Identification of stochastic models for describing the thermal performance of buildings

DTU-Tsinghua Workshop on
Energy, Technology and Behaviour in Buildings

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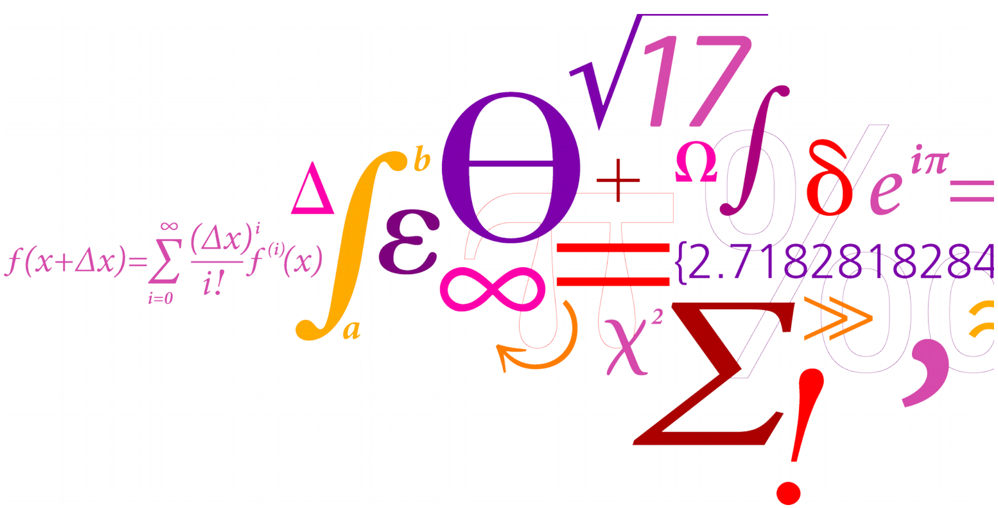
Henrik Madsen

www.henrikmadsen.org



DTU Compute
Department of Applied Mathematics and Computer Science

George Box:

All models are wrong – but some are useful

Modeling made simple

Suppose we have a time series of data:

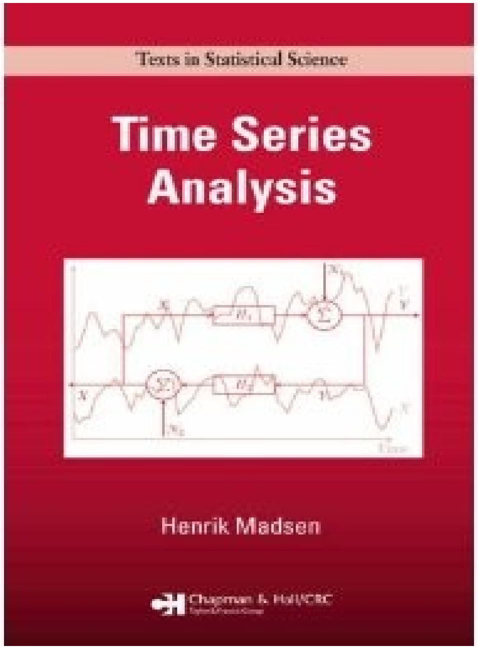
$$\{X_t\} = X_1, X_2, ... , X_t, ...$$

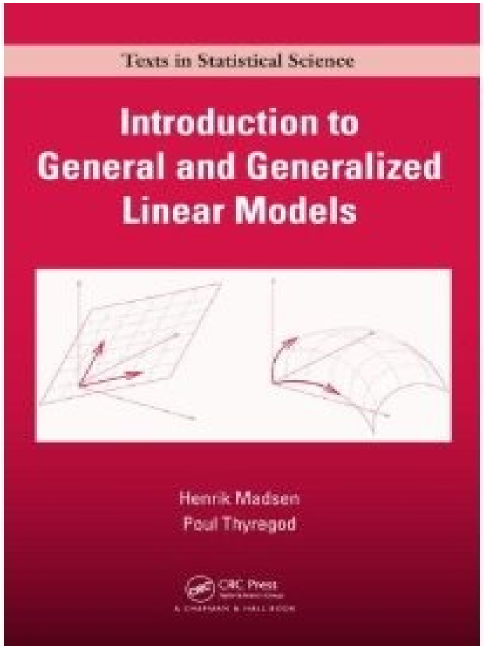
The purpose of any modeling is to find a nonlinear function $h(\{X_t\})$ such that

