Automated identification of grey-box control models for monitored buildings with JModelica.org

Roel De Coninck, *3E and KU Leuven*
Fredrik Magnusson, *Lund University*
Johan Åkesson, *Lund University*
Lieve Helsen, *KU Leuven*

Optimal control of thermal systems in buildings using Modelica
Freiburg, 23-24 March 2015

http://www.majhost.com/gallery/Puinkabouter/Boekentoren/pano_3.jpg

From data to models

Data

Automation of data-driven
low-order building modelling

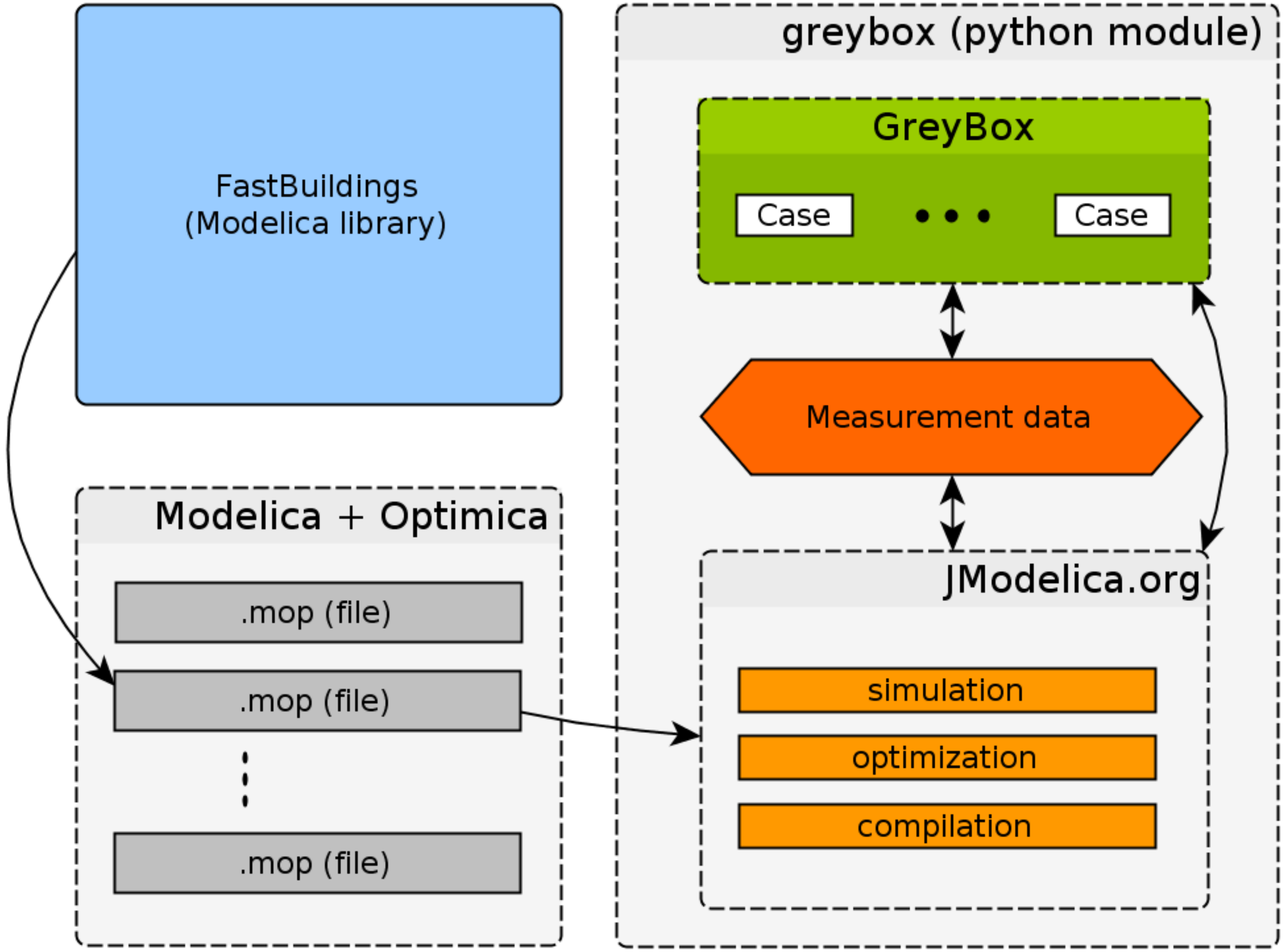
- Data exploration
- Model specification
- Parameter estimation
- Model validation

Models

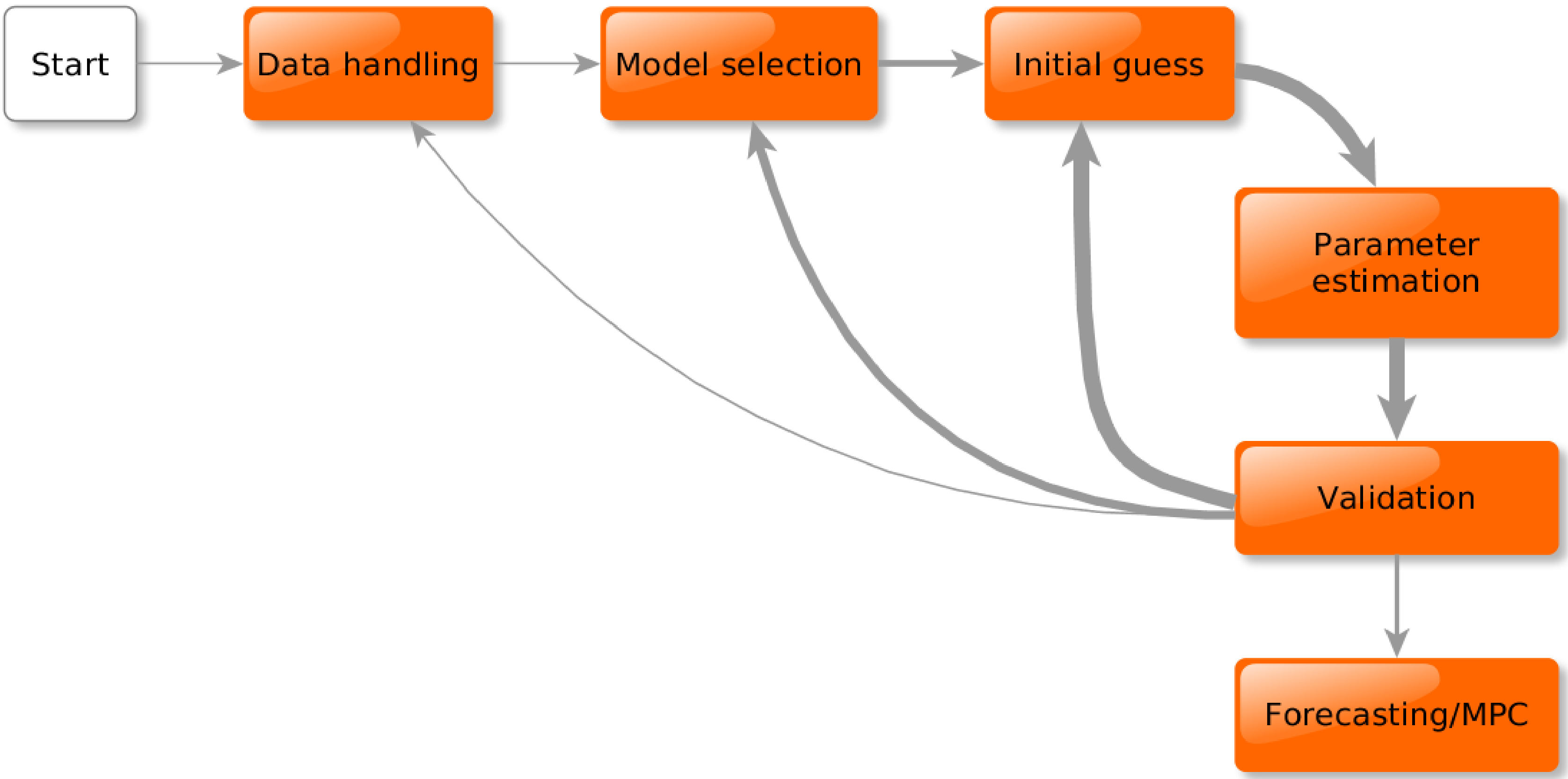
From:
- monitored buildings
- simulation

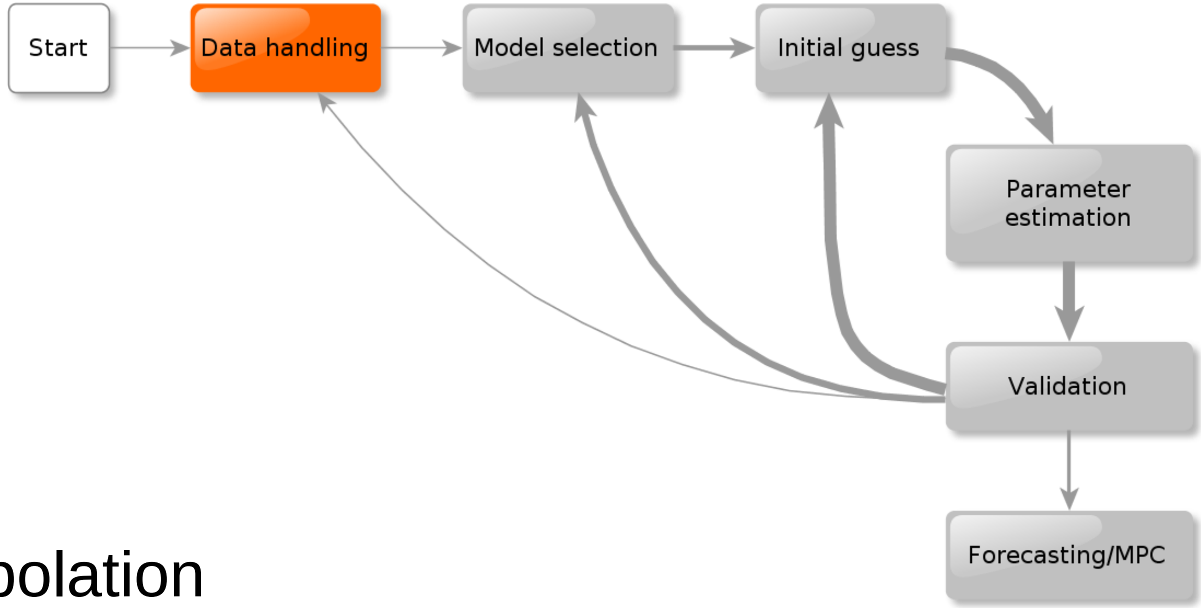
Use:
- Model Predictive Control (MPC)
- Forecasting
- Large-scale simulations with reduced-order models
- Fault detection and diagnostics (FDD)

Grey-box buildings toolbox



Toolbox functionality and work flow

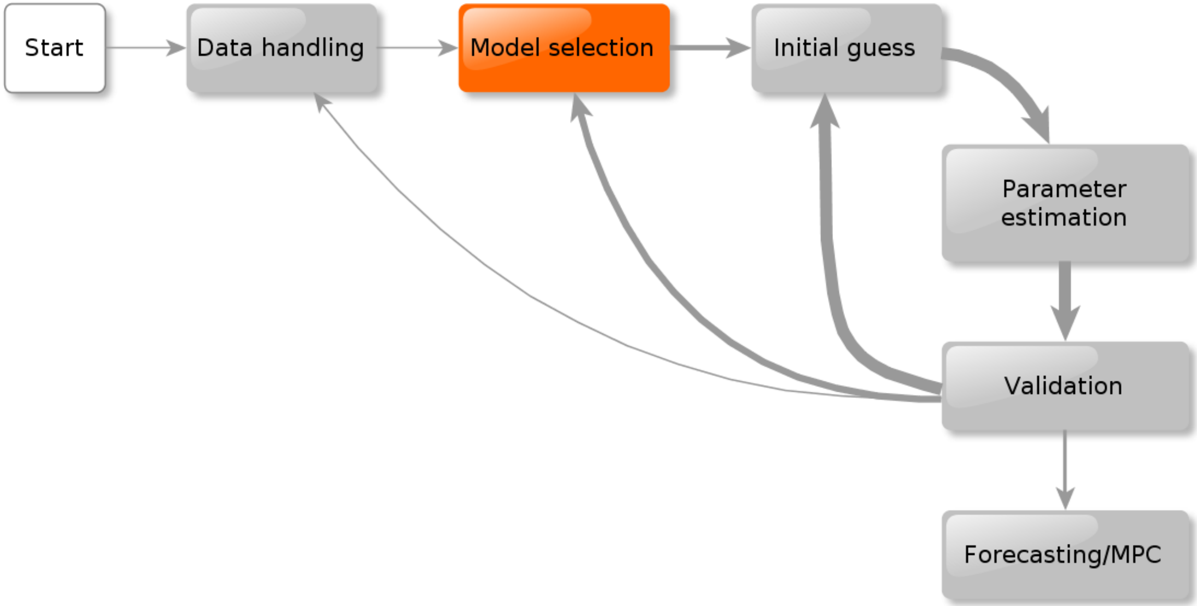




Data handling

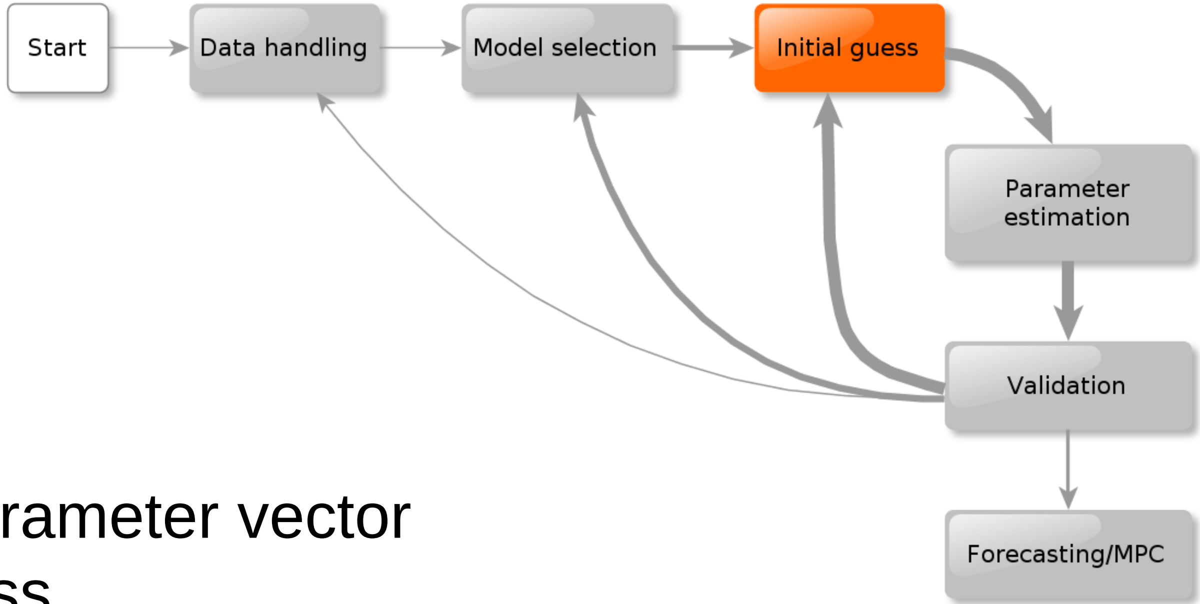
- Loading dataset
- Resampling / interpolation
- Selection of training and validation sets
- Visualization
  - Time series
  - Scatter plots
  - (lagged) cross-correlation

