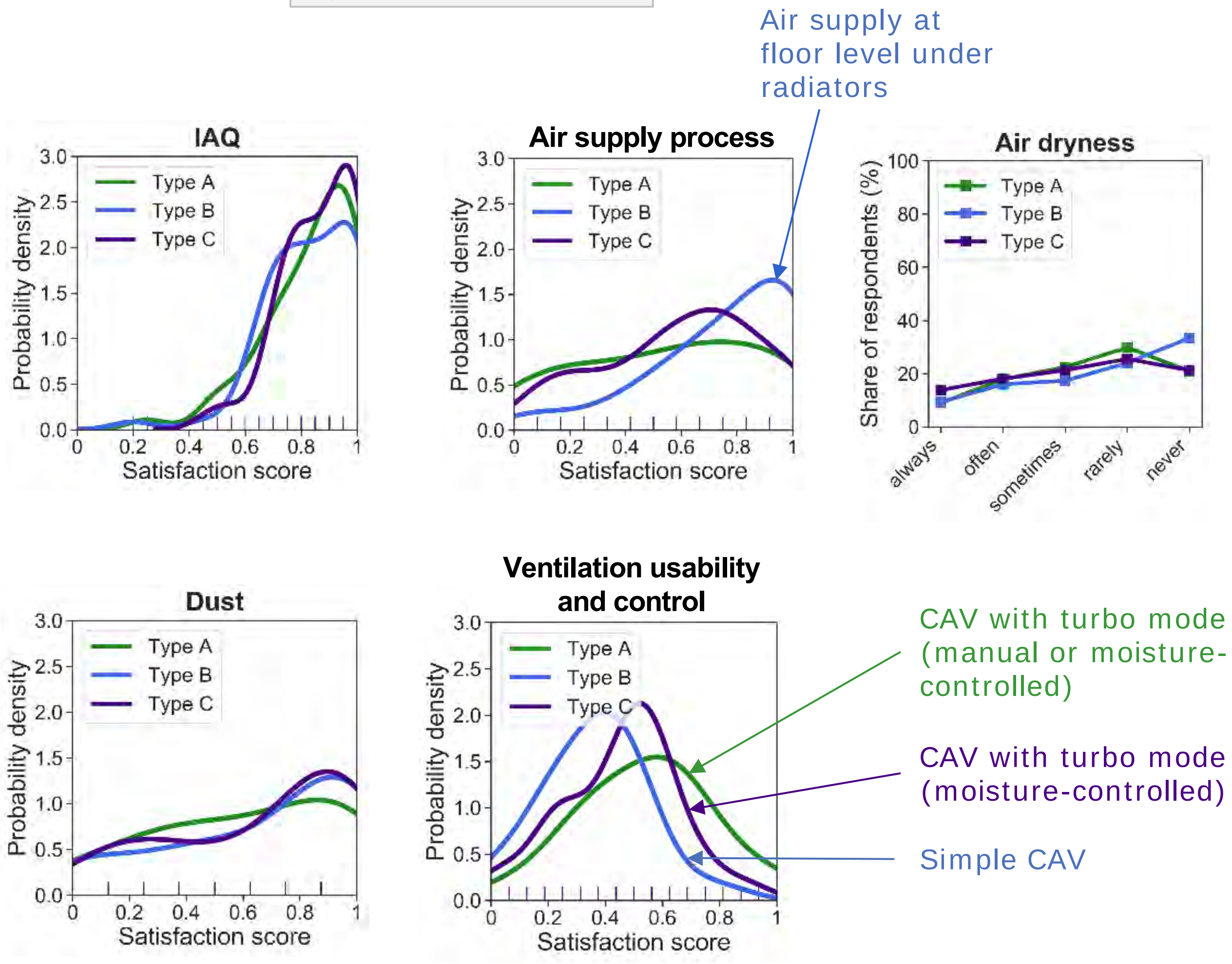


SEMI-STRUCTURED INTERVIEWS

- Temperature is **comfortable and stable**
- Floor heating: aesthetic, **pleasant** to be home without slippers, no temperature swings
- A lot of **overheating** complaints
- **Slow dynamics** of floor heating: difficult learning process
- The floor is actually **rarely warm**! Leads to **increased setpoints**
- General **lack of information** about efficient heating operation

Indoor air quality and ventilation

QUESTIONNAIRE



SEMI-STRUCTURED INTERVIEWS

Ventilation makes air **fresh**, **healthy** and **airing** almost unnecessary

Problems with automated operation:

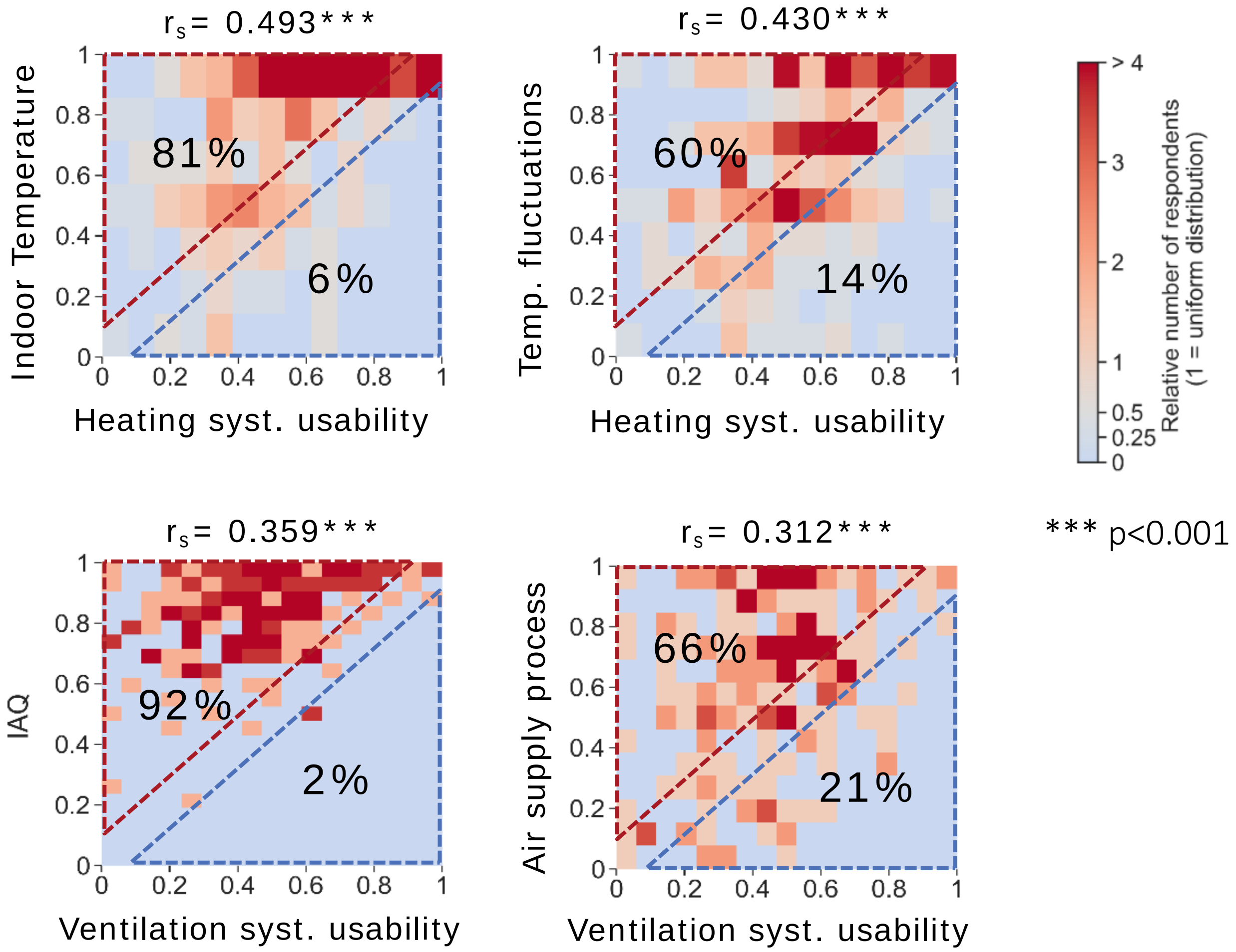
- People are told not to touch systems and given little **information**
- Can't do anything about **noise** and **draft**
- Perceived **waste of money** in summer and when windows are open

