SDU
ENERGY
INFORMATICS

Multi-objective model predictive control for smart and energy flexible buildings

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Center for Energy Informatics
SDU

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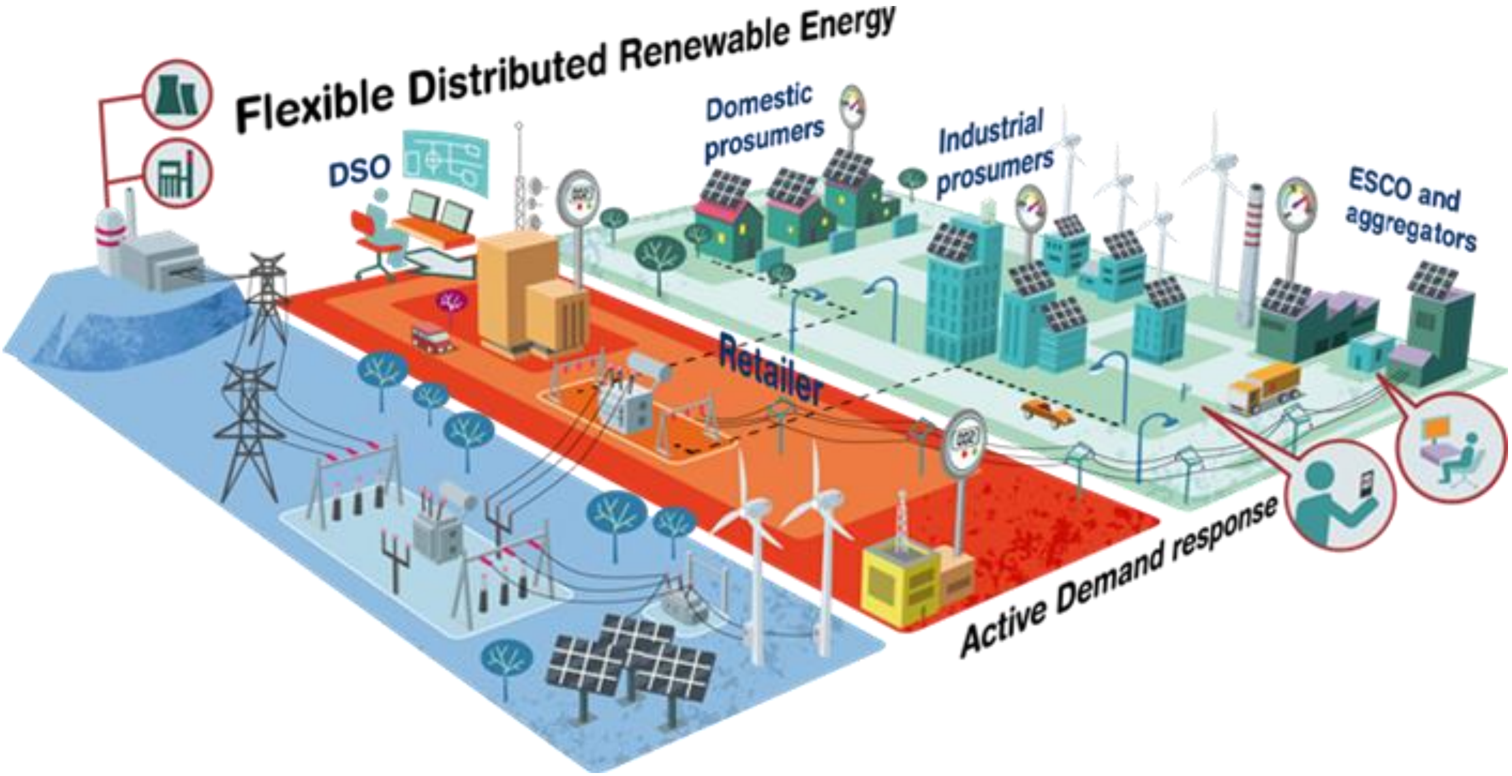
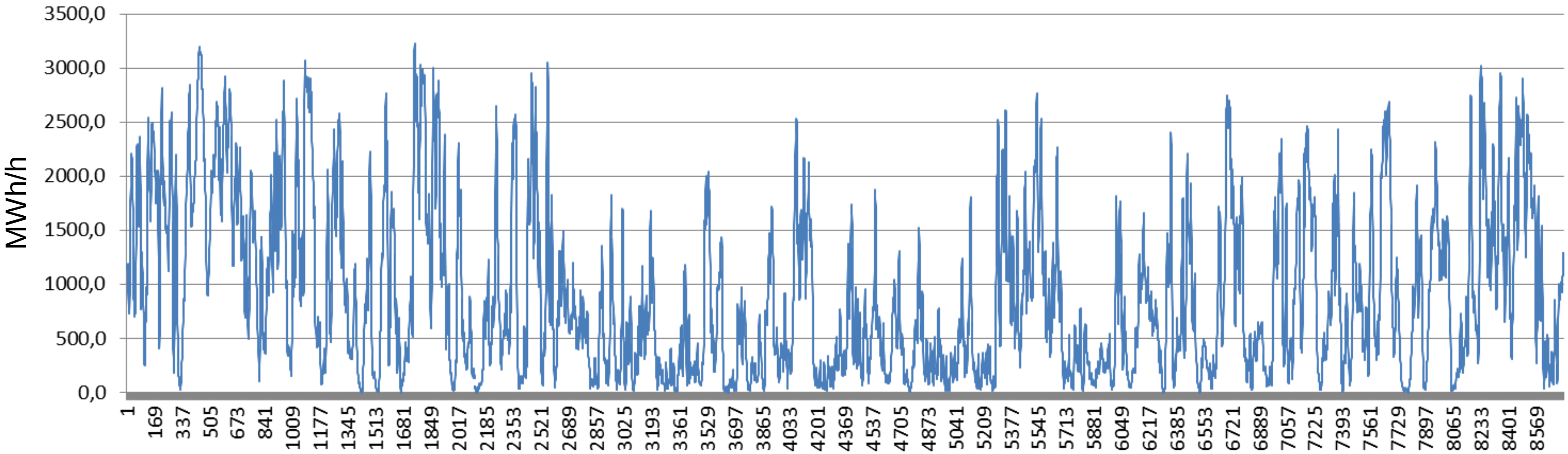
Climate Neutrality Conference
Sønderborg

CFEI’s mission

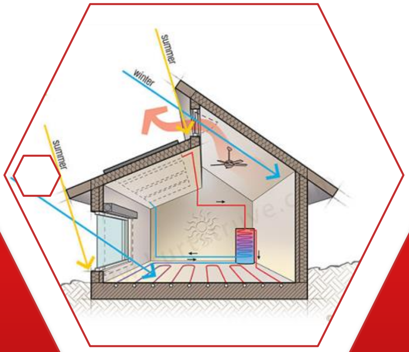


The Center’s mission is to participate in the green transition of the energy system by focusing on Innovative ICT-based solutions for energy-efficiency improvements in buildings and industrial processes and intelligent integration of the energy flexibility, at the consumer side, with the fluctuating production from renewable energy sources.

Renewable energy challenge

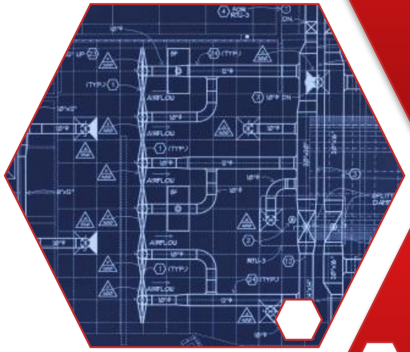


Smart buildings

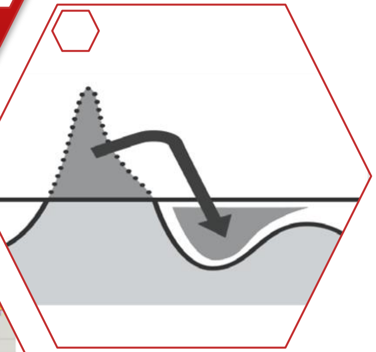


Passive heating and cooling

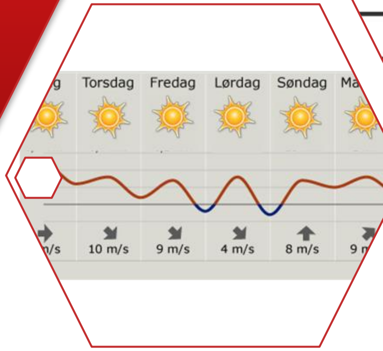
Demand-response services



Predictive control



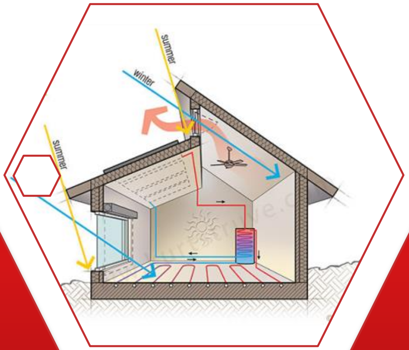
Coordinated control of all systems



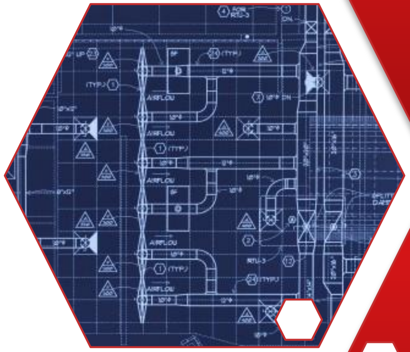
Smart buildings

Take the advantage of building dynamics, NOT WORK AGAINST IT

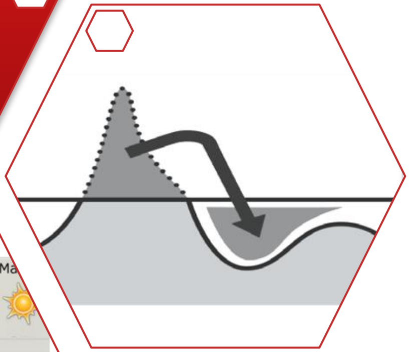
Passive heating and cooling



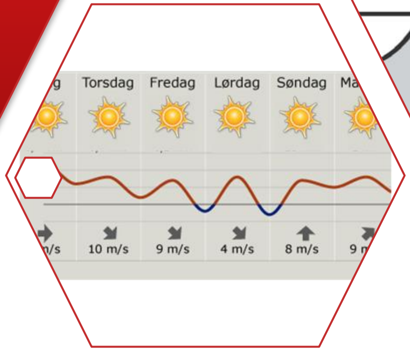
Demand-response services



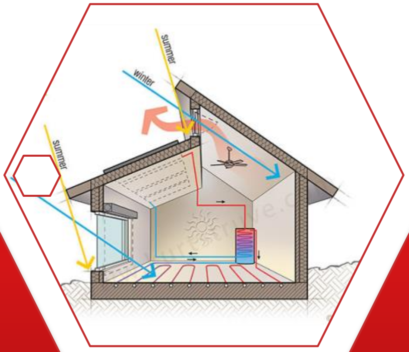
Predictive control



Coordinated control of all systems

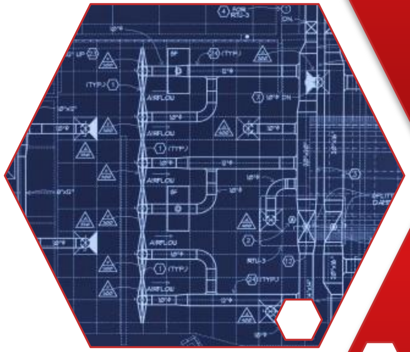


Smart buildings

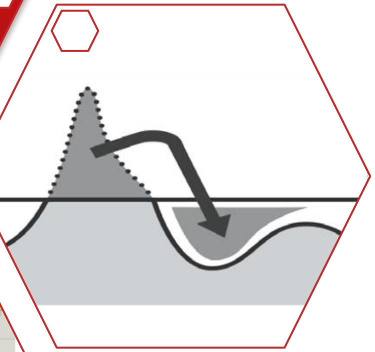


Passive heating and cooling

Demand-response services



Predictive control



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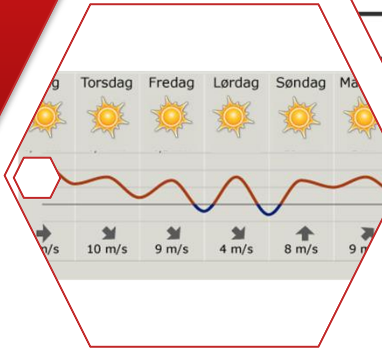
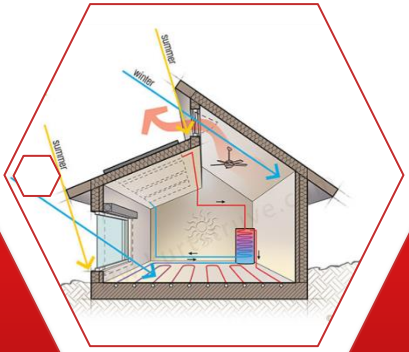


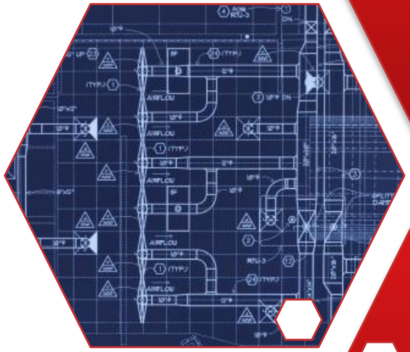
Optimize control based on the predicted indoor/outdoor conditions

Smart buildings

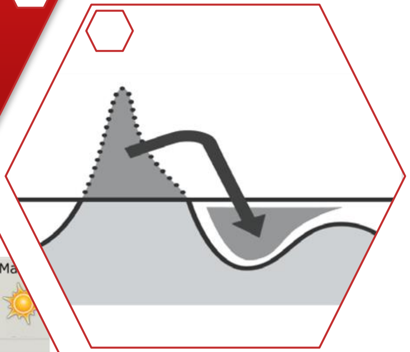


Passive heating and cooling

Demand-response services



Predictive control



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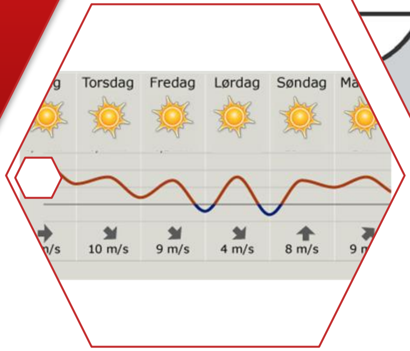
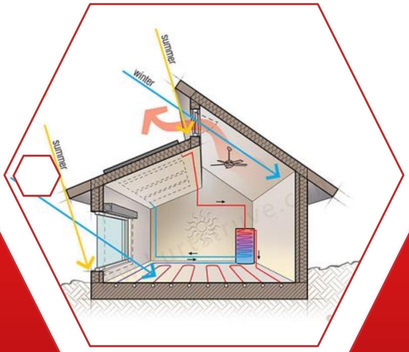