Model selection

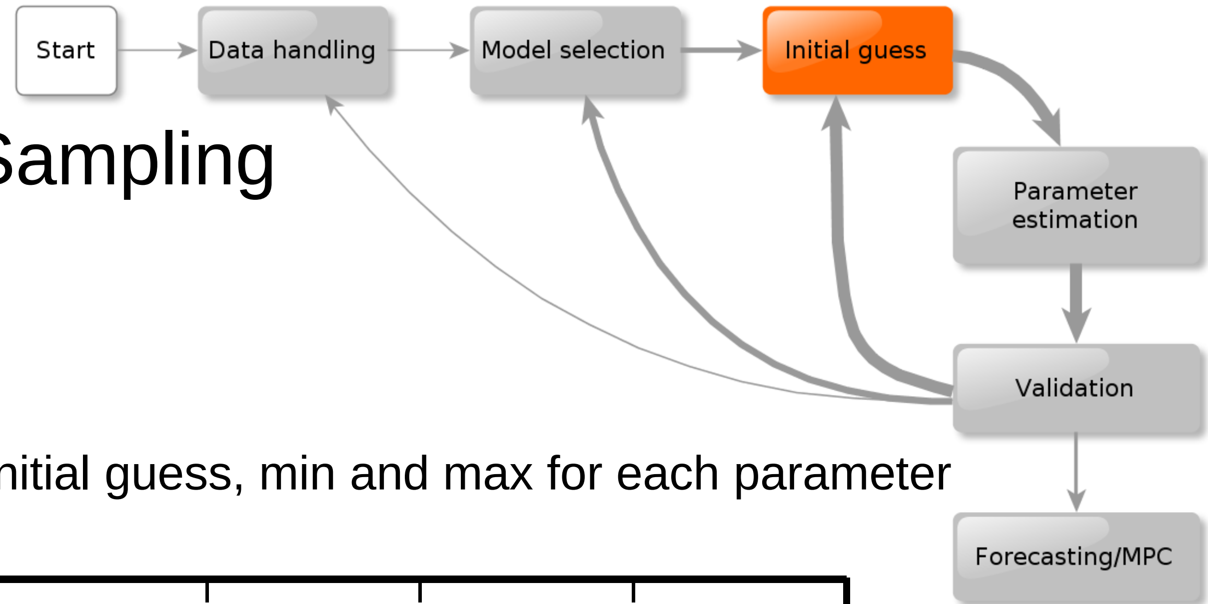


- Select a model from FastBuildings library
- Set fix and to-be-estimated parameters (.mop)

Initialization

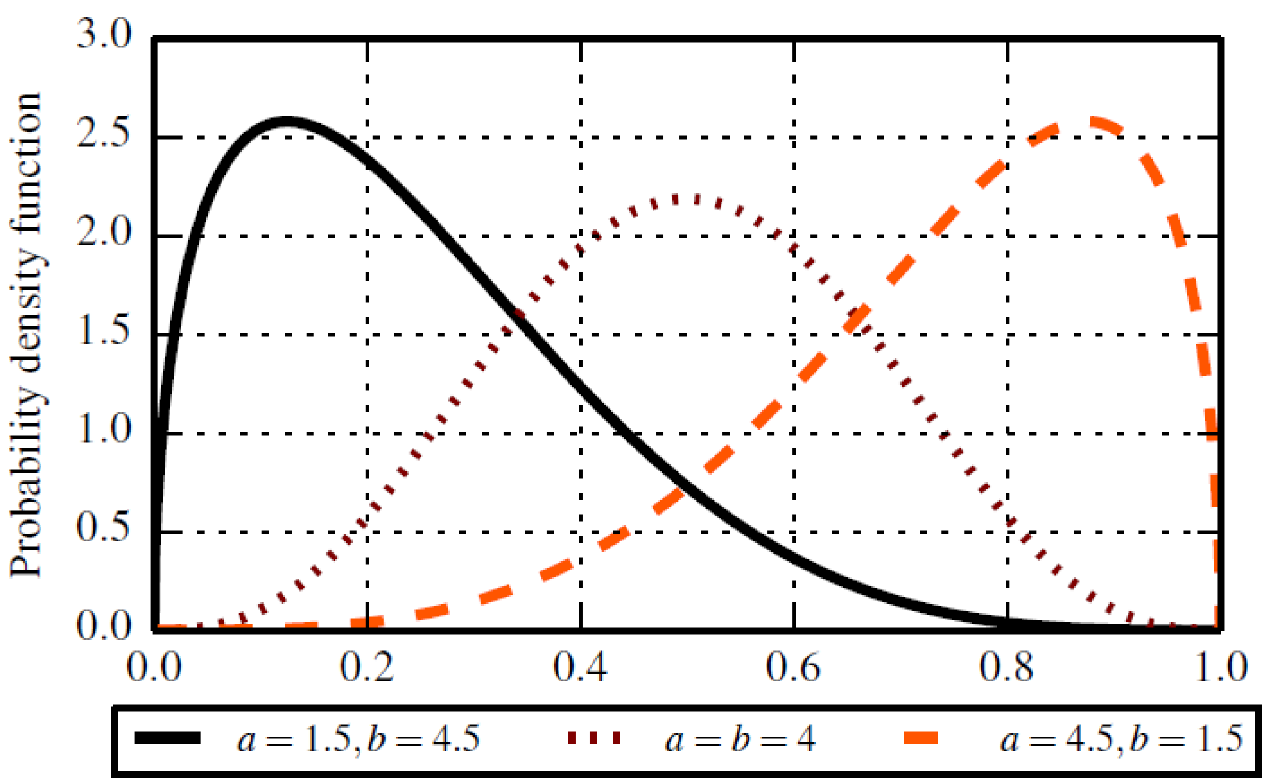


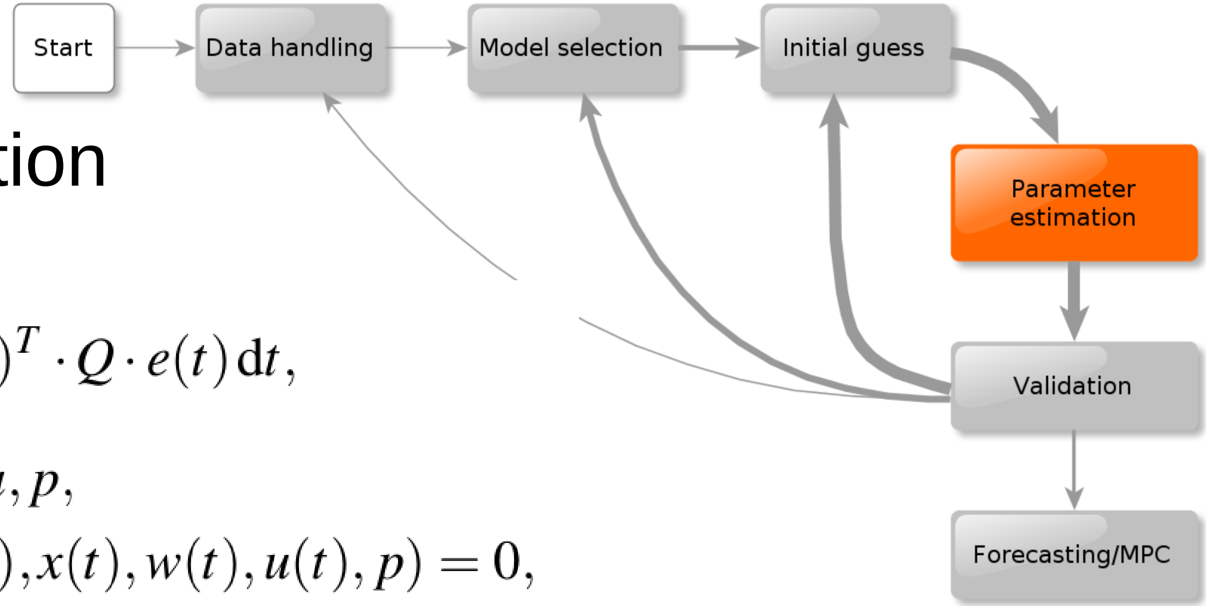
- Initial value for parameter vector
  - Educated guess
  - From a prior ***case***
- Initial simulation
  - Initial trajectories for all variables
  - Automatic scaling
- Visual check (optional)
- Latin hypercube sampling



Latin Hypercube Sampling

Beta distribution based on initial guess, min and max for each parameter

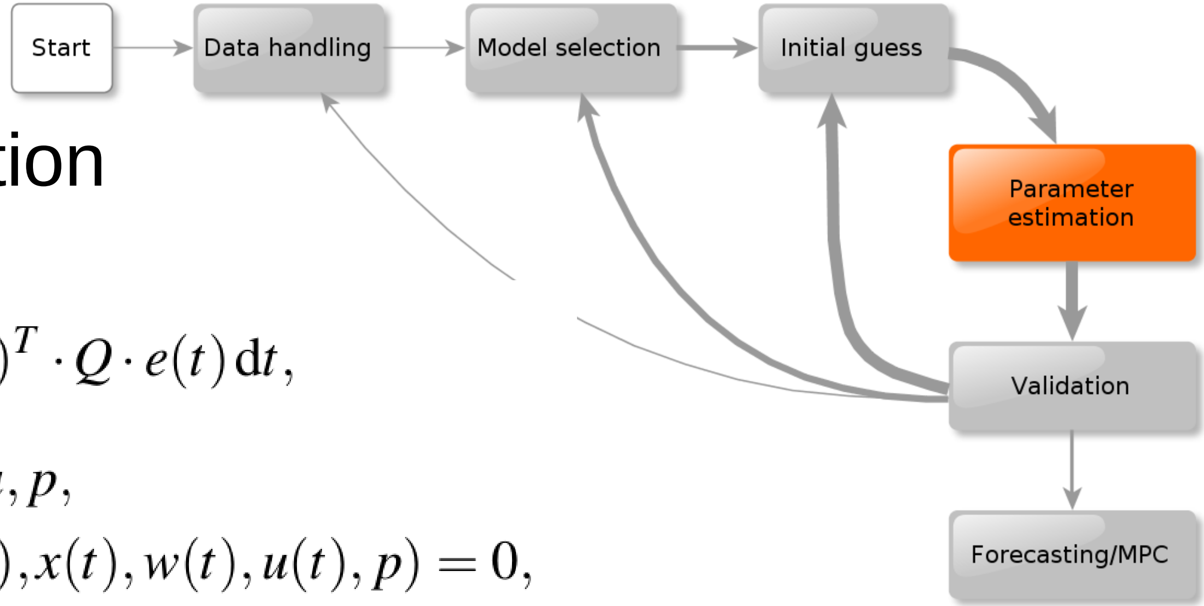




Parameter estimation

$$
\begin{aligned}
\text{minimize} \quad & \int_{t_0}^{t_f} e(t)^T \cdot Q \cdot e(t)\,\mathrm{d}t, \\
\text{with respect to} \quad & \dot{x}, x, w, u, p, \\
\text{subject to} \quad & F\left(t, \dot{x}(t), x(t), w(t), u(t), p\right) = 0, \\
& x(t_0) = x_0, \\
& \forall t \in [t_0, t_f].
\end{aligned}
$$

- $e(t) = w_{meas}(t) - w_{mod}(t)$
- *F()* needs to be twice continuously differentiable except towards time
- x_0 included in parameters to be estimated *p*
- *u(t)* (disturbances or inputs) can be included in *e(t)*
  in order to obtain an 'errors-in-variables' method



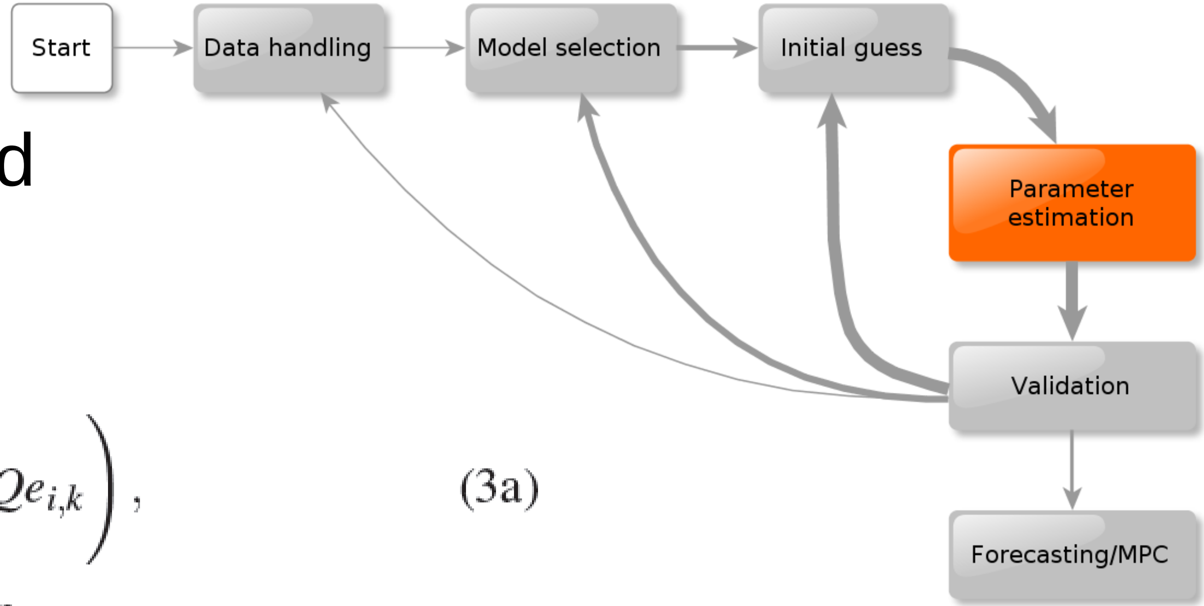
Parameter estimation

$$
\begin{aligned}
&\text{minimize} && \int_{t_0}^{t_f} e(t)^T \cdot Q \cdot e(t)\,\mathrm{d}t, \\
&\text{with respect to} && \dot{x}, x, w, u, p, \\
&\text{subject to} && F(t, \dot{x}(t), x(t), w(t), u(t), p) = 0, \\
& && x(t_0) = x_0, \\
& && \forall t \in [t_0, t_f].
\end{aligned}
$$

JModelica.org

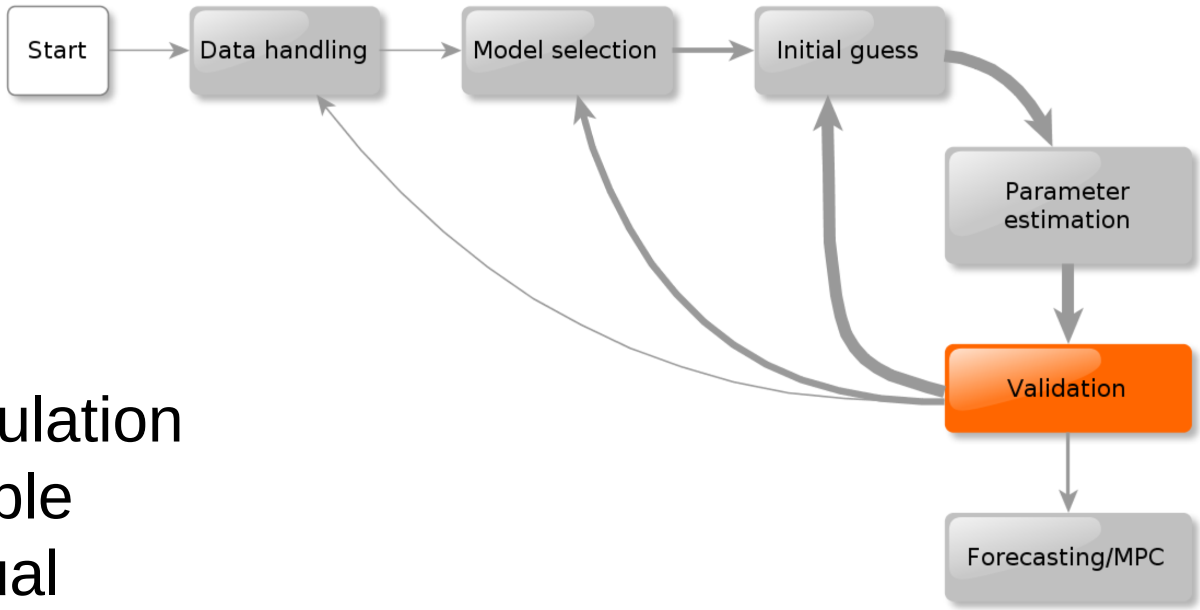
- Compilation, simulation and optimization
- Direct collocation with automatic differentiation (with CasADi).
- Resulting NLP solved with IPOPT

