

Data-driven models for demand-side management

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DATA ANALYSIS AND STATISTICS

- How can we gain as much as possible useful information from data?
- Statistical inference: the process of drawing conclusions from data that is subject to random variation
- Time-series models for describing a dynamical system

MODEL COMPLEXITY

- Einstein: *"Everything should be made as simple as possible, but not simpler"*
- Fundamental question: *"Which model and how complex should it be for *optimally* for providing the answers?"*

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- Einstein: *"Everything should be made as simple as possible, but not simpler"*
- Fundamental question: *"Which model and how complex should it be for optimally for providing the answers?"*
- Answer: it depends on the data!
 - 'simple data' \Rightarrow 'simple model'
 - 'complex data' \Rightarrow 'complex model'
- It is a matter of what we need to know or simply economical investment. Which sensors are needed for providing the needed information?
- or the other way around what can be achieved with current resources

MODEL COMPLEXITY

From statistical theory a wide range of techniques are available:

- Find the most suitable model to describe the data
- Estimate the uncertainty
- Validate the model fit (likelihood)

MODEL STRUCTURE

Different types of *time series* models:

- Static models, *no dynamics* (e.g. for daily values)
- ARMAX, discrete models based on transfer functions, *black-box dynamics, however for control and steady-state parameters (e.g. UA-value, gA-value) fully applicable*
- Grey-box models. *Continuous (or discrete) time models, combination of physics and statistics*

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Static models (linear function):

$$\text{Measurements} = \text{Function}(\text{Inputs}) + \text{Residual}$$

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ARMAX model:

$$\text{Measurements} = \text{Transferfun}_1(\text{Inputs}) + \text{Transferfun}_2(\text{Error})$$

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Grey-box model:

$$\text{States} = \text{Fun}_1(\text{States}, \text{Inputs}) + \text{Fun}_2(\text{SystemError})$$

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

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Note that part of the model is a description of the error(s)

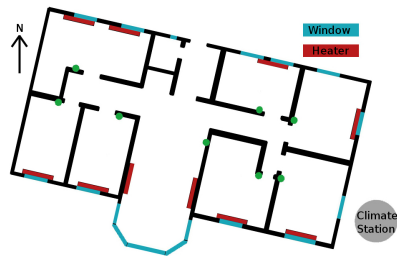
ANNEX 58: GUIDELINES

- In Annex 58 we developed guidelines (focus on *energy performance assessment*)
- 'Physical guidelines': setup of measuring campaign and experiments
- 'Statistical guidelines': models for data from buildings (unoccupied, e.g. from a test sequence run 3-7 days):
 - Static, ARX and grey-box models
 - Model selection procedure
 - Examples and implementations in R

TEST CASE: ONE FLOORED 120 M² BUILDING

Objective

Find the best model describing the heat dynamics of this building



DATA

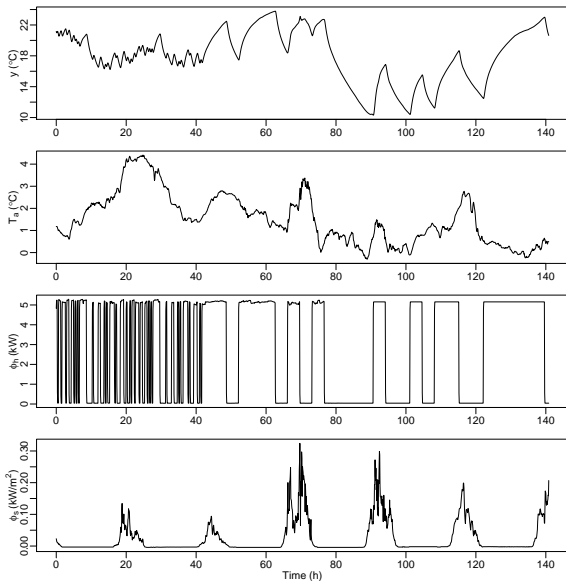
Measurements of:

y_t Indoor air temperature

T_a Ambient temperature

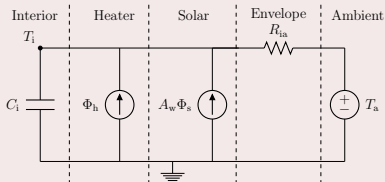
Φ_h Heat input

Φ_s Global irradiance



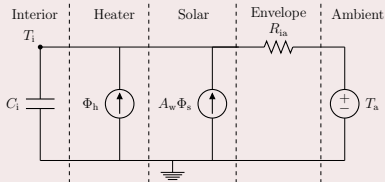
IDENTIFY THE BEST PHYSICAL MODEL FOR THE DATA

