From Smart Heat Meters to Diagnostics

Data-driven methodologies for building efficiency assessment within district heating

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Ph.D. defense – Copenhagen, 24th September 2024

About the Ph.D.

- PhD candidate at BUILD – Department of the Built Environment, Aalborg University.
- This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. **893945 (E-DYCE)**. This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. **958345 (PRELUDE)**.

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- **Co-supervision:**

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  Associated Professor Anna Marszal-Pomianowska

AALBORG UNIVERSITY

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- Hourly heating share estimation using smart heat meters — Chapter 3
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- Fault detection and diagnosis with district heating customers — Chapter 5
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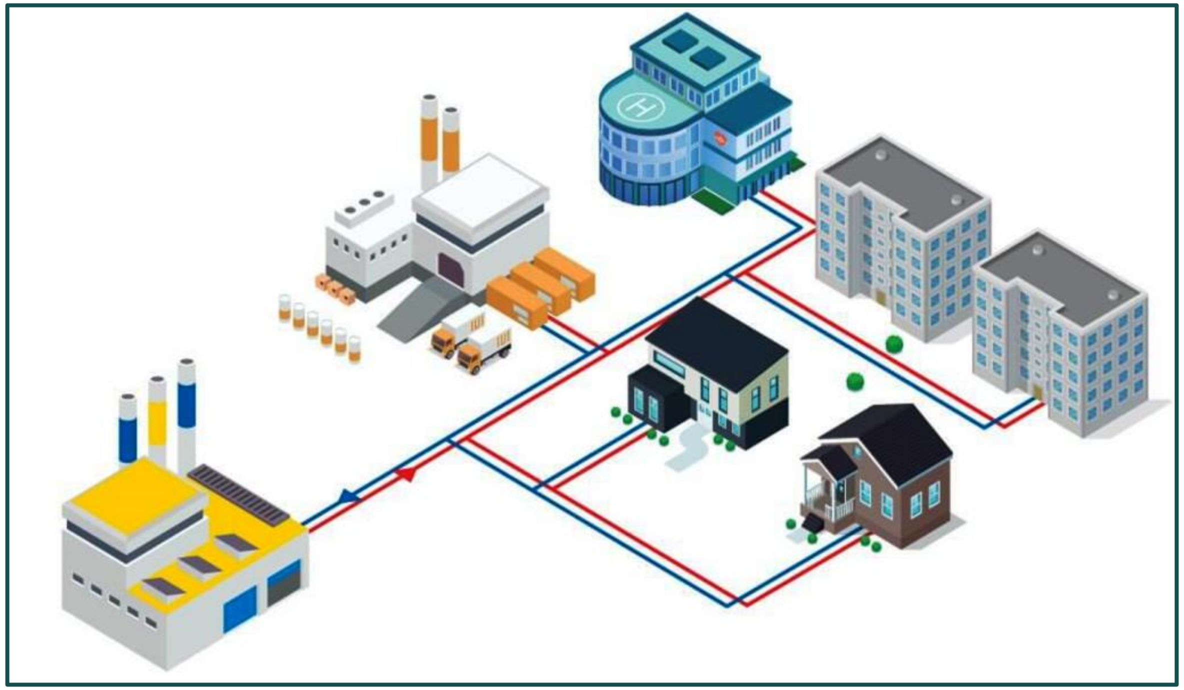
Background

What is district heating?



Source: *Support for renewable district heating in Slovenia," Solarthermalworld. https://solarthermalworld.org/news/support-renewable-district-heating-slovenia/*

District heating (DH) distribute heat from a **central source** to multiple buildings through insulated pipes. This **heat can come from various sources** like cogeneration plants (which produce both heat and electricity), heat-only boilers, geothermal energy, heat pumps, solar heating, or even waste heat from factories. **Compared to individual boilers**, DH systems can be more efficient and greener.

Background

What is EPBD?

Source: *"European Union (EU)," Corporate Finance Institute. https://corporatefinanceinstitute.com/resources/economics/european-union-eu/*

The **Energy Performance of Buildings Directive (EPBD)** is a key legislative framework from the European Union aimed at improving the energy efficiency of buildings. It sets **minimum energy performance standards** for both new and existing buildings, promotes nearly zero-energy buildings, and **encourages renovations** that reduce energy consumption. Additionally, the directive supports the **use of smart technologies** to enhance building efficiency and contributes to the EU's broader goal of achieving carbon neutrality by 2050.

Background

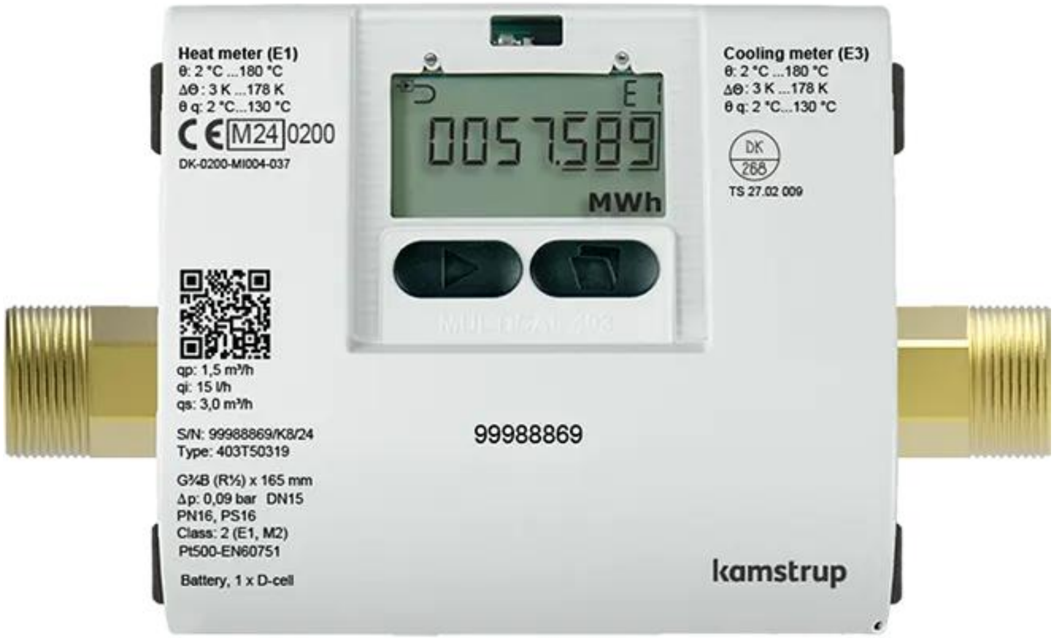
Smart heat meters (SHM) in DH systems

With the widespread of SHM in Denmark, it allows from the start:

- Straightforward billing process
- In-depth understanding of the consumers

But with proper handling, it may also lead to:

Better operational performance	Higher energy efficiency
Cost savings for the consumers	Data-driven decision-making
Environmental impact	Transparency/Trust between the heat provider and the consumers



Source: *Kamstrup, "Smart heat meters and devices,". https://www.kamstrup.com/en-en/heat-solutions/meters-devices (accessed Sep. 24, 2024)*

Content

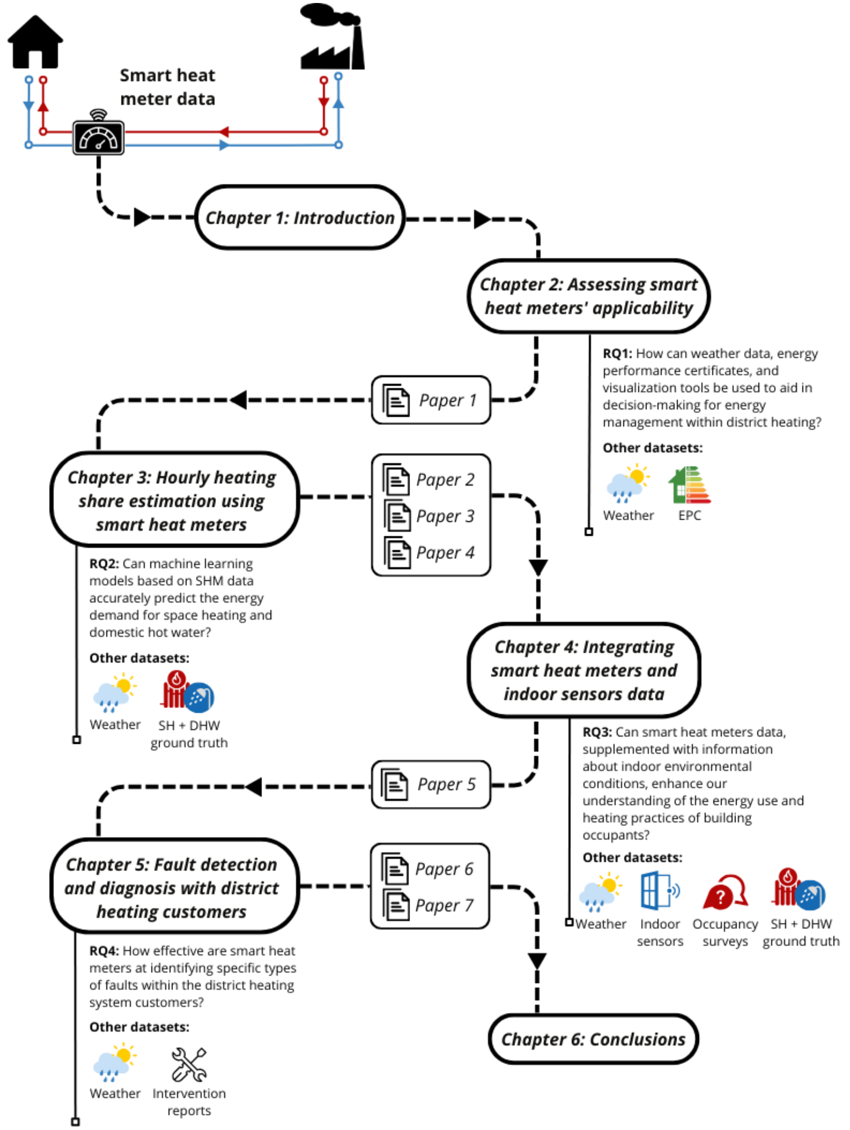
Research questions

RQ1. How can weather data, energy performance certificates, and visualization tools be used to aid in decision-making for energy management within district heating?

RQ2. Can machine learning models based on smart heat meter data accurately predict the energy demand for space heating and domestic hot water?

RQ3. Can smart heat meter data, supplemented with information about indoor environmental conditions, enhance our understanding of the energy use and heating practices of building occupants?

RQ4. How effective are smart heat meters at identifying specific types of faults within the district heating system customers?