Collocation method



$$
\begin{aligned}
\text{min.} \quad & \sum_{i=1}^{n_e} \left(h_i \sum_{k=1}^{n_c} \omega_k e_{i,k}^T Q e_{i,k} \right), && \text{(3a)} \\
\text{w.r.t.} \quad & \dot{x}_{i,k}, x_{i,l}, w_{i,k}, u_{i,k}, p, && \\
\text{s.t.} \quad & F\left(t_{i,k}, \dot{x}_{i,k}, x_{i,k}, w_{i,k}, u_{i,k}, p\right) = 0, && \text{(3b)} \\
& x_{1,0} = x_0, && \text{(3c)} \\
& x_{n,n_c} = x_{n+1,0}, \quad \forall n \in [1..n_e - 1], && \text{(3d)} \\
& \dot{x}_{i,k} = \frac{1}{h_i} \sum_{j=0}^{n_c} \alpha_{j,k} \cdot x_{i,j}, && \text{(3e)} \\
& \forall i \in [1..n_e], \quad \forall k \in [1..n_c], \quad \forall l \in [0..n_c].
\end{aligned}
$$

Validation



- Based on post-simulation
- In- and out-of-sample
- Numerical and visual
- Automation:
  - Set of tests (cap ratio, confidence intervals, heatflux, …)
  - Pass all tests ➔ accepted

→ back to initial guess, model selection or data handling

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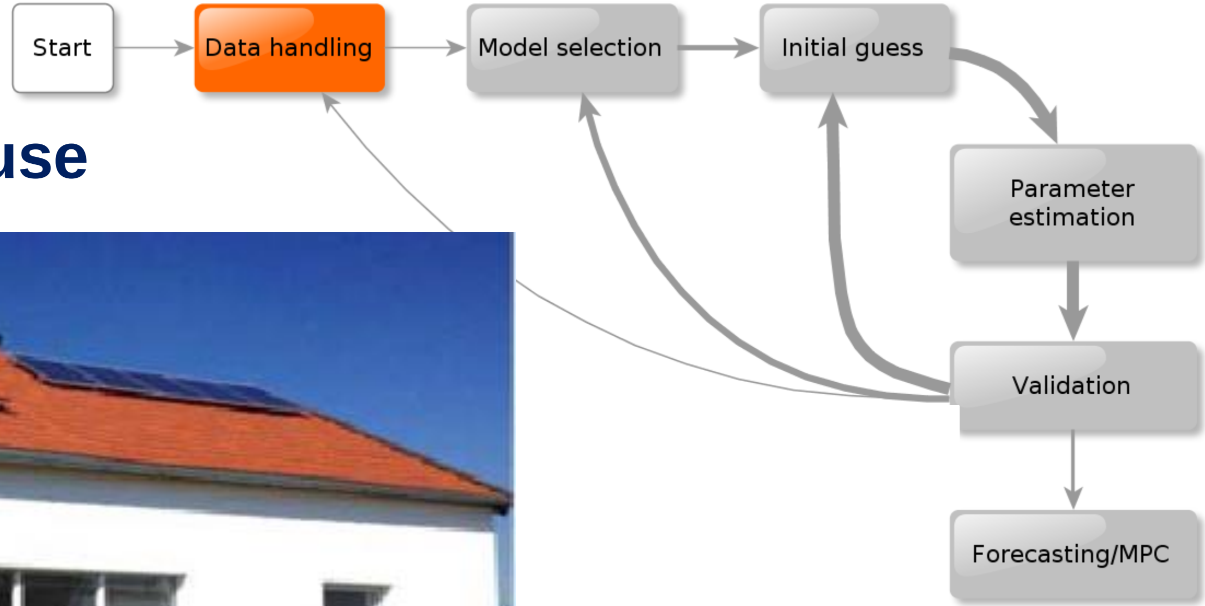
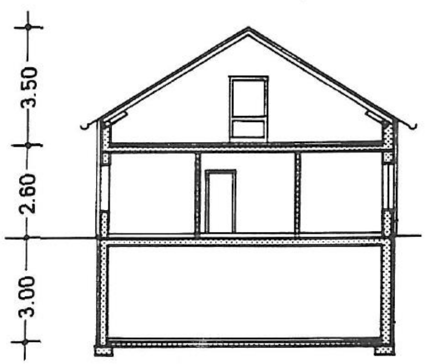
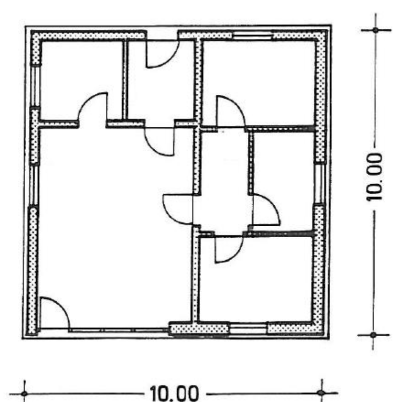
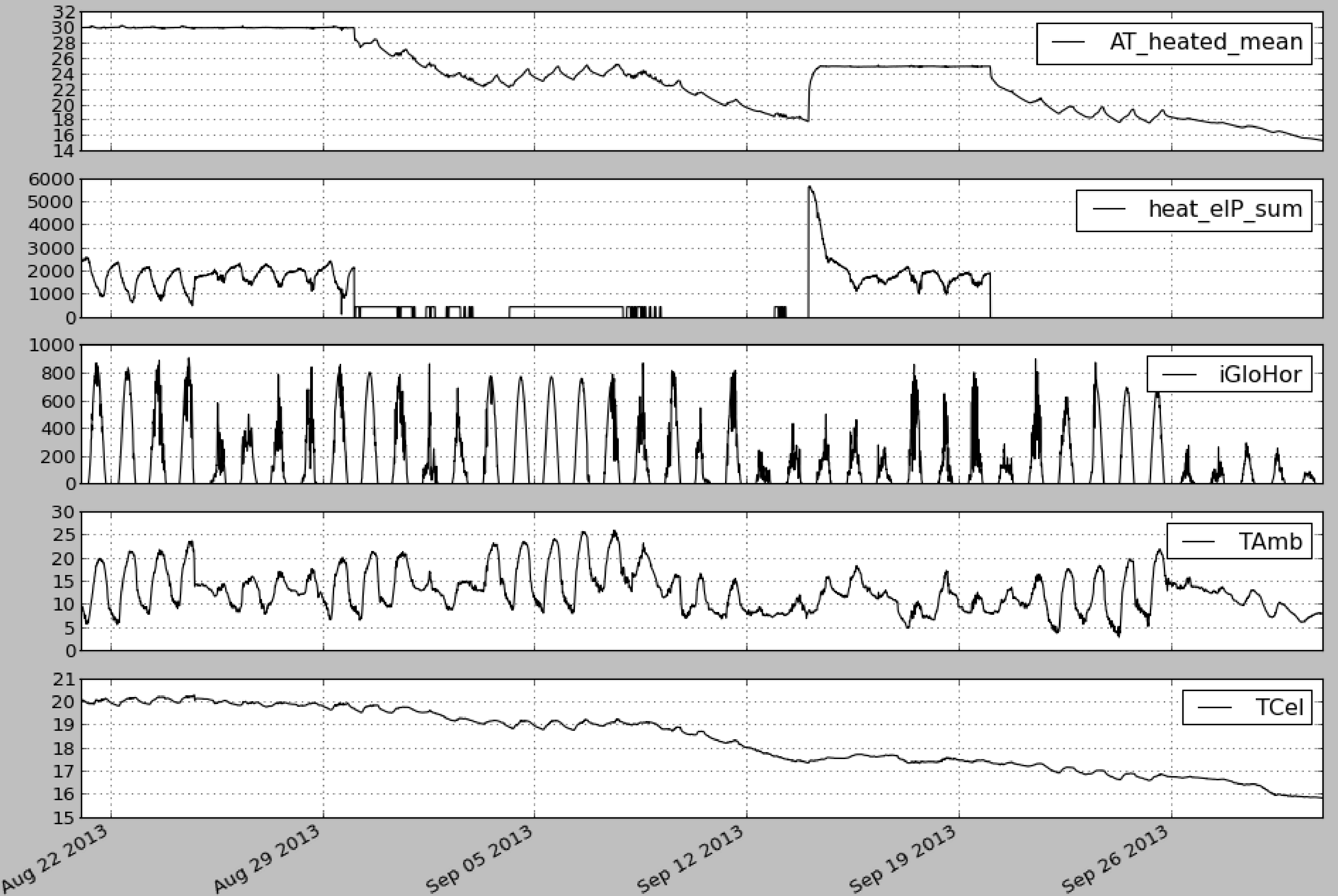


Case study twin house

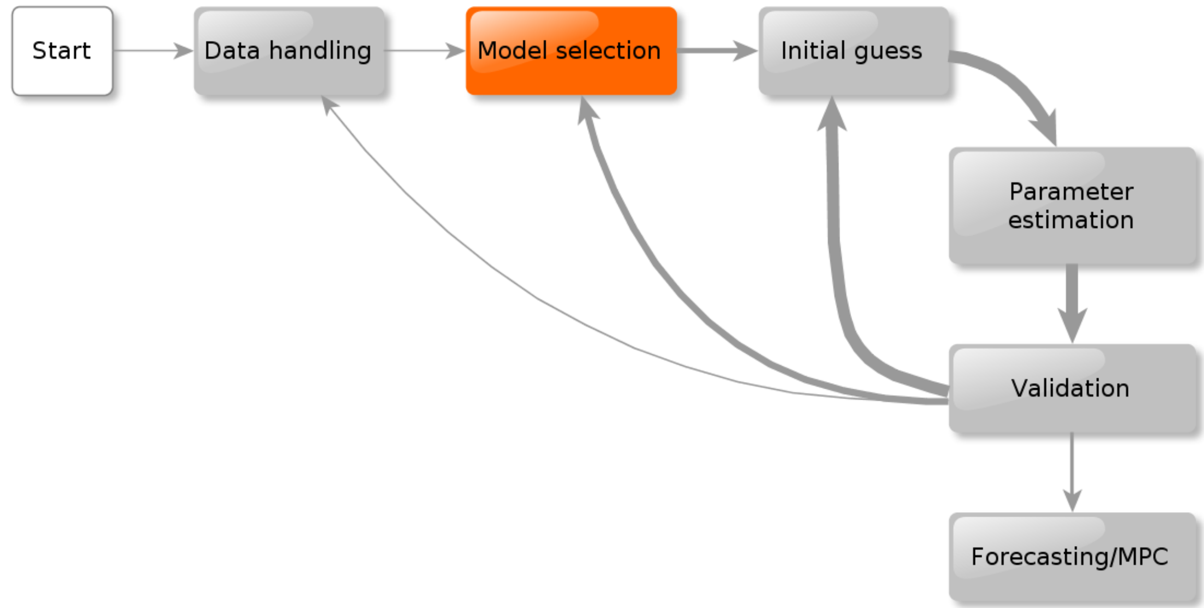


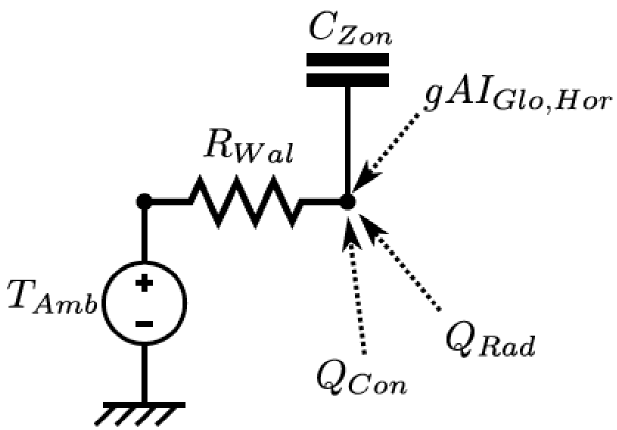


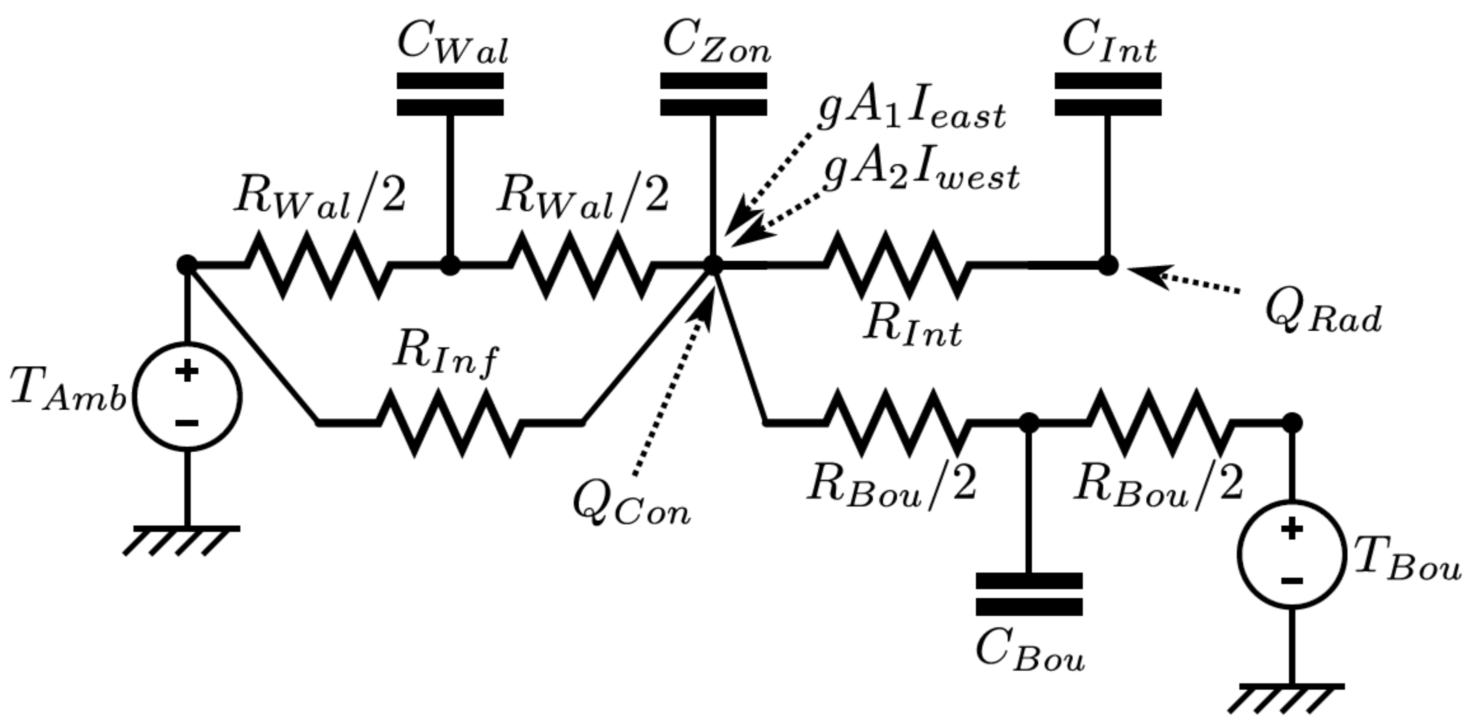


AT_heated_mean
heat_elP_sum
iGloHor
TAmb
TCel
Aug 22 2013
Aug 29 2013
Sep 05 2013
Sep 12 2013
Sep 19 2013
Sep 26 2013

