What can AI do to optimize electricity and thermal demand in buildings?

Igor Sartori – igor.sartori@sintef.no
SINTEF Byggforsk
WORK PACKAGES

1. WP1 Analytical framework for design and planning of ZEN
2. WP2 Policy measures, innovation and business models
3. WP3 Responsive and energy efficient buildings
4. WP4 Energy flexible neighbourhoods
5. WP5 Local energy system optimization within a larger system
6. WP 6 Pilot projects and living labs
What is energy flexibility?

The Energy Flexibility of a building or neighborhood is the ability to manage its demand and generation according to local climate conditions, user needs and grid requirements.

Definition by the IEA EBC Annex 67 "Energy flexible buildings"

What can it be used for?

- Minimize energy cost
- Minimize CO2 footprint of energy use
- Maximise self-consumption
- Minimize energy use during peak hours
Talking about solutions:

• Model Predictive Control to activate the buildings' flexibility
• Based on grey-box models (data-driven, mixed physical/statistical) of buildings and building technologies
  ➢ This is the most challenging (and time consuming) part: model identification and validation

Talking about ideas:

• What can AI do to help solve the problem?
The future smart energy system

Requires adequate modeling and control

Distributed Energy Resources

Source: H. Madsen et al. (2015)
Smart control of electric and thermal demand
The "easy" case

- If the flexible resource is independent of the building's load profile
- Load can be forecasted based on past observations and external factors, e.g. weather
- Consumption is affected by forecasts

Have the impression AI can do much here
Example: charging of battery with PV

Fast charging

Limiting peak export

Source: adapted from Luthander et al. (2015)
The "hard" case

- If the flexible resource is the building's load profile itself
- Load must be modelled together with building's internal "states", e.g. indoor temperature
- Consumption is affected by forecast & model used!

What can AI do here??

See next slide
Top plot: An example of the temperature in a building controlled by a penalty-aware controller (green, dashed) and a conventional controller (red, solid). Both controllers are restricted to stay within the dashed lines.

Middle plot: The black shading gives the penalties, while the green and red lines show when the two controllers heat, respectively.

Bottom plot: These graphs illustrate the accumulated penalty for each of the controllers.

Source: Junker et al. (2015)
Model Predictive Control

Thermostat (heating curve) uses: Required forecast and model prediction capability

Operational constraints

Weather forecast

Information supporting the decision

Cost signal

Optimised future temperature

Optimised heating sequence

Now

Source: Dr. Pierre Vogler Finck, 2017 (Neogrid)
Example of how Model Predictive Control (MPC) operates

Animation courtesy of Dr. Pierre Vogler Finck, 2017 (Neogrid)
The ZEB LivingLab at NTNU

Envelope and structure
- Super-insulated structure with wooden frame
- PCM in ceiling, and large window areas
- 100 m² inhabitable area, several rooms

Energy production
- PV on roof + solar collectors on facade

Source: Goia, Finocchiaro, Gustavsen (2015)
Heating setup for experiments

In practise, it is important to make experiments with the heating device which will be controlled by MPC.

An electrical heater was added.

Heating thermostats are disabled for PRBS (replaced by distant control).

Sources: Goia, Finocchiaro, Gustavsen (2015); Dr. Pierre Vogler Finck (Neogrid)
Dedicated experiments were carried out to gather data.

Indoor temperature outside ‘typical comfortable use’ conditions

Pseudo random (PRBS) excitation was used

Sources: Vogler-Finck, Clauß, Georges (2017); Bacher, Madsen (2011)
Example: a (very) simple grey-box model

- **Input**
  - H (power to heater)

- **Disturbances**
  - Ps (global solar irradiance)
  - HV (heat gain from ventilation)
  - IHG (internal heat gains)

- **Parameters**
  - Ci (heat capacity)
  - UA (heat loss)
  - Aw (solar gain)

- **Output**
  - Ti (equivalent indoor temperature)

Source: Dr. Pierre Vogler Finck (Neogrid)
Model parameters identification

Parameters:
- **UA** (heat loss)
- **Ci** (heat capacity)
- **Aw** (solar gain)

**UA** Estimate ~ 0.10 kW/K
> IDA ICE estimate ~ 0.07 kW/K

**Ci** Est. ~ 5 kWh/K
>> Air ~ 0.12 kWh/K

**Aw** Est. ~ 4.5 m²
<<Total window area ~36m²

Source: Vogler-Finck et al. (2018)
Model validation

Model 1 appears to be a better fit on training data – but it is not ROBUST
• Only after that a (grey-box) model has been validated, a building/neighborhood can be controlled in "real time" with MPC so to manage its demand and generation according to local climate conditions, user needs and grid requirements.

• But how do we move from detailed and dedicated experiments to large scale modelling without intrusive measurements?

• AI solves it and we relax ??
Thanks for your attention!
References


Goia, Finocchiaro, Gustavsen (2015) The ZEB Living Laboratory at NTNU: a zero emission house for engineering and social science experiments, 7th Passivhus Norden, Copenhagen, DK.


Vogler-Finck et al. (2018) Inverse model identification of the thermal dynamics of a Norwegian zero emission house, Cold Climate HVAC, Kiruna, SE.