Occupants take control:

- Tape, paper or magnet to **obstruct** diffusers
- **Switch off** power supply
- Sometimes maintenance people find **hacks** too!

Correlation study

Is there a link between comfort and perceived usability?



✓ Significant correlations between IEQ satisfaction and usability satisfaction

Is a high perceived usability a necessary condition for comfort? NO (IN MOST HOUSES)

Many occupants are satisfied with indoor environment and rate poorly the systems' usability

Interviews:

- Satisfactory comfort achieved with **passive** house qualities and **automatic** features of building services
- Complaints about lack of manual control mainly in case of **dysfunctional systems** or **wrong operational settings** giving bad IEQ

Discussion and conclusion

Limitations: representativeness

- Limited response rate (17.1%)
- Average age higher than general population
- Particularly high user engagement in retrofit

Learnings

- Shorter questionnaire
- Better engagement of housing association

Conclusions

- Large **IEQ satisfaction** (except for summer **overheating**)
- **Usability** issues observed:
  - Caused by lack of **communication** and **information**
  - Can lead to energy-intensive or unhealthy **hacks**
- Significant correlation between **IEQ** perception and **usability** satisfaction
- Occupants can however achieve comfort **in spite of poor usability**
- **Low usability and excessive automation** are problematic when **dysfunctional** systems and **operational failures** give bad IEQ

If automated, building services must be commissioned often and occupants must be better informed

Thank you for your attention!

Lucile Sarran

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Lucile Sarran

Presentations

Session 6 - Fourth presenter

Barthelmes, Verena

EPFL, Switzerland

Session 6

Day 2, 15:20

Capturing Real-Time Motivations Behind Human-Building Interactions: The OBdrive App

V. Barthelmes

Despite significant advances in the field of energy-related behavioural research in buildings, gaining a more comprehensive and “multi-dimensional” understanding of drivers and perceived motivations behind human-building interactions remains an open challenge. Increasing effort is put on understanding how the combined effect of IEQ factors affects user perception and behaviour in real buildings. Oftentimes, the motivations behind actions are deducted solely from physical measurements of the environment, which might not always reflect the real triggers behind occupants’ actions. On the other hand, certain combinations of perceived motivations related to different dimensions of comfort (e.g. thermal comfort and indoor air quality) might be stronger linked than others. In the context of the eCOMBINE project (“Interaction between energy use, COMfort, Behaviour, and INdoor Environment in office buildings”), we developed an ad-hoc designed mobile application aimed at gathering feedback from the occupants each time they interact with windows, window blinds, and lights. In that way, perceived motivations can be compared to results from the environmental monitoring campaign. Further, the compact design of the app allows for gaining basic information on group dynamics and social interactions before interacting with controls. This contribution is aimed at presenting the OBdrive mobile application and provide first insights into the analysis of perceived motivations behind the interactions with windows and blinds, and their link to physical measurements of the global indoor environment. The study was carried out in Swiss open space offices over two-weeks monitoring campaigns during the Fall and Winter season.

IEA-EBC Annex 79 – 5th International symposium on Occupant Behaviour
Southampton, 20-23 April 2020
Session: Case studies of Occupant-Centric Modelling, Design and Operations

Capturing Real-Time Motivations Behind Human-Building Interactions: The OBdrive App

Verena M. Barthelmes, Dolaana Khovalyg

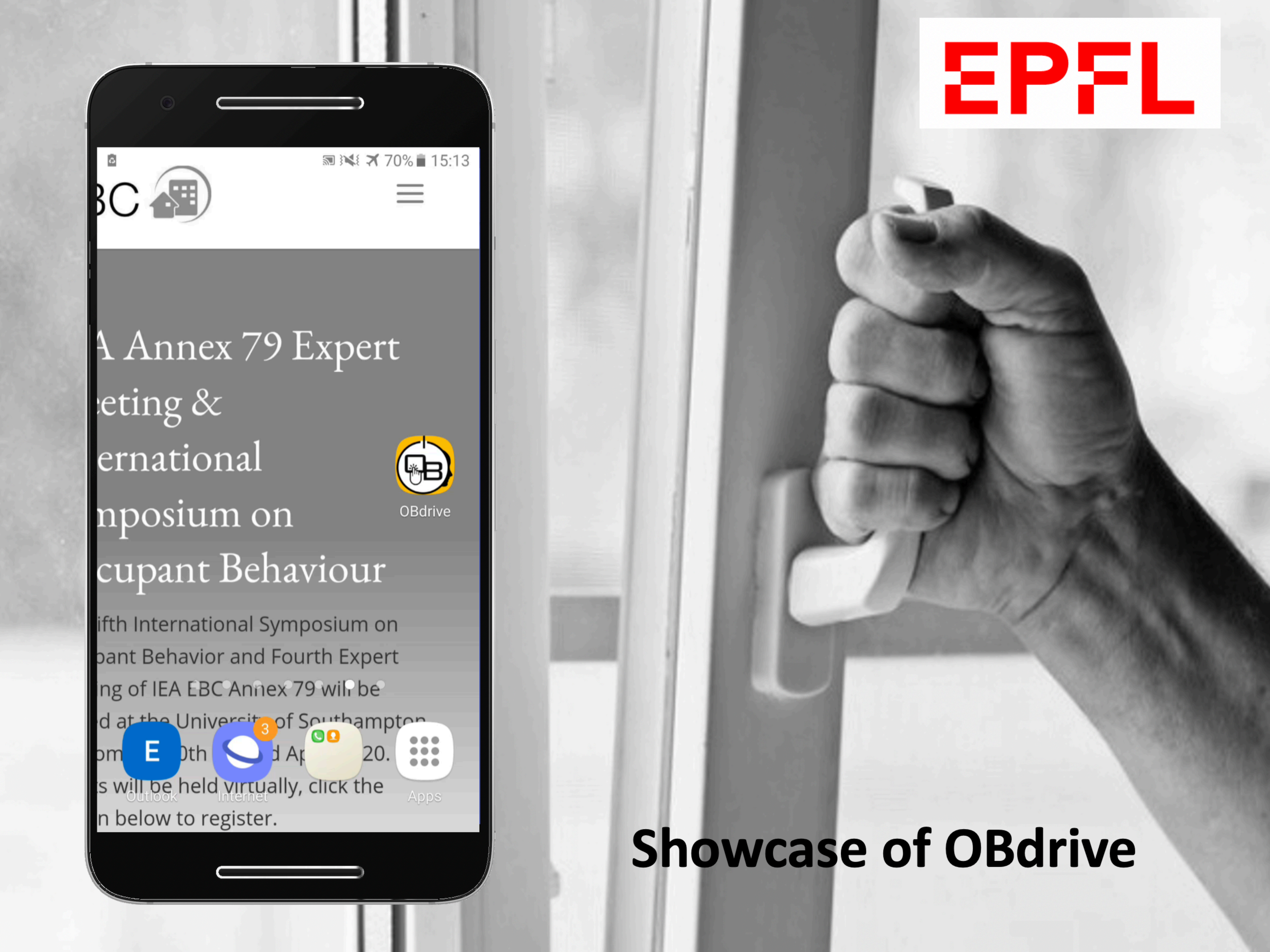
Thermal Engineering for the Built Environment Laboratory (TEBEL)
Ecole polytechnique fédérale de Lausanne (EPFL), Switzerland

