FACULTY OF ENGINEERING
AND ARCHITECTURE

DEPARTMENT OF ARCHITECTURE AND URBAN PLANNING
BUILDING PHYSICS, CONSTRUCTION AND SERVICES RESEARCH GROUP

ENERGY PERFORMANCE ASSESSMENT OF BUILDINGS USING MEASUREMENTS: EXPERIENCE FROM SMART METER DATA ANALYSIS

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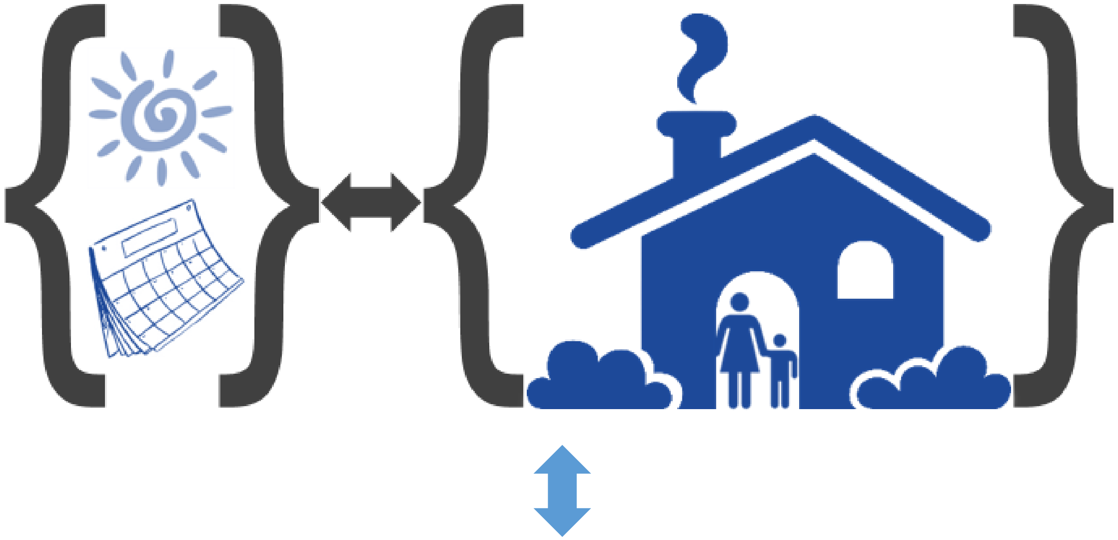
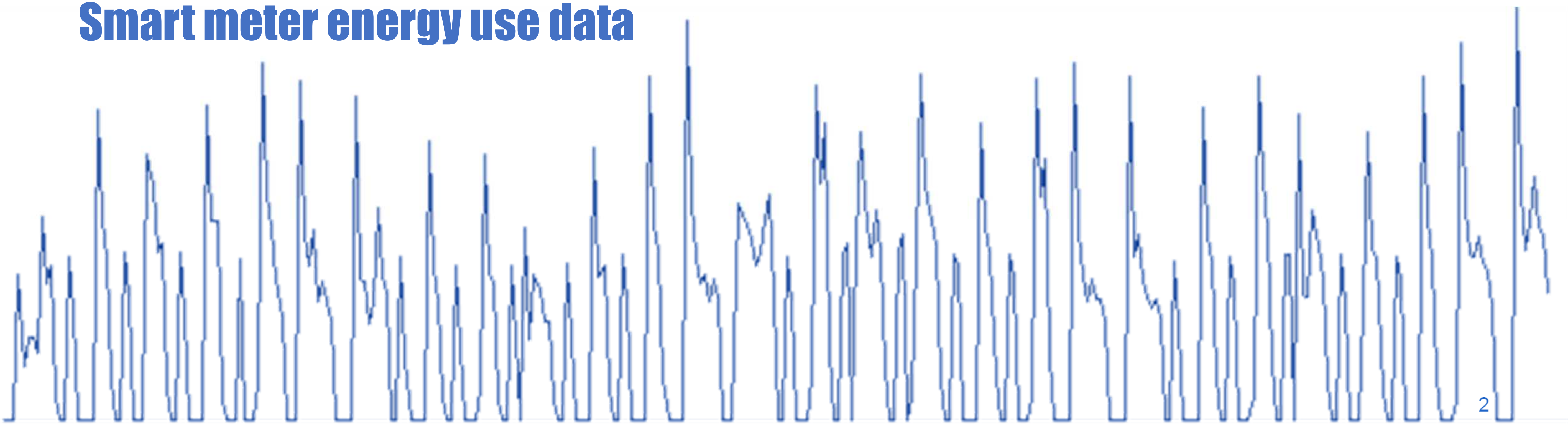


Energy Signatures

Smart meter energy use data



I. Research Overview

Characterisation of residential energy use for heating using smart meter data

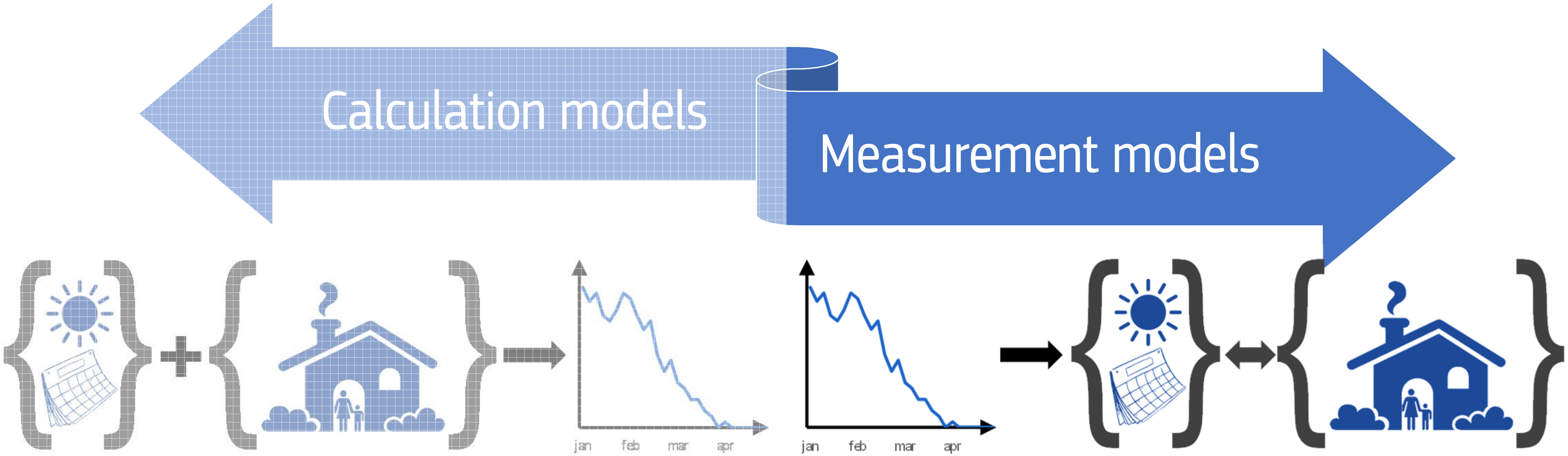
II. Findings and Views

Energy performance assessment of buildings using measurements

I. Research Overview

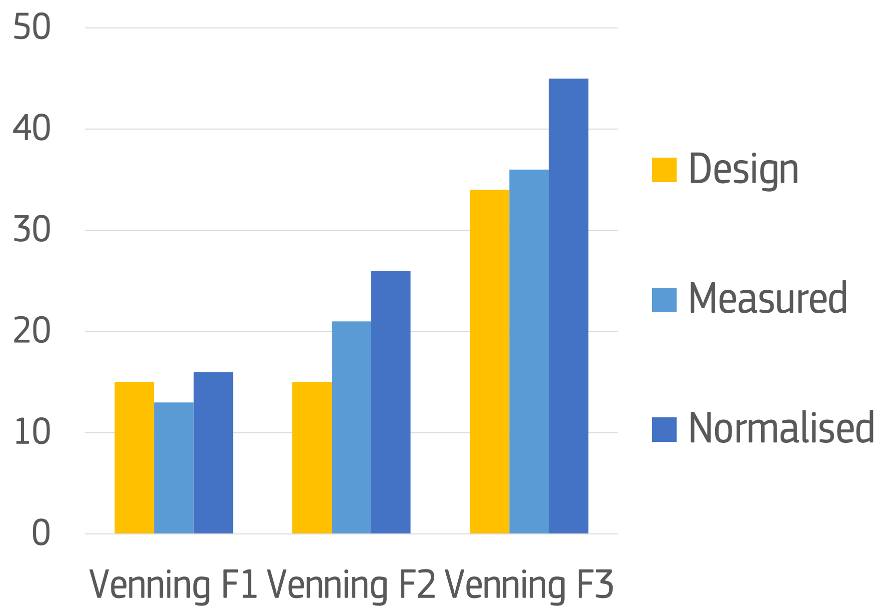
Characterisation of residential energy use for heating using smart meter data (Ghent University, 2017)

Energy use estimations starting from measurements



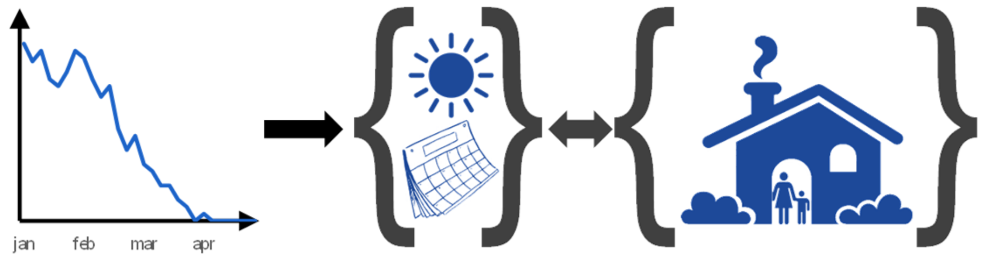
MODELLING	forward, white-box	Backward, black- and grey-box
INPUT	Information of building and user, assumptions	Measurements of energy use, weather, energy-related parameters…
EXAMPLE	epb-calculations, dynamic simulation models	Energy Signature models

