Simurex 2018

Characterisation of building envelope properties by in situ measurements and statistical learning

Simon Rouchier LOCIE, Université Savoie Mont-Blanc

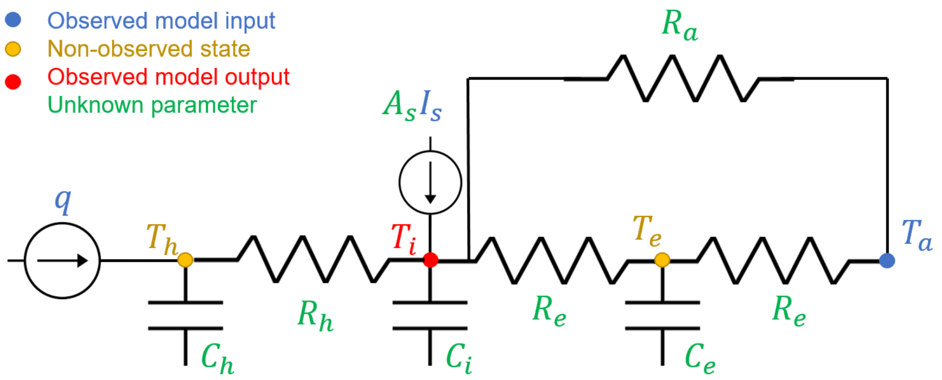
- Heat transfer coefficient H
- Transmission coefficient H_{tr}
- Infiltration coefficient H_v

1. Data collection

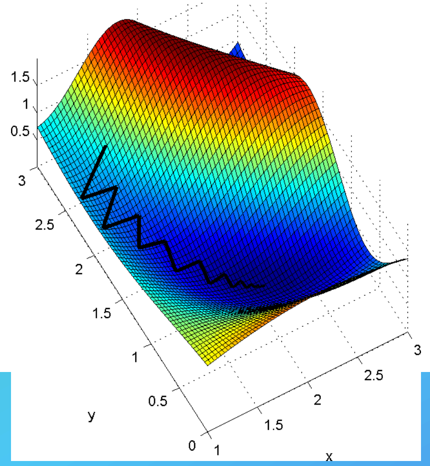
Database

Input 1	Input 2	Output 1	Output 2	Output 3
...	..	...	...	...
...	...	...	...	...
...	...	...	...	...
...	...	...	...	...

2. Modelling

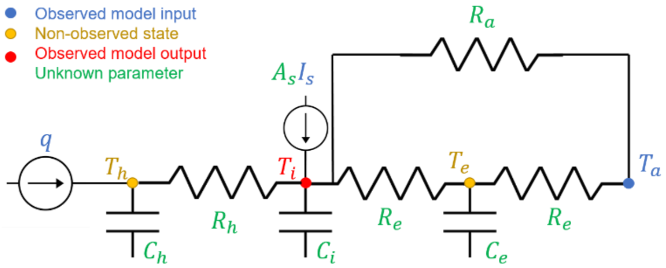


3. Parameter estimation

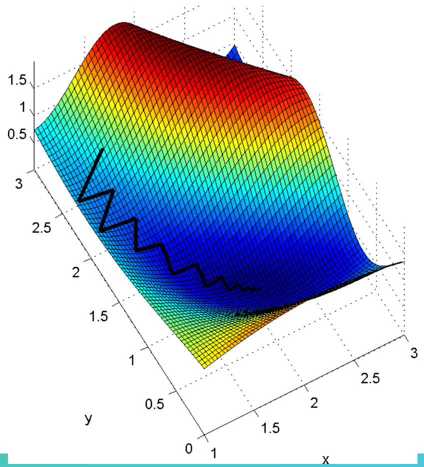


4. Success!

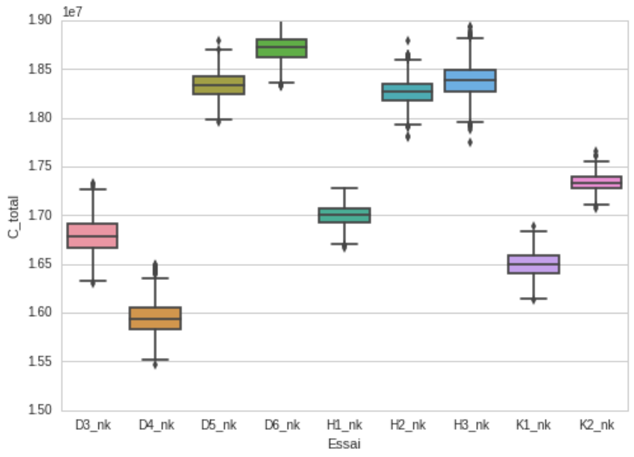
Should I get more data?



Should I try a new model?



Is my method wrong?



How do I know this?

Is anyone right ?

1. The model calibration procedure

2. The validation of results

3. Model selection and experiment design

1. The model calibration procedure

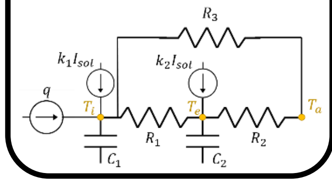
Reality

Observed output

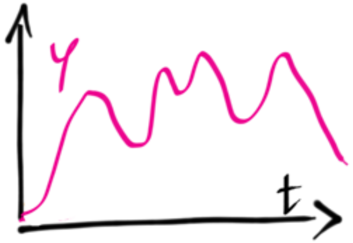
$r^2(\theta) = (y(\theta) - y_{obs})^2$

Unknown θ

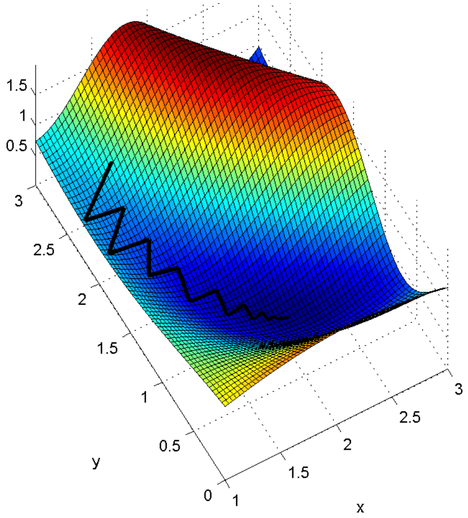
Model



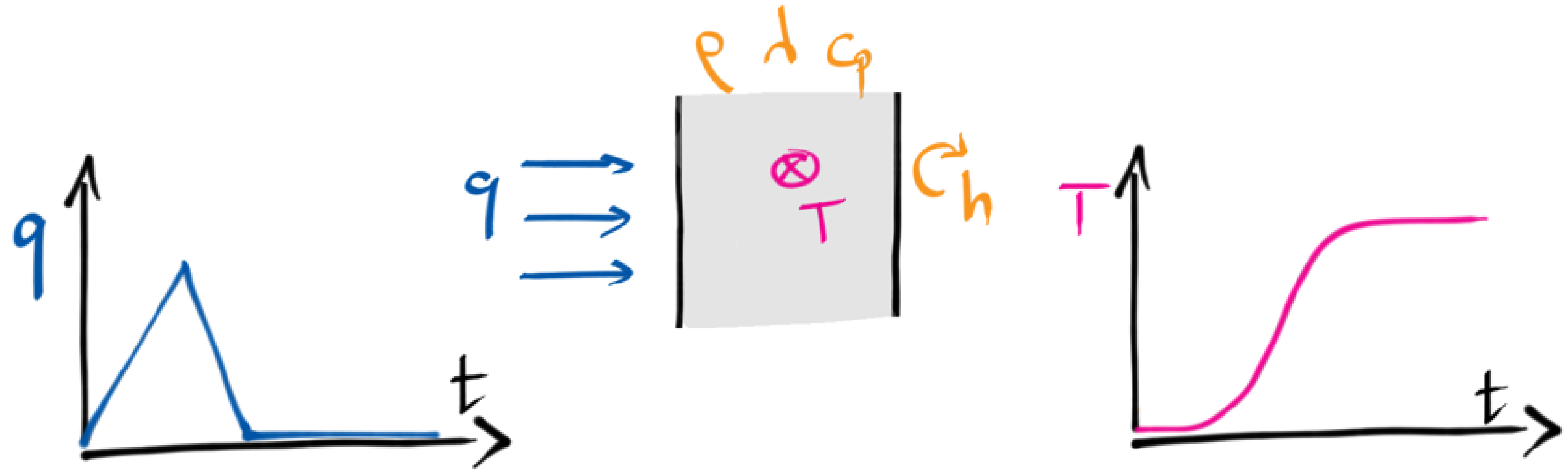
Calculated output



Find θ that minimises $r^2(x)$



Levenberg-Marquardt
Genetic Algorithm
Bayesian inference
etc.



Direct problem

I know the properties of the material and the heat flow. I predict the temperature.

Easy

Inverse problem

First example: I measured the heat flow and the temperature. I want to estimate the properties.

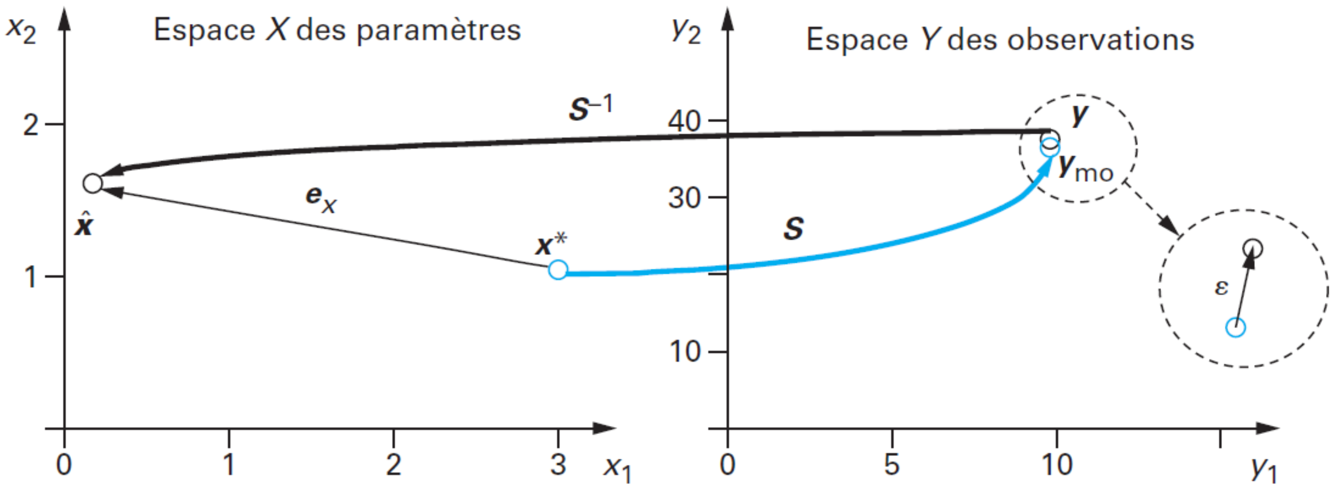
Medium

Second example: I measured the temperature and I know the properties. I want to estimate the heat flow.

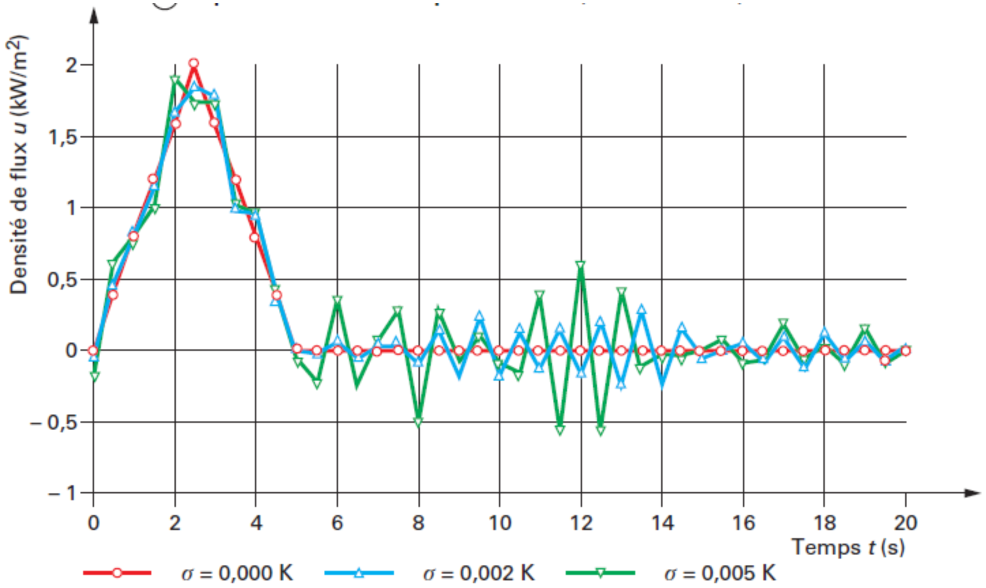
Difficult

https://srouchier.github.io/InverseBuilding/

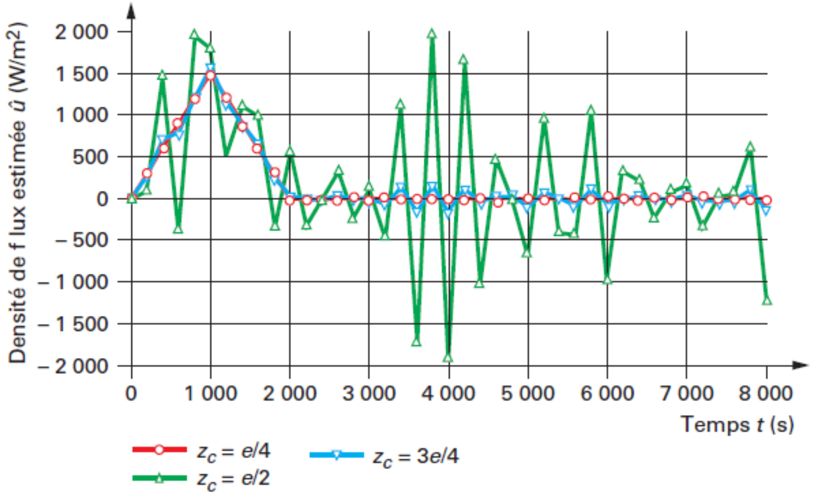
A very small error can make your results very wrong.
There are always errors.



D. Maillet
Problèmes inverses en diffusion thermique
Techniques de l'ingénieur

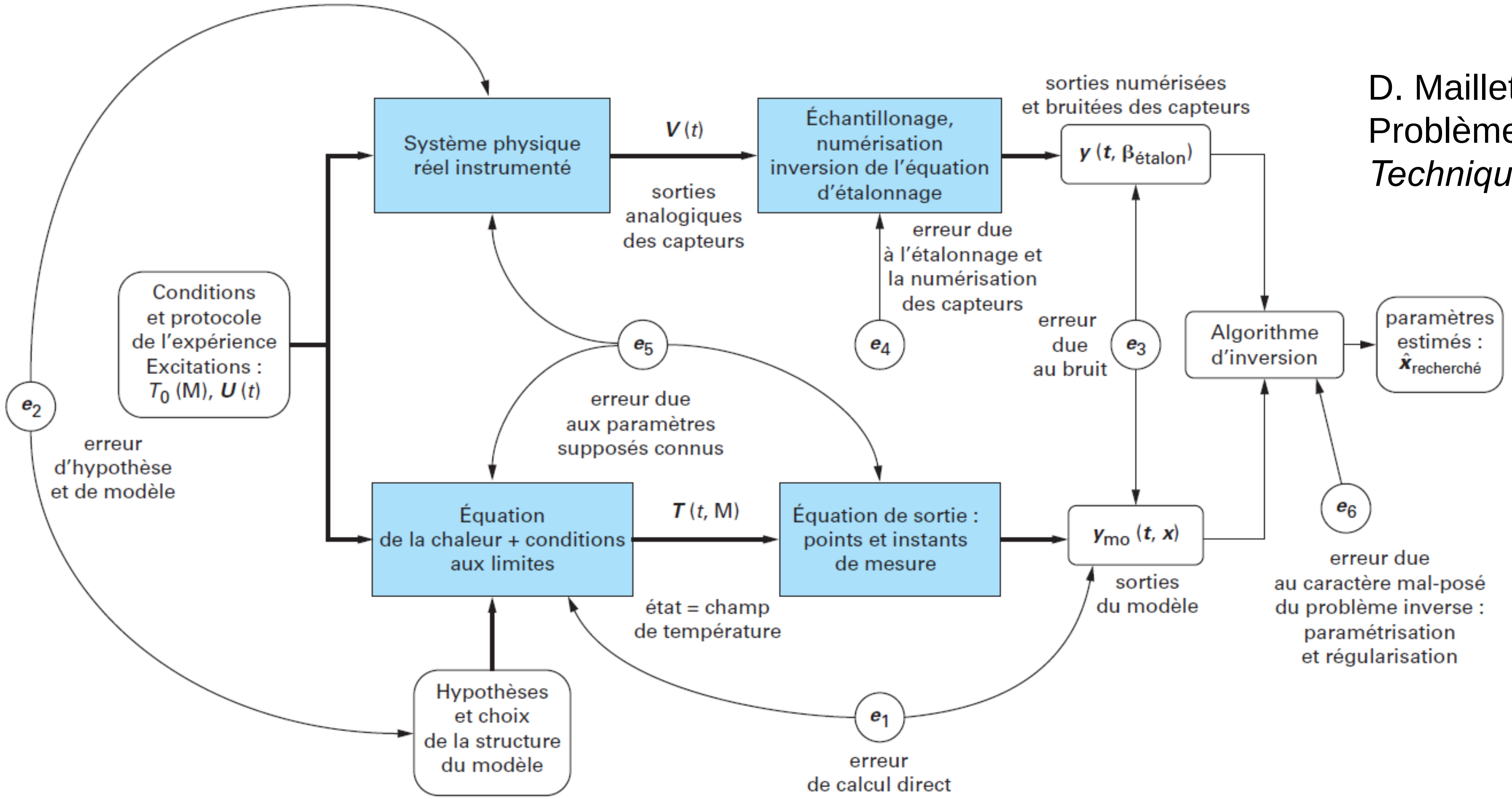


(b) valeur exacte de la densité de flux reconstruite à partir de la réponse bruitée en température Δt = 0,5 s pour trois niveaux du bruit σ



(b) densité de flux estimée $\hat{u}$ à partir des réponses internes en trois points (Δt = 200 s ; σ = 0,02 K)

A very small error can make your results very wrong.
There are always errors.