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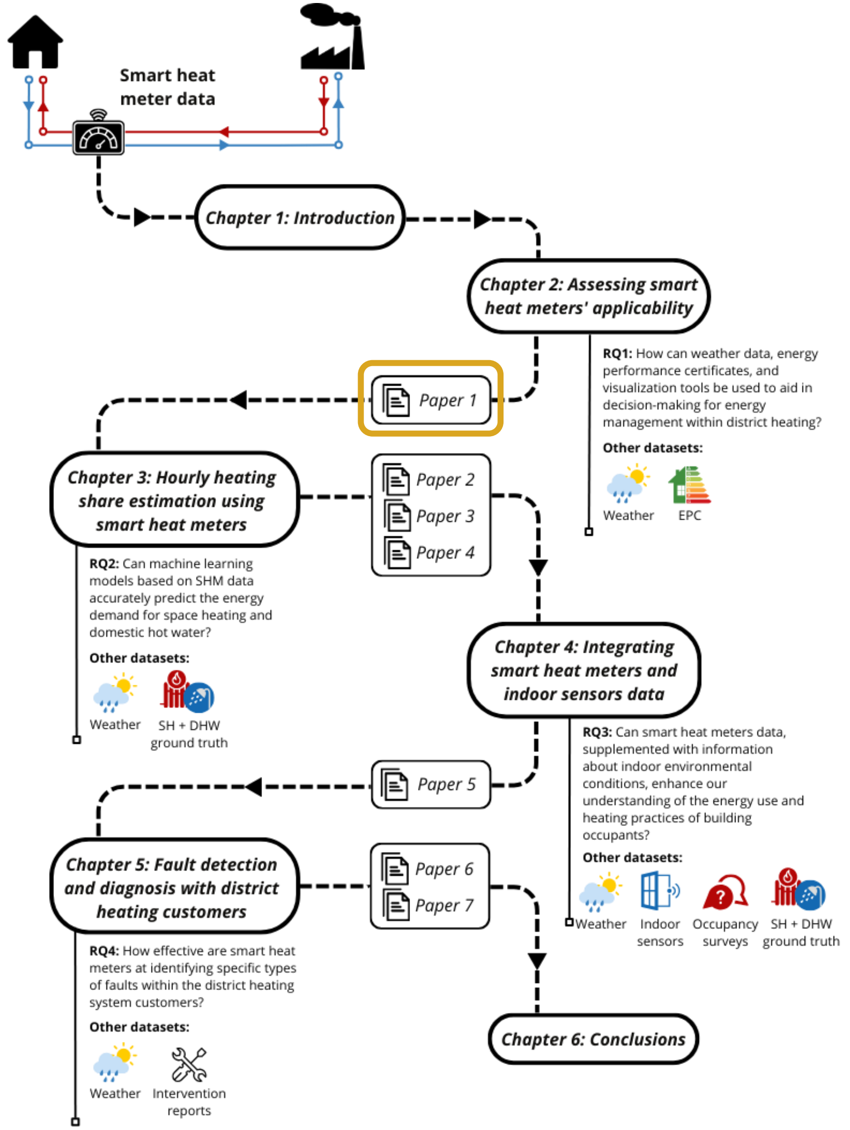

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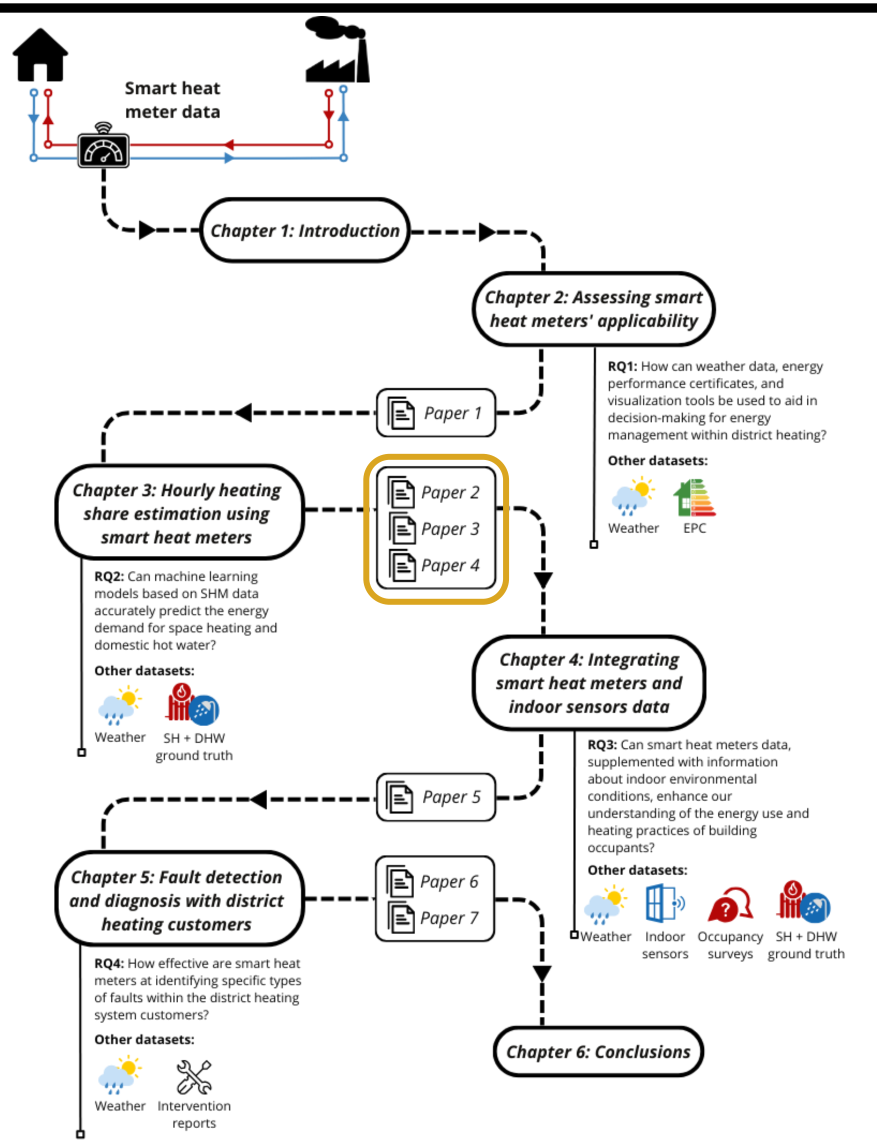

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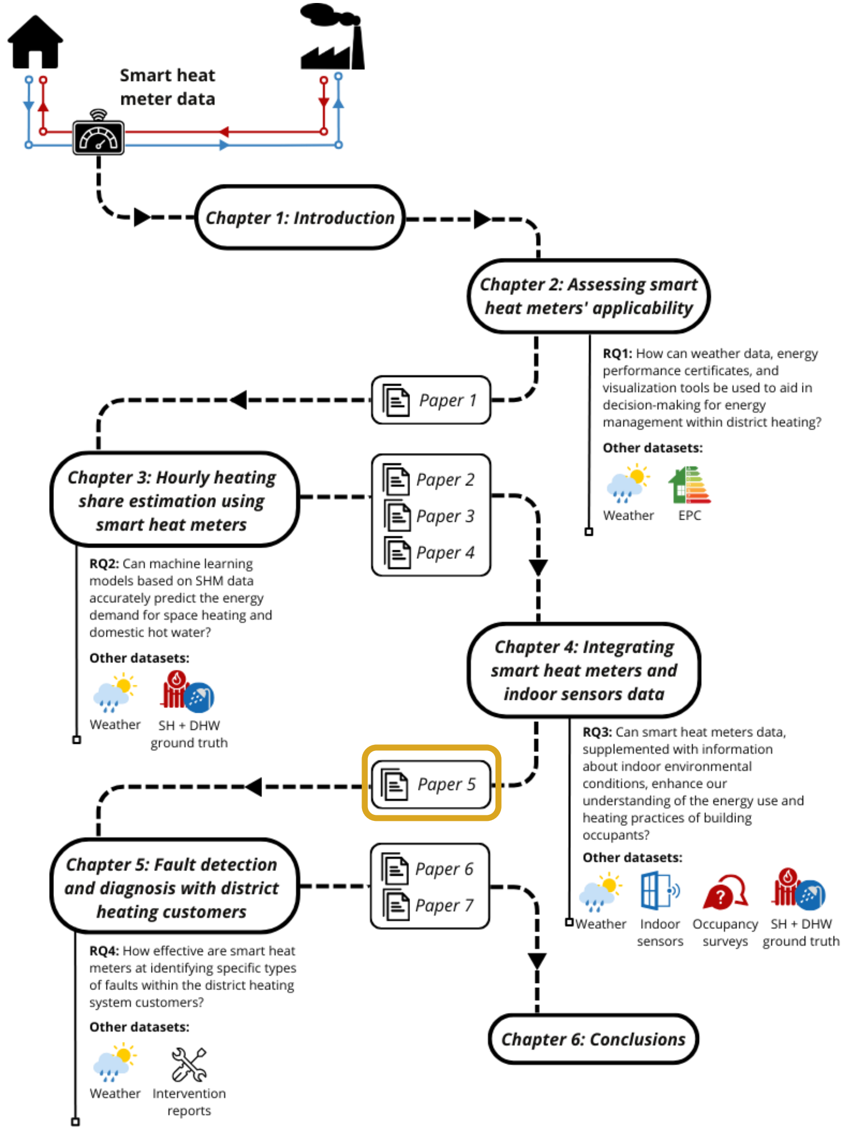

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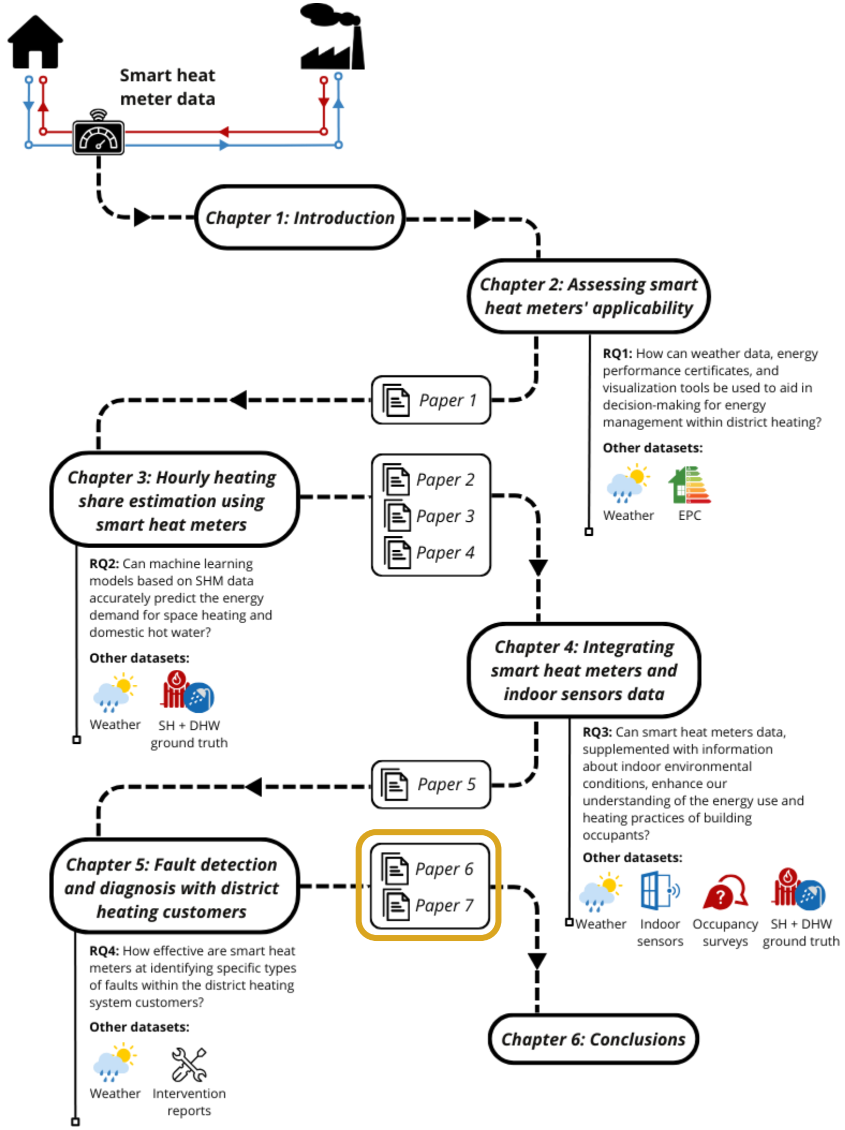

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Publications overview

Main research

Paper 1. ***Using data from smart energy meters to gain knowledge about households connected to the district heating network: A Danish case***

D. Leiria, H. Johra, A. Marszal-Pomianowska, M. Z. Pomianowski, P. K. Heiselberg, Smart Energy 2021

Paper 2. ***A methodology to estimate space heating and domestic hot water energy demand profile in residential buildings from low-resolution heat meter data***