Energy use estimations starting from measurements



Net space heating demand

in Venning dwellings (kWh/m²/year)

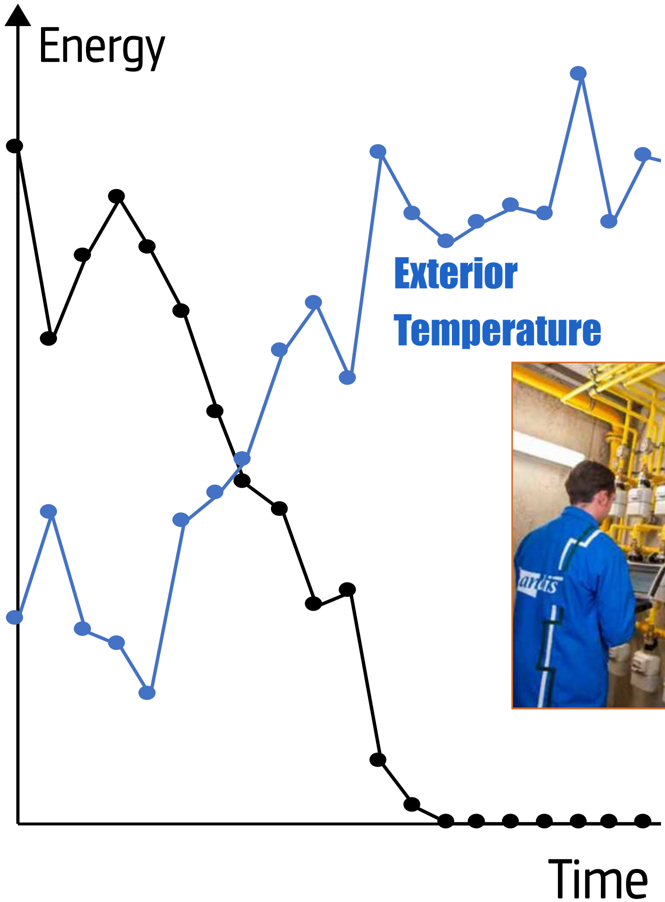


→ **Measured energy use is also influenced by external conditions**

→ **It needs to be CHARACTERISED: mathematically described in function of external variables**

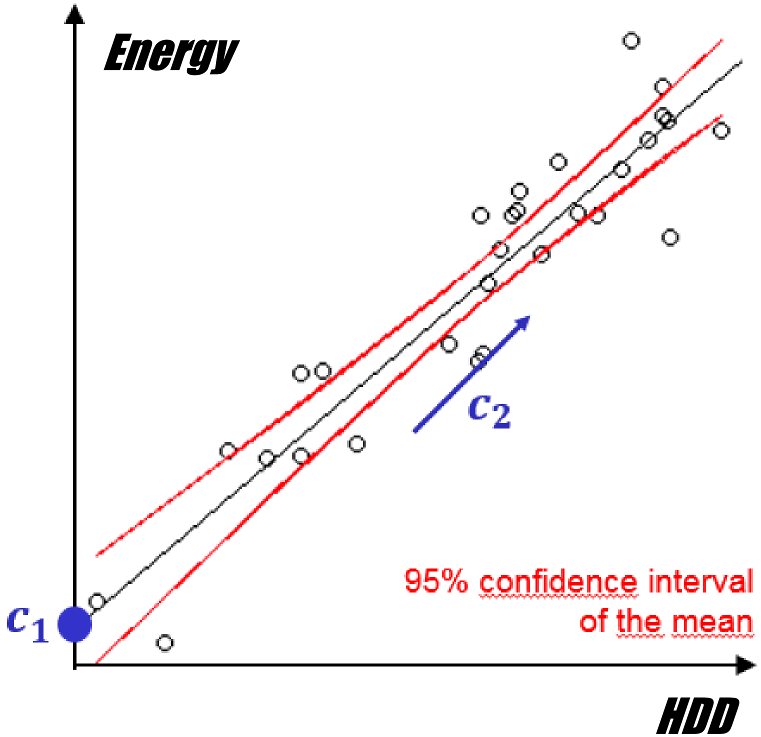
→ **Allowing energy use NORMALISATION**

Energy signature models are a classical approach
For characterising the energy use in function of weather variables



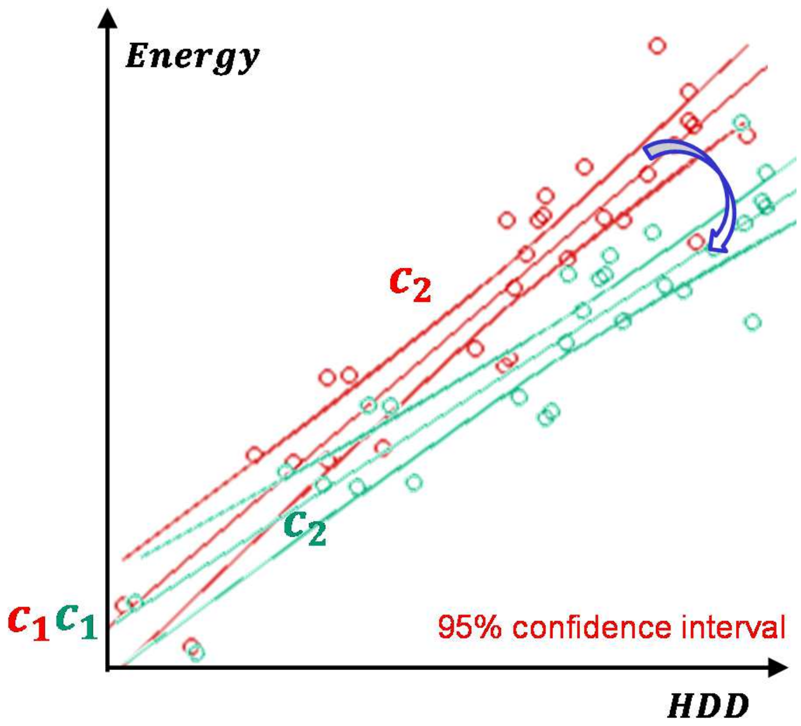
$$\text{Energy} = c_1 + c_2 \times \text{HDD} + \varepsilon_t$$

HDD = Heating Degree Days = 16,5°C – Te,eq

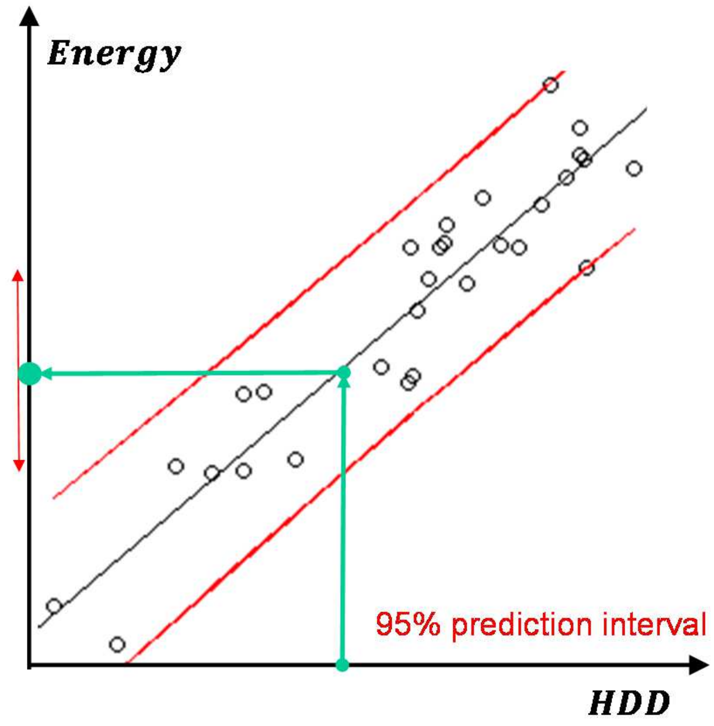


Energy Signature models can be used to

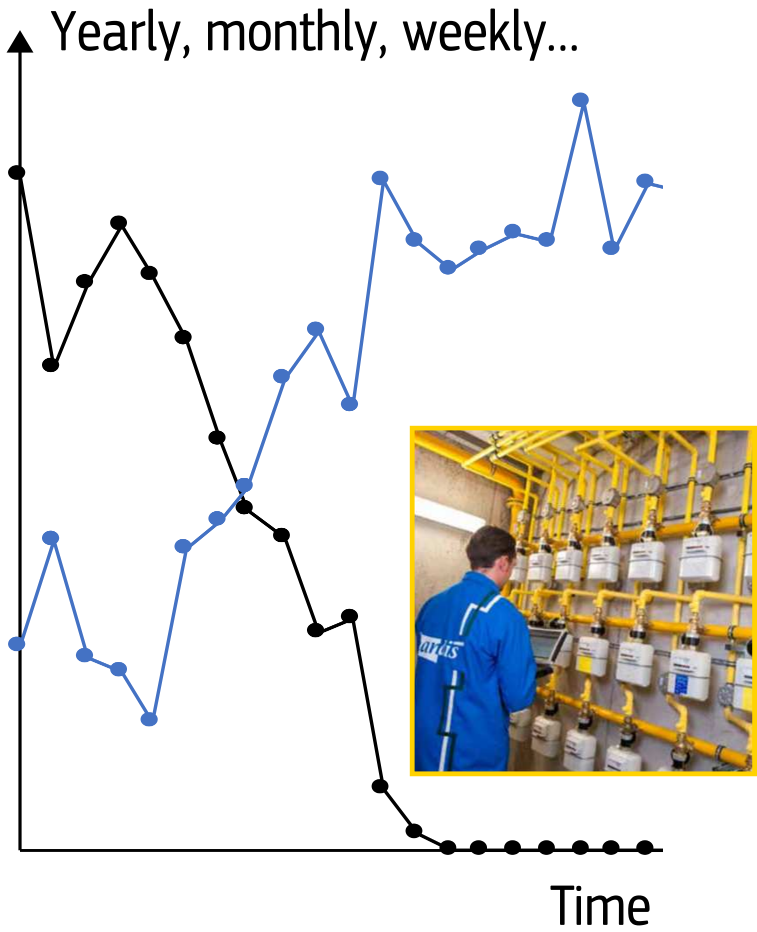
Compare the energy use
for different periods or houses

