What can we learn from meter data?

Kamstrup-AVA-DTU Meeting
August 2015

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Kamstrup-DTU Meeting, August 2015

Contents

- Non-parametric, conditional-parametric and semi-parametric models, ..
- RC-network, Lumped, ARMAX and grey-box models, ..
- Markov chain models, Generalized linear models, ..

Examples only!
Part 1
Non-parametric methods

Typically only data from smart meter (and a nearby existing MET station)
Case Study No. 1

Split of total readings into space heating and domestic hot water using data from smart meters
Data

- 10 min averages from a number of houses
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Splitting of total meter readings

- Raw Data
  - Heating Consumption
    - House Characteristic
      - e.g. size, insulating power, solar absorption
    - Occupants Characteristic
      - e.g. open/close windows, turn up/down the heating, night-time drop
  - Hot Water Consumption
    - e.g. shower, dishwashing

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Holiday period

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Non-parametric regression

\[
\hat{g}(x) = \frac{\sum_{s=1}^{N} Y_s k\left\{\frac{x-X_s}{h}\right\}}{\sum_{s=1}^{N} k\left\{\frac{x-X_s}{h}\right\}}
\]

\[
k(u) = \frac{1}{2\pi} \exp\left\{-\frac{u^2}{2}\right\}
\]

Weighted average

Every spike above \(1.25 \cdot \hat{g}(x)\) is regarded as hot water use.
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Robust Polynomial Kernel

To improve the kernel method

Rewrite the kernel smoother to a Least Square Problem

\[
\arg \min_\theta \frac{1}{N} \sum_{s=1}^{N} w_s(x) (Y_s - \theta)^2 \\
\text{with} \quad w_s(x) = \frac{k\{x - X_s\}}{\frac{1}{N} \sum_{s=1}^{N} k\{x - X_s\}}
\]

Make the method robust by replacing \((Y_s - \theta)^2\) with

\[
\rho_{\text{Huber}}(\varepsilon) = \begin{cases} 
\frac{1}{2\gamma} \varepsilon^2 & \text{if } |\varepsilon| \leq \gamma \\
|\varepsilon| - \frac{1}{2}\gamma & \text{if } |\varepsilon| > \gamma 
\end{cases} \\
\varepsilon_s = Y_s - \theta
\]

Make the method polynomial by replacing \(\theta\) with

\[
P_s = \theta_0 + \theta_1 (X_t - x) + \theta_2 (X_t - x)^2
\]
Robust Polynomial Kernel

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Case Study No. 2

Ident. of Thermal Performance using Smart Meter Data
Example

Consequence of good or bad workmanship (theoretical value is $U=0.16 \text{W/m}^2\text{K}$)
Examples (2)

Whole House Heat Loss - Measured versus Predicted for New Build UK Dwellings (n=18)

Measured versus predicted energy consumption for different dwellings

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Characterization using HMM and Smart Meter Data

- Energy labelling
- Estimation of UA and gA values
- Estimation of energy signature
- Estimation of dynamic characteristics
- Estimation of time constants
Energy Labelling of Buildings

Today building experts make judgements of the energy performance of buildings based on drawings and prior knowledge.

This leads to 'Energy labelling' of the building

However, it is noticed that two independent experts can predict very different consumptions for the same house.
Simple estimation of UA-values

Consider the following model (t=day No.) estimated by kernel-smoothing:

\[ Q_t = Q_0(t) + c_0(t)(T_{i,t} - T_{a,t}) + c_1(t)(T_{i,t-1} - T_{a,t-1}) \]  \hspace{1cm} (1)

The estimated UA-value is

\[ \hat{UA}(t) = \hat{c}_0(t) + \hat{c}_1(t) \]  \hspace{1cm} (2)

With more involved (but similar models) also gA and wA values can be estimated.
## Results

<table>
<thead>
<tr>
<th>UA W/°C</th>
<th>σUA</th>
<th>gA_{max} W</th>
<th>wA_{E_{max}} W/°C</th>
<th>wA_{S_{max}} W/°C</th>
<th>wA_{W_{max}} W/°C</th>
<th>T_i °C</th>
<th>σ_{T_i}</th>
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</thead>
<tbody>
<tr>
<td>4218598</td>
<td>211.8</td>
<td>10.4</td>
<td>597.0</td>
<td>11.0</td>
<td>3.3</td>
<td>8.9</td>
<td>23.6</td>
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<tr>
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<td>228.2</td>
<td>12.6</td>
<td>1012.3</td>
<td>29.8</td>
<td>42.8</td>
<td>39.7</td>
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<td>4711160</td>
<td>155.4</td>
<td>6.3</td>
<td>518.8</td>
<td>14.5</td>
<td>4.4</td>
<td>9.1</td>
<td>22.5</td>
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<td>1578.3</td>
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<tr>
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<td>715.7</td>
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<td>7.2</td>
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<td>1.6</td>
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<td>15.4</td>
<td>657.7</td>
<td>41.4</td>
<td>29.4</td>
<td>16.5</td>
<td>21.0</td>
</tr>
</tbody>
</table>
Based on measurements from the heating season 2009/2010 your typical indoor temperature during the heating season has been estimated to 24 °C. If this is not correct you can change it here \[24\] °C.

If your house has been left empty in longer periods with a partly reduced heat supply you have the possibility of specifying the periods in this calendar.

