Long-term heat load forecasts using hierarchical archetype modelling and hourly smart meter data

by

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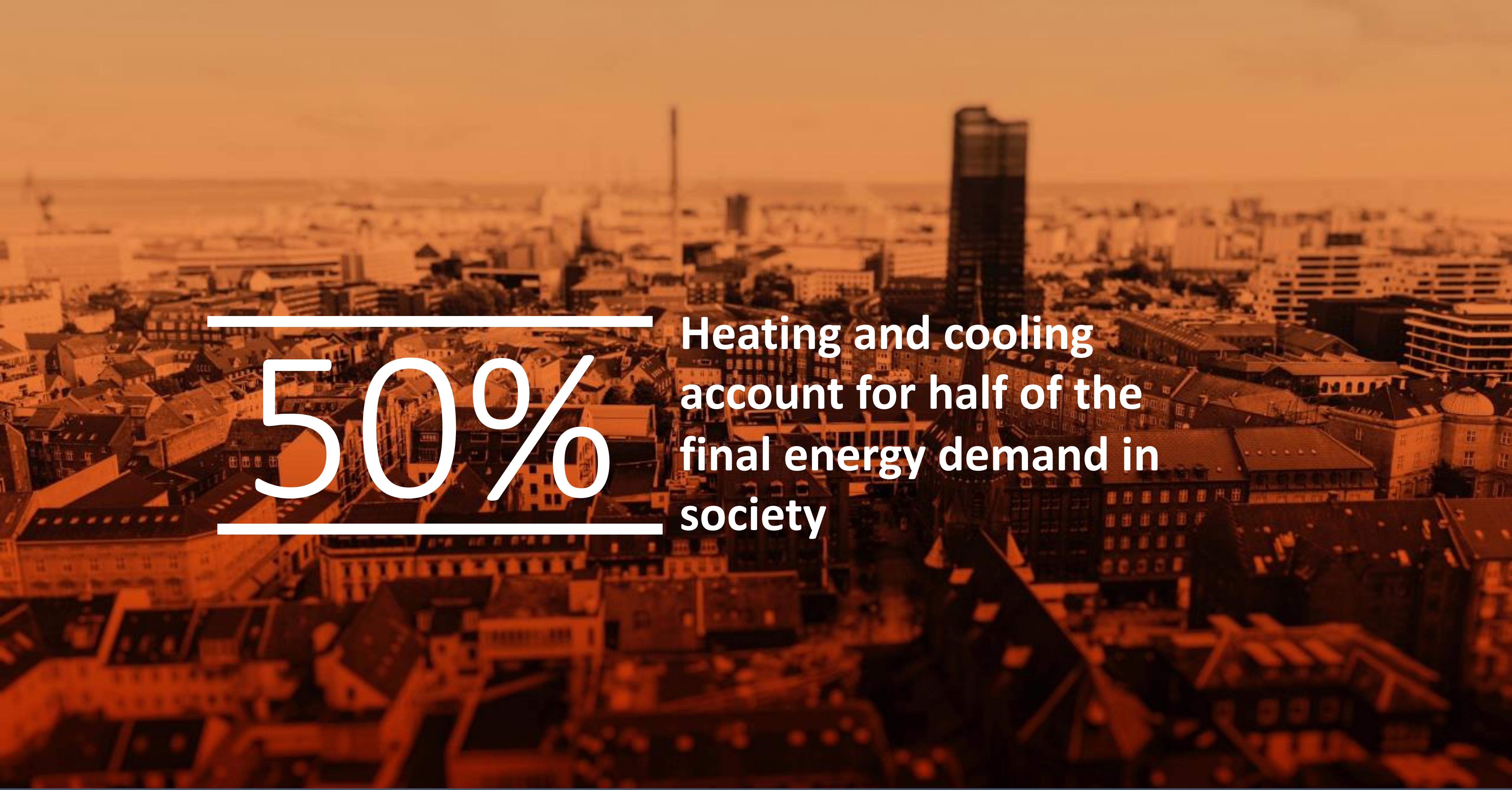
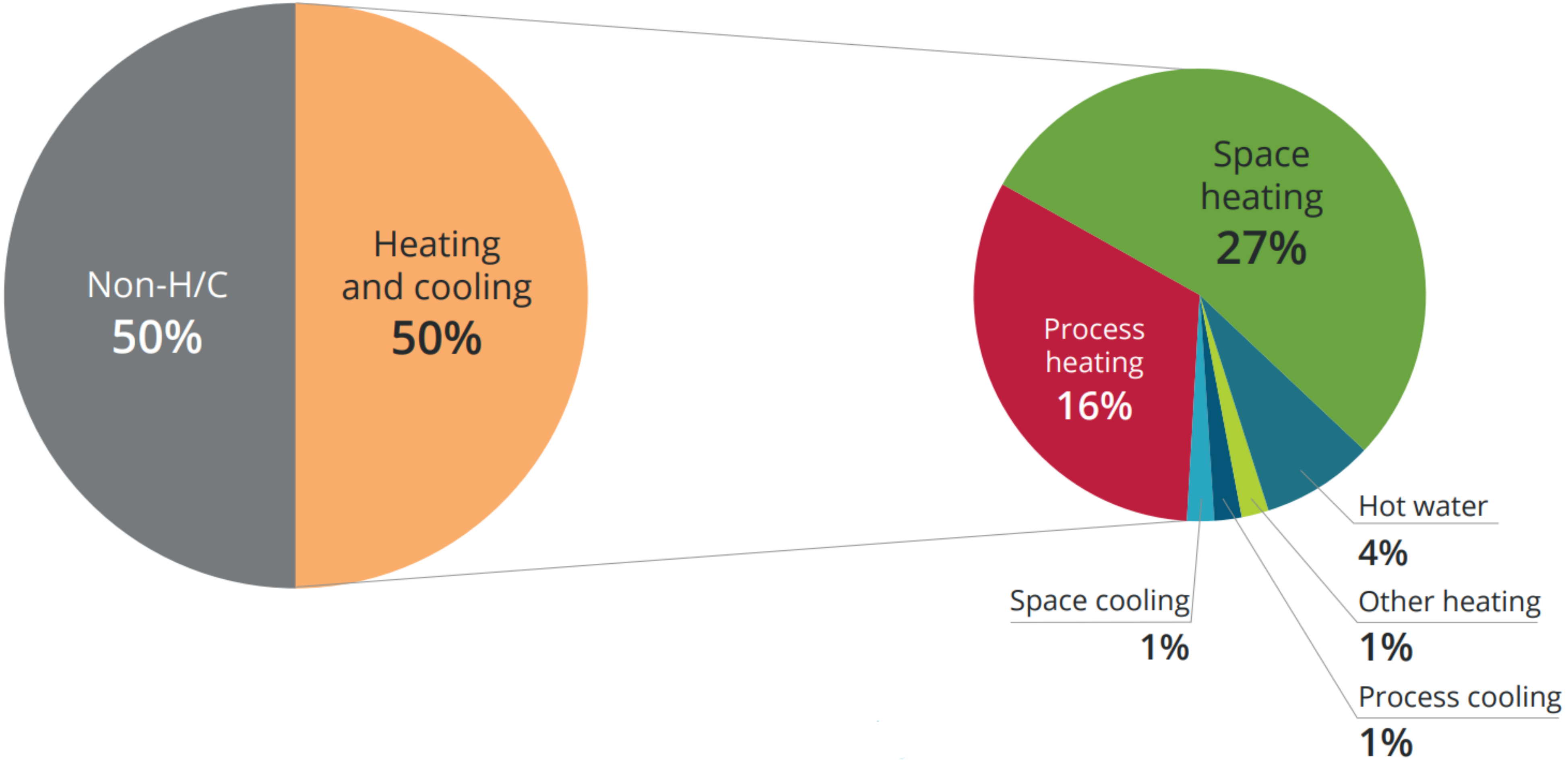
AFFALDVARME
AARHUS

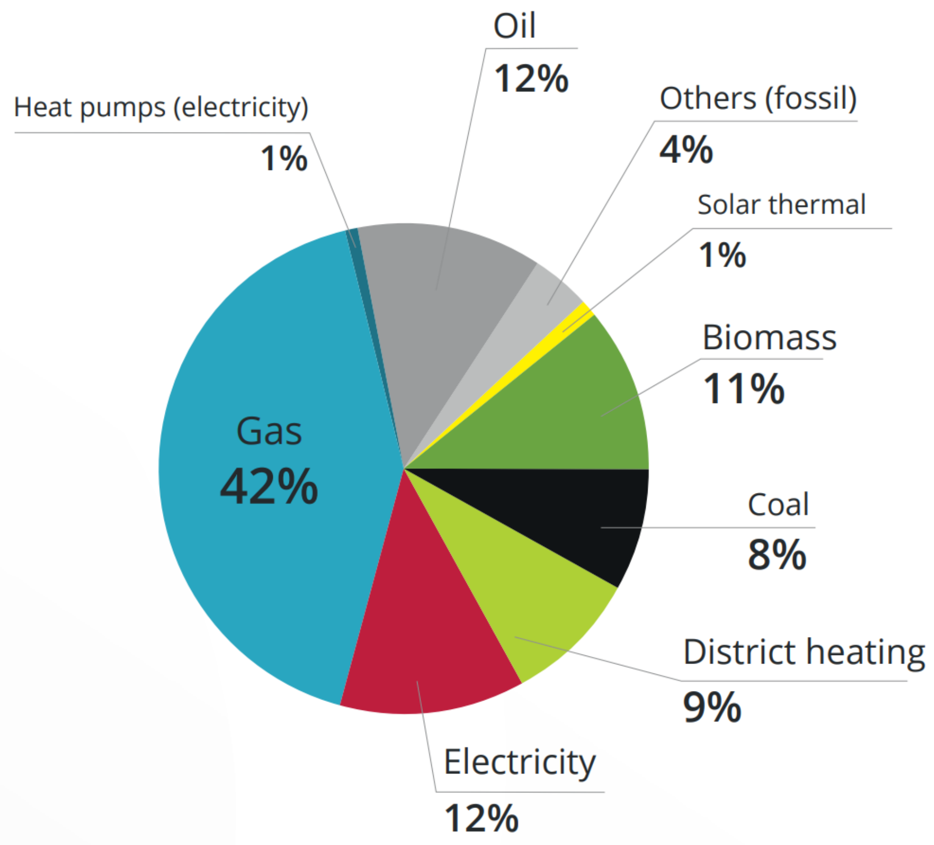

50%
Heating and cooling account for half of the final energy demand in society

Total final energy by end-use in the EU28



Heating & Cooling, facts and figures
www.heatroadmap.eu (June 2017)