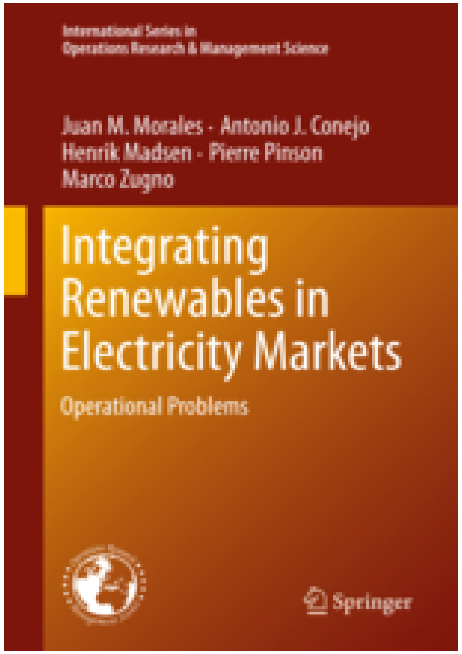
$$h(\{X_t\}) = \varepsilon_t$$

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

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



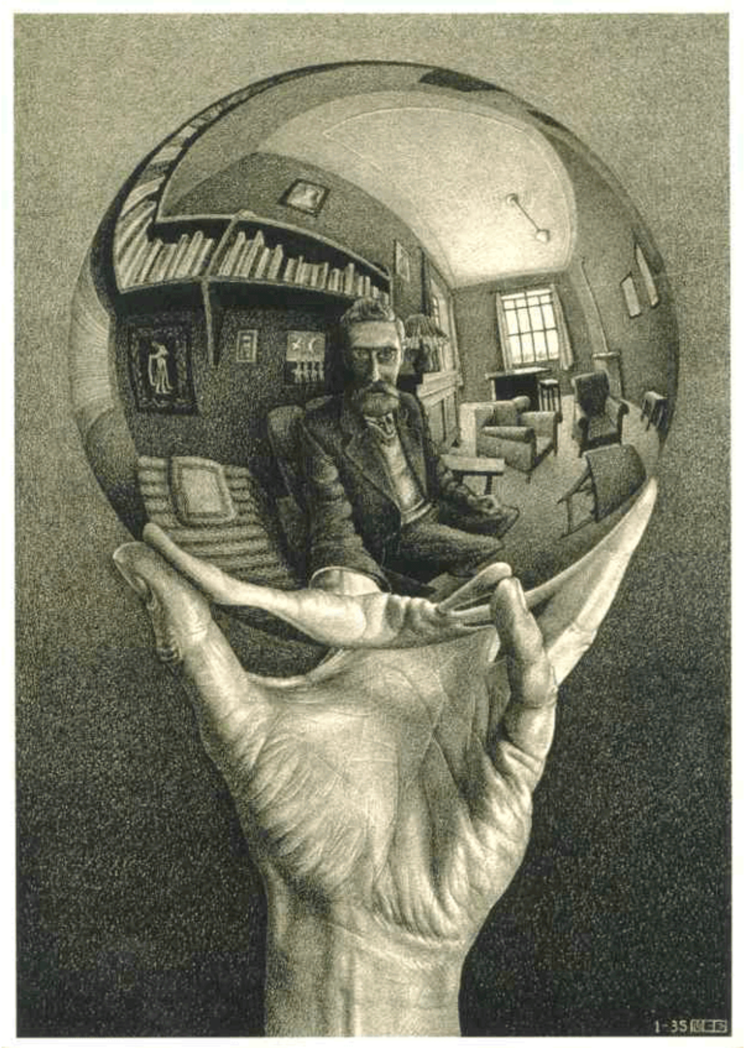




Contents

1. A single sensor (a smart meter)
2. Several sensors (and grey-box modelling)
3. Special sensors (model for occupant behavior)

Part 1
A single sensor (smart meter)



- Smart Meters and data splitting
- Smart Meters and Thermal Characteristics
    - Problem setting
    - Simple tool

Case Study No. 1

Split of total readings into space heating and domestic hot water using data from smart meters