D. Maillet
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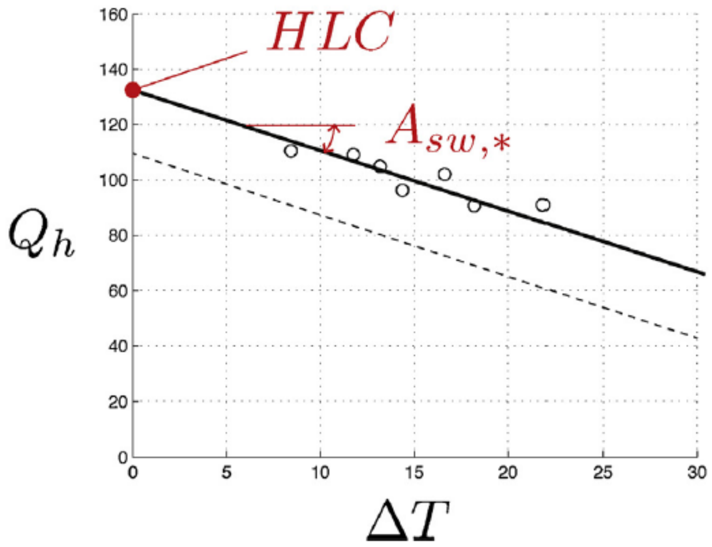
➢ be aware of all your mistakes and take them into account

First example: steady-state methods

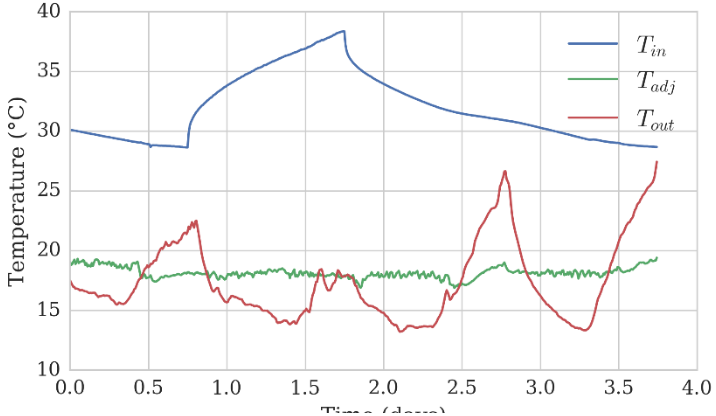
Steady-state energy balance over the building

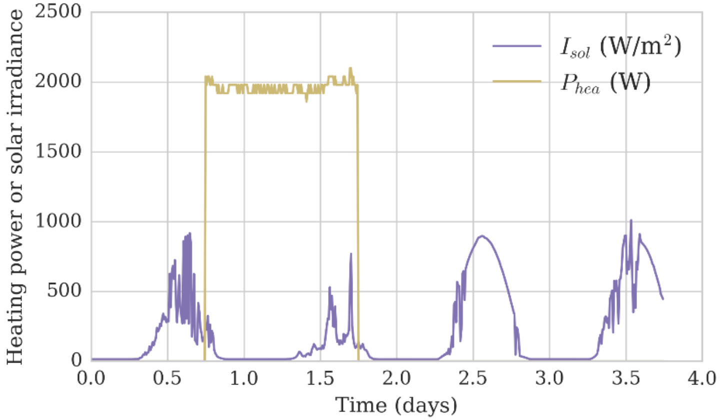
$$Q_h = -A_s I_{sol} + HLC(T_{in} - T_{ext}) + c$$

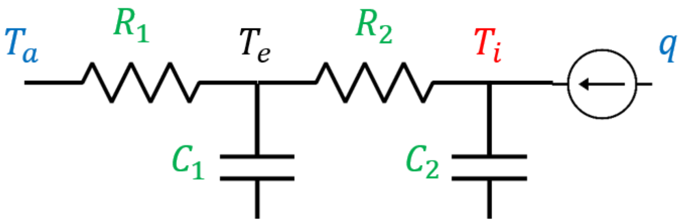


Bauwens, G., & Roels, S. (2014). Co-heating test: A state-of-the-art. *Energy and Buildings*, *82*, 163-172

Second example: dynamic methods







$$u = \begin{bmatrix} T_a \\ q \end{bmatrix} \qquad x = \begin{bmatrix} T_e \\ T_i \end{bmatrix} \qquad y = T_i \qquad \theta = \begin{bmatrix} R_1 \\ R_2 \\ C_1 \\ C_2 \end{bmatrix}$$

$$\begin{bmatrix} \dot{T}_e(t) \\ \dot{T}_i(t) \end{bmatrix} = \begin{bmatrix} -\frac{1}{R_1 C_1} - \frac{1}{R_2 C_1} & \frac{1}{R_2 C_1} \\ \frac{1}{R_2 C_2} & -\frac{1}{R_2 C_2} \end{bmatrix} \begin{bmatrix} T_e(t) \\ T_i(t) \end{bmatrix} + \begin{bmatrix} \frac{1}{R_1 C_1} & 0 \\ 0 & \frac{1}{C_2} \end{bmatrix} \begin{bmatrix} T_a(t) \\ q(t) \end{bmatrix}$$

- Pick an initial value for θ
- Predict T_i and see if it matches measurements
- Repeat until the best fit is found

- Include the influence of modelling errors with a <u>stochastic</u> state-space model

State space model (continuous)

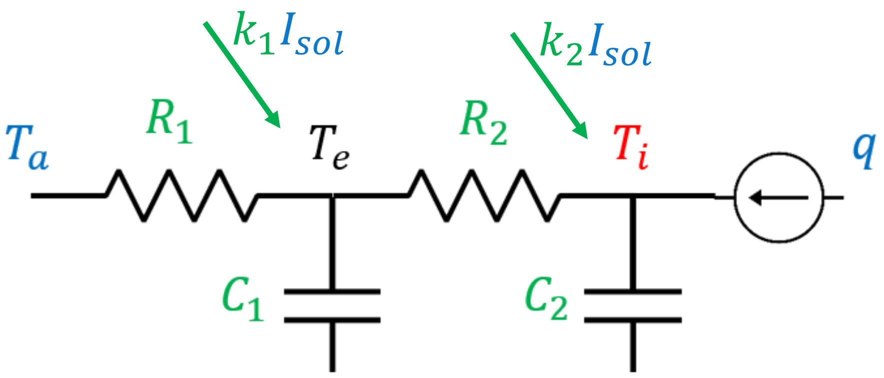
$$\dot{\mathbf{T}}(t) = \mathbf{A}(\theta)\,\mathbf{T}(t) + \mathbf{B}(\theta)\,\mathbf{u}(t) + \mathbf{w}(t)$$
$$\mathbf{y}(t) = \mathbf{C}(\theta)\,\mathbf{T}(t) + \mathbf{v}(t)$$

State space model (discrete)

$$\mathbf{x}_{t+1} = \mathbf{F}\,\mathbf{x}_t + \mathbf{G}\,\mathbf{u}_t + \mathbf{w}_t$$
$$\mathbf{y}_t = \mathbf{C}\,\mathbf{x}_t + \mathbf{v}_t$$

Modelling and measurement errors

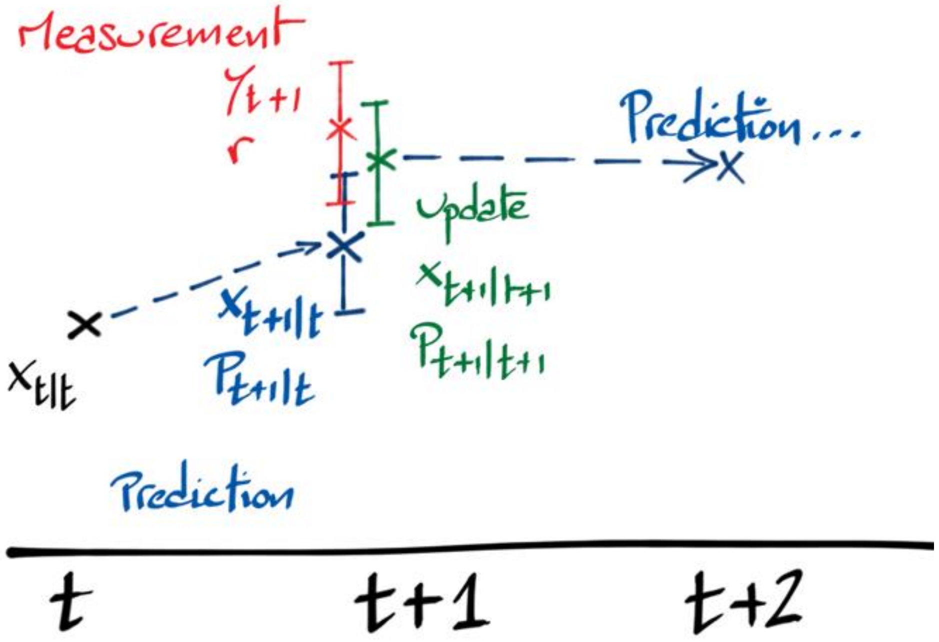
$$\boldsymbol{w_t} \sim N(0, \mathbf{Q})$$
$$\boldsymbol{v_t} \sim N(0, \mathbf{R})$$



$$u = \begin{bmatrix} T_a \\ q \end{bmatrix} \qquad x = \begin{bmatrix} T_e \\ T_i \end{bmatrix} \qquad y = T_i \qquad \theta = \begin{bmatrix} R_1 \\ R_2 \\ C_1 \\ C_2 \end{bmatrix}$$

k_1
k_2

Kalman filter: estimate the new state, given the prediction and measurement errors



Notations

$\mathbf{x}_{t|s} = \mathrm{E}(x_t | y_{1:s}, \theta)$

$\mathbf{P}_{t|s} = \mathrm{Var}(x_t | y_{1:s}, \theta)$

Prediction

$\mathbf{x}_{t+1|t} = \mathbf{F}\,\mathbf{x}_{t|t} + \mathbf{G}\,\mathbf{u}_t$

$\mathbf{P}_{t+1|t} = \mathbf{F}\,\mathbf{x}_{t|t}\mathbf{F}^{\mathbf{T}} + \mathbf{Q}$

Innovation

$\epsilon_{t+1} = \mathbf{y}_{t+1} - \mathbf{C}\,\mathbf{x}_{t+1|t}$

$\boldsymbol{\Sigma}_{t+1} = \mathbf{C}\,\mathbf{P}_{t+1|t}\mathbf{C}^T + \mathbf{R}$

$\mathbf{K}_{t+1} = \mathbf{P}_{t+1|t}\,\mathbf{C}^T\,\boldsymbol{\Sigma}_{t+1}^{-1}$

Update

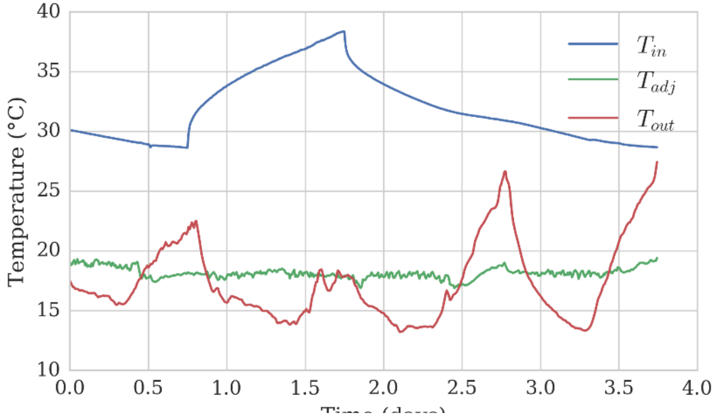
$\mathbf{x}_{t+1|t+1} = \mathbf{x}_{t+1|t} + \mathbf{K}_{t+1}\epsilon_{t+1}$

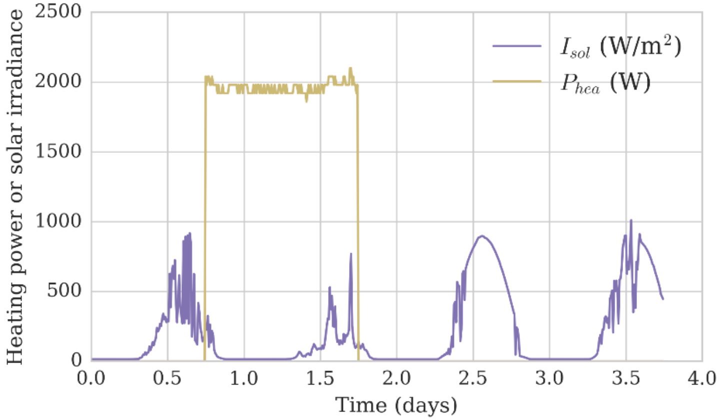
$\mathbf{P}_{t+1|t+1} = (\mathbf{I} - \mathbf{K}_t\mathbf{C})\mathbf{P}_{t+1|t}$

Likelihood

$$-\ln \boldsymbol{L}_y(\theta) = \frac{1}{2}\sum_{t=1}^{N} \ln|\boldsymbol{\Sigma}_t(\theta)| + \frac{1}{2}\sum_{t=1}^{N} \epsilon_t(\theta)^T \boldsymbol{\Sigma}_t(\theta)^{-1}\epsilon_t(\theta)$$

Second example: dynamic methods





- Pick a model $$\dot{\mathbf{T}}(t) = \mathbf{A}(\theta)\,\mathbf{T}(t) + \mathbf{B}(\theta)\,\mathbf{u}(t) + \mathbf{w}(t)$$ $$\mathbf{y}(t) = \mathbf{C}(\theta)\,\mathbf{T}(t) + \mathbf{v}(t)$$