Systems need to talk to one another, e.g. to avoid simultaneous heating and cooling

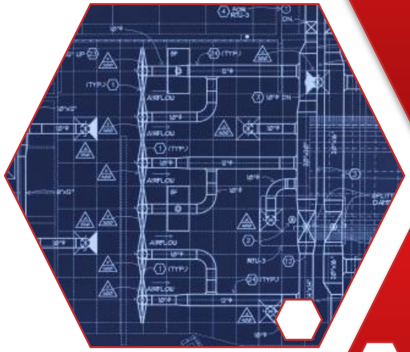
Smart buildings

Increase/decrease/shift energy consumption based on the grid needs



Passive heating and cooling

Demand-response services



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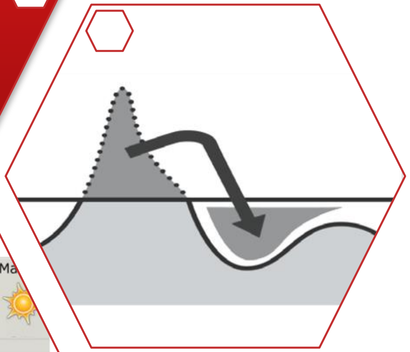

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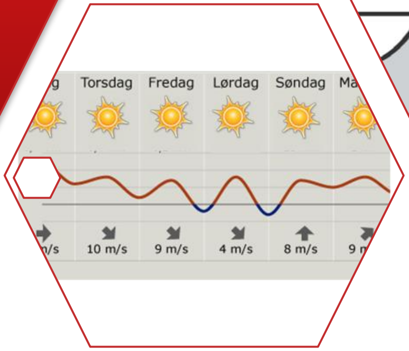
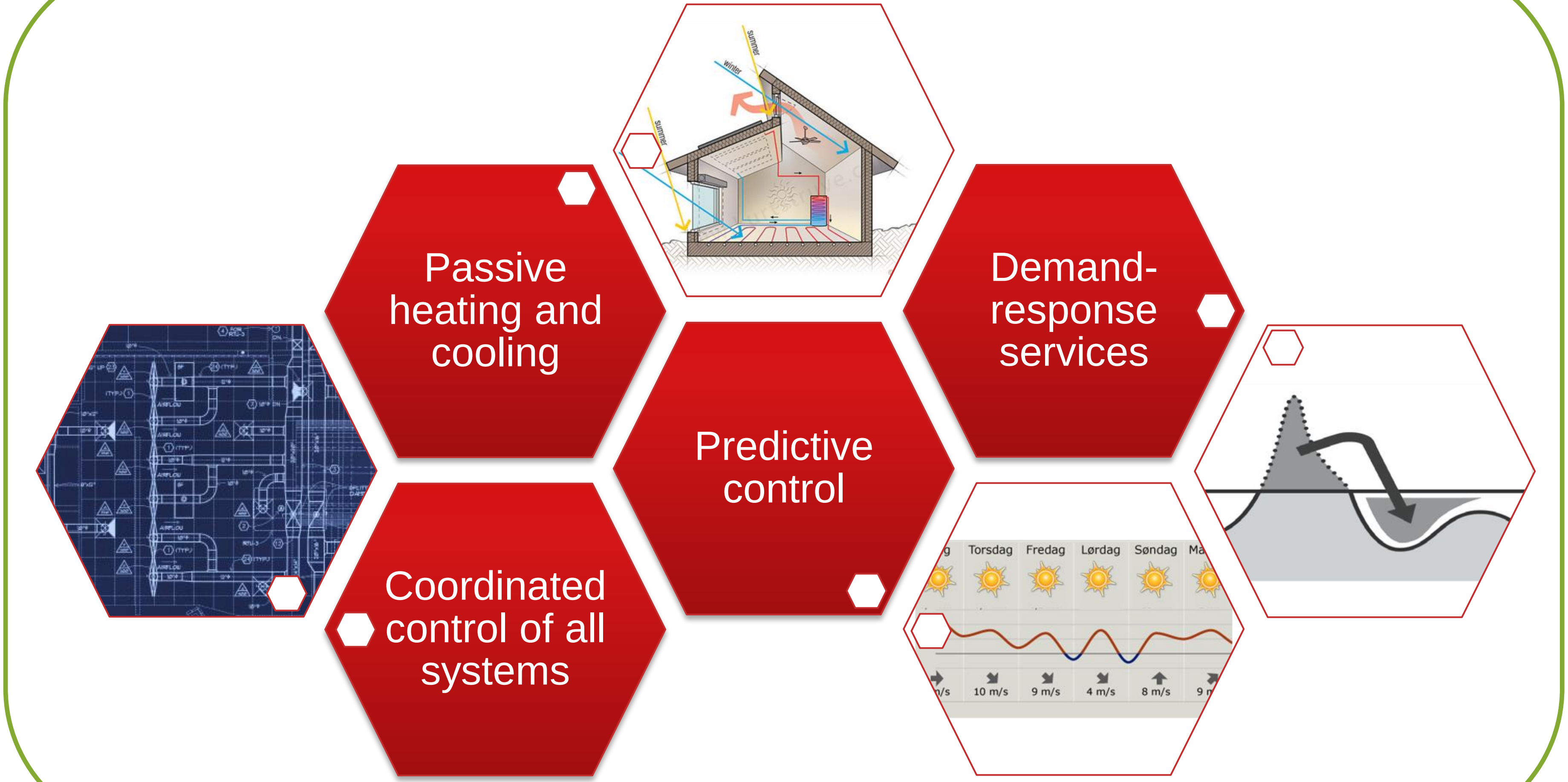


Smart buildings



Passive heating and cooling

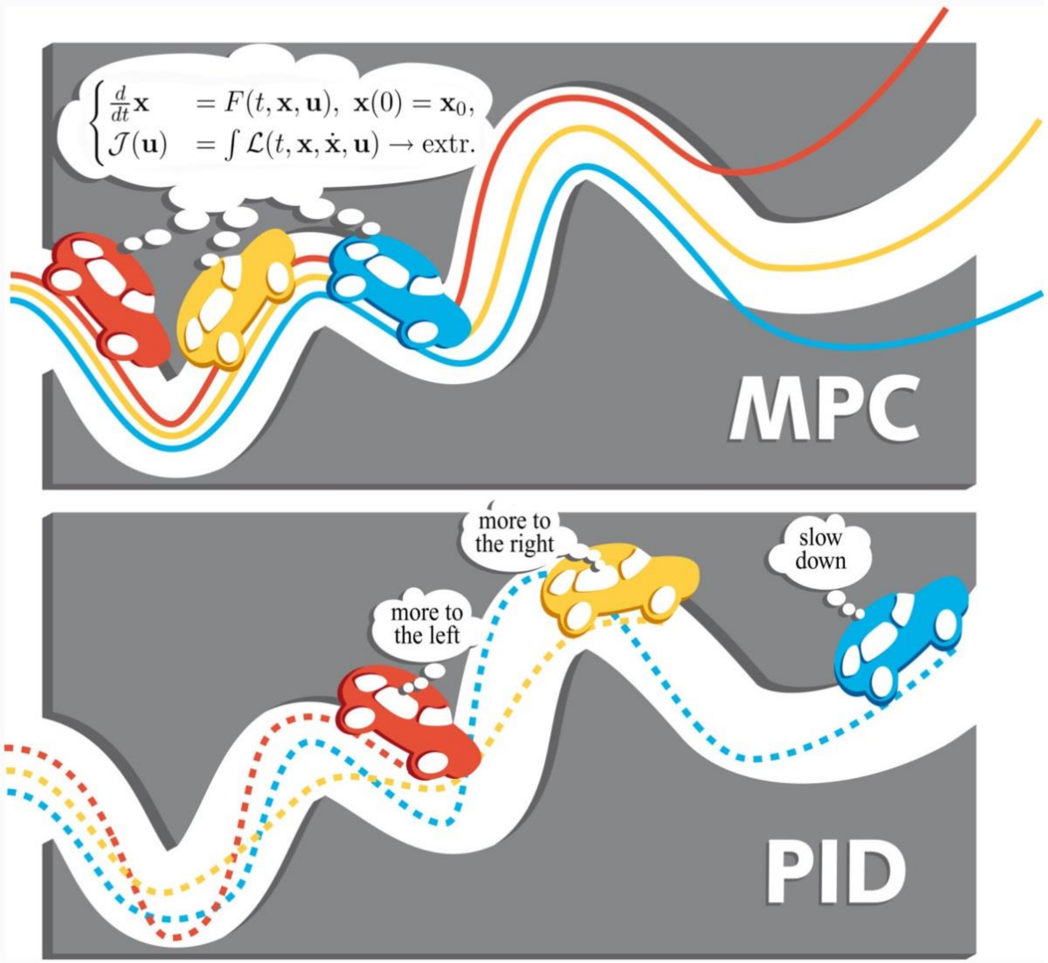
Demand-response services

Predictive control

Coordinated control of all systems

HOLISTIC APPROACH NEEDED!

Standard vs. predictive control

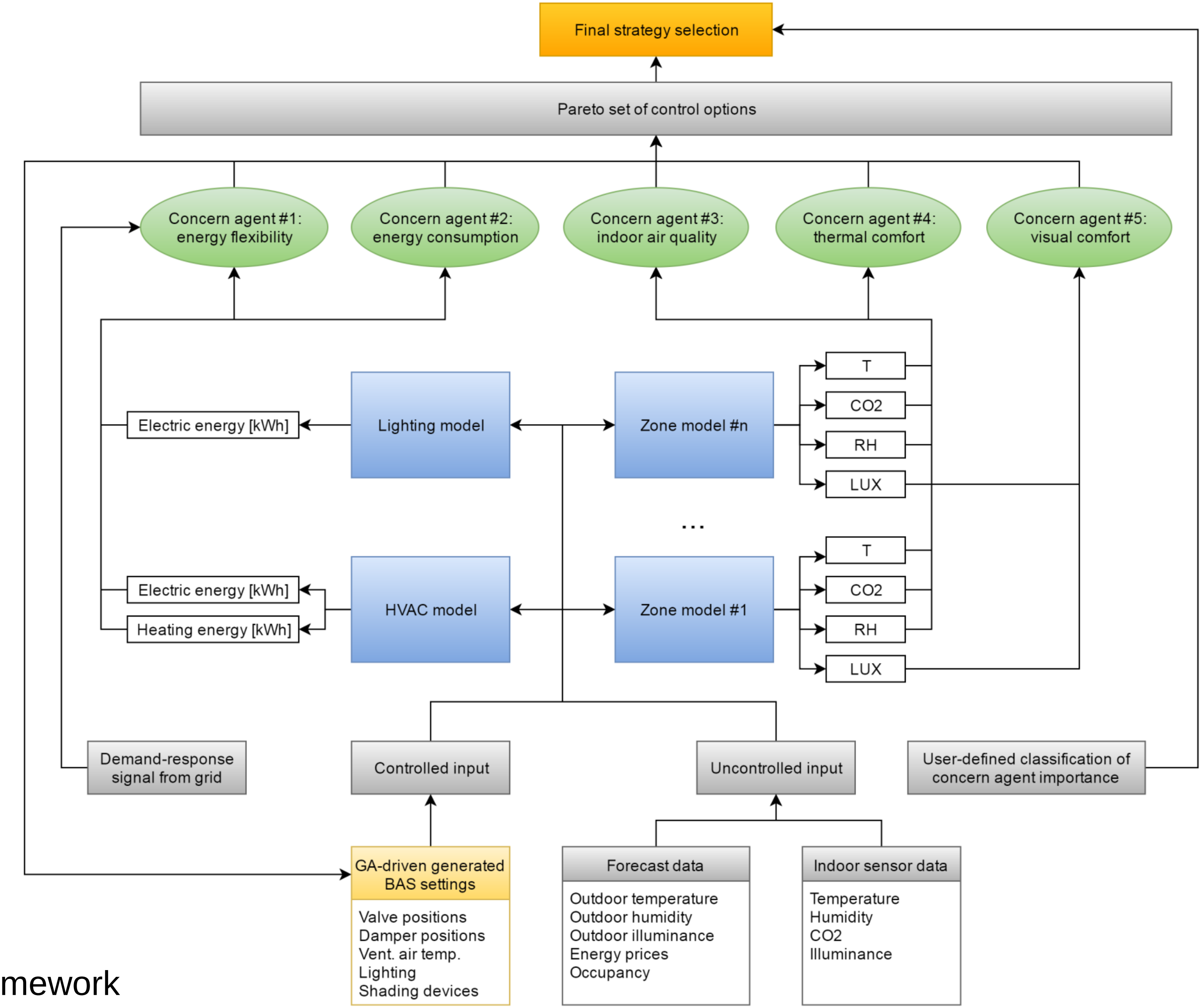


Model Predictive Control (MPC) control strategy adapting to the predicted future conditions

