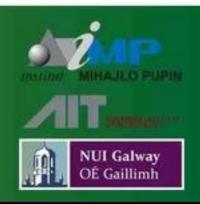


Sensing Optimization for Home Thermostat Retrofit

Dr. Federico Seri

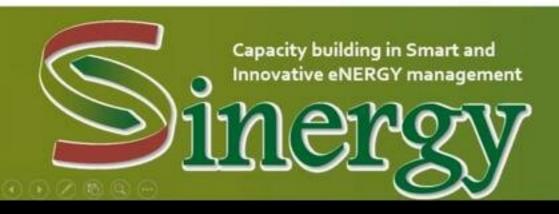






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IRUSE group at the National University of Ireland Galway











Projects



Publications



IBPSA Ireland



Vacancies



Collaborations



Live weather

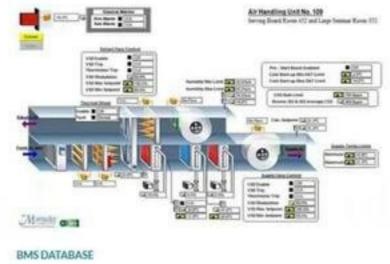
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Agenda:

- > Introduction
- Methodology
- > Test case
- > Discussion
- > Conclusion

Introduction

- > If you can not measure it, you can not improve it Lord Kelvin (Physicist)
- Are you measuring it correctly?

Introduction — Monitoring air temperature

- Monitoring spatial phenomena as indoor air temperature is a challenging task, especially when applied to indoor spaces
- The air temperature, in indoor spaces, is not always homogeneously distributed, so the monitored values can be different from point to point at a given instant.
- Phenomena as air stratification and stagnation may be present, causing significant horizontal and vertical temperature gradients
- This phenomena are generally due to large floor area, high height, high percentage of glazing surfaces, incoming direct solar radiation and heating/cooling sources randomly distributed in the space
- The indoor thermal condition are normally monitored using traditional methods as single temperature sensors



Introduction — Residential building stock

- More than 40% of residential buildings stock in the EU was built before 1960, 90% before 1990 & replacement rate to new building is 1% a year → Old buildings consume more energy → Renovation of exiting building is fundamental!
- Residential building stock has 1-2% a year renovation cycle (low)
- → Construction materials degradation & obsolete heating equipment → Poor Thermal comfort & High Energy consumption!
- > IEA estimates 53% of household energy consumption is for space heating



Building retrofits of heating/cooling control systems could provide an important contribution.



Introduction — Smart thermostat & TRVs

- > Cheap Market Solution -> Smart Thermostats (ST) & Thermostatic radiator valves (TRVs)
- > ST -> Position of installation & Advanced heating control algorithms



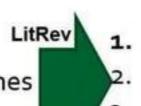


> TRVs -> Extend the monitoring system & Optimal thermal load distribution

Netatmo

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- > ST
 - > Pre-defined temperature setpoint
 - > Shifting setpoints during day/night times
 - Weather compensation



Variation Setpoint temperature – Energy savings

Night Setback temperature – Low Energy savings

Override the default schedule to temperature setpoint that assure **Thermal Comfort**/No energy savings

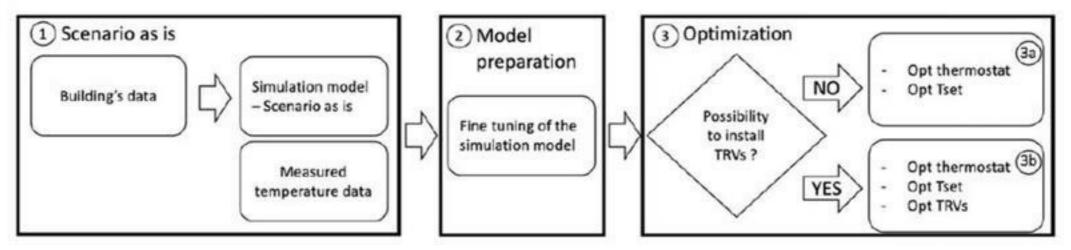
- TRVs
 - > Energy savings: 2-10% Italy
 - > Payback time less than 2.5 heating seasons Poland

Introduction – Novelty

- > Heating system design and operation -> Energy Thermal Comfort Cost
- > Thermal control of multiple rooms → Single-zone thermostat measuring the air temperature in one room, without considering the air temperature differences in the adjacent rooms → Thermal comfort not satisfied in all rooms – only in controlled room
- Thermostat placement design based on experience > Sensing air temperature at the right location in the dwelling is important !!!
- > Studies on indoor air temperature measurement accuracy and thermostat placement have focused on large spaces, not in residential buildings.
- Novelty: Optimal residential heating retrofit α thermostat placement, thermal comfort, advanced heating strategies, and costs.