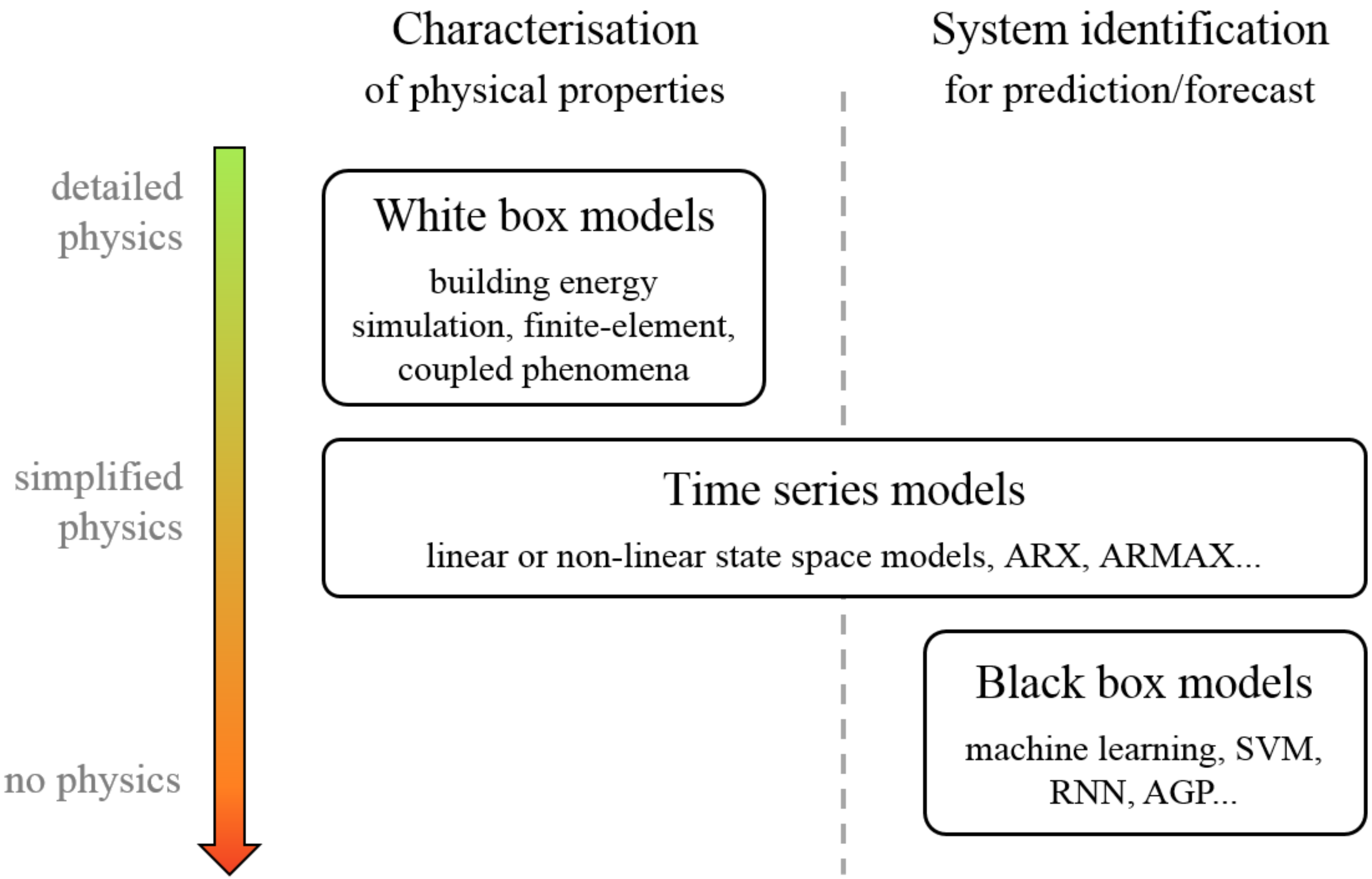
- Pick an initial value for θ

- Run the Kalman filter to get the log-likelihood

$$-\ln \boldsymbol{L}_y(\theta) = \frac{1}{2}\sum_{t=1}^{N} \ln|\boldsymbol{\Sigma}_t(\theta)| + \frac{1}{2}\sum_{t=1}^{N} \epsilon_t(\theta)^T \boldsymbol{\Sigma}_t(\theta)^{-1}\epsilon_t(\theta)$$

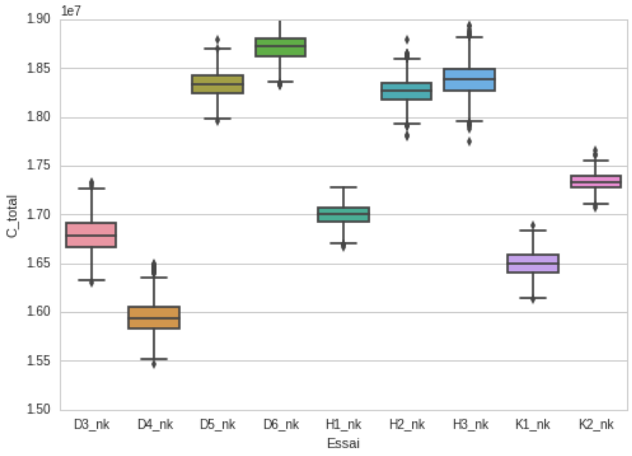
- Minimise the log-likelihood with your favorite method

$$\rightarrow \hat{\theta}, \mathrm{cov}\left(\hat{\theta}\right)$$


Characterisation
of physical properties
System identification
for prediction/forecast
detailed
physics
simplified
physics
no physics
White box models
building energy
simulation, finite-element,
coupled phenomena
Time series models
linear or non-linear state space models, ARX, ARMAX...
Black box models
machine learning, SVM,
RNN, AGP...

$$\hat{\theta}$$

$$\mathrm{cov}(\hat{\theta})$$



2. The validation of results

How do I know if I can trust my results?

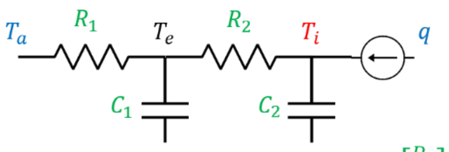
Identifiability

Ability of a parameter to be identified by a given data set and choice of model

$$y(\theta) = y(\tilde{\theta}) \Rightarrow \theta = \tilde{\theta}$$

Structural identifiability

tells if parameter estimation is theoretically possible with a given model structure



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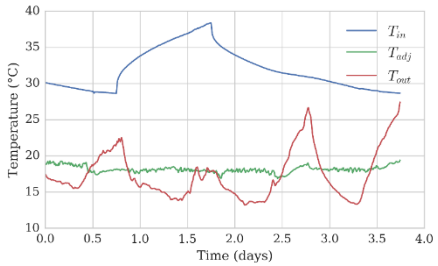
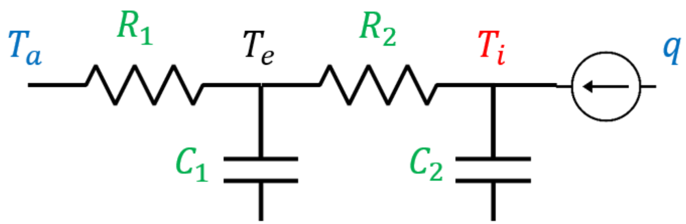
Practical identifiability

relates parameter estimation results with the available data



Before model calibration

1. Test for structural identifiability (linear models)



$u = \begin{bmatrix} T_a \\ q \end{bmatrix}$ $\quad x = \begin{bmatrix} T_e \\ T_i \end{bmatrix}$ $\quad y = T_i$ $\quad \theta = \begin{bmatrix} R_1 \\ R_2 \\ C_1 \\ C_2 \end{bmatrix}$

$$\dot{\mathbf{x}}(t) = \mathbf{A}(\theta)\mathbf{x}(t) + \mathbf{B}(\theta)\mathbf{u}(t)$$
$$\mathbf{y}_k = \mathbf{C}(\theta)\mathbf{x}_k$$

$$s\,\mathbf{X}(s) = \mathbf{A}\,\mathbf{X}(s) + \mathbf{B}\,\mathbf{U}(s)$$
$$\mathbf{Y}(s) = \mathbf{C}\,\mathbf{U}(s)$$

$$\mathbf{H}(s,\theta) = \frac{\mathbf{Y}(s)}{\mathbf{U}(s)} = \mathbf{C}\left(s\mathbf{I}_2 - \mathbf{A}\right)^{-1}\mathbf{B}$$
$$= \frac{1}{s^2 + \frac{C_1R_1 + C_2R_1 + C_2R_2}{C_1C_2R_1R_2}s + \frac{1}{C_1C_2R_1R_2}} \begin{bmatrix} \frac{1}{C_1C_2R_1R_2} & \frac{1}{C_2}s + \frac{R_1+R_2}{C_1C_2R_1R_2} \end{bmatrix}$$

$$\frac{C_1R_1 + C_2R_1 + C_2R_2}{C_1C_2R_1R_2} = \frac{\tilde{C}_1\tilde{R}_1 + \tilde{C}_2\tilde{R}_1 + \tilde{C}_2\tilde{R}_2}{\tilde{C}_1\tilde{C}_2\tilde{R}_1\tilde{R}_2}$$
$$\frac{1}{C_1C_2R_1R_2} = \frac{1}{\tilde{C}_1\tilde{C}_2\tilde{R}_1\tilde{R}_2}$$
$$\frac{1}{C_2} = \frac{1}{\tilde{C}_2}$$
$$\frac{R_1+R_2}{C_1C_2R_1R_2} = \frac{\tilde{R}_1+\tilde{R}_2}{\tilde{C}_1\tilde{C}_2\tilde{R}_1\tilde{R}_2}$$

$$y(\theta) = y(\tilde{\theta}) \Rightarrow \theta = \tilde{\theta}$$

Before model calibration

2. Sensitivity analysis

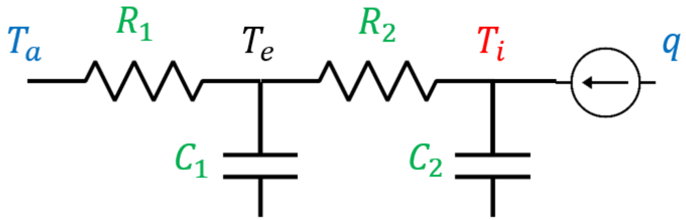


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Table 3: FAST sensitivity analysis of the 2R2C parameters to the least-square criterion

Parameter	First order index	Total order index
R_1 (W/K)	0.467	0.753
R_2 (W/K)	0.012	0.049
C_1 (J/K)	0.001	0.030
C_2 (J/K)	0.001	0.005
$T_e(0)$ (C)	0.207	0.467

LOCIE

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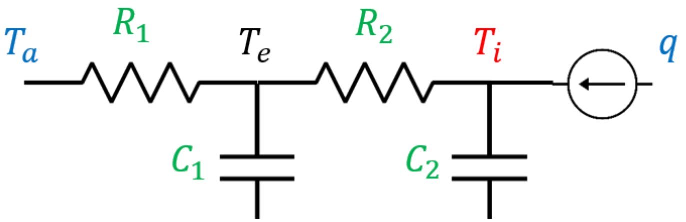
After model calibration



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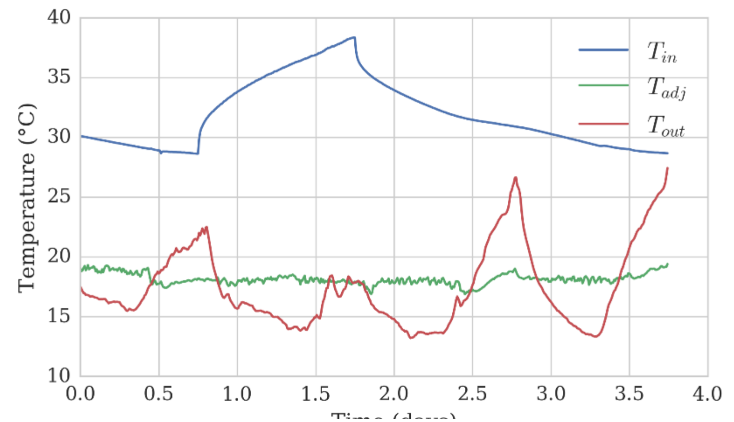
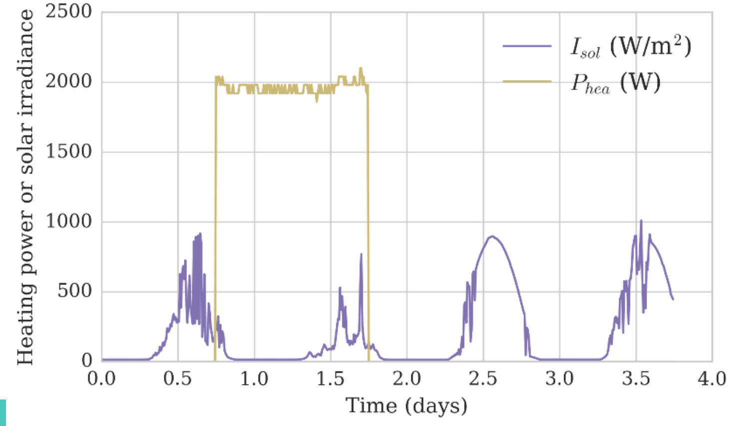




Statistical test for parameter significance

Parameter	Initial guess	$\hat{\theta}_{LS}$	$\sigma_{\hat{\theta}}$	t-statistic	p-value
R_1 (W/K)	1×10^{-2}	2.13×10^{-2}	5.45×10^{-5}	392	< 0.01
R_2 (W/K)	1×10^{-2}	2.37×10^{-3}	2.27×10^{-5}	104	< 0.01
C_1 (J/K)	1×10^{7}	1.56×10^{7}	8.93×10^{4}	175	< 0.01
C_2 (J/K)	1×10^{7}	1.93×10^{6}	5.22×10^{4}	37	< 0.01
$T_e(0)$ (C)	20	30.27	2.36×10^{-2}	1281	< 0.01

Identifiability analysis

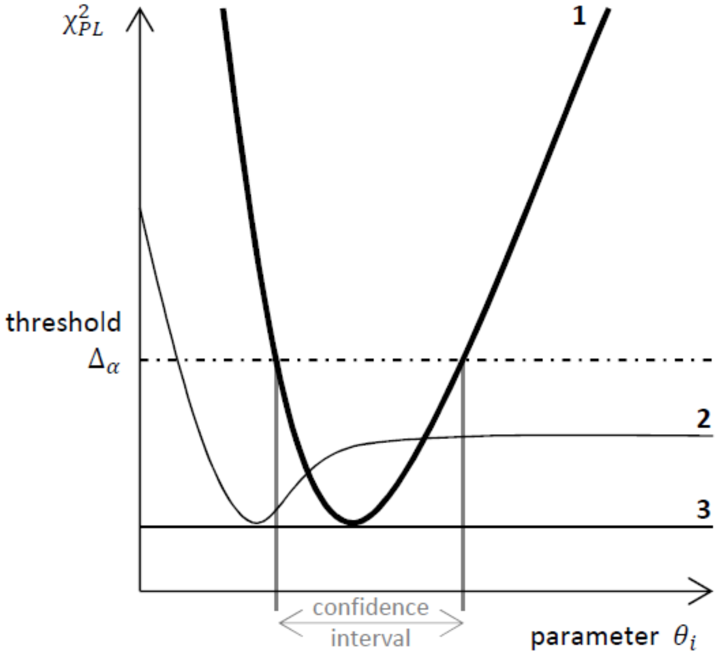
"Profile likelihood" function

$$L(\boldsymbol{\theta}; \boldsymbol{Y}_N) = p(\boldsymbol{Y}_N|\boldsymbol{\theta}) = \left(\prod_{k=1}^{N} p(\boldsymbol{y}_k|\boldsymbol{Y}_{k-1}, \boldsymbol{\theta})\right) p(\boldsymbol{y}_0|\boldsymbol{\theta})$$

$$\hat{\boldsymbol{\theta}} = arg \max_{\boldsymbol{\theta}} \left(L(\boldsymbol{\theta}; \boldsymbol{Y}_N|\boldsymbol{y}_0)\right)$$

$$PL(\theta_i) = \max_{\theta_{j\neq i}} \left(L(\boldsymbol{\theta}; \boldsymbol{Y}_N)\right)$$

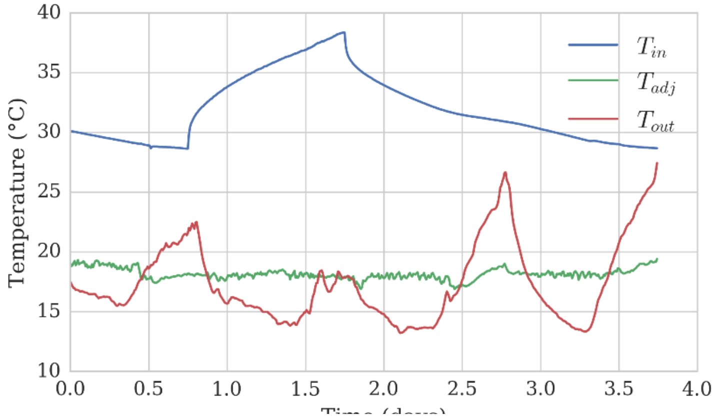
$$\left\{\theta_i : \chi^2_{PL} = -2log\left(\frac{PL(\theta_i)}{L(\hat{\boldsymbol{\theta}}; \boldsymbol{Y}_N)}\right) < \Delta_\alpha\right\}$$

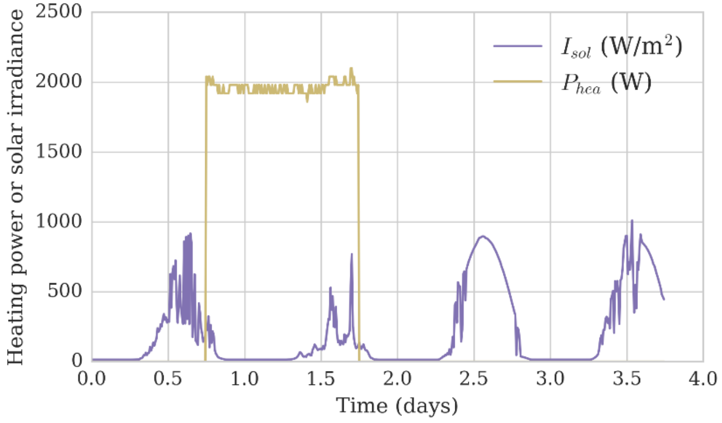


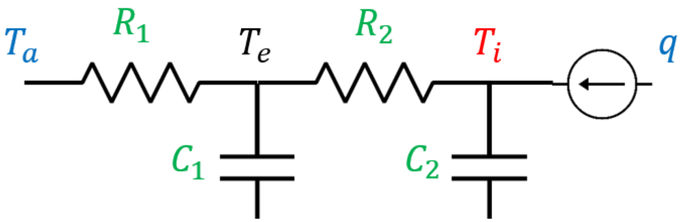
1. identifiable
2. practically unidentifiable
3. structurally unidentifiable

Deconinck, A. H., & Roels, S. (2017). Is stochastic grey-box modelling suited for physical properties estimation of building components from on-site measurements?. *Journal of Building Physics*, *40*(5), 444-471.

