ZERO EMISSION
NEIGHBOURHOODS
IN SMART CITIES

Bridging the Gap between Physical and Statistical Modelling

ZEN Workshop, Trondheim, December 2017

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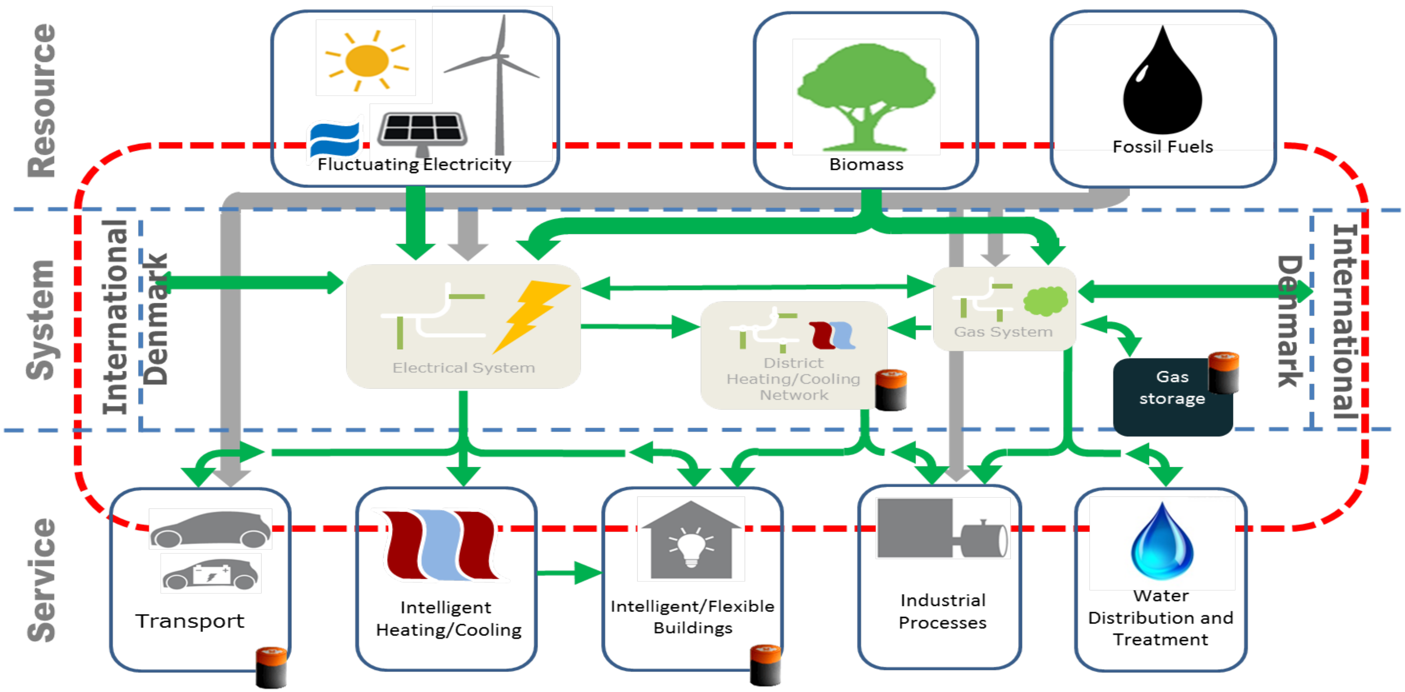
Models for Integrated Energy Systems

Grey-box models for intelligent energy systems integration
using **data and ICT solutions**



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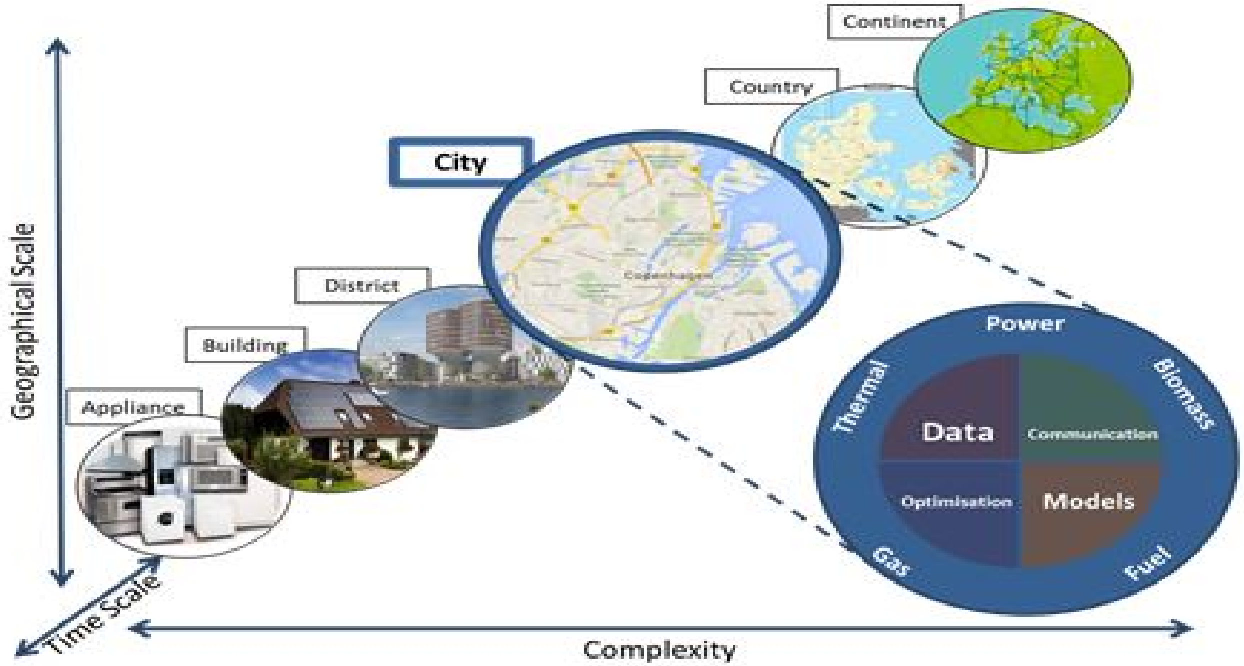
Temporal and Spatial Scales

A ***Smart-Energy Operating-System (SE-OS)*** is used to develop, implement and test solutions (layers: data, models, optimization, control, communication) for ***operating flexible electrical energy systems*** at **all scales**.



George Box:

All models are wrong – but some are useful

Modeling made simple

Suppose we have a time series of data:

$$\{X_t\} = X_1, X_2, ... , X_t, ...$$

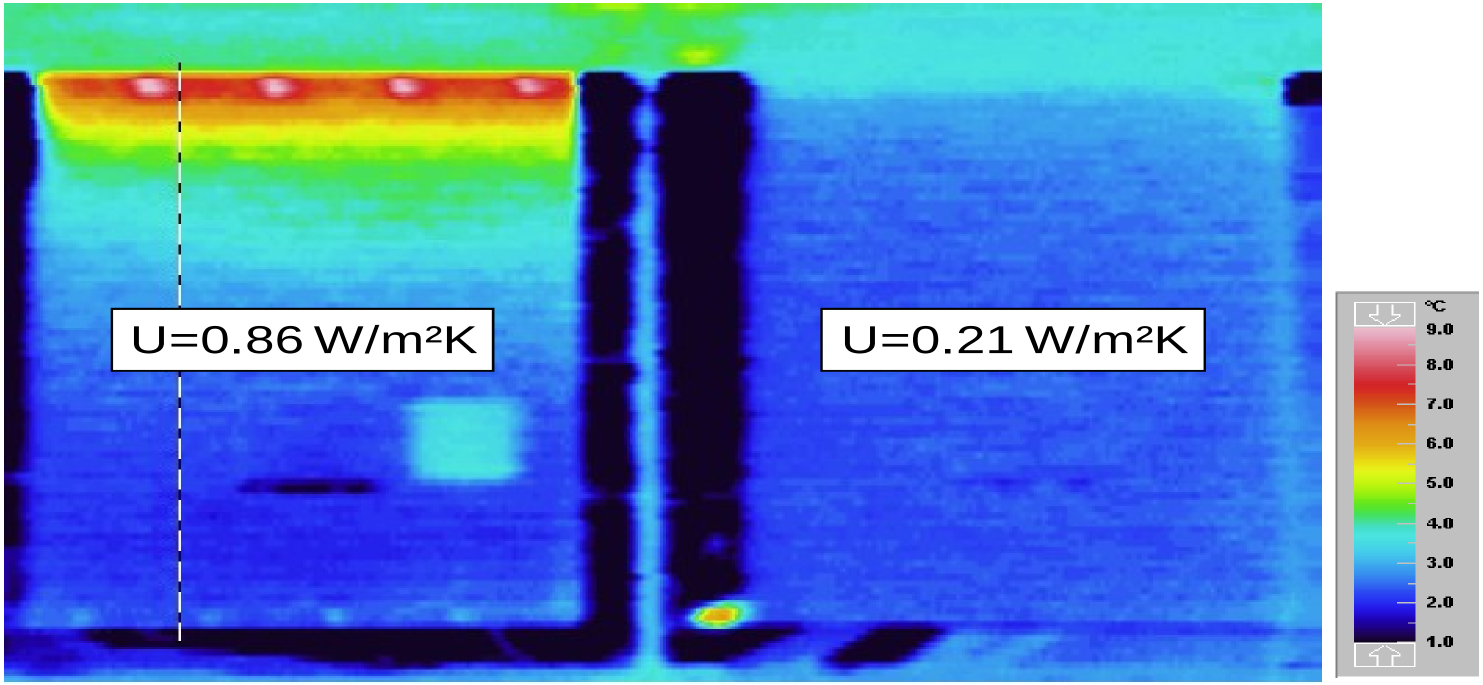
The purpose of any modeling is to find a function $h(\{X_t\})$ such that