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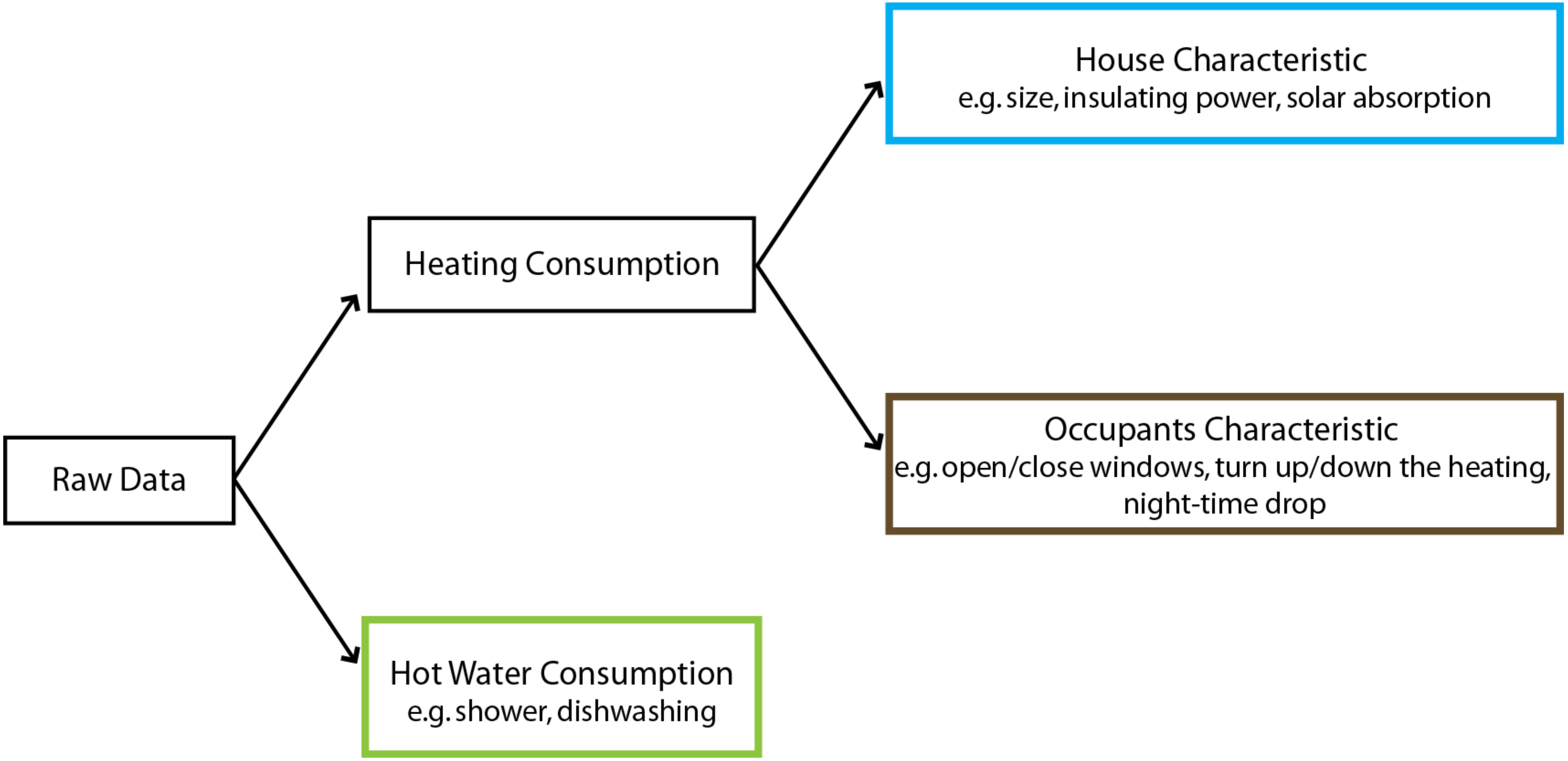
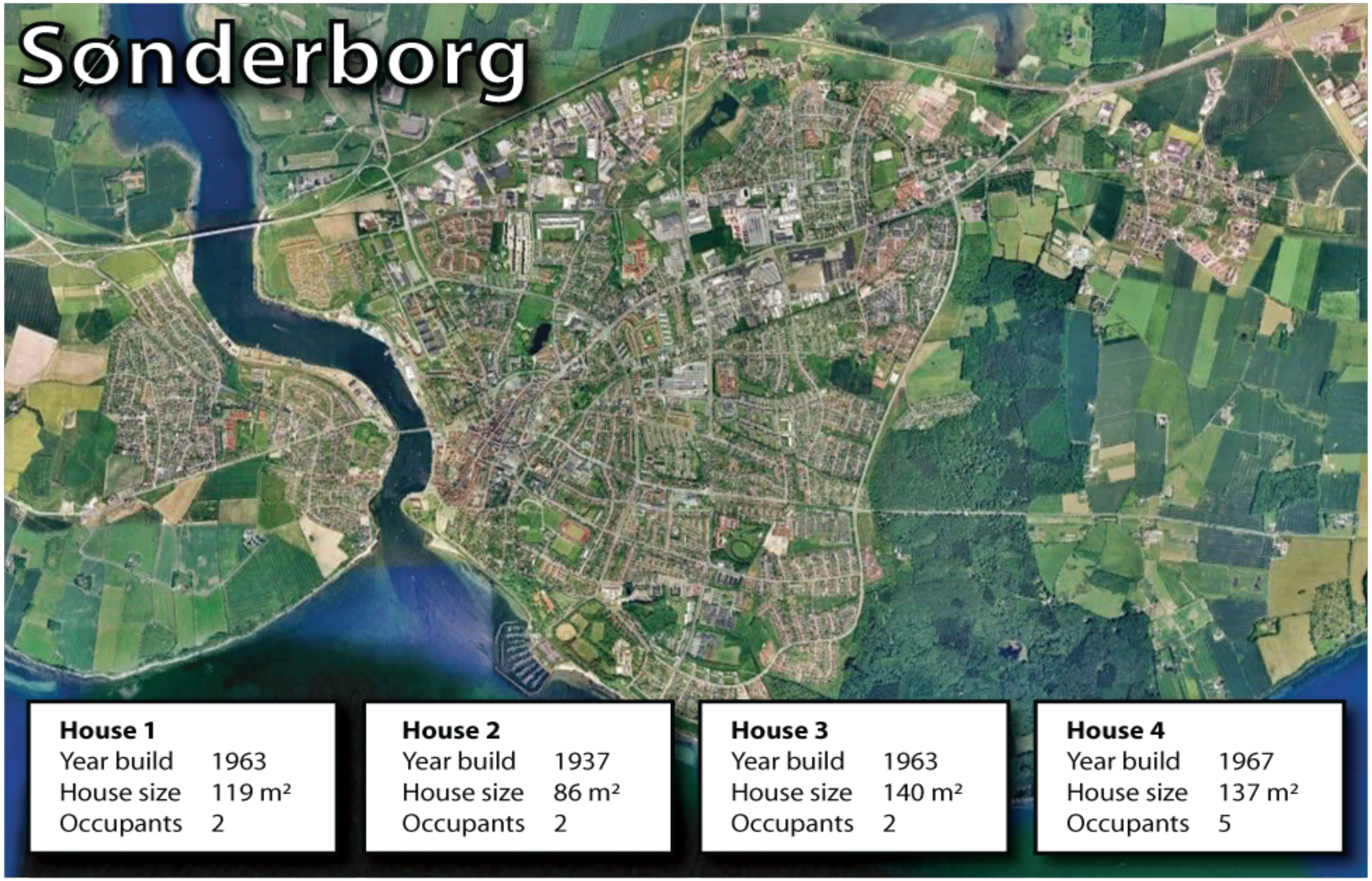
Data separation principle