After model calibration







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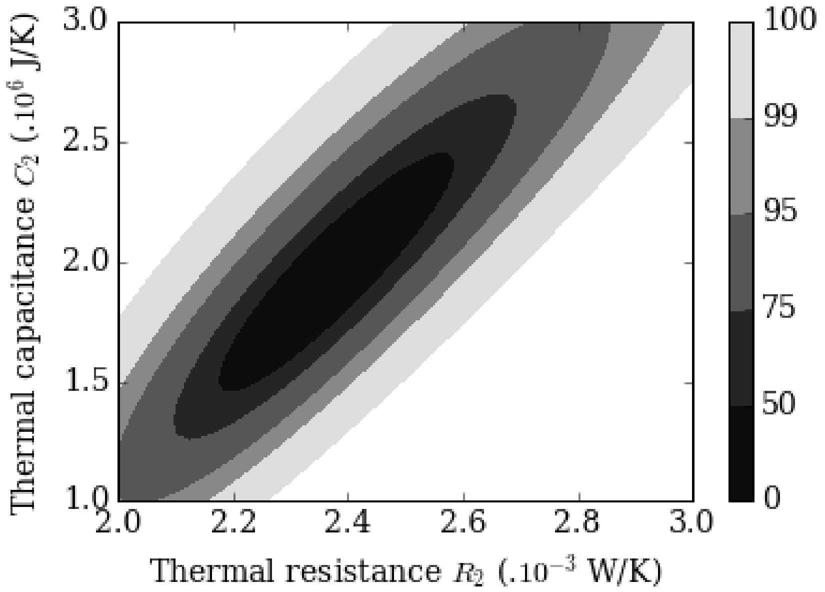
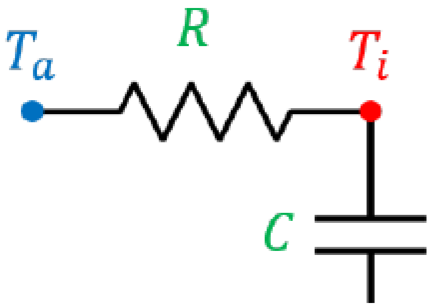
Test for parameter interactions

	R_1	R_2	C_1	C_2	$T_e(0)$
R_1	1	-0.22	0.09	-0.41	-0.59
R_2	-0.22	1	0.37	0.79	-0.43
C_1	0.09	0.037	1	0.13	-0.24
C_2	-0.41	0.79	0.13	1	-0.10
$T_e(0)$	-0.59	-0.43	-0.24	0.10	1

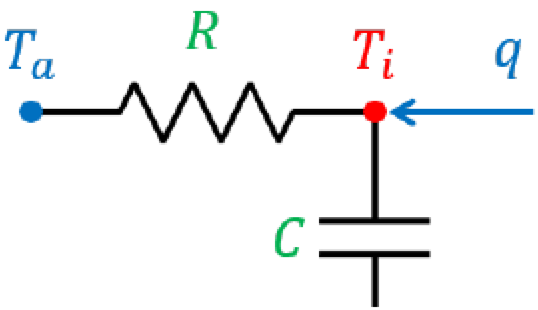


Identifiability analysis



(a)

Structurally non-identifiable

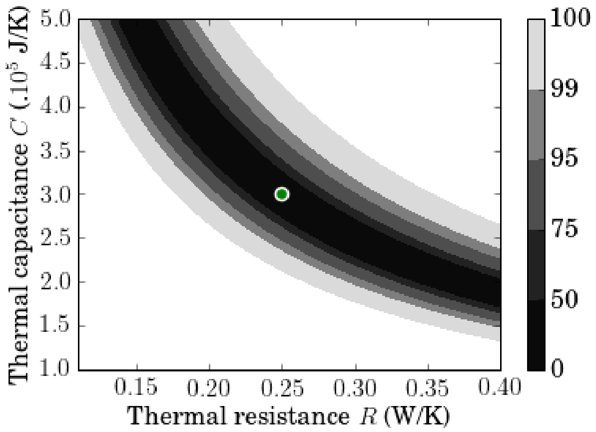


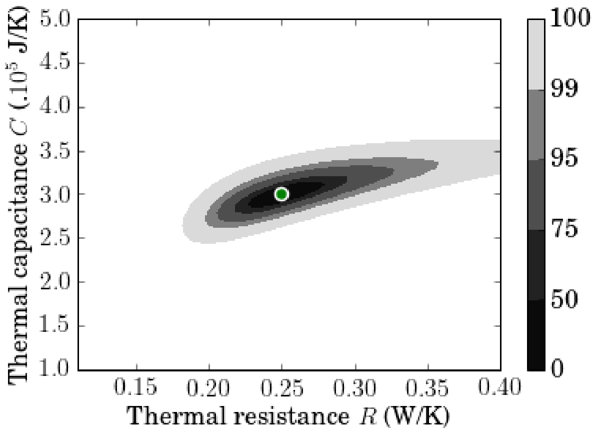
(b)