According to BBR the area of your house is 155 m² and from 1971.

Based on BBR information it is assumed that you do not use any supplementary heat supply. If this is not correct you can specify the type and frequency of use here:

- Wood burning stove used \(0\) times per week in cold periods.
- Solar heating \(y/n\), approximate size of solar panel \(0 \times 0\) meters.

Based on the indoor temperature 24 °C, the use of a wood burning stove 0 times per week, and no solar heating installed, the response of your house to climate is estimated as:

- The response to outdoor temperature is estimated to 200 \(W/°C\) which given the size and age of your house is expectable\(^a\).

- On a windy day the above value is estimated to increase with 60 \(W/°C\) when the wind blows from easterly directions. This response to wind is relatively high and indicates a problem related to the air sealing on the eastern side of the house.

- On a sunny day during the heating season the house is estimated to receive 800 \(W\) as an average over 24 hours. This value is quite expectable.

\(^a\)Many kind of different recommendations can be given here.
Perspectives for using data from Smart Meter

- Reliable Energy Signature.
- Energy Labelling
- Time Constants (eg for night set-back)

Proposals for Energy Savings:
- Replace the windows?
- Put more insulation on the roof?
- Is the house too untight?
- ......

- Optimized Control
- Integration of Solar and Wind Power using DSM
Case Study No. 3

Control of Power Consumption (DSM)
The Danish Wind Power Case

... balancing of the power system

In 2008 wind power did cover the entire demand of electricity in 200 hours (West DK)

In December 2013 and January 2014 more than 55 pct of electricity load was covered by wind power. And for several days the wind power production was more than 120 pct of the power load.

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Wind integration in Denmark

Power right now
Measured in MW:
- Central power stations: 1,575
- Local CHP plants: 401
- Wind turbines: 4,088
- Solar cells: 113
- Net exchange export: 1,845
- Electricity consumption: 4,331
- CO2 emissions: 179 g/kWh

LEGEND

- Jutland - Sweden
  - Exports: 728 MW
- Jutland - Norway
  - Exports: 953 MW
- Zealand - Sweden
  - Exports: 1,048 MW
- Bornholm - Sweden
  - Exports: 2 MW
- Jutland - Germany
  - Imports: 284 MW
- Zealand - Germany
  - Imports: 601 MW

The Great Belt
--- 590 MW

Last updated 15. Februar 2014 12:41
Data from BPA

Olympic Peninsula project

- 27 houses during one year
- Flexible appliances: HVAC, cloth dryers and water boilers
- 5-min prices, 15-min consumption
- Objective: limit max consumption
Price responsivity

*Flexibility is activated by adjusting the temperature reference (setpoint)*

- **Standardized price** is the % of change from a price reference, computed as a mean of past prices with exponentially decaying weights.
- **Occupancy mode** contains a price sensitivity with its related comfort boundaries. 3 different modes of the household are identified (work, home, night).

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Aggregation (over 20 houses)

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Non-parametric Response on Price Step Change

Model inputs: price, minute of day, outside temperature/dewpoint, sun irradiance

Olympic Peninsula

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Control of Energy Consumption

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Control performance

*With a price penalty avoiding its divergence*

- Considerable **reduction in peak consumption**
- Mean daily consumption shift

![Graph showing consumption and price over the day](image-url)
A model for the thermal characteristics of a small office building

A nonlinear model for a ventilated facade
Case study

Model for the thermal characteristics of a small office building
Flexhouse at SYSLAB (DTU Risø)
Model found using Grey-box modelling (using CTSM-R and a RC-model)
Here we estimate the physical parameters
Modelling the thermal dynamics of a building integrated and ventilated PV module

Several non-linear and time-varying phenomena.

Consequently linear RC-network models are not appropriate.

A grey-box approach using CTSM-R is described in Friling et.al. (2009)
Part 3
Non-gaussian models (Annex 66)

- Occupancy modelling is a necessary step towards reliable simulation of energy consumption in buildings
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Occupant presence (office building in SF!)
2.1.1.2. Two-state Markov chains with covariates. Covariates in Markov chains with only the two states, 0 and 1, can be modeled as

\[
\text{logit} \left( \mathbb{P} \left( X_{n+1} = 0 \mid X_n = 0 \right) \right) = Z_{1,n} \theta_1, \quad \theta_1 Z_{1,n} \in \mathbb{R}^p
\]

\[
\text{logit} \left( \mathbb{P} \left( X_{n+1} = 1 \mid X_n = 1 \right) \right) = Z_{2,n} \theta_2, \quad \theta_2 Z_{2,n} \in \mathbb{R}^q
\]

where the logistic function denoted logit is defined as

\[
\text{logit}: \mathbb{R} \rightarrow (0, 1], \quad \text{logit}(x) = \log \left( \frac{x}{1-x} \right)
\]

Fig. 3. A Markov chain with exponential smoothing as covariate in the transition probabilities.
Model simulations

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Remarks and Summary

Other examples ... but not shown here:
- Shading (.. also dirty windows)
- Time-varying phenomena (.. eg. moisture in materials)
- Behavioural actions (opening of doors, windows, etc.)
- Appliance modelling
- Interactions with HVAC systems

... in general data and statistical methods (including tests) can be used to describe or model a number phenomena that cannot be described neither deterministically nor from first principles.
For more information ...

• See for instance
  www.henrikmadsen.org
  www.smart-cities-centre.org

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