The role of district heating

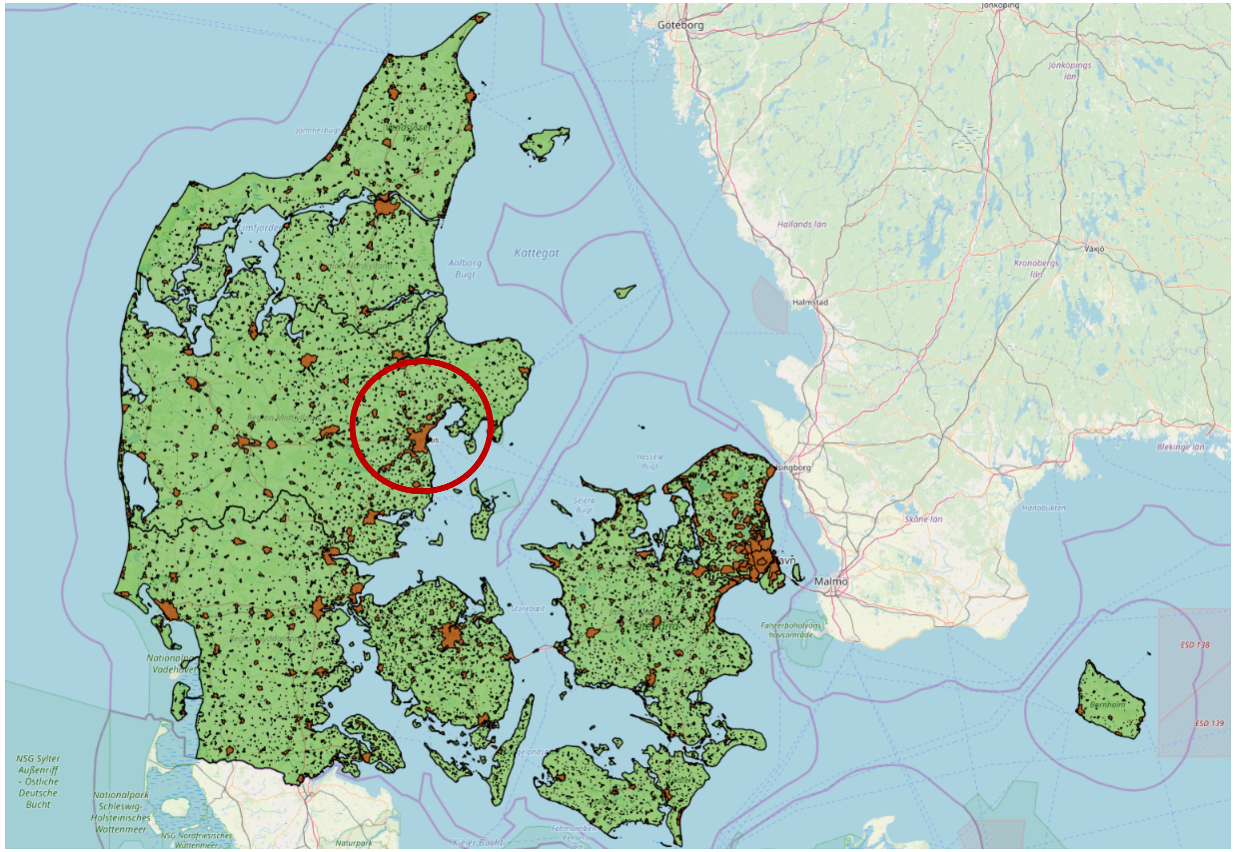


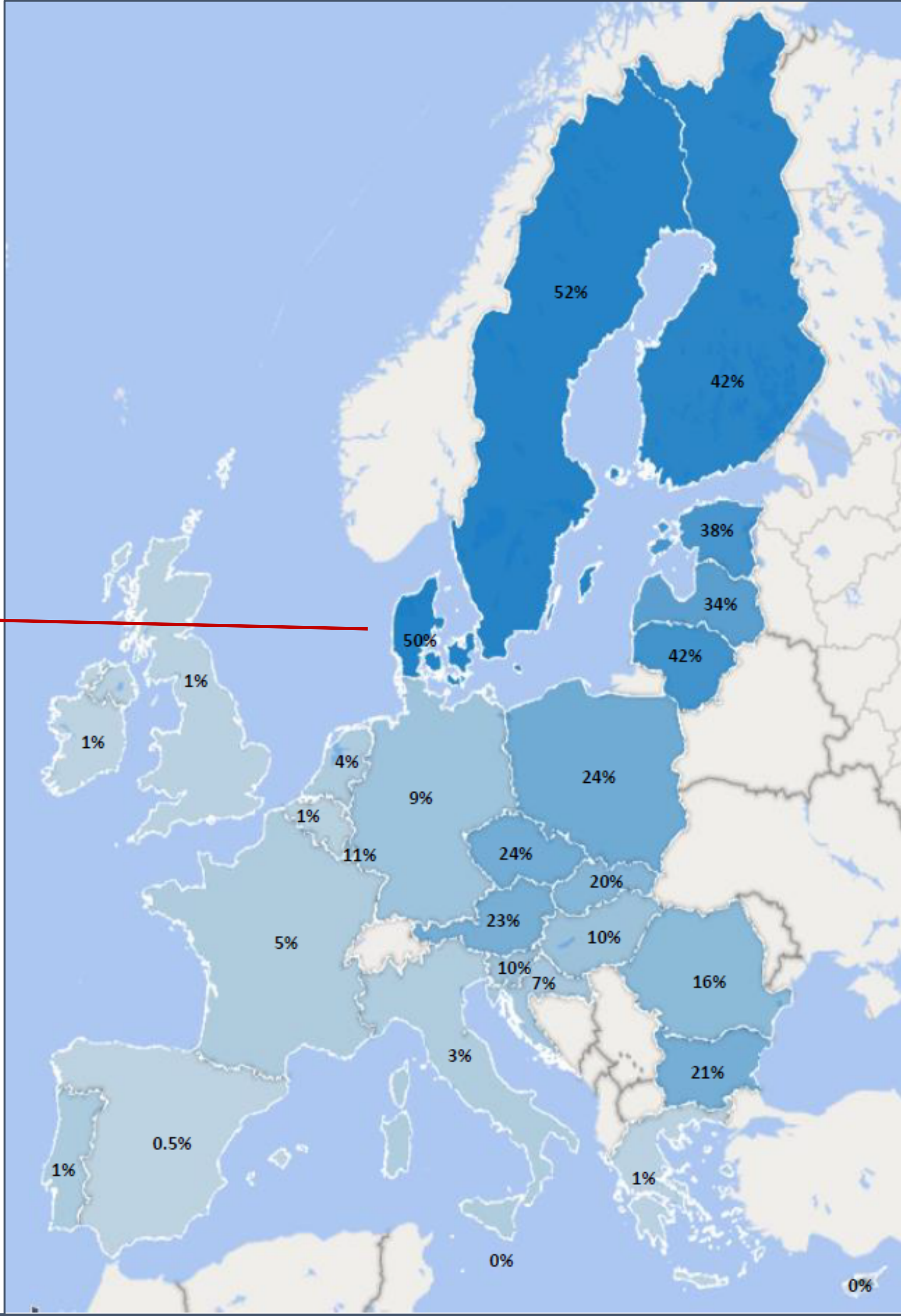
“District energy can play a key role in decarbonising heating and cooling, by enabling high levels of energy efficiency and renewable energy and sector coupling”

Towards a decarbonized heating and cooling sector in Europe, Aalborg University (2019)

Heating & Cooling, facts and figures
www.heatroadmap.eu (June 2017)

Large differences across the EU!





Towards a decarbonized heating and cooling sector in Europe,
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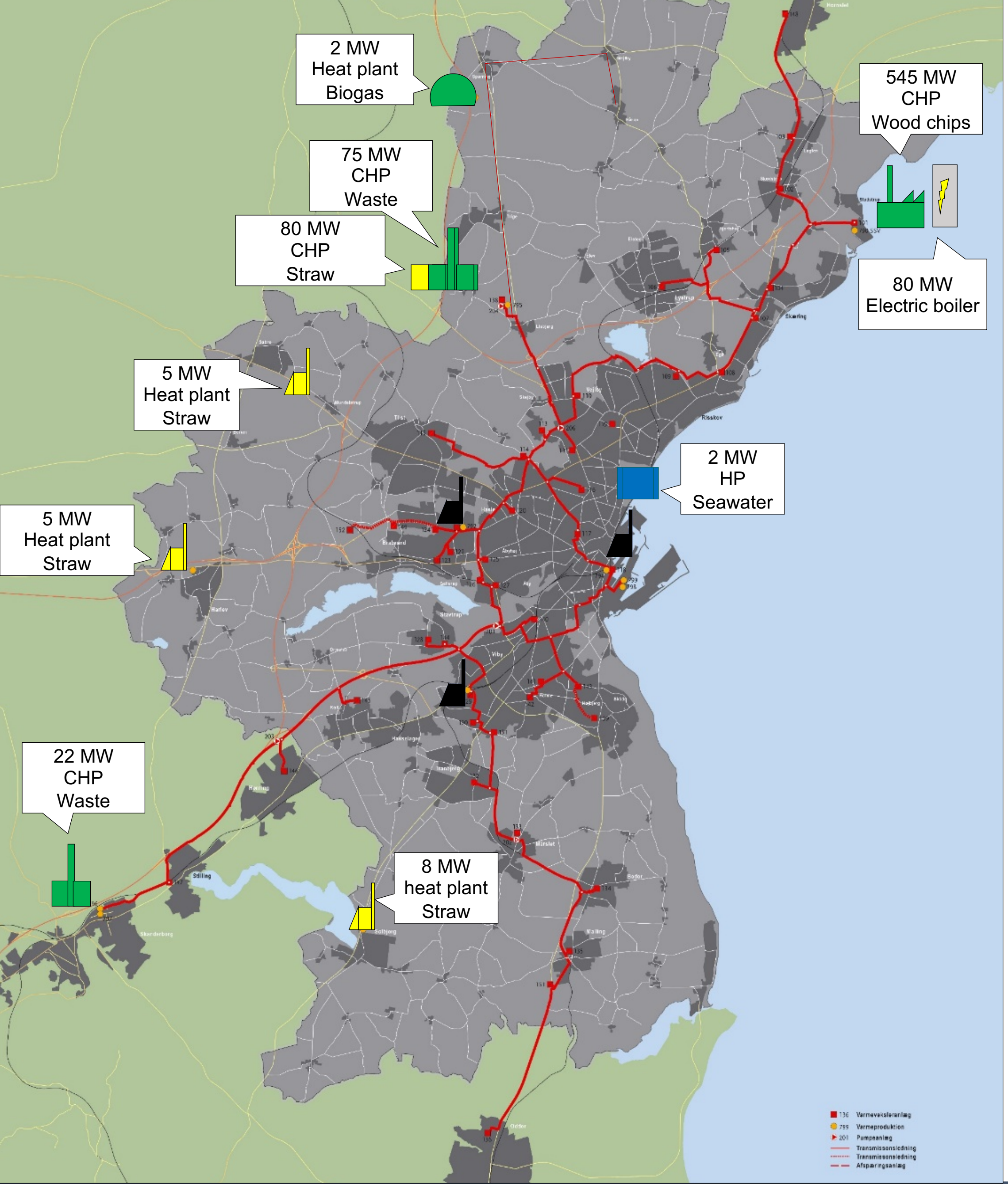