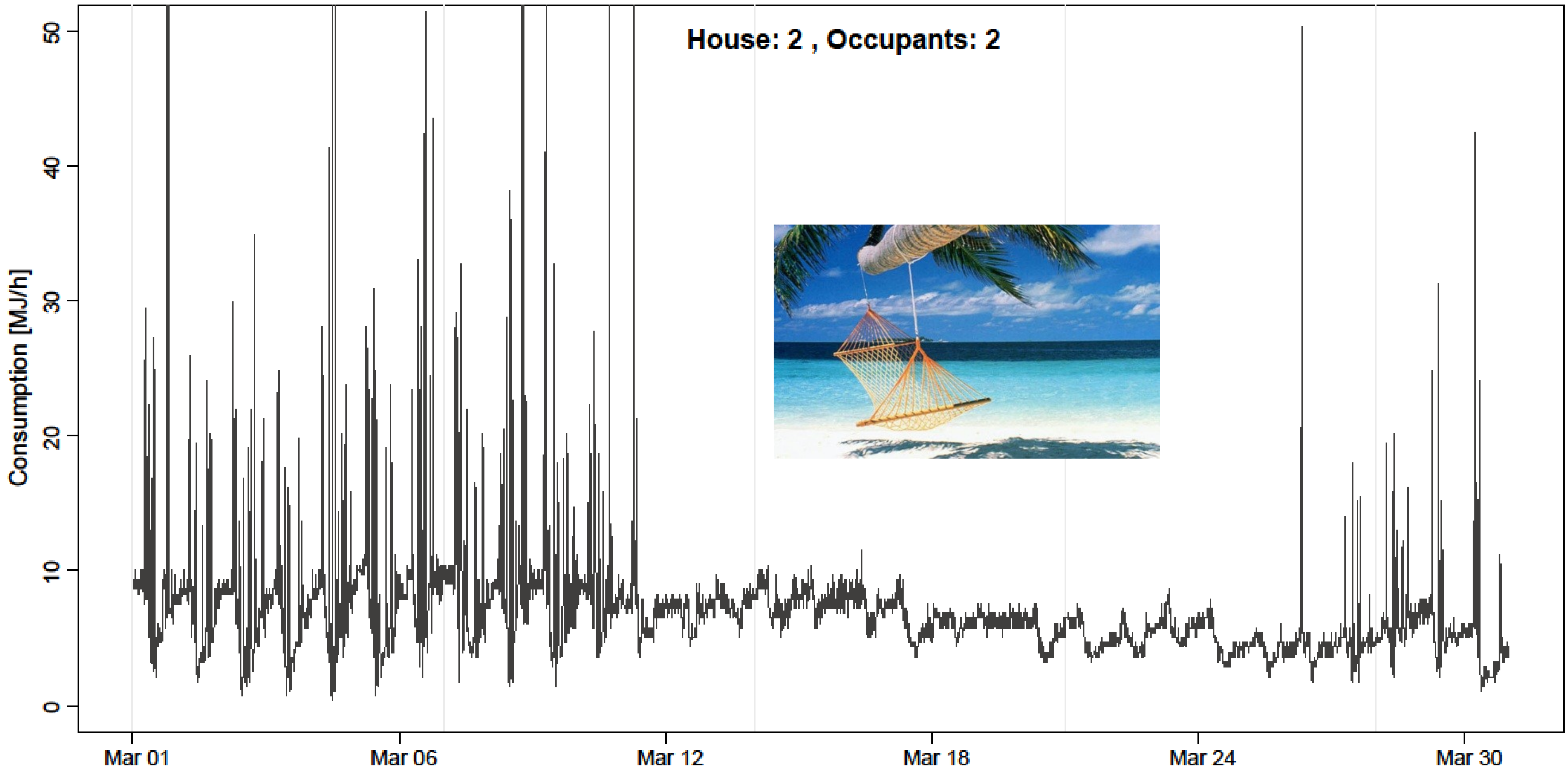


Data

- 10 min averages from a number of houses



Holiday period



Robust Polynomial Kernel

To improve the kernel method

Rewrite the kernel smoother to a Least Square Problem

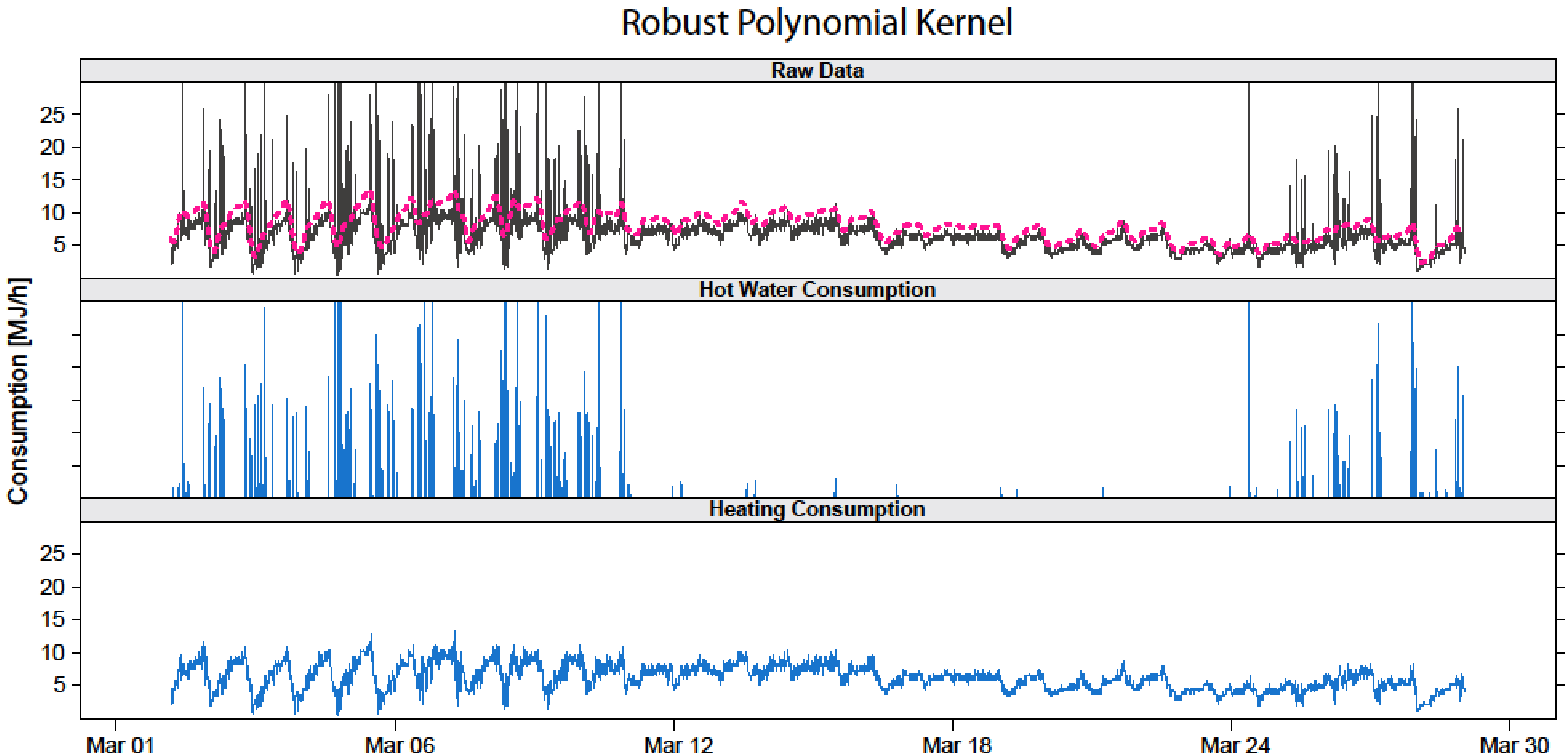
$$\arg\min_{\theta} \frac{1}{N} \sum_{s=1}^{N} w_s(x) \left(Y_s - \theta\right)^2 \qquad w_s(x) = \frac{k\{x - X_s\}}{\frac{1}{N}\sum_{s=1}^{N} k\{x - X_s\}}$$

Make the method robust by replacing $\left(Y_s - \theta\right)^2$ with