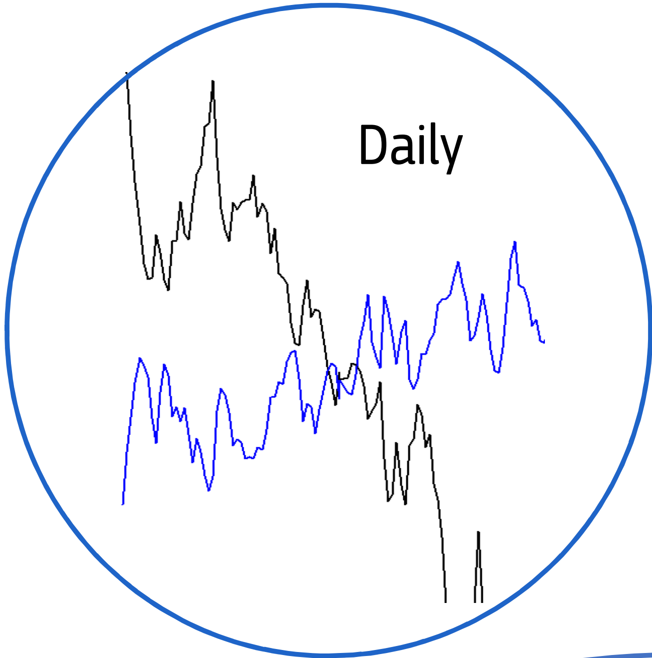


To predict or normalise
the energy use

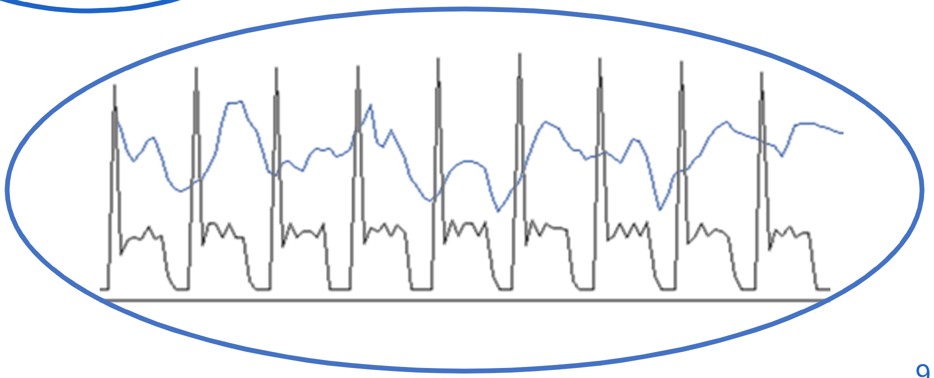


From manual meter readings to smart meter data



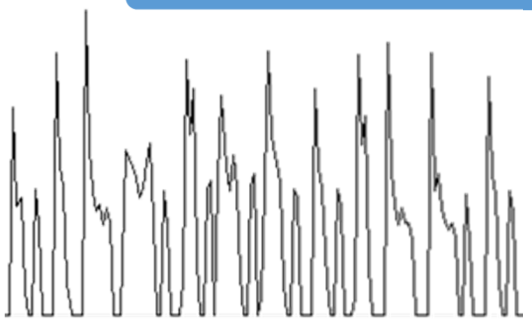


Hourly



Do (sub-)daily data allow to improve Energy Signature models?

Energy Use Data



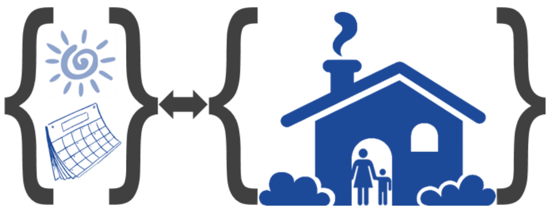
Model?

$$\text{Energy} = c_1 + c_2 \times \text{HDD} + \varepsilon_t$$

Linear Regression

Static & Dynamic

Energy Signatures



Applications: normalisation, prediction…

in

Energy Feedback, Energy Auditing, Commissioning

e.g. assessment of energy-efficiency measures (e.g. by comparison)

The data consists of residential energy use data

Buildings:

- 25 single-family dwellings in Flanders
- mostly > 10 years old
- Gas used for space heating only

Measurements:

- Smart meters: hourly gas use
- Local Weather station: weather data

(WEEKLY) DAILY DATA

1 • Classical Linear regression models (LM)

2 • Auto-Regressive models (ARX)

3 • Clustering Energy Use Time Patterns

4 • Classifying Energy Use Time Patterns

2-HOURLY DATA

5 • LM- & ARX-models with EUTP

Classical linear regression base model

$$Q_t = c_1 + c_2 \times Te_t + c_3 \times Rg_t + c_4 \times Ws_t + c_5 \times Te_{t-1}$$

Exogenous inputs (weather inputs)

DAILY DATA

1 • Classical Linear regression models (LM)

2 • Auto-Regressive models (ARX)

3 • Clustering Energy Use Time Patterns

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2-HOURLY DATA

5 • LM- & ARX-models with EUTP

Auto-regressive model with exogenous inputs (ARX)

$$Q_t = c_1 + c_2 \times \underbrace{Te_t + c_3 \times Rg_t + c_4 \times Ws_t + c_5 \times Te_{t-1}}$$

Exogenous inputs (weather inputs)

$$+c_6 \times \mathbf{Q_{t-1}} + c_7 \times \mathbf{Q_{t-2}} + \cdots + c_{12} \times \mathbf{Q_{t-7}}$$

Auto-regressive terms

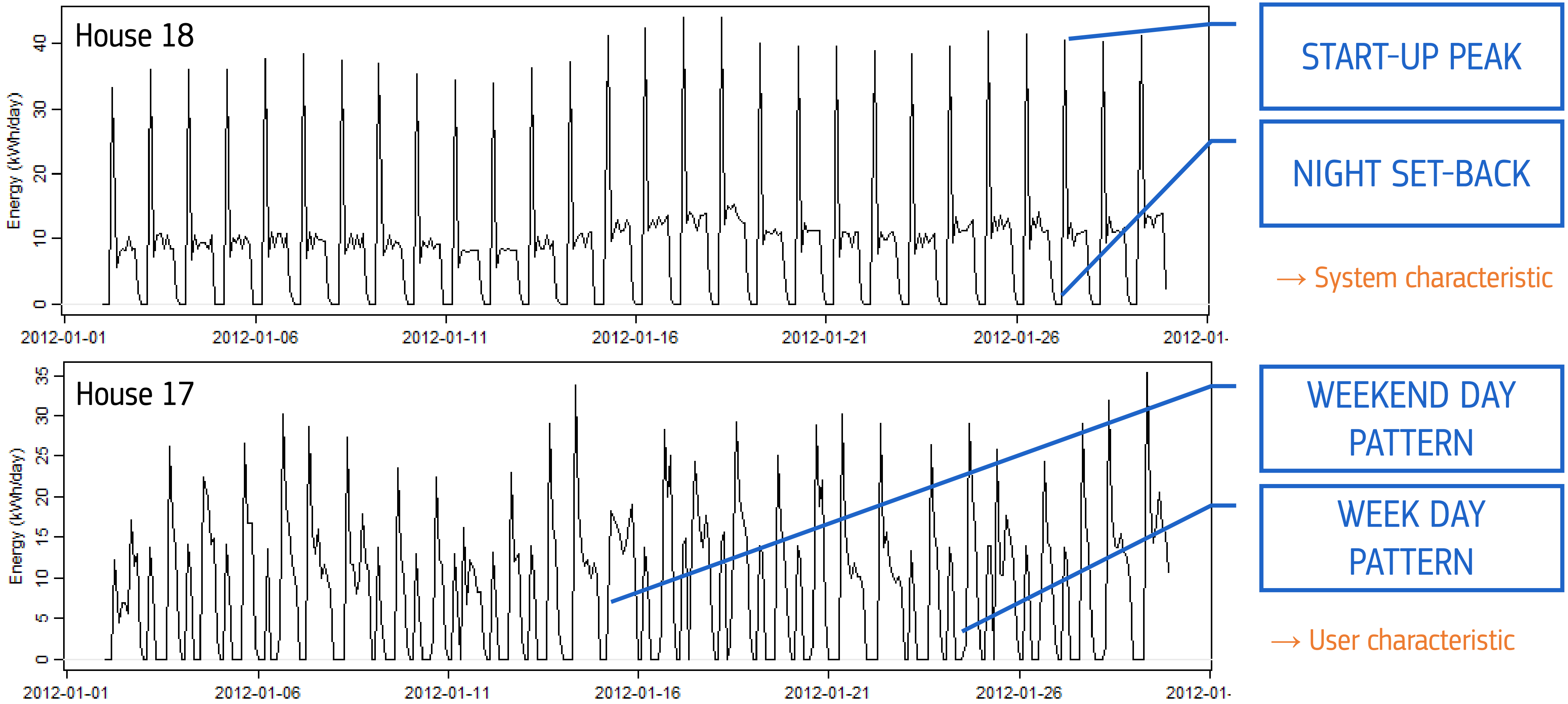
DAILY DATA

1. Classical Linear regression models (LM)
2. Auto-Regressive models (ARX)
3. Clustering Energy Use Time Patterns
4. Classifying Energy Use Time Patterns

2-HOURLY DATA

5. LM- & ARX-models with EUTP

When observing 2-hourly energy use time series (one winter month) energy use time patterns can be visually recognised