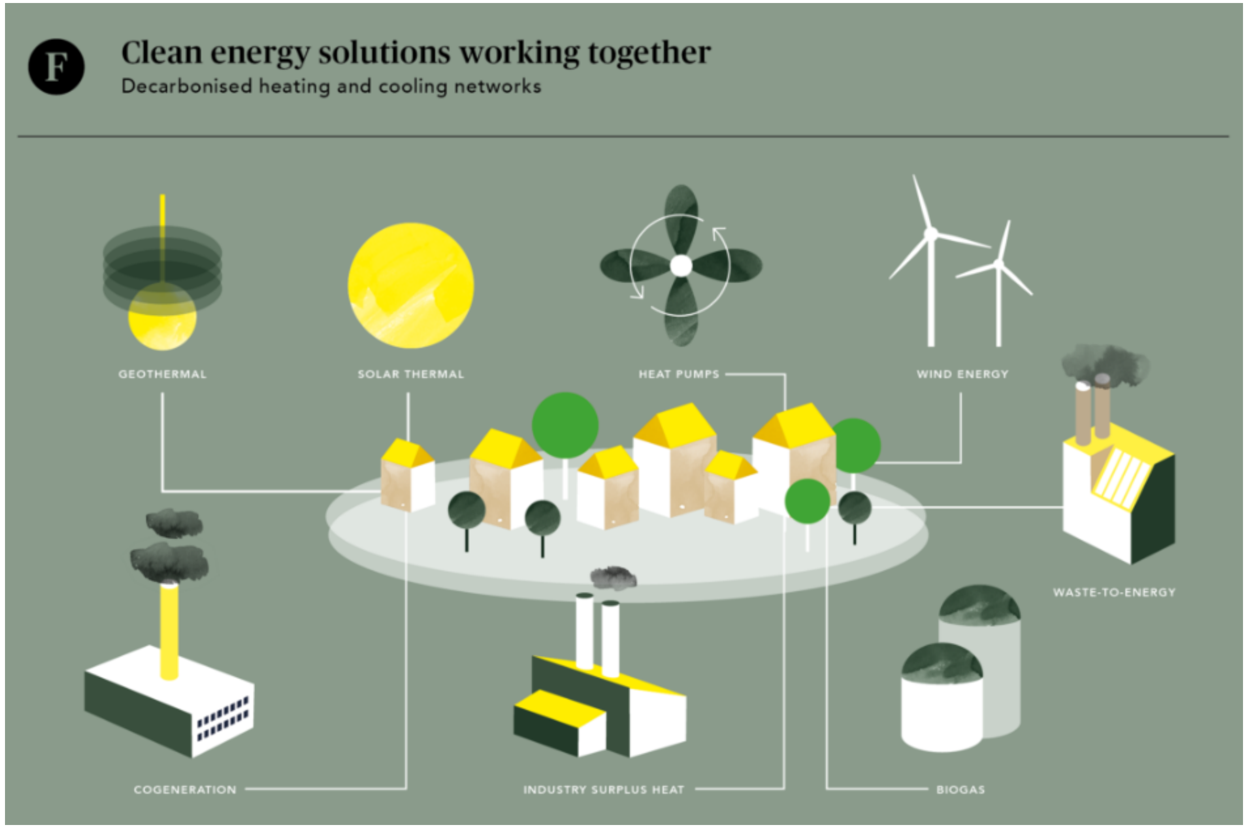
Aarhus district heating system

- Supply 350,000 people (95% of population)
- 60,000 consumer substations

- 1500 MW heating peak capacity
- 100% CO_2-neutral heating production
- 3200 GWh annual heating production
- Central transmission line at 80-100°C
- 54 independent distribution systems at 60-80°C
- 2300 km pipeline in total

Strategic energy planning

GOAL: A fully decarbonised and renewable smart energy system in 2050



HOW?: More renewable heat production

↓

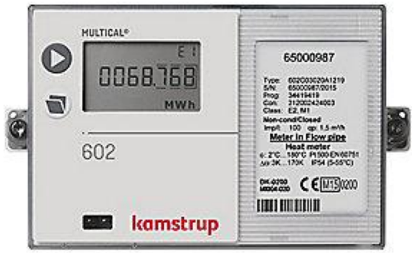
Reduce heating demand
+ lower distribution temperatures

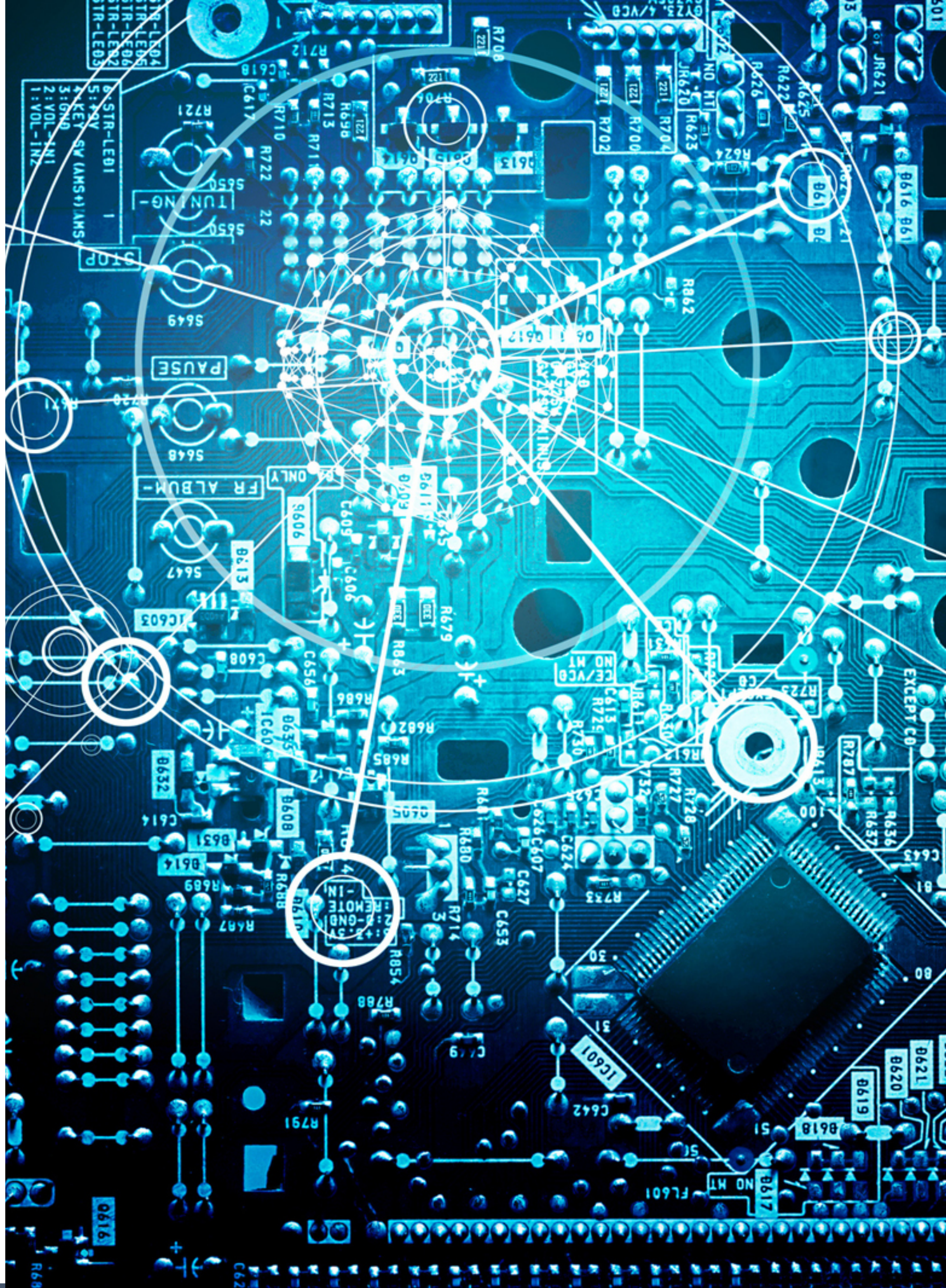
↓

Need a better basis for decision → Long-term heat load forecast + platform for analysis → Data intelligence

Smart meter consumption data

- 60,000 heat meters
- Hourly readings
- Heating consumption, volume flow, temperature, etc.
- Data available from 2017 onwards





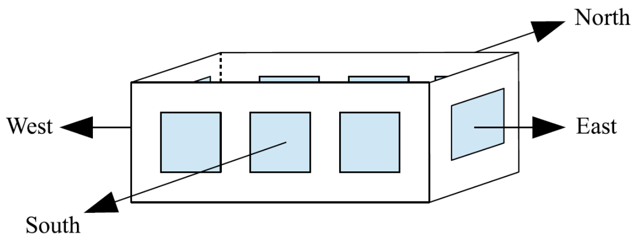
Urban building energy modelling

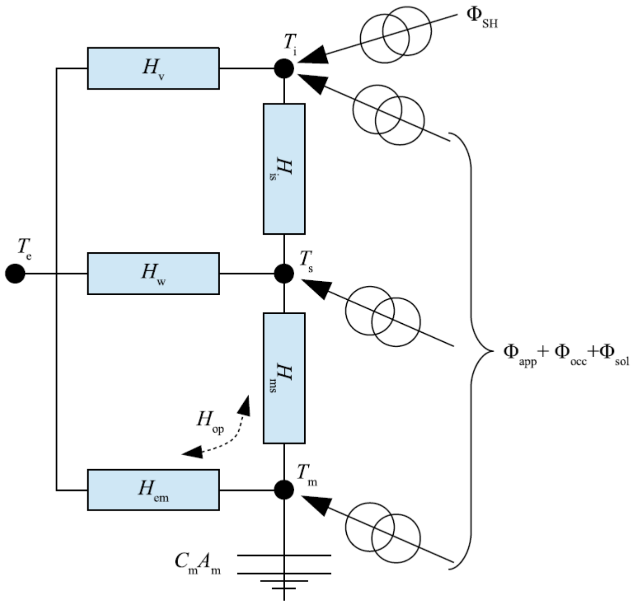
Urban building energy modelling

Urban building energy modelling seeks to facilitate analyses on the building stock by combining effects of individual bottom-up building models into an aggregated urban-scale model:

- ❖ Heat load forecasting
- ❖ Analysis of how building heat load is affected by, for example:
  - Retrofit
  - Climate change
  - Demand response (flexible heating demand)
  - …

Individual buildings





- ❖ Buildings are modelled individually
- ❖ Simplified geometry
- ❖ Space heating model
- ❖ Domestic hot water model

- ❖ Around 20-25 unknown input parameters per building!

Challenges of urban modelling

- Model complexity and simulation time
- Data requirements

Solution

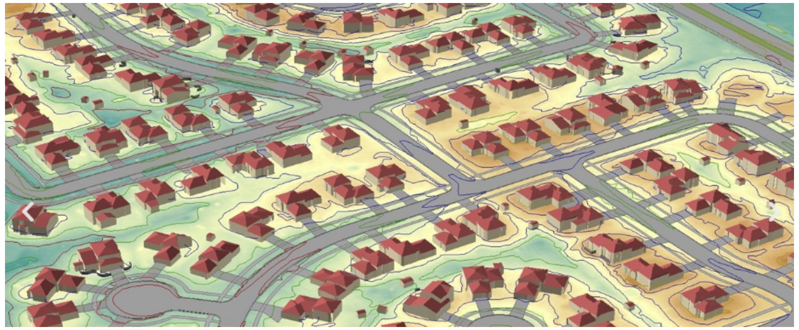
- Simplify the models
- Rely on data to infer parameter values