$$\rho_{\text{Huber}}(\varepsilon) = \begin{cases} \frac{1}{2\gamma}\varepsilon^2 & \text{if } |\varepsilon| \le \gamma \\ |\varepsilon| - \frac{1}{2}\gamma & \text{if } |\varepsilon| > \gamma \end{cases} \qquad \varepsilon_s = Y_s - \theta$$

Make the method polynomial by replacing θ with

$$P_s = \theta_0 + \theta_1(X_t - x) + \theta_2(X_t - x)^2$$

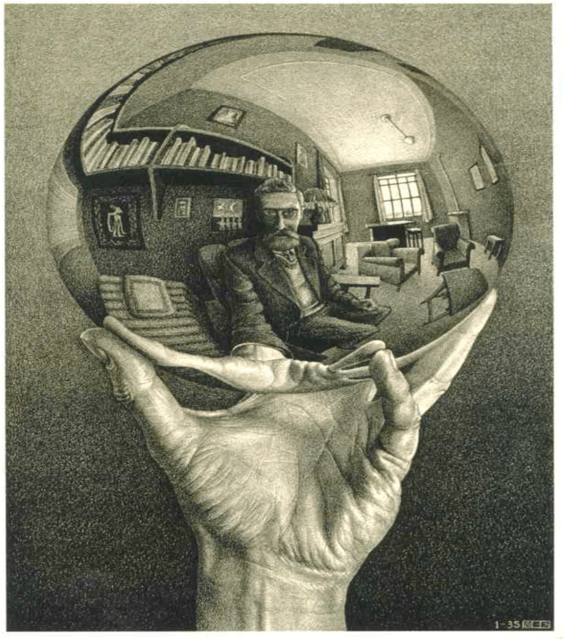


Robust Polynomial Kernel
Raw Data
Hot Water Consumption
Heating Consumption
Consumption [MJ/h]
25
20
15
10
5
Mar 01
Mar 06
Mar 12
Mar 18
Mar 24
Mar 30