D. Leiria, H. Johra, A. Marszal-Pomianowska, M. Z. Pomianowski, Energy 2022

Paper 3. ***Validation of a new method to estimate energy use for space heating and hot water production from low-resolution heat meter data***

D. Leiria, H. Johra, E. Belias, D. Quaggiotto, A. Zarrella, A. Marszal-Pomianowska, M. Z. Pomianowski, BuildSim Nordic Conference 2022, Copenhagen, Denmark

Paper 4. ***Estimating residential space heating and domestic hot water from truncated smart heat data***

D. Leiria, M. Schaffer, H. Johra, A. Marzsal-Pomianowska, M. Z. Pomianowski, CISBAT 2023, Lausanne, Switzerland

Publications overview

Main research

Paper 5. ***From showers to heaters: Evaluating the different factors that play a role in buildings' energy signature***

D. Leiria, H. Johra, Y. Hu, O. K. Larsen, A. Marszal-Pomianowska, M. Frandsen, M. Z. Pomianowski, Submitted in Energy and Buildings, 2024

Paper 6. ***Towards automated fault detection and diagnosis in district heating customers: generation and analysis of a labeled dataset with ground truth***

D. Leiria, K. H. Andersen, S. P. Melgaard, H. Johra, A. Marszal-Pomianowska, M. S. Piscitelli, A. Capozzoli, M. Z. Pomianowski, IBPSA Building Simulation 2023, Shanghai, China

Paper 7. ***Is it returning too hot? Time series segmentation and feature clustering of end-user substation faults in district heating systems***

D. Leiria, H. Johra, J. Anoruo, I. Praulins, M. S. Piscitelli, A. Capozzoli, A. Marszal-Pomianowska, M. Z. Pomianowski, Submitted in Applied Energy, 2024

Publications overview

Supplementary research

Paper I. ***Increasing the accuracy of low-resolution commercial smart heat meter data and analysing its error***

M. Schaffer, D. Leiria, J. E. Vera-Valdés, A. Marszal-Pomianowska, EC3 Conference 2023, Crete, Greece

Paper II. ***Who Produces the Peaks? Household Variation in Peak Energy Demand for Space Heating and Domestic Hot Water***

A. R. Hansen, D. Leiria, H. Johra, A. Marszal-Pomianowska, Energies 2022

Paper III. ***Detailed operational building data for six office rooms in Denmark: Occupancy, indoor environment, heating, ventilation, lighting and room control monitoring with sub-hourly temporal resolution***

S. P. Melgaard, H. Johra, V. Ø. Nyborg, A. Marszal-Pomianowska, R. L. Jensen, C. Kantas, O. K. Larsen, Y. Hu, K. M. Frandsen, T. S. Larsen, K. Svidt, K. H. Andersen, D. Leiria, M. Schaffer, M. Frandsen, M. Veit, L. F. Ussing, S. M. Lindhard, M. Z. Pomianowski, L. Rohde, A. R. Hansen, P. K. Heiselberg. Data in Brief 2024

Paper IV. ***A Mixed-Method Approach to Understand Energy-Related Occupant Behavior and Everyday Practices in Multi-Story Residential Buildings***

K. H. Andersen, A. R. Hansen, A. Marszal-Pomianowska, H. N. Knudsen, D. Leiria, P. K. Heiselberg. Under review in Energy and Buildings (2024).

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Assessing smart heat meters applicability

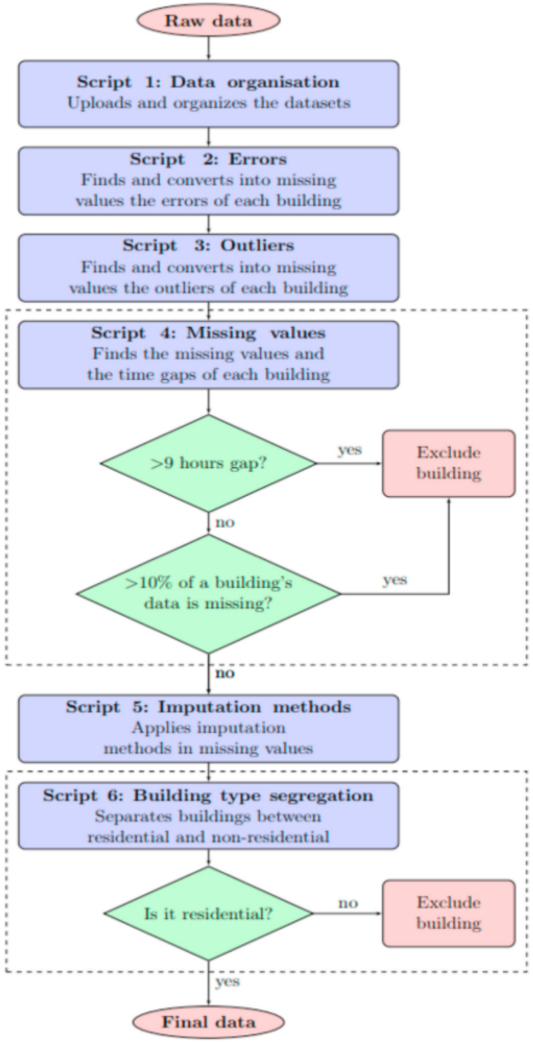
Methodology: Data pre-processing

SHM measurements:

Variable	Type	Units
Heat energy	Cumulative	1 kWh
Volume (flow)	Cumulative	0.01 m^3
Volume (supply) × Supply temp.	Cumulative	1 m^3°C
Volume (supply) × Return temp.	Cumulative	1 m^3°C
Supply temperature	Instantaneous	1°C
Return temperature	Instantaneous	1°C

Hourly resolution

Several scripts were developed to treat the data before its analysis, reducing the initial dataset of 1665 buildings to 969 (≈58%).



Assessing smart heat meters applicability

Methodology: Data pre-processing

Weather data: outdoor temperature, wind speed and solar radiation retrieved from DMI* – the closest weather station.

Energy performance certificates (EPC) – extracted manually

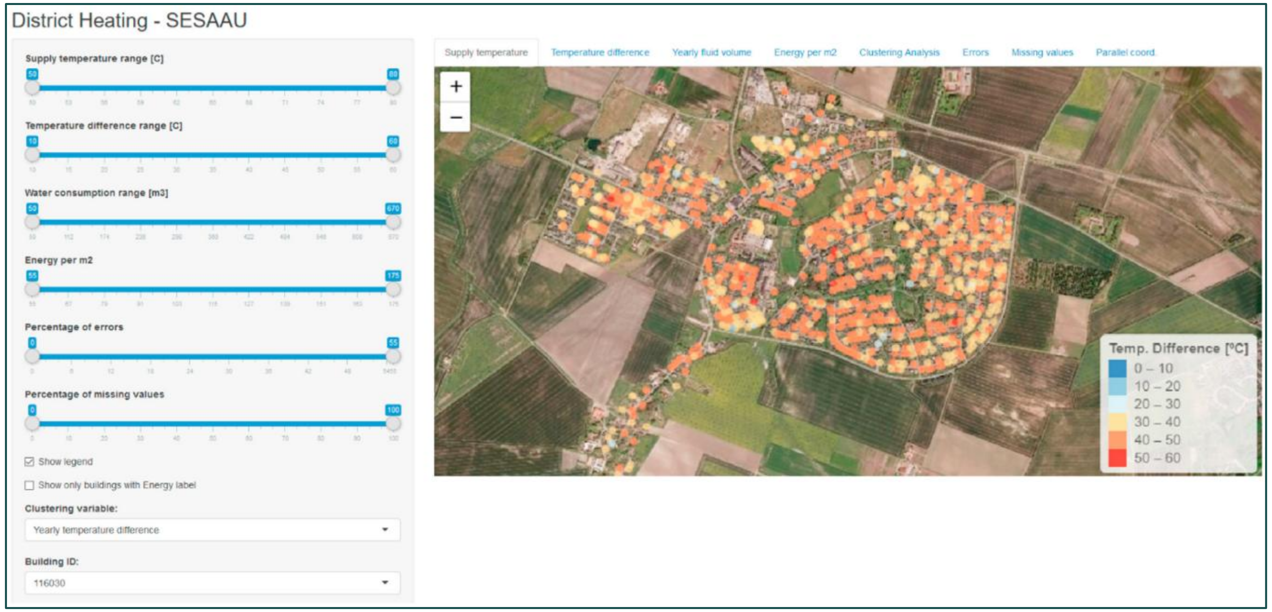
EPC label	Nr. of buildings
A2020	2
B	16
C	8
D	10
E	3
F	1
G	1
Total	41

DMI: Danish Meteorological Institute

Assessing smart heat meters applicability

Methodology

- Data filtering to observe weather conditions impact on the heating usage.
- Development of visualization tools



$$E_{demand} = E(T_{out}) = -(UA + nc_p\rho)T_{out} + (UA + nc_p\rho)T_{int} - E_{solar} - E_{int}$$

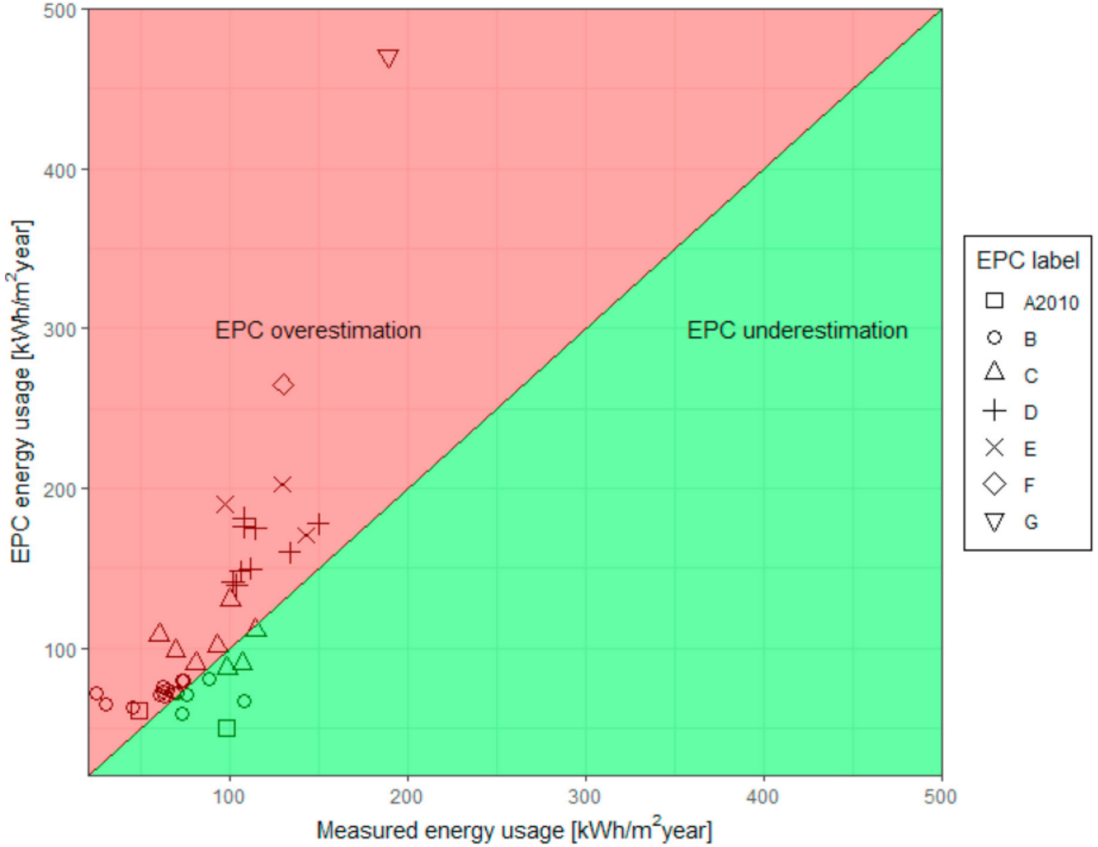
Subset filtering conditions.