Archetype simplification

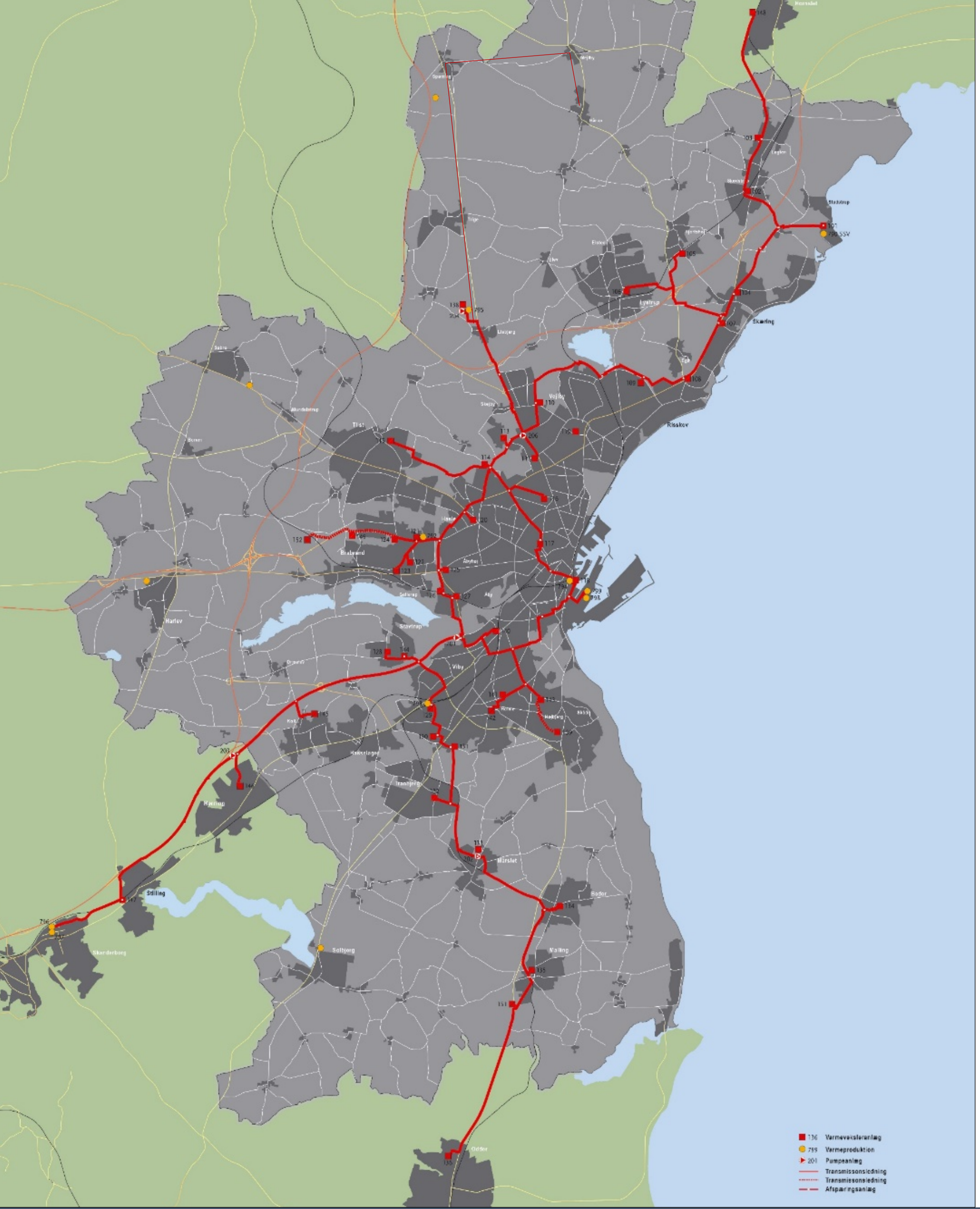
1. Identify a reduced number of unique building typologies (archetypes), which are representative for the building stock.

2. The archetypes are carefully examined and their technical parameters are either measured or calibrated using observed data.

3. The archetype values are used to populate input parameters of all similar buildings in the urban building energy model.

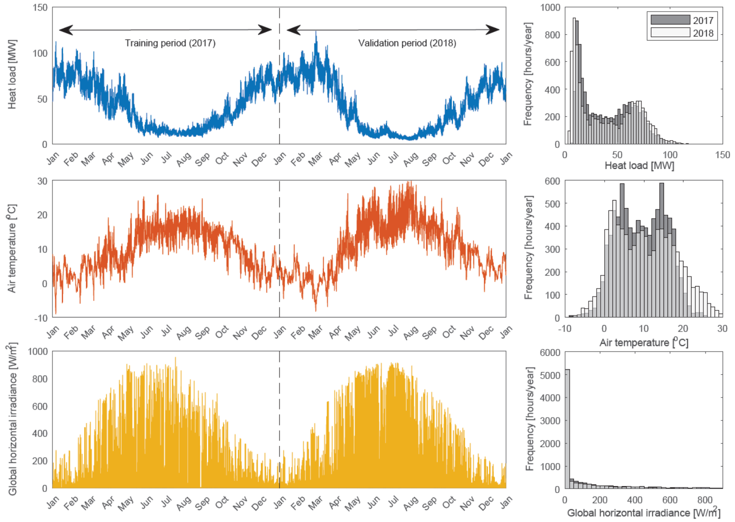


<u>Case study:</u>
Heat load of single-family houses in Aarhus, Denmark



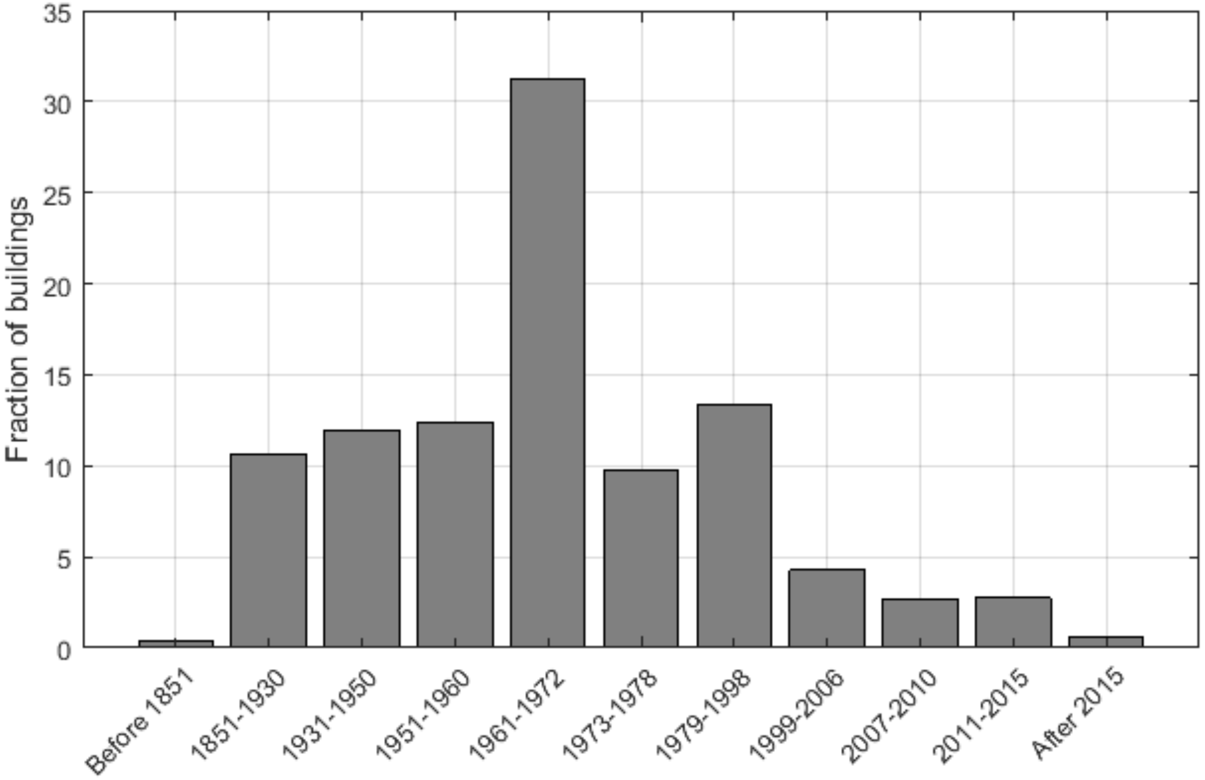
Case study: District heating-supplied Single-family houses in Aarhus

- 18,475 SFH's after data preprocessing
- Known data:
  1. Danish Building and Dwelling Register
  2. Hourly district heating consumption
  3. Weather data



Archetype segmentation

All 18,475 buildings were assigned an archetype label



Archetype, *k*	Example	Building period	Segmentation argument
Archetype 1		Before 1851	Single-family dwellings consist of smallholdings and detached farmhouses
Archetype 2		1851-1930	Shift in building tradition
Archetype 3		1931-1950	Cavity walls introduced
Archetype 4		1951-1960	Insulated cavity walls introduced
Archetype 5		1961-1972	First energy requirements in BR1961
Archetype 6		1973-1978	Tightened energy requirements in BR1972
Archetype 7		1979-1998	Tightened energy requirements in BR1978.
Archetype 8		1999-2006	Tightened energy requirements in BR1998.
Archetype 9		2007-2010	Tightened energy requirements in BR2006/BR2008
Archetype 10		2011-2015	Tightened energy requirements in BR2010
Archetype 11		After 2015	Tightened energy requirements in BR2015

Uncertain model parameter	Unit	Prior range Min.	Prior range Max.	Archetype 1	2	3	4	5	6	7	8	9	10	11
Geometry														
Length-width-ratio	[-]	0.10	1.00	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50
Room height	[m]	2.30	3.00	2.40	2.60	2.50	2.50	2.50	2.50	2.50	2.60	2.70	2.70	2.70
Window-floor-ratio*	[m^2/m^2]	0.10	0.50											
Window frame fraction	[%]	10	50	30	30	25	25	25	25	20	15	15	15	15
Transmission														
Temp. factor (ground)	[-]	0.50	1.00	0.70	0.70	0.70	0.70	0.70	0.70	0.70	0.70	0.70	0.70	0.70
U-value (floor)	[$W/(m^2K)$]	0.10	0.50	0.50	0.38	0.36	0.30	0.30	0.20	0.12	0.12	0.12	0.12	0.12
U-value (basement)	[$W/(m^2K)$]	0.10	1.20	1.00	1.00	1.00	0.65	0.40	0.35	0.30	0.20	0.18	0.18	0.18
U-value (walls/roof)*	[$W/(m^2K)$]	0.10	0.50											
U-value (windows)*	[$W/(m^2K)$]	0.70	5.00											
Solar heat gain coef.	[-]	0.50	0.70	0.60	0.60	0.60	0.60	0.60	0.60	0.50	0.50	0.50	0.50	0.50
Thermal capacity (mass)*	[$kJ/(m^2K)$]	50	2000											
Effective area (mass)**	[m^2/m^2]	2.5	3.5	Building specific, see the ISO 13790:2008 standard										
Heat conduction (mass)**	[$W/(m^2K)$]	9.10	9.10	9.10	9.10	9.10	9.10	9.10	9.10	9.10	9.10	9.10	9.10	9.10
Heat transfer coef. (surf.-air)**	[$W/(m^2K)$]	3.45	3.45	3.45	3.45	3.45	3.45	3.45	3.45	3.45	3.45	3.45	3.45	3.45
Ventilation														
Infiltration airflow*	[$l/(sm^2)$]	0.10	8.0											
Mechanical ventilation	[Yes/No]	No	Yes	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Heat recovery efficiency	[%]	50	90	N/A	N/A	N/A	N/A	N/A	N/A	60	70	85	85	85
Design ventilation airflow	[$l/(sm^2)$]	0.10	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30
Occupancy														
Occupant density*	[m^2/pers.]	10	150											
Heating setpoint temp.*	[°C]	18.0	24.0											
24h profile weekdays*	[%]	0	100											
24h profile weekends/holidays*	[%]	0	100											
Domestic hot water														
DHW temperature	[°C]	40.0	60.0	55.0	55.0	55.0	55.0	55.0	55.0	55.0	55.0	55.0	55.0	55.0
Mains temperature	[°C]	5.0	15.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0
Circulation pipe heat loss	[W/K]	0.00	20.0											
Hot water consumption*	[m^3/(pers.yr)]	5	20											