Case Study No. 2

Identification of Thermal Performance using Smart Meter Data

Characterization Smart Meter Data



- Energy labelling
- Estimation of UA and gA values
- Estimation of energy signature
- Estimation of dynamic characteristics
- Estimation of time constants

Simple estimation of UA-values

- Consider the following model (t=day No.) estimated by kernel-smoothing:

$$Q_t = Q_0(t) + c_0(t)(T_{i,t} - T_{a,t}) + c_1(t)(T_{i,t-1} - T_{a,t-1}) \qquad (1)$$

- The estimated UA-value is

$$\hat{UA}(t) = \hat{c}_o(t) + \hat{c}_1(t) \qquad (2)$$

- With more involved (but similar models) also gA and wA values can be stimated

Results

	UA	σ_{UA}	$\mathrm{gA}^{\max}$	$\mathrm{wA}_E^{\max}$	$\mathrm{wA}_S^{\max}$	$\mathrm{wA}_W^{\max}$	T_i
	W/°C		W	W/°C	W/°C	W/°C	°C
4218598	211.8	10.4	597.0	11.0	3.3	8.9	23.6
4218600	98.7	10.8	-96.2	23.6	10.1	13.0	22.3
4381449	228.2	12.6	1012.3	29.8	42.8	39.7	19.4
4711160	155.4	6.3	518.8	14.5	4.4	9.1	22.5
4711176	178.5	7.3	800.0	1.9	-7.6	8.5	26.4
4836681	155.3	8.1	591.0	39.5	28.0	21.4	23.5
4836722	236.0	17.7	1578.3	4.3	3.3	18.9	23.5
4986050	159.6	10.7	715.7	10.2	7.5	7.2	20.8
5069878	144.8	10.4	87.6	3.7	1.6	17.3	21.8
5069913	207.8	9.0	962.5	3.7	8.6	10.6	22.6
5107720	189.4	15.4	657.7	41.4	29.4	16.5	21.0

Notice: Still some issues with negative values but often they are not significiant.

Perspectives for using Smart Meters

- Reliable Energy Signature.
- Energy Labelling
- Time Constants (eg for night set-back)
- Proposals for Energy Savings:
  - Replace the windows?
  - Put more insulation on the roof?
  - Is the house too untight?
  - ......
- Optimized Control
- Integration of Solar and Wind Power using DSM

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Part 2
Several sensors

- Introduction to Grey-Box Modelling (a continuous-discrete state space models)
- A model for the thermal characteristics of a small office building
- Models for control

Introduction to Grey-Box modelling

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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

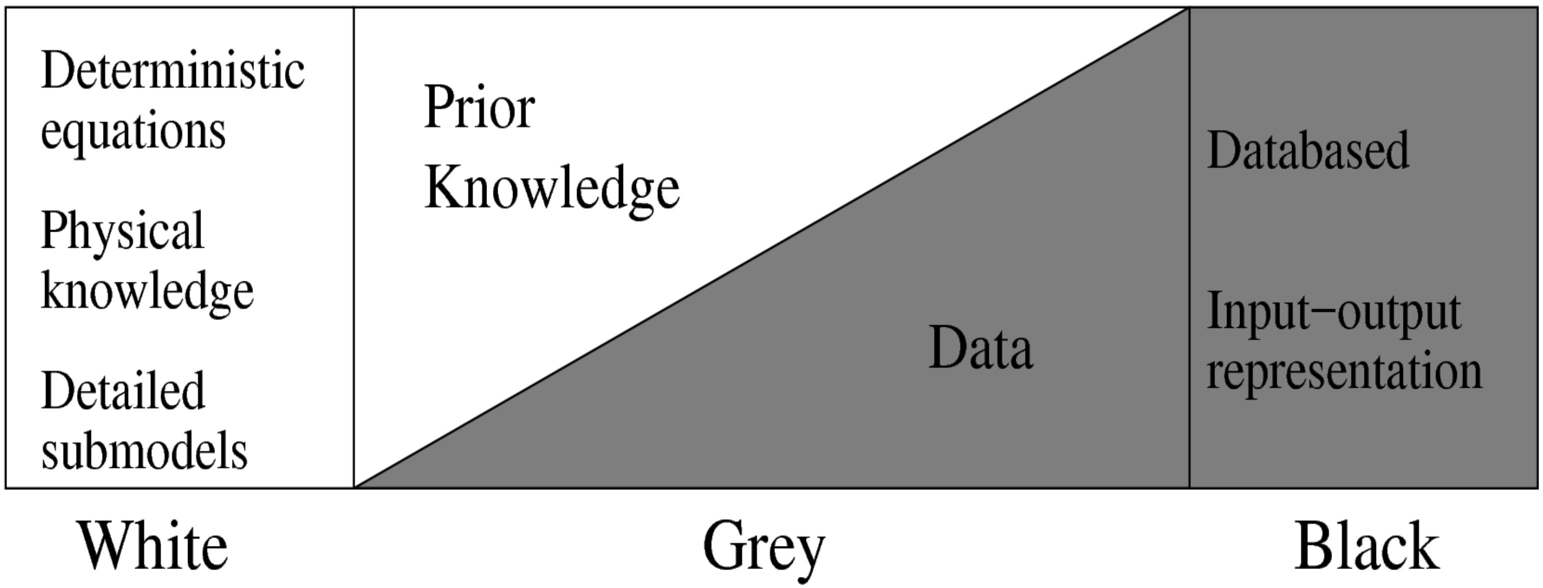
$$Y_k = h(X_k, u_k, t_k, \theta) + e_k,$$ Observation equation