$$h(\{X_t\}) = \varepsilon_t$$

Where $\{\varepsilon_t\}$ is white noise – ie **no autocorrelation**

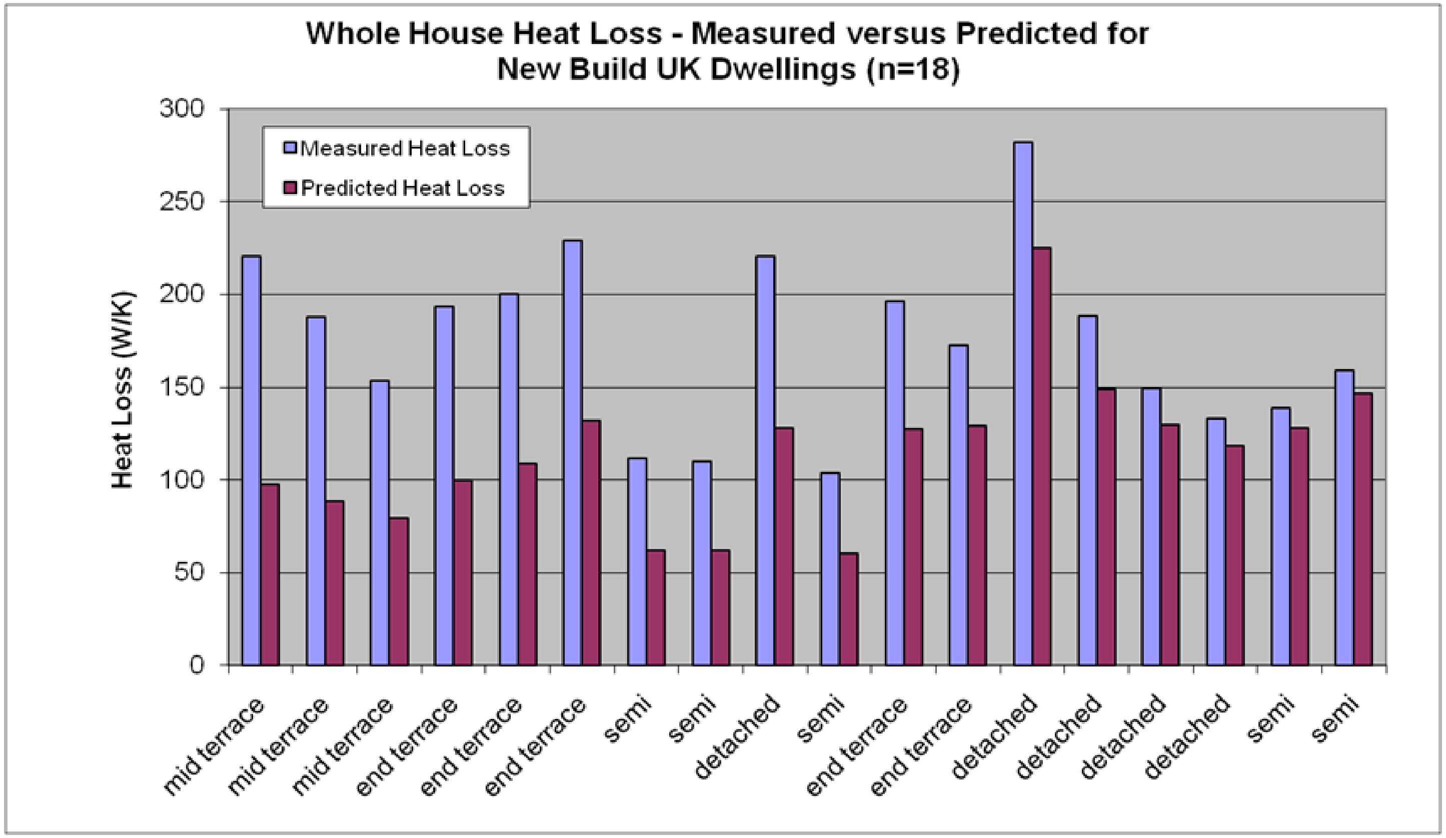
Why do we need models based on data?

Example

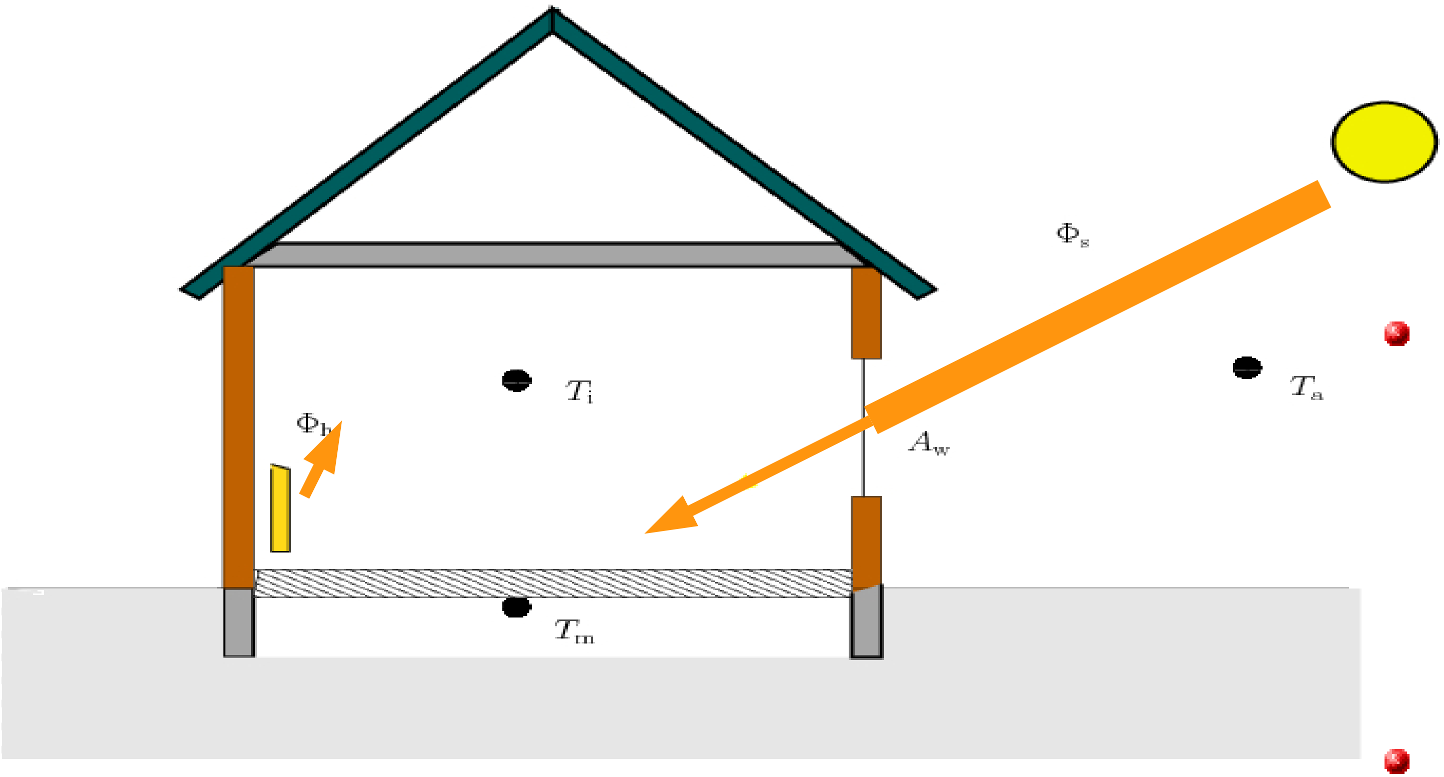


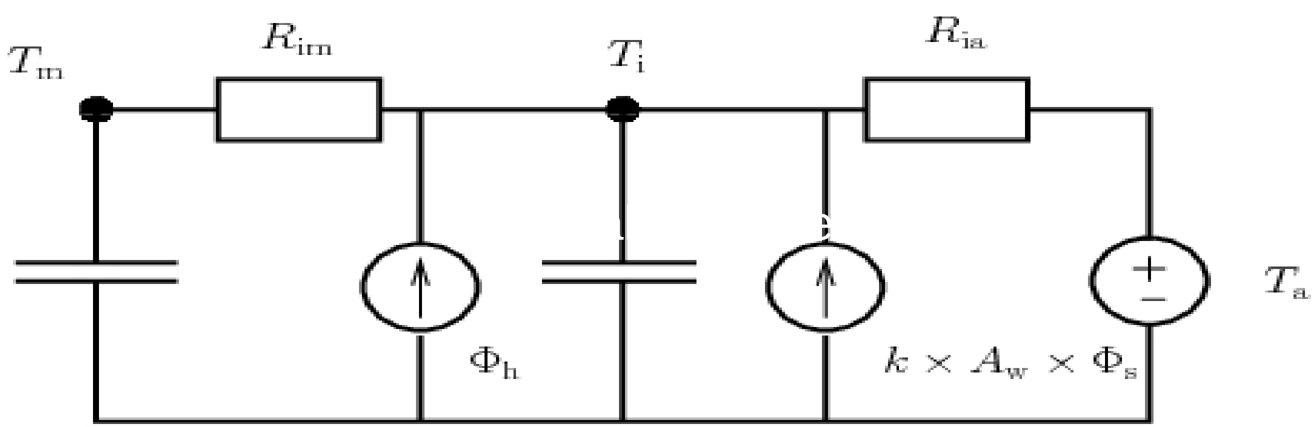
Consequence of good or bad workmanship (theoretical value is U=0.16W/m2K)

Examples (2)


Whole House Heat Loss - Measured versus Predicted for
New Build UK Dwellings (n=18)
Measured Heat Loss
Predicted Heat Loss
Heat Loss (W/K)
300
250
200
150
100
50
0
mid terrace
mid terrace
mid terrace
end terrace
end terrace
end terrace
semi
semi
detached
semi
end terrace
end terrace
detached
detached
detached
detached
semi
semi

A simple 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 (2)

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

Introduction to Grey-Box modelling

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Thermal performance characterization using time series data - statistical guidelines

IEA EBC Annex 58

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November 28, 2016

Guidelines from Annex 58

Static and dynamic conditions: estimate the Heat Loss Coefficient (HLC) and gA-value from 'simple' data:

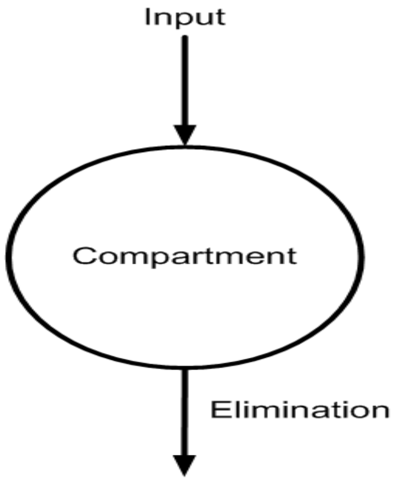
- Constant indoor temperature
- *Model input*: ambient temperature and global radiation (wind not included in guideline models)
- *Model output*: heat load