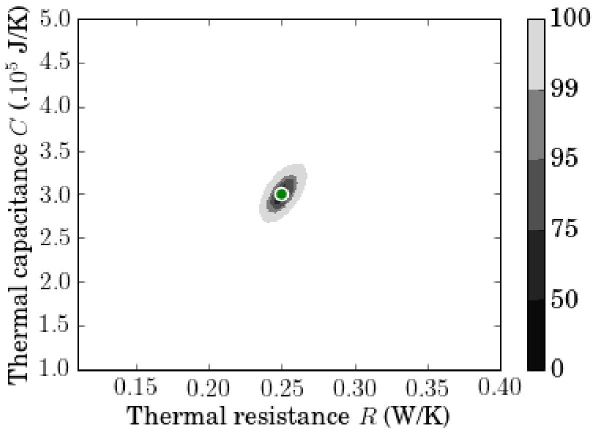
Structurally identifiable

Very poor heating signal q

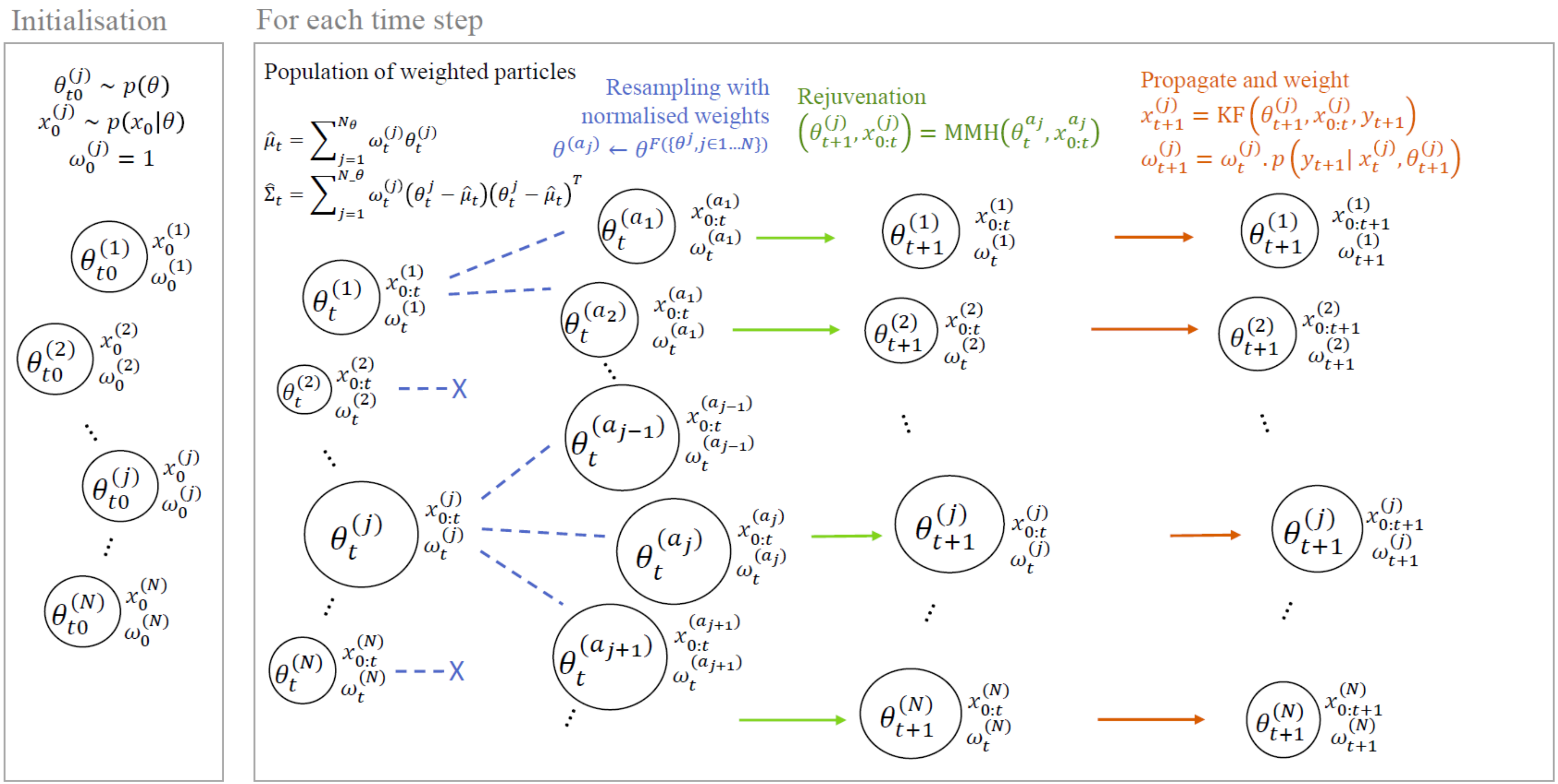
Very rich heating signal q

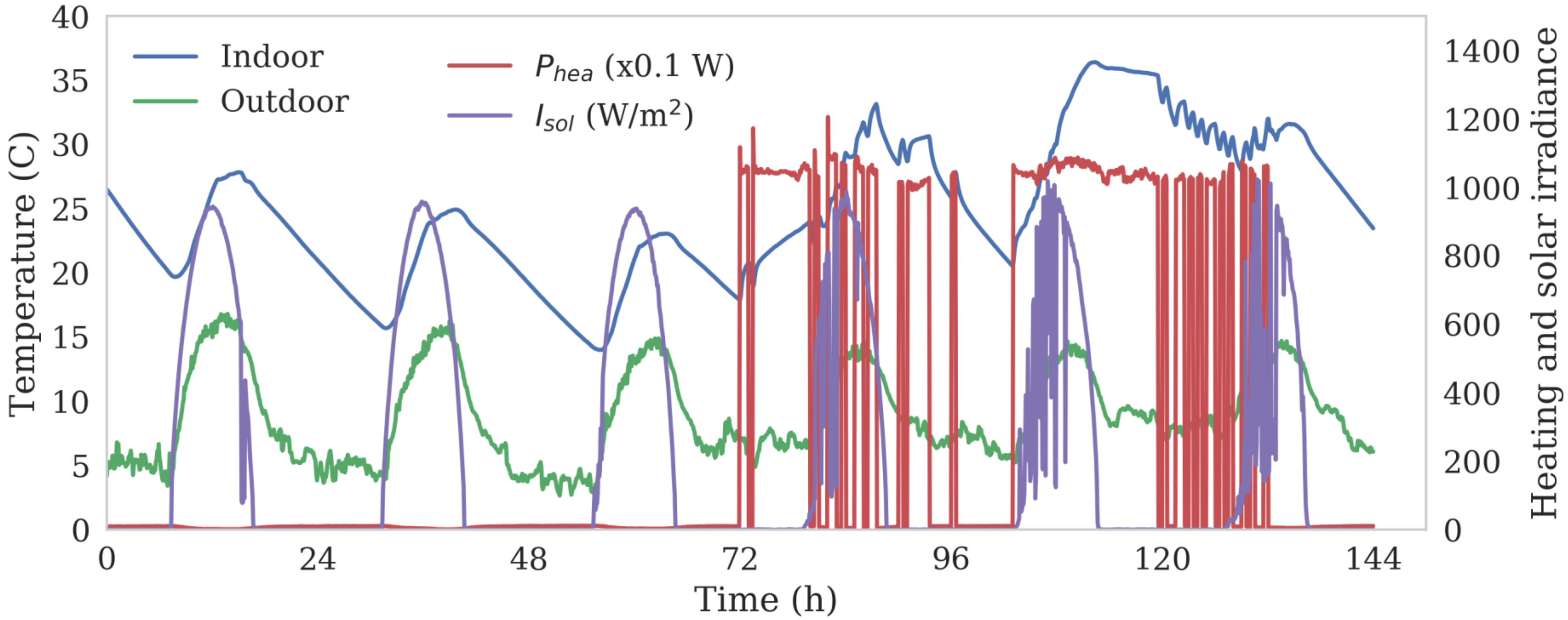


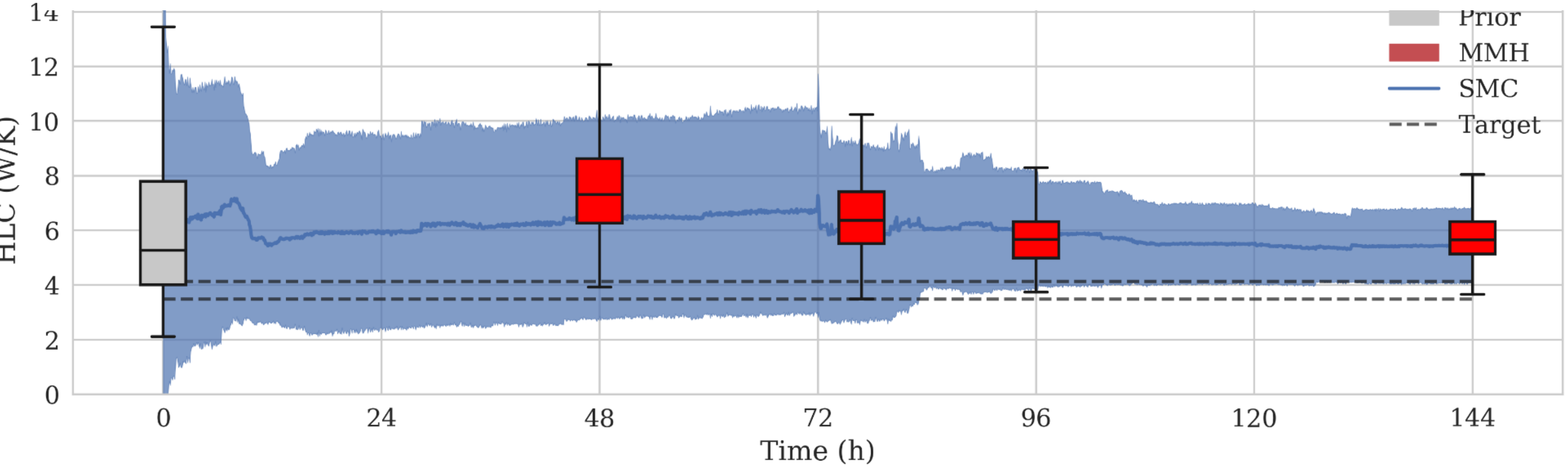




Sequential Monte Carlo



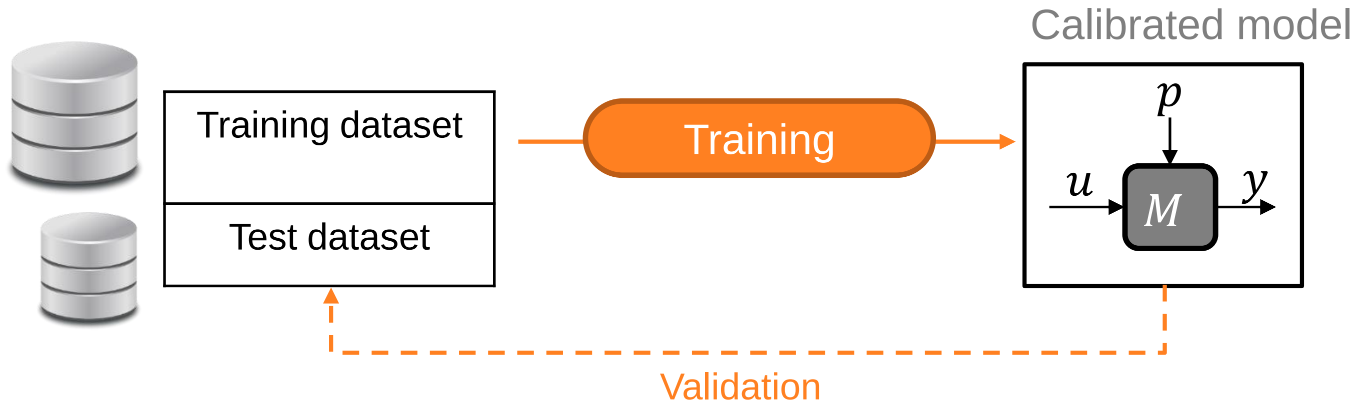


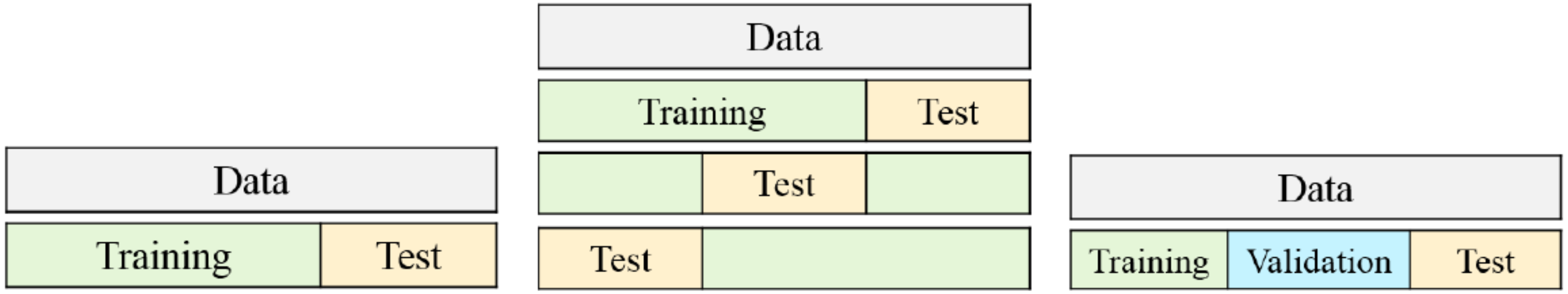


Rouchier S, Jiménez MJ, Castaño S (2018) Sequential Monte Carlo for on-line parameter estimation of a lumped building energy model, *Energy and Buildings* (under publication)

Out-of-sample validation

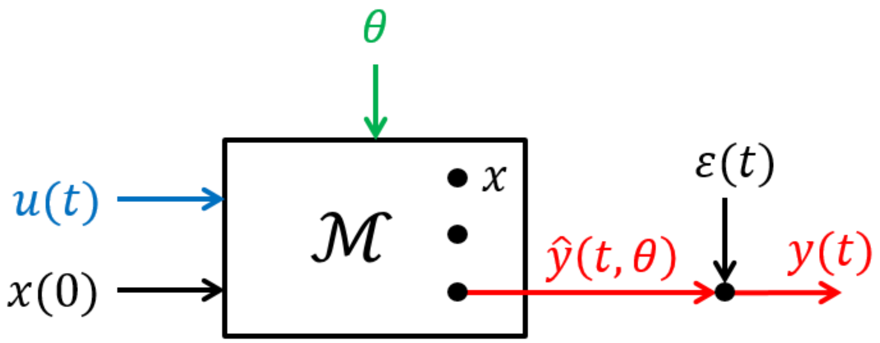
Test for prediction ability

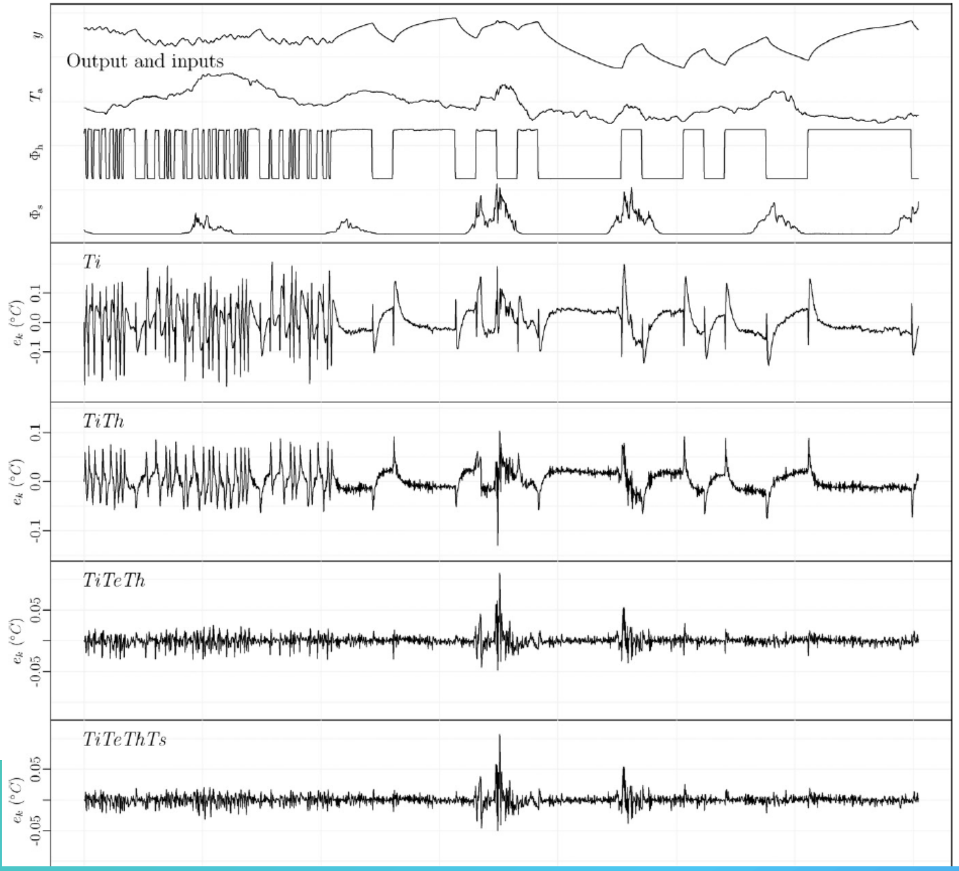




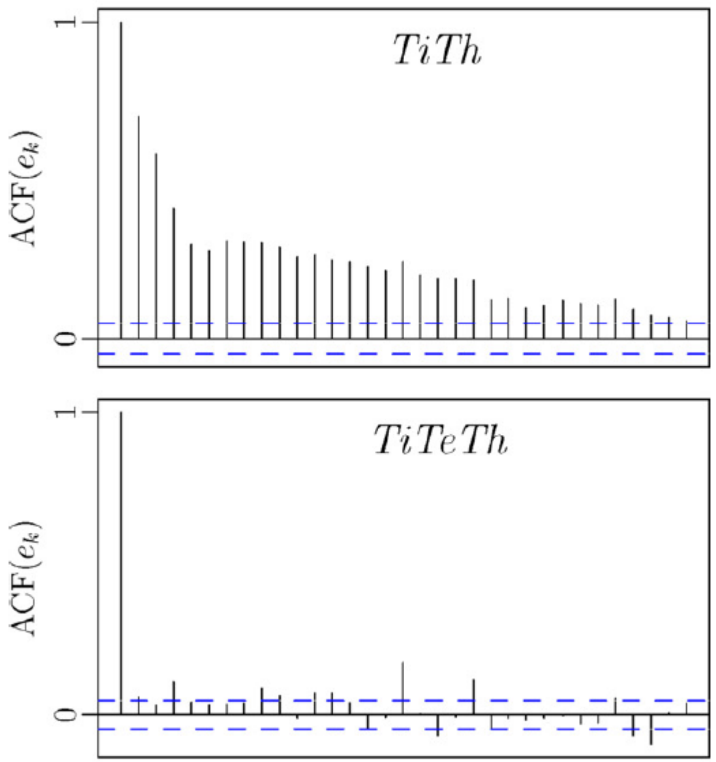
In-sample validation

Test for white-noise residuals



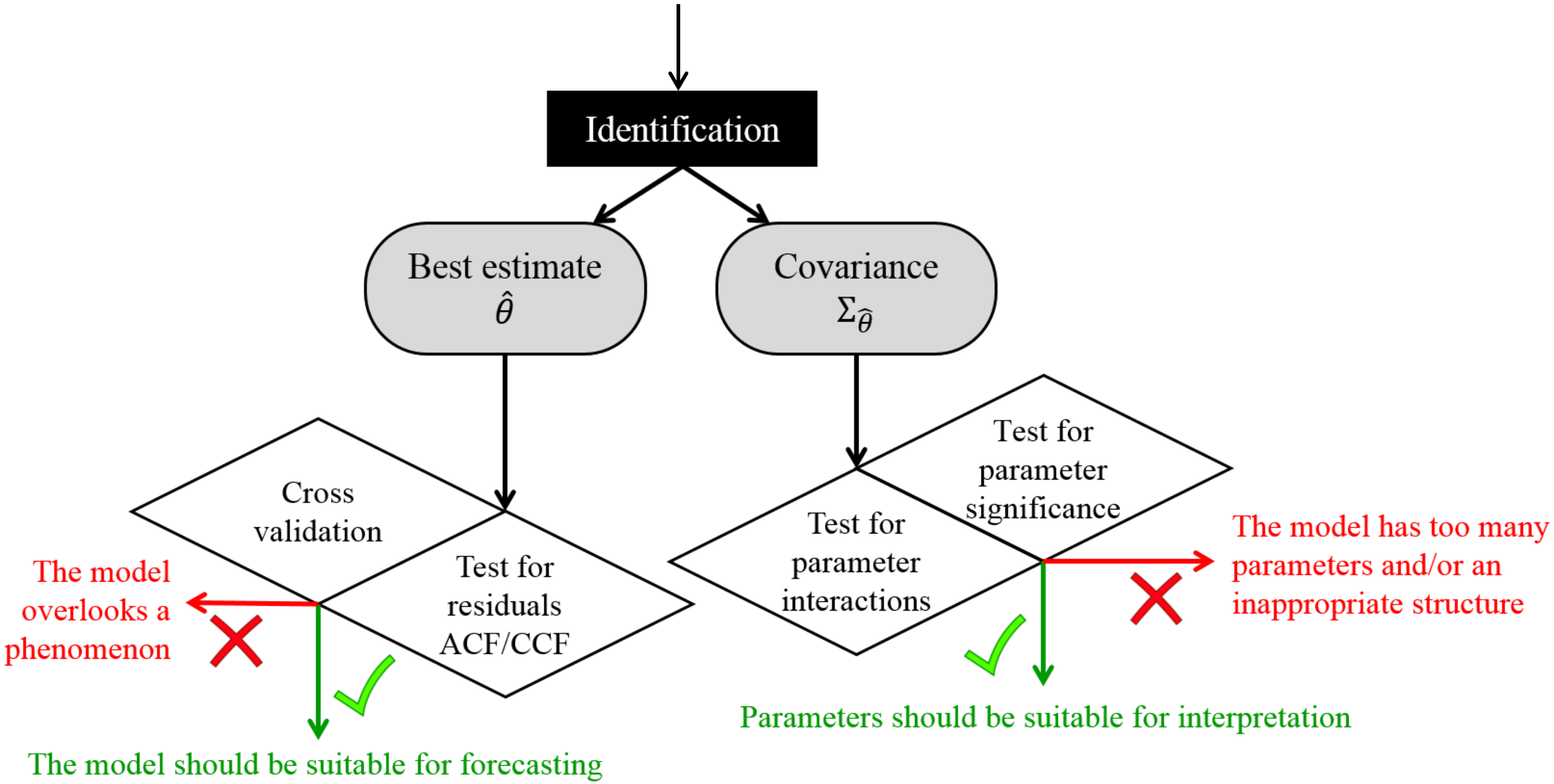


Autocorrelation function
Cross-correlation function



Bacher, P., & Madsen, H. (2011). Identifying suitable models for the heat dynamics of buildings. *Energy and Buildings*, *43*(7), 1511-1522.

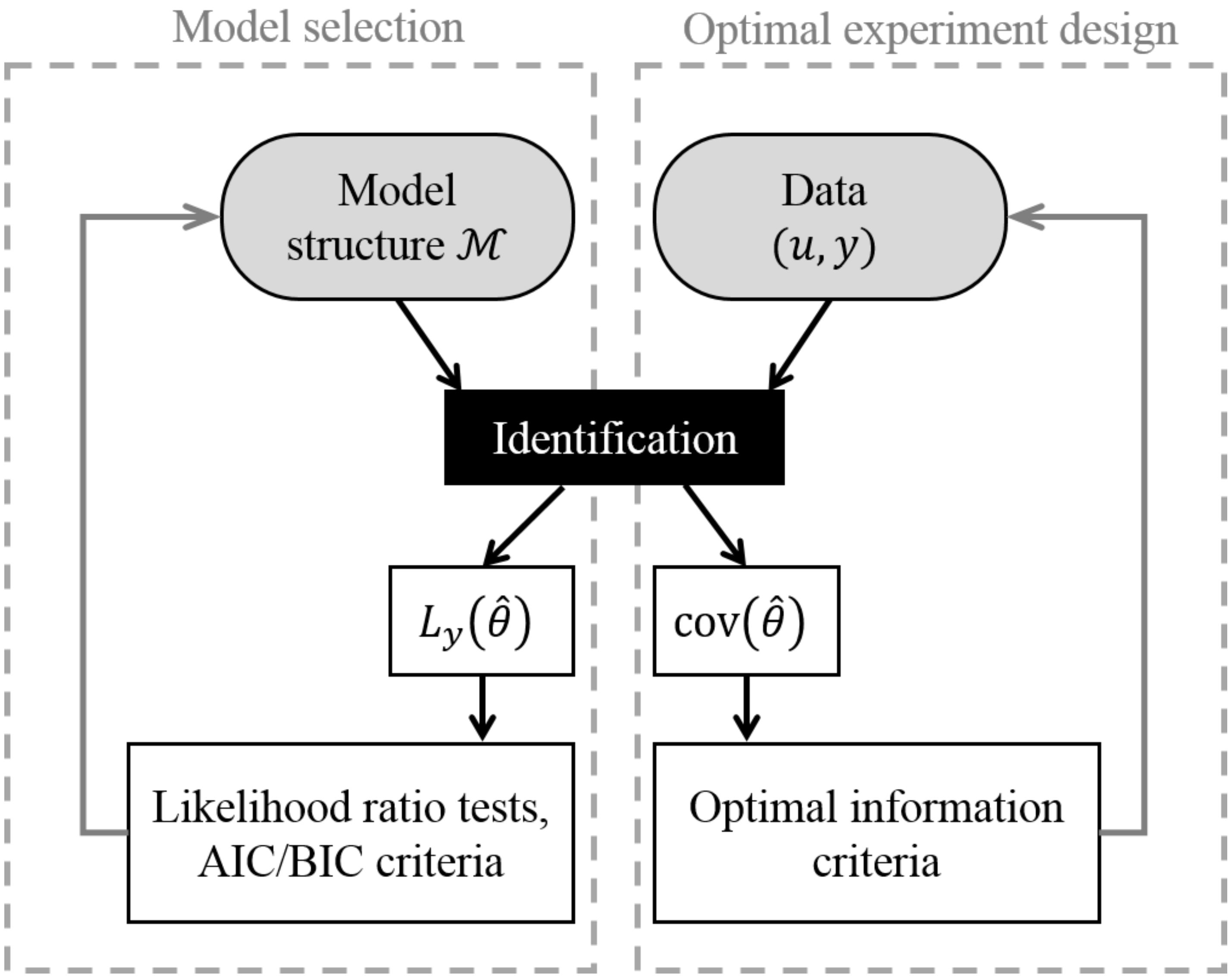
- Test for structural identifiability
- Sensitivity analysis



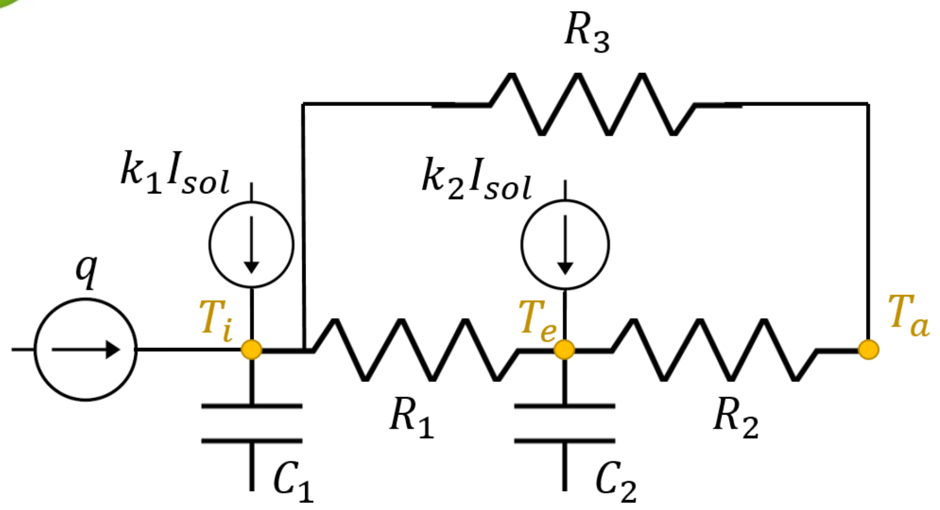
Rouchier S (2018) Solving inverse problems in building physics: An overview of guidelines for a careful and optimal use of data, *Energy and Buildings*, vol. 166, p. 178-195 okay but what if my results don’t pass all these tests?