Isolated energy component	Solar radiation (R_d) [W/m^2]	Wind speed (v_{wind}) [m/s]
Transmission losses (Outdoor temperature)	0	≤2
Solar gains (Solar radiation)	>30	≤2
Ventilation and infiltration losses (Wind speed)	0	>3

Assessing smart heat meters applicability

Results

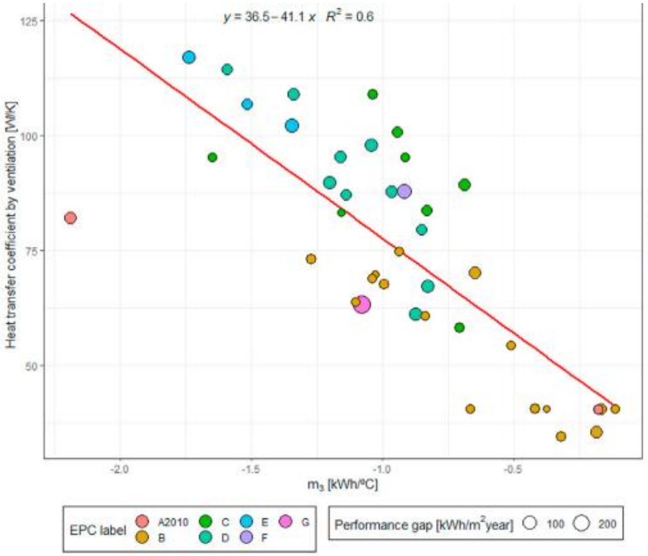
- Mostly analyzed buildings have an **overestimated EPC.**

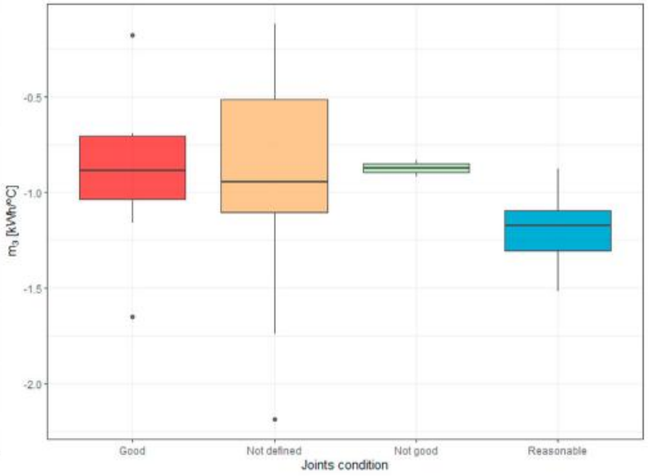


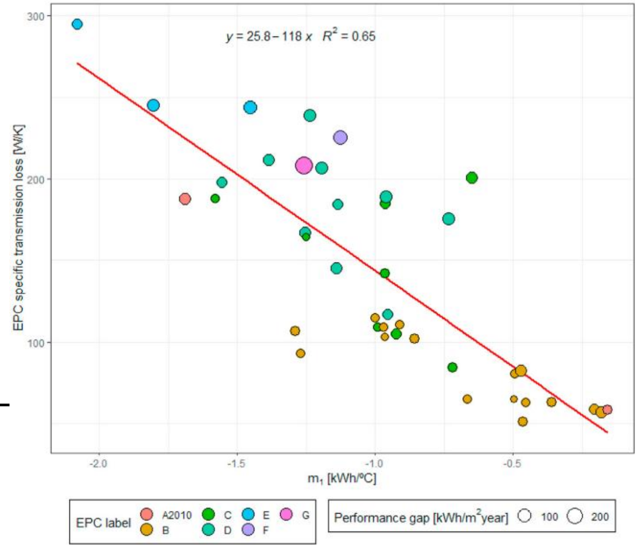
Assessing smart heat meters applicability

Results

- Mostly analyzed buildings have an **overestimated EPC.**
- **Outdoor temperature and wind speed** show **interesting** values while **solar radiation is inconclusive** (due to Aalborg weather).
- The EPC data also shown a **lot of problems** as they are highly dependent on the **assessor's knowledge** and inputs as well as the **building standard values** provided in the national building standards.







Assessing smart heat meters applicability

Influence of this research on subsequent studies

Topic	Ref.	Description
DH data curation	Schaffer, Tvedebrink, and Marszal-Pomianowska (2022)	Explored missing data imputation with a larger DH dataset.
DH data curation	Søndergaard, Shaker, and Jørgensen (2024)	Referenced **Paper 1** for data preprocessing in a study in Odense.
Energy and weather data analysis	**Hansen et al. (2022)***	Investigated household factors (employment, income, etc.) affecting energy peaks at consumer level.
Energy and weather data analysis	Schaffer, Vera-Valdés, and Marszal-Pomianowska (2024)	Used co-clustering to group similar energy patterns and linked them to EPC reports.

Assessing smart heat meters applicability

Further discussion

- One of the limitations of this work was the lack of understanding of the heating demand regarding the space heating (SH) and domestic hot water (DHW).
- The **next step of this work** focuses on developing a methodology using weather data and machine learning (ML) to estimate these energy shares individually.

Content

Hourly heating share estimation using SHM

Background

- There is a need to estimate SH and DHW in residential cases.
- Previous methods to disaggregate heating measurements have drawbacks, such as:
  - Reliance on multiple sources of information (usually inexistent)
  - Difficulties with 1-hour resolution data (usually require higher measurements resolution)

Hourly heating share estimation using SHM

Methodology

Paper 2:

- Proposal of the disaggregation and estimation of SH and DHW
- Validation of the method with Danish dataset
- Comparison with Danish Standards to estimate DHW

Paper 3:

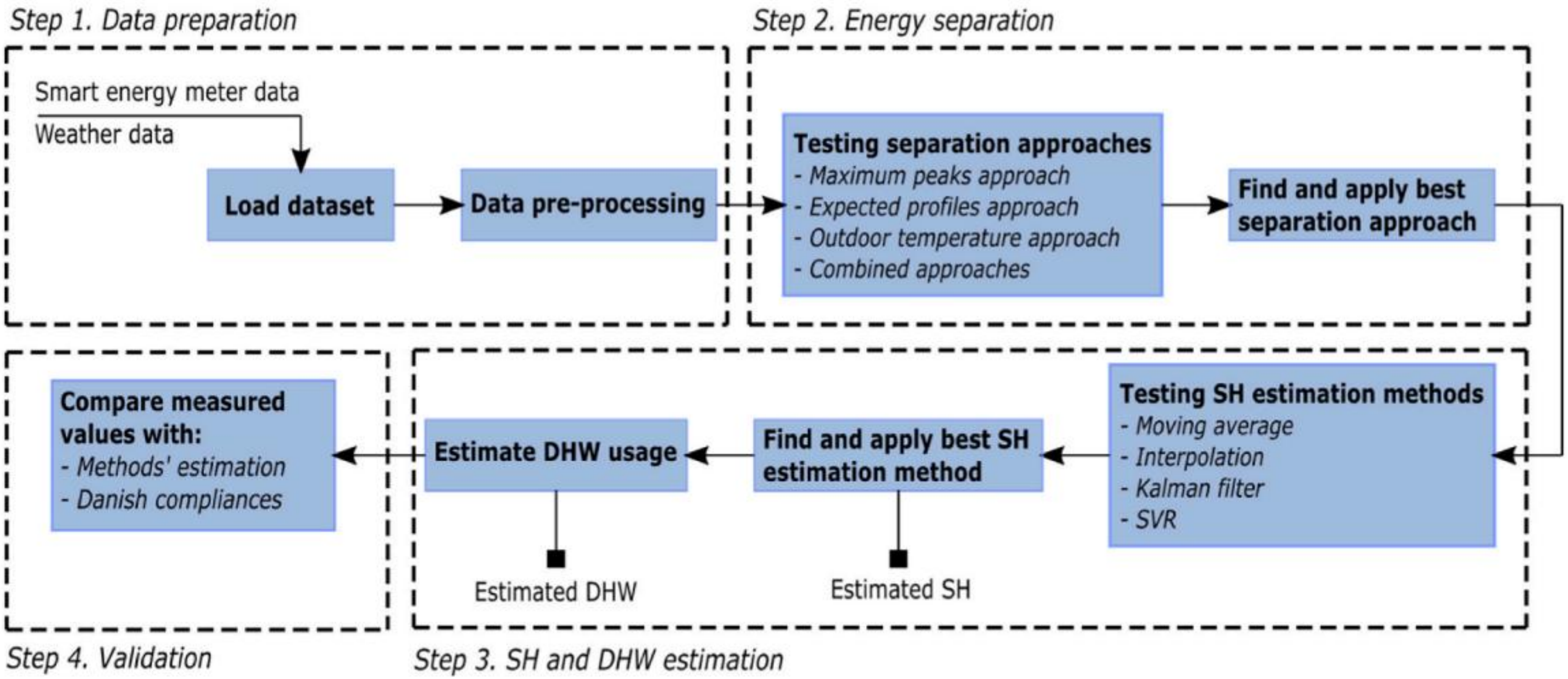
- Application of the methodology in Swiss and Italian cases (non-residential buildings)
- Assessment of the SHM data truncation on the estimation methodology

Paper 4:

- Application SPMS method (Schaffer et al., 2024) to "de-truncate" SHM data before SH+DHW estimation methodology.

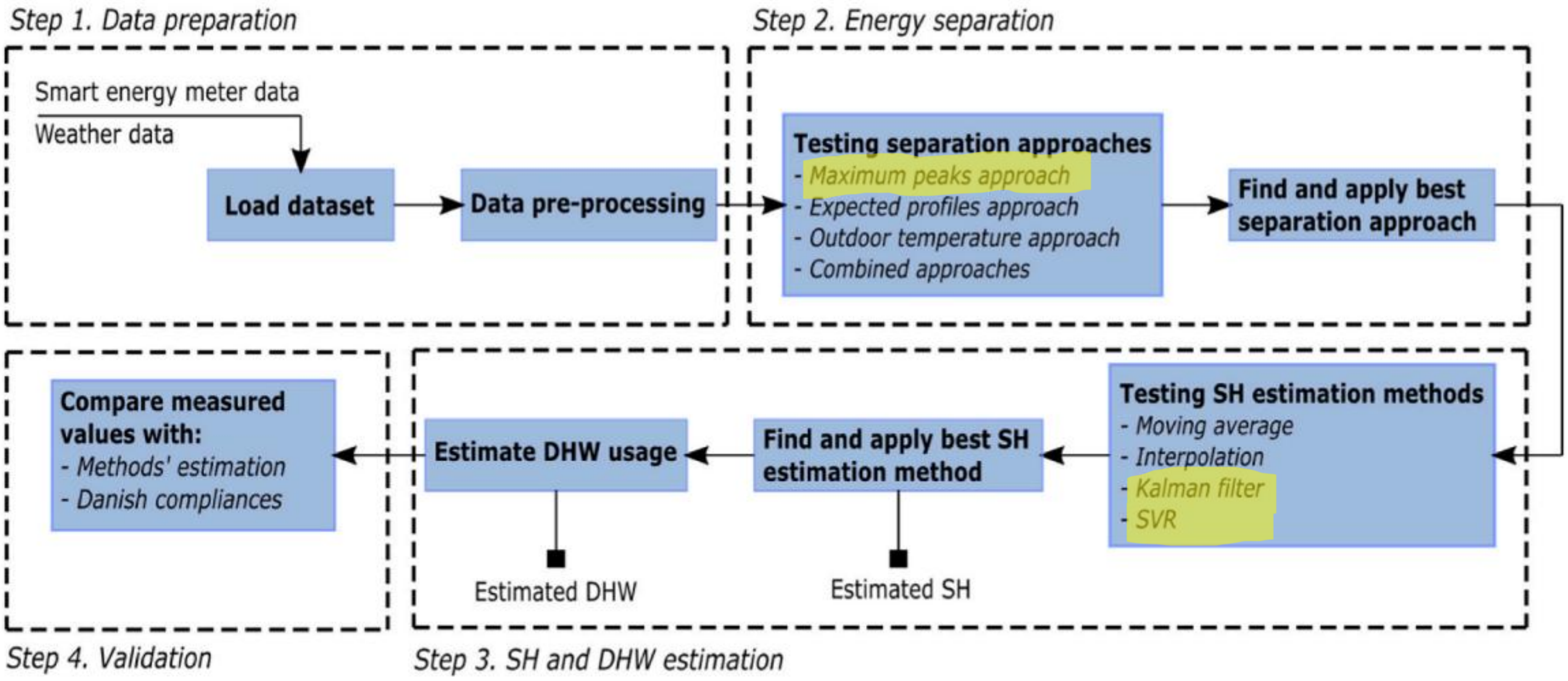
Hourly heating share estimation using SHM