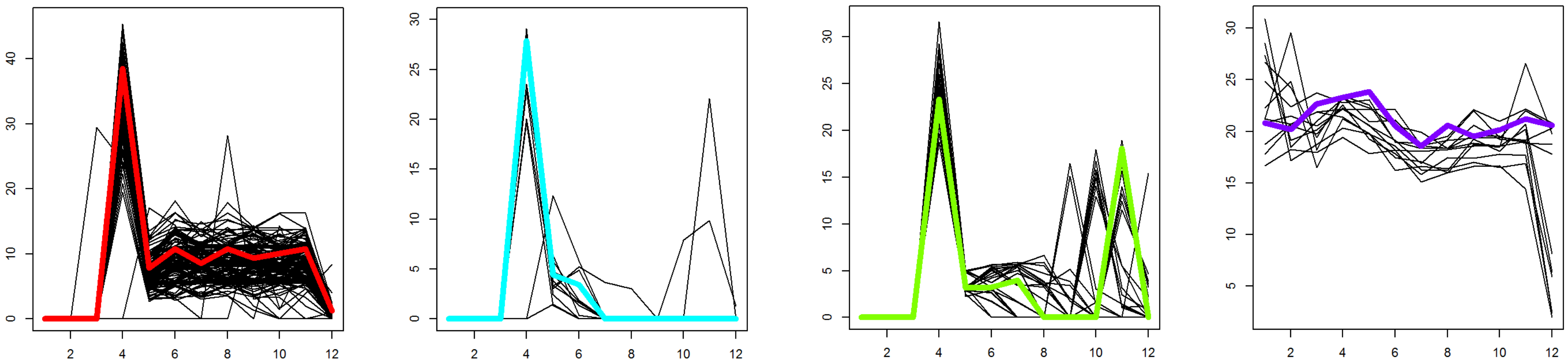


When observing 2-hourly energy use time series energy use time patterns can be visually recognised

How can these patterns also be mathematically recognised,

and similar patterns be grouped?

Clustering of energy use time patterns using CLUSTER ANALYSIS

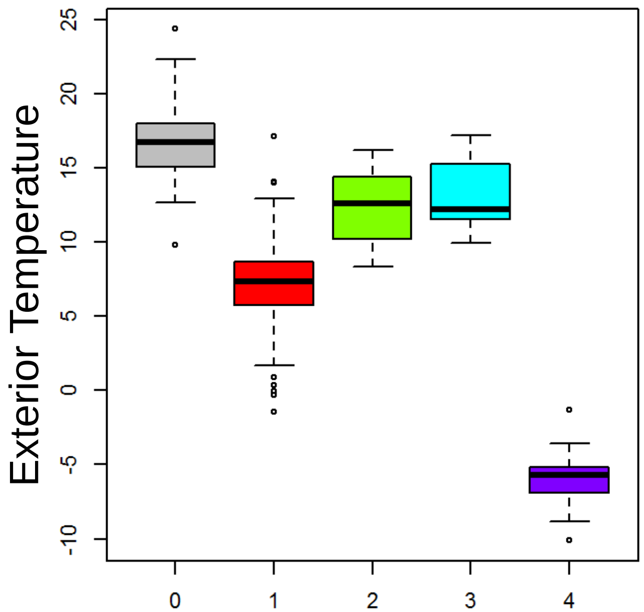


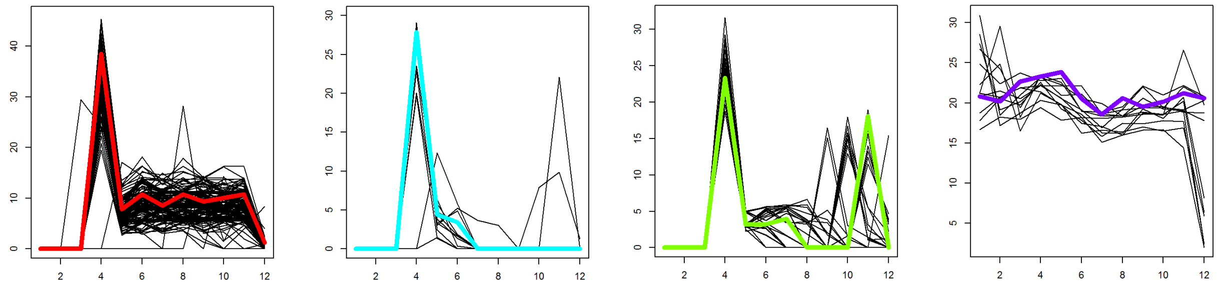
When observing 2-hourly energy use time series energy use time patterns can be visually recognised

How can groups of similar patterns be characterised

in function of weather conditions or calendar information?

Classification of energy use time patterns





DAILY DATA

1. Classical Linear regression models (LM)
2. Auto-Regressive models (ARX)
3. Clustering Energy Use Time Patterns
4. Classifying Energy Use Time Patterns

2-HOURLY DATA

5. LM- & ARX-models with EUTP

LMC- and ARXC-models with cluster variable

$$Q_t = c_1 + c_2 \times Te_t + c_3 \times Rg_t + c_4 \times Ws_t + c_5 \times Te_{t-1}$$

Exogenous inputs (weather inputs)

$$+ c_6 \times \mathbf{Q_{t-1}} + c_7 \times \mathbf{Q_{t-2}} + \cdots + c_{12} \times \mathbf{Q_{t-7}}$$

Auto-regressive terms

$$+ c_{13 \rightarrow (n+13)} \times \mathbf{C_{1 \rightarrow n}}$$

Cluster variable as constant

$$+ (c_{13 \rightarrow (n+13)} \times \mathbf{C_{1 \rightarrow n}} \times \mathbf{Te_t} + (\ldots)) + \varepsilon_t$$

Cluster variable in interaction with other variables

- The cluster variable describes to which cluster each day belongs
- The Energy Signature may vary per cluster or ‘state’ of the system

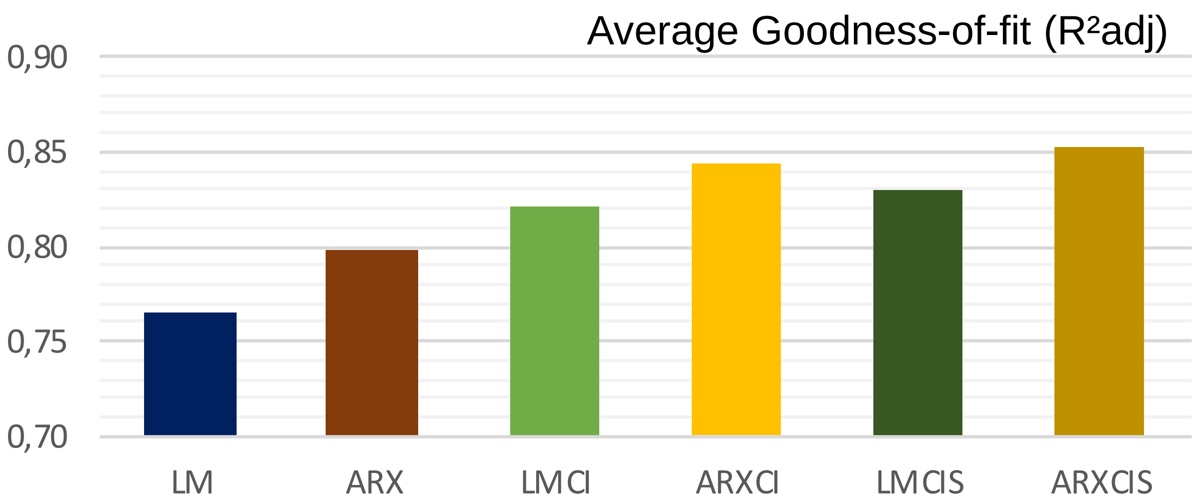
The LMC- and ARXC models are statistically valid and fit the data better than LM- and ARX-models

LM invalid in about half of the cases, issue: autocorrelated

ARX errors

LMC valid for most cases, minor issue: non-constant variance

ARXC part of autocorrelations resolved by cluster variable



Linear regression models: data $\leftrightarrow$ model selection?

Weekly	• Use LM
Daily	• Use ARX (LM)
Sub-Daily	• Use LM or ARX, with cluster variable: LMC, ARXC