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 $N(\mathbf{0}, \boldsymbol{S})$

Grey-box modelling concept



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

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

Case study

Model for the thermal characteristics of a small office building

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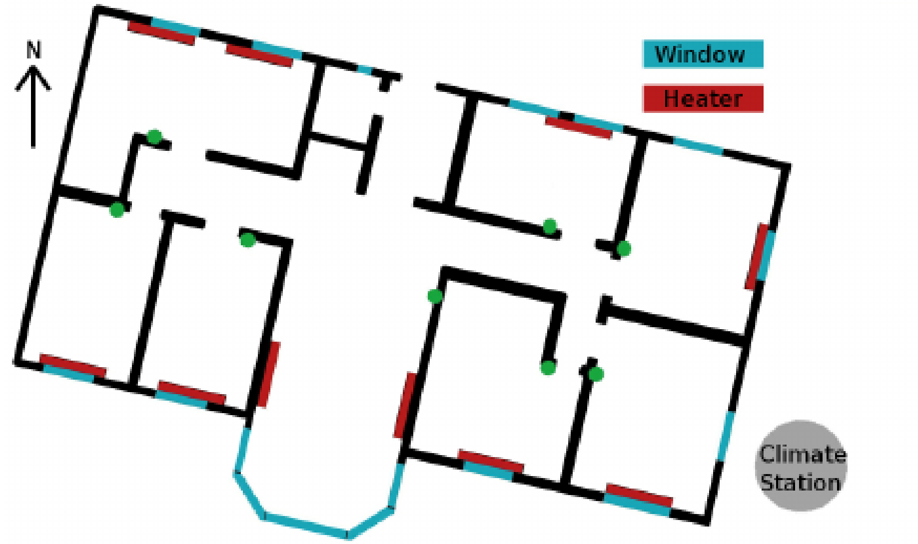
Test case: One floored 120 m^2 building

Objective

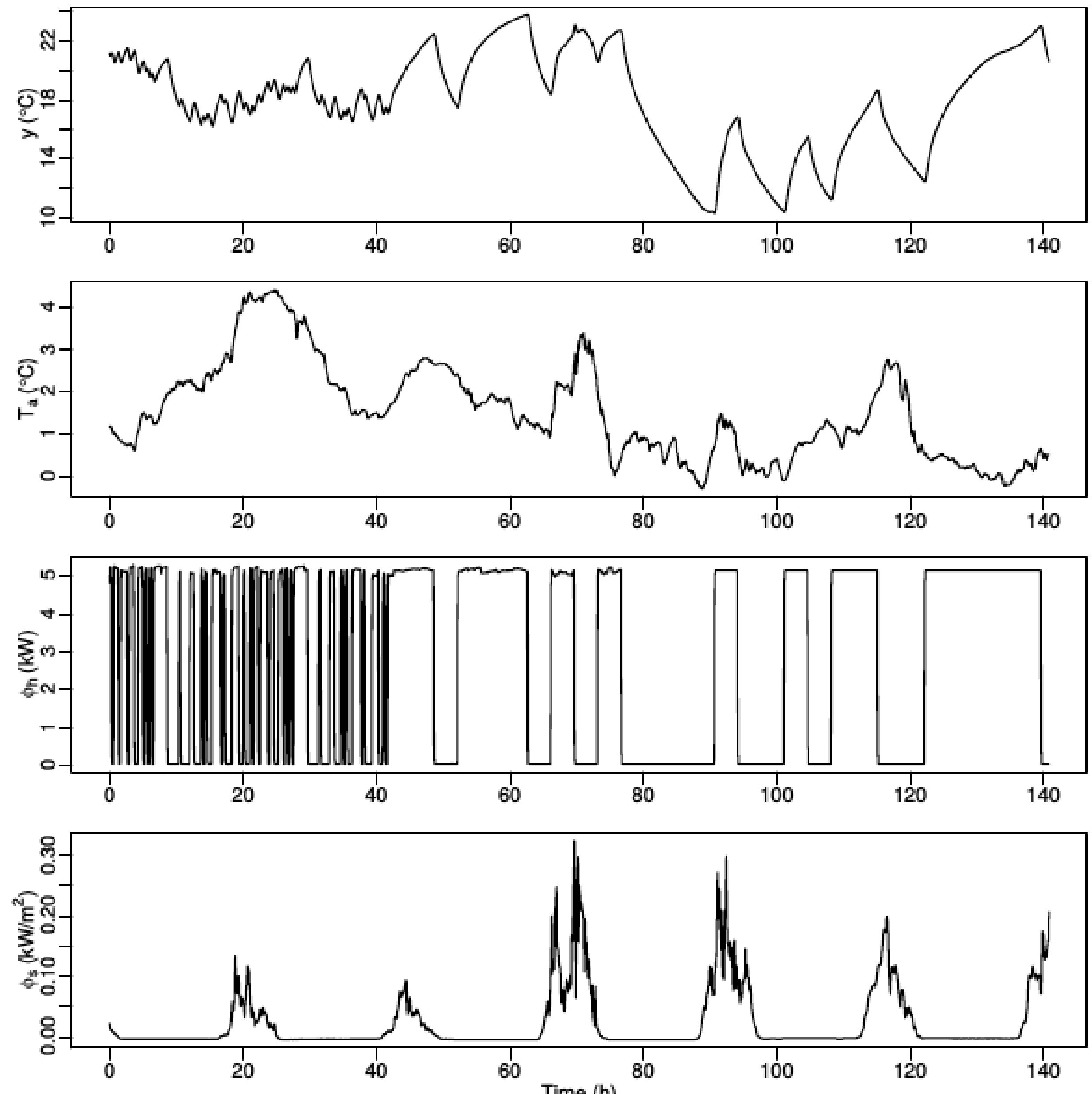
Find the best model describing the heat dynamics of this building ([1], [4])