Simplest model

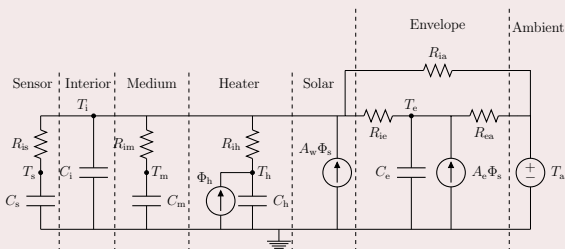


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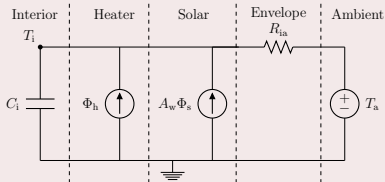


Most complex model applied



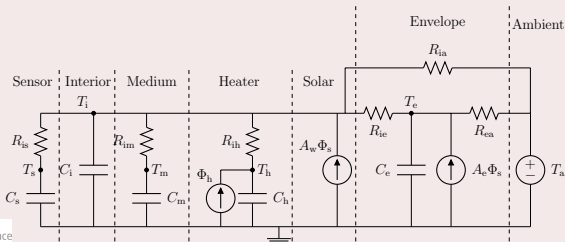
IDENTIFY THE BEST PHYSICAL MODEL FOR THE DATA

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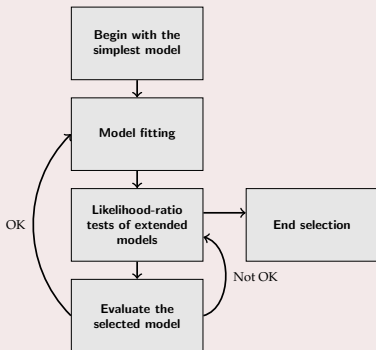
The best model for the given data is probably in between

Most complex model applied

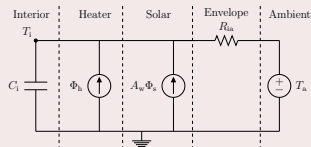


SELECTION PROCEDURE

Iterative procedure using statistical tests

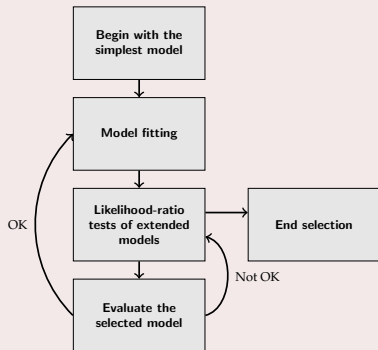


Simplest model

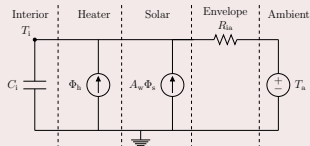


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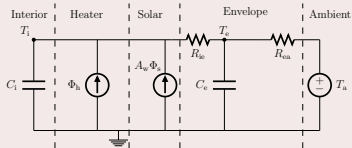
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Simplest model

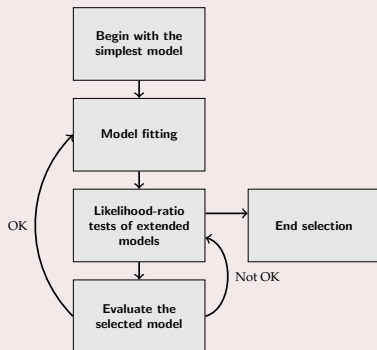


First extension: building envelope part

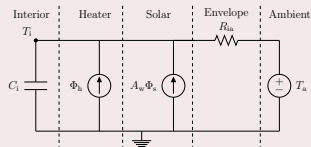


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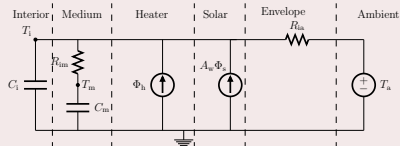
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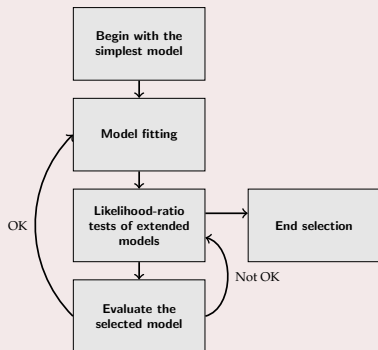