Methodology



Hourly heating share estimation using SHM

Methodology



Hourly heating share estimation using SHM

Results – Paper 2

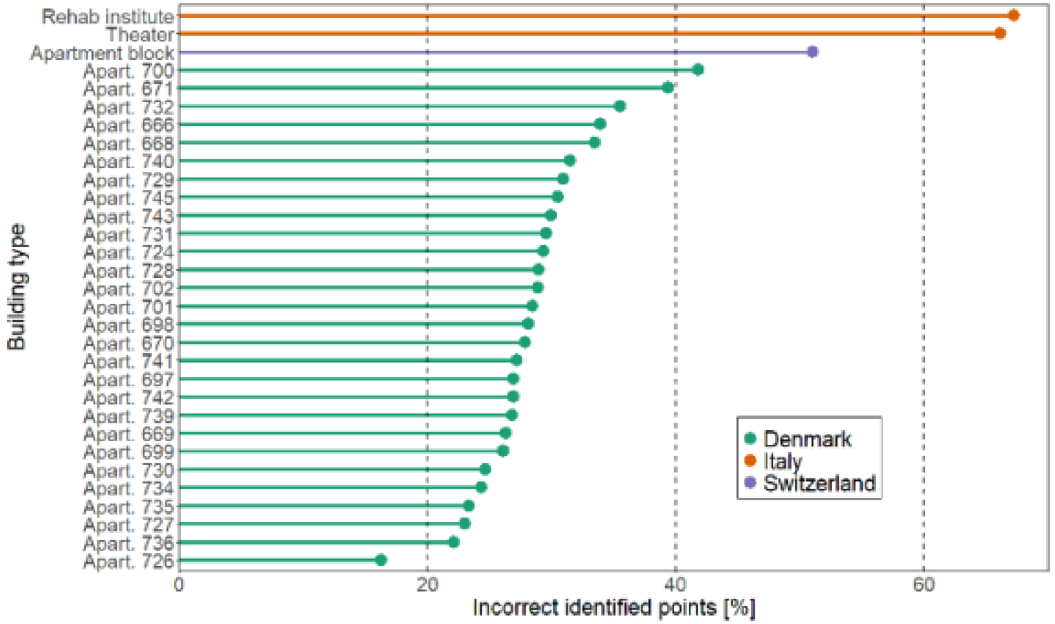
- The estimator predict better the DHW usage than the Danish standards.
- However, this method was tested with decimal data and not truncated.

Apartment ID	Area [m^2]	E_{DHW} [kWh/h]	$E_{DHW, compl}$ [kWh/h]	$E_{DHW, estim}$ [kWh/h]	Error between E_{DHW} and $E_{DHW, compl}$	Error between E_{DHW} and $E_{DHW, estim}$
666	112	0.314	0.167	0.315	−47%	**0%**
668	111	0.286	0.165	0.346	−42%	**21%**
669	110	0.184	0.164	0.224	**−11%**	22%
670	111	0.588	0.165	0.555	−72%	**−6%**
671	110	0.247	0.164	0.295	−34%	**20%**
697	111	0.692	0.165	0.606	−76%	**−12%**
698	111	0.674	0.165	0.627	−75%	**−7%**
699	110	0.678	0.164	0.588	−76%	**−13%**
700	111	0.074	0.165	0.137	123%	**85%**
701	111	0.167	0.165	0.196	**−1%**	18%
702	110	0.088	0.164	0.115	87%	**32%**
724	110	0.229	0.164	0.255	−28%	**11%**
726	111	0.116	0.165	0.132	43%	**14%**
727	111	0.103	0.165	0.121	61%	**18%**
728	110	0.148	0.164	0.203	**11%**	37%
729	110	0.144	0.164	0.161	14%	**12%**
730	111	0.388	0.165	0.406	−57%	**5%**
731	111	0.087	0.165	0.142	90%	**63%**
732	110	0.406	0.164	0.347	−60%	**−15%**
734	97	0.091	0.145	0.106	59%	**17%**
735	111	0.328	0.165	0.347	−50%	**6%**
736	111	0.336	0.165	0.34	−51%	**1%**
739	111	0.524	0.165	0.561	−68%	**7%**
740	111	0.164	0.165	0.159	**1%**	−3%
741	111	0.237	0.165	0.253	−30%	**7%**
742	97	0.145	0.145	0.167	**−1%**	15%
743	111	0.461	0.165	0.403	−64%	**−13%**
745	111	0.093	0.165	0.157	78%	**69%**

Hourly heating share estimation using SHM

Results – Paper 3

- Non-residential buildings were tested from other countries.



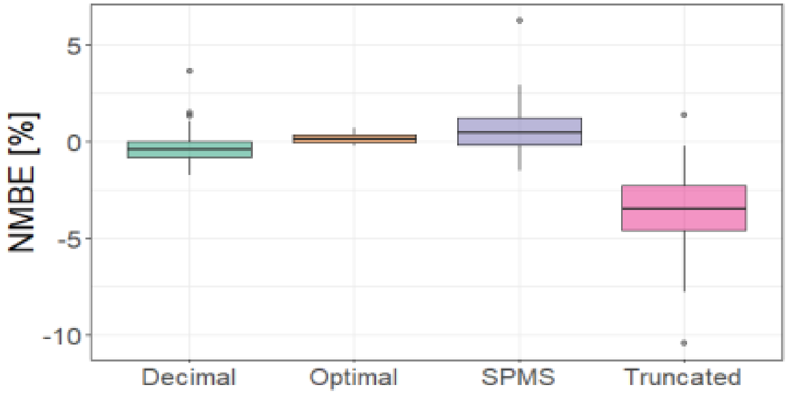
- The estimation methodology was applied with Danish SHM truncated data **(great underperformance)**.

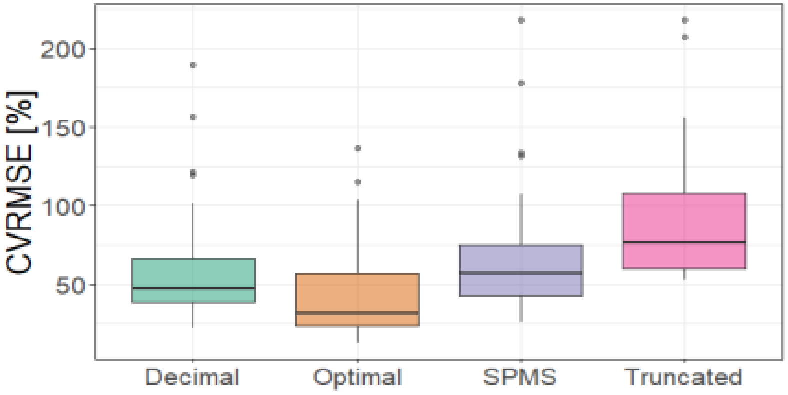
Data	Case-building	Error		
		Compliance	Round	Decimal
DK	Apart 666	-47%	97%	0%
DK	Apart 668	-42%	103%	21%
DK	Apart 669	-11%	102%	22%
DK	Apart 670	-72%	21%	-6%
DK	Apart 671	-34%	108%	20%
DK	Apart 697	-76%	12%	-12%
DK	Apart 698	-75%	21%	-7%
DK	Apart 699	-76%	10%	-13%
DK	Apart 700	123%	510%	85%
DK	Apart 701	-1%	93%	18%
DK	Apart 702	87%	182%	32%
DK	Apart 724	-28%	89%	11%
DK	Apart 726	43%	70%	14%
DK	Apart 727	61%	149%	18%
DK	Apart 728	11%	152%	37%
DK	Apart 729	14%	119%	12%
DK	Apart 730	-57%	43%	5%
DK	Apart 731	90%	273%	63%
DK	Apart 732	-60%	24%	-15%
DK	Apart 734	59%	144%	17%
DK	Apart 735	-50%	44%	6%
DK	Apart 736	-51%	40%	1%
DK	Apart 739	-68%	34%	7%
DK	Apart 740	1%	75%	-3%
DK	Apart 741	-30%	59%	7%
DK	Apart 742	0%	121%	15%
DK	Apart 743	-64%	29%	-13%
DK	Apart 745	78%	265%	69%
CH	Apart. block	4%	-9%	-
IT	Rehab inst.	-59%	-79%	-
IT	Theater	-35%	154%	-

Hourly heating share estimation using SHM

Results – Paper 4

- Application of the Smooth – Pointwise Move – Scale (**SPMS**) method to "de-truncate" data.
- Also observed the case where DHW usage detection is flawless (**optimal**)
- SPMS improves the results but does not outperform estimation with decimal data.





Hourly heating share estimation using SHM

Influence of this research on subsequent studies

Topic	Ref.	Description
Methodology improvement	Schaffer et al. (2024)	Tested the disaggregation method by incorporating cold water meter data to distinguish SH and DHW usage and applied it to other machine learning models.
Non-intrusive monitoring	Ritosa, Saelens, and Roels (2024)	Examined how non-intrusive monitoring and statistical models assess household energy performance.

Hourly heating share estimation using SHM

Further discussion

- In this work it was proposed a novel approach for estimating **SH and DHW usage** using low-resolution, hourly data.
- Accessing to indoor condition data (e.g., temperature, CO2 levels, room-specific heat allocation) could significantly improve the accuracy of energy usage estimations and allow for a deeper understanding of SH and DHW contributions to building heating performance.
- The **next step of this research** investigates the application of the Energy Signature (ES) model for deeper investigations into the relationship between building energy performance and occupant behavior.