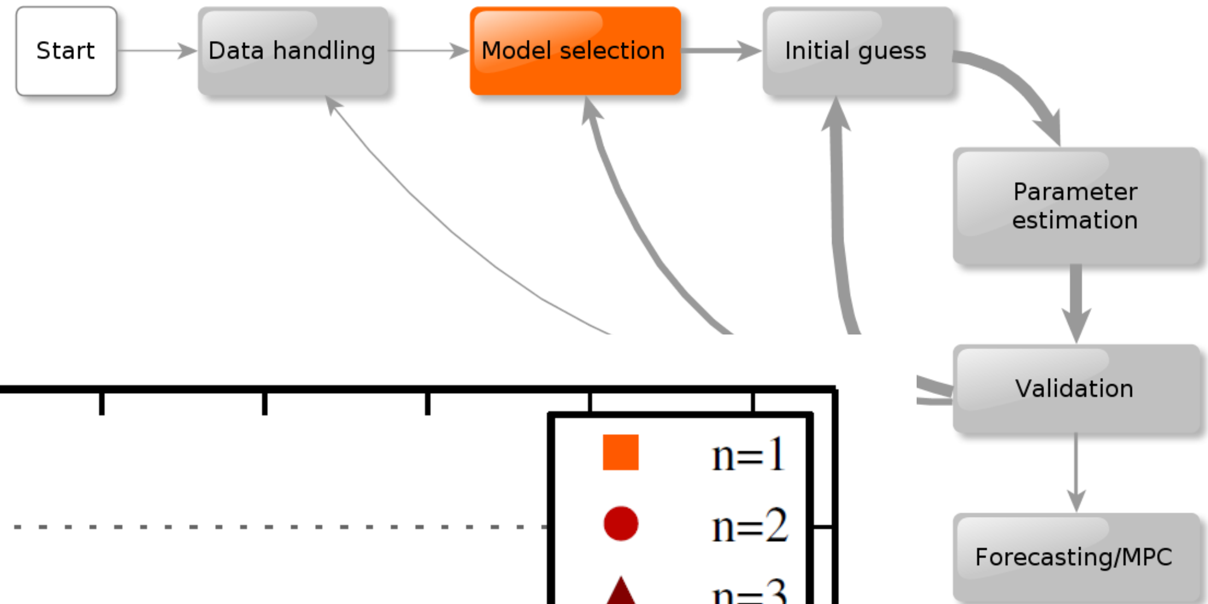
Model selection

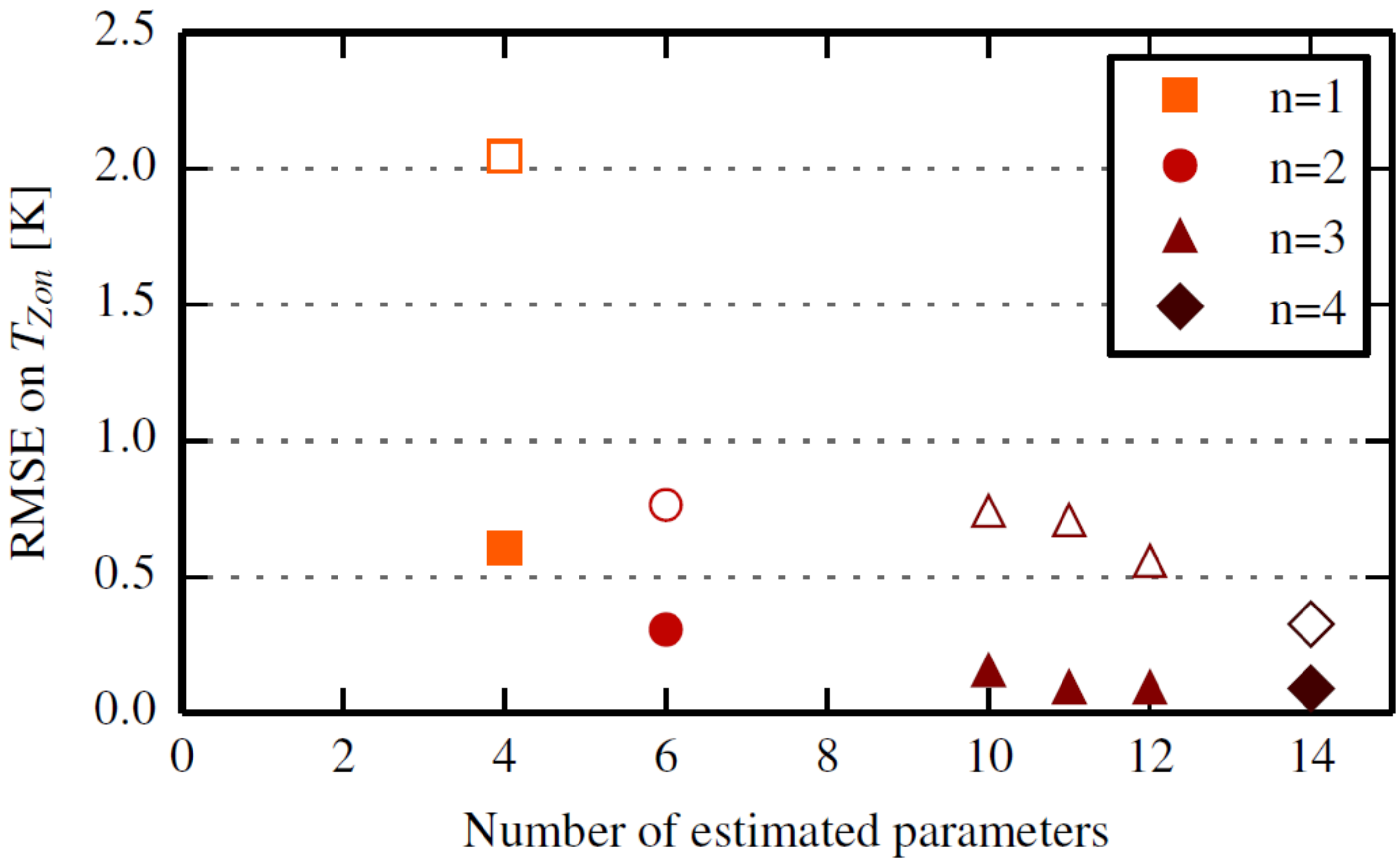




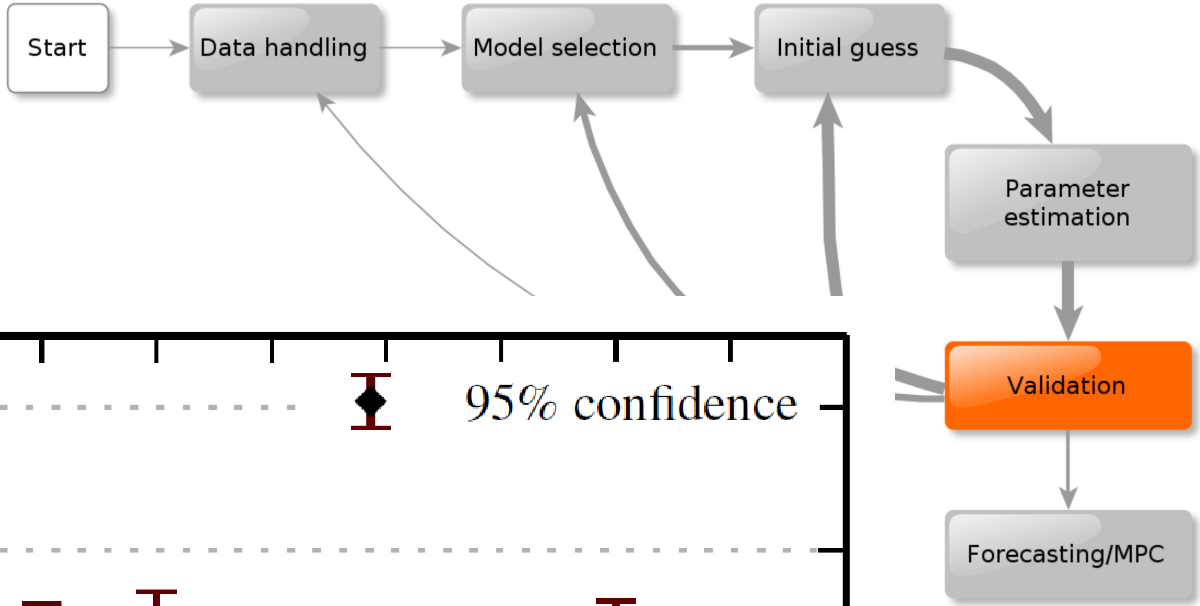


Model selection

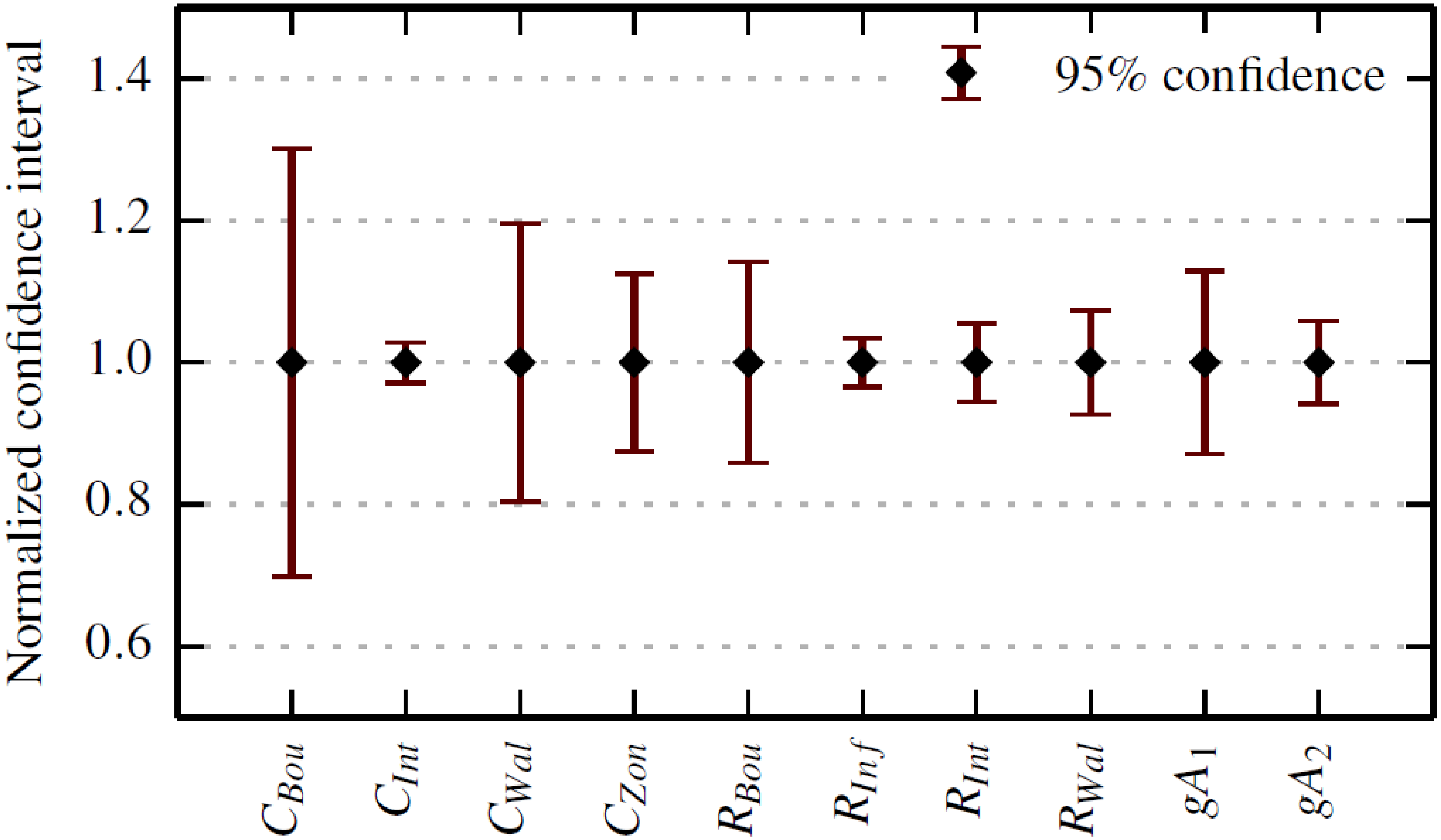




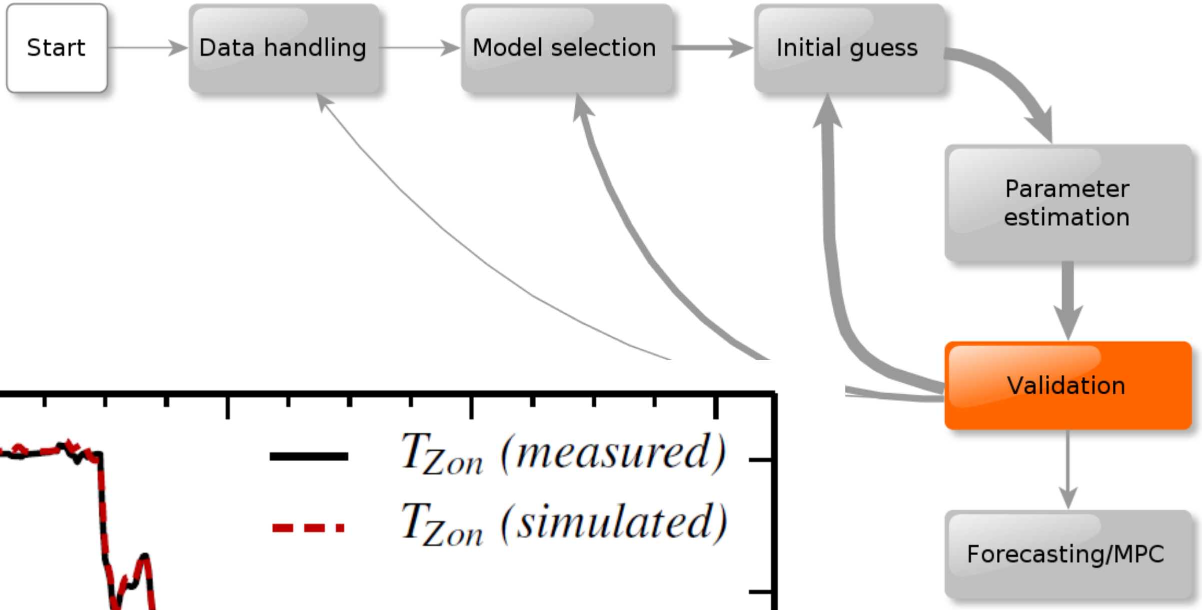
Validation



Start
Data handling
Model selection
Initial guess
Parameter estimation
Validation
Forecasting/MPC