Archetype characterization

- Uncertain input parameters were assigned values based on expert knowledge
- Buildings with a given archetype label shared uncertain parameter values

Most sensitive parameters should to be calibrated with data

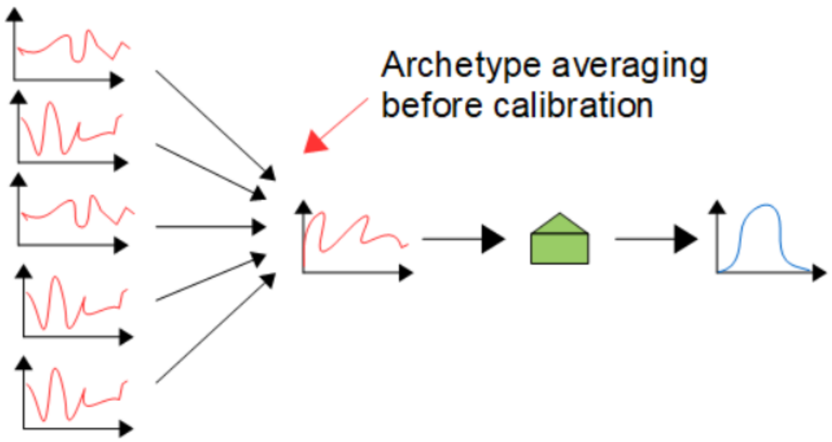
Archetype calibration

Archetype calibration

Booth et al. (2012)

❖ Full pooling of data

❖ Only the archetype model is calibrated

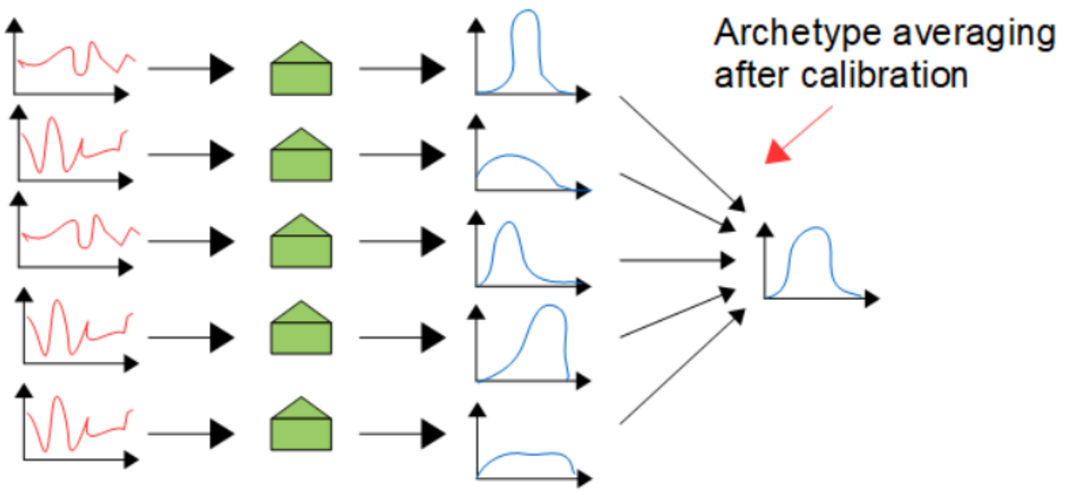


Cerezo et al. (2017)

❖ No pooling of data

❖ All training buildings are modelled independently

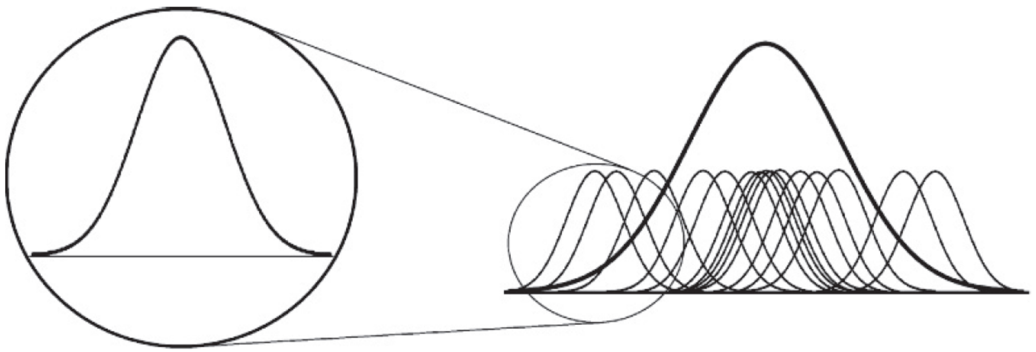
❖ Post pooling of calibration result



Hierarchical calibration: A new method

Kristensen et al. (2012)

- ❖ Bayesian probability
- ❖ Archetype model is **modelled** as the mean



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Hierarchical calibration of archetypes for urban building energy modeling

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ABSTRACT

The application of building archetypes is a widespread approach used in urban building energy modeling. Working with archetypes has a range of benefits, but it is important that modelers avoid using oversimplified approaches when establishing the archetype as they lead to loss of uncertainty and, consequently, to models with inferior predictive capabilities. In this paper, we propose a multilevel take on the challenge of establishing archetypes. A simultaneous modeling and calibration framework is formulated using Bayesian inference techniques – a technique that allows for the propagation of uncertainty throughout the calibration process. By means of hierarchical modeling, information from training buildings is partially pooled together to form an optimal solution between separate building energy models and a completely pooled model. This enables the inference of uncertain archetype parameters that are less prone to building outliers than what is achieved using ordinary aggregation of individual building estimates. The proposed framework incorporates dynamic building energy modeling of arbitrary temporal resolution where uncertain parameters are fitted for individual building models and the archetype model simultaneously. The application of the framework is demonstrated using case-study data from the Danish residential building stock, containing 3-hourly measurements of energy use for 50 training buildings. The model is tested for the prediction of 100 out-of-sample test buildings' aggregated energy use time series on a holdout validation period. With a prediction error of only NMBE = 2.9% and CVRMSE = 7.8%, the archetype framework promises well for urban modeling applications.

1. Introduction

City governments, utility companies, and other energy policy stakeholders work on the urban scale of neighborhoods, cities, or even entire building stocks when planning and predicting the effect of various energy efficiency and production strategies. They are in need of tools and platforms that enable the analysis of aggregated effects rather than individual building-level effects.

Urban building energy modeling (UBEM) is a growing research field that seeks to facilitate such analyses by combining the effects of individual buildings into an aggregated urban model. The modeling approach of UBEM is either to model buildings independently and then aggregate their simulated energy use, or to model buildings collectively in an all-inclusive urban model with context-specific boundary conditions and interactive effects. Regardless of the modeling approach, the overall challenge of UBEM is to collect and assign all the necessary data inputs for establishing sufficiently detailed building energy models of all buildings in the urban area without introducing too many assumptions and simplifications [1]. Because of this, the establishment of an accurate all-inclusive physics-based UBEM persists to be an extremely difficult task. However, one can make use of different techniques for reasonable tradeoffs between feasibility and accuracy to overcome this; of these techniques, the application of archetype models seems to offer an attractive solution.

1.1. Archetype modeling

The archetype approach seeks to reduce the number of buildings in a given building stock or urban area to a much smaller subset of homogeneous archetypes that represent groups of typologically identical buildings where information that would allow further differentiation is typically not available. This approach inevitably obscures the natural variability of occupant behavior and construction elements, but in turn reduces requirements for data acquisition and computational load.

The definition and use of building archetypes for urban-scale modeling have undergone a lot of work in recent years. In general, the literature describes the process of defining archetypes as consisting of three steps before simulation: (1) classification of build-

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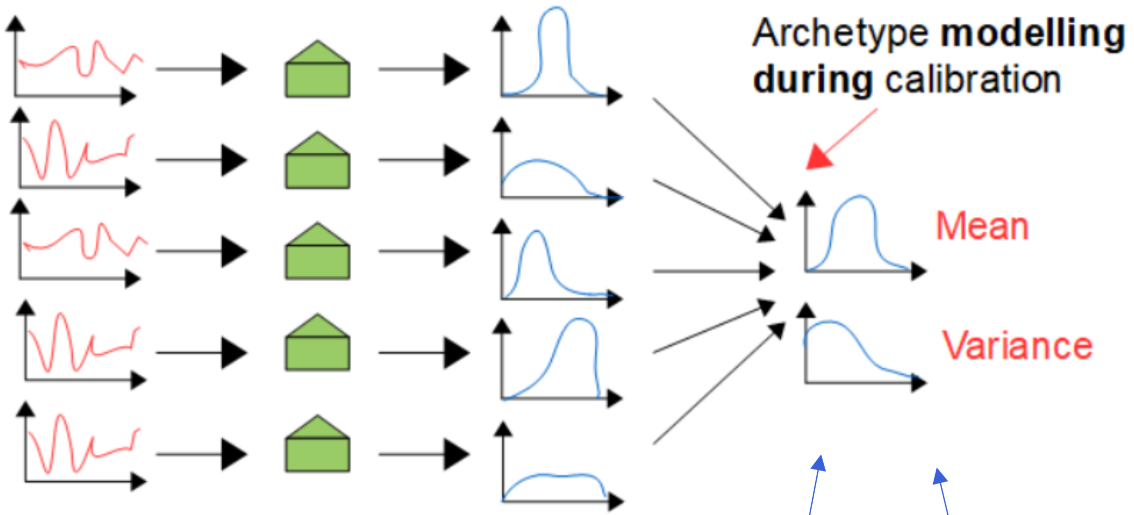
Hierarchical calibration: A new method

Kristensen et al. (2012)

- ❖ Bayesian probability
- ❖ Archetype model is **modelled** as the mean
- ❖ This allows us to assess the **heterogeneity** of the archetype



$$\boldsymbol{\theta}_b \sim \mathrm{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma}), \qquad b = 1, 2, \ldots, n_b.$$

Calibration parameters

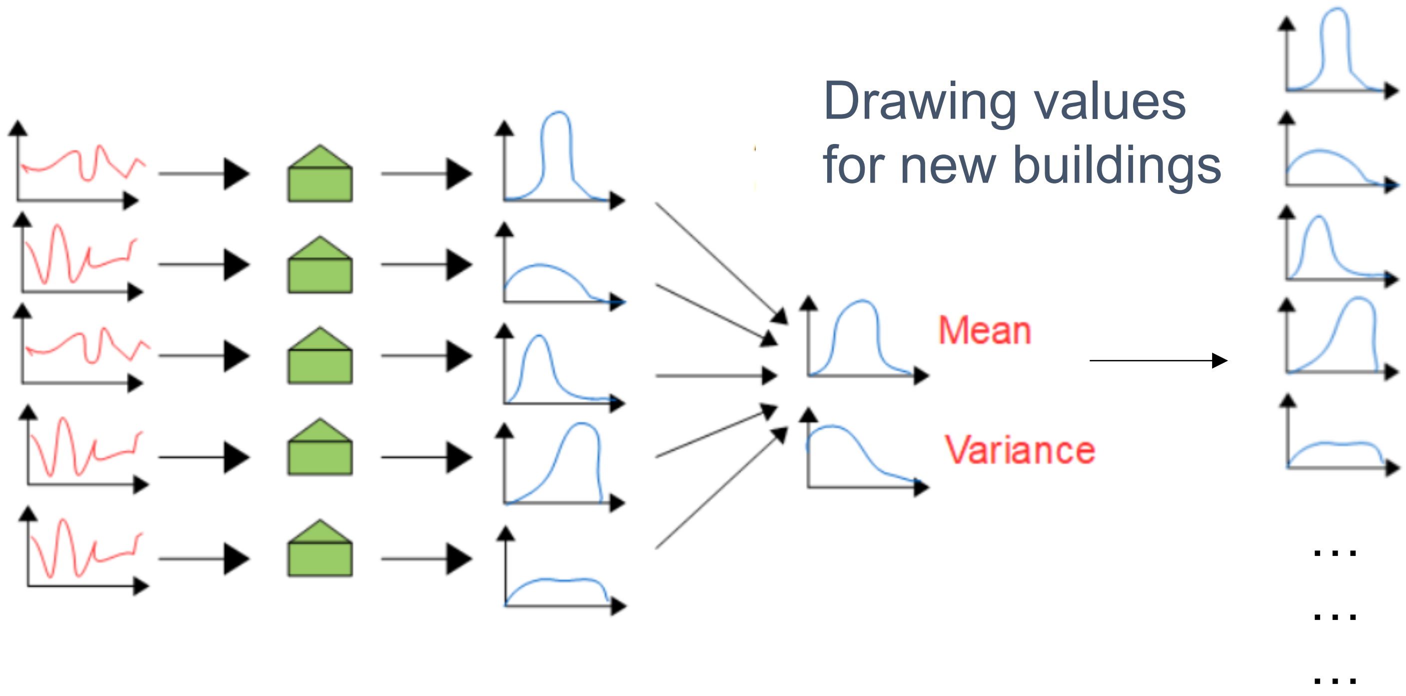
Mean of calib. params.