Grey-box models for detailed building behavior characterization:

- Varying indoor temperature (turn the heating on/off)
- *Model input*: ambient temperature, global radiation, wind
- *Model output*: indoor air temperature

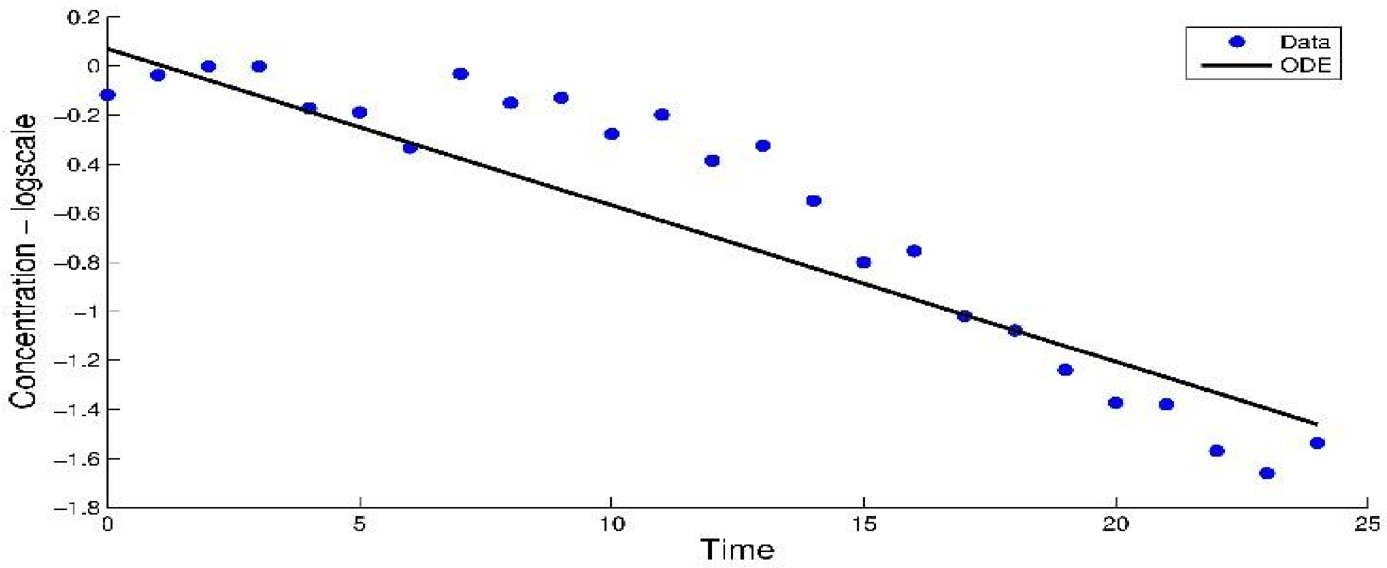
Procedures (recipes) for model selection and validation, with examples in R

Traditional Dynamical Model

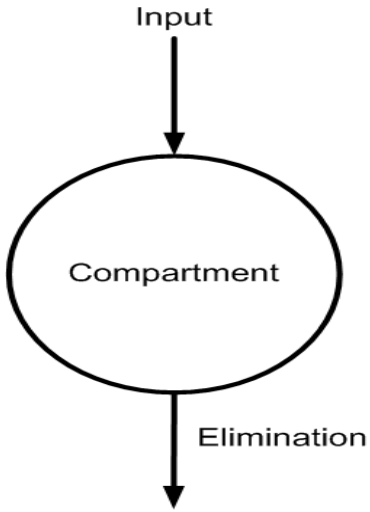


- Ordinary Differential Equation:

$$
\begin{aligned}
dA &= -KA\,dt \\
Y &= A + \epsilon
\end{aligned}
$$

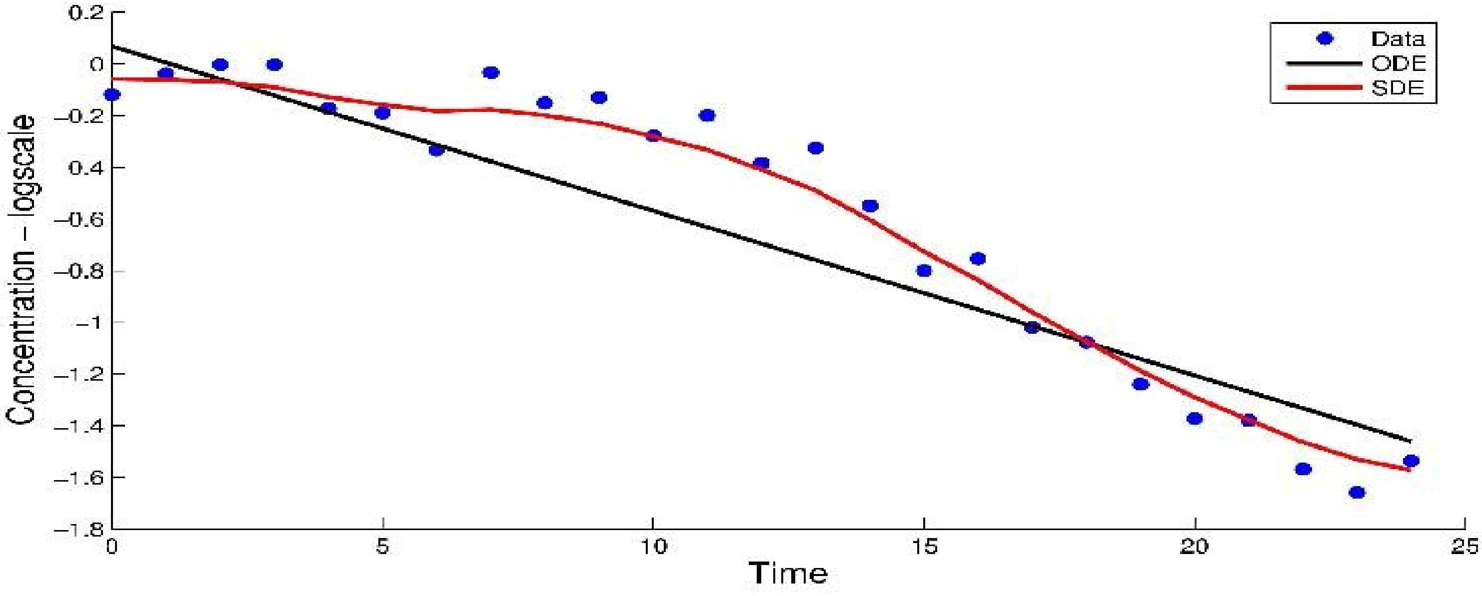


Stochastic Dynamical Model



- Stochastic Differential Equation:

$$\begin{aligned} dA &= -KAdt + \sigma dw \\ Y &= A + e \end{aligned}$$



The grey box model

Drift term

Diffusion term

$$dX_t = f(X_t, u_t, t, \theta)dt + \sigma(X_t, u_t, t, \theta)d\omega_t$$

System equation

$$Y_k = h(X_k, u_k, t_k, \theta) + e_k,$$

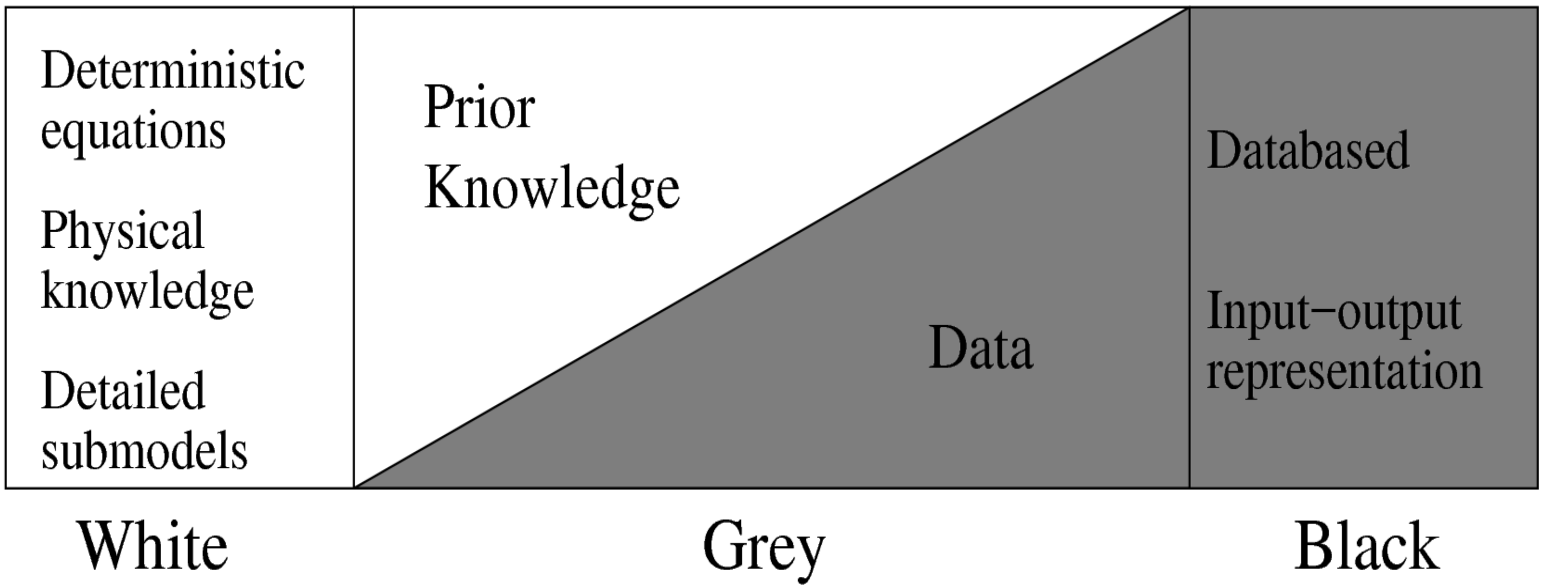
Observation equation

Observation noise

Notation:

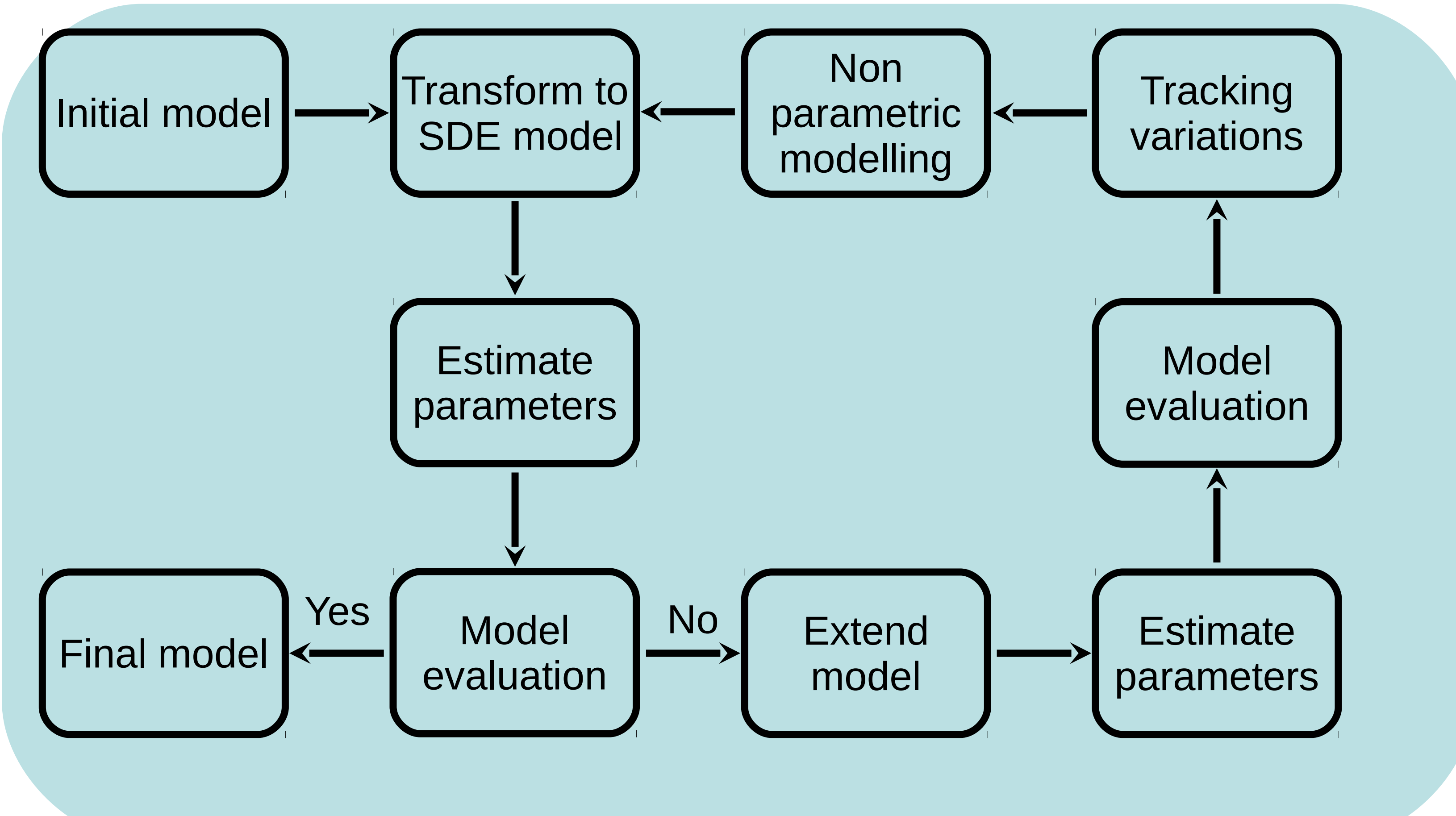
X_t: State variables
u_t: Input variables
θ: Parameters
Y_k: Output variables
t: Time
ω_t: Standard Wiener process
e_k: White noise process with $N(0, S)$

Grey-box modelling concept



- Combines prior physical knowledge with information in data
- Equations and parameters are physically interpretable

Grey box model building framework



l. A method for systematic improvement of stochastic grey-box models. Computers a

Forecasting and Simulation

Grey-Box models are well suited for ...

- One-step forecasts
- K-step forecasts
- Simulations
- Control
- … of both *observed* and *hidden* states.

- **It provides a framework for pinpointing model deficiencies – like:**
  - Time-tracking of unexplained variations in e.g. parameters
  - Missing (differential) equations
  - Missing functional relations
  - Lack of proper description of the uncertainty

Grey-Box Modelling

- Bridges the gap between physical and statistical modelling
- Provides methods for model identification
- Provides methods for model validation
- Provides methods for pinpointing model deficiencies
- Enables methods for a reliable description of the uncertainties, which implies that the same model can be used for **k-step forecasting**, **simulation** and **control**

Case study

Model for the thermal characteristics of a small office building

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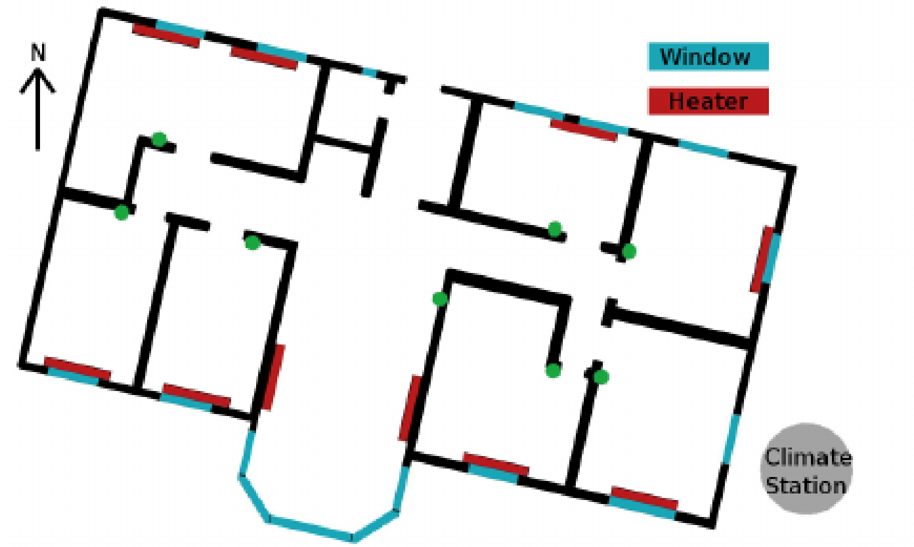
TEST CASE: ONE FLOORED 120 M^2 BUILDING

Objective

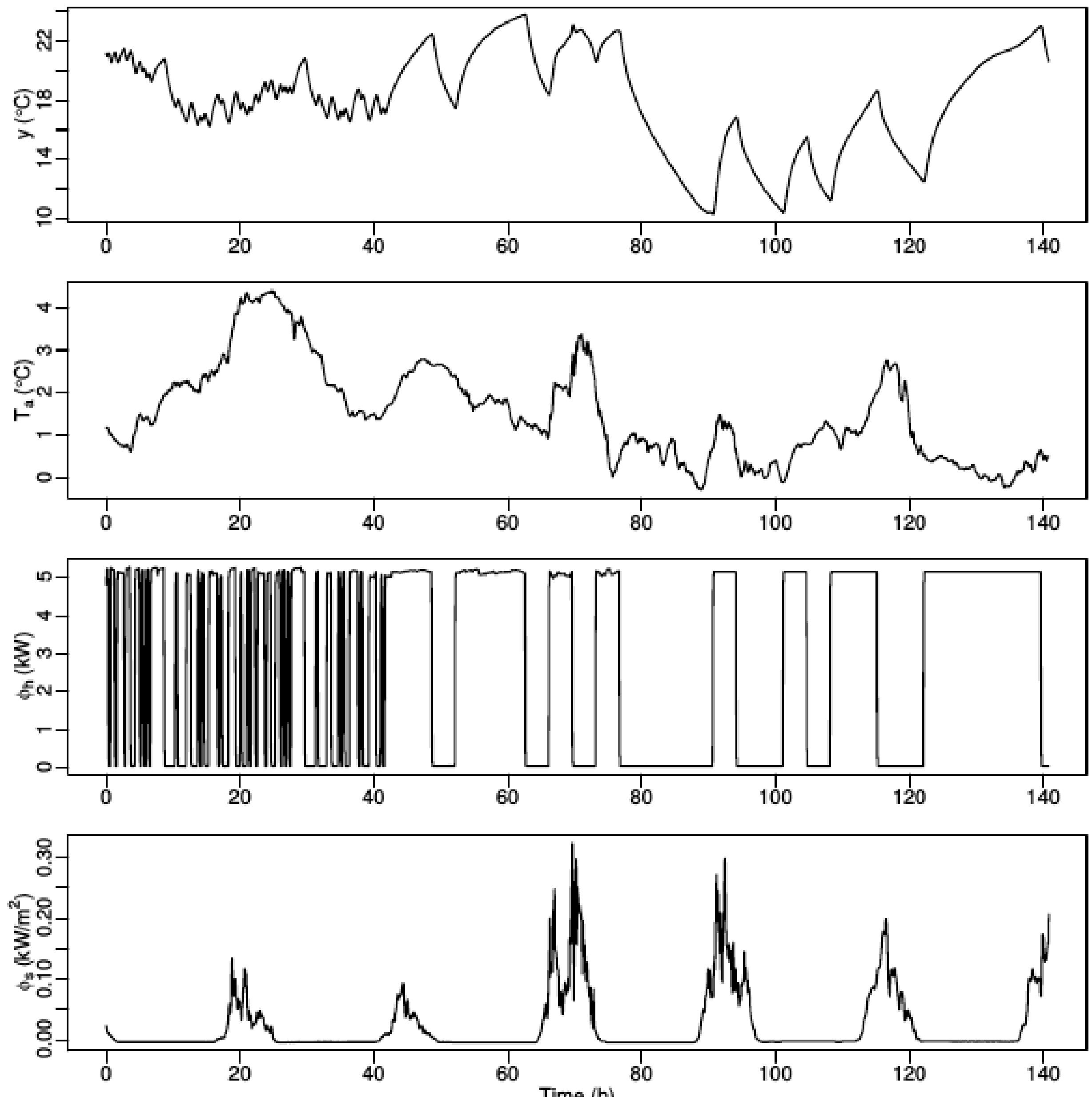
Find the best model describing the heat dynamics of this building ([1], [4])



DATA

Measurements of:

- y_t Indoor air temperature
- T_a Ambient temperature
- Φ_h Heat input
- Φ_s Global irradiance