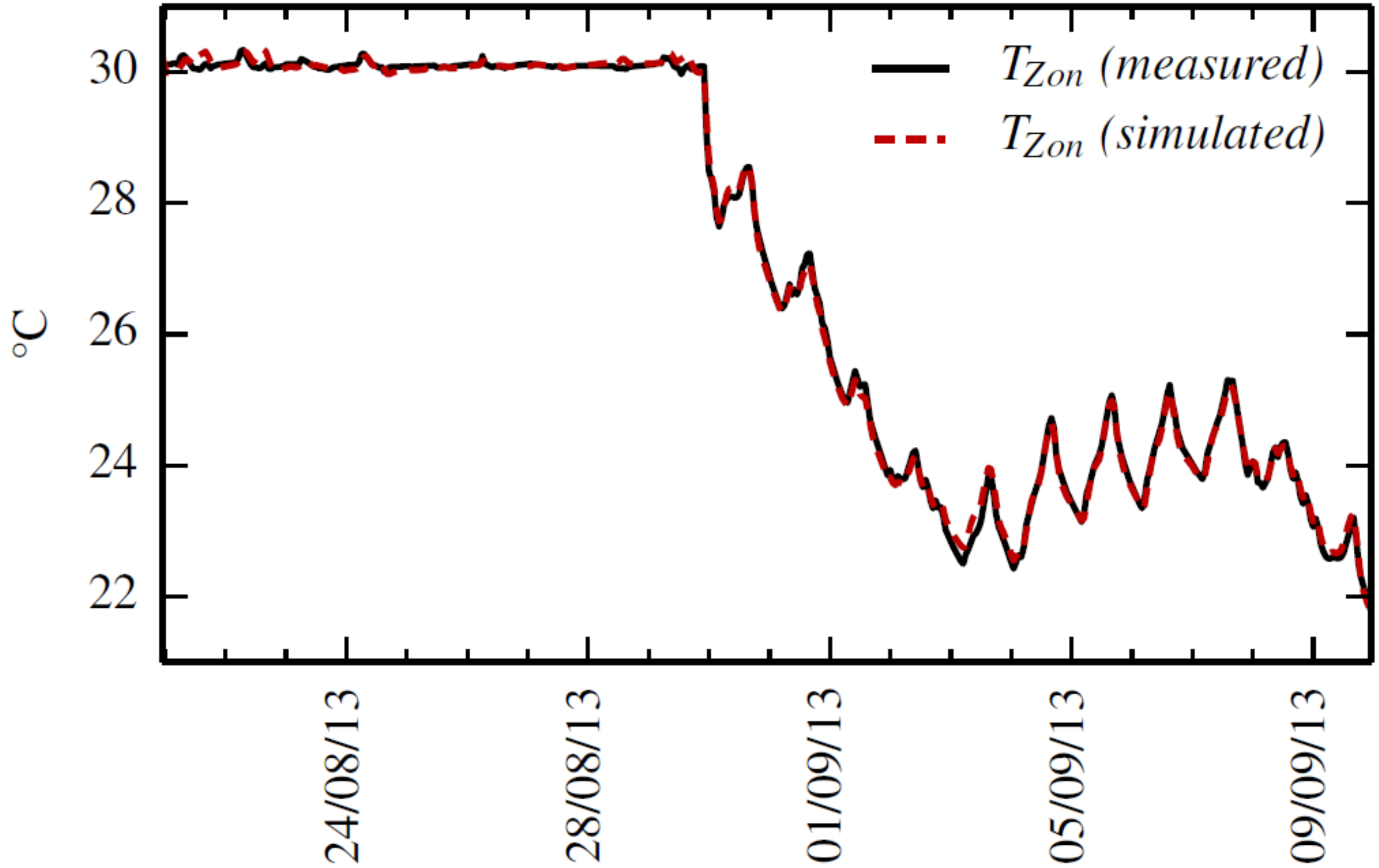


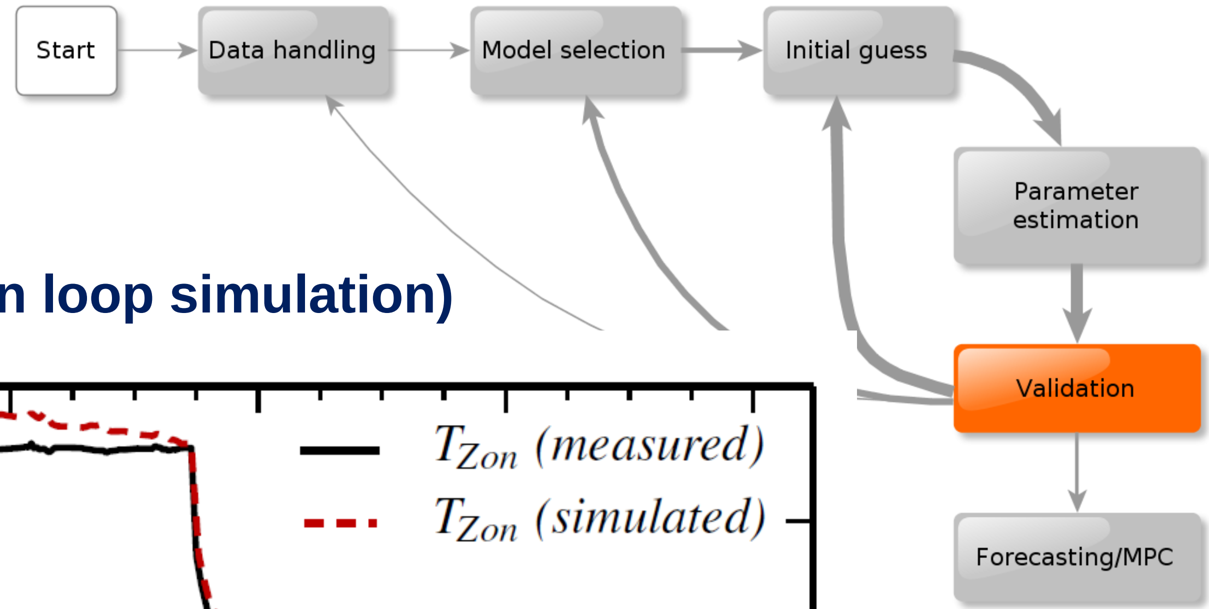
Normalized confidence interval
1.4
1.2
1.0
0.8
0.6
95% confidence
C_{Bou}
C_{Int}
C_{Wal}
C_{Zon}
R_{Bou}
R_{Inf}
R_{Int}
R_{Wal}
gA_1
gA_2



Validation

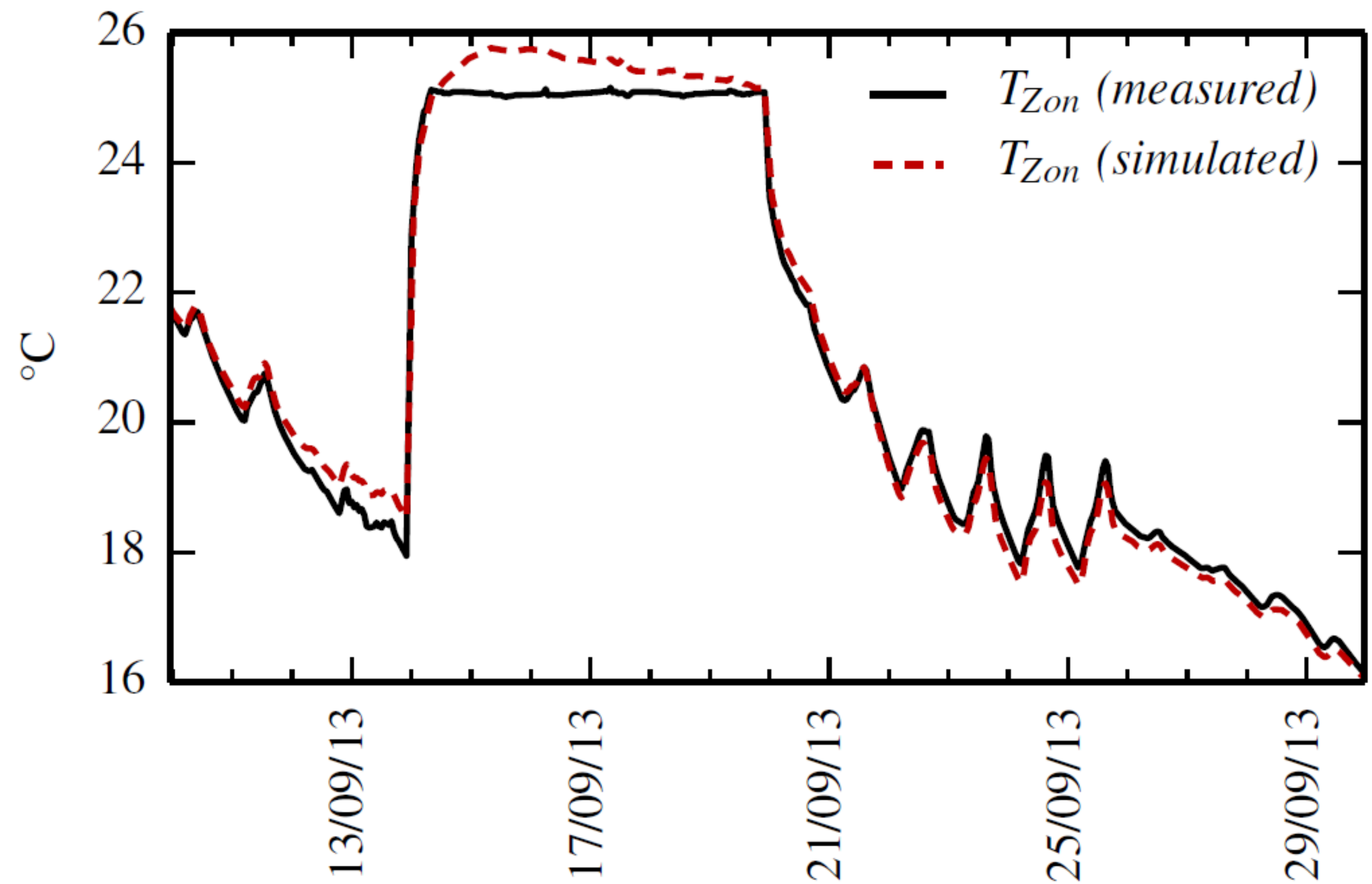
Auto-validation

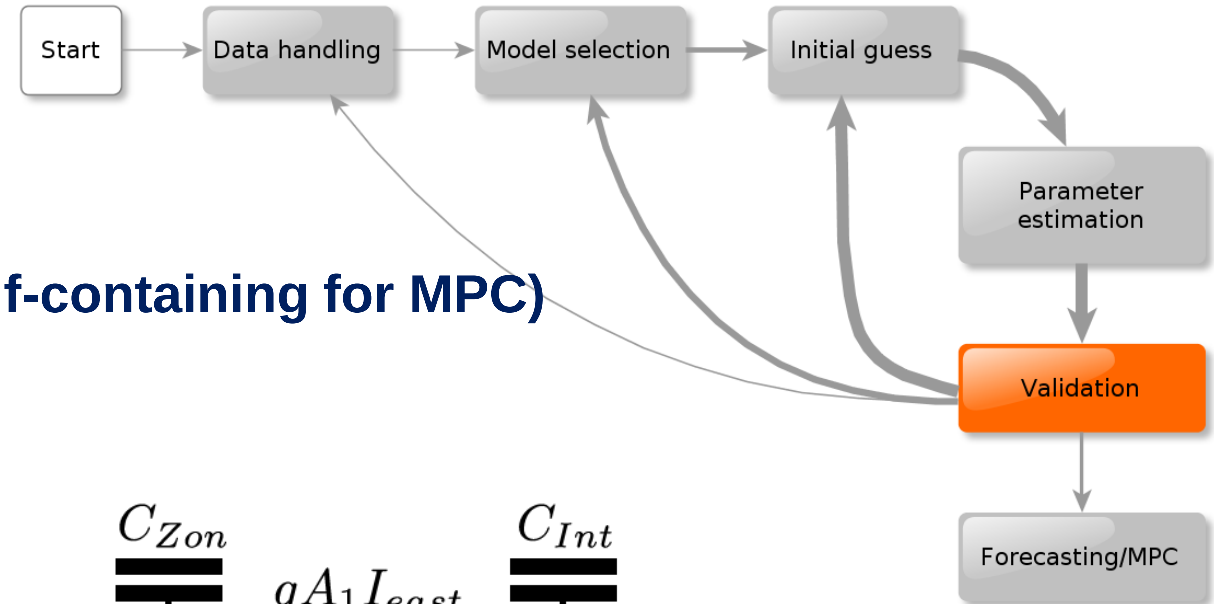




Validation

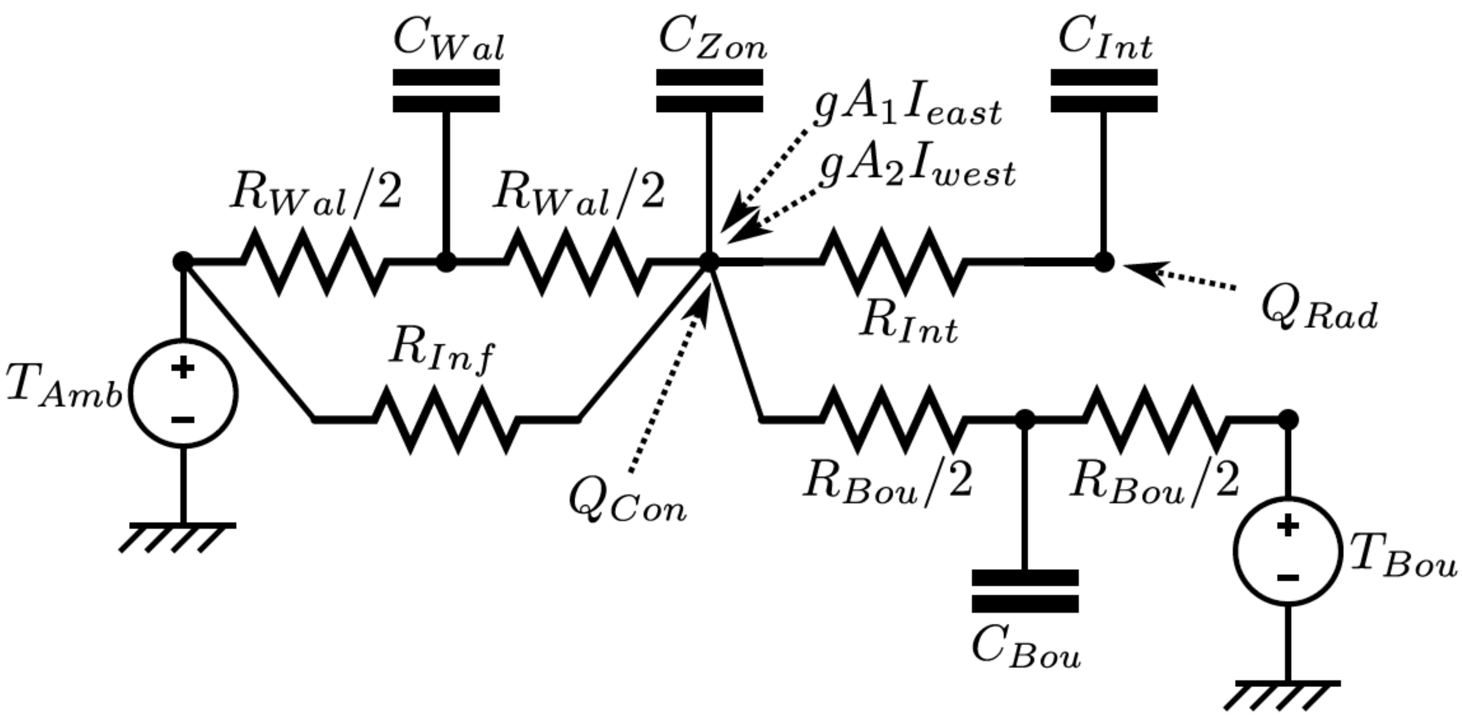
Cross-validation (= open loop simulation)