Covariance of calib. params.

θ μ Σ

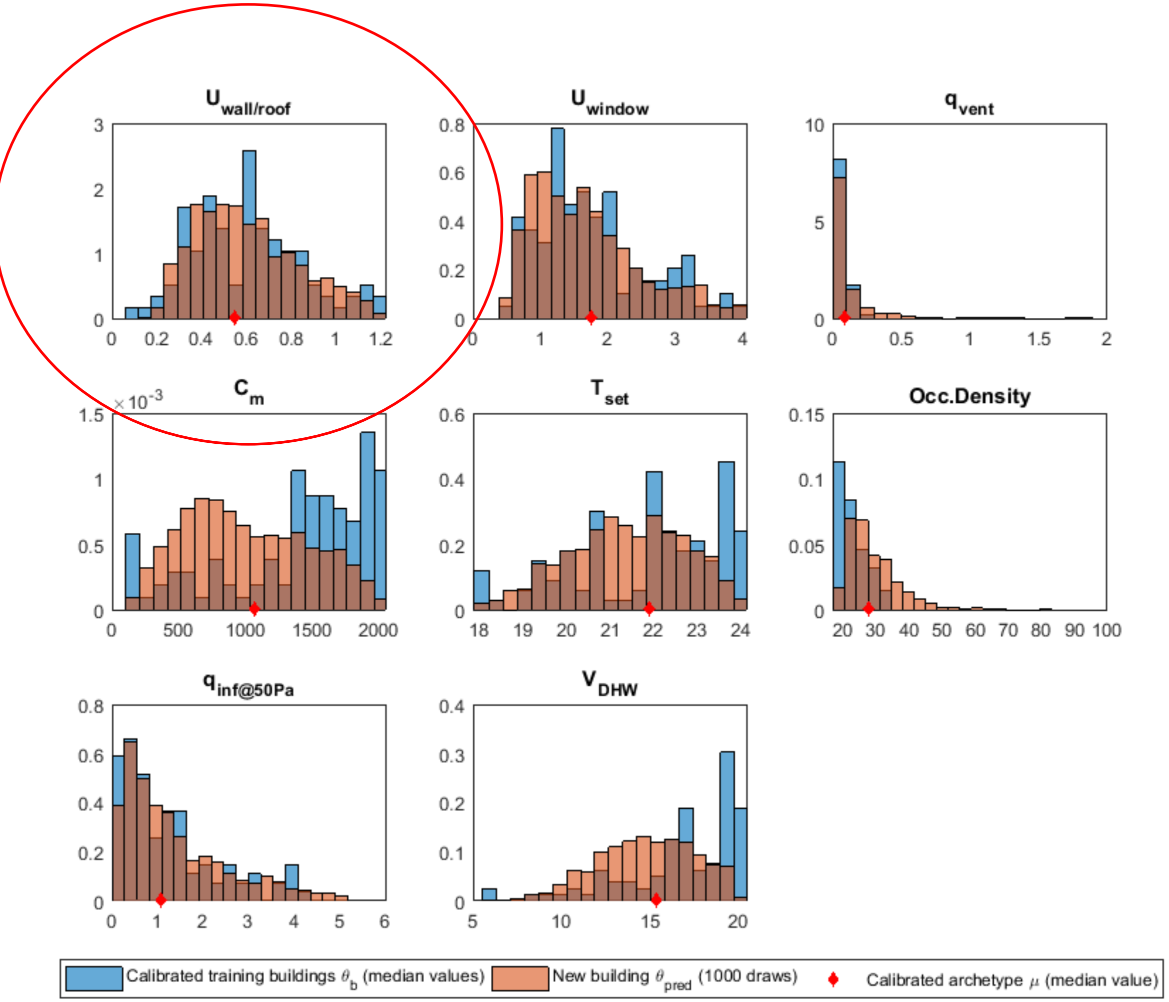
Hierarchical calibration: A new method

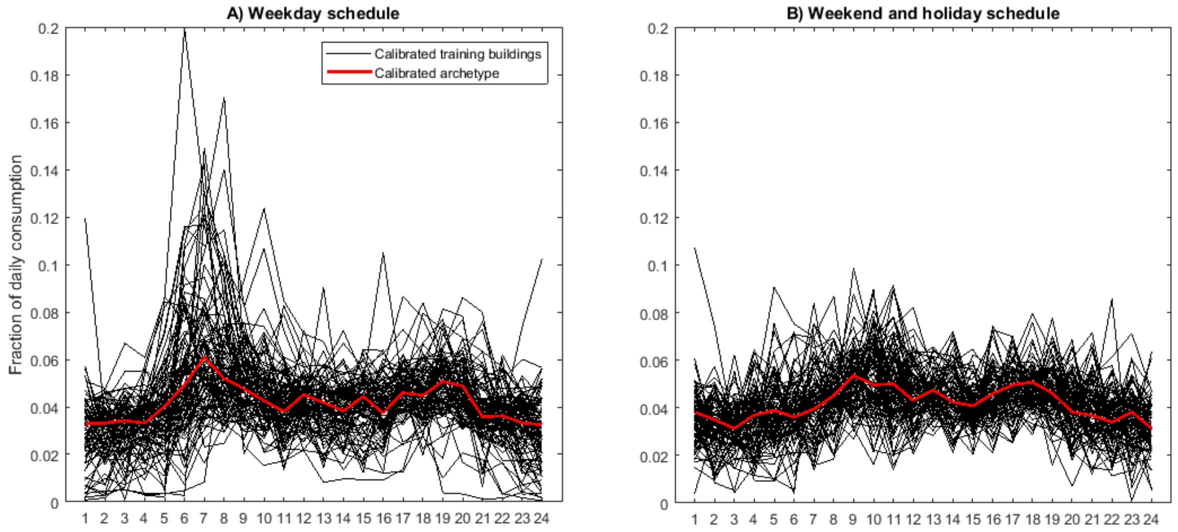
❖ Parameters for new unseen buildings belonging to the archetype are drawn stochastically



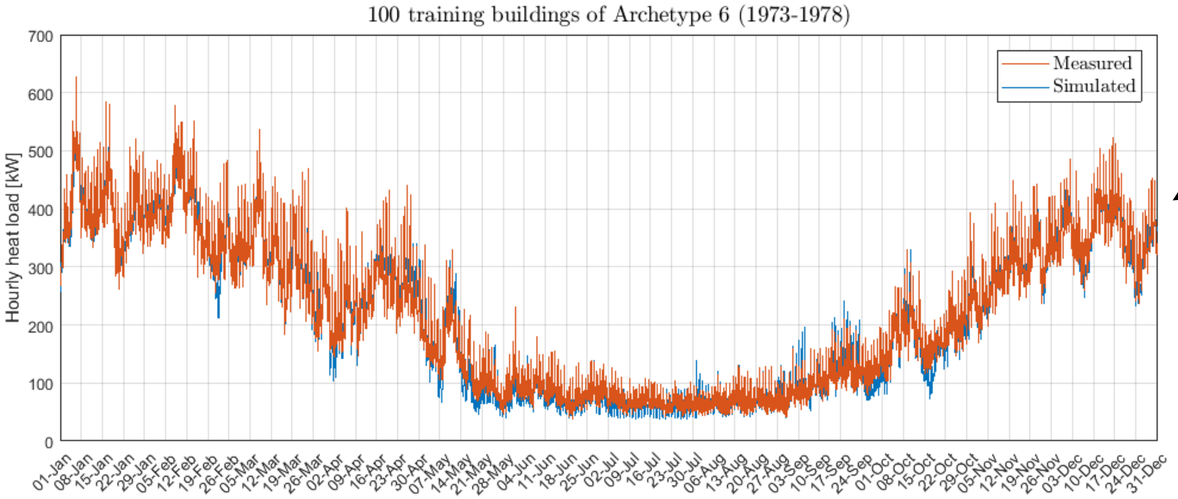
Results

Calibrated archetype parameters





Archetype predictive performance

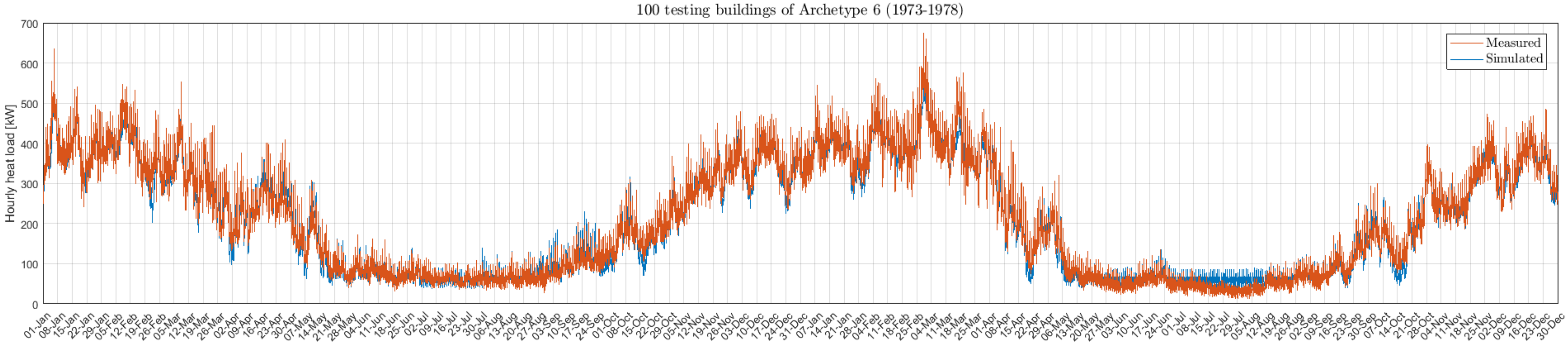


100 archetype **training** buildings calibrated using 2017 data.