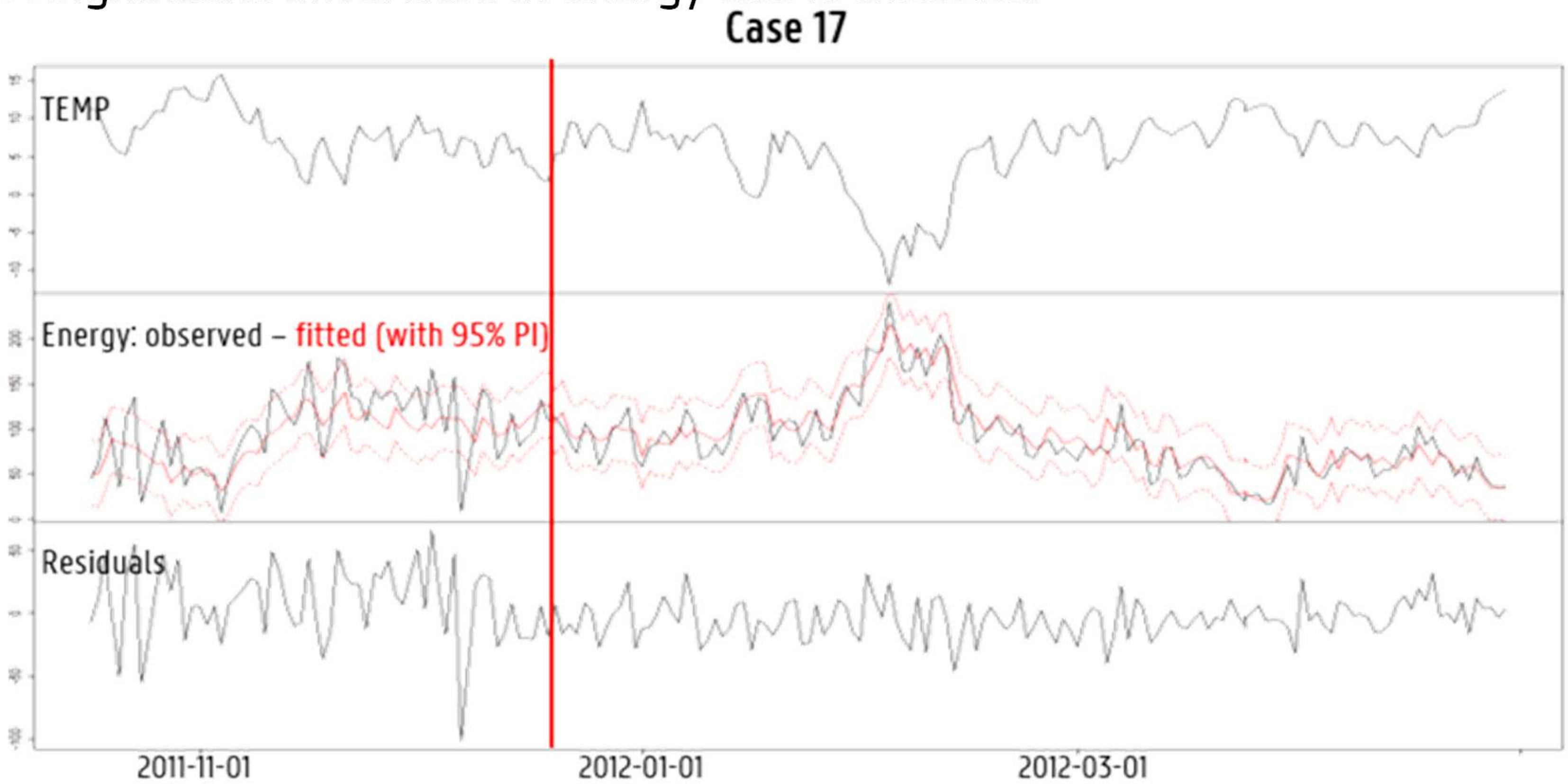
Note:

- Beware of aggregating daily values into 2, 3… 6 day values
- Study on houses with average or high energy use

$\rightarrow$ applicability on low-energy dwellings to be evaluated!

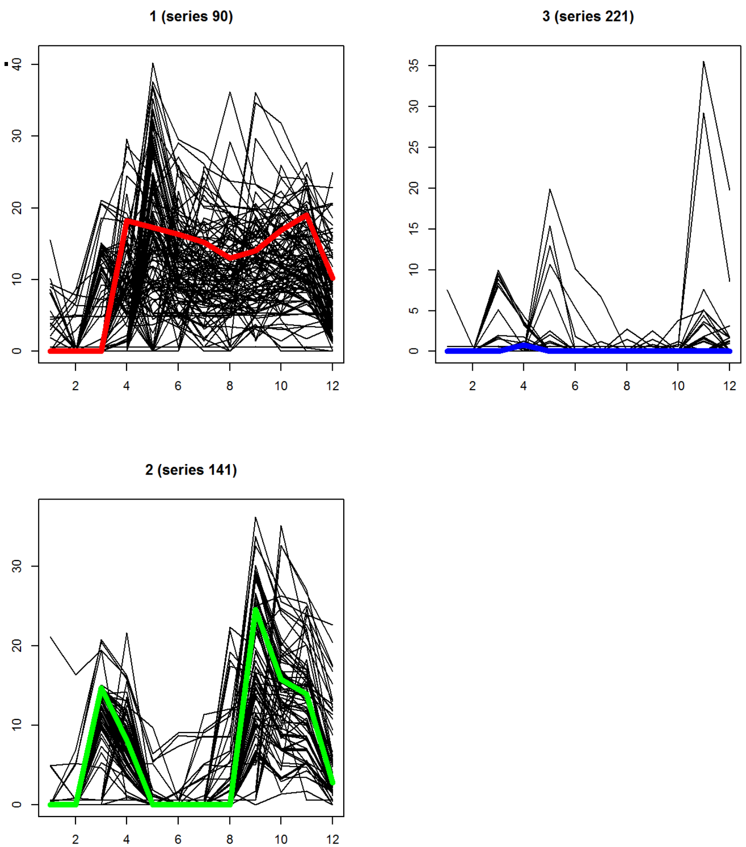
Identify changes in energy use over time: comparison of Energy Signatures

- Energy Signature Coefficients → classical parameters
- A significant difference in energy use is detected



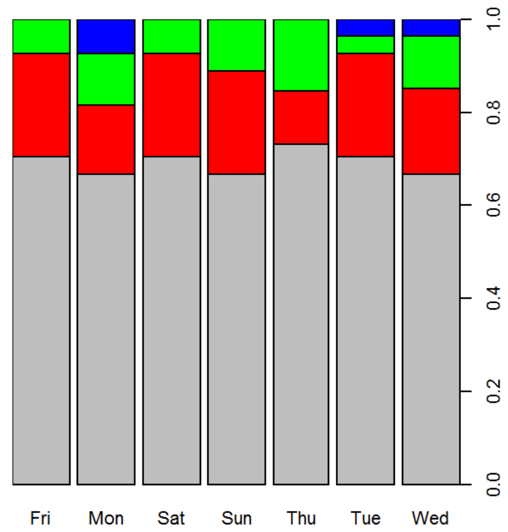
Identify changes in energy use over time: comparison of patterns

– Energy Use Time Patterns ⟶ additional insights in energy use related behaviour of building

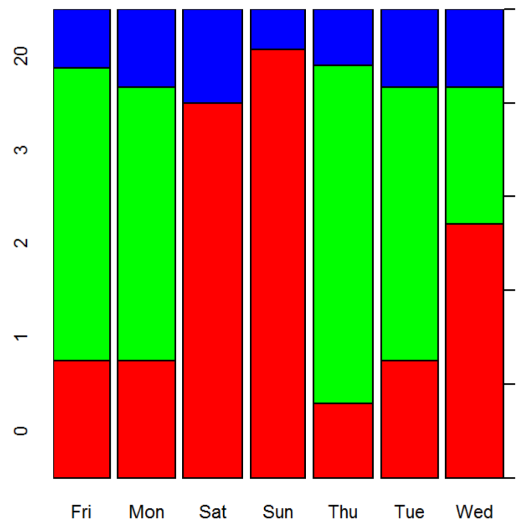


the patterns (Saturday and Sunday)

Period 1



Period 2



Characterisation of energy use time patterns

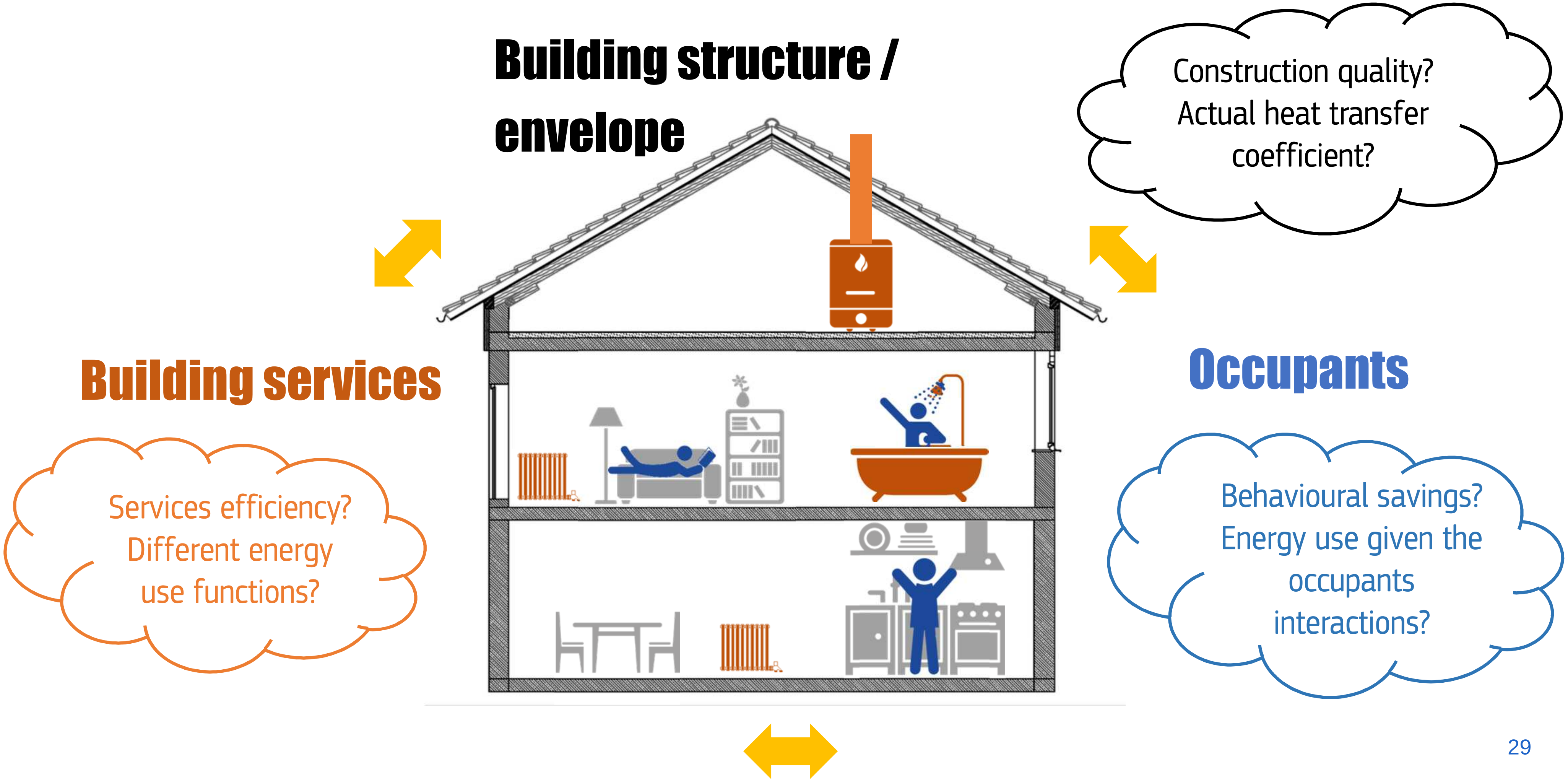
- Energy use time patterns allow to recognise energy use profiles in the data, identify:
  - ‘states’ of the building (where no other building info or measurements are available)
  - system settings,
  - occupational characteristics,
  - properties of hot water vs. space heating energy use
  - Changes in energy related behaviour of the building over time
- Possible Applications:
  - Energy Audit
  - Commissioning
  - Research: e.g. Building Stock Analysis, Occupant behaviour…