April 21, 2020

CONTEXT

The mobile application OBdrive was developed in the context of the ***e*COMBINE project**
(*Interaction between **e**nergy use, **COM**fort, **B**ehaviour, and **IN**door **E**nvironment in Office Buildings*)
- the goal of this project is **to study the dynamic cause-effect relationship between occupants and combined environmental factors.**

Motivations behind interaction with controls is not only retrieved by objective measurements, but also by **collecting motivations behind actions directly from the user** each time he/she interacts with controls (windows, window blinds, and desk lights)



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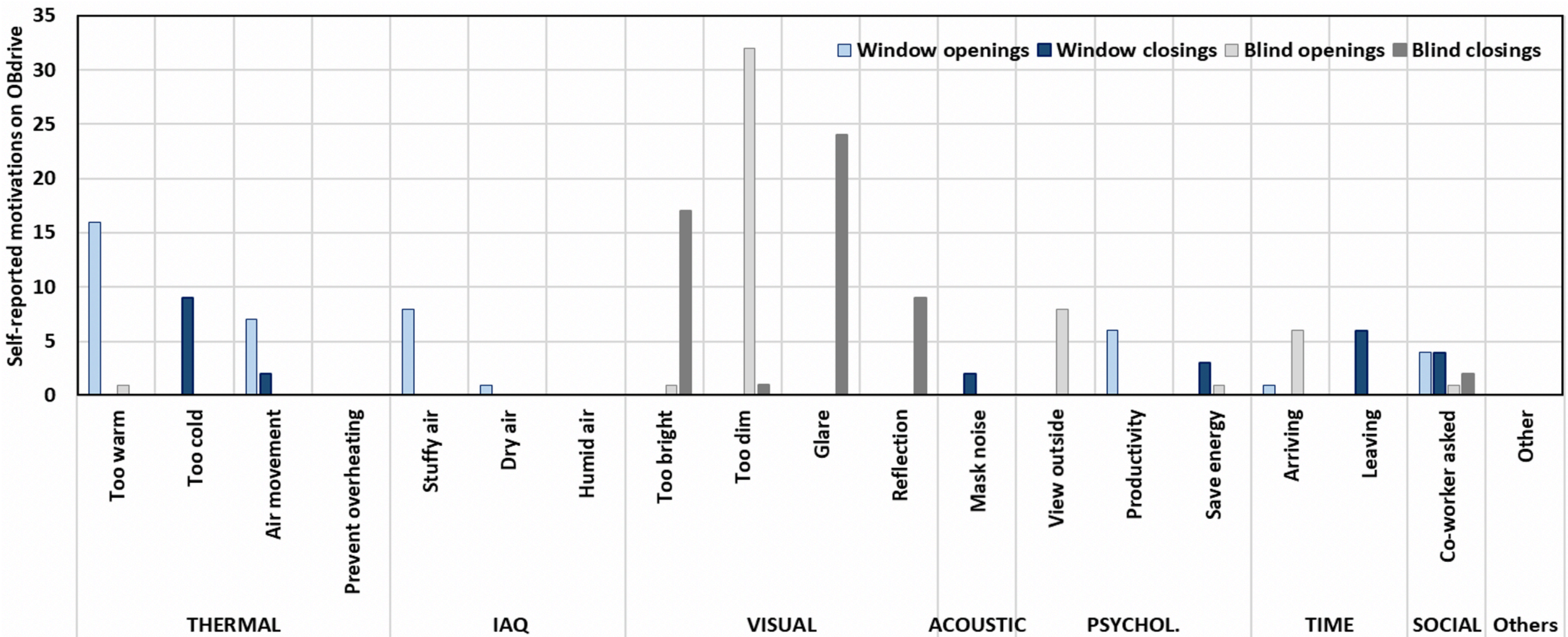
s will be held virtually, click the
n below to register.
Outlook
Internet
Apps
Showcase of OBdrive

DISCUSSION and CONCLUSION

Results of the OBdrive mobile application can be compared to what objective data tells us about the environment and the relationships between environmental data and the human-building interaction



Next improvements might include:

- ✓ **Order of priority of different motivations** («I open the window because I feel too hot, but I also enjoy some fresh air»)
- ✓ Open answer: employees can give a **personalized answer** if one of the predefined motivations does not fit
- ✓ Translation into **other languages** (currently only available in English, even if used in the French and German speaking context)

IEA-EBC Annex 79 – 5th International symposium on Occupant Behaviour
Southampton, 20-23 April 2020
Session: Case studies of Occupant-Centric Modelling, Design and Operations

Thank you

eCOMBINE team:

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Presentations

Session 6 - Fifth presenter

Raw,
Gary

GRPS,
UK

Session 6

Day 2, 15:24

Evaluating Varying Comfort

G. Raw

Understanding behaviour entails understanding the environmental perceptions that underlie behaviour. In the case of thermal comfort, numerical scales for measuring human response have emerged largely in the context of environmental conditions and respondents' activities that vary little over time – for example in climate chambers or conditioned offices. In this context, asking "how do you feel" makes sense and lends itself to understanding how comfort is determined at a point in time. But many people live or work in conditions that vary markedly over time, and where their physical activity varies too – even within seasons or within a day. It is questionable how people in these circumstances would give a single scale rating. We have therefore tested an alternative approach. In a pilot study in a UK primary school, we asked staff to report the percentage of the time when it is (a) too cold and (b) too warm. They were asked to report separately for summer and winter and within a single day. Students also separately indicated whether they had felt too hot or too cold during the day. Both staff and students were able to report without difficulty and could state, for example, that the same room was sometimes too cold and sometimes too warm, even within one day. Furthermore, the findings show a logical relationship with other subjective variables and with objectively measured conditions in different parts of the school. Further research should serve to refine this approach and set benchmarks, thus allowing the performance of an indoor or outdoor space to be evaluated in a way that better matches how people experience that space.