Methodology - Workflow



- > KPIs: thermal comfort & payback period
- > Output:
- 1. Air temperature sensing strategy (thermostat location) & TRVs
- 2. Optimal air temperature setpoint to be used during the occupied hours.



Methodology – KPIs – POR

- > EN 16798 thermal comfort -> Predictive and Adaptive comfort models

- Residential buildings Occupants: operable windows, adapt their clothing to the thermal conditions, thermal response differs from occupants of buildings with HVAC systems and depends outdoor climate
- > Indoor operative temperatures are compared to external running mean temperature
- Thermal Comfort KPI POR: the percentage of time during which the building operated outside the comfort limits

Methodology – KPIs – POR

- For each room, the hourly operative temperature To was extracted from the simulation model
- > For each day, the outdoor running mean temperature, *Trm* is calculated as:

$$T_{rm,j} = \frac{T_{ed-1} + 0.8T_{ed-2} + 0.6T_{ed-3} + 0.5T_{ed-4} + 0.4T_{ed-5} + 0.3T_{ed-6} + 0.2T_{ed-7}}{3.8} [°C]$$

- Ted-1 is the daily average of hourly external temperatures for the previous day
- Ted-2...7 are the daily averages of hourly external temperatures for the 2nd-7th prior days
- For every room and every hour, the difference between the operative and running mean temperature is calculated as: $\Delta T_i = T_{o,i} 0.33 T_{rm,j} 18.8$ [°C]

Methodology – KPIs – POR

- For every room the number of occupied hours outside the range $(h_{or,i})$ was calculated as the number of occupied hours when $|\Delta Ti| \ge |\Delta T_{lim}|$
- > EN 16798 classification criteria $\rightarrow \Delta T_{lim} = \pm 3 \, ^{\circ}\text{C}$
- > The percentage of occupied hours outside the range is calculated as:

$$POR_i = \frac{h_{or,i}}{h_{tot}} * 100 [\%]$$

- The POR of the entire dwelling is calculated as the average of the POR_i for each
- room, weighted according to the floor area:

$$POR = \frac{\sum_{i=1}^{n} POR_{i} * S_{i}}{\sum_{i=1}^{n} S_{i}} \ [\%] \quad \text{n = number of rooms } \\ \text{Si = floor areas}$$

POR equal or lower than 5% of the occupied hours was considered acceptable

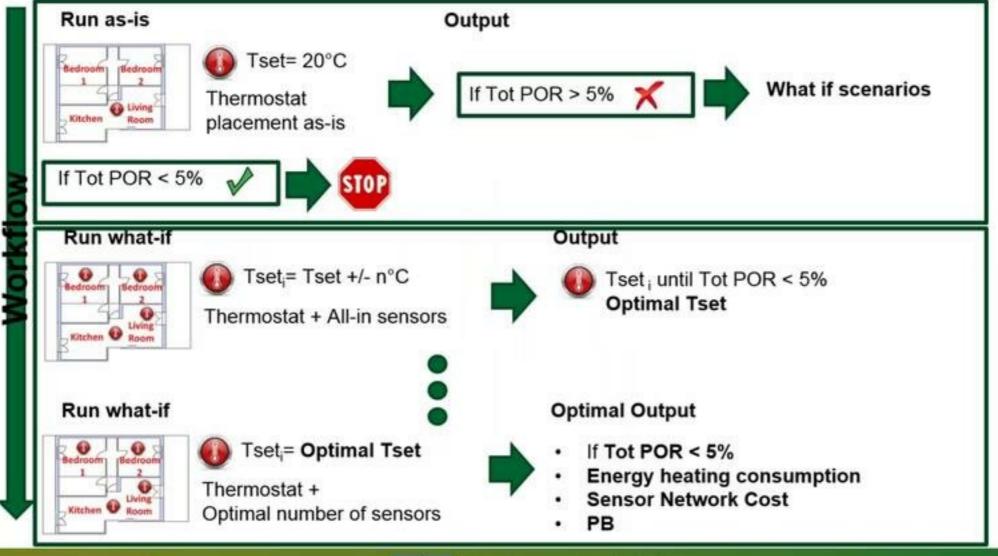
Methodology – KPIs – PB

PB -> simplified payback period for cost analysis

$$PB = \frac{C_{retrofit}}{\left(HC_{baseline, year} - HC_{retrofit, year}\right)}[y]$$

- > C_{retrofit} is the cost of the retrofit solution (smart thermostat and TRVs)
- > HCbaseline, year is the yearly heating energy cost before the retrofit
- > HCretrofit, year is the yearly heating energy cost after the retrofit
- > The lower the PB -> More convenient the retrofit