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Integrating SHM and indoor sensors data

Methodology

- Four similar apartments
- Interviews to the occupants

Level	Shape (color)	Parameter	Units
Apartment	Pentagon (green)	SH flow	m^3/h
		SH supply/return temperature	ºC
		DHW flow	m^3/h
		DHW supply temperature	ºC
Room	Circle (purple or yellow)	Indoor temperature	ºC
		Relative humidity	%
	Circle (purple)	CO2 concentration	ppm
	Triangle (pink)	Window opening rate	%
	Square (red)	Surface pipe supply temperature	ºC
		Radiator surface temperature (middle)	ºC
		Surface pipe return temperature	ºC

Integrating SHM and indoor sensors data

Methodology

Important to remember:

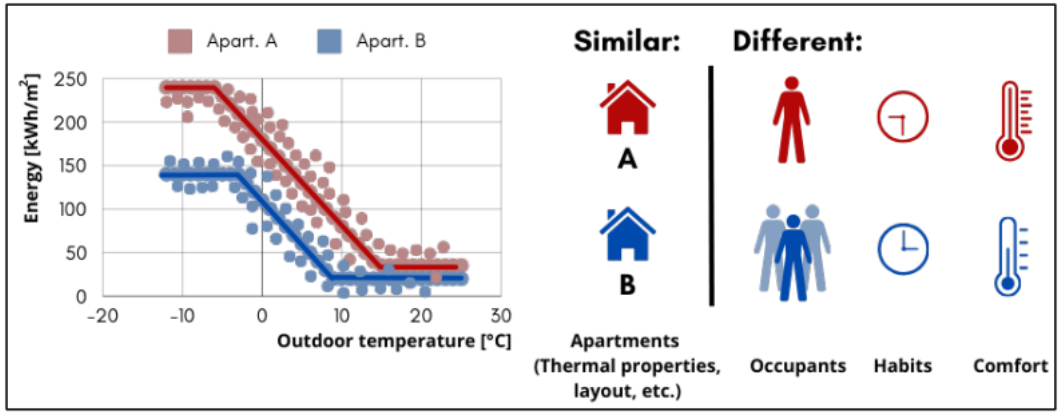
- Apart. A & D → One person
- Apart. B → Family of 5 people
- Apart. C → 2 people (couple)

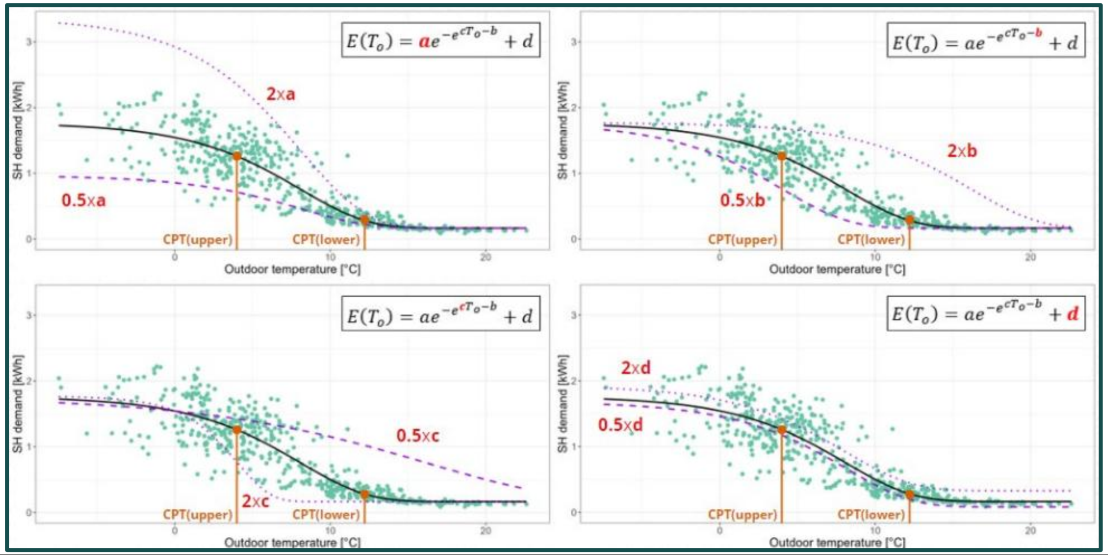
	Apt. A	Apt. B (B.1)	Apt. C	Apt. D
OCCUPANTS				
Nr. of adults	1	3	2	1
Nr. of children	0	2	0	0
Weekly occupancy	Not at home from 9-12h and Thursdays from 12-15h	Adults are always at home. Children at school from 8-15h	Always at home	Out of apartments in the afternoons
AIR QUALITY				
Which rooms are vented?	All rooms	All rooms	Bedroom and bathroom	Bedroom (every day) and living room (summer only)
How long and when do you vent the apartment?	Each day bedroom, bathroom, and living room 2-3 times a week. Long venting in summer (every day) and short in winter (10 minutes)	Summer: All day Winter: 1-2 h in the morning	Summer: All day Winter: 1-2 h per day	Summer: All day Winter: 3-4 h in the morning
THERMAL COMFORT				
What is the setting on the radiators' thermostats?	Bedroom is set to be cold (setting 1). Bathroom set on 2.	Different settings in the rooms.	Only the radiator in the living room is open (setting 4-5). Underfloor heating in bathroom (operating).	All radiators are set on 3. Radiator not used in the bedroom. Bathroom underfloor heating is always in use.
Is the temperature in the apartment uniform?	-	Yes, except for one bedroom (where no heating is used)	-	-
ENERGY SAVING MOTIVATION				
Do you pay too much for energy?	Yes	Yes	No	No

Integrating SHM and indoor sensors data

Methodology

- Analysis of the **energy signatures** from **similar buildings**.
- Analysis of the **radiators operation** (contact temperatures) and correlate it with **occupants behavior**.
- Proposing a **sigmoid energy signature** and investigating its characteristics based on **indoor data**.

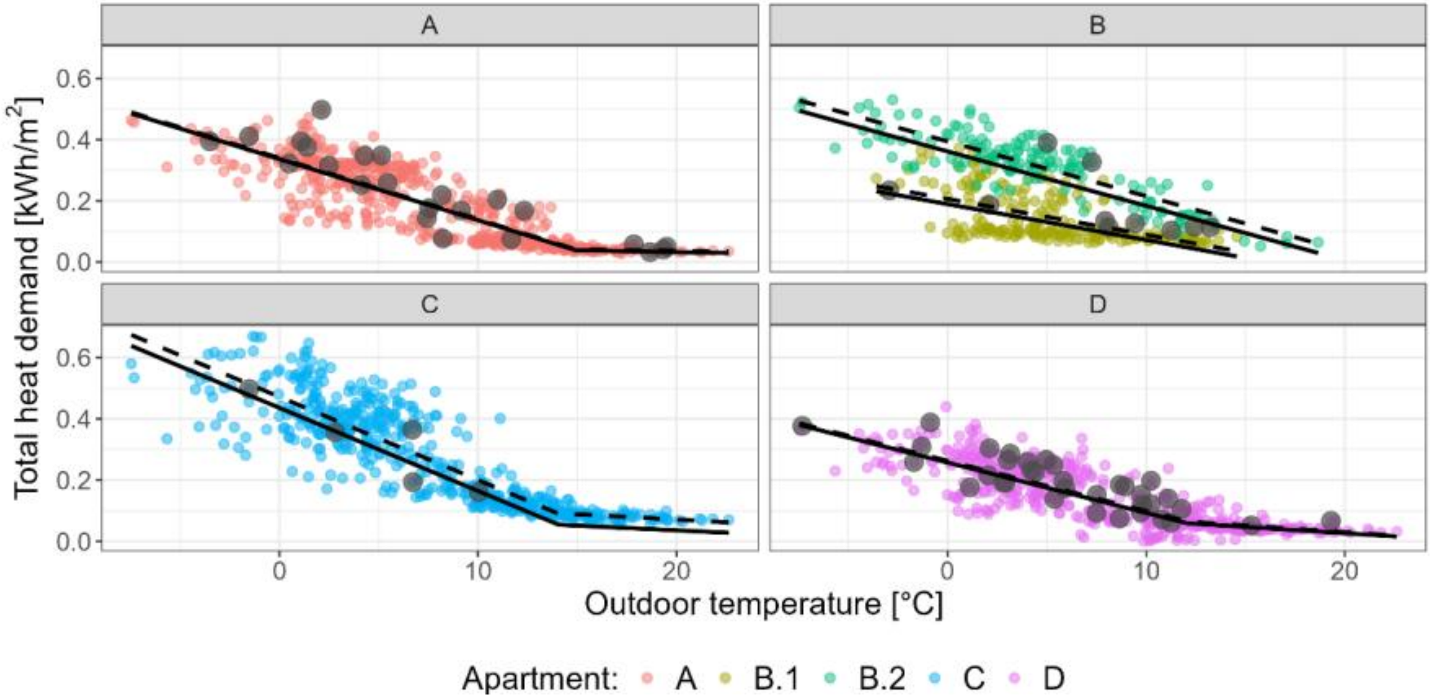




Integrating SHM and indoor sensors data

Results

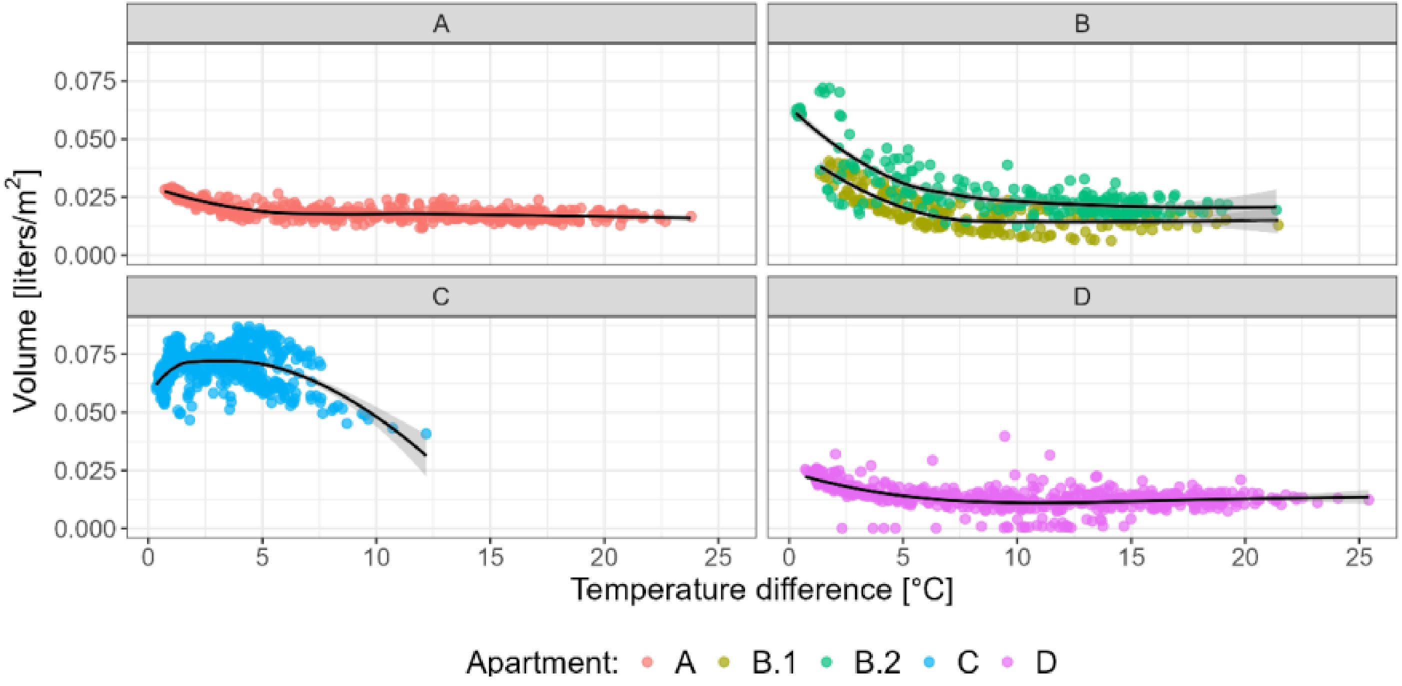
- **Similar** buildings display **different** energy signatures.