Evaluating varying comfort

Gary J Raw
GRPS and UCL Energy Institute

In collaboration with **Paul Ajiboye**, CETEC UK Manager

CETEC
Professional Scientific Solutions

Why evaluate varying comfort?

Schools are not climate chambers.

- The temperature varies.
- Activities vary.
- Occupants are present typically for an hour at a time.

Asking “how do you feel” or “how have you been feeling” makes little sense in these conditions.

So we tried something different – something as simple as possible.

New questions

For staff

What percentage of the time is/was it
(a) too cold and (b) too warm? … in winter … in summer … today.

For students

In your classroom today … do you remember …

Feeling too hot (yes/no)

Feeling too cold (yes/no)

(And many other questions on thermal conditions and other environmental conditions.)

The pilot study

Questionnaires issued in a primary school in South East England.

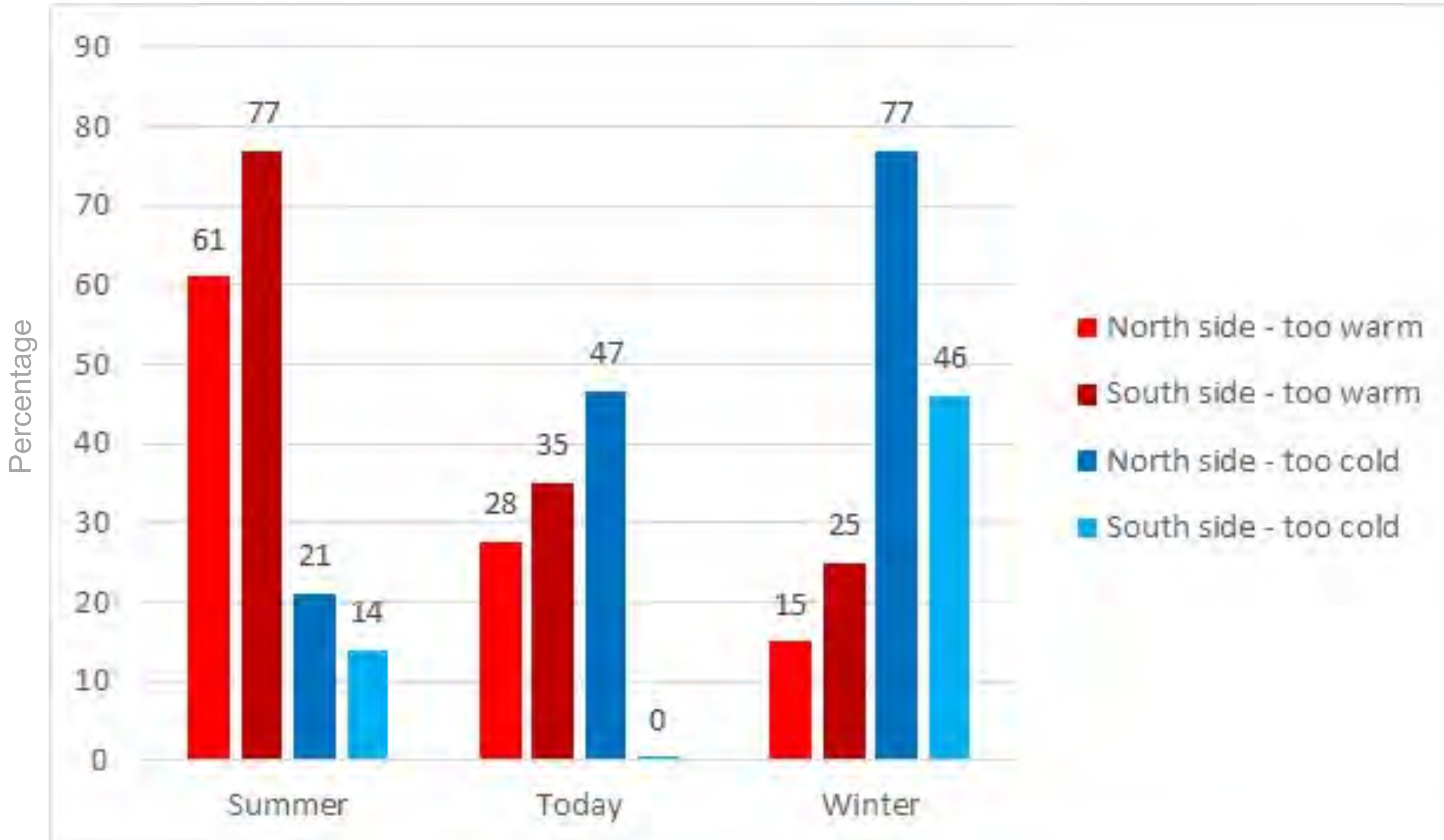
- End of school day (warm day in September).
- Staff – 13 classrooms plus non-classroom staff (n=27).
- Students in Years 3-6 (ages 7-11) – eight classes (n=227).

Objective environmental measurements in selected classrooms.

- Thermal conditions.
- Indoor air quality.
- Noise level.

