Data-driven Methods;
General introduction and specific examples

Henrik Madsen
DTU Compute

http://www.smart-cities-centre.org
http://www.henrikmadsen.org
General introduction

The Problem and a Generic Solution
Example

Consequence of good or bad workmanship (theoretical value is $U=0.16 \text{W/m}^2\text{K}$)
Efficiency and Flexibility identified using AI and grey-box modelling

Data-driven methods for energy efficiency and flexibility
Case Study No. 1

Characterization of Energy Efficiency of Buildings using (Smart) Meter Data
Model for the heat dynamics

Measurements:
- Indoor air temp
- Radiator heat sup.
- Ambient air temp
- Solar radiations

Hidden states are:
- Heat accumulated in the building
- $k$: Fraction of solar radiation entering the interior
Perspectives ...

"Skat, jeg kan se på k-værdierne, at vinduerne skal pudses"
Perspectives

- Identification of most problematic buildings
- Automatic energy labelling
- Recommendations:
  - Should they replace the windows?
  - Or put more insulation on the roof?
  - Or tighten the building?
  - Should the wall against north be further insulated?
  - ......
- Better control of the heat supply (using the flexibility)
Case study No. 2

Control of Power Consumption using the Thermal Mass of Buildings (Peak shaving)
Aggregation (over 20 houses)
Response on Price Step Change

Olympic Peninsula

![Graph showing consumption step response (Olympic Pen.) with a 5-hour response time.](image)
Control of Energy Consumption

Data-driven methods for energy efficiency and flexibility
Considerable *reduction in peak consumption*
Mean daily consumption shift
General Introduction

Flexibility Function and Flexibility Index
Characteristics

Figure 1: A smart building is able to respond to a penalty or external control signal.
Figure 2: The energy consumption before and after an increase in penalty. The red line shows the normalized penalty while the black line shows the normalized energy consumption. The time scale could be very short with the units being seconds or longer with units of hours. At time 2.5 the penalty is increased,
Penalty Function (examples)

- **Real time CO₂.** If the real time (marginal) CO₂ emission related to the actual electricity production is used as penalty, then, a smart building will minimize the total carbon emission related to the power consumption. Hence, the building will be *emission efficient*.

- **Real time price.** If a real time price is used as penalty, the objective is obviously to minimize the total cost. Hence, the building is *cost efficient*.

- **Constant.** If a constant penalty is used, then, the controllers would simply minimize the total energy consumption. The smart building is, then, *energy efficient*. 
Data-driven methods for energy efficiency and flexibility

Smart Grid Application

Figure 8: Smart buildings and penalty signals.
Data-driven methods for energy efficiency and flexibility
FF for three buildings

Figure 5: The Flexibility Function for three different buildings.
Reference Penalties

Figure 7: Reference scenarios of penalty signals related to ramping or peak issues as well as the integration of wind and solar power.
Flexibility Index

Table 2: Flexibility Index for each of the buildings based reference penalty signals representing wind, solar and ramp problems.

<table>
<thead>
<tr>
<th></th>
<th>Wind (%)</th>
<th>Solar (%)</th>
<th>Ramp (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Building 1</td>
<td>36.9</td>
<td>10.9</td>
<td>5.2</td>
</tr>
<tr>
<td>Building 2</td>
<td>7.2</td>
<td>24.0</td>
<td>11.1</td>
</tr>
<tr>
<td>Building 3</td>
<td>17.9</td>
<td>35.6</td>
<td>67.5</td>
</tr>
</tbody>
</table>
Data-driven methods for energy efficiency and flexibility

Center Denmark, Living Labs, Partnerships

UNILAB consortium
- Cardiff University
- Danmarks Tekniske Universitet (DTU), Denmark
- Royal Institute of Technology (KTH), Sweden
- German Technical and Scientific Association for Gas and Water (DVGW), Germany
- Imperial College, United Kingdom
- Tsinghua University, P.R. China
- TNO - Netherlands
- Toshiba Research Laboratory (TRL), UK
- Tonghua University - P.R. of China
- Katholieke Universiteit Leuven (KUL), Belgium
- Mälardalen University, Sweden
- University of Pisa (UP), Italy

International Cooperating labs
- NREL (US)
- CESI (UK)
- ZEN (NORWAY)
- Berkeley (US)
- Argonne (US)
- KIER (KOREA)
- ESIPP (IRELAND)
- PSA (SPAIN)
- KUBIK (SPAIN)

UNI-LAB.dk
- Partner Centers In Denmark & Northern Europe

L7: Gate 21 Labs
- Green Labs DK
- Water Center Syd
- AU Foulum

L1: CENTER DENMARK
- Flexible Energy Denmark
- EERA JP ESI
- IEA ANNEX 74
- IEA ANNEX 71
- IEA ANNEX 67
- iiESI

L2: Grundfos Dormitory Lab
- Brint Center Northern DE
- Greenlab Skive

L3: Hole Transrup Lab

L4: Novasol Summer Houses

L5: Aalborg Smart City

L8: GreenTech Center

Powerlab.dk

Ecogrid Bornholm

Google

NTNU
Summary

- We need more focus on data-driven technologies for energy efficiency and flexibility – simply by using frequent meter data.
- Procedures for data intelligent control of power load using the flexibility are also suggested.
- The controllers can provide:
  - Energy Efficiency
  - Cost Minimization
  - Emission Efficiency
  - Peak Shaving
  - Smart Grid demand (like ancillary services needs, ...) 
- We have demonstrated a large potential in Demand Response. Automatic solutions, and end-user focus are important.
- We see large problems with the tax and tariff structures in many countries (e.g. Denmark; we are working on a new design of taxes and tariffs.)
Some references

Grey-box models for buildings:


Some references

Grey-box modelling techniques:


Data-driven methods for energy efficiency and flexibility

Some references (cont.)

Forecasting, Flexibility and Control:


Some references (cont.)

Indoor climate and occupancy:


Nienaber, F., Wolf, S., Wesseling, M., Calì, D., Müller, D., & Madsen, H. (2019). Validation, optimisation and comparison of carbon dioxide-based occupancy estimation algorithms. Indoor and Built Environment,