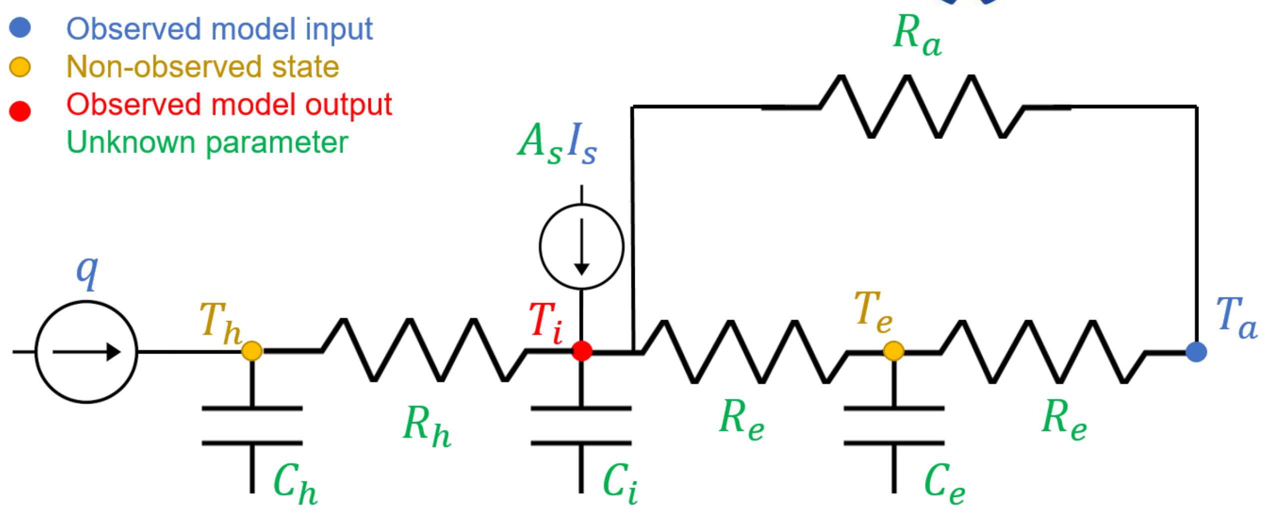
3. Model selection and optimal experiment design

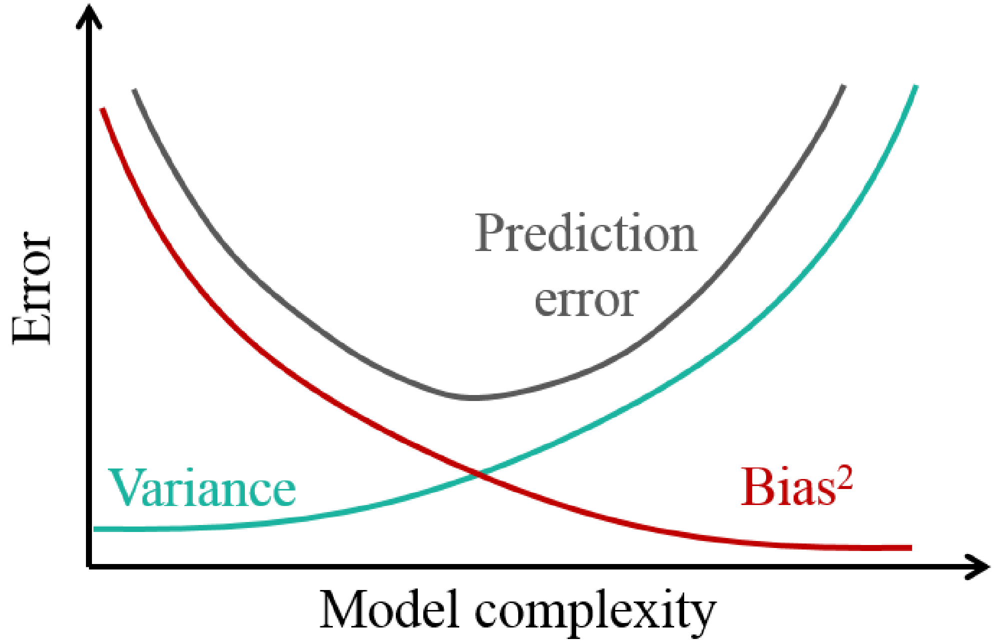
how to make results better!



Model selection
Optimal experiment design
Model structure $\mathcal{M}$
Data (u, y)
Identification
$L_y(\hat{\theta})$
$\mathrm{cov}(\hat{\theta})$
Likelihood ratio tests, AIC/BIC criteria
Optimal information criteria

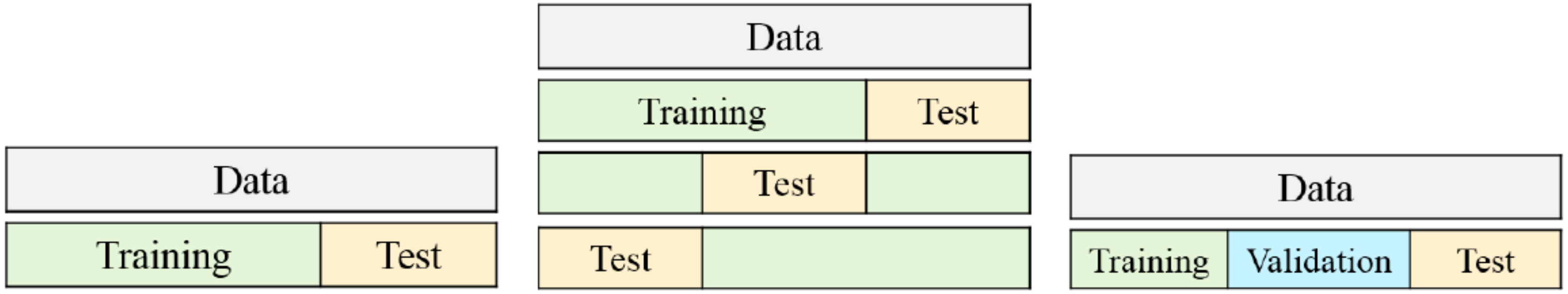

R_3
$k_1 I_{sol}$
$k_2 I_{sol}$
q
T_i
T_e
T_a
R_1
R_2
C_1
C_2


Observed model input
Non-observed state
Observed model output
Unknown parameter
R_a
$A_s I_s$
q
T_h
T_i
T_e
T_a
R_h
R_e
R_e
C_h
C_i
C_e

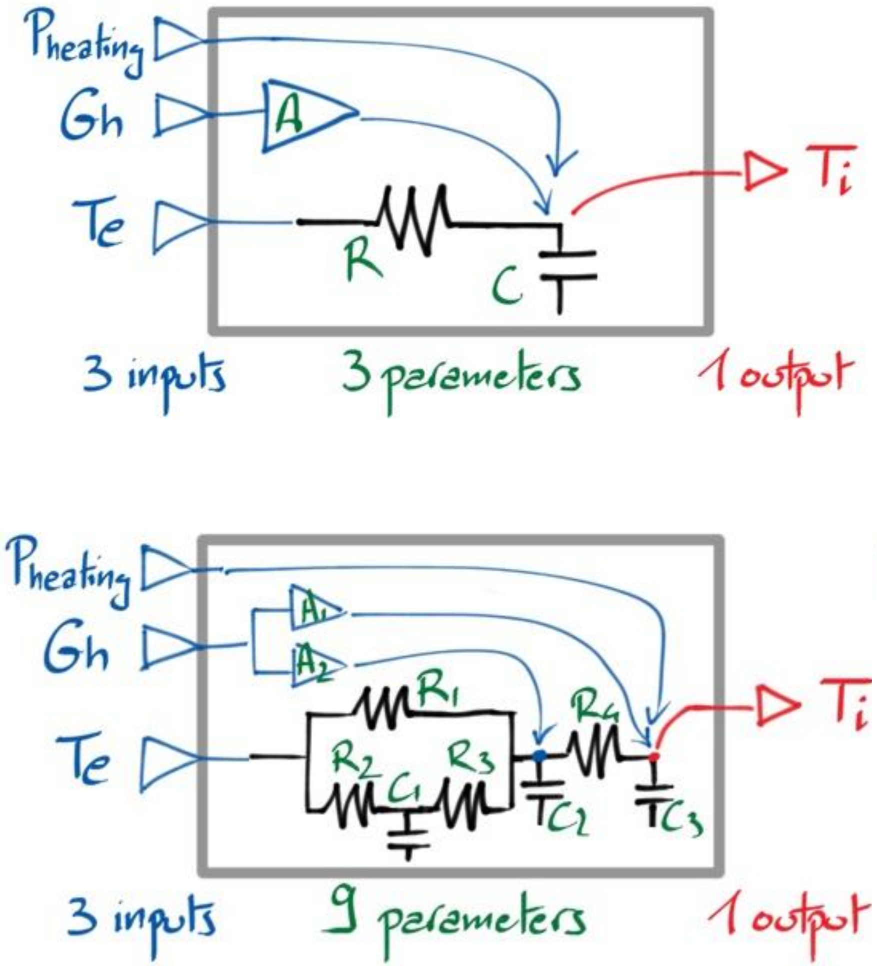

Error
Prediction error
Variance
Bias²
Model complexity

How to select the best model?

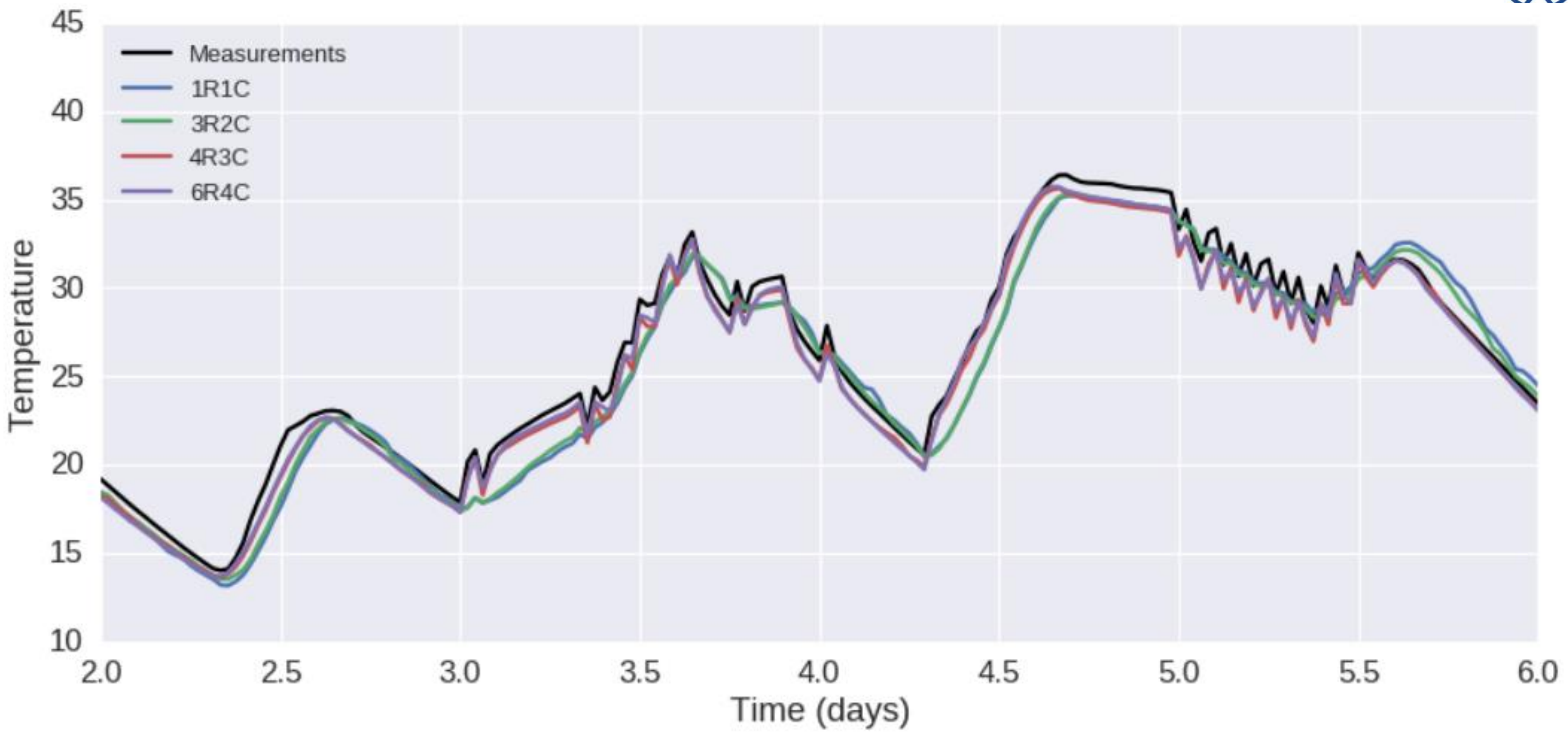
- Out-of-sample selection
    - Prediction error method