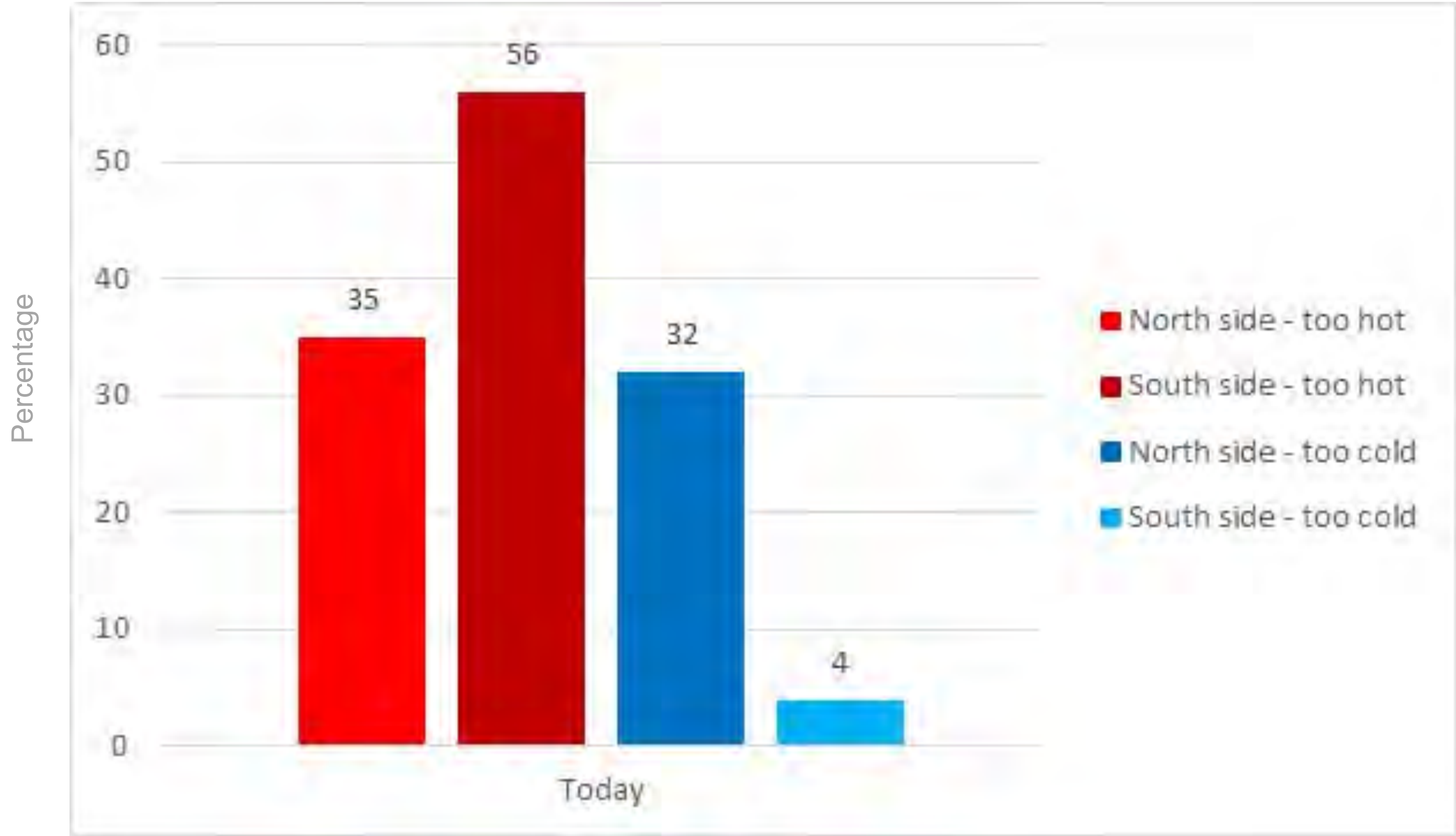
Staff thermal comfort

Able to report being sometimes too warm, sometimes too cold, within a day or season.



Student thermal comfort

Able to report being sometimes too warm, sometimes too cold, within a day.



Consistency with other measurements

South side only – two classrooms with ceiling fans, two without.

Fans make it feel cooler – more so at the front of classrooms
(perhaps because of greater downward displacement of HVAC supply air).

With fans running, in two classrooms (centre of the room):

- temperature reduced by 0.3-1.2 °C
- air speed increased by 0.12-0.18 ms^{-1}
- CO_2 concentration reduced by 369-384 ppm

Also consistent with objective and subjective measurements of other environmental variables – overall and by location.

So much to say.

But time's up!

I commend further development of this method to the House

Gary Raw

rawgj@hotmail.com

Supported by **CETEC Foray Ltd**

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Additional slides in case of questions

Students – location and fans

South side only – two classrooms with ceiling fans, two without.

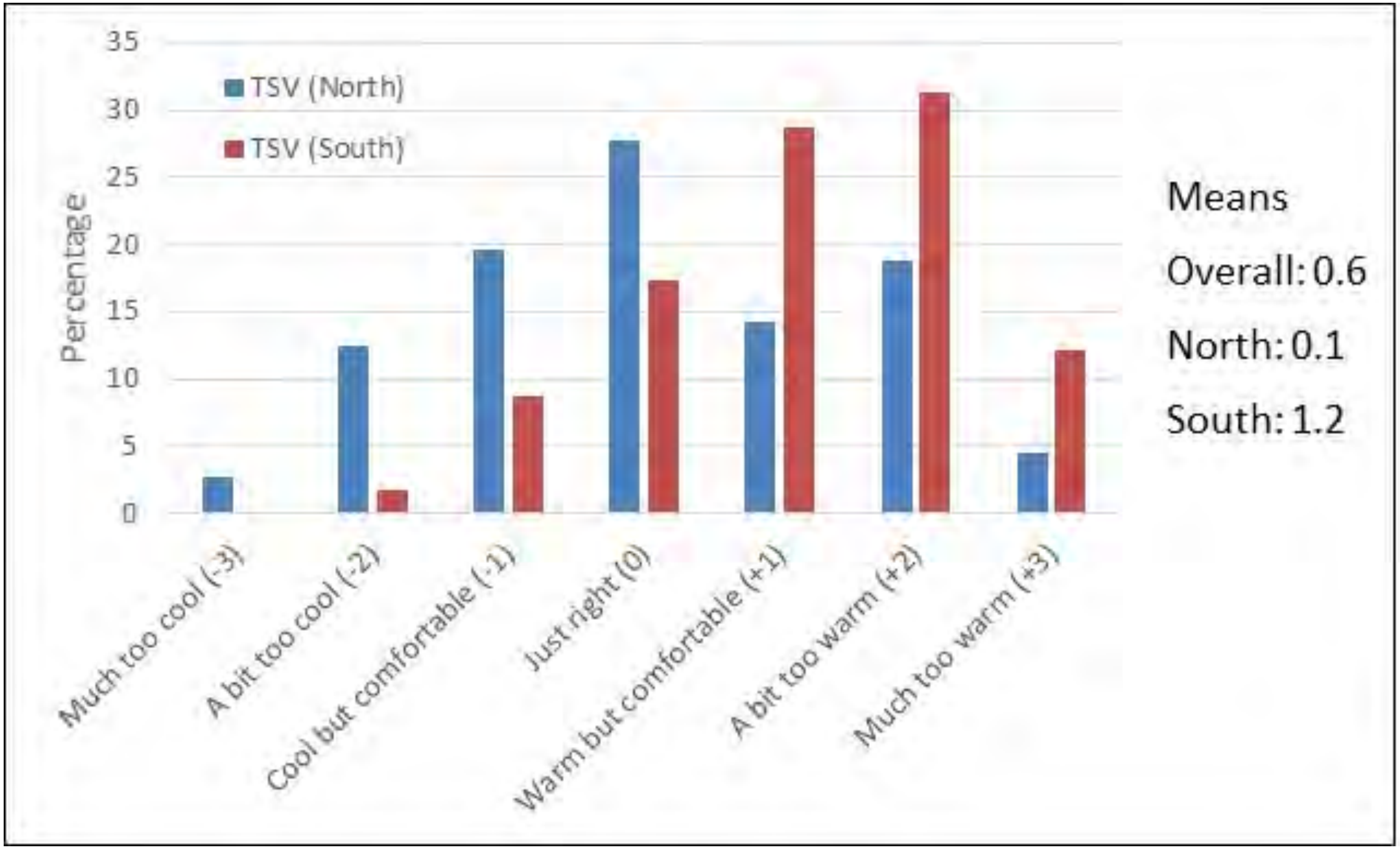
Ratio of [% too hot]:[% too cold].

	Fans	No fans
Front of class	6.9	21.2
Rear of class	15.0	17.4

Fans make it feel cooler – more so at the front of classrooms (perhaps because of greater downward displacement of HVAC supply air).

Student thermal comfort rating

Percentages giving each rating on a 7-point scale.