Integrating SHM and indoor sensors data

Results

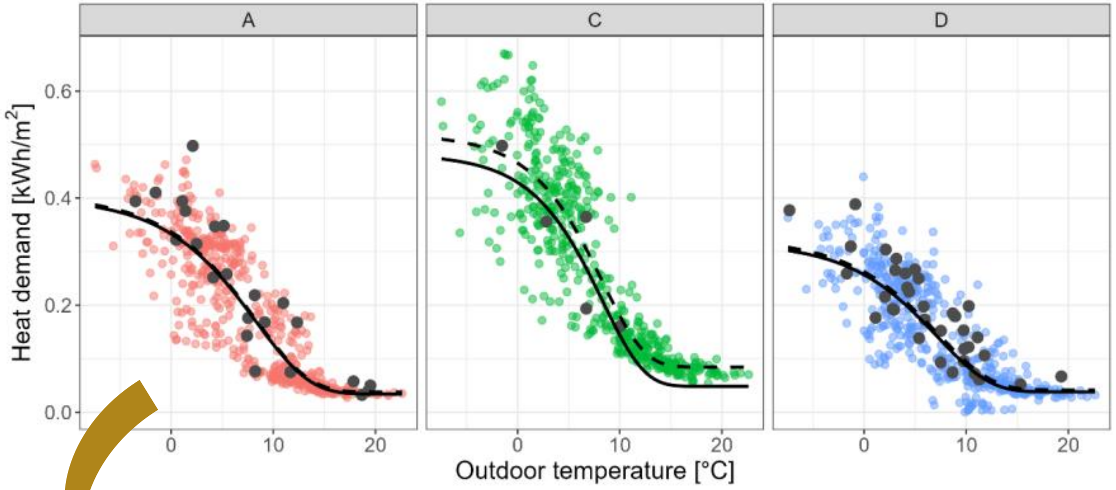
- **Similar** buildings display **different** energy signatures.
- **Occupants' habits** might seem the reason behind such differences.

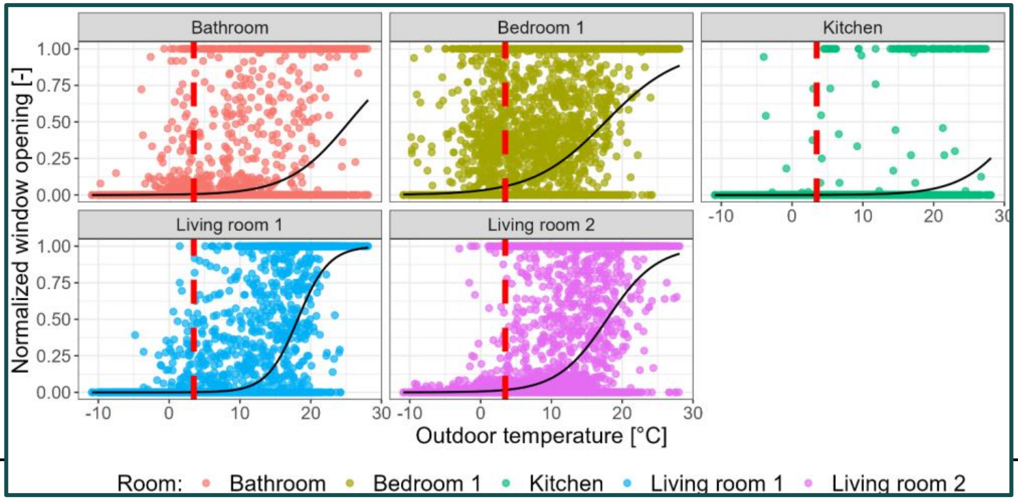


Integrating SHM and indoor sensors data

Results

- **Similar** buildings display **different** energy signatures.
- **Occupants' habits** might seem the reason behind such differences.
- Proposed **sigmoid energy signature** might help in understanding **occupancy-driven ventilation.**

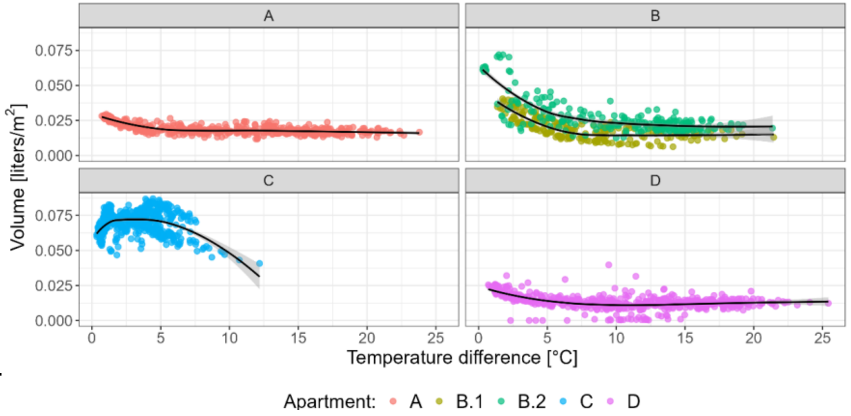




Integrating SHM and indoor sensors data

Further discussion

- Indoor sensors data combined with SHM helped in identifying potential faults in heating systems by analyzing data patterns that displayed large deviations in the heating performance.
- These faults were due to occupants' behavior, nevertheless recognizing and diagnosing these faults is crucial to optimizing energy usage in buildings and improving overall grid efficiency.
- The **next step of this research** explored the application of data-driven approaches for effective fault detection and diagnosis (FDD) within the DH consumers.



Content

Fault detection and diagnosis within DH customers

Background

- Gadd and Werner (2015) argues that approx. 74% of buildings connected to the DH grid present faulty patterns.
- This means a sizeable economic potential of solving such faults.
  - Approx. **0.05 to 0.5€/MWh·ºC** by reducing the return temperature – Frederiksen and Werner (2013) and Gadd and Werner (2014).

Definitions:

- Fault detection: Finding anomalies in the data
- Fault diagnosis: Knowing the reason for the anomalies

Fault detection and diagnosis within DH customers

Methodology

Paper 6:

- Coupling 351 fault reports with SHM data.
- Providing an overview of typical faults occurring in DH end-user heating installations.
- Assess the current FDD indicators and investigate others to assess the DH customers.
- Assess the fault impact of the different faults to investigate their consequences on the buildings' energy usage.

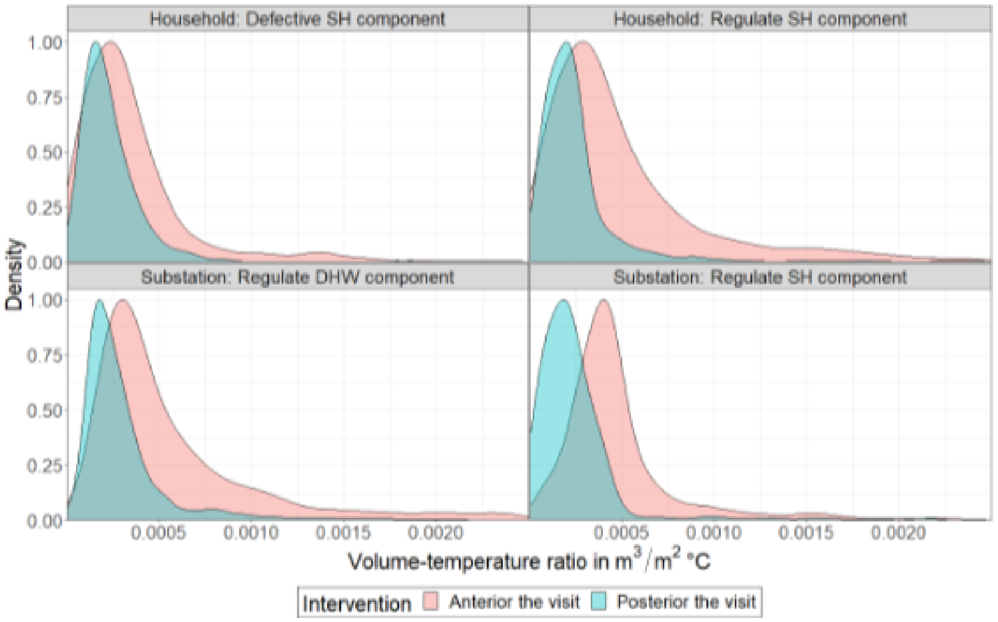
Paper 7:

- Explanation of the characteristics and challenges in collecting fault reports.
- Comprehensive analysis of SHM data from 50 DH household substations with verified faults.
- Proposal for employing time series decomposition to identify and isolate anomalous data.
- Proposal of a clustering framework for categorizing symptoms and patterns of faults **(diagnosis)**.

Fault detection and diagnosis within DH customers

Results – Paper 6

- Several KPIs were analyzed to detect faults. **Volume (flow) and return temperatures** should be used instead.

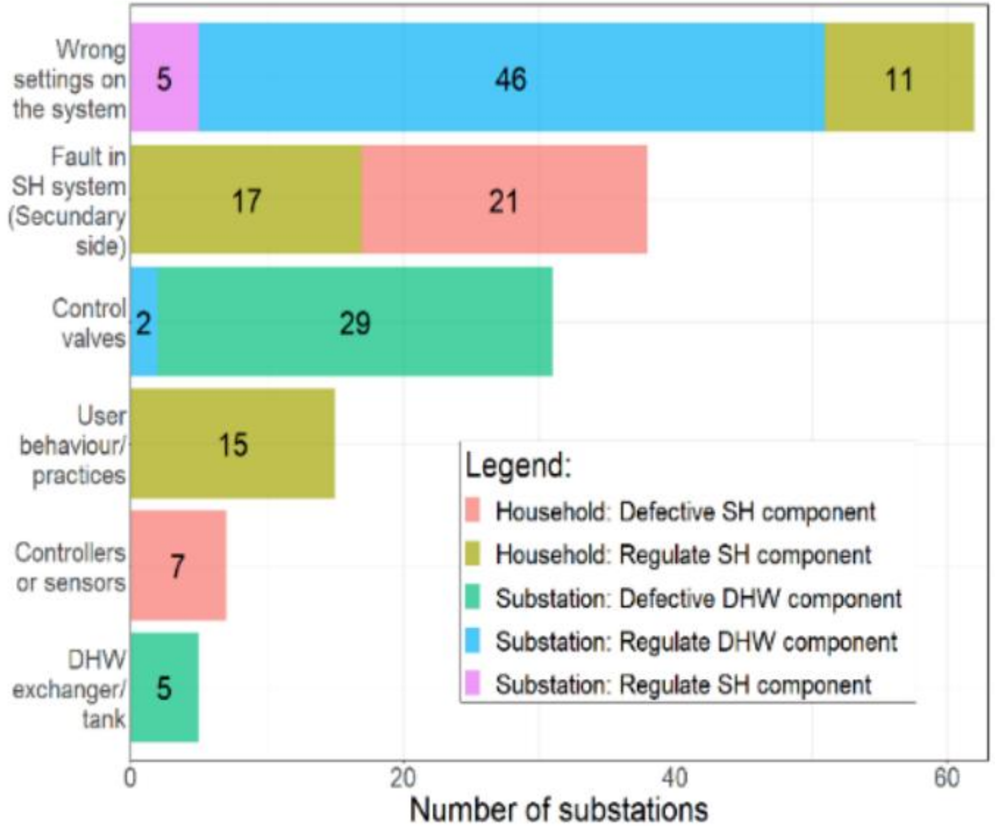


Fault detection and diagnosis within DH customers

Results – Paper 6

- Several KPIs were analyzed to detect faults. **Volume (flow) and return temperatures** should be used instead.
- From the dataset, a large set of faults are due to **high settings / Occupants' behavior.**