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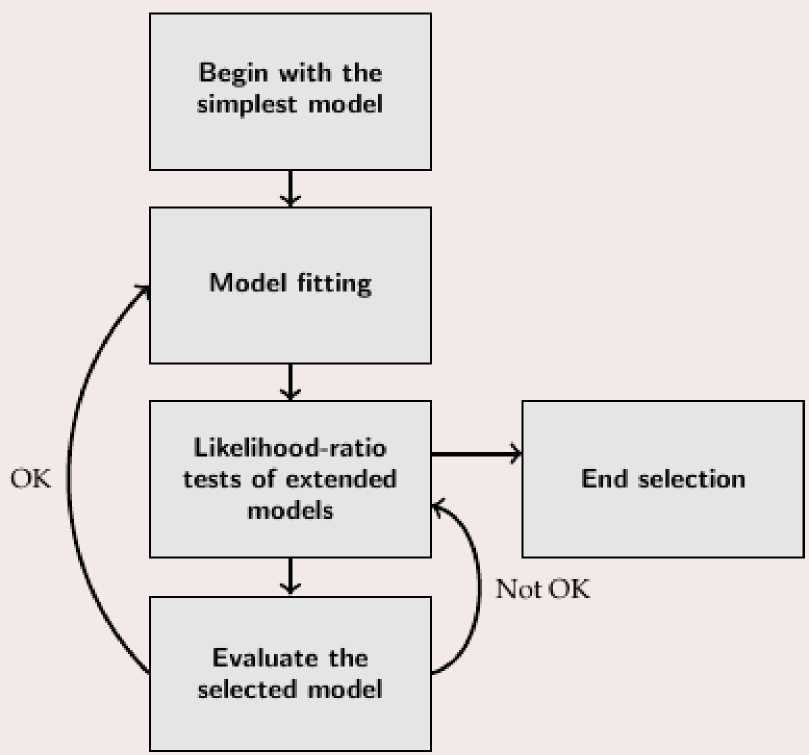
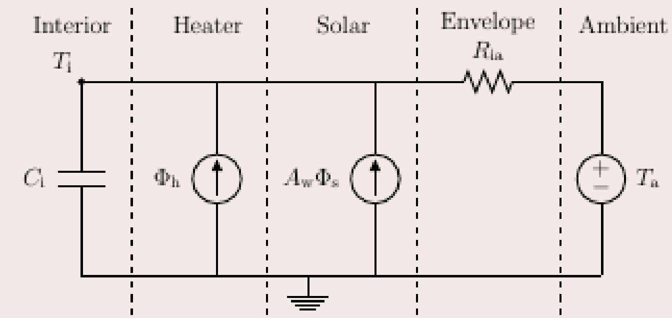
SELECTION PROCEDURE

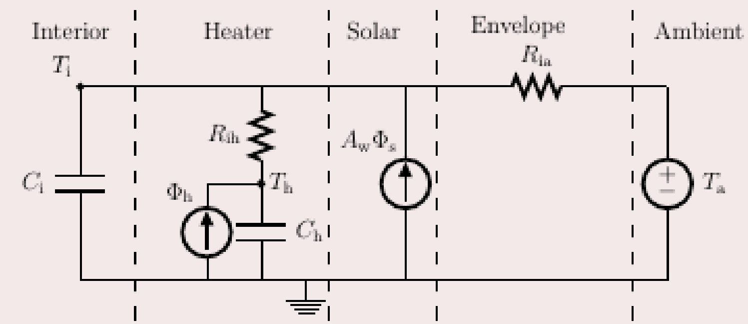
Iterative procedure using statistical tests



Simplest model

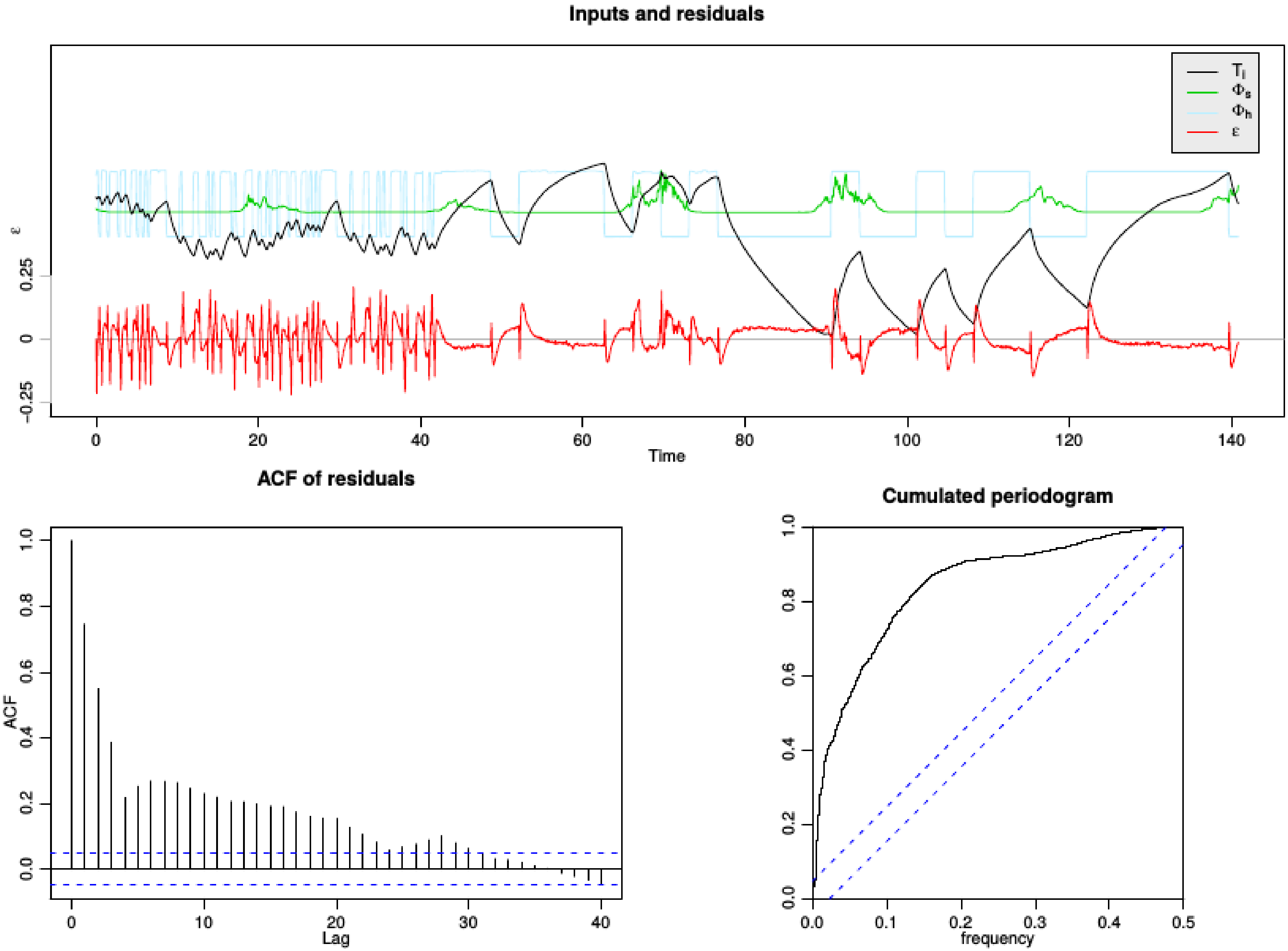


First extension: heater part



Start	$Model_{Ti}$			
$l(\theta;\mathcal{Y}_N)$	2482.6			
m	6			
1	$Model_{TiTe}$	$Model_{TiTm}$	$Model_{TiTs}$	$Model_{TiTh}$
$l(\theta;\mathcal{Y}_N)$	3628.0	3639.4	3884.4	3911.1
m	10	10	10	10
2	...			