Traditional control strategy reacting to unexpected conditions

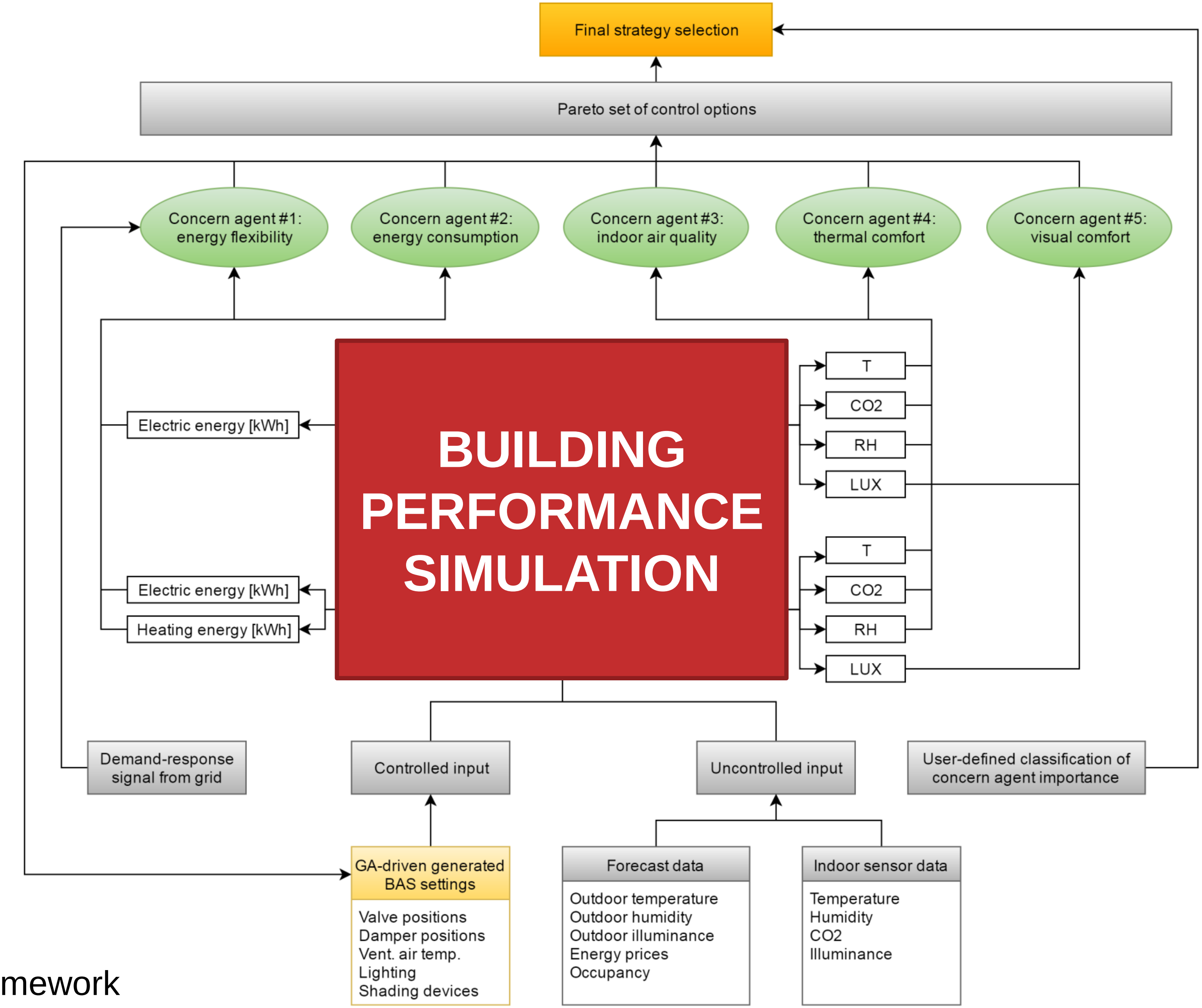
Image source: M. Hoekstra, M Vogelzang, E. Verbitsky, M.W.N. Nijtsen, Health technology assessment review: Computerized glucose regulation in the intensive care unit – how to create artificial control, *Critical Care 2009* (13): 223.

Implementation of smart control solutions in OU44



MPC framework

Implementation of smart control solutions in OU44

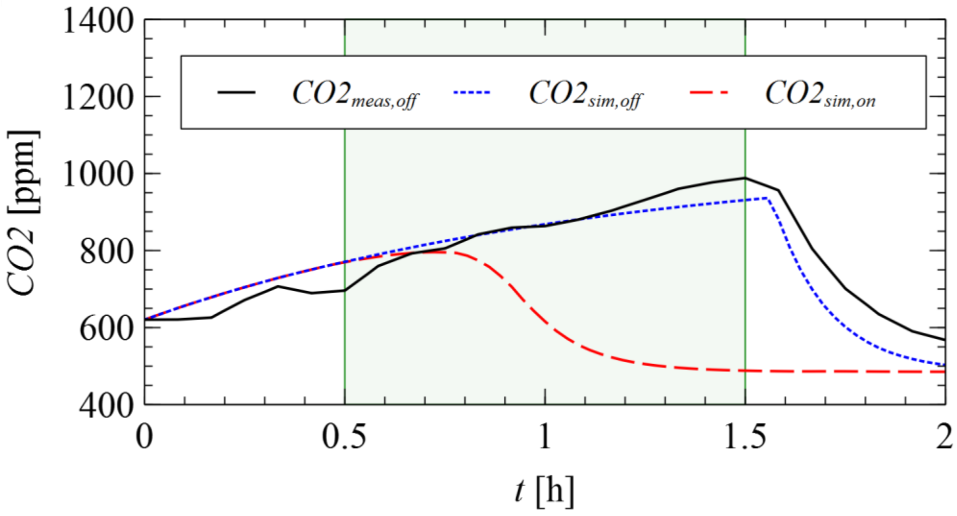


MPC framework

Building models

Capabilities:

- Prediction of future indoor conditions
- Possibility to compare the effect of different control strategies beforehand (see figure)



CO2 measured (ventilation OFF)
CO2 simulation (ventilation OFF)
CO2 simulation (ventilation ON)

Difficulties:

- Limited model portability (numerical model is tailored for a specific building)
- Calibration of model parameters is difficult

Building models

Capabilities:

- Prediction of future indoor conditions
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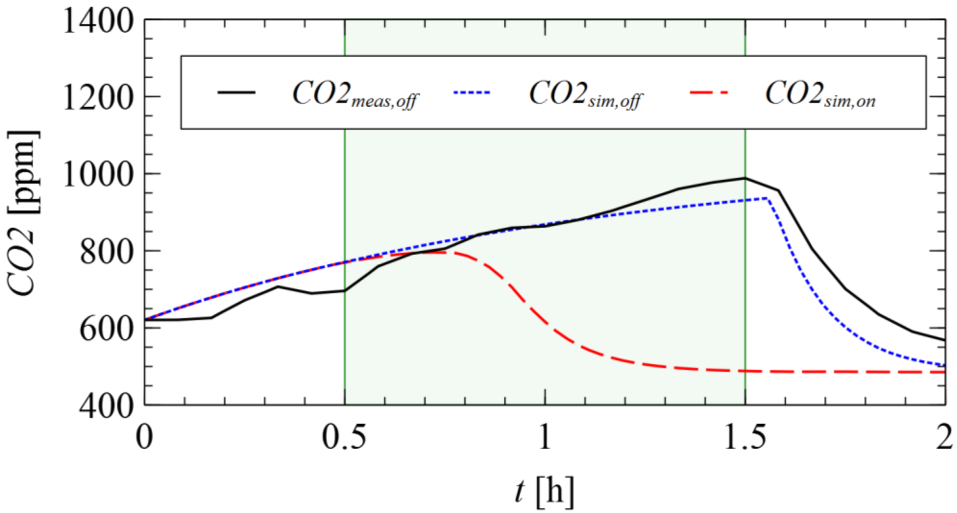

CO2 measured (ventilation OFF)
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Difficulties:

- Limited model portability (numerical model is tailored for a specific building)
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Can we get automatic model generation and calibration?

Zone model for indoor environment prediction

Inputs:

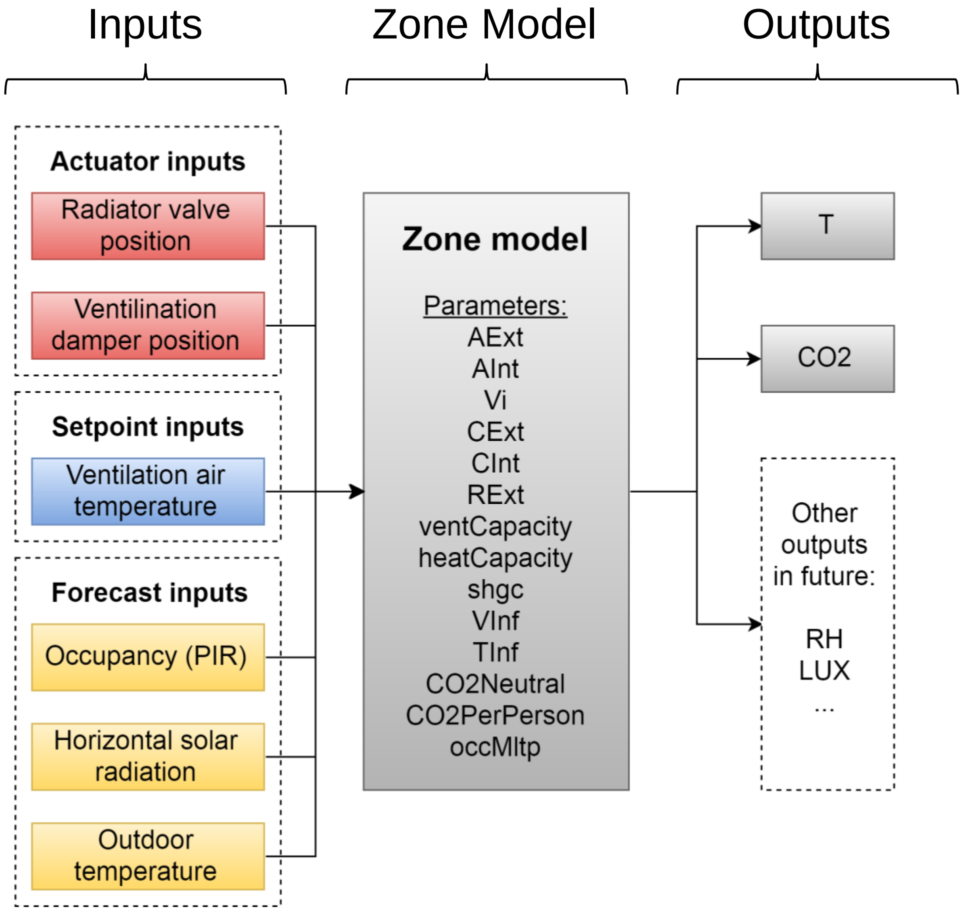
- Actuator positions
- Setpoints
- Forecast data

Model parameters:

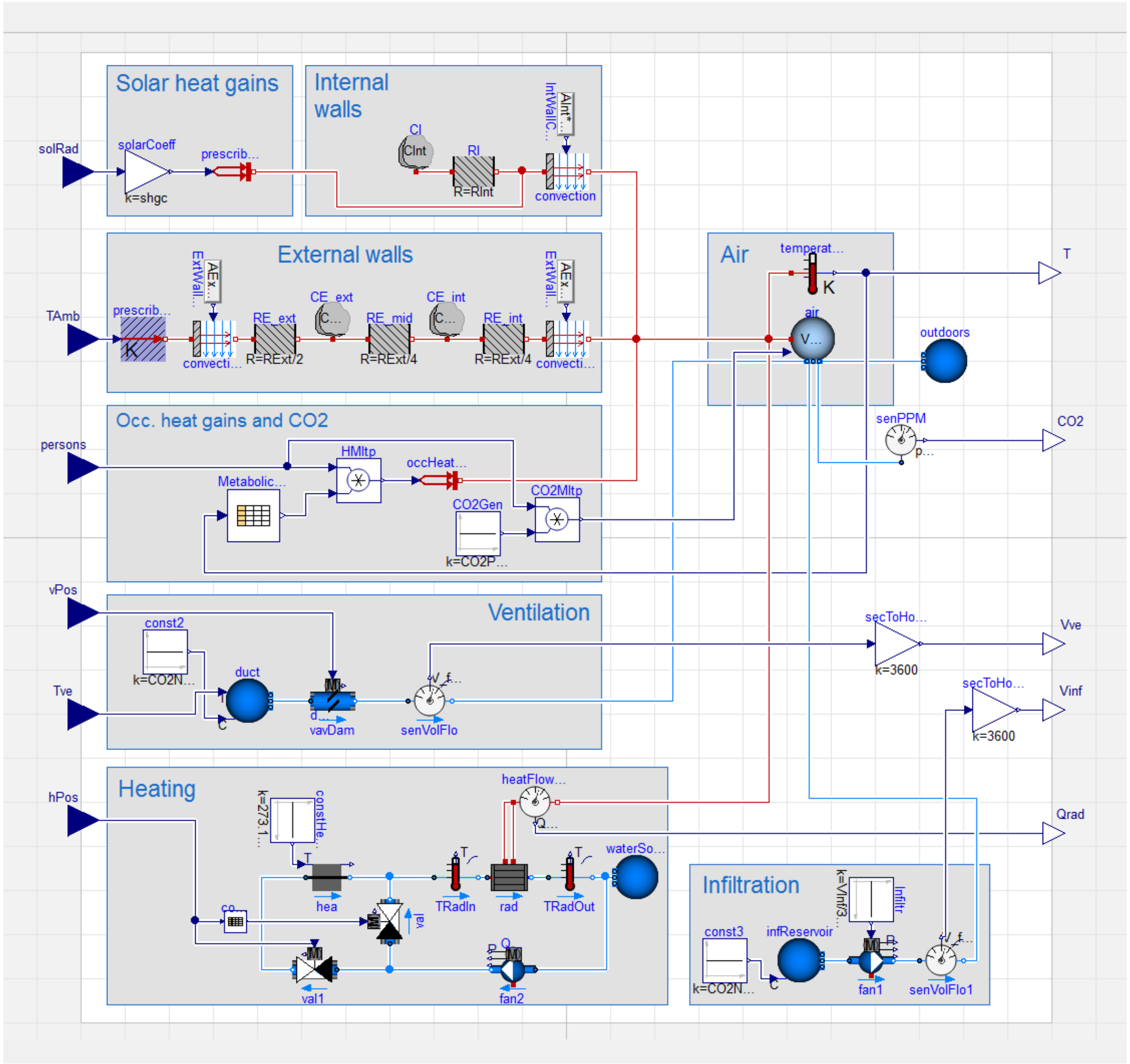
- Geometrical parameters
- Material parameters
- HVAC system capacity
- Typical occupancy behavior

Outputs:

- Indoor temperature
- Indoor CO2



Zone model: implementation



Solar radiation

Outdoor temperature

Number of occupants

Ventilation damper

Ventilation air temp.