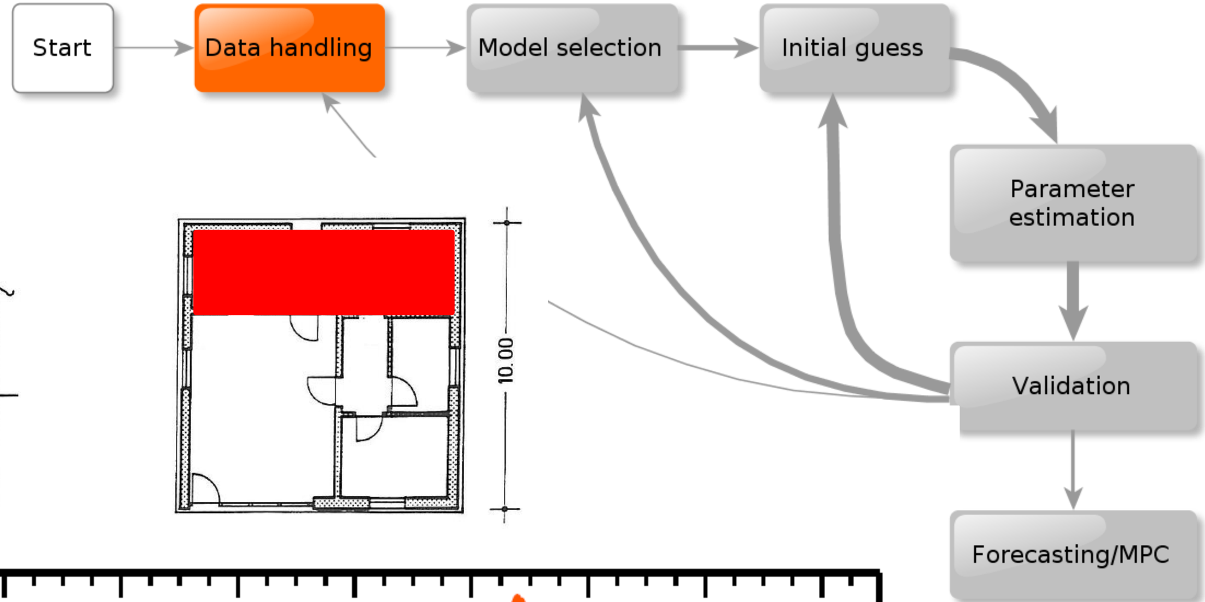


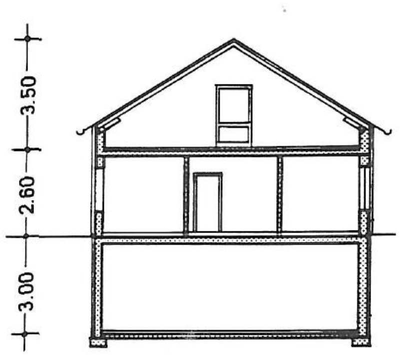
Validation

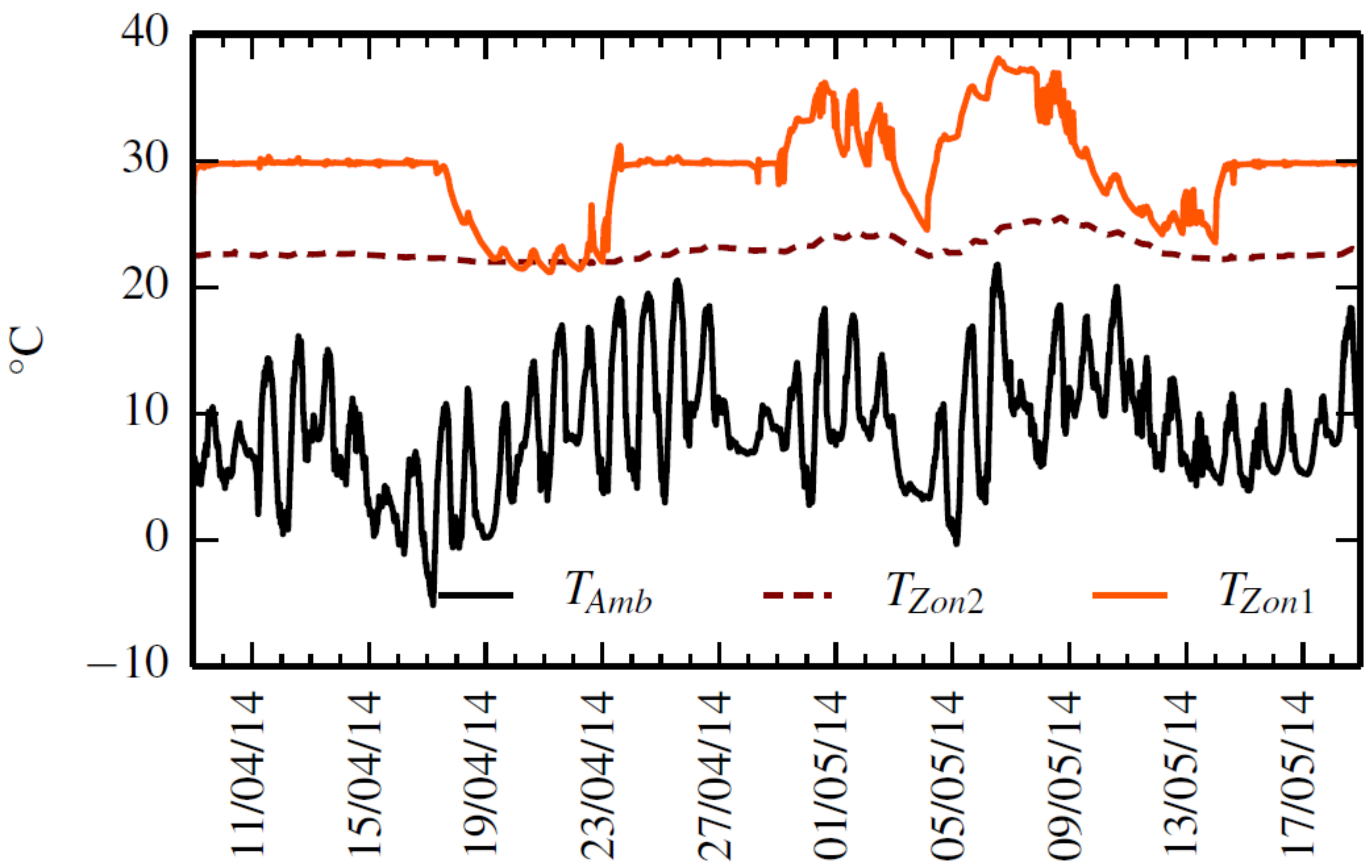
Selected model (not self-containing for MPC)

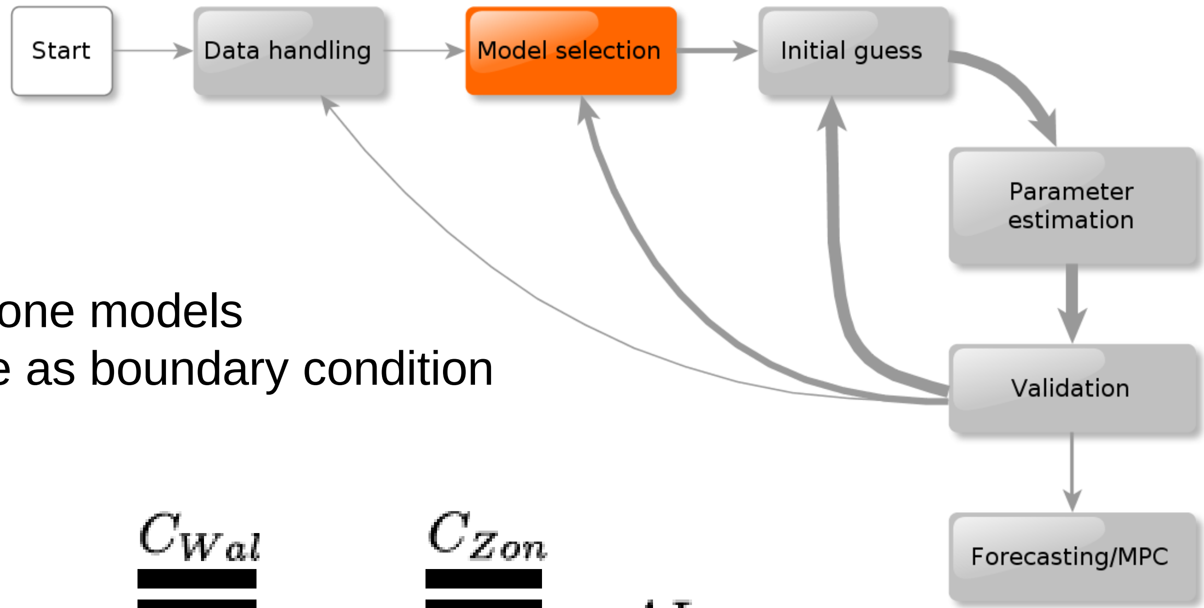


Experiment 2
Data



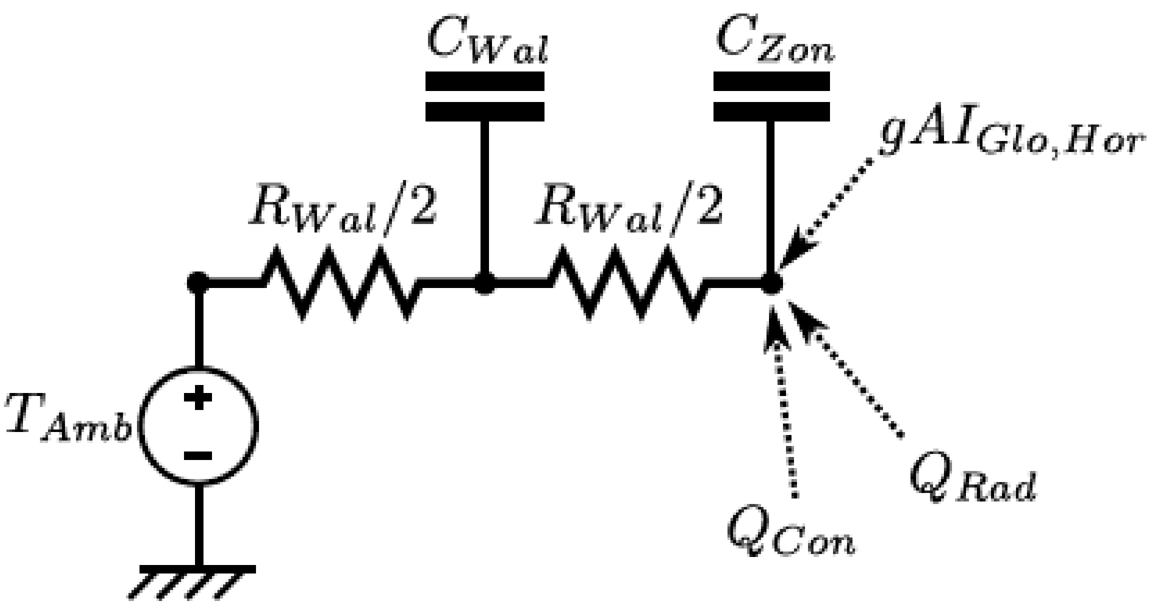




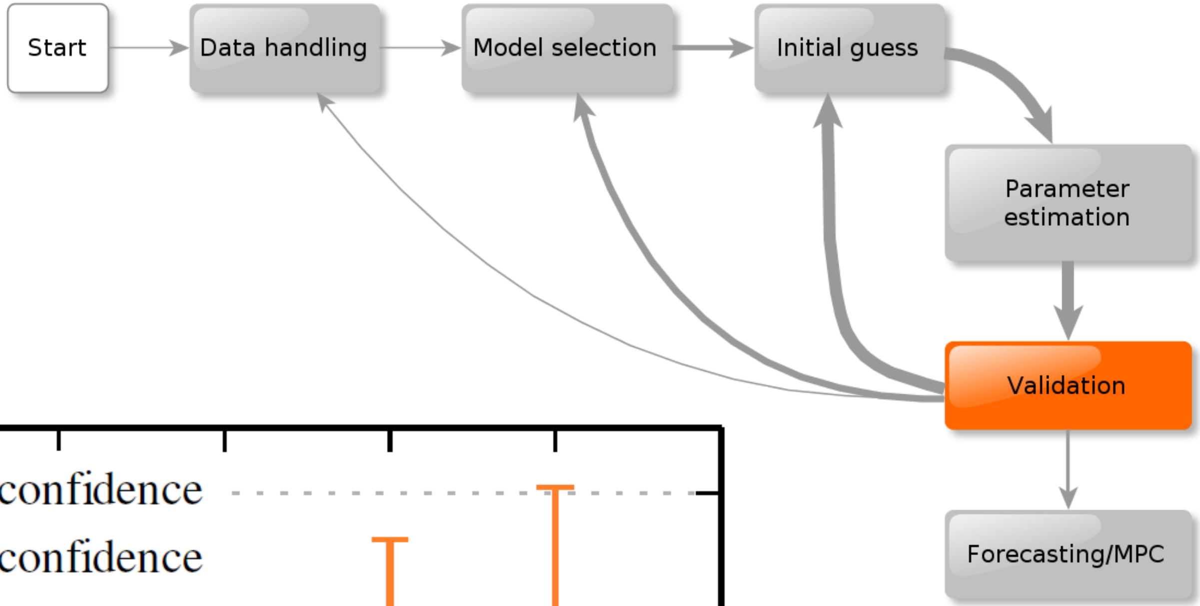


Model selection

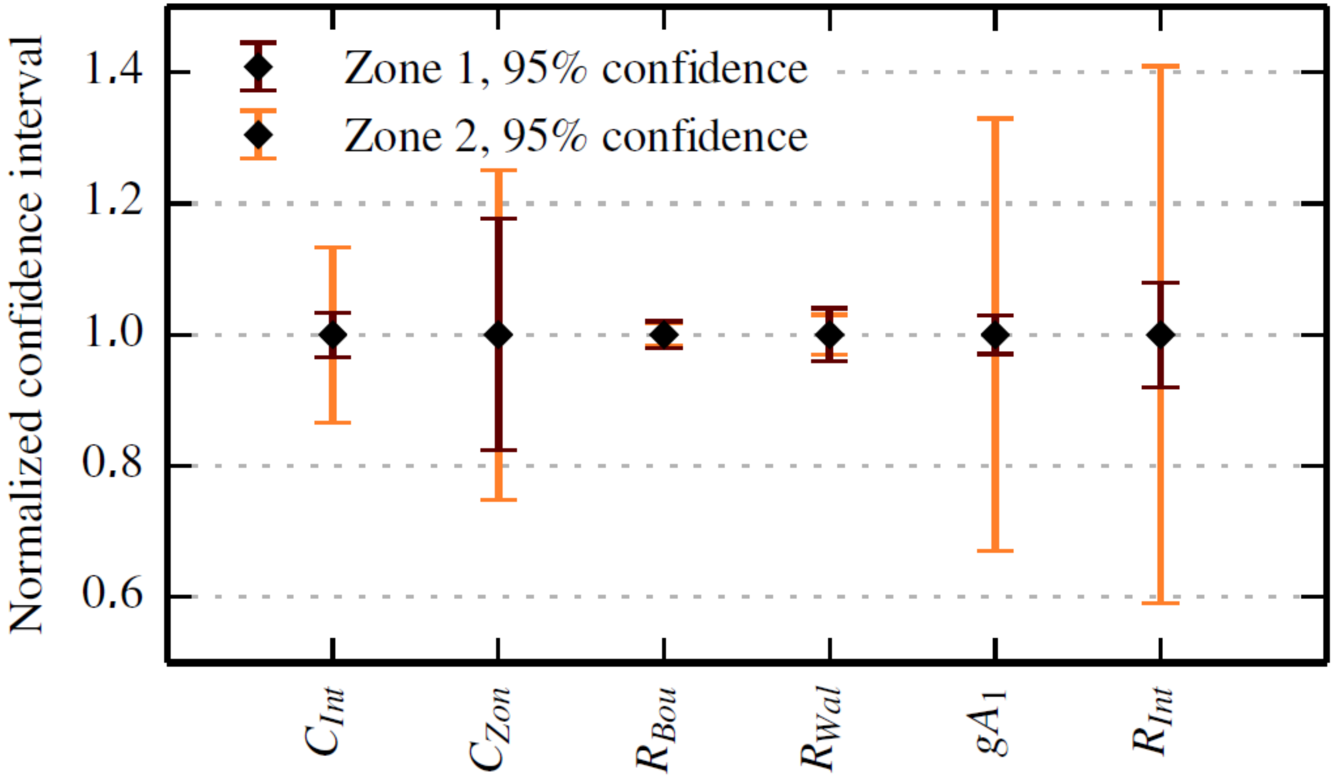
- First attempt: two single zone models
- Temperature in other zone as boundary condition