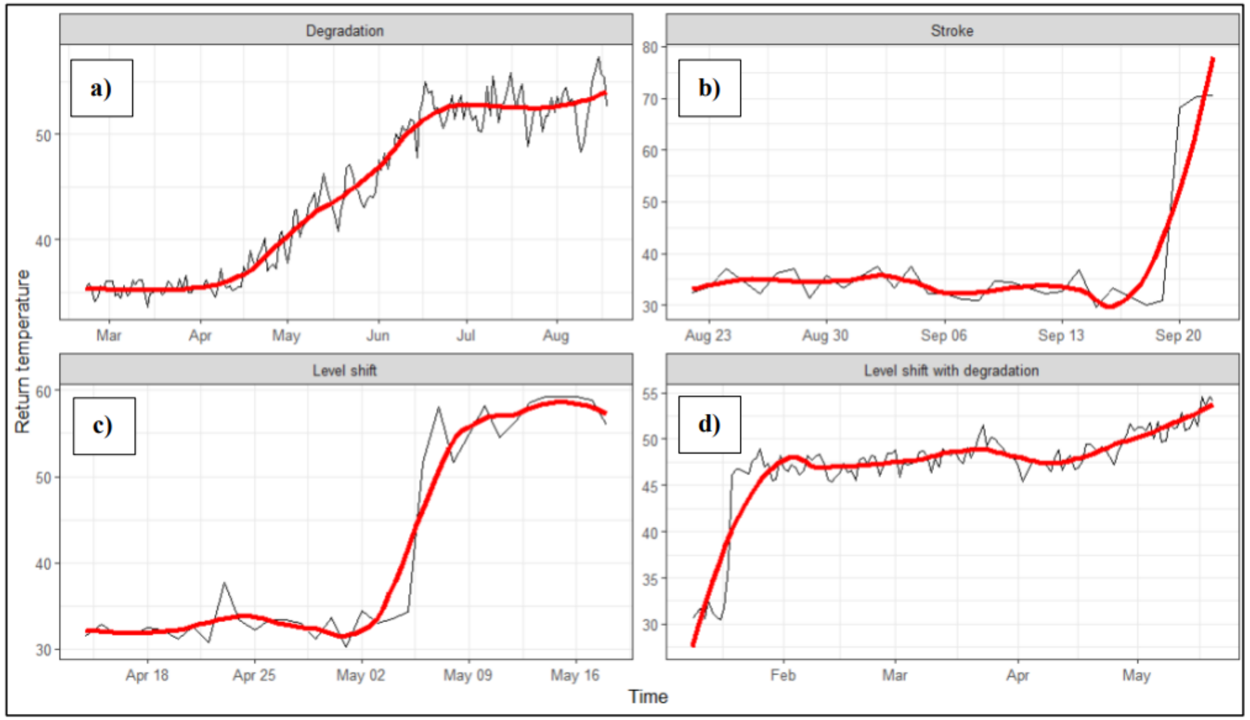
"Easily" fixed!



Fault detection and diagnosis within DH customers

Results – Paper 7

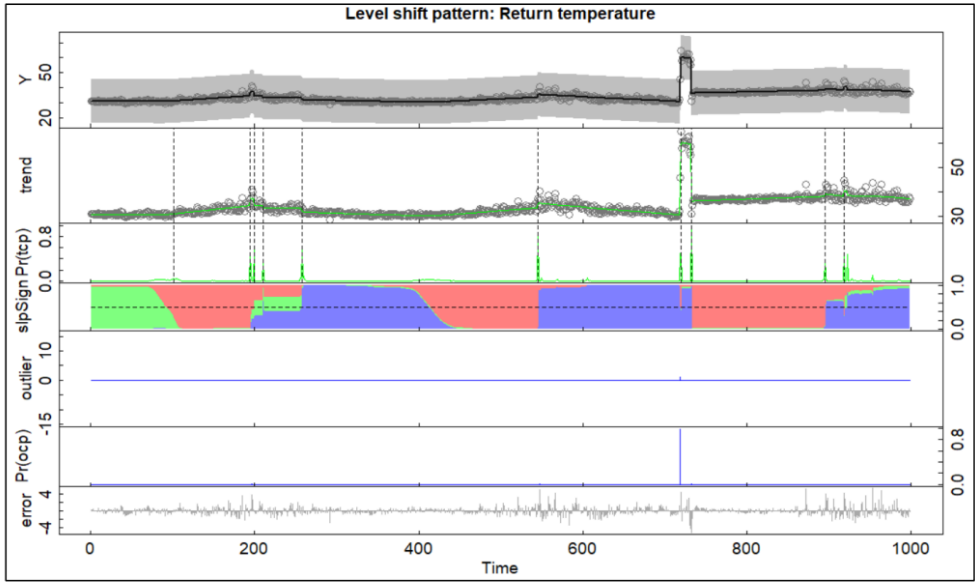
- **Four** faulty patterns were found in the **return temperature**.

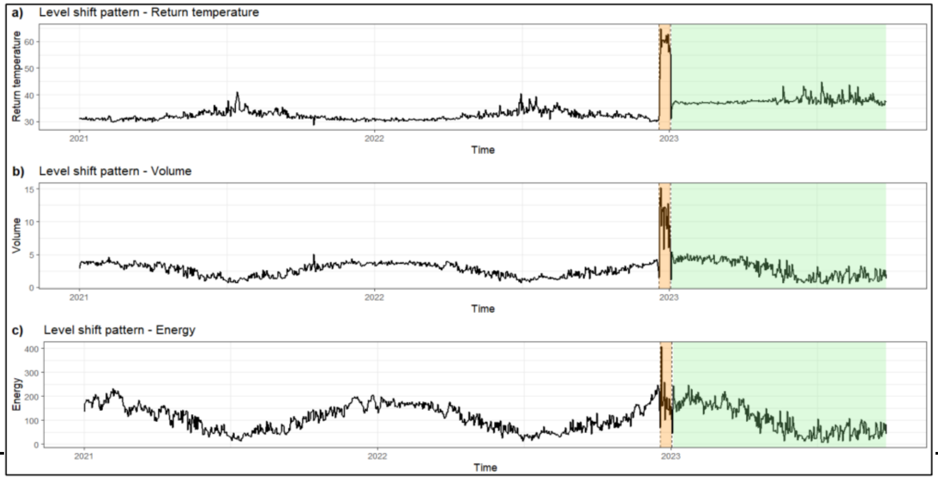


Fault detection and diagnosis within DH customers

Results – Paper 7

- **Four** faulty patterns were found in the **return temperature**.
- **BEAST method seems promising** for time series segmentation applied to FDD.



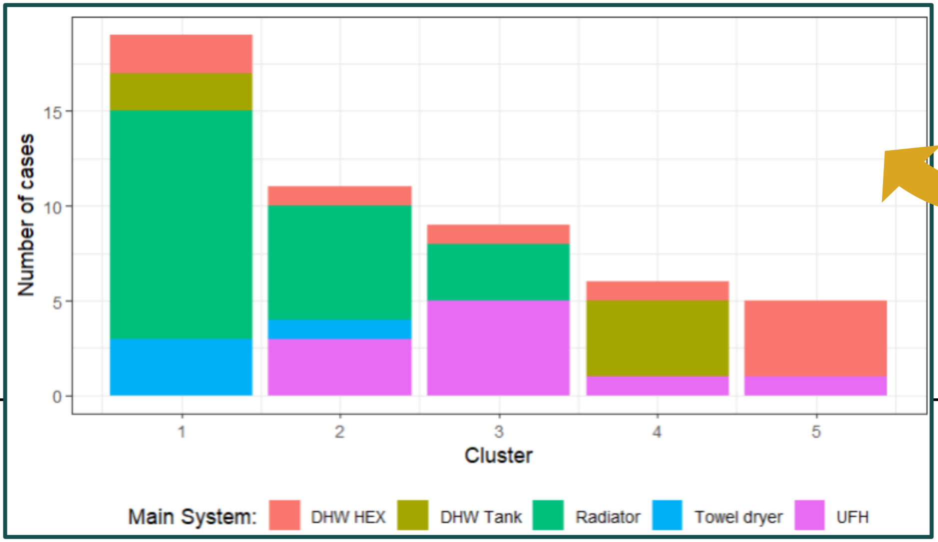


Fault detection and diagnosis within DH customers

Results – Paper 7

- **Four** faulty patterns were found in the **return temperature**.
- **BEAST method seems promising** for time series segmentation applied to FDD.
- **Self-organizing maps (SOM)** shows also promising results for **fault diagnosis.**

Cluster	Nr. of points	Nr. of nodes	Season	Return temperature		Volume flow		Energy	
				Pattern	Volatility	Pattern	Volatility	Pattern	Volatility
1	19	5	Mid	S	Low	S	Low	S NO	Low Medium
2	11	3	Mid Cold	LS	Medium Low	LS	High Low	LS NO	Low
3	9	3	Mid Cold	D	High Medium	D	Medium	NO D	High Medium
4	6	3	Warm Mid	LS + D	Low	LS + D S LS	Medium Low	NO	Medium
5	5	2	Warm	D LS + D	Low Medium	NO D	Medium High	NO	Medium High



Content

Conclusions

Addressing the research questions

RQ1: How can weather data, energy performance certificates (EPC), and visualization tools be used to aid in decision-making for energy management within district heating?

- Weather data helps predict energy usage fluctuations.
- EPC data identifies buildings with poor energy performance for targeted interventions.
- Visualization tools make complex data easier to understand, supporting informed decision-making.

Conclusions

Addressing the research questions

RQ2: Can machine learning (ML) models based on SHM data accurately predict the energy demand for space heating and domestic hot water?

- ML models can be used to predict SH and DHW demand using weather data.
- Mitigated issues caused by truncated SHM data through aggregation techniques.

Conclusions

Addressing the research questions

RQ3: Can smart heat meters data, supplemented with information about indoor environmental conditions, enhance our understanding of the energy use and heating practices of building occupants?

- Occupant behavior significantly affects energy consumption, even in similar buildings.
- Combining SHM with indoor condition data provides a fuller picture of energy usage patterns.
- Modifying the Energy Signature (ES) model improves energy usage predictions.

Conclusions

Addressing the research questions

RQ4: How effective are smart heat meters at identifying specific types of faults within the district heating system customers?

- SHM can detect faults through anomalies in flow rates, return temperatures, and energy usage.
- High-dimensional data clustering and self-organizing maps improve fault diagnosis accuracy.
- Accurate ground truth data is essential for refining fault detection algorithms.

Directions for future research

- Deeper analysis of energy usage patterns across different building types and demographic groups to better understand variability.
- Further refinement of fault detection algorithms to improve sensitivity, reliability, and fault diagnosis through better data collection and preprocessing.
- Investigating the impact of occupant behavior on energy usage and developing user feedback systems to encourage energy-saving behavioral changes.

Acknowledgements

Regarding these last steps of my Ph.D., I would like to thank to:

- My oponents that have accepted the challenge to be here today.
  - Research Director Ruut Hannele Peuhkuri (Aalborg University)
  - Senior Lecturer Henrik Gadd (Halmstad University)
  - Associate Professor Michele Tunzi (Technical University of Denmark)
- The moderator Associate Professor Rasmus Lund Jensen
- The AAU team that managed to help me here today, with a special thanks to **Linda Vabbersgaard Andersen** (one of the most caring/helpful person regarding PhD students).

Tak, Thank you, Grazie, Obrigado.

Acknowledgements

Completing this Ph.D. has been an immensely **challenging and rewarding** journey, one that I could **not** have embarked upon without any of the following:

- My supervisors: Michal Pomianowski, Hicham Johra, and Anna Marszhal-Pomianowska.
- AAU and the colleagues that I enjoyed meeting and working with.
- All partners and collaborators of E-DYCE and PRELUDE projects.
- The **Corner Office** – The best place any Ph.D. could work (it was a h**l of a ride!).
- The Ph.D. colleagues and the support of Marco and Prof. Alfonso from Politecnico di Torino (visiting PhD period).
- My parents and family (sem vocês não teria chegado aqui).
- My Giuly – the support and love was undeniable.

Tak, Thank you, Grazie, Obrigado.

From Smart Heat Meters to Diagnostics

Data-driven methodologies for building efficiency assessment within district heating

Thank you for your attention

Daniel Leiria

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