EVALUATE THE SIMPLEST MODEL



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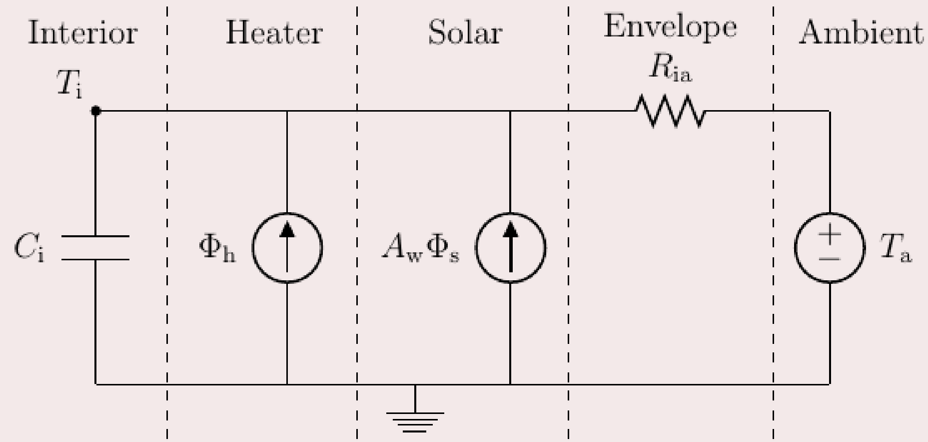
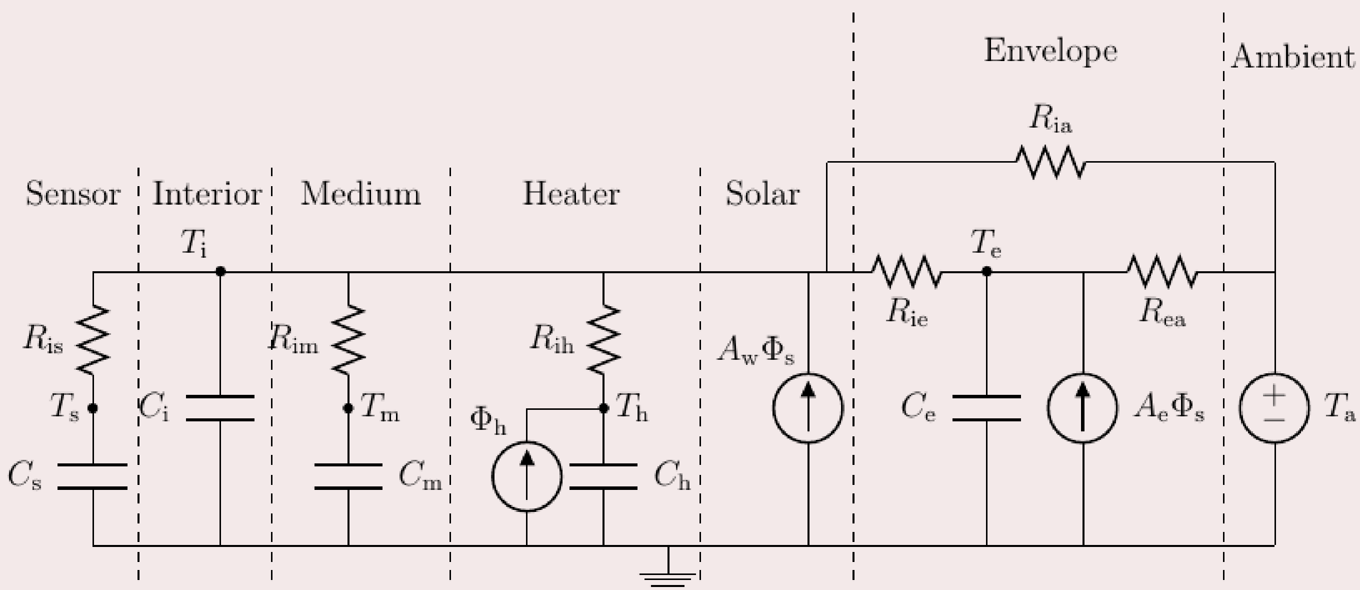
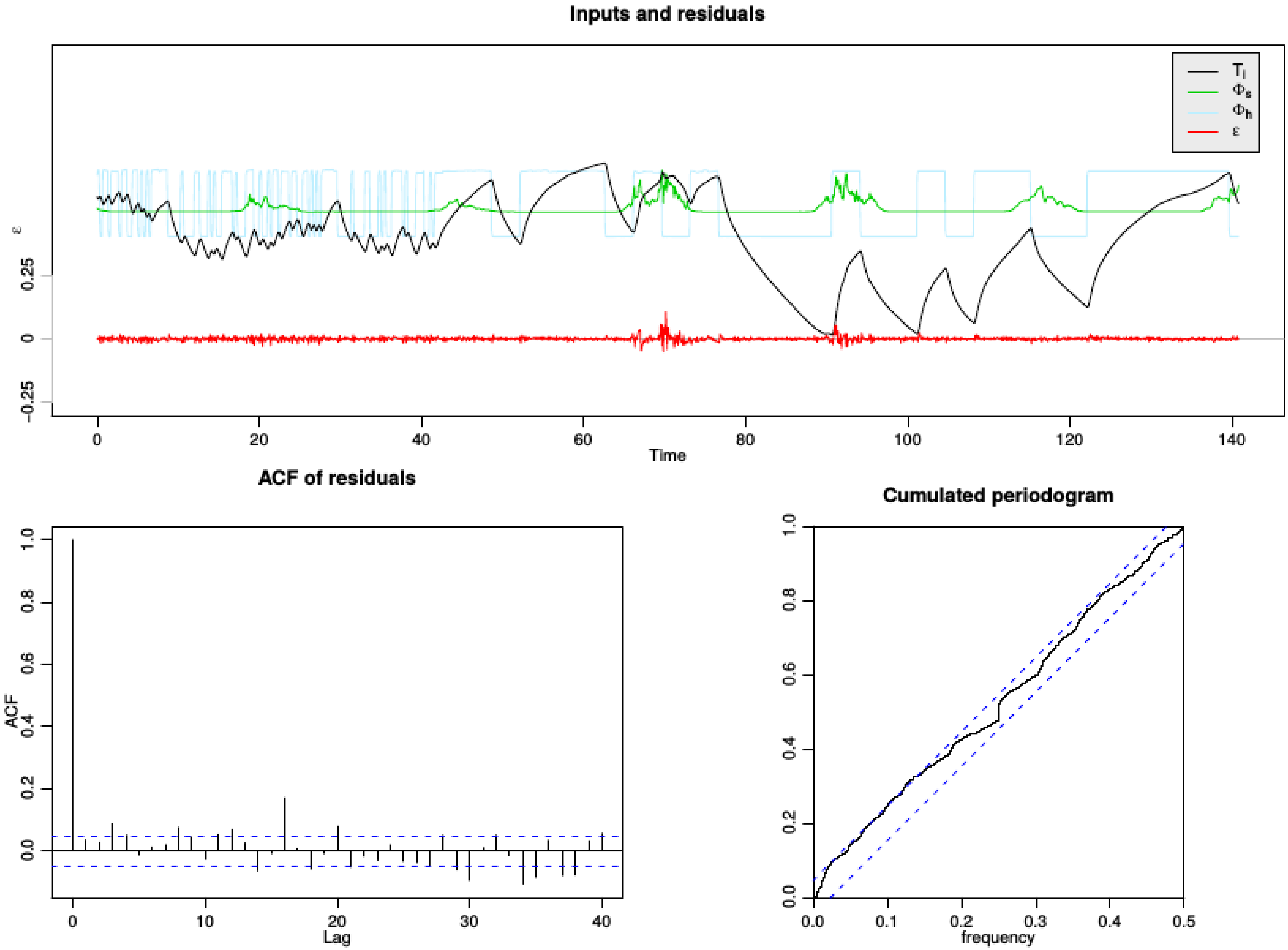
Simplest model



Most complex model applied




Inputs and residuals
T_i
Φ_s
Φ_h
ε
ε
0.25
0
−0.25
0
20
40
60
80
100
120
140
Time
ACF of residuals
ACF
1.0
0.8
0.6
0.4
0.2
0.0
0
10
20
30
40
Lag
Cumulated periodogram
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.1
0.2
0.3
0.4
0.5
frequency

Grey-box modelling

Continuous time models *(grey-box: stochastic state-space model)*

$$\text{States} = \text{Fun}_1(\text{States}, \text{Inputs}) + \text{Fun}_2(\text{Inputs}) \cdot \text{SystemError}$$
$$\text{Measurements} = \text{Fun}_3(\text{States}, \text{Inputs}) + \text{Fun}_4(\text{Inputs}) \cdot \text{MeasurementError}$$

- Used for buildings (single- and multi-zone), walls, systems (hot water tank, integrated PV, heat pumpts, heat exchanger, solar collectors, ...)
- Formulate the model based on physical knowledge
- Maximum likelihood estimation
  (we have the entire statistical framework available)
- Description of the system noise is part of the model provides some very useful possibilities
  (e.g. control the weight of data in the estimation depending on input signals)
- Software, for example our R package `CTSM-R` [1]

[1] `http://ctsm.info`

Case study

Models for electricity markets

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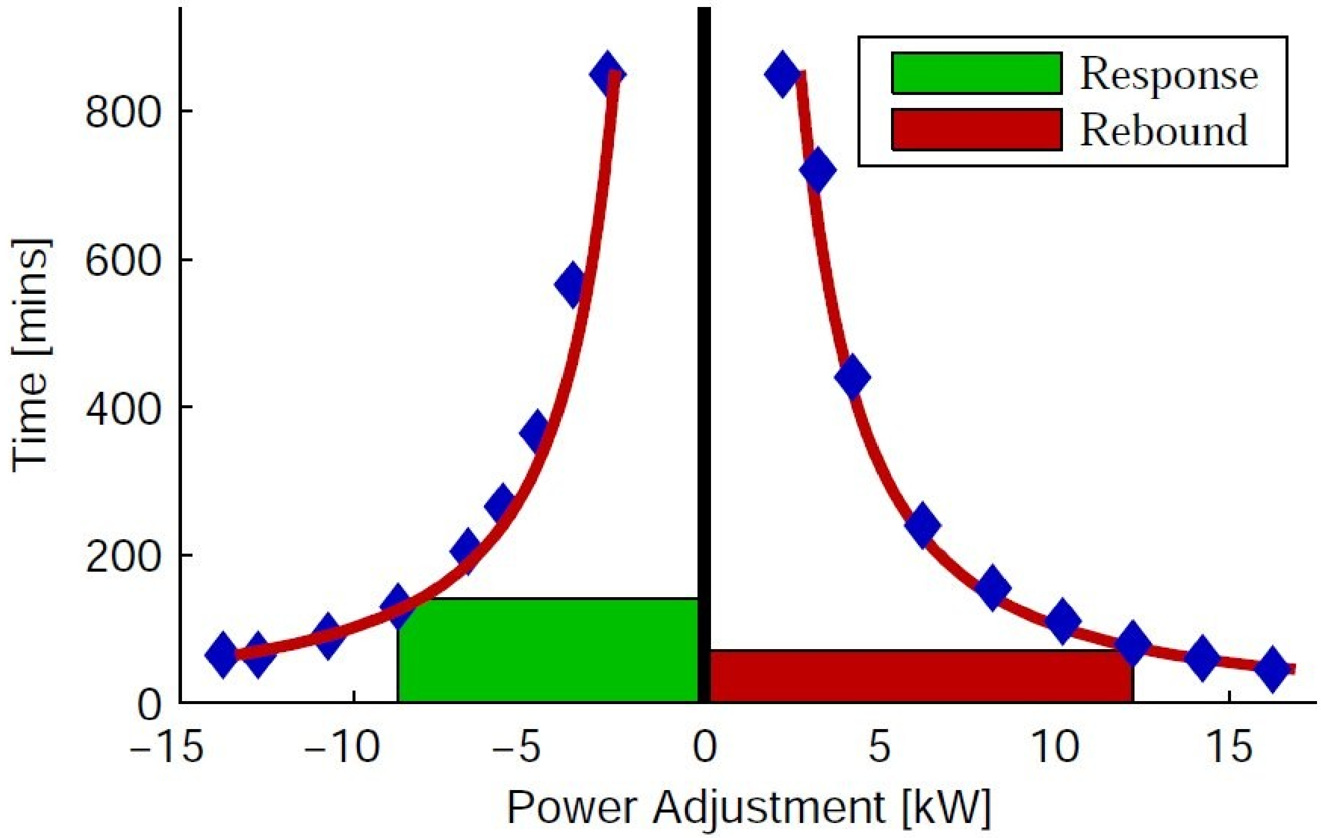
Flexibility Represented by Saturation Curves
(for market integration using block bids)