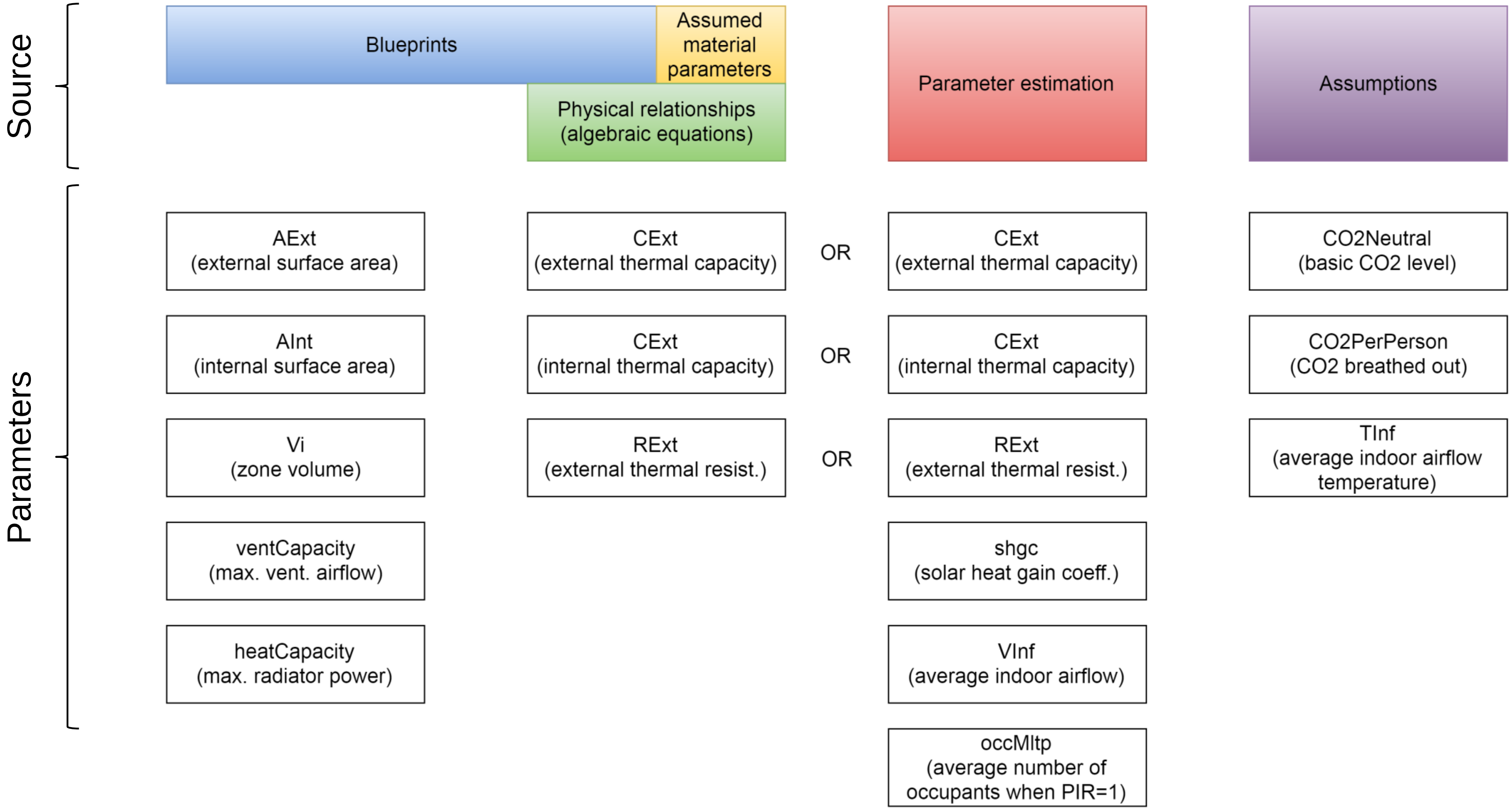
Radiator valve

Indoor temperature

Indoor CO2

Tool: Dymola / Modelica

Parameter sources



Source

Blueprints

Assumed material parameters

Physical relationships (algebraic equations)

Parameter estimation

Assumptions

Parameters

AExt (external surface area)

AInt (internal surface area)

Vi (zone volume)

ventCapacity (max. vent. airflow)

heatCapacity (max. radiator power)

CExt (external thermal capacity) OR CExt (external thermal capacity)

CExt (internal thermal capacity) OR CExt (internal thermal capacity)

RExt (external thermal resist.) OR RExt (external thermal resist.)

shgc (solar heat gain coeff.)

VInf (average indoor airflow)

occMltp (average number of occupants when PIR=1)

CO2Neutral (basic CO2 level)

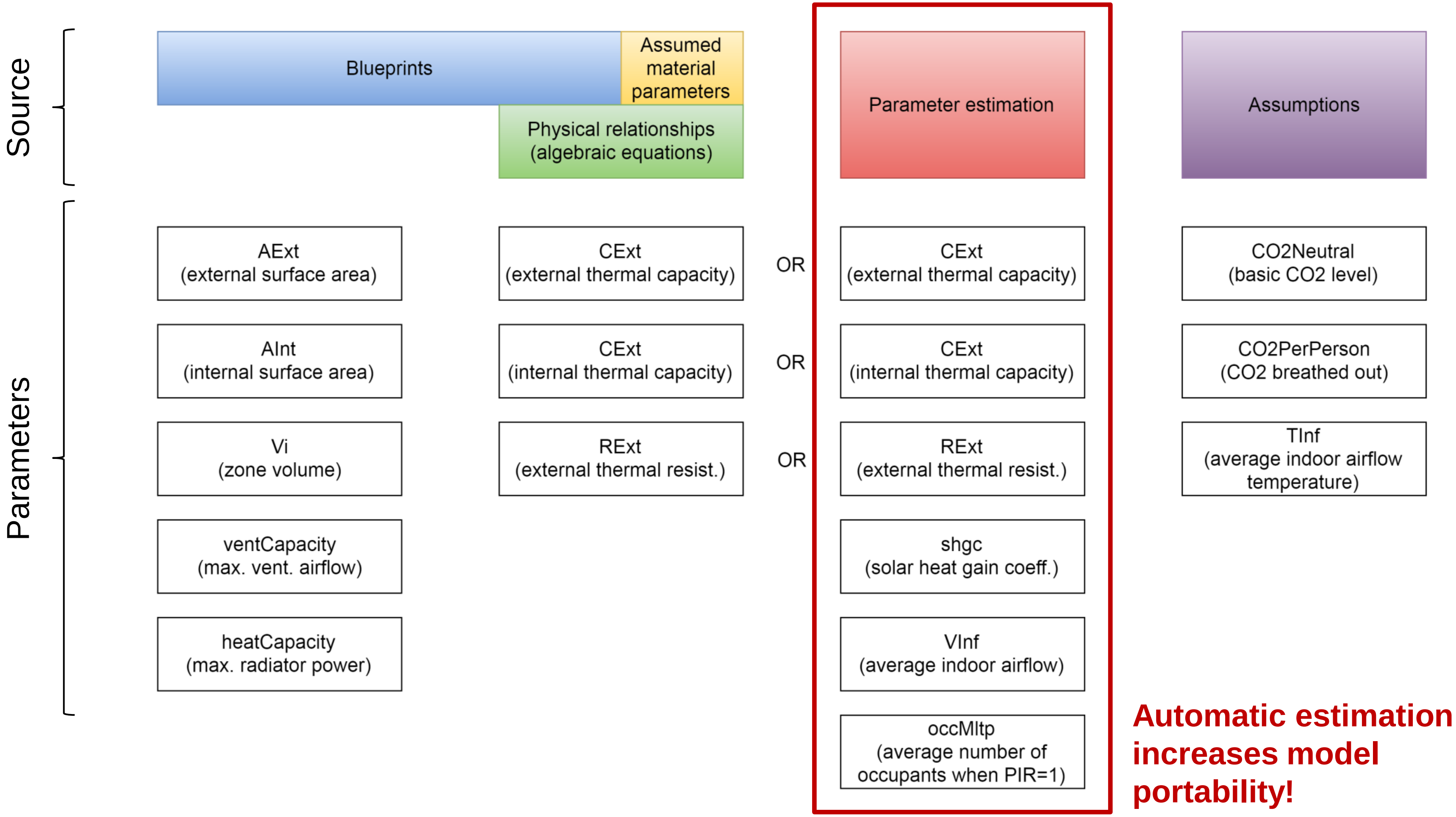
CO2PerPerson (CO2 breathed out)

TInf (average indoor airflow temperature)

Model paramaters are:

(1) read from blueprints/BIM, (2) calculated from blueprints/BIM, (3) estimated, (4) assumed

Parameter sources



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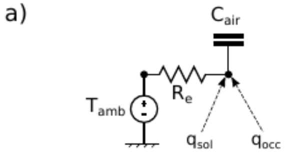
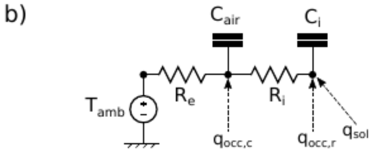
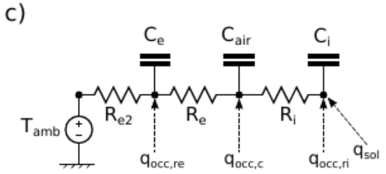
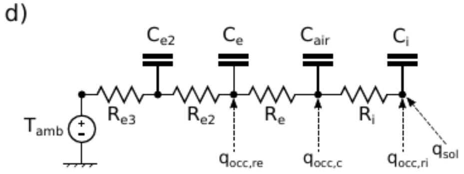
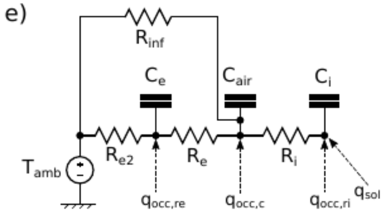
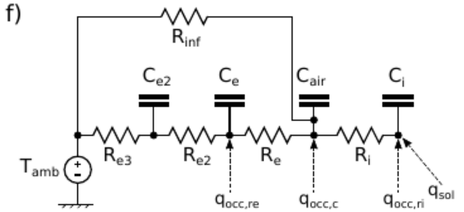
Automatic estimation increases model portability!

Model paramaters are:

(1) read from blueprints/BIM, (2) calculated from blueprints/BIM, (3) estimated, (4) assumed

Low-order zone thermal models

R1C1		Convex
R2C2		Convex / non-convex
R3C3		Non-convex
R4C4		Non-convex
R4C3		Non-convex
R5C4		Non-convex

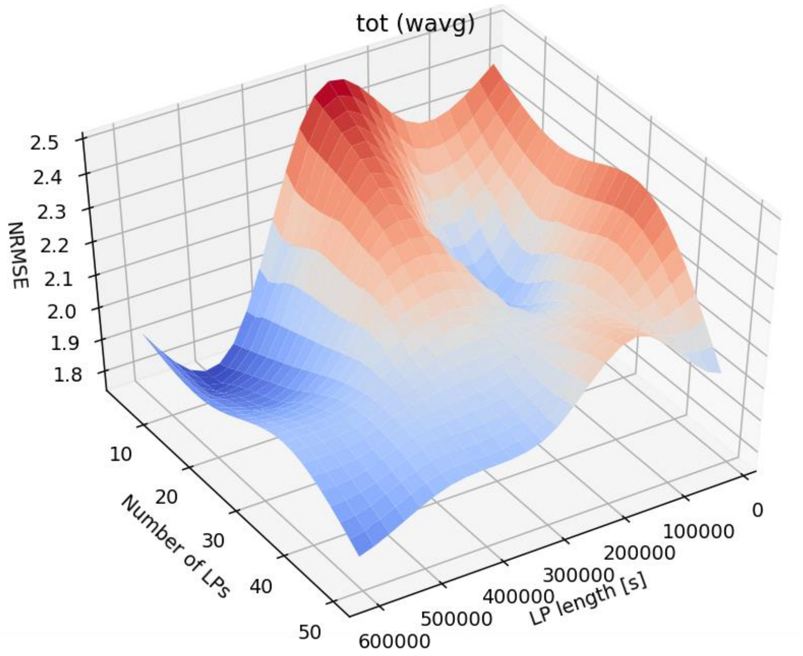


Fig: Non-convex function: model error depending on number and length of learning periods

Low-order model results: all cases

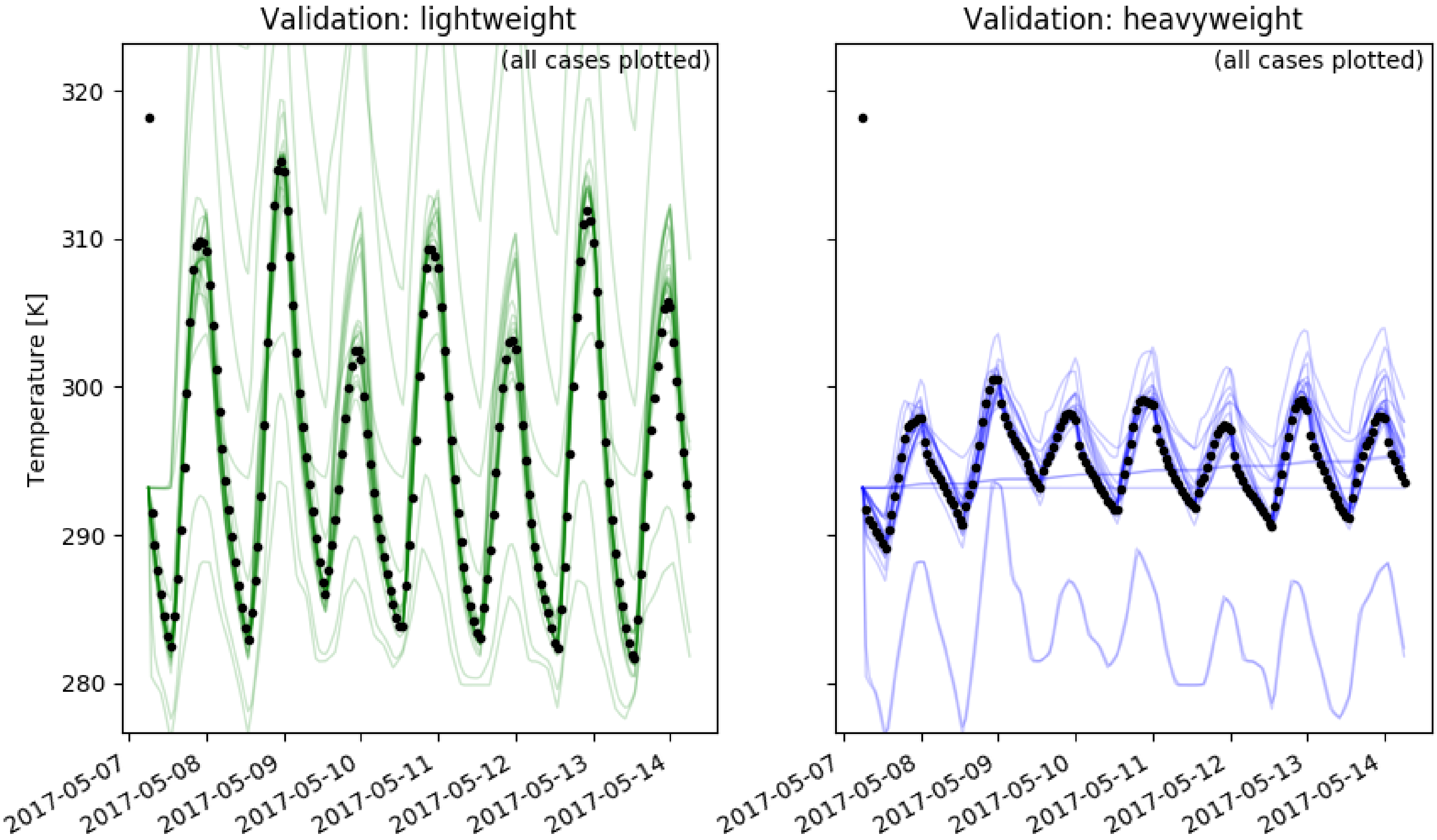


Fig: Actual temperature (dotted) vs. low-order model results (green/blue) for all estimated parameters – highlights the need for robust parameter estimation method