II. Findings & Views

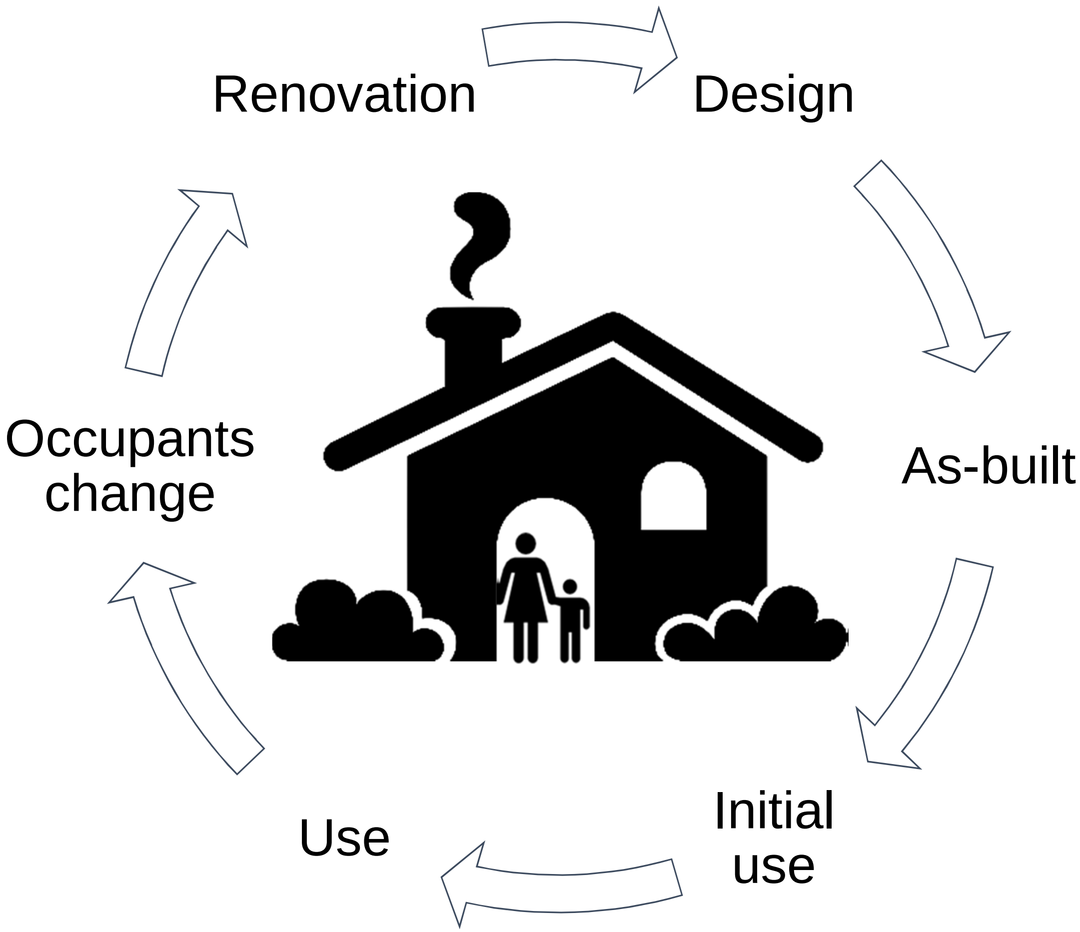
Energy performance assessment of buildings using measurements

What do we want to identify?
($\longleftrightarrow$ what is being measured?)

The building ‘system’: an interaction



The heat use of the building 'system' is influenced by external conditions, and changes through time



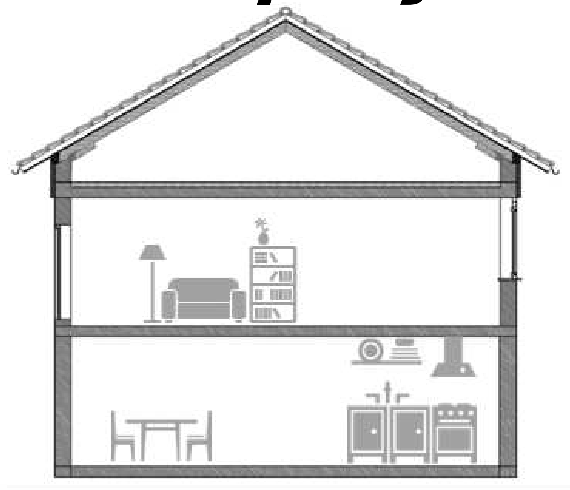
What do we want to identify? (example)