Flexibility Function

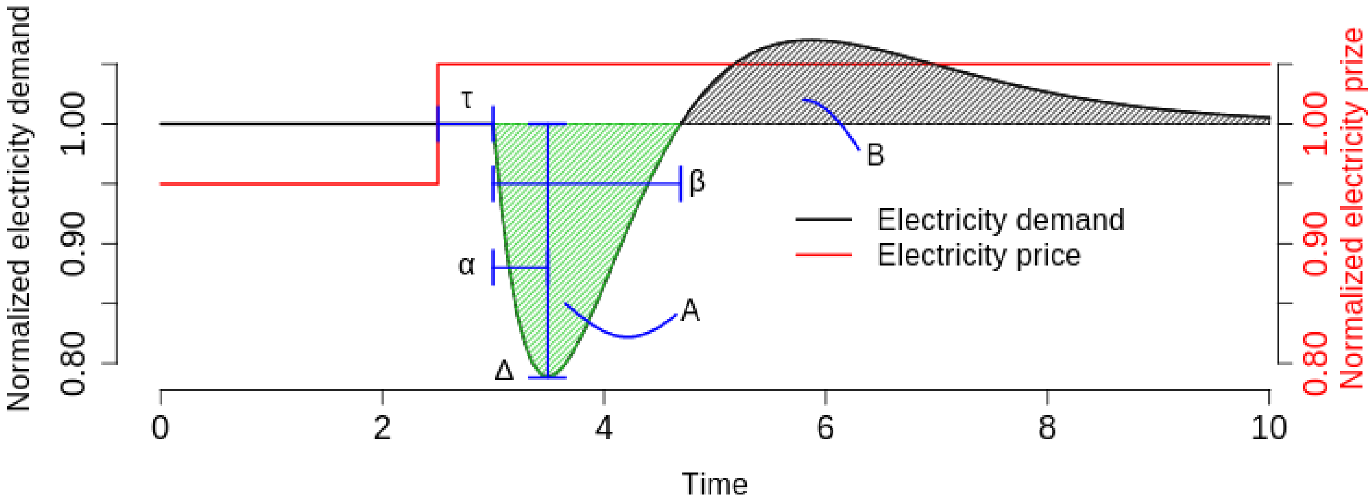


Figure 4: Six characteristics of the demand response to a step increase in electricity price. τ: The delay from adjusting the electricity prize and seeing an effect on the electricity demand, equal to approximately 0.5 here. Δ: The maximum change in demand following the price change, in this case close to 0.2. α: The time it takes from the change in demand starts until it reaches the lowest level, approximately equal to 0.5 here. β: The total time of decreased electricity demand, roughly equal to 2 here. A: The total amount of decreased energy demand, given by the green-shaded area. B: The total amount of increased energy demand, given by the grey-shaded area.

Case study

Models for Control
(Control of Heat Pumps)

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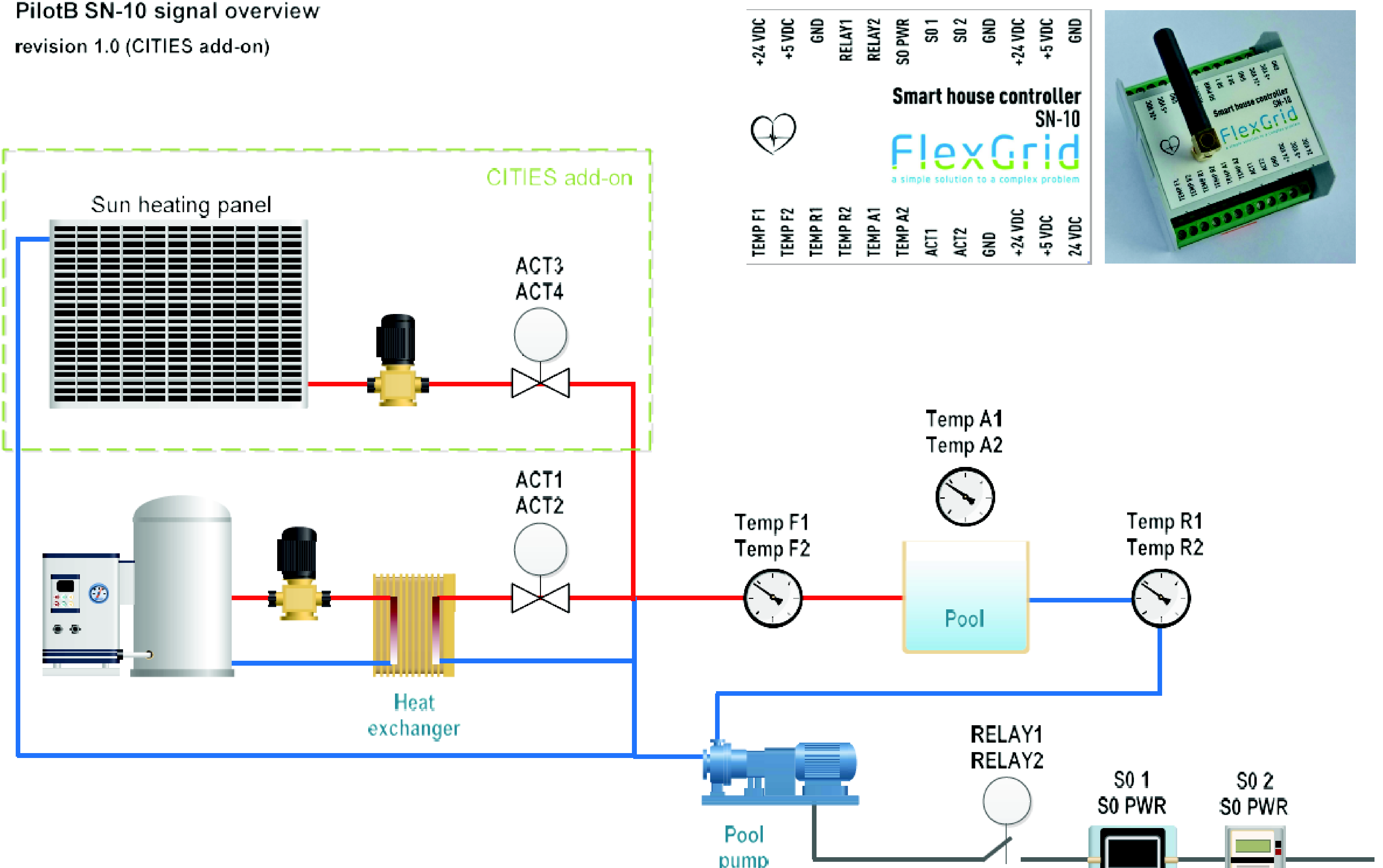
Smart Control of Houses with a Pool

PilotB SN-10 signal overview

revision 1.0 (CITIES add-on)



3.2 OPTIMIZATION PROBLEM

The MPC controller solves the following mixed integer linear optimization problem:

$$\min_{u} \quad \sum_{k=0}^{N-1} c_k u_k \tag{3.2a}$$

$$s.t. \quad x_{k+1} = A_d(T_o, w, T_a) x_k + B_d(T_o, w, T_a) u_k \tag{3.2b}$$

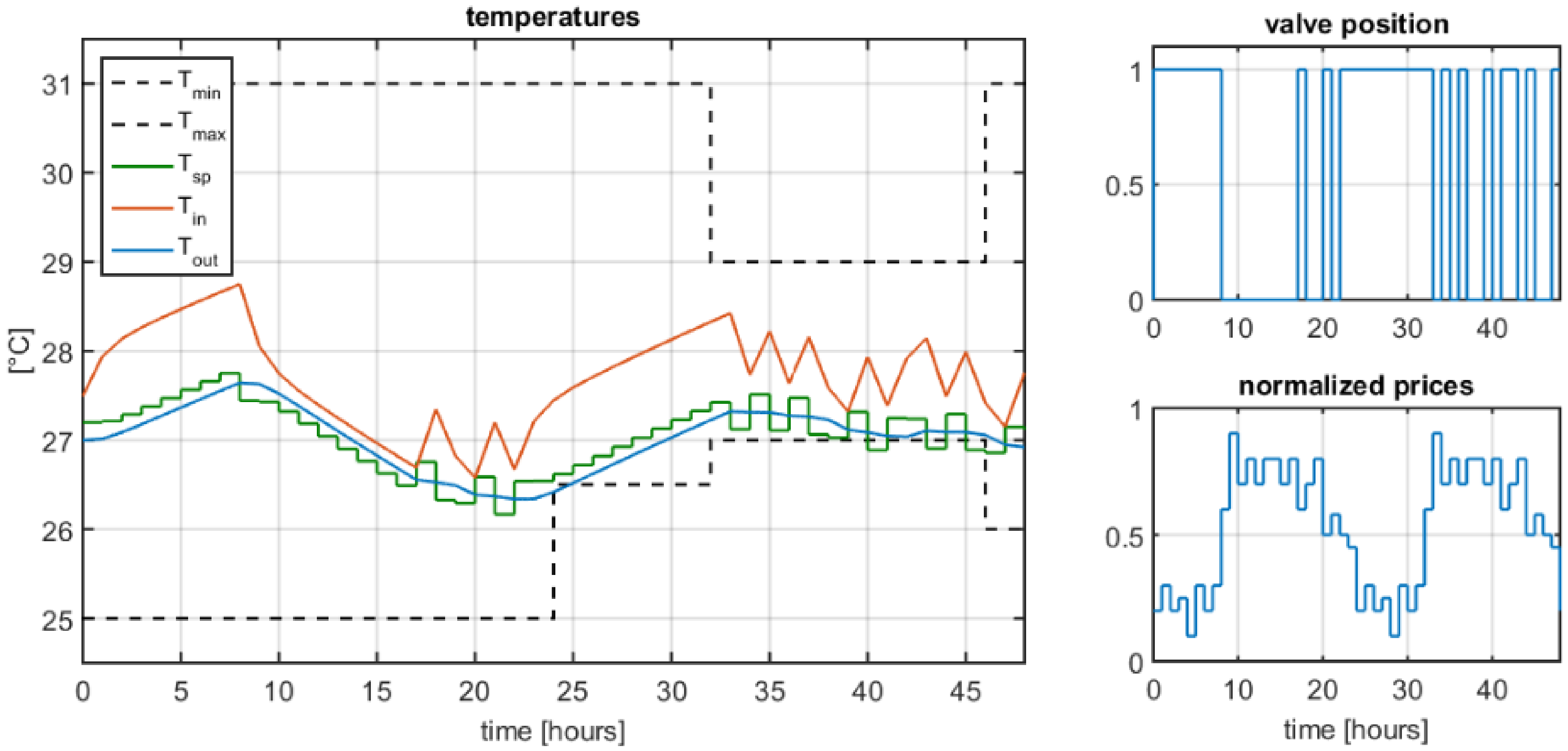
$$y_k = C_d(T_o, w, T_a) x_k \tag{3.2c}$$

$$u_k \in \{0, 1\} \tag{3.2d}$$

$$y_{min} \leq y_k \leq y_{max} \tag{3.2e}$$

where (3.2b) and (3.2c) is discretized state-space model of (2.6); u_k is the valve position (1 - open; 0 - closed); $y_k = [T_{in,k}\ T_{out,k}]^T$; N is the predictive horizon; c_k is the electricity price.