First extension: indoor medium part

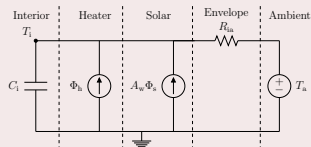


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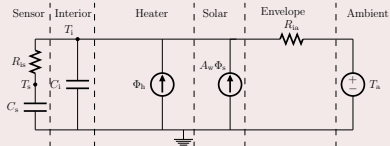
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Simplest model

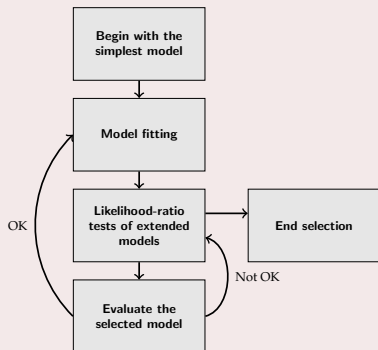


First extension: sensor part

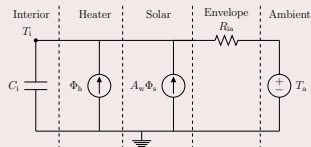


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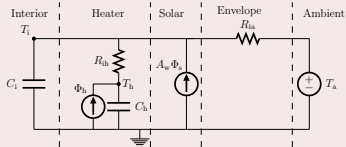
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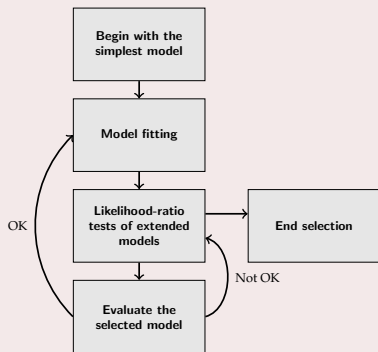


First extension: heater part

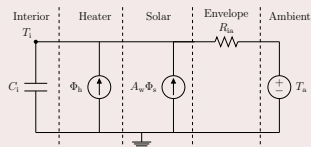


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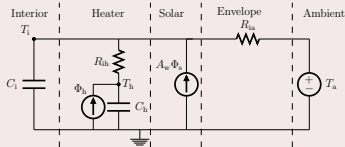
Iterative procedure using statistical tests



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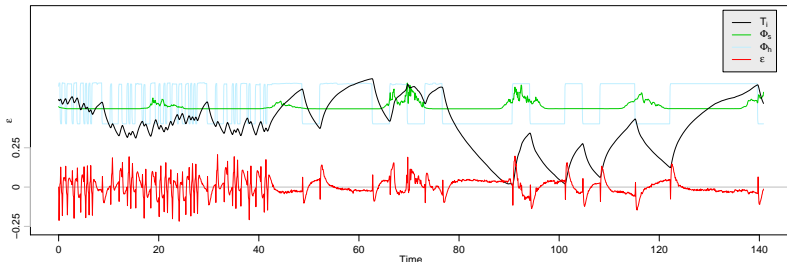
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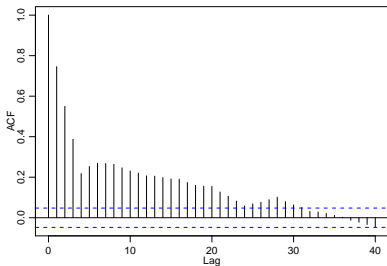
| Start | $Model_{T_i}$ | | | |
|----------------------------|-------------------|-------------------|-------------------|-------------------|
| $l(\theta; \mathcal{Y}_N)$ | 2482.6 | | | |
| m | 6 | | | |
| 1 | $Model_{T_i T_e}$ | $Model_{T_i T_m}$ | $Model_{T_i T_s}$ | $Model_{T_i T_h}$ |
| $l(\theta; \mathcal{Y}_N)$ | 3628.0 | 3639.4 | 3884.4 | 3911.1 |
| m | 10 | 10 | 10 | 10 |
| 2 ... | | | | |