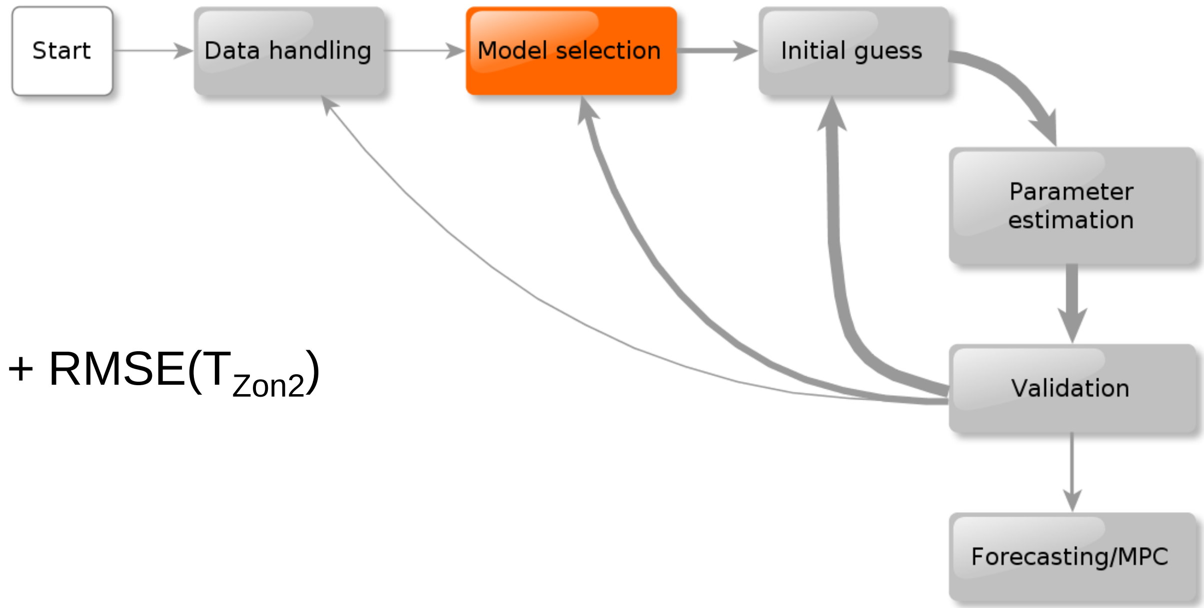
Validation



Start
Data handling
Model selection
Initial guess
Parameter estimation
Validation
Forecasting/MPC

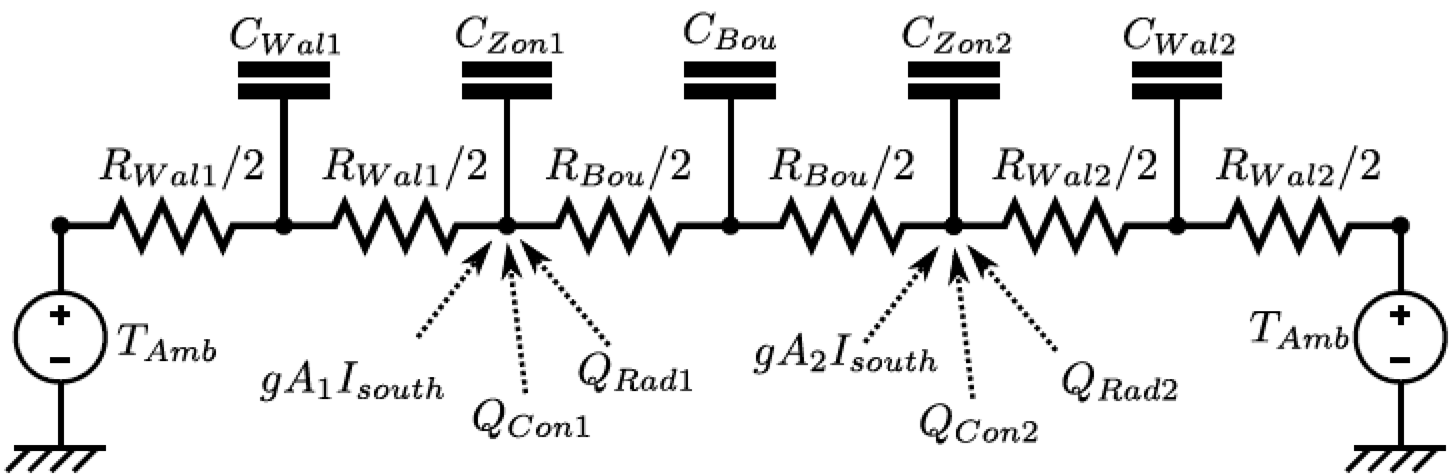


Normalized confidence interval
Zone 1, 95% confidence
Zone 2, 95% confidence
1.4
1.2
1.0
0.8
0.6
C_{Int}
C_{Zon}
R_{Bou}
R_{Wal}
gA_1
R_{Int}



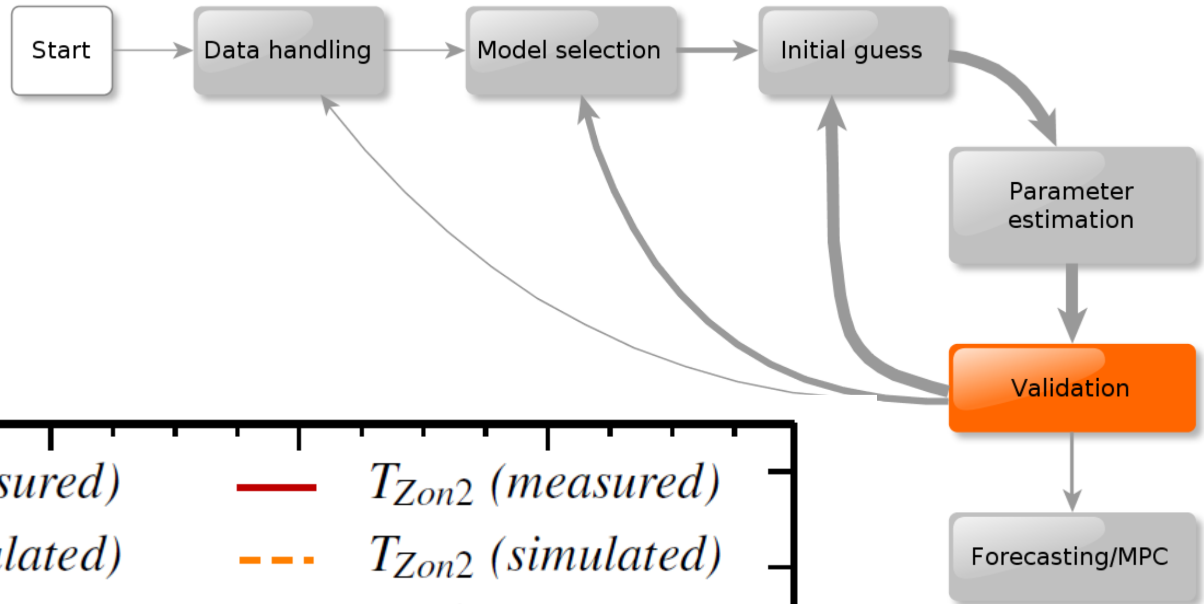
Model selection

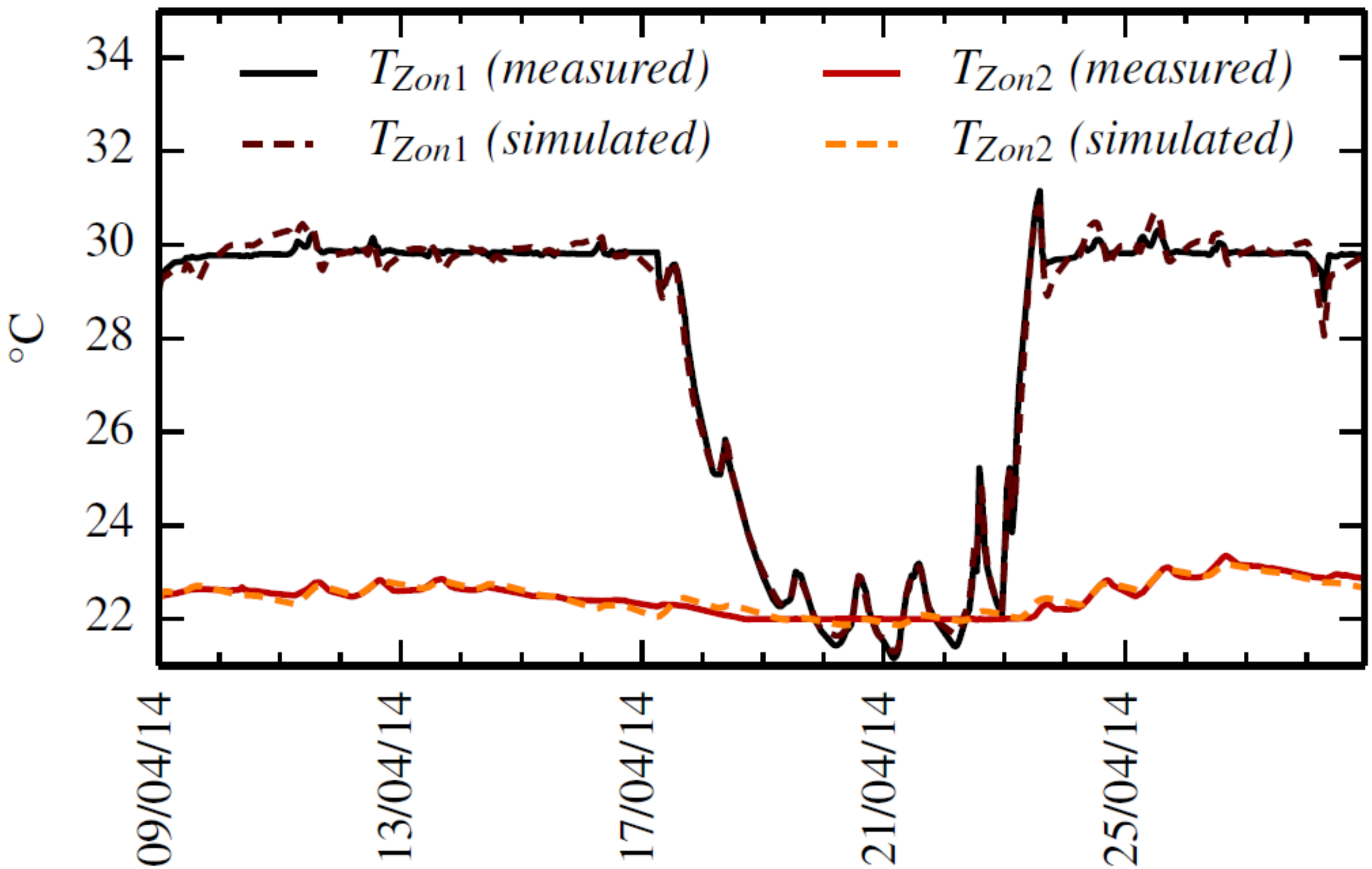
- Two-zone model
- Objective = RMSE(T_{Zon1}) + RMSE(T_{Zon2})

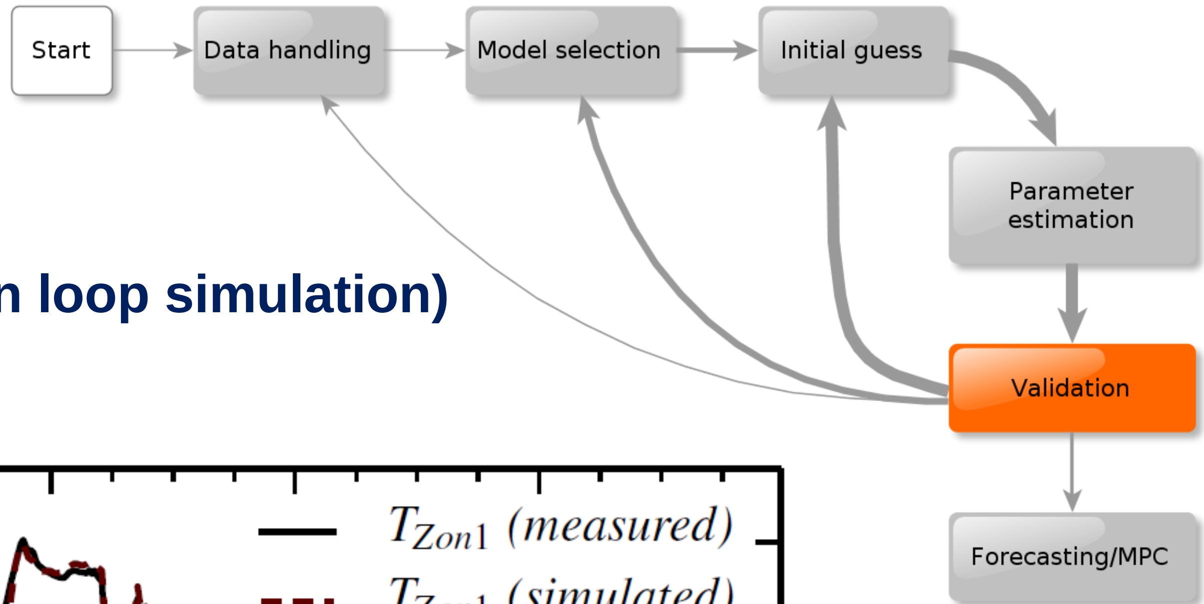


Validation

Auto-validation

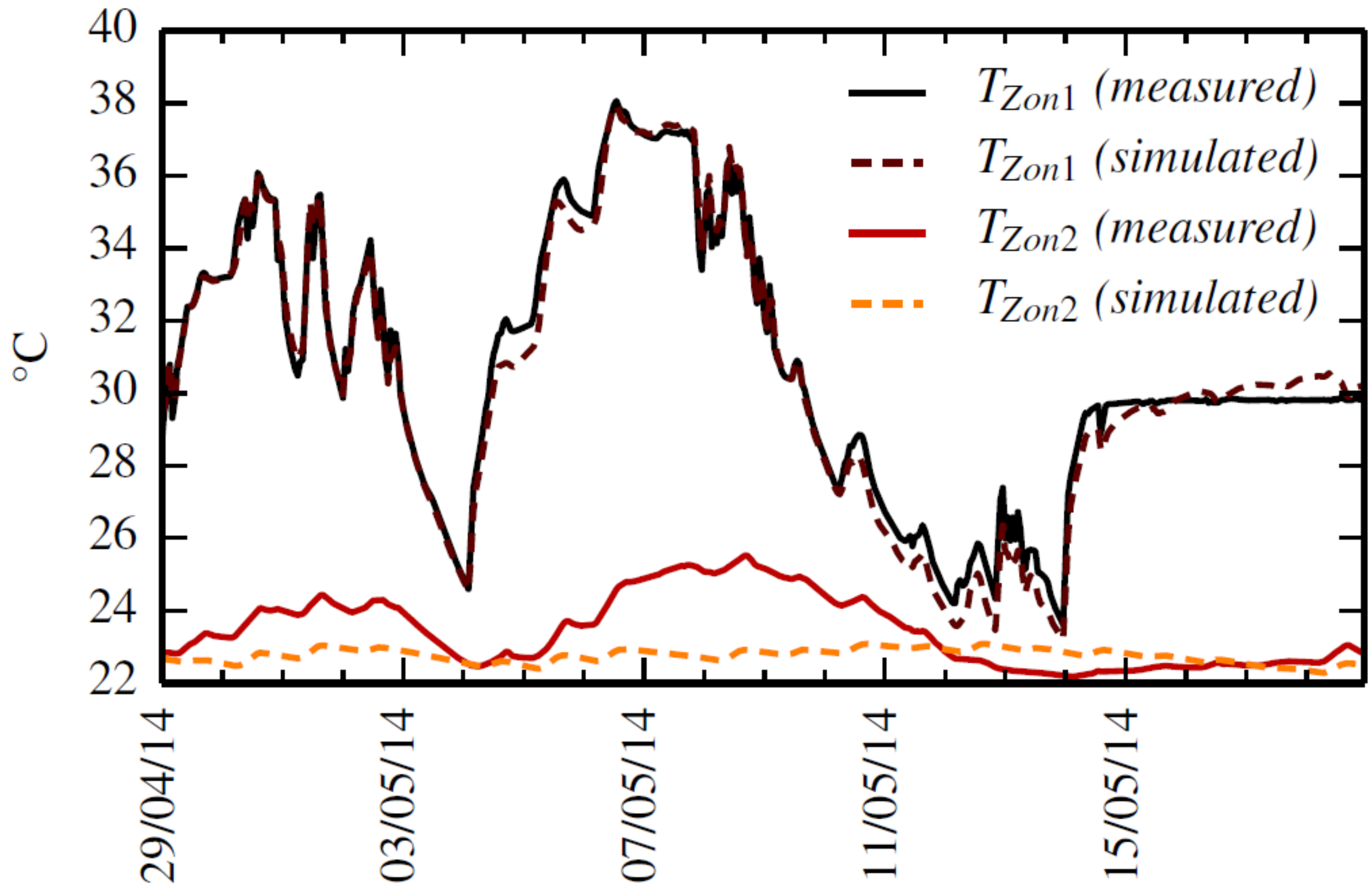






Validation

Cross-validation (= open loop simulation)