Presentations

Session 6 - Sixth presenter

Weiner, Sarah

Fraunhofer Institute, Germany

Session 6

Day 2, 15:28

Case Study: Reasons of Office Occupant's Dissatisfaction with an Automated Lighting Control System

S. Weiner

In order to reduce the energy demand of buildings, building automation systems are being used more and more frequently, especially in office buildings. For instance, the presence and brightness in an office room are measured in order to control the lighting based on this data. Such automated lighting control system focus primarily on energy efficiency rather than on the comfort of occupants. Potentially leading to the often reported higher dissatisfied of occupants with automated systems than with a manual controlled systems. This contribution presents data on the current spread of automated lighting control systems in German office buildings, based on survey data from 2018/19. The results confirm an increased dissatisfaction among the occupants with automated control systems. In order to investigate the background to this tendency in more detail, a further survey was carried out in an exemplary office building, together with the evaluation of the building automation data. In this building an automated lighting system, which adjusts the level of illumination depending on the brightness in the room once it has been activated and automatically switches off after an hour of inactivity in the office, is used. The results of this study characterize several sources of discomfort in the context of the building under investigation and highlight differences in the occupant behavior based on the distinct levels of satisfaction with the lighting control system. The presented findings contribute to a better understanding of the reasons for dissatisfaction and adaptive occupant behavior regarding automated office lighting control systems.

CASE STUDY:
REASONS OF OFFICE OCCUPANT DISSATISFACTION WITH AN AUTOMATED LIGHTING CONTROL SYSTEM

M. Sc. Sarah Weiner

Fraunhofer
IBP

Gefördert durch:
Bundesministerium für Wirtschaft und Energie
aufgrund eines Beschlusses des Deutschen Bundestages

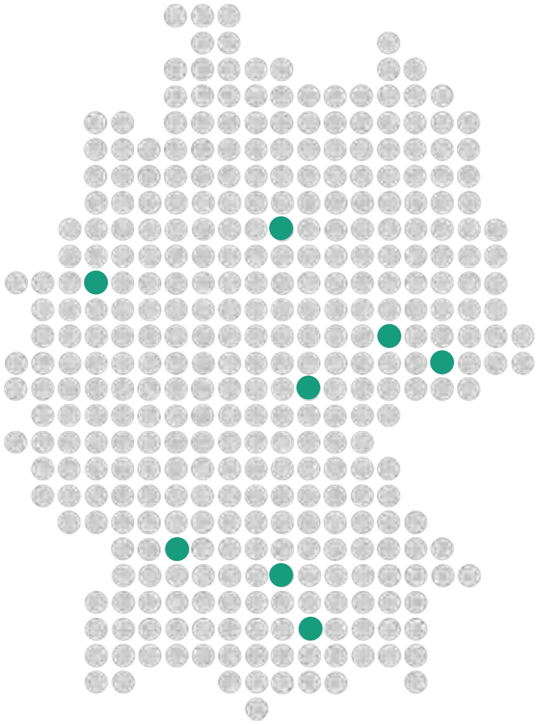
offen

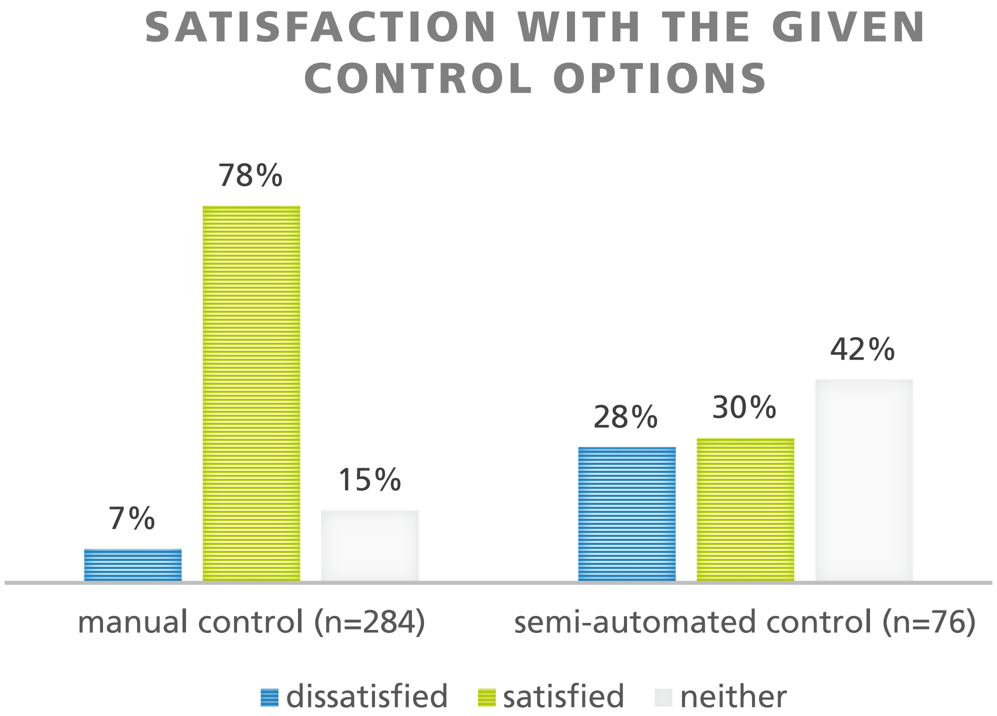
Case Study - CONTEXT
Lighting control options in German Offices

Results of a German-wide survey conducted in February 2019:

365 valid questionnaires

25 buildings in 8 cities





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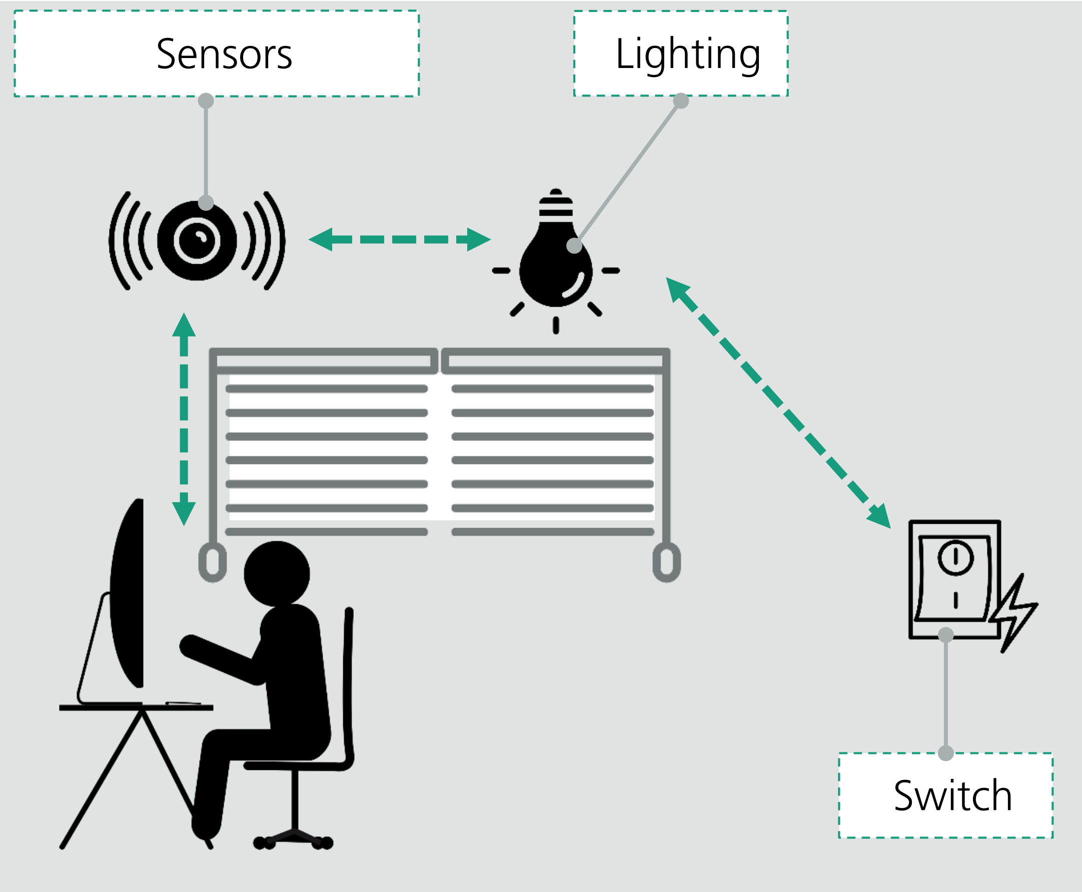
Case Study - QUESTIONS