- In-sample selection
    - Information criteria
    - Likelihood ratio method



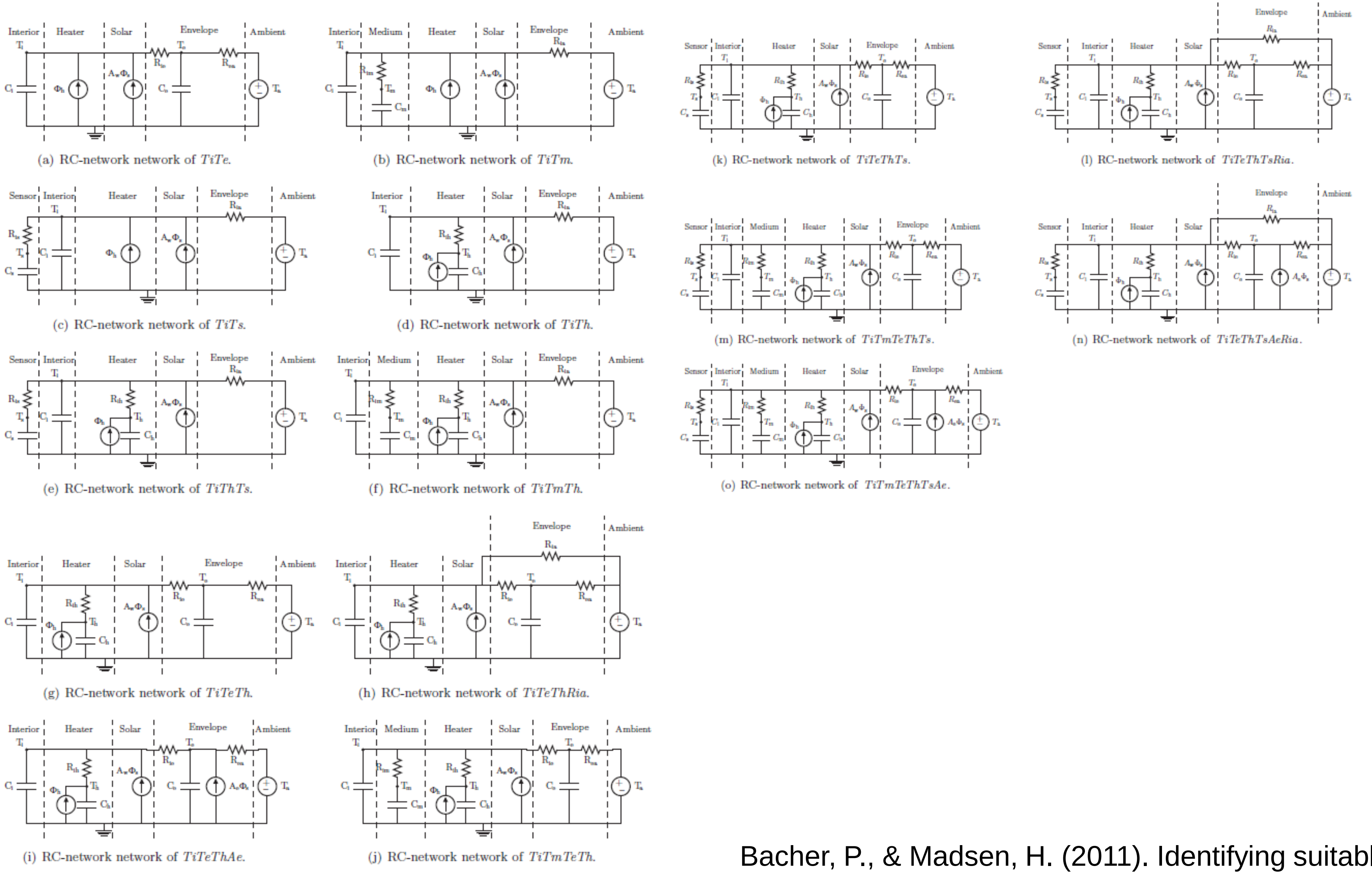
Pheating
Gh
Te
A
R
C
Ti
3 inputs
3 parameters
1 output
Pheating
Gh
Te
A
R1
R2
C1
R3
C2
Ti
3 inputs
6 parameters
1 output
Pheating
Gh
Te
A1
A2
R1
R2
C1
R3
C2
R4
C3
Ti
3 inputs
9 parameters
1 output
Pheating
Gh
Te
C4
A1
A2
R5
R6
R1
R2
C1
R3
C2
R4
C3
Ti
3 inputs
12 parameters
1 output



$$\mathrm{AIC} = r^2(\hat{\theta}) + 2\,k$$

$$\mathrm{BIC} = r^2(\hat{\theta}) + \ln(n)\,k$$

Model	Parameters	$r^2(\hat{\theta})$	AIC	BIC
1R1C	3	450.54	456.54	471.29
3R2C	6	375.25	387.25	416.74
4R3C	9	231.24	249.25	293.49
6R4C	12	205.13	**229.12**	**288.13**



(a) RC-network network of *TiTe*.

(b) RC-network network of *TiTm*.

(c) RC-network network of *TiTs*.

(d) RC-network network of *TiTh*.

(e) RC-network network of *TiThTs*.

(f) RC-network network of *TiTmTh*.

(g) RC-network network of *TiTeTh*.

(h) RC-network network of *TiTeThRia*.

(i) RC-network network of *TiTeThAe*.

(j) RC-network network of *TiTmTeTh*.

(k) RC-network network of *TiTeThTs*.

(l) RC-network network of *TiTeThTsRia*.

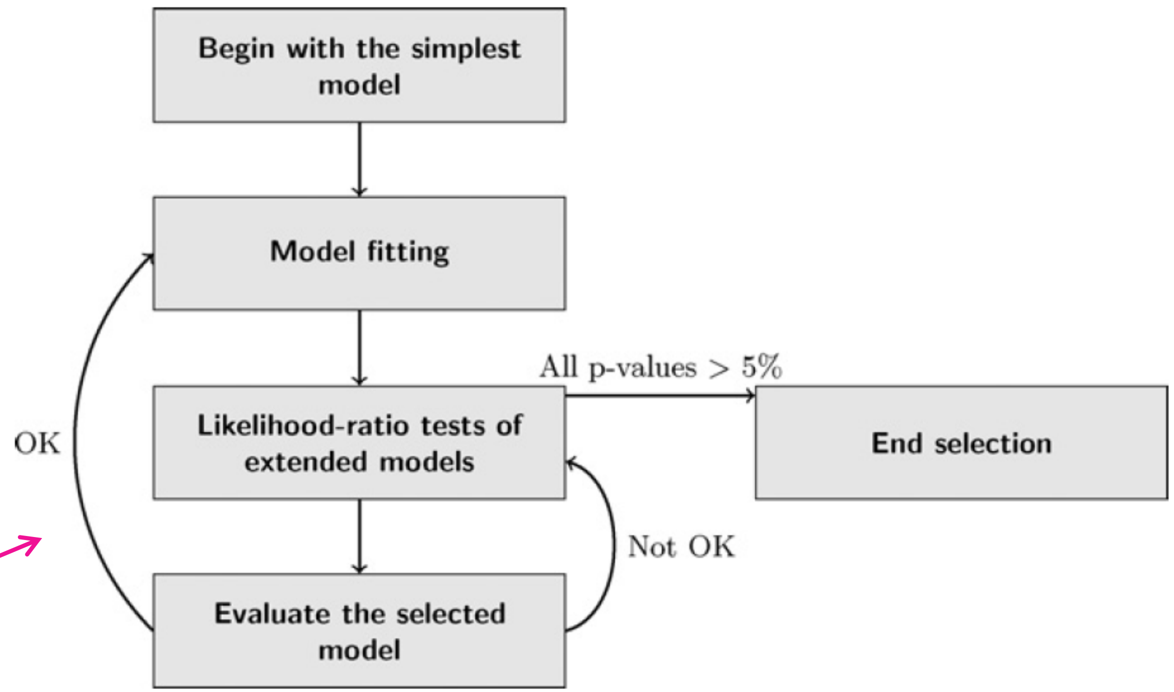
(m) RC-network network of *TiTmTeThTs*.

(n) RC-network network of *TiTeThTsAeRia*.

(o) RC-network network of *TiTmTeThTsAe*.

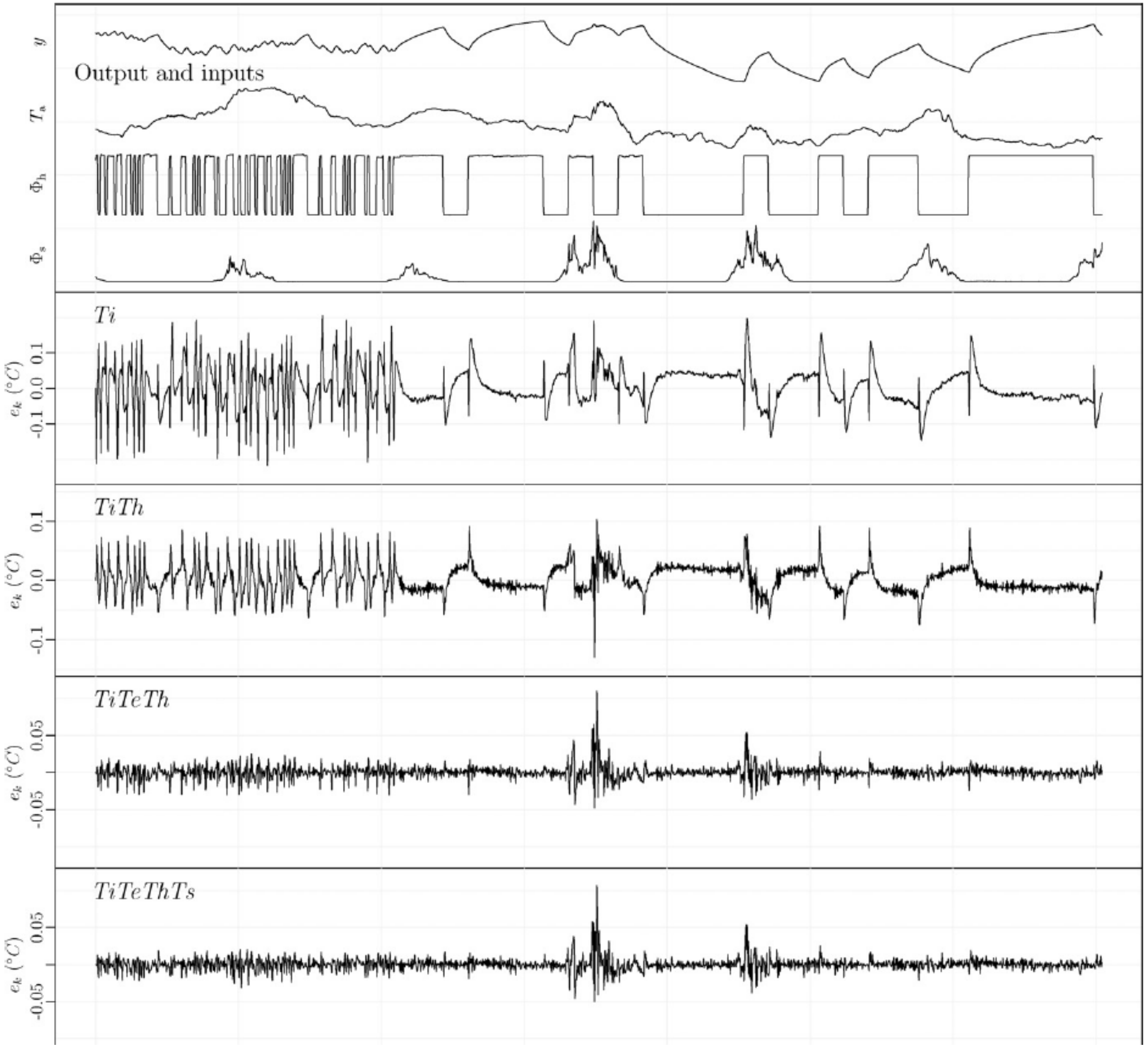
Bacher, P., & Madsen, H. (2011). Identifying suitable models for the heat dynamics of buildings. *Energy and Buildings*, *43*(7), 1511-1522.

Iteration	Models			
Start	*Ti*			
$l(\theta; y_N)$	2482.6			
m	6			
1	*TiTe*	*TiTm*	*TiTs*	*TiTh*
	3628.0	3639.4	3884.4	3911.1
	10	10	10	10
2	*TiThTs*	*TiTmTh*	*TiTeTh*	
	4017.0	5513.1	5517.1	
	14	14	14	
3	*TiTeThRia*	*TiTeThAe*	*TiTmTeTh*	*TiTeThTs*
	5517.3	5520.5	5534.5	5612.4
	15	15	18	18
4	*TiTeThTsRia*	*TiTmTeThTs*	*TiTeThTsAe*	
	5612.5	5612.9	5614.6	
	19	22	19	
5	*TiTmTeThTsAe*	*TiTeThTsAeRia*		
	5614.6	5614.7		
	23	20		



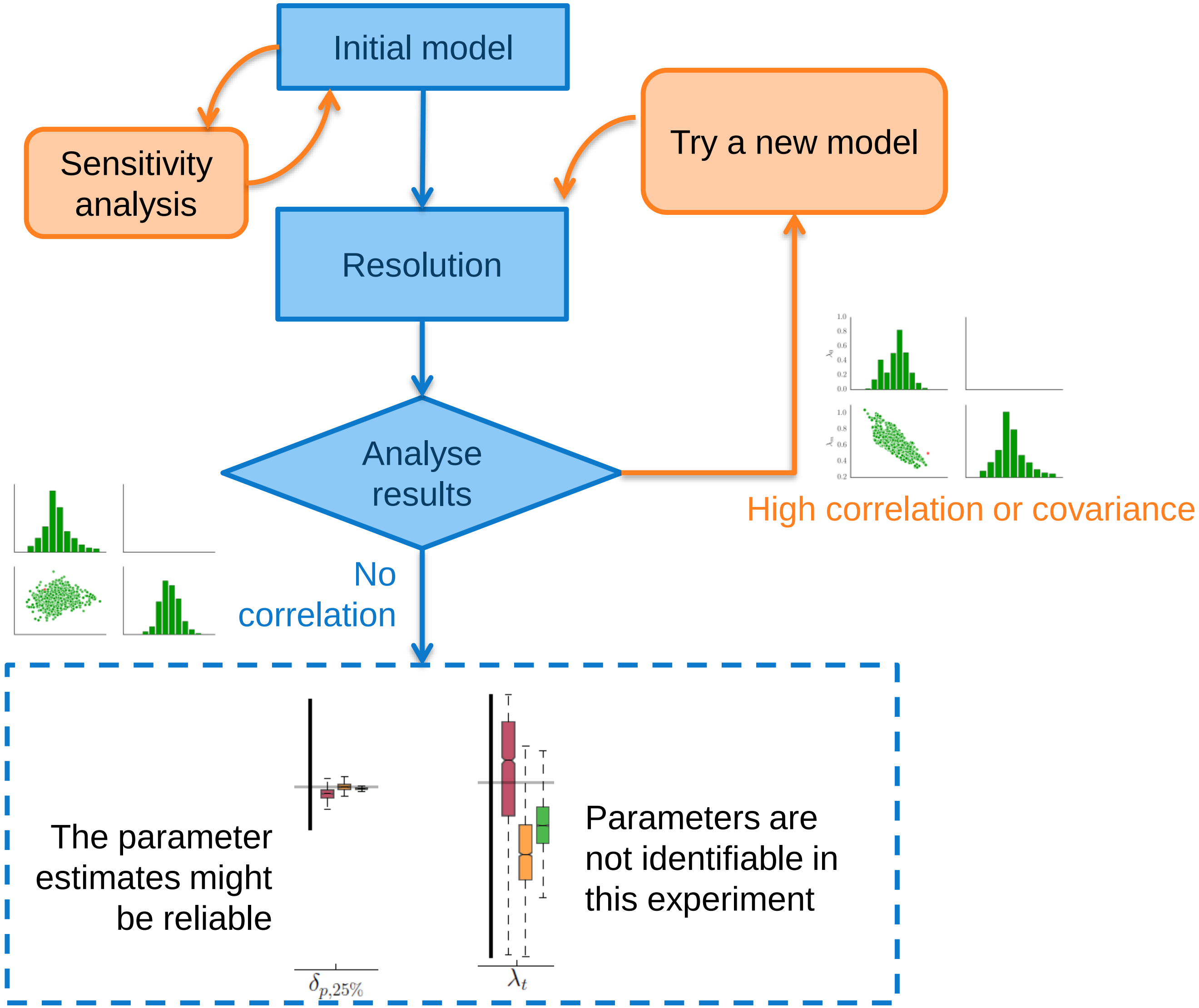
Does increasing model complexity bring me a noticeably better likelihood?