ModestPy: model estimation in Python

https://github.com/sdu-cfei/modest-py

- ✓ Parameter estimation
- ✓ Optimization
- ✓ Genetic algorithm (global search)
- ✓ Hooke-Jeeves (local search)
- ✓ Open source (BSD)
- ✓ Windows & Linux
- ✓ Non-convex optimization
- ✓ Non-linear models
- ✓ Non-differentiable models
- ✓ FMI-compliant

ModestPy: step 1 – genetic algorithm

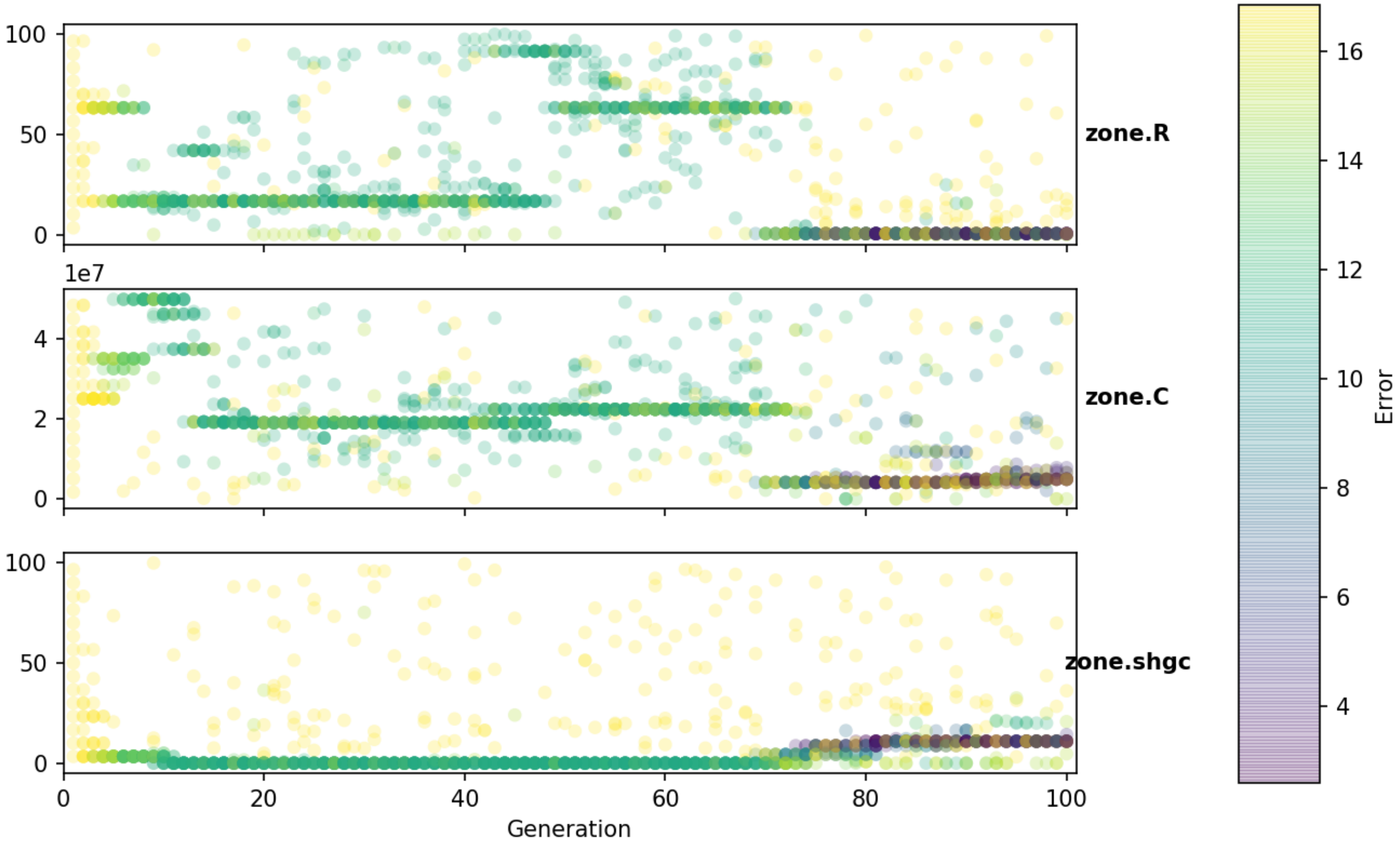


Fig: Visual representation of the genetic algorithm evolution

ModestPy: step 2 – Hooke-Jeeves

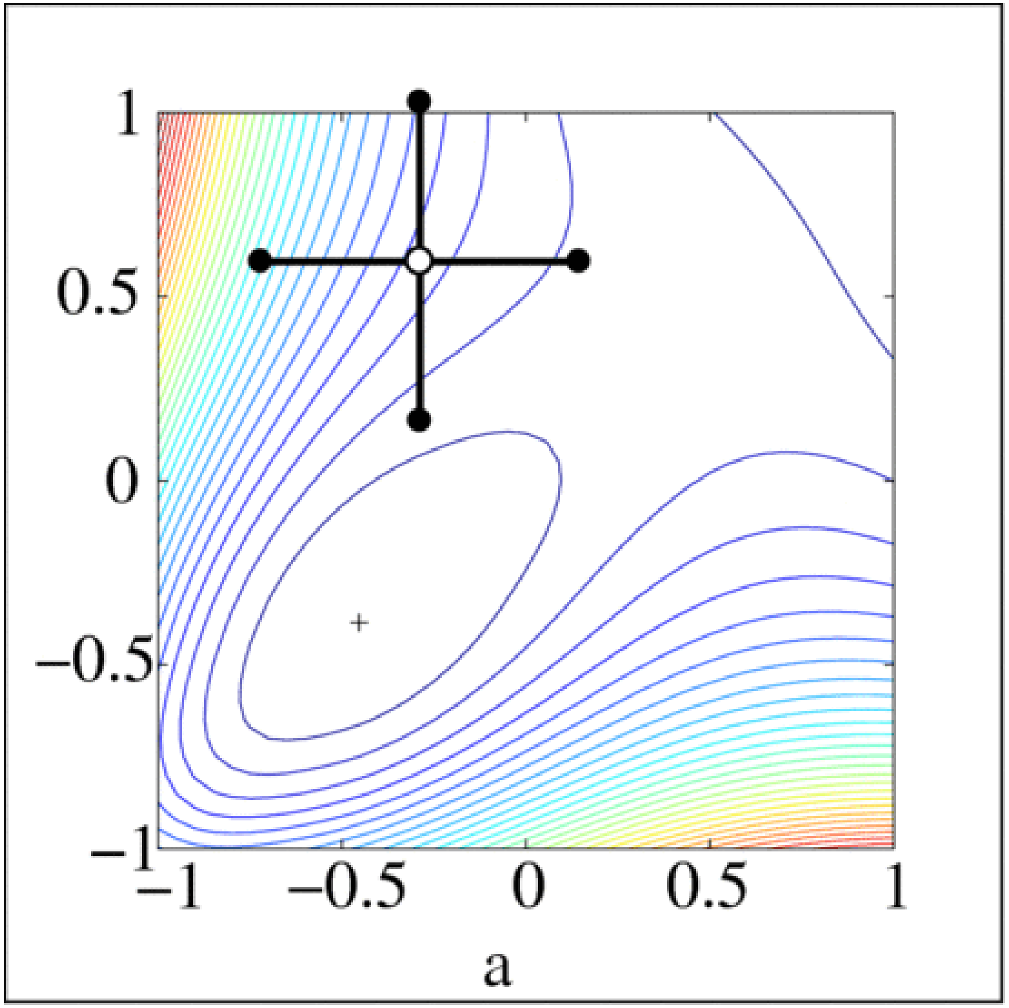


Fig: Hooke-Jeeves (pattern search) algorithm

Image: https://en.wikipedia.org/wiki/Pattern_search_(optimization)

ModestPy: step 2 – Hooke-Jeeves

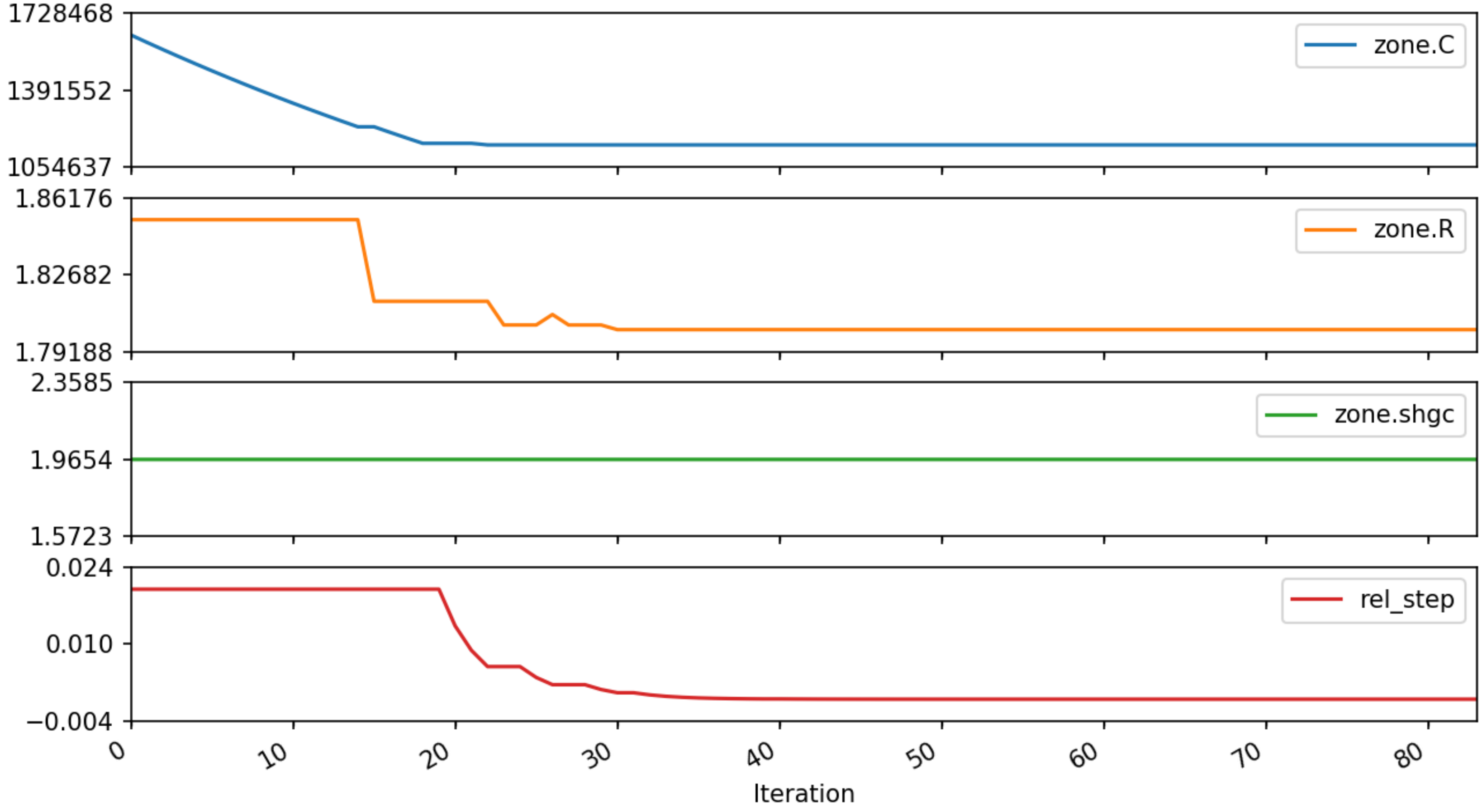
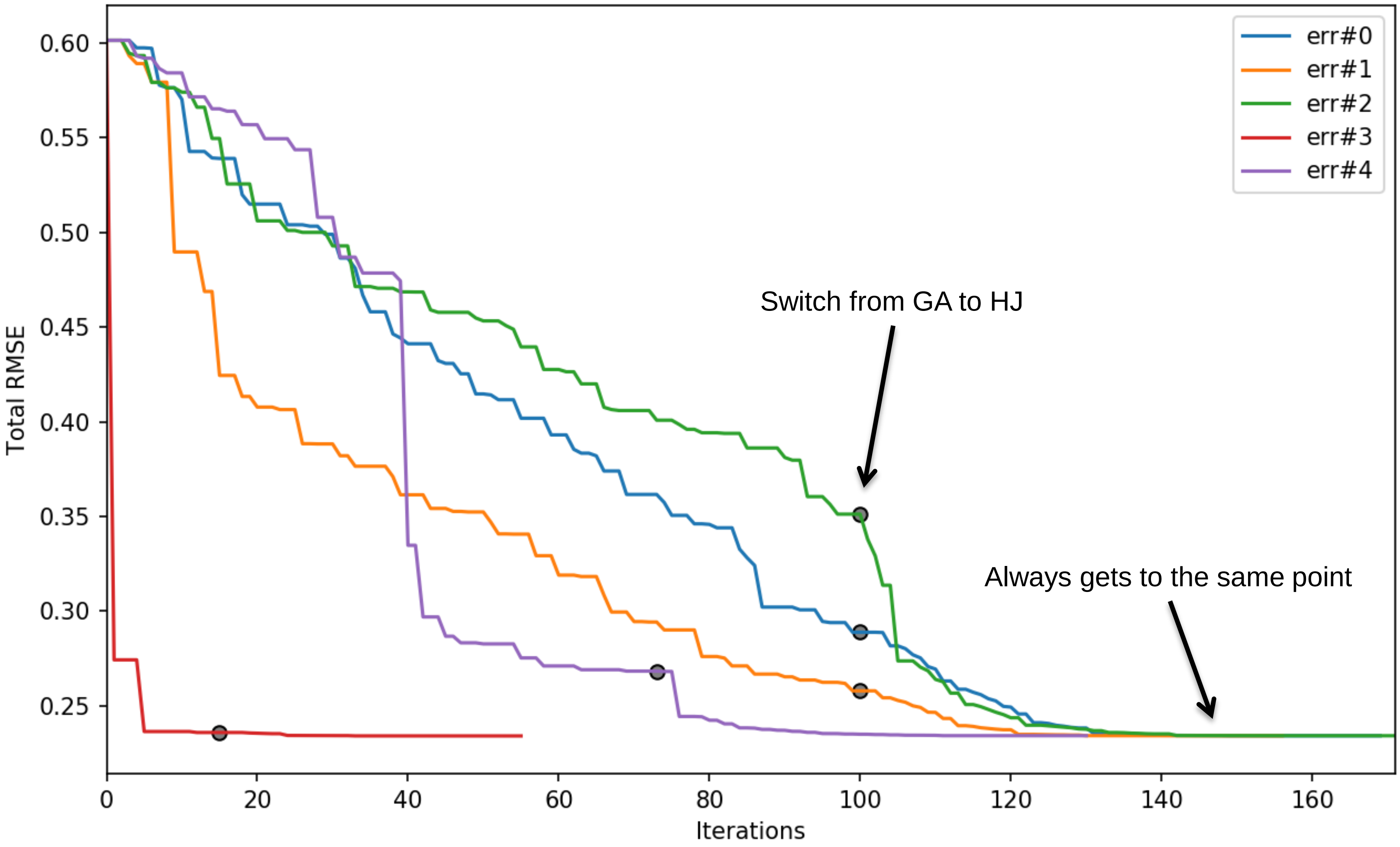