Grey-box based MPC Results



Summary

- Data can be used for reliable performance characterization of buildings (energy dynamics, energy savings, labelling, etc.)
- Grey-box modelling bridges the gap between physical and statistical modelling
- Procedures for data intelligent control of power load in buildings, using grey-box models, are suggested.
- The grey-box model based controllers can focus on
  - Energy Efficiency
  - Peak Shaving
  - Smart Grid demand (like ancillary services needs, ...)
  - Cost Minimization
  - Emission Efficiency (CO_2 minimization)
- Controllers based on CO_2 minimization can accelerate the transition to a fossil-free society / city
- We see a large potential in Demand Response using grey-box models. Automatic solutions, and end-user focus are important

Thanks ...

- For more information

  www.ctsm.info

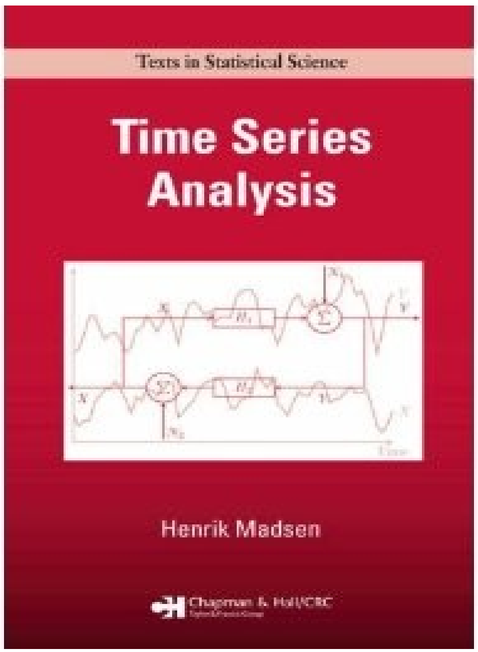
  www.henrikmadsen.org

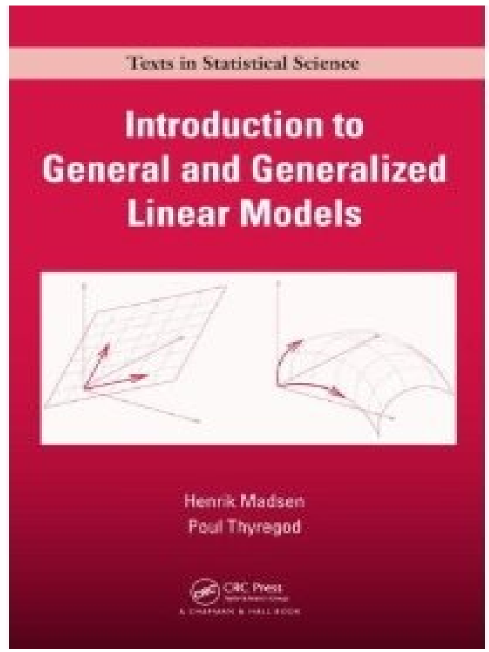
- ...or contact
  - Henrik Madsen (DTU/NTNU ZEN)

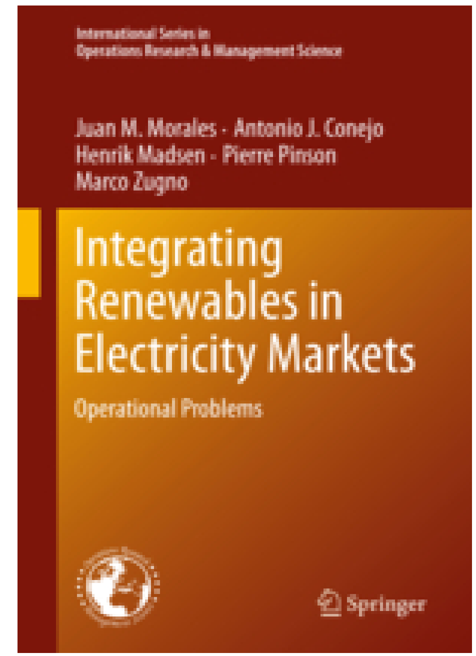
    hmad@dtu.dk

- Acknowledgement ZEN Project

Some 'randomly picked' books on modeling ....







Some references

- Madsen, Henrik; Holst, Jan. Estimation of Continuous-Time Models for the Heat Dynamics of a Building. In: Energy and Buildings, Vol. 22, 1995
- Andersen, Klaus Kaae; Madsen, Henrik; Hansen, Lars Henrik. Modelling the heat dynamics of a building using stochastic differential equations. In: Energy and Buildings, Vol. 31, No. 1, 2000, p. 13-24.
- Kristensen, Niels Rode; Madsen, Henrik; Jørgensen, Sten Bay. Using continuous time stochstic modelling and nonparametric statistics to improve the quality of first principles models. In: Computer – Aided Chemical Engineering, Vol. 10, 2002, p. 901-906
- Kristensen, N.R.; Madsen, Henrik; Jørgensen, Sten Bay. A unified framefork for systematic model improvement. In: Process Systems Engineering, Vol. 15, 2003, p. 1292-1297.
- Kristensen, Niels Rode; Madsen, Henrik; Jørgensen, Sten Bay. Parameter Estimation in Stochastic Grey-Box Models. In: Automatica, Vol. 40, No. 2, 2004, p. 225-237.
- Nielsen, Henrik Aalborg; Madsen, Henrik. Modelling the Heat Consumption in District Heating Systems using a Grey-box approach. In: Energy and Buildings, Vol. 38, No. 1, 2006, p. 63-71.
- Friling, N.; Jimenez, M.J.; Bloem, H.; Madsen, Henrik. Modelling the heat dynamics of building integrated and ventilated photovoltaic modules. In: Energy and Buildings, Vol. 41, No. 10, 2009, p. 1051-1057.
- Bacher, Peder; Madsen, Henrik. Identifying suitable models for the heat dynamics of buildings. In: Energy and Buildings, Vol. 43, No. 7, 2011, p. 1511-1522.
- Lodi, C.; Bacher, Peder; Cipriano, J.; Madsen, Henrik. Modelling the heat dynamics of a monitored Test Reference Environment for Building Integrated Photovoltaic systems using stochastic differential equations. In: Energy and Buildings, Vol. 50, 2012, p. 273-281.
- Morales González, Juan Miguel; Pinson, Pierre; Madsen, Henrik. A Transmission-Cost-Based Model to Estimate the Amount of Market-Integrable Wind Resources. In: I E E E Transactions on Power Systems, Vol. 27, No. 2, 2012, p. 1060-1069 .
- Halvgaard, Rasmus; Bacher, Peder; Perers, Bengt; Andersen, Elsa; Furbo, Simon; Jørgensen, John Bagterp; Poulsen, Niels Kjølstad; Madsen, Henrik. Model predictive control for a smart solar tank based on weather and consumption forecasts. In: Energy Procedia, Vol. 30, 2012, p. 270-278.

Some references (cont.)

- Morales González, Juan Miguel; Pinson, Pierre; Madsen, Henrik. A Transmission-Cost-Based Model to Estimate the Amount of Market-Integrable Wind Resources. In: I E E E Transactions on Power Systems, Vol. 27, No. 2, 2012, p. 1060-1069
- Dorini, Gianluca Fabio ; Pinson, Pierre; Madsen, Henrik. Chance-constrained optimization of demand response to price signals. In: I E E E Transactions on Smart Grid, Vol. 4, No. 4, 2013, p. 2072-2080.
- Bacher, Peder; Madsen, Henrik; Nielsen, Henrik Aalborg; Perers, Bengt. Short-term heat load forecasting for single family houses. In: Energy and Buildings, Vol. 65, 2013, p. 101-112.
- Corradi, Olivier; Ochsenfeld, Henning Peter; Madsen, Henrik; Pinson, Pierre. Controlling Electricity Consumption by Forecasting its Response to Varying Prices. In: I E E E Transactions on Power Systems, Vol. 28, No. 1, 2013, p. 421-430.
- Zugno, Marco; Morales González, Juan Miguel; Pinson, Pierre; Madsen, Henrik. A bilevel model for electricity retailers' participation in a demand response market environment. In: Energy Economics, Vol. 36, 2013, p. 182-197.
- Meibom, Peter; Hilger, Klaus Baggesen; Madsen, Henrik; Vinther, Dorthe. Energy Comes Together in Denmark: The Key to a Future Fossil-Free Danish Power System. In: I E E E Power & Energy Magazine, Vol. 11, No. 5, 2013, p. 46-55.
- Andersen, Philip Hvidthøft Delff ; Jiménez, María José ; Madsen, Henrik ; Rode, Carsten. Characterization of heat dynamics of an arctic low-energy house with floor heating. In: Building Simulation, Vol. 7, No. 6, 2014, p. 595-614.
- Andersen, Philip Hvidthøft Delff; Iversen, Anne; Madsen, Henrik; Rode, Carsten. Dynamic modeling of presence of occupants using inhomogeneous Markov chains. In: Energy and Buildings, Vol. 69, 2014, p. 213-223.
- Madsen, H, Parvizi, J, Halvgaard, RF, Sokoler, LE, Jørgensen, JB, Hansen, LH & Hilger, KB 2015, 'Control of Electricity Loads in Future Electric Energy Systems'. in AJ Conejo, E Dahlquist & J Yan (eds), Handbook of Clean Energy Systems: Intelligent Energy Systems. vol. 4, Wiley.
- Halvgaard, RF, Vandenberghe, L, Poulsen, NK, Madsen, H & Jørgensen, JB 2016, Distributed Model Predictive Control for Smart Energy Systems IEEE Transactions on Smart Grid, vol 7, no. 3, pp. 1675-1682.
- Bacher, P, de Saint-Aubain, PA, Christiansen, LE & Madsen, H 2016, Non-parametric method for separating domestic hot water heating spikes and space heating Energy and Buildings, vol 130, pp. 107-112.