Energy use of occupied building

e.g. energy use feedback

Building heat transfer coefficient

e.g. construction quality



Energy Signature coefficients

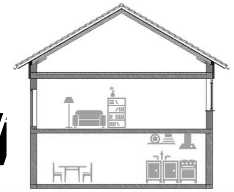
Energy use of occupied

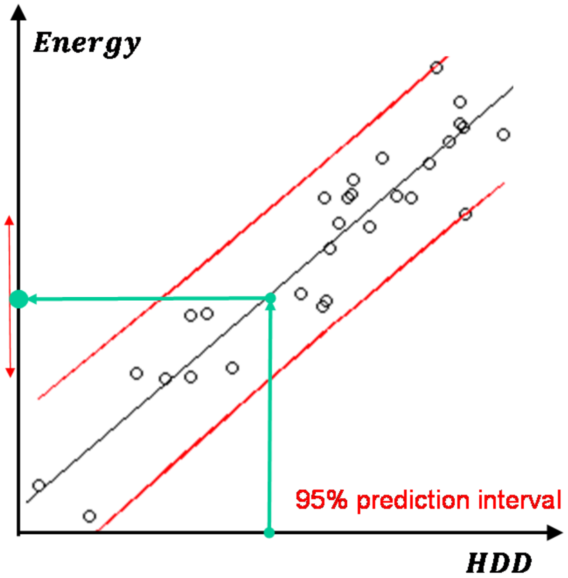
g

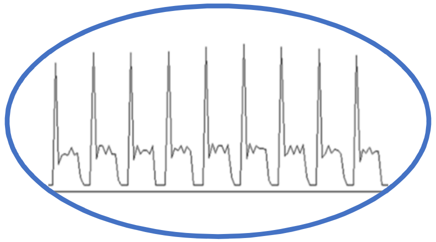
g. energy use feedback

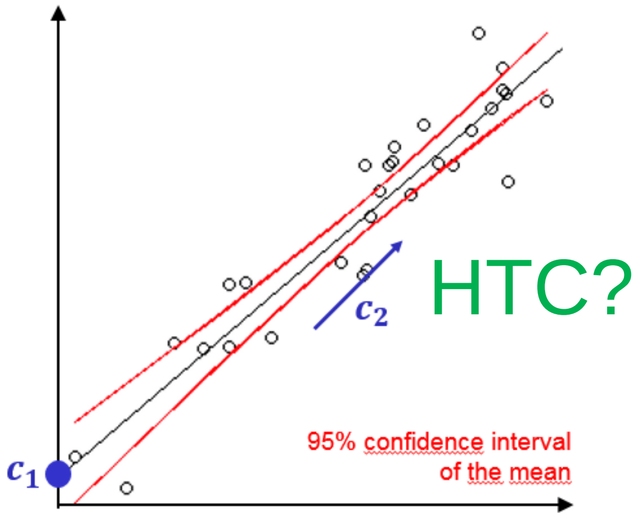
Building heat transfer coefficient

e.g. construction quali



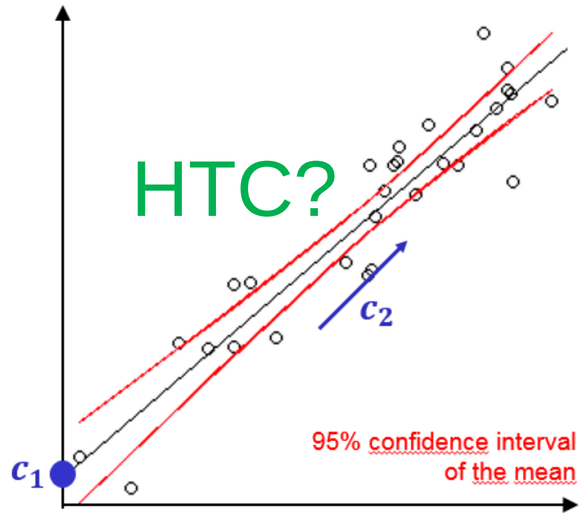






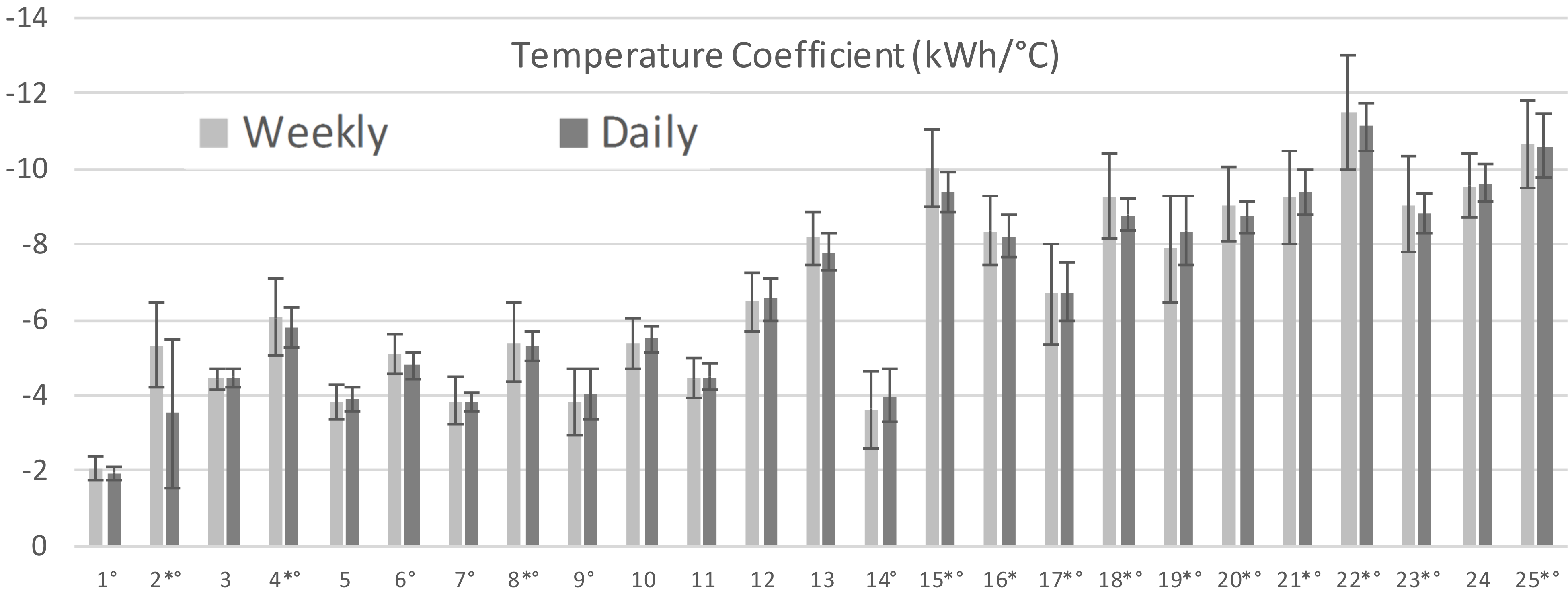
Energy Signature coefficients ↔ building physical values

- Energy Signature Coefficients are related to HTC, but it is not (yet) proven
  - how close they are to calculated / physical values
  - How they are influenced by building services characteristics (e.g. efficiencies…)
  - How they are influenced by occupational characteristics (e.g. opening of windows…)
- To be further investigated…
  - Use of additional measurements (e.g. indoor climate)
  - …
  - e.g. Annex 71 – ST3

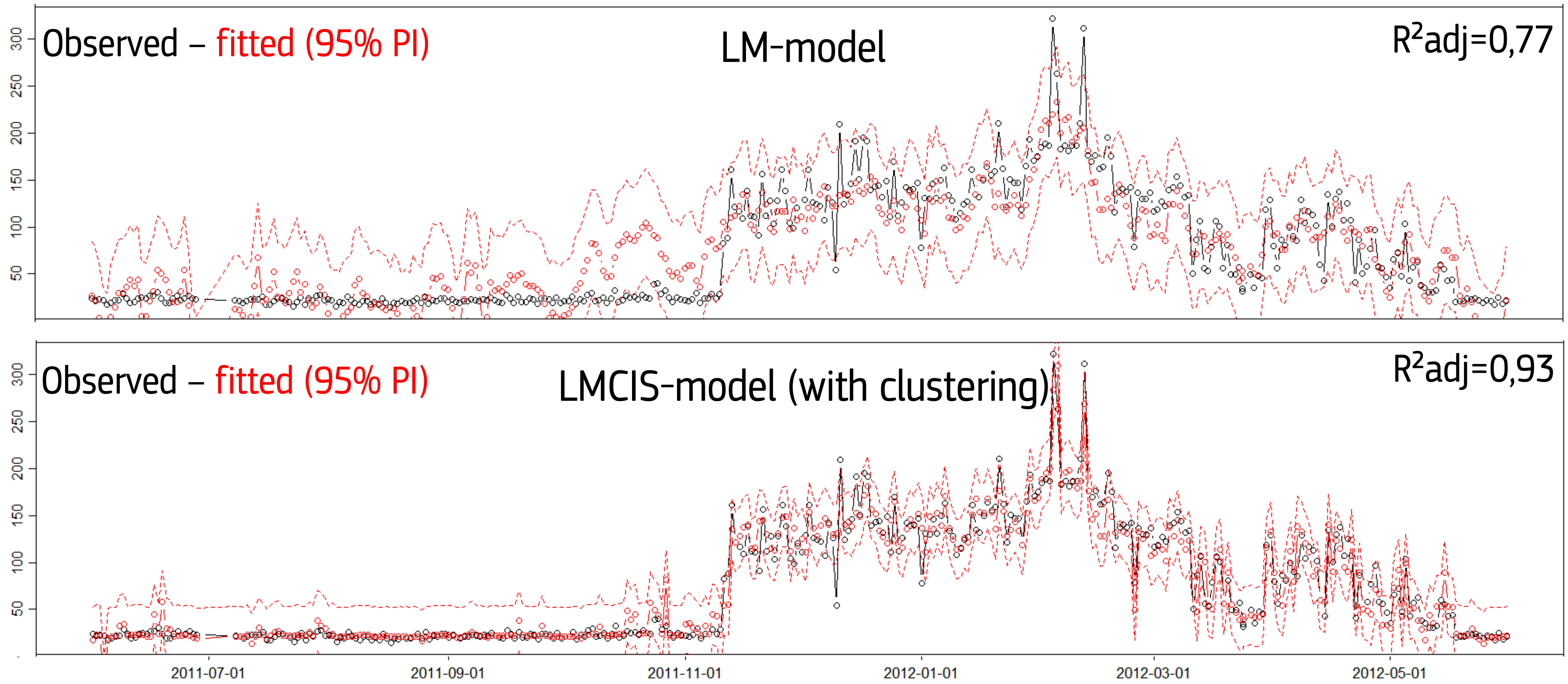


What is the obtained/needed accuracy?

95% Confidence Intervals for exterior temperature coefficient



95% Prediction Intervals

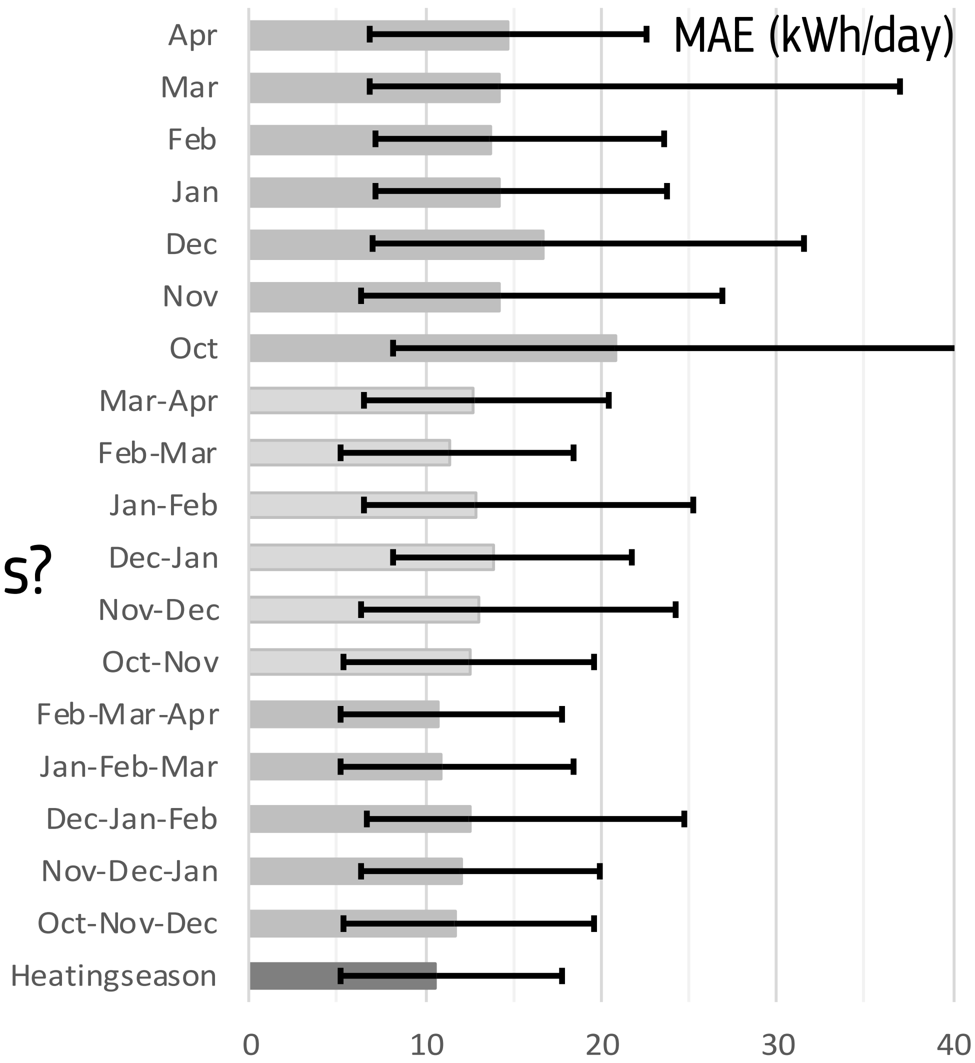


How long and when to measure?
(model valid for entire year)

How long does the measurement period need to be?