Methodology – KPIs – PB



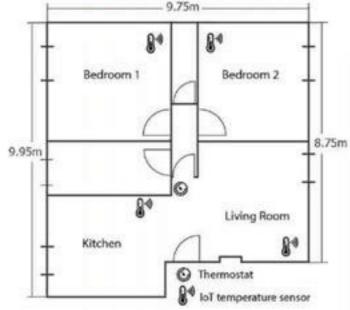


Test case - Residential building

Info	o Value					
Building type	Residential					
Dwelling	Second floor					
Room usage	Kitchen, Living room, Bedroom 1, Bedroom 2, Bathroom 1, Bathroom 2					
Balcony	Two balconies					
Floor hight	3 m					
Location	Jesi (AN), Italy					
Latitude	43.52° N					
Longitude	13.24° E					
Elevation	24 [m]					
External walls	Brickwork (outer leaf) 180 mm, Glass wool 10 mm, Brickwork (inner leaf) 180 mm, Plasterboard 10 mm					
External windows	Outer pane 4 mm, air cavity 8 mm, inner pane 4 mm					
Internal partitions	Plasterboard 10 mm, common brick 100 mm, plasterboard 10 mm					
Roof	Insulation 20 mm, membrane 2 mm, concrete deck 100 mm, plasterboard 10 mm					
Ground/Exposed floor	Insulation 100 mm, Reinforced concrete 100 mm, cavity 50 mm, chipboard flooring 20 mm					
Boiler efficiency	0.73					
Boiler power	23 kW					
Terminals	6 Radiators: 4 Main, 2 Small					
Thermostat location	Kitchen					
Thermostat Tset point	20 °C					
Scheduling	07:00-9:00 a.m. and 06:00-11:00 p.m.					
Heating system	Boiler plus a single-zone thermostat with a dead-band of 1 °C					



Test case – Measurement campaign



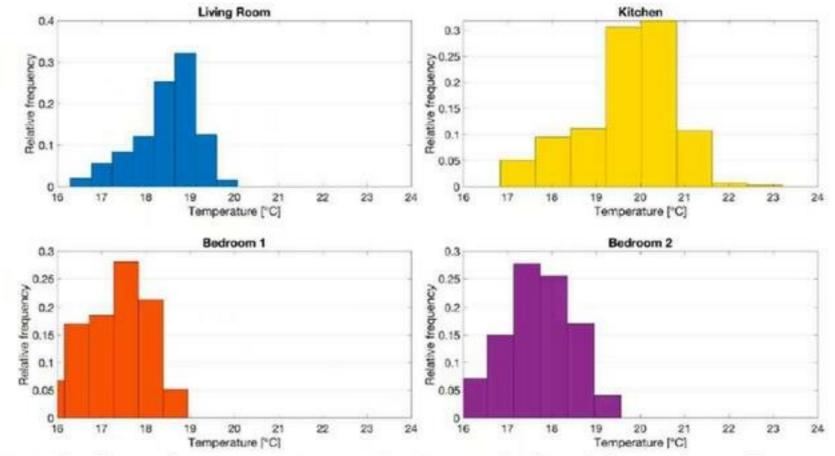
Measurement:

2 weeks in December



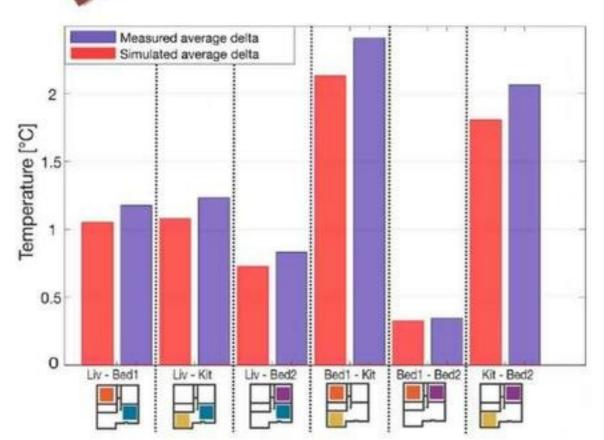
Waspmote board Sensirion SHT75:

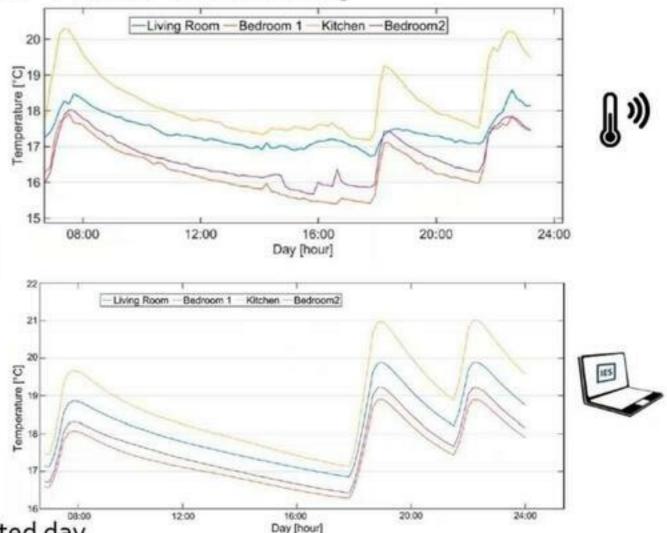
- accuracy 0.4°C
- resolution 0.1°C



Results from the monitoring campaign underlined thermal comfort issues due to the inhomogeneous temperature distribution.