Fig: Hooke-Jeeves (pattern search) results

Convex example: R1C1



Switch from GA to HJ

Always gets to the same point

Fig: RMSE in 5 estimation runs on convex problem

Non-convex example: R5C4

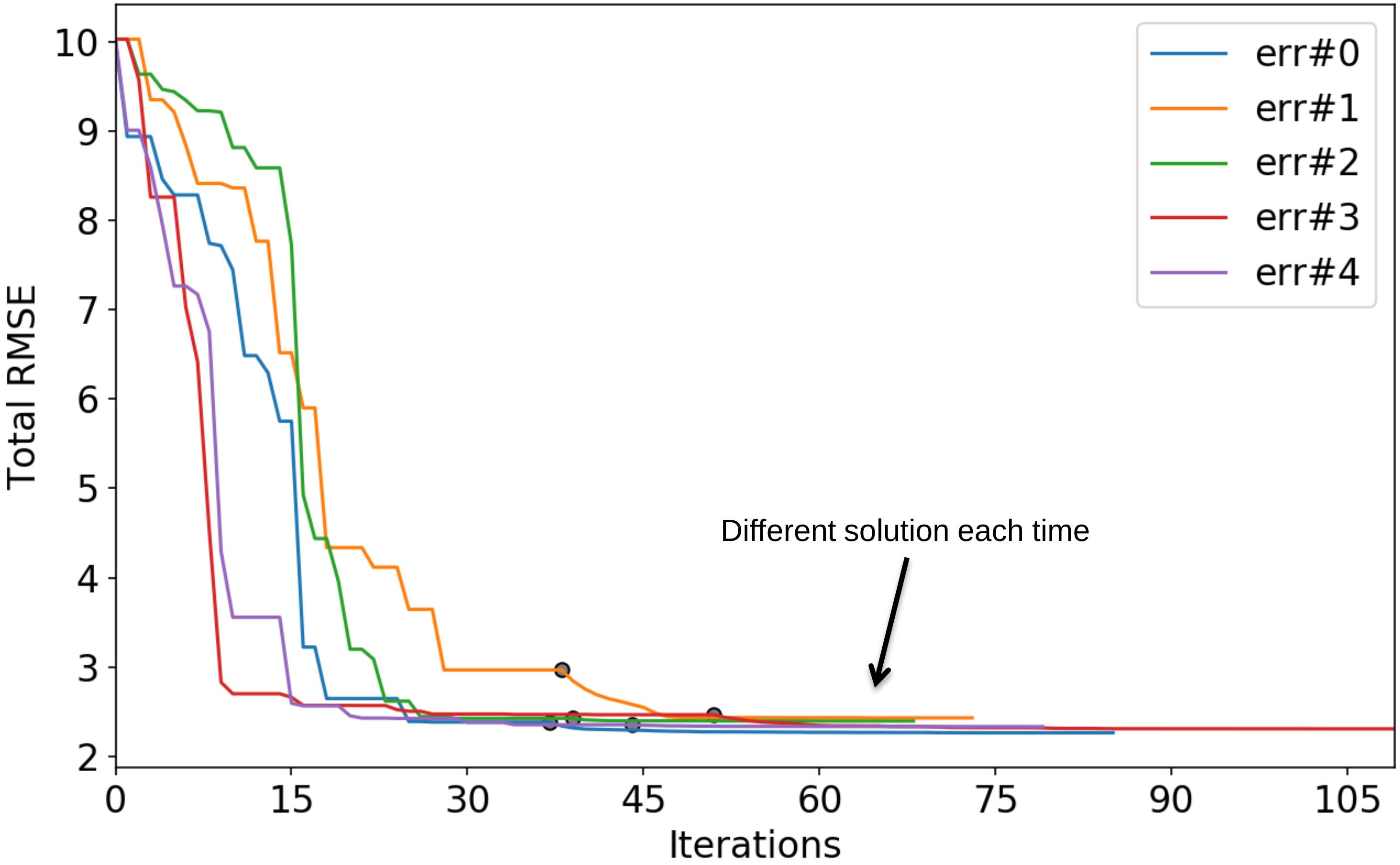
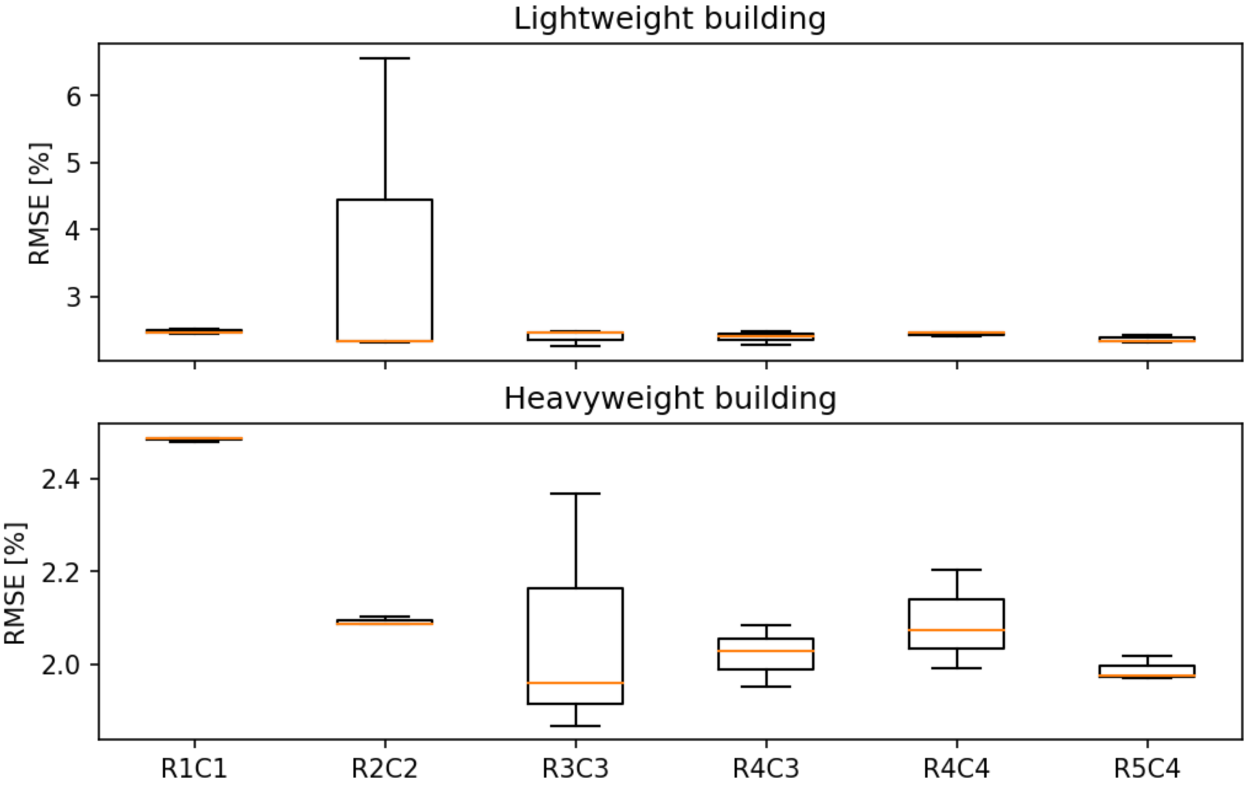


Fig: RMSE in 5 estimation runs on non-convex problem

Model accuracy vs. building type



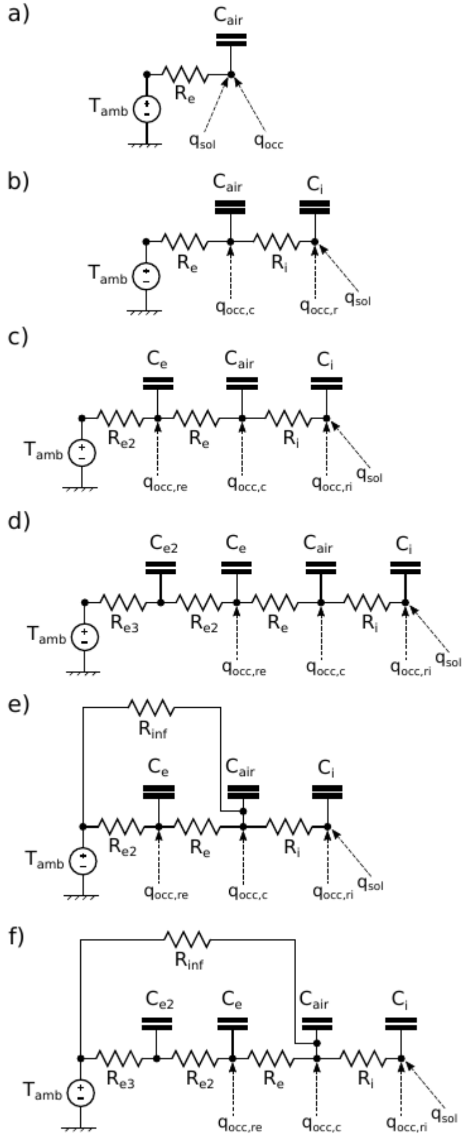
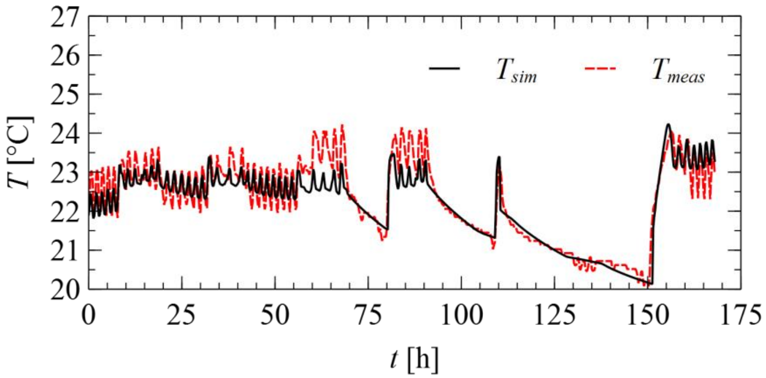


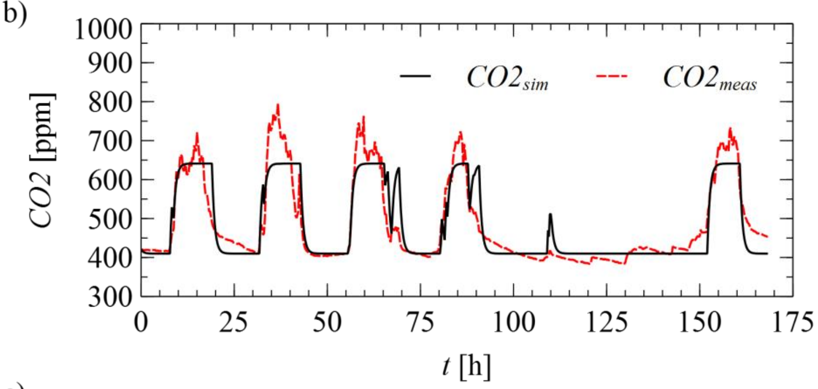
Fig: RMSE of 5 low order models (on the right) depending on the building type

Calibrated model results: GTH, room 1H1

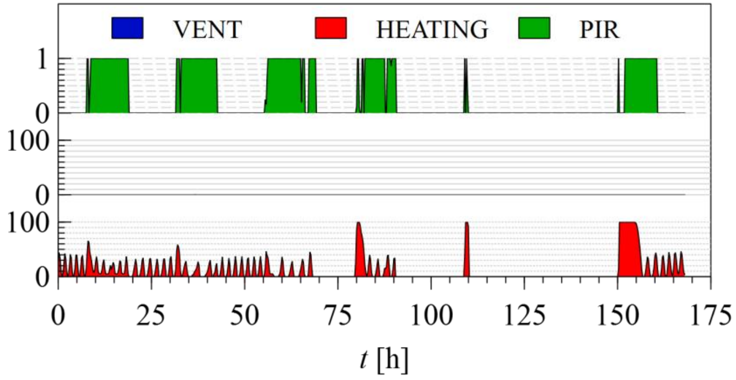
a)



b)



c)