EVALUATE THE SIMPLEST MODEL

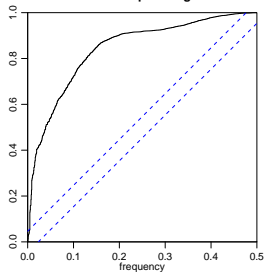
Inputs and residuals



ACF of residuals

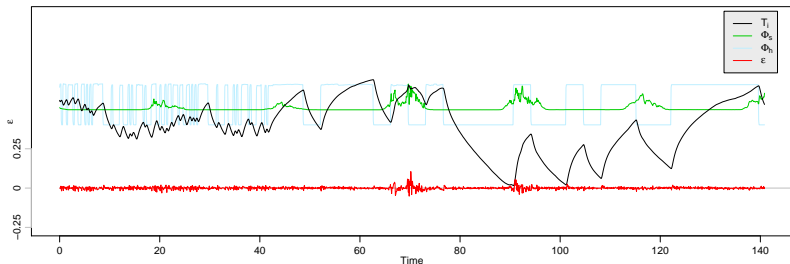


Cumulated periodogram

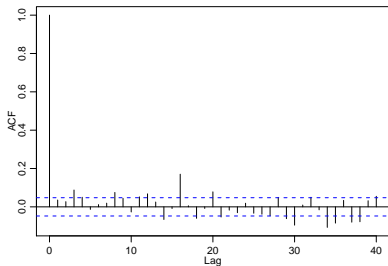


EVALUATE THE SELECTED MODEL

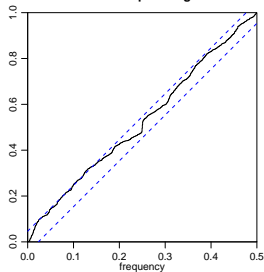
Inputs and residuals



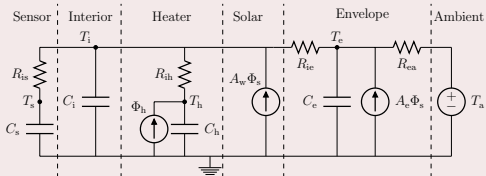
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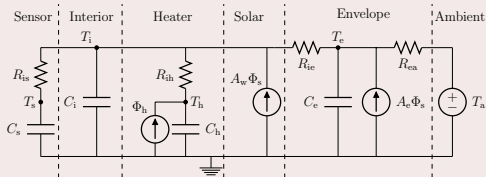
Cumulated periodogram



Selected model



Selected model



Estimated parameters

| | | |
|----------------|--------|-------------------|
| \hat{C}_i | 0.0928 | (kWh/C) |
| \hat{C}_e | 3.32 | - |
| \hat{C}_h | 0.889 | - |
| \hat{C}_s | 0.0549 | - |
| \hat{R}_{ie} | 0.897 | (°C/kW) |
| \hat{R}_{ea} | 4.38 | - |
| \hat{R}_{ih} | 0.146 | - |
| \hat{R}_{is} | 1.89 | - |
| \hat{A}_w | 5.75 | (m ²) |
| \hat{A}_e | 3.87 | - |

Estimated time constants

| | | |
|----------------|--------|-------|
| $\hat{\tau}_1$ | 0.0102 | hours |
| $\hat{\tau}_2$ | 0.105 | - |
| $\hat{\tau}_3$ | 0.788 | - |
| $\hat{\tau}_4$ | 19.3 | - |

IMPORTANT POINTS

- Need to excite the dynamics of the system!
- Hence you need data with variation in the inputs:
 - Turn on/off the heaters
 - Low ambient temperature preferable
 - You need direct solar radiation
- Data from buildings with thermostatic control wont work (flexibility can be with hot water tank)

MPC

- We have a model to predict the indoor temperature:
 - Input: heating and climate
 - Output: indoor temperature
- Model Predictive Control (MPC):
 - Setup a cost function (e.g. monetary and indoor climate)
 - Constrains (max heating etc.)
 - Use weather forecasts and calculate an optimized heat input

MORE TIME SERIES MODELLING TECHNIQUES

- Model selection (likelihood-ratio test, AIC, BIC)
- Parametric, semi-parametric and non-parametric models:
 - splines, kernels, regression trees, neural-networks, ...

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- Parametric, semi-parametric and non-parametric models:
 - splines, kernels, regression trees, neural-networks, ...
- Kalman filtering (grey-box models)
- Hidden Markov models (regime models)
- Robust estimation and outlier detection
- Time adaptive models

We are setting up a new Annex: focus models for occupied buildings(contact Staf Roels, KU Leuven)

SOME LINKS

- Annex 58 Statistical Guidelines
- Summer school on these matters (time-series modelling for buildings), 19. to 24. June, Grenada, Spain
- DTU Compute, Dynamical Systems
 - Solar and wind forecasting, load forecasting, data-driven models for: buildings, user behaviour, EVs, district heating, grids
 - MPC and optimization
- CITIES project
- Send me a mail pbac@dtu.dk

Thanks for your time!