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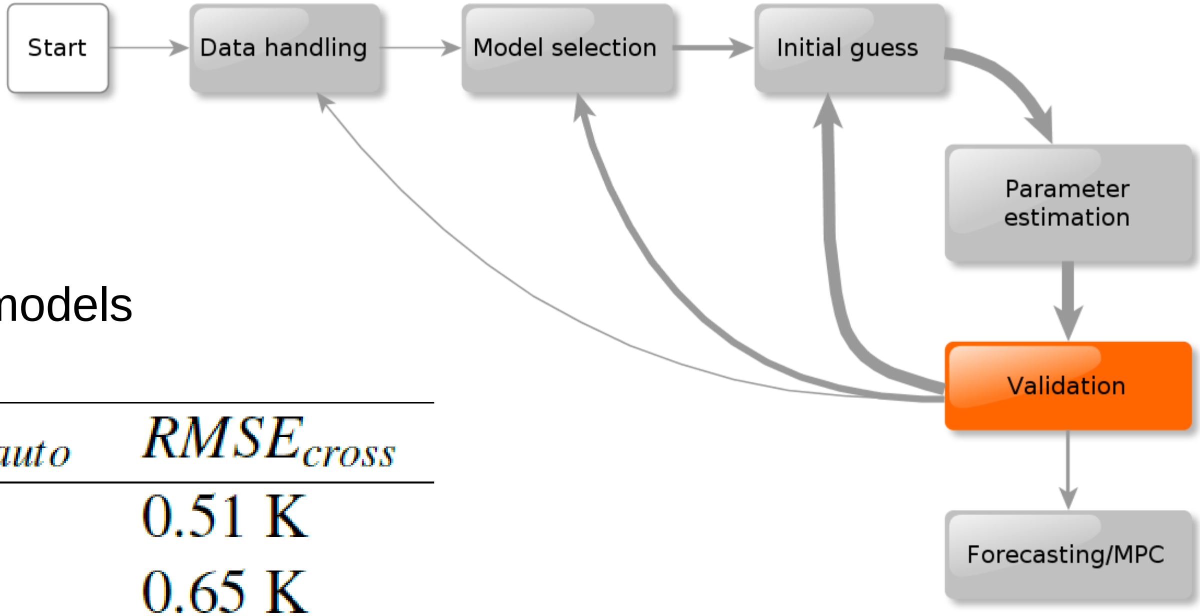

Validation

RMSE for both single zone models

	$RMSE_{auto}$	$RMSE_{cross}$
Zone 1	0.27 K	0.51 K
Zone 2	0.07 K	0.65 K
SE	0.34 K	1.16 K

RMSE for two-zone model

	$RMSE_{auto}$	$RMSE_{cross}$
Zone 1	0.23 K	0.51 K
Zone 2	0.10 K	1.14 K
SE	0.33 K	1.65 K

Summary

- Python tool chain for parameter estimation of non-linear Modelica models
- Interactive and scripting/automation
- JModelica.org for compilation, simulation and optimization
- FastBuildings library (https://github.com/open-ideas/FastBuildings)
- Latin hypercube sampling for search space coverage
- Application to monitored dwelling with good results except if unsufficient excitation in identification data
- License: free with GPL-like license for non-commercial use.

Thank you for your attention!

Roel De Coninck
KU Leuven
roel.deconinck@mech.kuleuven.be
http://www.mech.kuleuven.be/en/tme/research/thermal_systems

3E
roel.deconinck@3e.eu
www.3e.eu

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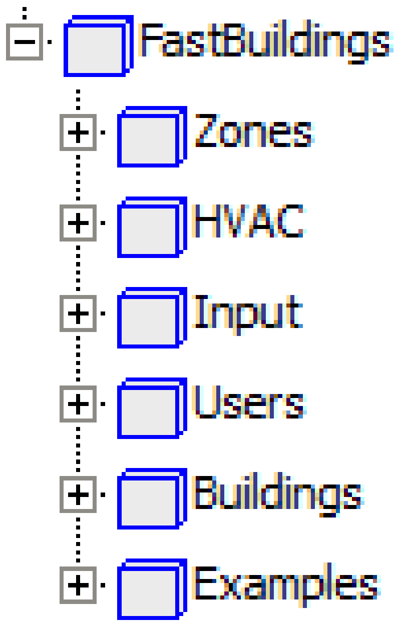
Backup slides

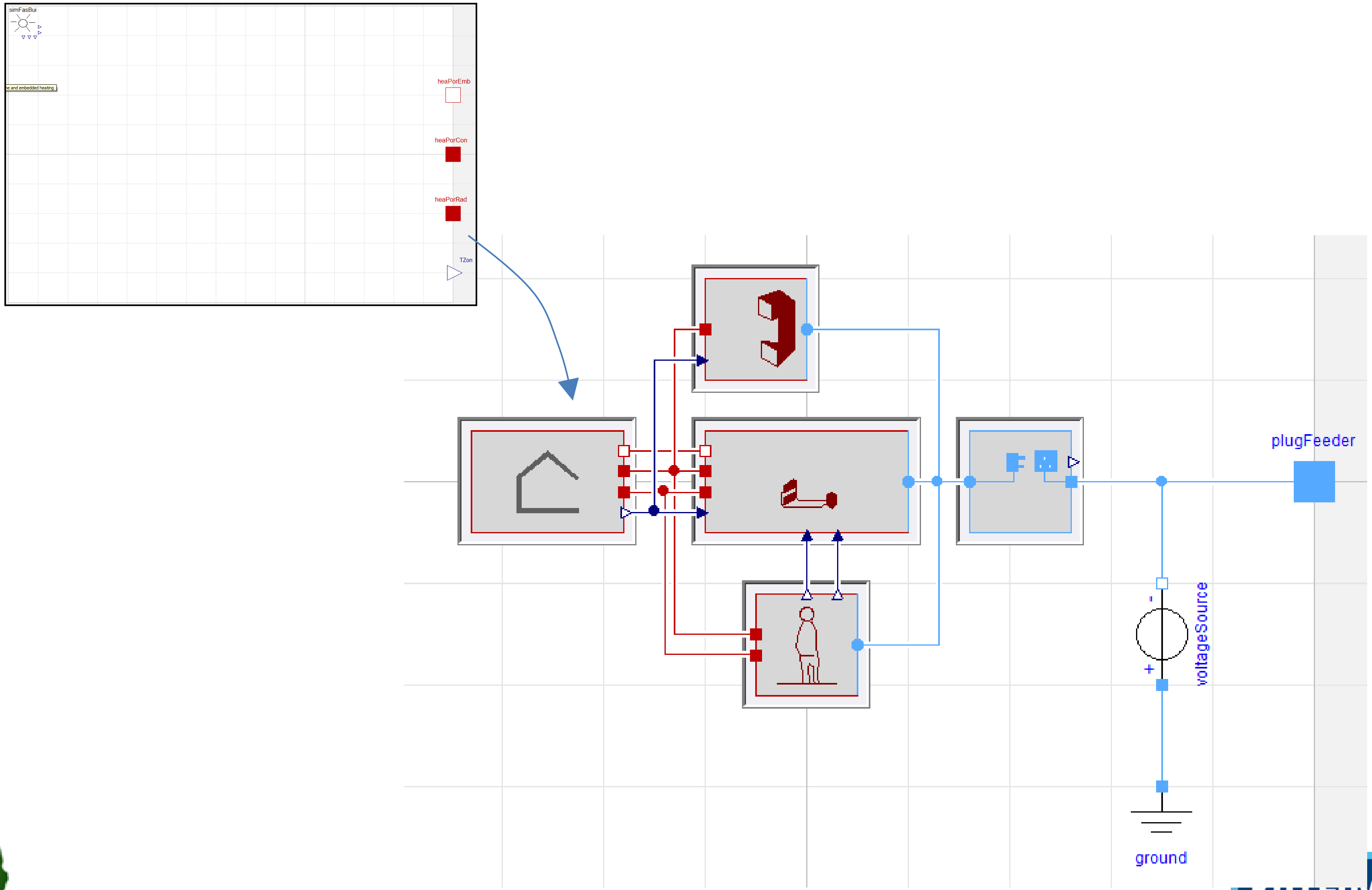
FastBuildings library



FastBuildings library

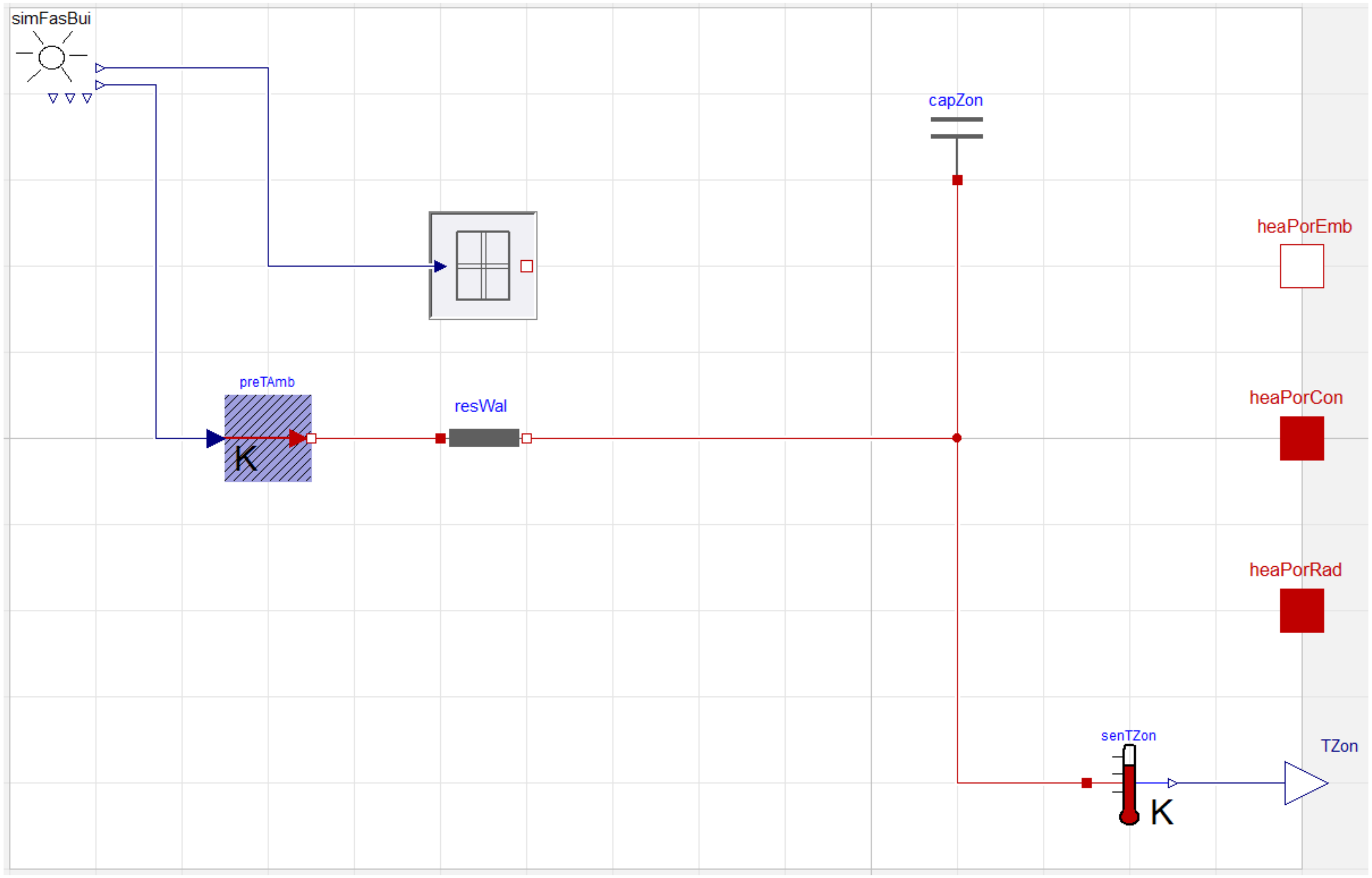
Partial_SZ

Identical interface as `IDEAS.Interfaces.BaseClasses.Structure`



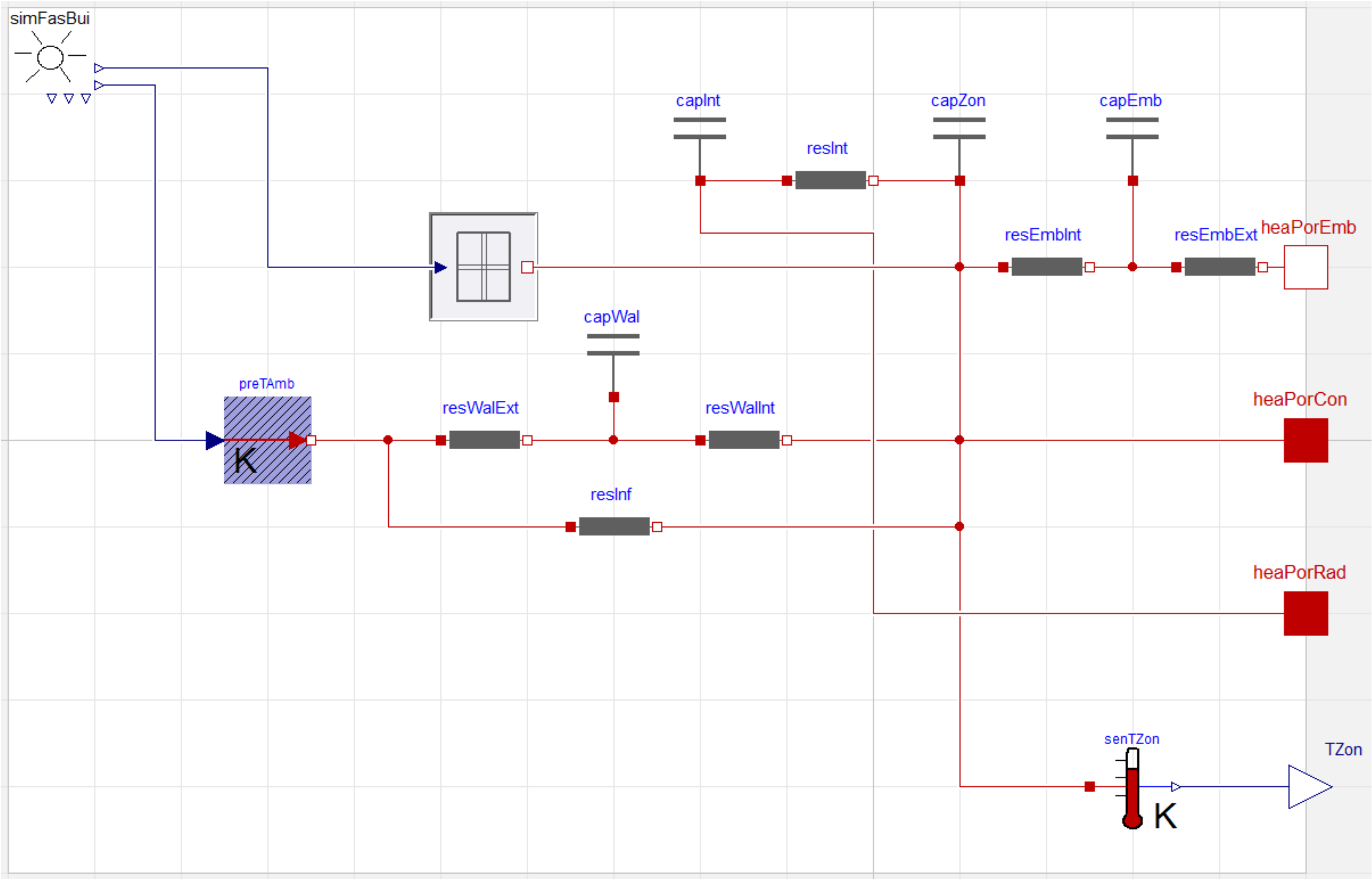
FastBuildings library

Partial_SZ_Zon



FastBuildings library

SZ_ZonWalEmbInt_B



FastBuildings library
A building model