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Figures:

a) Temperature: simulation vs. measured
b) CO2: simulation vs. measured
c) Ventilation, heating, PIR inputs

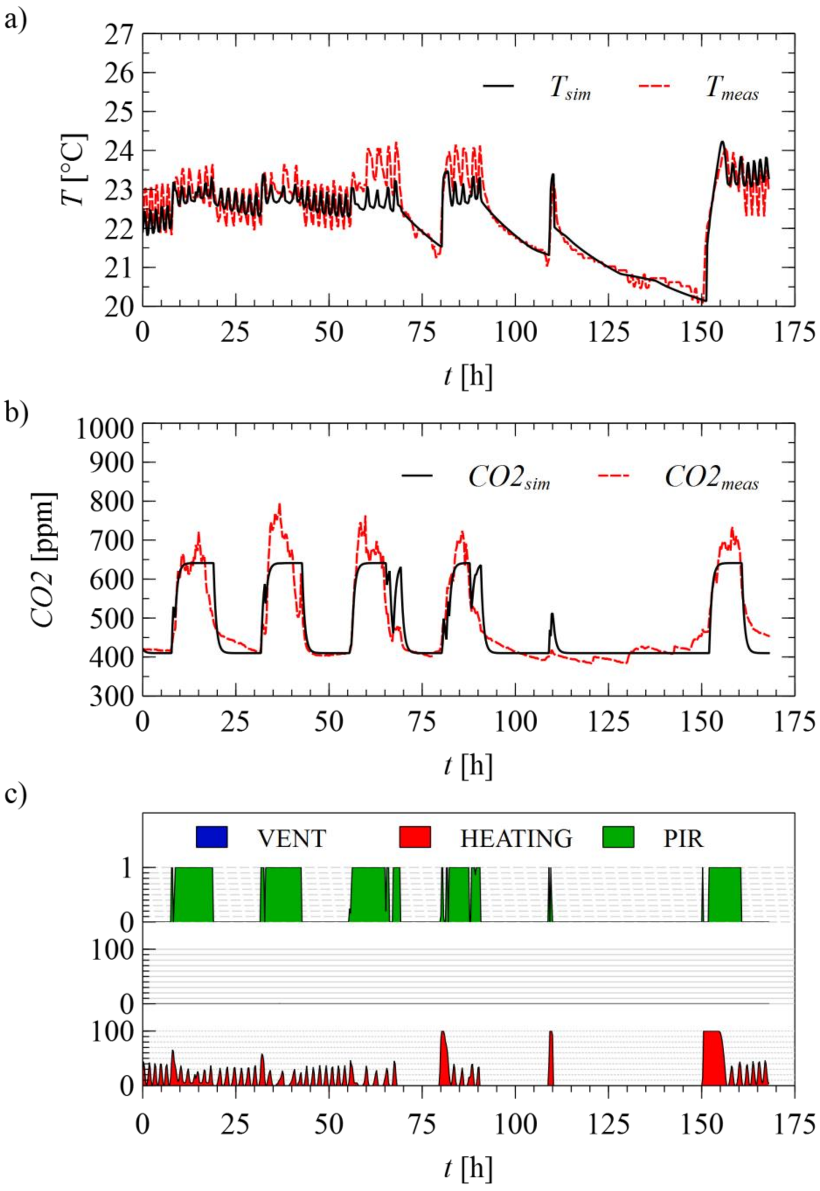
Estimated parameters:

1. average number of occupants
2. thermal resistance of external walls
3. thermal capacitance of external walls
4. thermal capacitance of internal walls
5. average interzonal airflow rate
6. CO_2 generation per person
7. solar heat gain coefficient

Estimation method:

Genetic Algorithm

Calibrated model results: GTH, room 1H1



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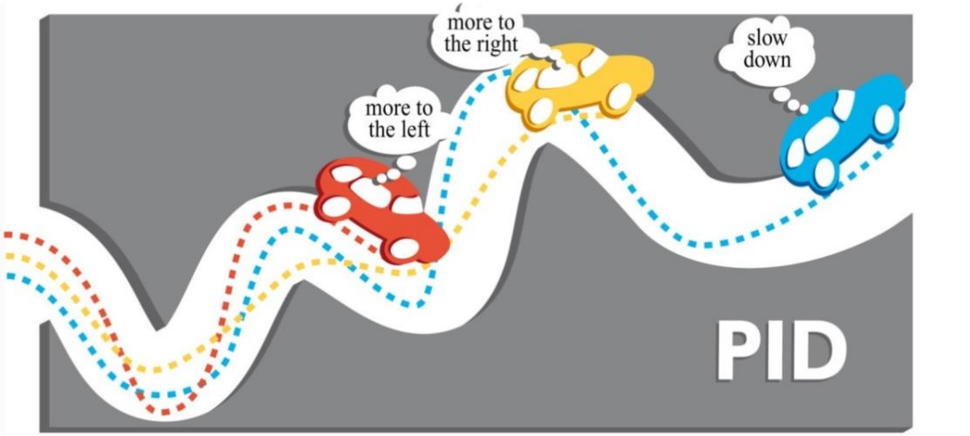
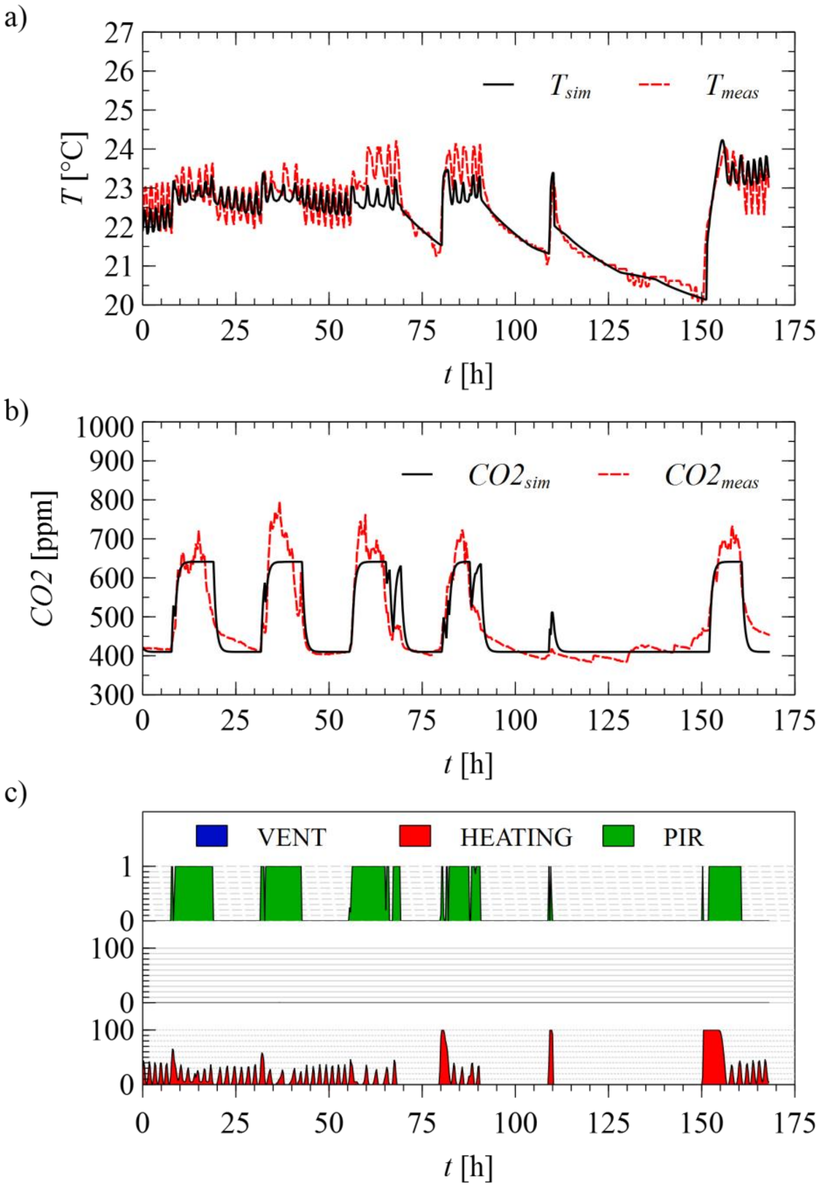


TOO HOT! Close valve!
TOO COLD! Open valve!

Image source: M. Hoekstra, M Vogelzang, E. Verbitsky, M.W.N. Nijtsen, Health technology assessment review: Computerized glucose regulation in the intensive care unit – how to create artificial control, *Critical Care 2009* (13): 223.

Calibrated model results: GTH, room 1H1



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Occupancy predictions needed
to increase the accuracy
of the zone model

T/CO$_2$ vs. camera based occupancy estimation

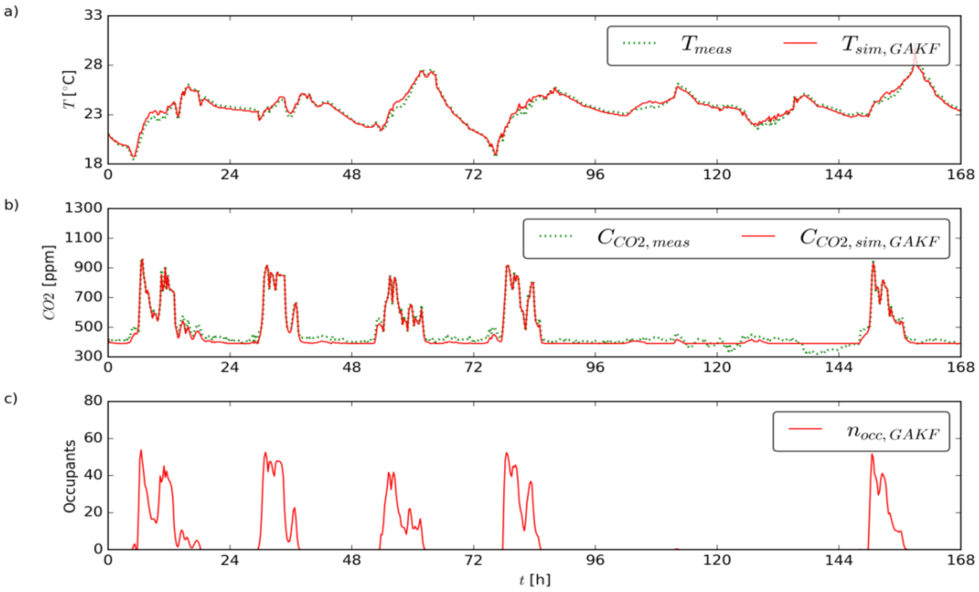

Fig. 1: a) Temperature, b) CO$_2$, c) Estimated number of occupants

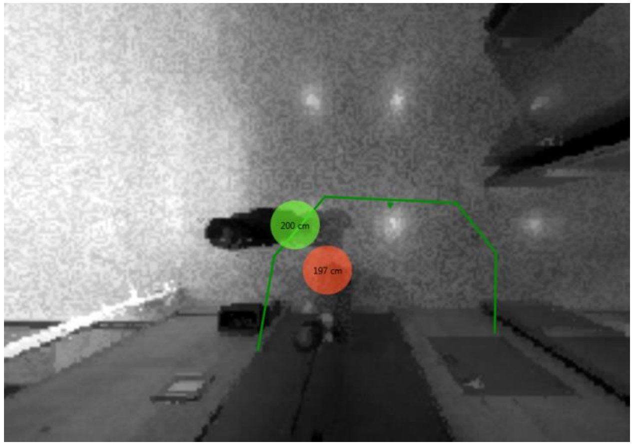

Fig. 2: Stereo vision camera view with count lines in green and detected persons shown by circles.

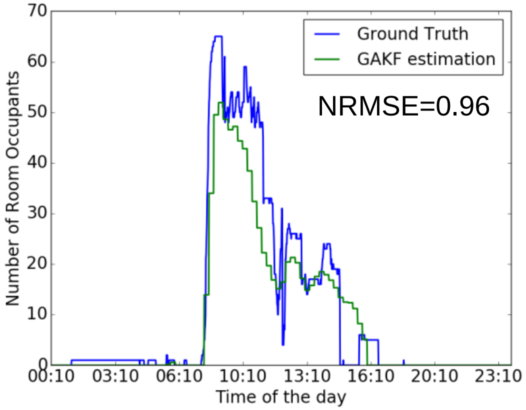

Fig. 3: T/CO2 based estimation accuracy

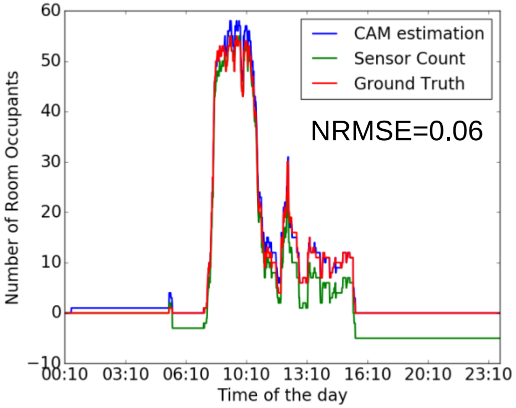

Fig. 4: Stereo vision camera based estimation accuracy

SDU
ENERGY
INFORMATICS

Thank you for attention!