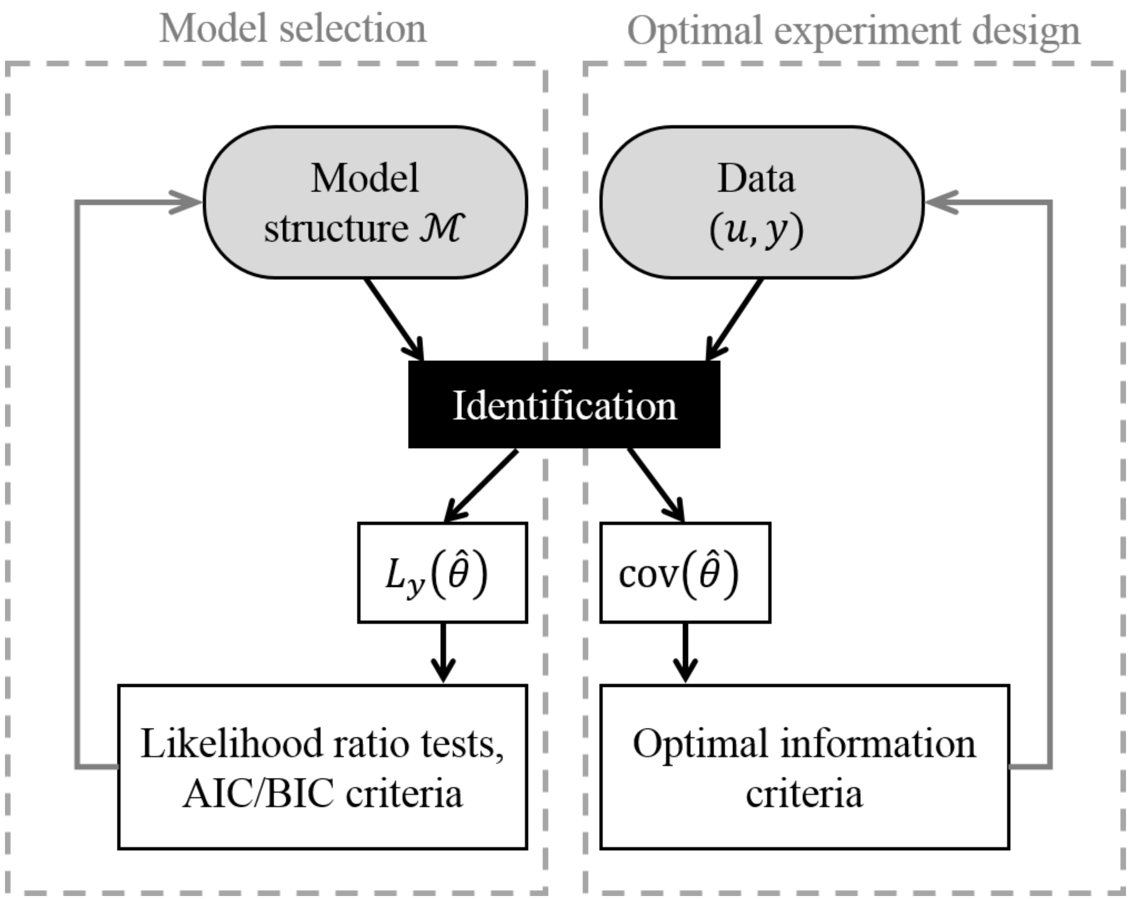
Bacher, P., & Madsen, H. (2011). Identifying suitable models for the heat dynamics of buildings. *Energy and Buildings*, *43*(7), 1511-1522.



Bacher, P., & Madsen, H. (2011). Identifying suitable models for the heat dynamics of buildings. *Energy and Buildings*, *43*(7), 1511-1522.

Output-based selection or parameter-based selection?





Optimal experiment design

$$\mathrm{cov}\left(\hat{\theta}_{ML}\right) = E\left[\left(\hat{\theta}_{ML} - \theta^*\right)\left(\hat{\theta}_{ML} - \theta^*\right)^T\right] \geq \mathbf{F}(\hat{\theta}_{ML})^{-1}$$

$$\mathbf{F}(\theta) = E\left[\left(\frac{\partial \ln L_y(\theta)}{\partial \theta}\right)^T \left(\frac{\partial \ln L_y(\theta)}{\partial \theta}\right)\right]$$

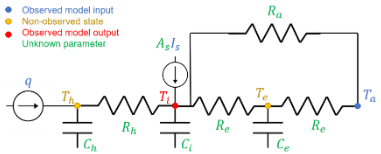
- Optimality criteria $\Psi = \det(\mathbf{F})$

Berger, J., Dutykh, D., & Mendes, N. (2017). On the optimal experiment design for heat and moisture parameter estimation. *Experimental Thermal and Fluid Science*, *81*, 109-122.

Summary

1. The model calibration procedure

+



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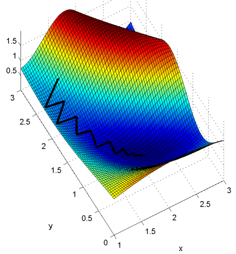
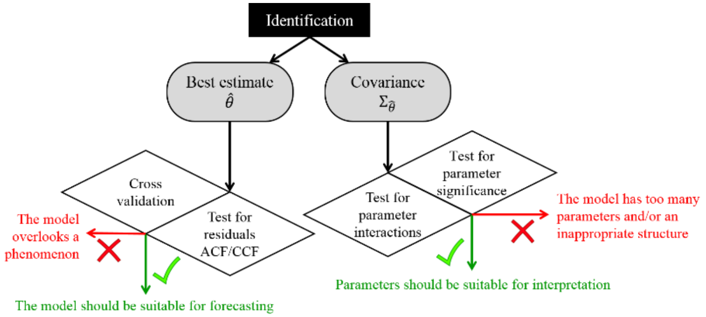


=

$$\hat{\theta}$$
$$\mathrm{cov}(\hat{\theta})$$

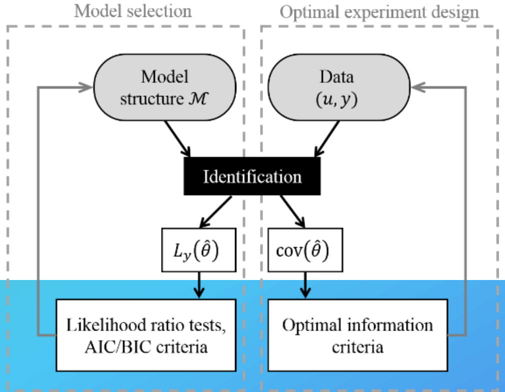
2. The validation of results

$$\hat{\theta}$$
$$\mathrm{cov}(\hat{\theta})$$



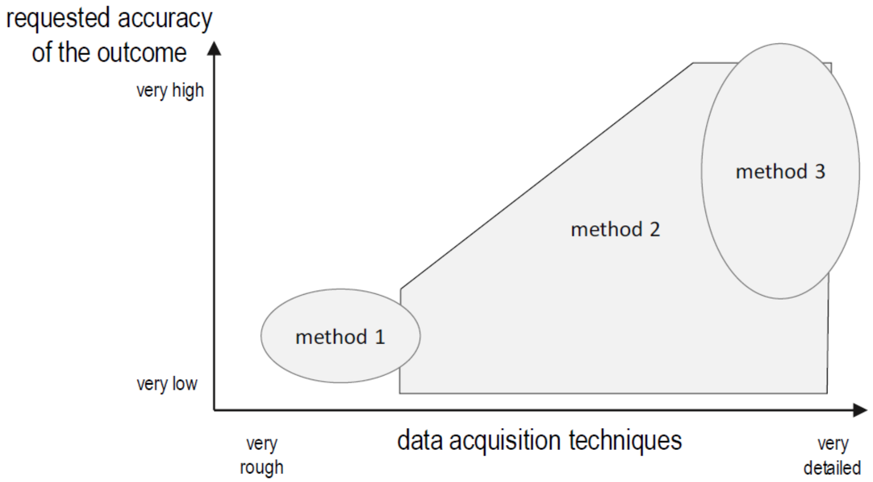
- Identifiability analysis
- Residual analysis
- Prediction error

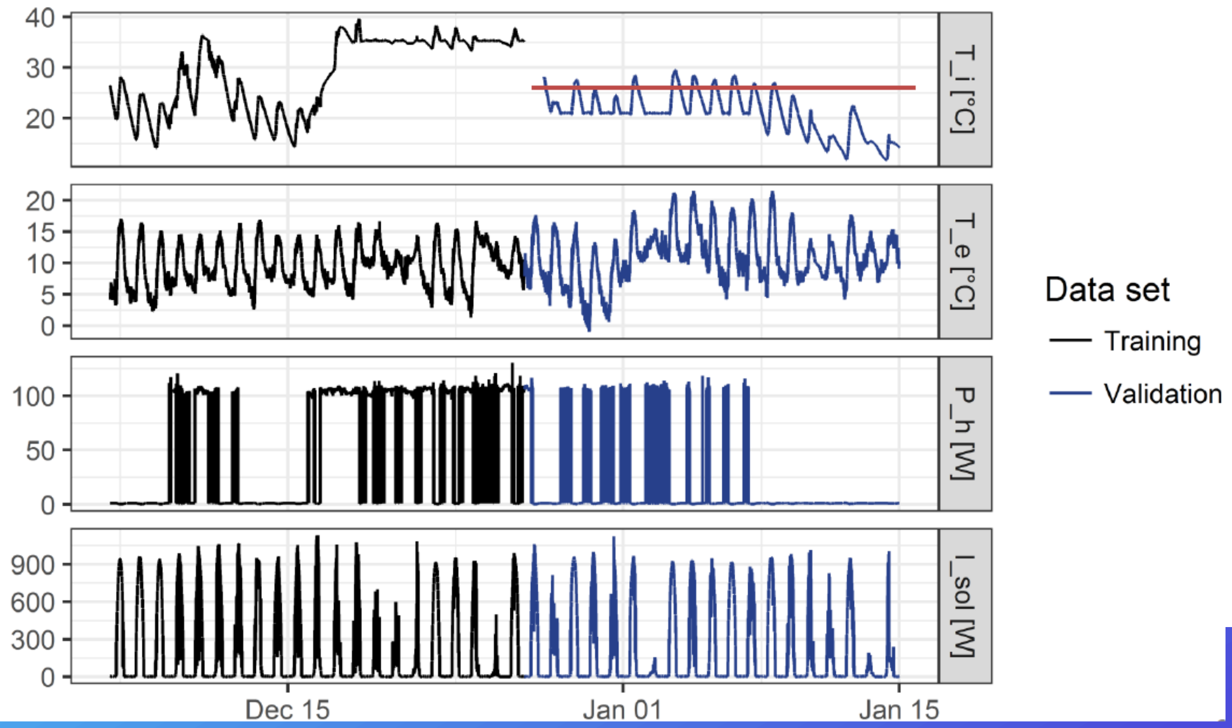
3. Model selection and optimal experiment design



- Prediction error method
- Information criteria
- Likelihood ratio tests

IEA EBC Annex 71
Building Energy Performance Assessment Based on In-situ Measurements





LOCIE

UNIVERSITÉ SAVOIE MONT BLANC

Advanced Autumn School

Thermal Measurements

&

Inverse Techniques

- **7th** Edition -

Sept 29th – Oct. 04th, 2019

Ile de Porquerolles

Hyères, France

cnrs

Aix*Marseille université

Registration Fees†:

PhD Student	**450 €**
CNRS employee	**free***
Academic	**840 €**
Other	**1200 €**

†The price includes accommodation, meals, proceedings, etc.

* to be confirmed (a specific request to CNRS for fee exemption is under way)

If you are considering attending the school, you are requested to follow the registration procedure explained on the web site, from October 2018 onwards.

Contact: Fabrice Rigollet
Tel: (33)491106885; Fax: (33)491106969
fabrice.rigollet@univ-amu.fr
http://iusti.cnrs.fr/metti7

After final registration, participants will be asked to complete the travel schedule and tutorial registration form. All the forms, travel details, registration and tutorial selection can be downloaded from the school web-site.

- **Venue**

The school will be held in the '*IGESA centre*' on the beautiful island Porquerolles, near Hyères (15min of boat from La Tour Fondue, at the end of Giens peninsula) in the south-east of France (Provence Alpes Côte d'Azur region).

- **Accommodation**

Double and single room accommodations as well as meals are provided within the IGESA centre.

- **Access** : to reach the Tour Fondue (boat departure)

By plane: http://www.toulon-hyeres.aeroport.fr/ then bus N°63 to *Arromanches* and N°67 to *La Tour Fondue*.
By train: several daily connections (from Paris, Marseille, etc.) to Hyères station then Bus N° 67 to *La Tour Fondue*.
By bus: From Hyères : Bus N° 67 to *La Tour Fondue*.
https://www.reseaumistral.com/
By road: From Hyères follow *Presqu'île de Giens, Tour Fondue*, 12km via the villages of La Capte, La Bergerie. Several car parks at *La Tour Fondue*.

First announcement

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Thermal Measurements

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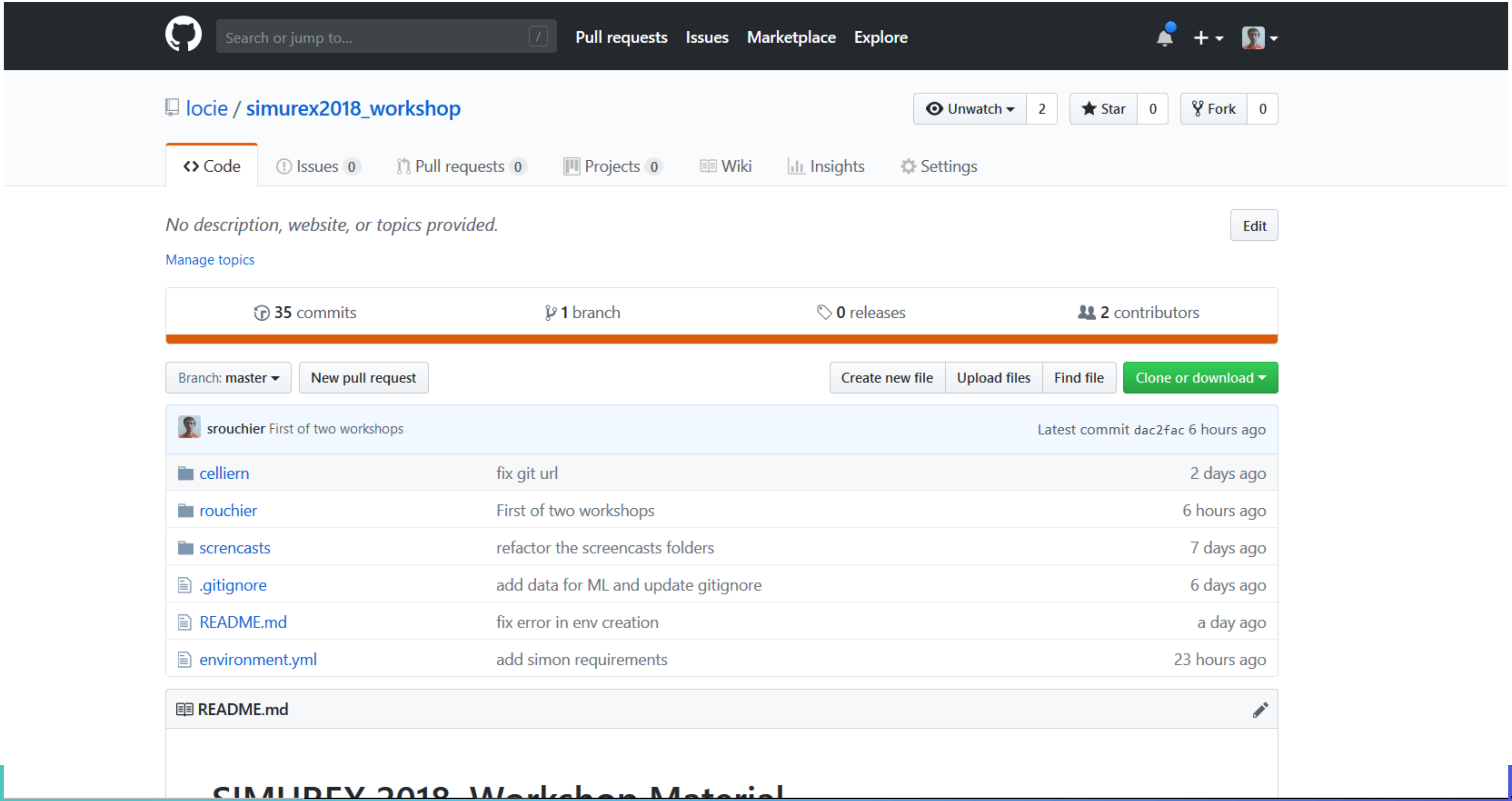
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Manage topics
35 commits
1 branch
0 releases
2 contributors
Branch: master
New pull request
Create new file
Upload files
Find file
Clone or download
srouchier First of two workshops
Latest commit dac2fac 6 hours ago
celliern fix git url 2 days ago
rouchier First of two workshops 6 hours ago
screncasts refactor the screencasts folders 7 days ago
.gitignore add data for ML and update gitignore 6 days ago
README.md fix error in env creation a day ago
environment.yml add simon requirements 23 hours ago
README.md

Thank you

Rouchier S (2018) Solving inverse problems in building physics: An overview of guidelines for a careful and optimal use of data, *Energy and Buildings*, vol. 166, p. 178-195

Rouchier S, Rabouille M, Oberlé P (2018) Calibration of simplified building energy models for paramater estimation and forecasting: stochastic versus deterministic modelling, *Building and Environment*, vol. 134, p.181-190

Rouchier S, Jiménez MJ, Castaño S (2018) Sequential Monte Carlo for on-line parameter estimation of a lumped building energy model, *Energy and Buildings* (under publication)