Accuracy:
- Bias < 1%
- Hourly absolute error < 10%

100 **holdout testing** buildings predicted for 2017+2018

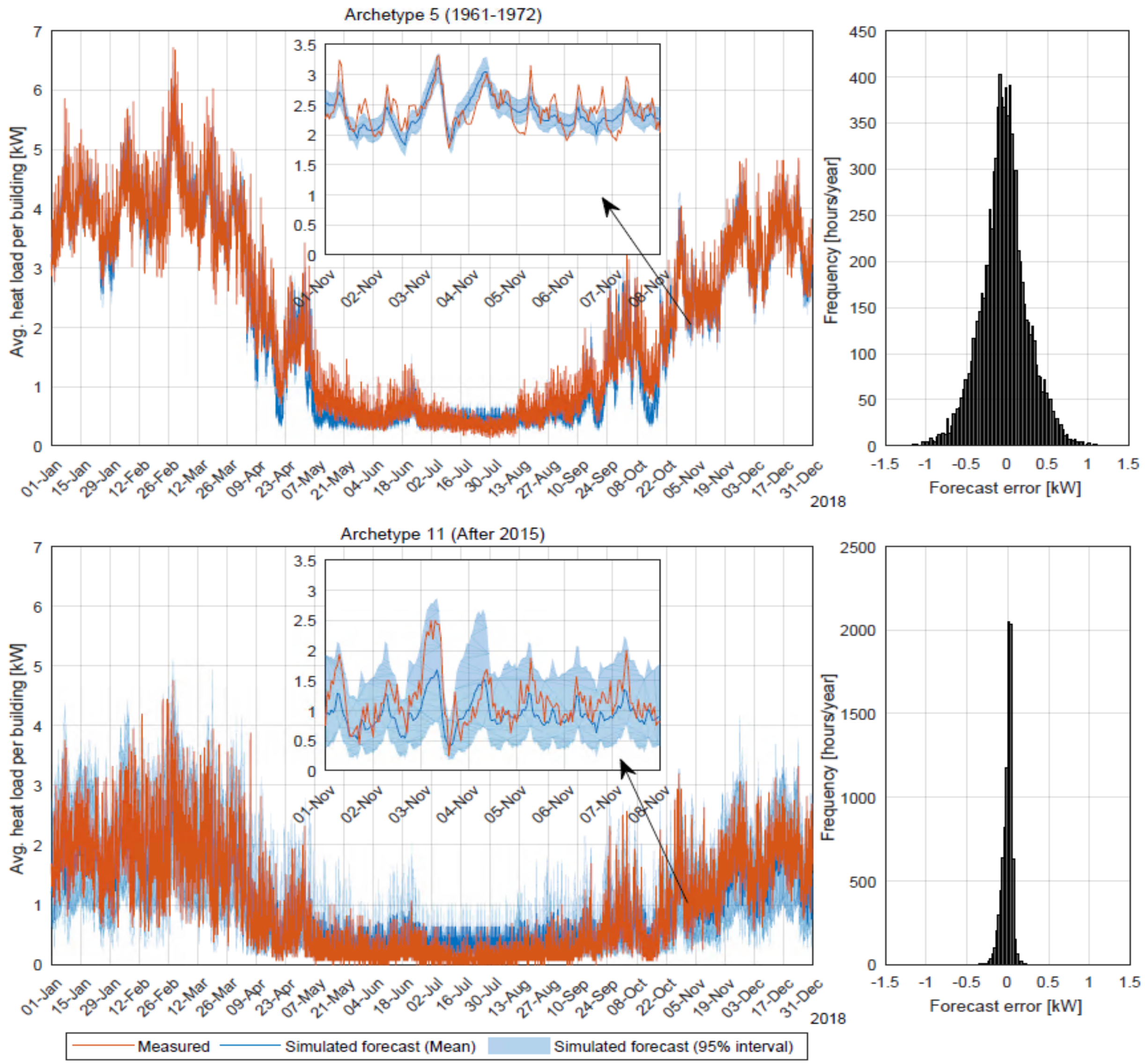
Accuracy:
- Bias < 2%
- Hourly absolute error < 15%



Archetypes are very different

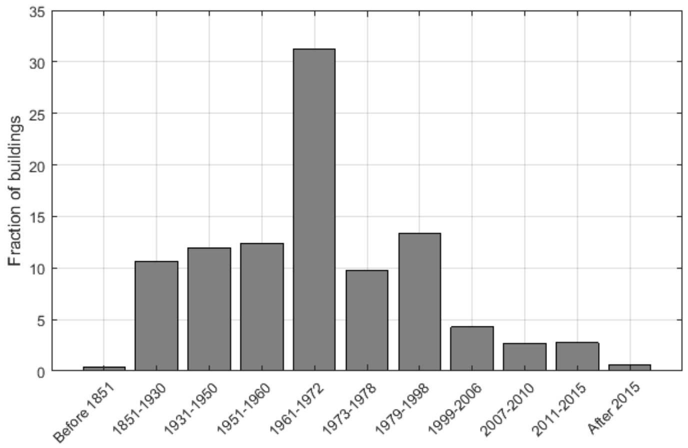
- Old archetypes have a large and “steady” consumption pattern

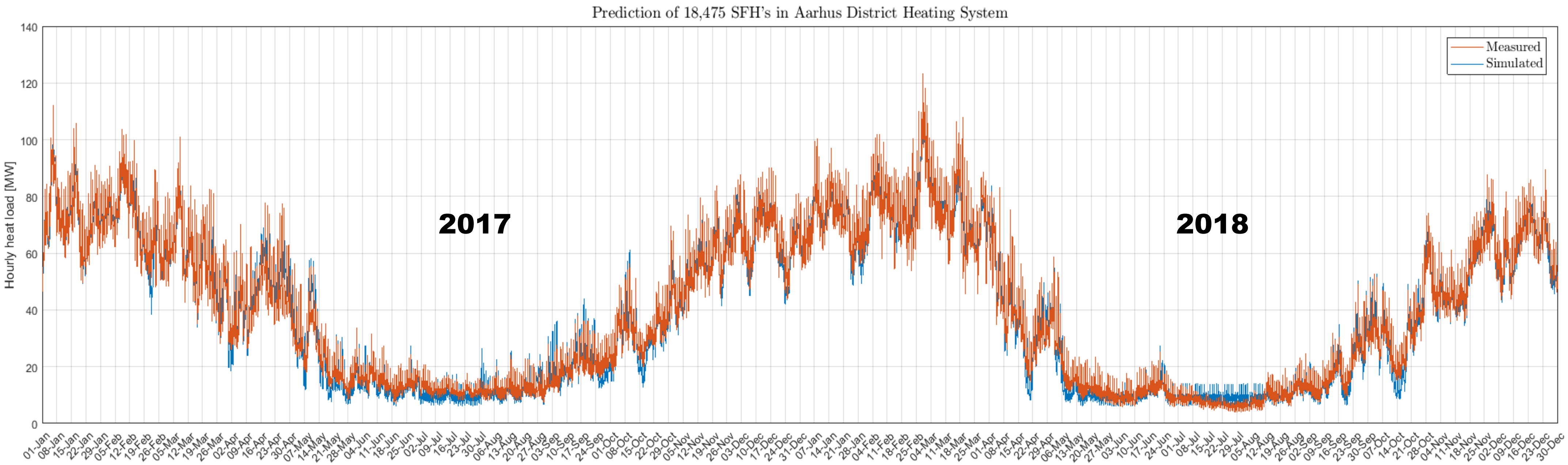
- New archetypes exhibit a lower and a more volatile consumption pattern

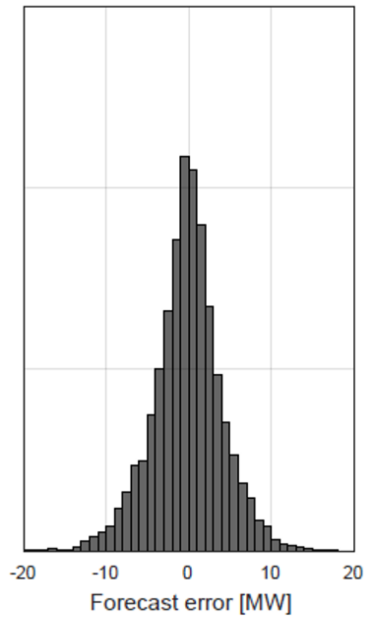


Long-term city-scale predictions

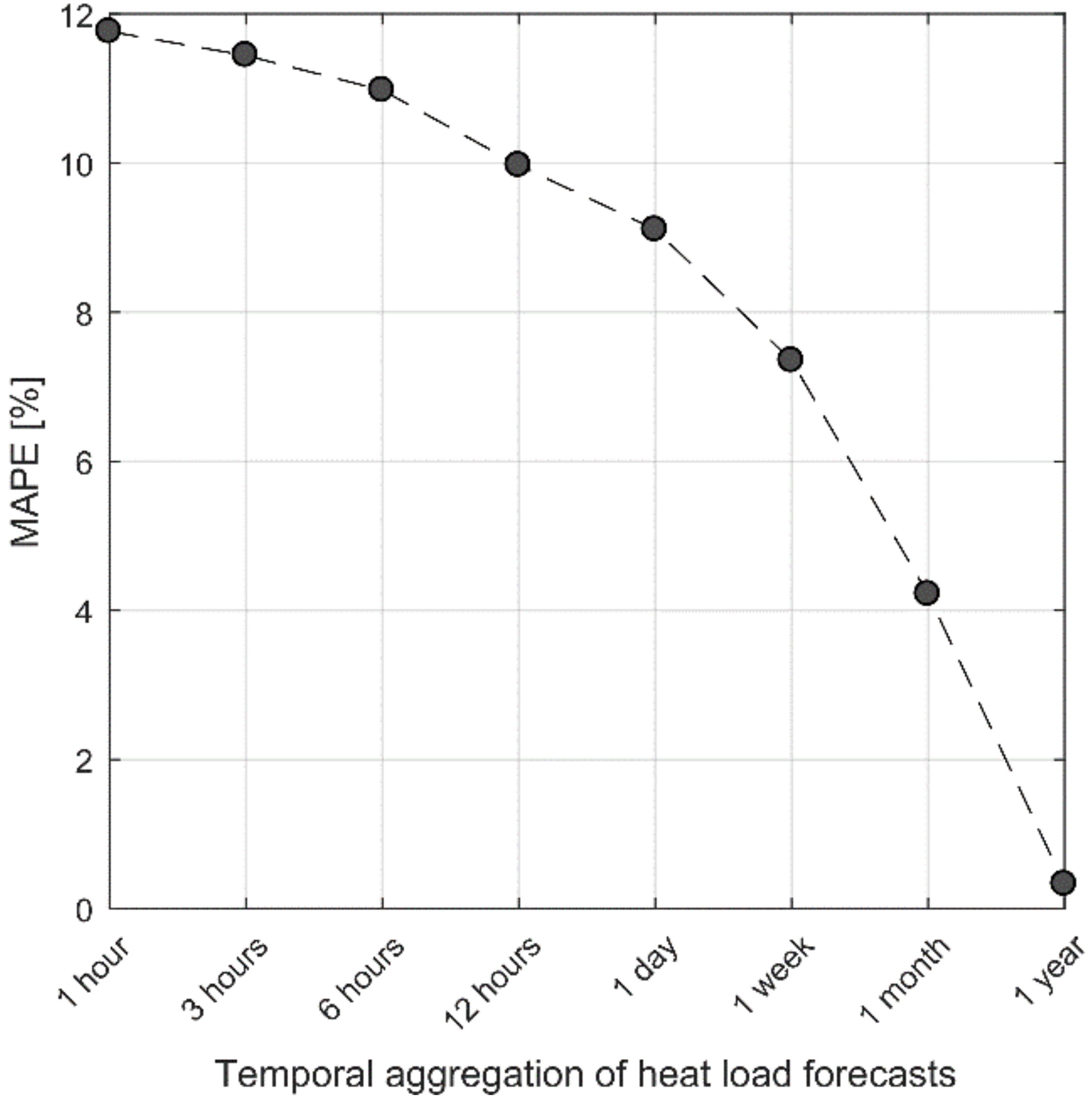
- 18,475 building models
- Period: 2017 + 2018 with hourly resolution
- Simulation time for 100 stochastic repetitions: appox. 4 hours.
- Accuracy: Bias = -0.3% bias; MAPE = 11.8%