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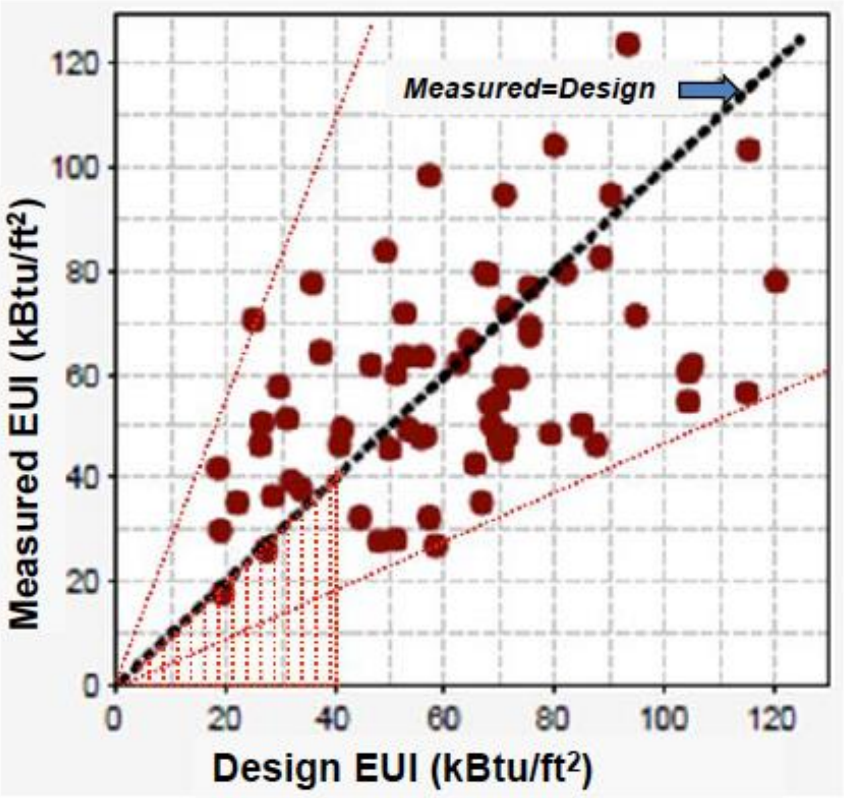
krza@mmmi.sdu.dk

https://github.com/sdu-cfei/modest-py

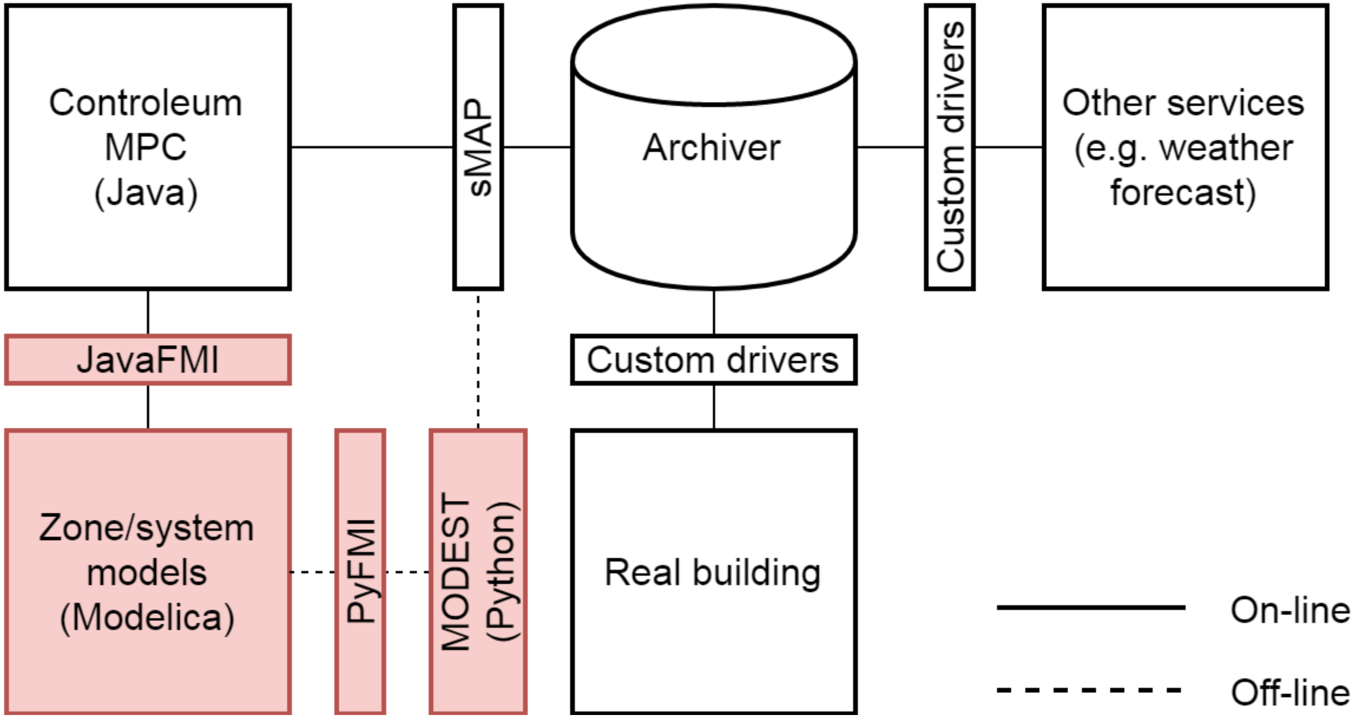
APPENDIX

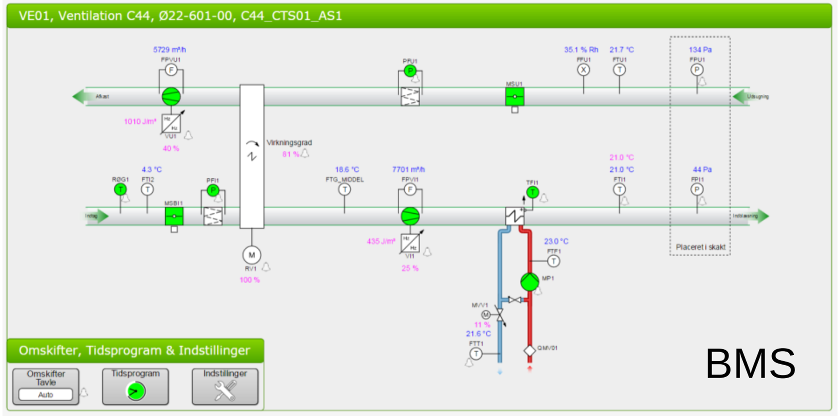
Building energy challenge



Source: Energy performance of LEED-NC buildings, NBI, 2008

SDU MPC framework

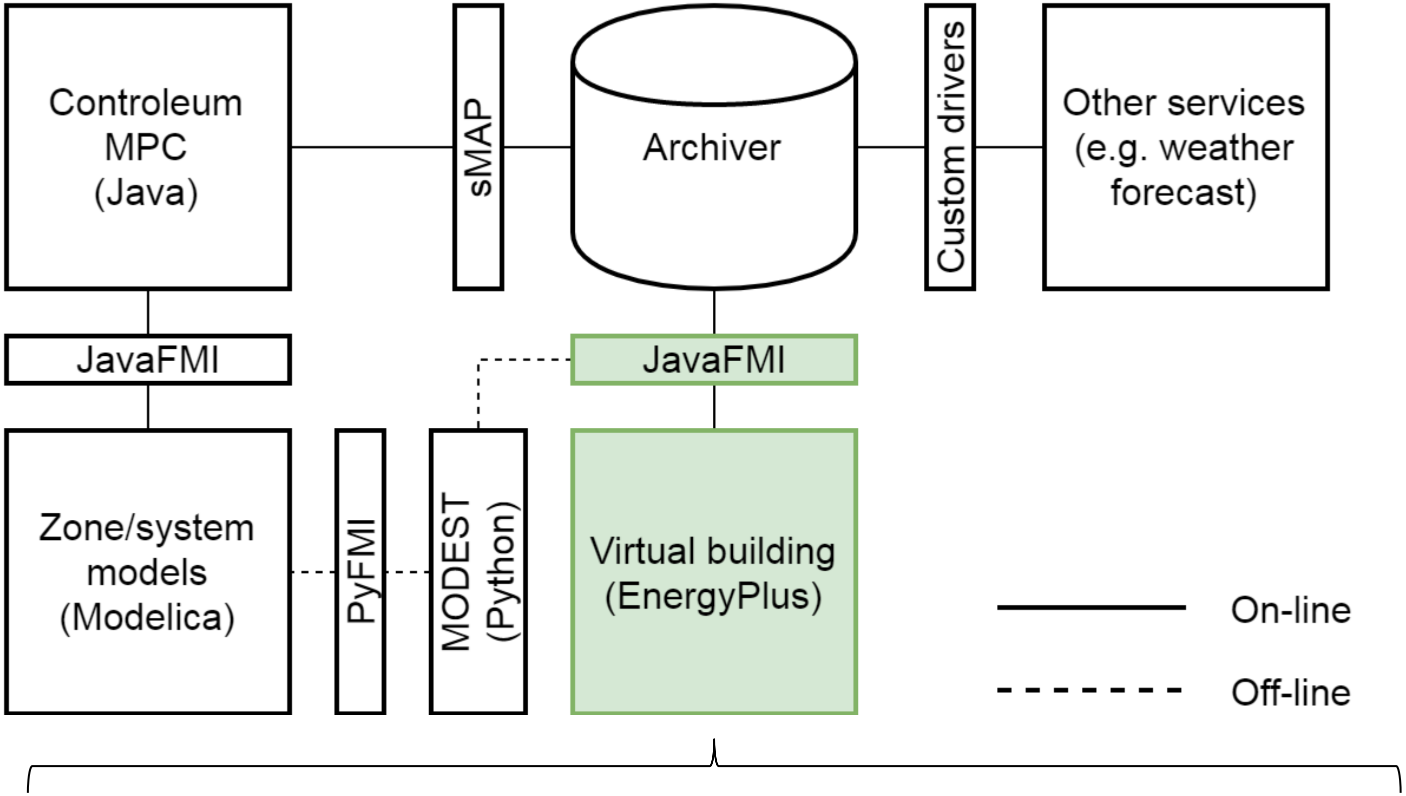




BMS

OU44
8300 m^2
4 floors

SDU MPC Framework



Controleum
MPC
(Java)

sMAP

Archiver

Custom drivers

Other services
(e.g. weather
forecast)

JavaFMI

JavaFMI

Zone/system
models
(Modelica)

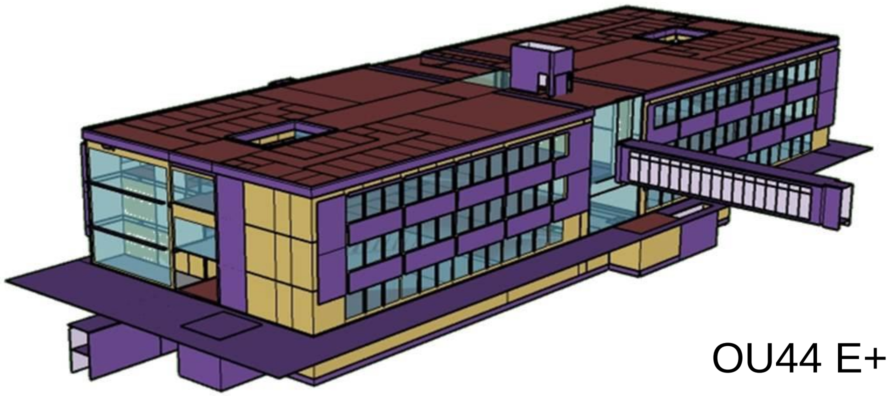
PyFMI

MODEST
(Python)

Virtual building
(EnergyPlus)

On-line

Off-line



OU44 E+ model

Non-convex example: R5C4

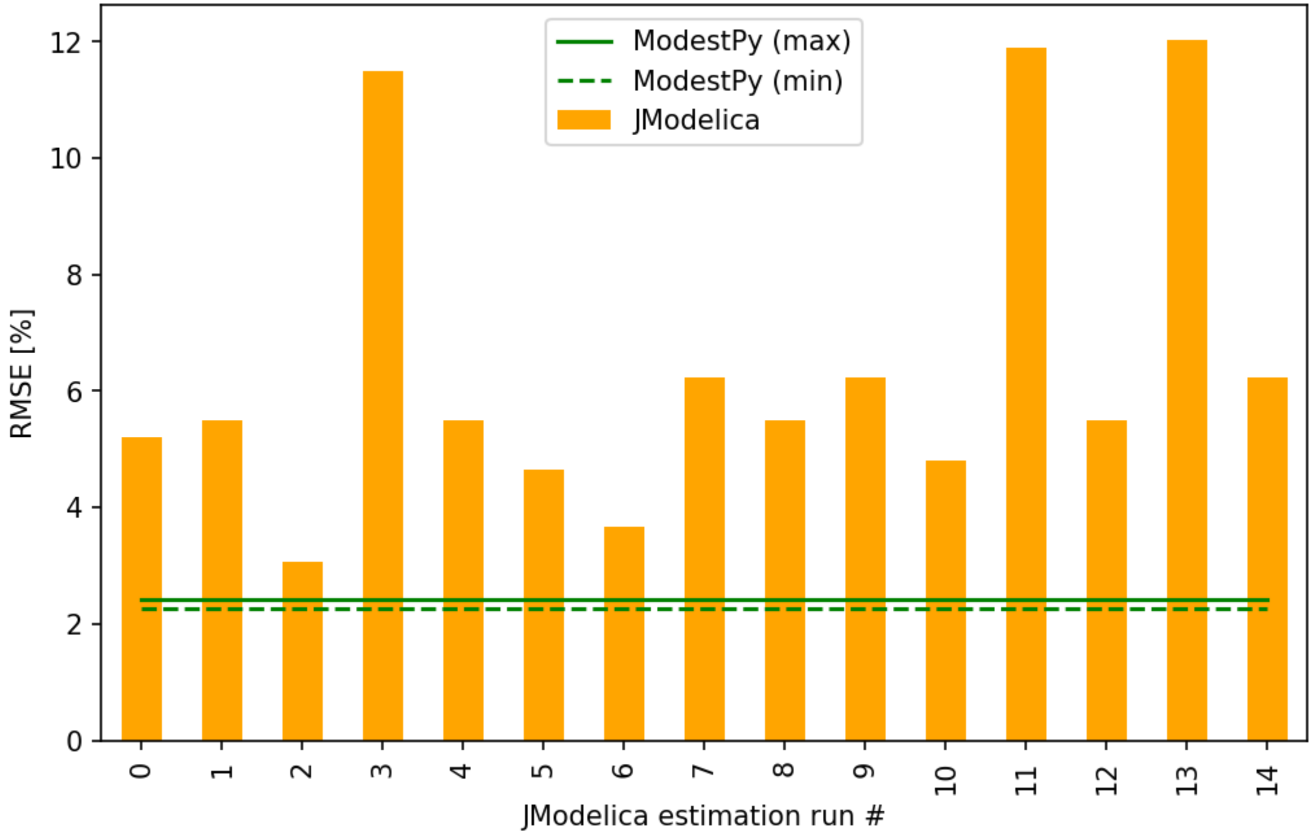


Fig: Gradient-descent (JModelica) vs. GA+HJ (ModestPy) *

- This is just an example! In many cases gradient-descent outperforms GA+HJ
- Each estimation run in JModelica used different initial guess
- Ground-truth data emulated on BESTEST 600FF

* Results produced in collaboration with **LBNL (D. Blum, L. Rivalin, M. Wetter)** using MPCPy framework: https://github.com/lbl-srg/MPCPy