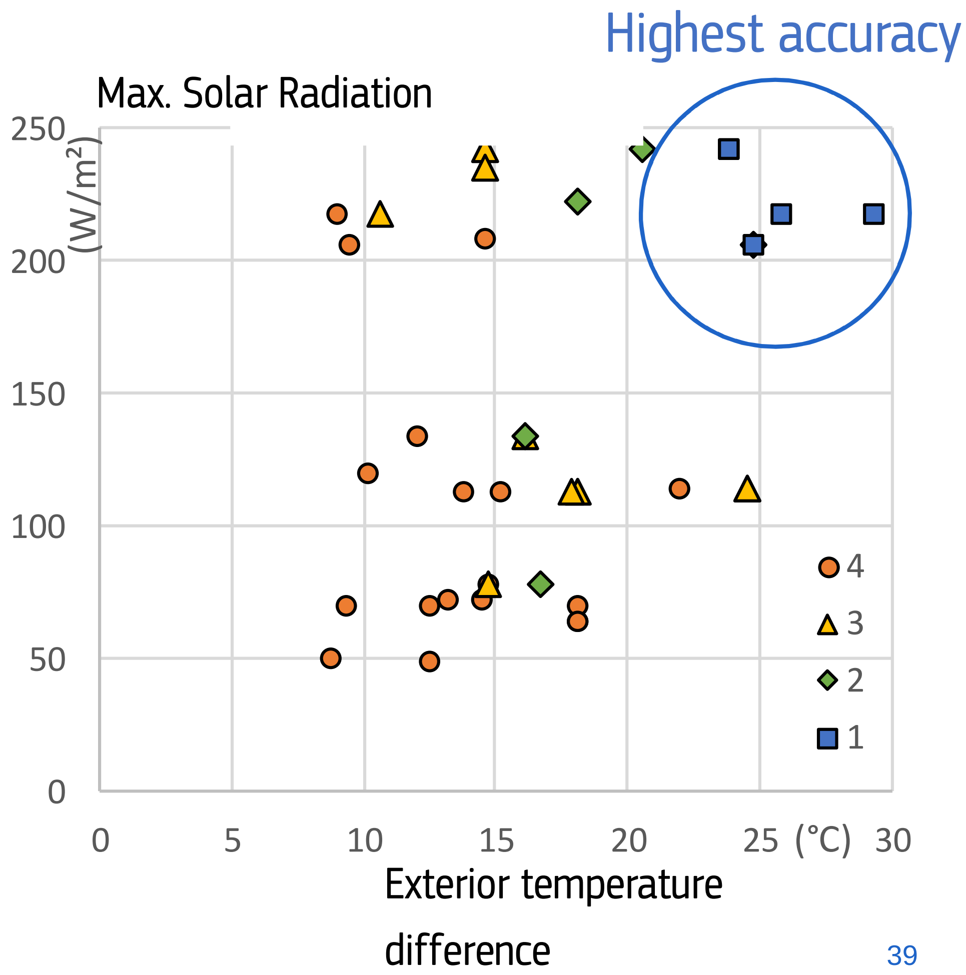
Approach:

- From full heating season to 3, 2, 1 month
- Compare prediction accuracy
- Characteristics of the ‘good’ periods?



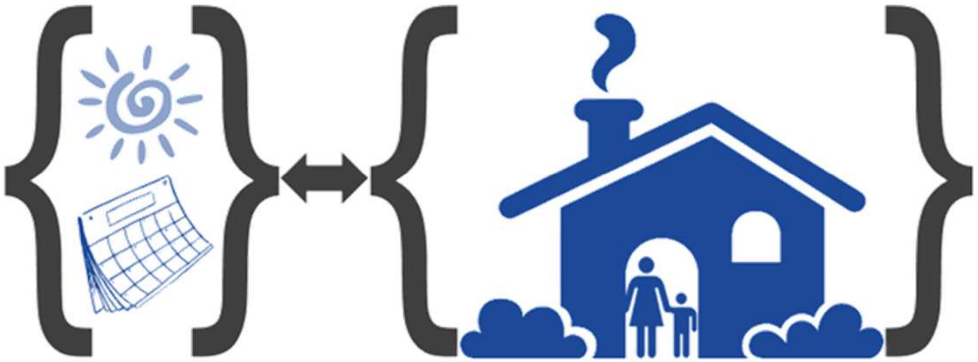
How long does the measurement period need to be?

The period can be reduced to 3 or 2 months
(during the heating season)
with negligible loss in accuracy,
if the variation in weather variables
(e.g. temperature and solar radiation)
is sufficiently high!

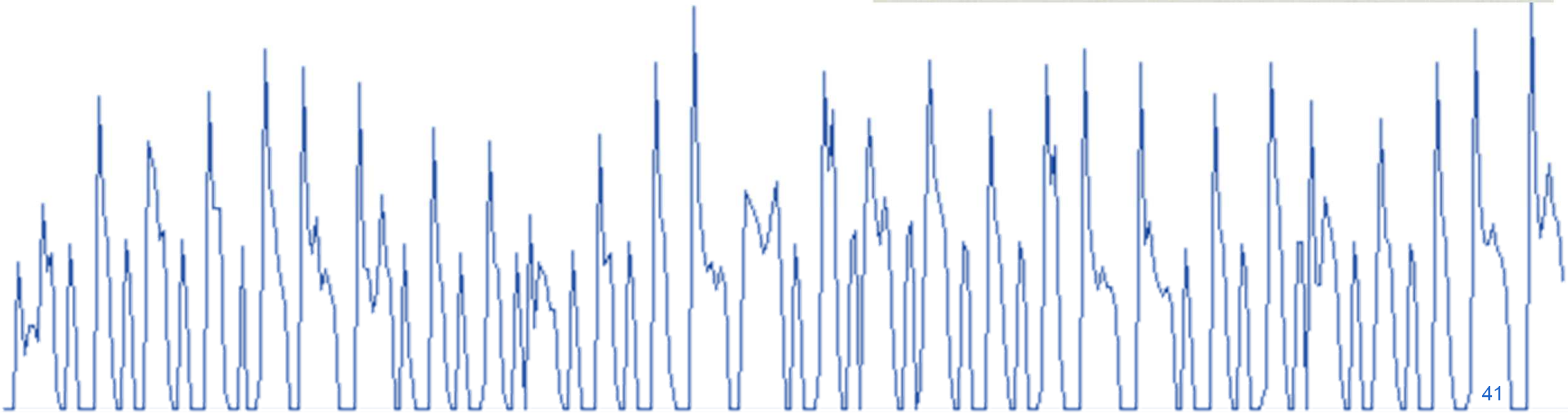


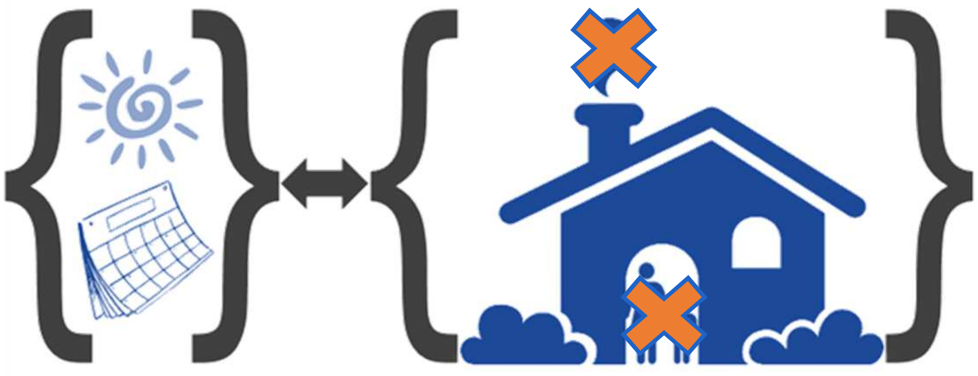
CONCLUSIONS

Energy performance assessment of buildings using measurements

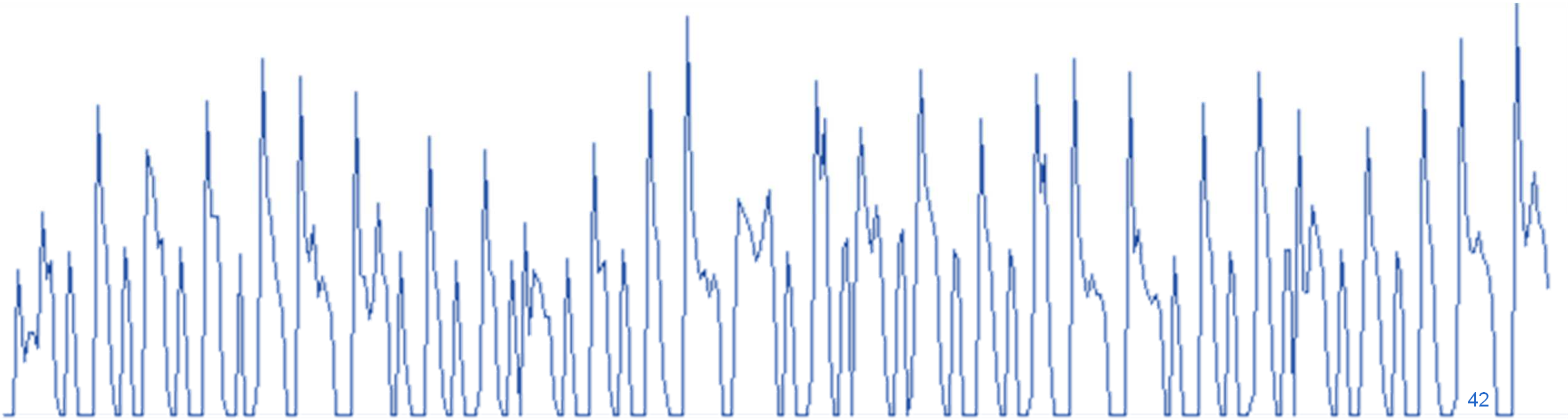


Jouw energiegebruik van het voorbije jaar
TIJD: 24/06/2013
GEBRUIK: 17,71 KWH
+4%
TOV VORIG JAAR
GEBRUIK
TIJD
- 6 MAANDEN
- 18 MAANDEN
25/07/2013
25/07/2012
- 6 MAANDEN





A
B
C
D
E
F
G
Energy
Efficiency



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Read more:

Characterisation of residential energy use for heating using smart meter data

https://lib.ugent.be/catalog/pug01:8526870