Long-term city-scale predictions

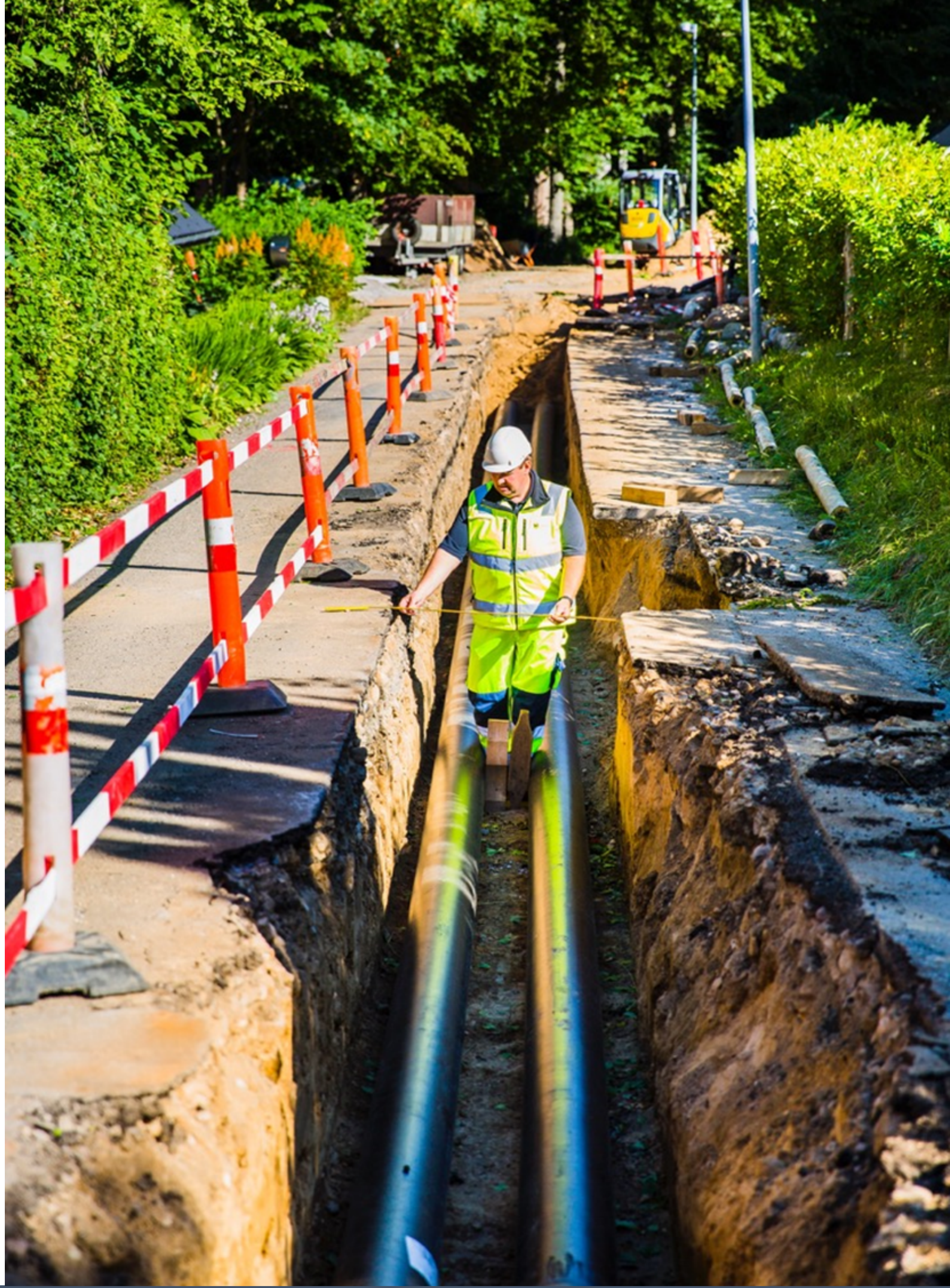


- Prediction accuracy increases if lower temporal resolution of heat load forecasts is accepted

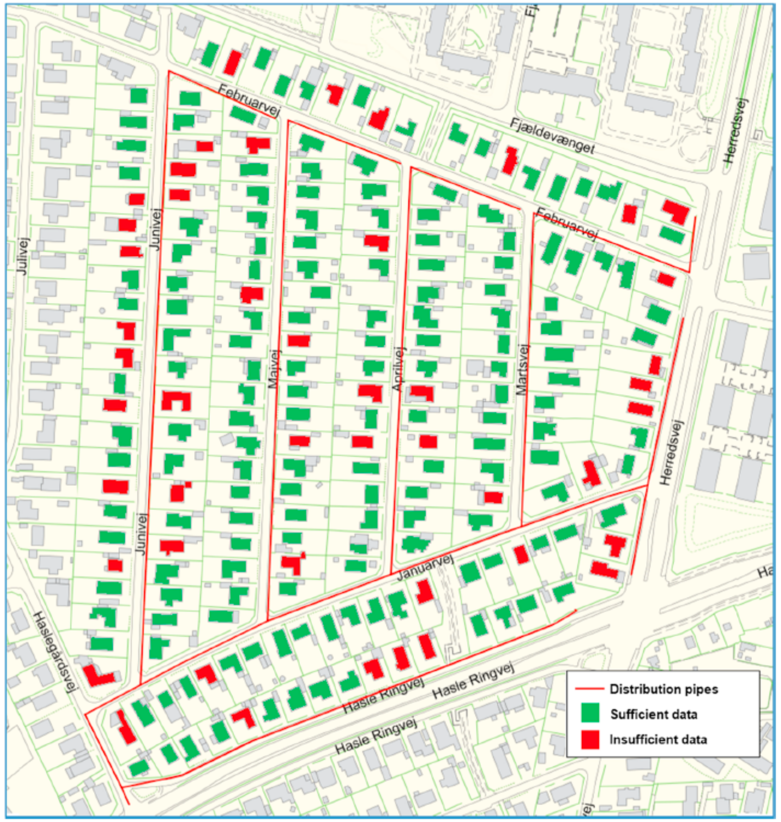
Applications

Applications

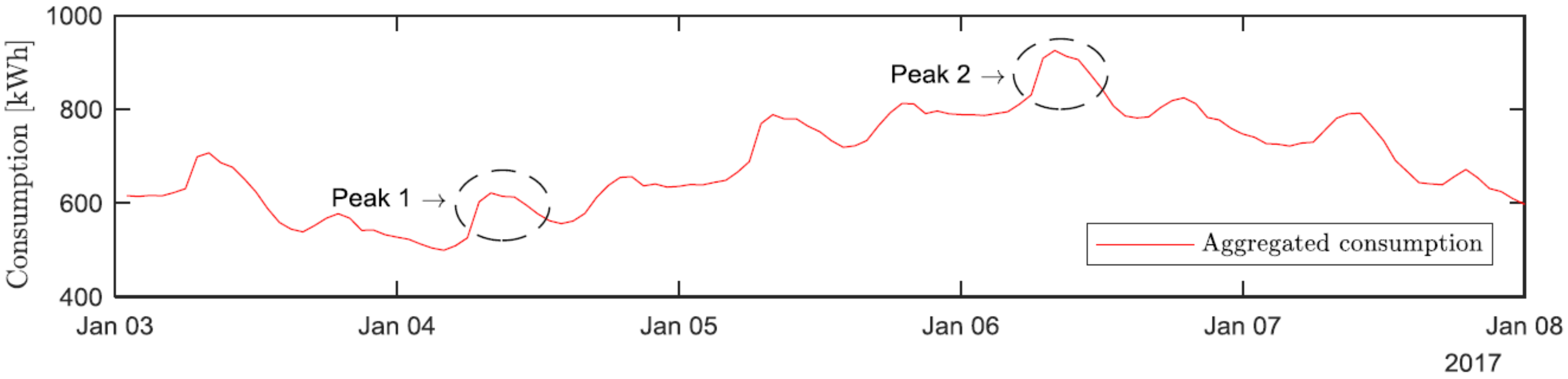
- Sizing district heating networks for new urban areas
- Forecasting future production needs and heat load patterns
- Analyzing the consequences of energy renovation and future weather conditions
- Analyzing the effect of demand response and energy flexibility of the building stock



Demand response application with model predictive control (MPC)

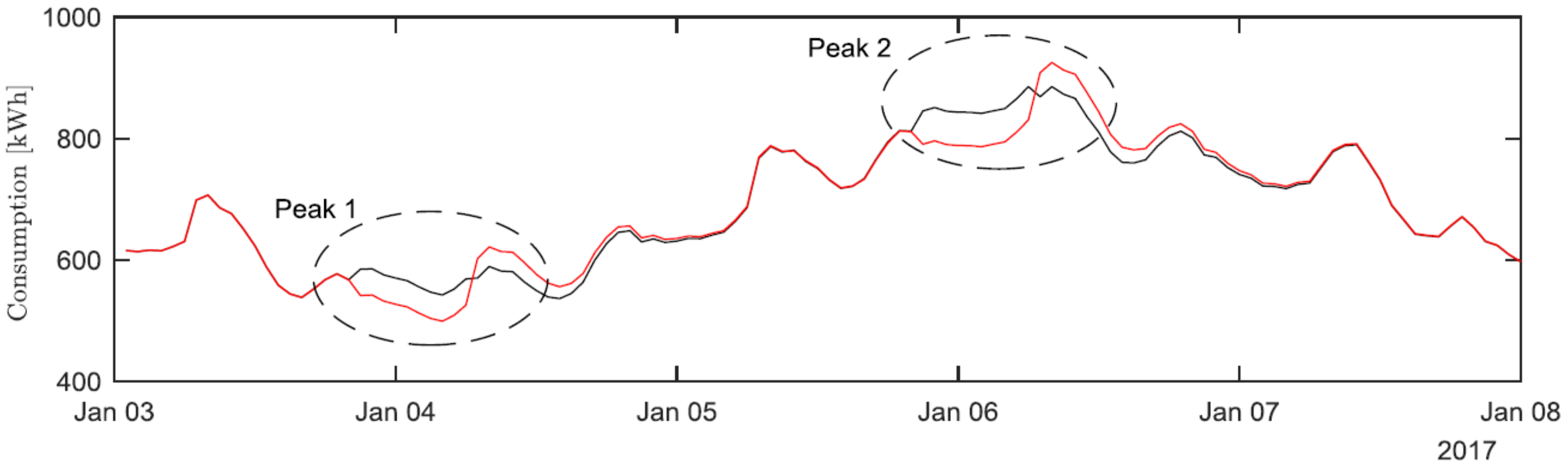


- 159 out of 206 buildings were modelled and calibrated
- Two periods identified for demand response analysis
- **Optimize: find price at which the lowest aggregated heat loads occur while maintaining thermal comfort**



Demand response application with model predictive control (MPC)

- Constraints: $20°C \leq T_{\text{indoor}} \leq 24\ °\text{C}$
- Prices increased by approx. +60% in peak periods to obtain lowest heat loads
- Peak load reductions of approx. 5% in peak periods
- Buildings engage in DR at different price levels depending on their energy efficiency



Thank you for your attention

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