WHAT ARE THE REASONS FOR OCCUPANT DISSATISFACTIONS?

DO DISSATISFIED OCCUPANTS BEHAVE DIFFERENT THAN THE OTHERS?

Case Study - SITE
Characteristics of offices and lighting control



Offices:

- ribbon facade
- 3 floors
- computer-based desk work

Manual Control via Switch :

- manual switch on / off
- manual dimming

Semi Automated Control:

- automated dimming according to illuminance in the room
- automatic switch-off for absences longer than 60 min

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Case Study – MAIN FINDINGS

Questionnaire Survey: August 2019

SAMPLE

1 building

58 valid responses

Reasons for Dissatisfaction

- Automatic dimming is irritating
- No switching off, although the room is bright enough
- Individualized configurations are not possible
- Control logic not comprehensive

Building Data: 02. – 20. December 2019

SAMPLE

9 single occupied rooms

3 rooms per type of satisfaction (satisfied, neither, dissatisfied)

orientation to the east

Behavior of Dissatisfied Occupants

- highly demand-oriented behavior:
  - Actively increase the lighting levels when automation has dimmed it down
  - Usage primarily in the twilight hours

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Presentations

Session 6 - Seventh presenter

Mahdavi, Ardeshir &

Berger, Christiane

TU Wien, Austria

Session 6

Day 2, 15:32

Impact of Visual and Auditory Factors on Perceived Thermal Comfort: A Case Study

A. Mahdavi, C. Berger

The present contribution reports on a case study of multi-aspect indoor-environmental exposure situations. As with a number of similar efforts, this research is motivated by the circumstance that most available human comfort models (as well as related standards and guidelines) focus on one indoor-environmental independent variable at a time. In other words, thermal, visual, auditory, and olfactory aspects are typically addressed in isolation. Whereas past research has – to some extent – explored multi-domain exposure situations, there is a need for continued research in this area. In this context, the present contribution describes an empirical research study that was conducted under controlled conditions in two small office-like units in a laboratory. The thermal conditions can be controlled in these units. Moreover, the lighting settings in the units can be arranged in different ways. In addition, outdoor soundscape (for example, traffic noise) can be emulated in the larger laboratory space that houses the office units. Small groups of participants experienced – on a short-term occupancy basis – similar thermal conditions in the two units, but different visual or acoustical conditions. Using customized evaluation scales, the participants provided feedback regarding their perception of thermal, visual, and acoustical conditions. The results of the experiments were analyzed to determine if and to which extent evaluations of similar thermal conditions were influenced by differences in other (i.e., visual or auditory) variables.

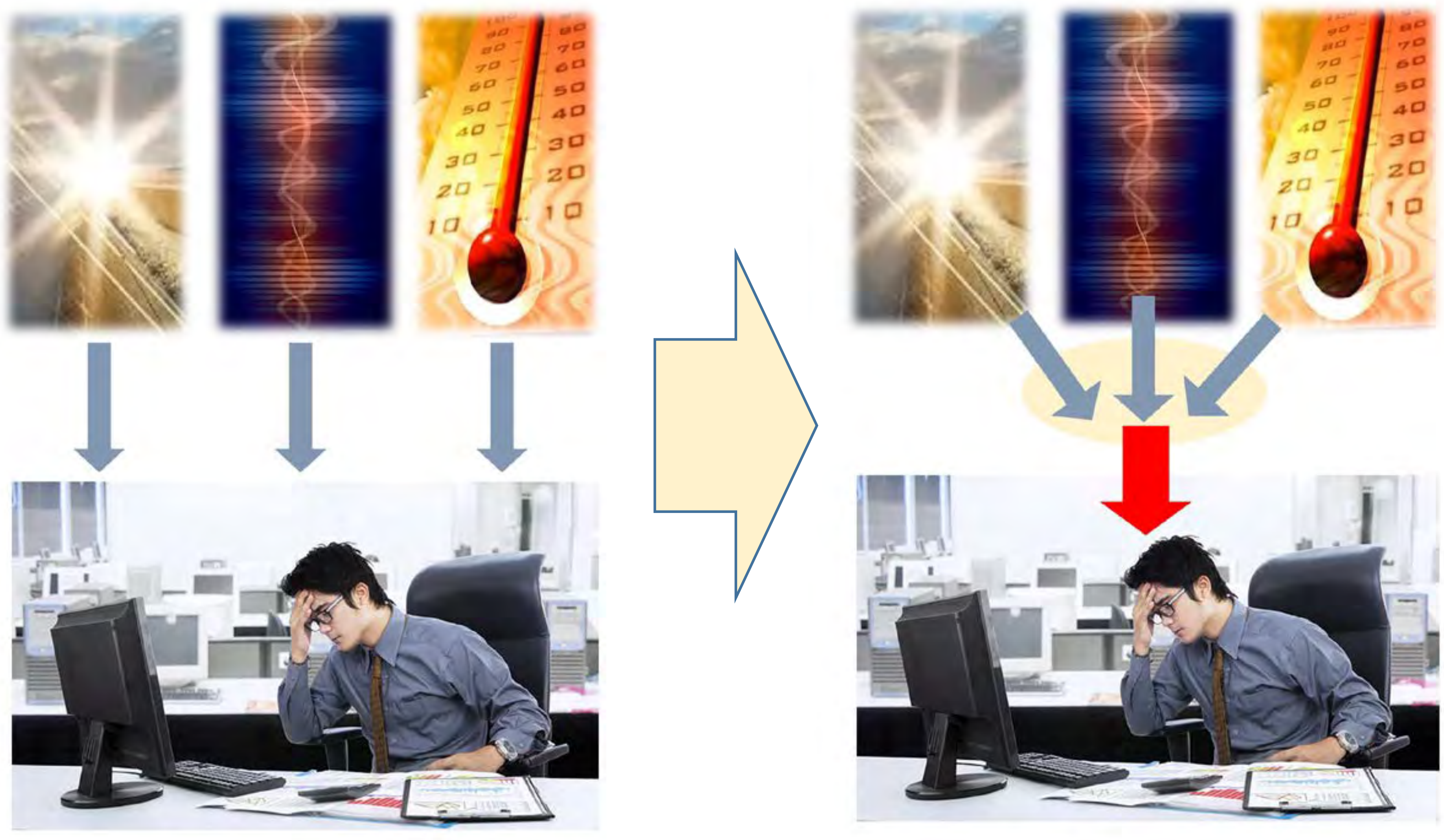
Impact of visual and auditory factors on perceived thermal comfort: A case study