Test case – Model fine tuning





Maximum deviance of 10% between the measured and simulated data (Bedroom1 versus Kitchen) for the selected day

Test case – Optimization results

As-is scenario > Thermostat placed in the kitchen, Tsetpoint 20 °C & POR = 35%

Retrofit Solution	Tset Point	Thermostat Location	POR	Heating Consumption	Energy Cost Post-Retrofit	Retrofit Cost	PB
Raising Tset of existing single zone thermostat	24 °C	Kitchen	3.5%	852 Nm ³	554 €	9	
Smart thermostat + 3 TRVs	21 °C	Kitchen + TRVs in each room	3.7%	717 Nm ³	466 €	375 €	4.2 y
Smart thermostat single zone	21 °C	Bed 1	3.8%	$782\ Nm^3$	508 €	165 €	3.6 y
Smart thermostat single zone	21 °C	Bed 2	4.0%	745 Nm ³	484 €	165€	2.4 y
Smart thermostat single zone	21 °C	Living R	7.7%	686 Nm ³	446 €	165 €	1.5 y

- 1. The best configuration -> the thermostat located in Bedroom 2 with a Tsetpoint of 21 °C
- 2.ST cost of 165 Euro and TRV cost of 70 Euro



Uncertainty Thermostat Placement

Reference Temperature $T_r(t) = \frac{\sum_{i=1}^{n} T_i(t) \cdot A_i}{\sum_{i=1}^{n} A_i}$

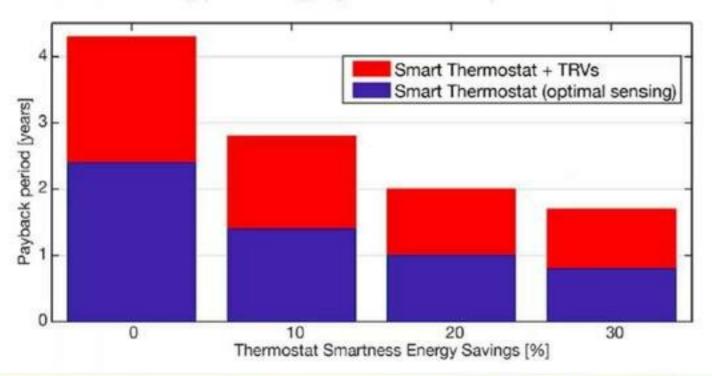
Temperature Timeseries	Mean	STD	Min	Max	
T_r	18.2 °C	±0.8 °C	15.9 °C	22.9 °C	
Tkitchen	19.7 °C	±1.0 °C	16.8 °C	22.2 °C	
$T_{bedroom2}$	17.7 °C	±0.8 °C	14.7 °C	19.6 °C	

- Thermostat installed in the kitchen > Deviation of 1.5 ± 0.4 °C
- Thermostat installed in bedroom 2 > Deviation of 0.6 ± 0.3 °C
- Reducing the uncertainty due to thermostat placement can provide more efficient control of the heating system.



ST algorithms impact

- The retrofit scenario applied to the case study was analysed considering a new thermostat that is capable of simple on/off control with a dead-band of 1°C
- > Energy savings provided by the ST could range from 0 to 30%, compared to non-ST



Best what-if scenario >> PB decreased from two and a half years to less than one year



Reduction of the measurement uncertainty due to the thermostat placement provides properly balanced heating control and right level of thermal comfort, with low PB.

Ref. Seri, F.; Arnesano, M.Keane, M.M.; Revel, G.M. Temperature Sensing Optimization for Home Thermostat Retrofit. Sensors 2021, 21, 3685. https://doi.org/10.3390/s21113685

General comments:

- Data quality and addressing measurement uncertainty is fundamental for development and application of data driven models and optimization algorithms in the context of buildings, and widely to smart grid (i.e. Demand Response applied to residential buildings)
- Collaboration between designers of field measurement system and data scientist in the early stage of the project is fundamental for avoiding high impact on data uncertainty propagation on simulation models and optimization algorithms.

Al application, Ref. Paulo Lissa, Conor Deane, Michael Schukat, Federico Seri, Marcus Keane, Enda Barrett. Deep reinforcement learning for home energy management system control, Energy and Al, Volume 3, 2021, 100043, ISSN 2666-5468, https://doi.org/10.1016/j.egyai.2020.100043.





Thank you - Questions?