Ardeshir Mahdavi and Christiane Berger

Department of Building Physics and Building Ecology
TU Wien, Austria

OB 2020

From mono-causal to multi-domain comfort and behavior models



Challenges of multi-domain research

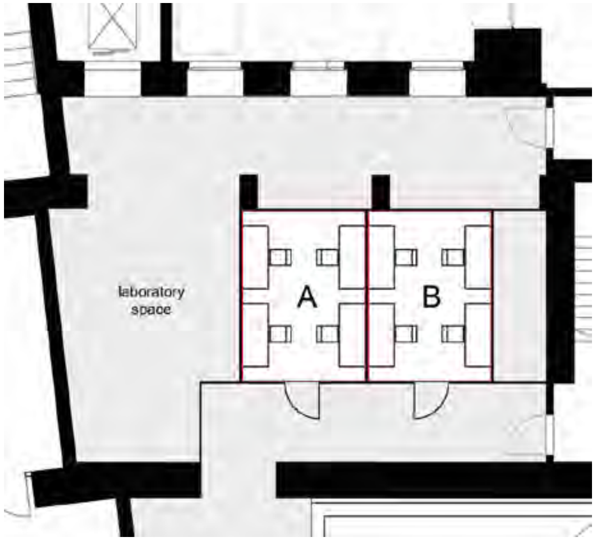
The observed cross-sensory influences:

- Frequently insignificant
- At times contradictory
- Inconclusive

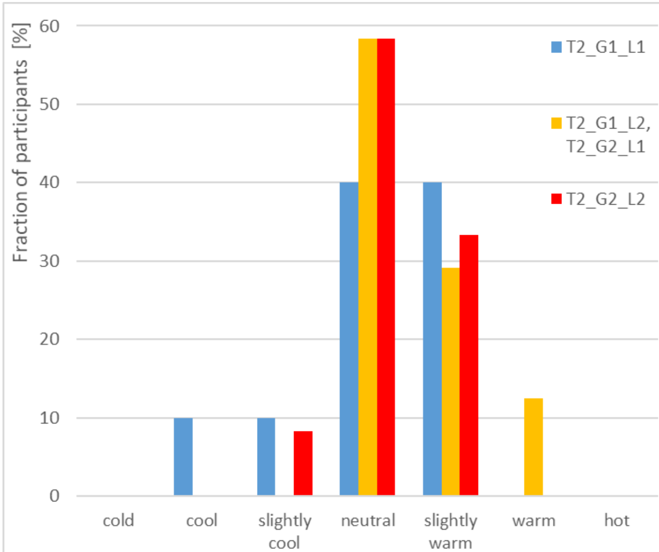
- Short-term
- **Small number of participants** ← 78 + 266 = **344**
- Limited profile of participants
- Mostly artificial (office) settings
- **Privacy and ethical issues**
- **Hawthorne effect**
- Expenditures (time/cost/…)

Experimental settings and design

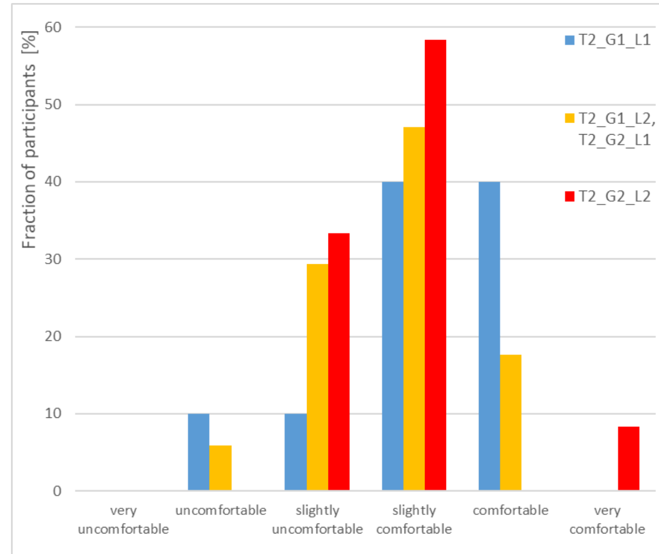
- **Participants**: 78 (49 f + 29 m); 24 to 26 y.o.
- **Sessions**: 45 min; simulated office work
- **Measurements**:
  Temperature, humidity, sound level, illuminance, UGR, CO_2
- **Subjective votes**:
  Thermal, visual, auditory sensation and comfort



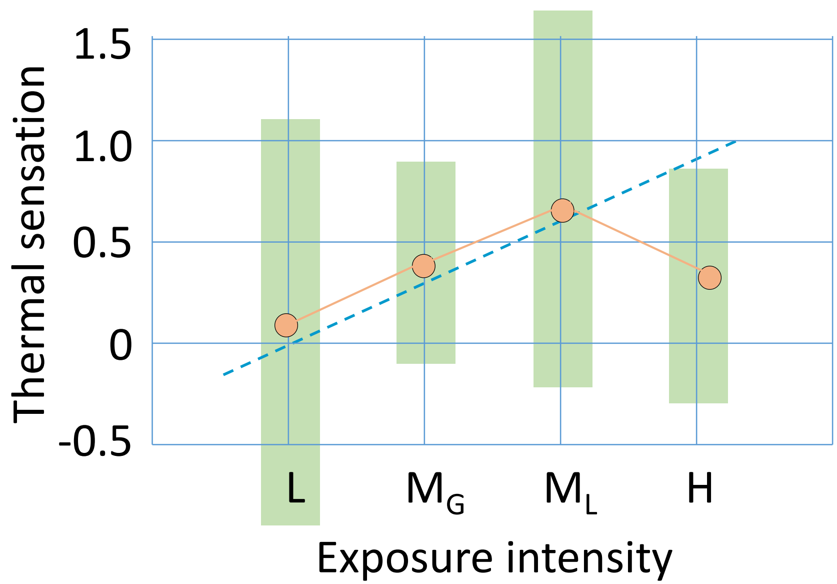
Setting		Temperature [°C]	UGR	L [dB(A)]
i	T1_G1_L1	L	L	L
ii	T1_G2_L1	L	H	L
iii	T1_G1_L2	L	L	H
iv	T1_G2_L2	L	H	H
v	T2_G1_L1	H	L	L
vi	T2_G2_L1	H	H	L
vii	T2_G1_L2	H	L	H
viii	T2_G2_L2	H	H	H



Thermal sensation



Thermal comfort



Challenges of multi-domain research

- Short-term
- **Small number of participants**
- Limited profile of participants
- Mostly artificial (office) settings
- **Privacy and ethical issues**
- **Hawthorne effect**
- Expenditures (time/cost/...)

Looking into the future...

- More long-term and in-situ studies
- Buildings' affordance and social interactions
- **Collaborative and interdisciplinary studies**

Impact of visual and auditory factors on perceived thermal comfort: A case study

Ardeshir Mahdavi and Christiane Berger

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