DATA

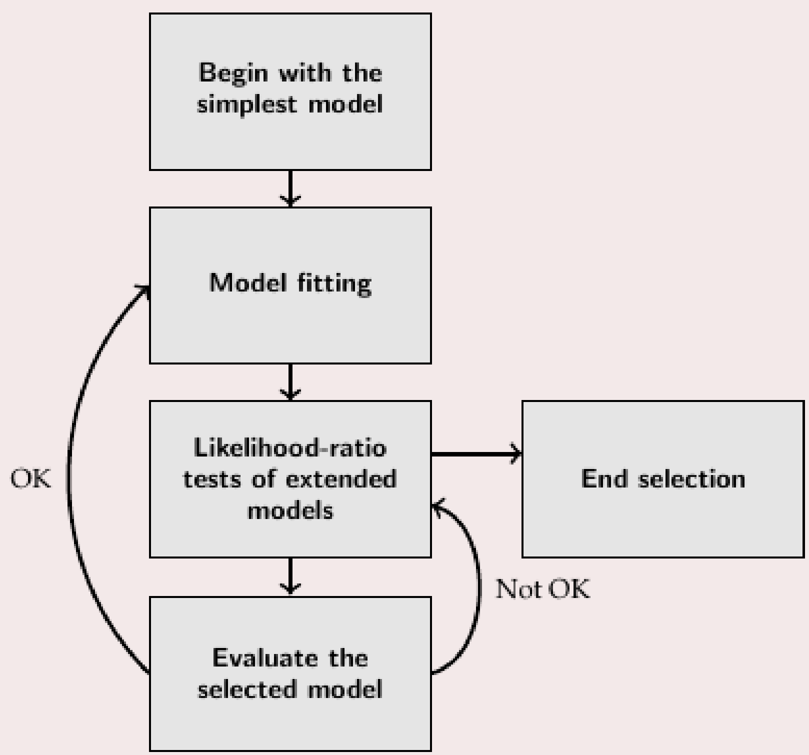
Measurements of:

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

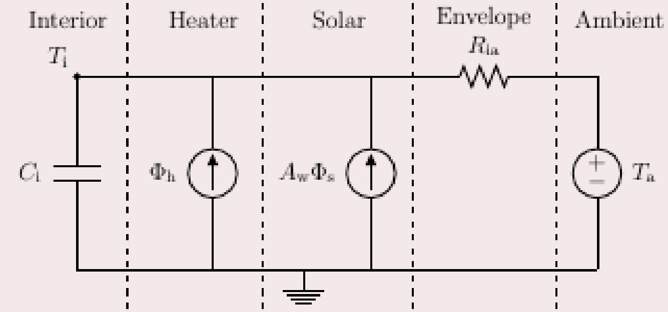


SELECTION PROCEDURE

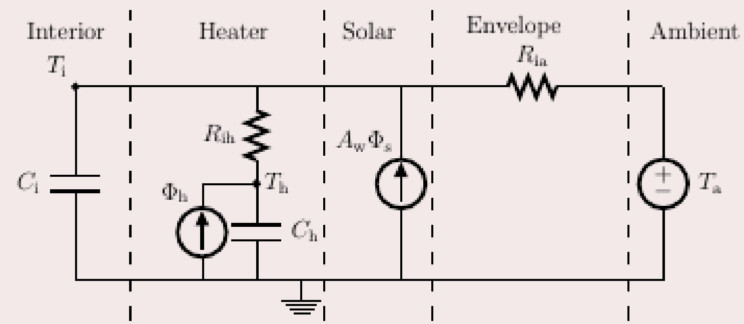
Iterative procedure using statistical tests



Simplest model

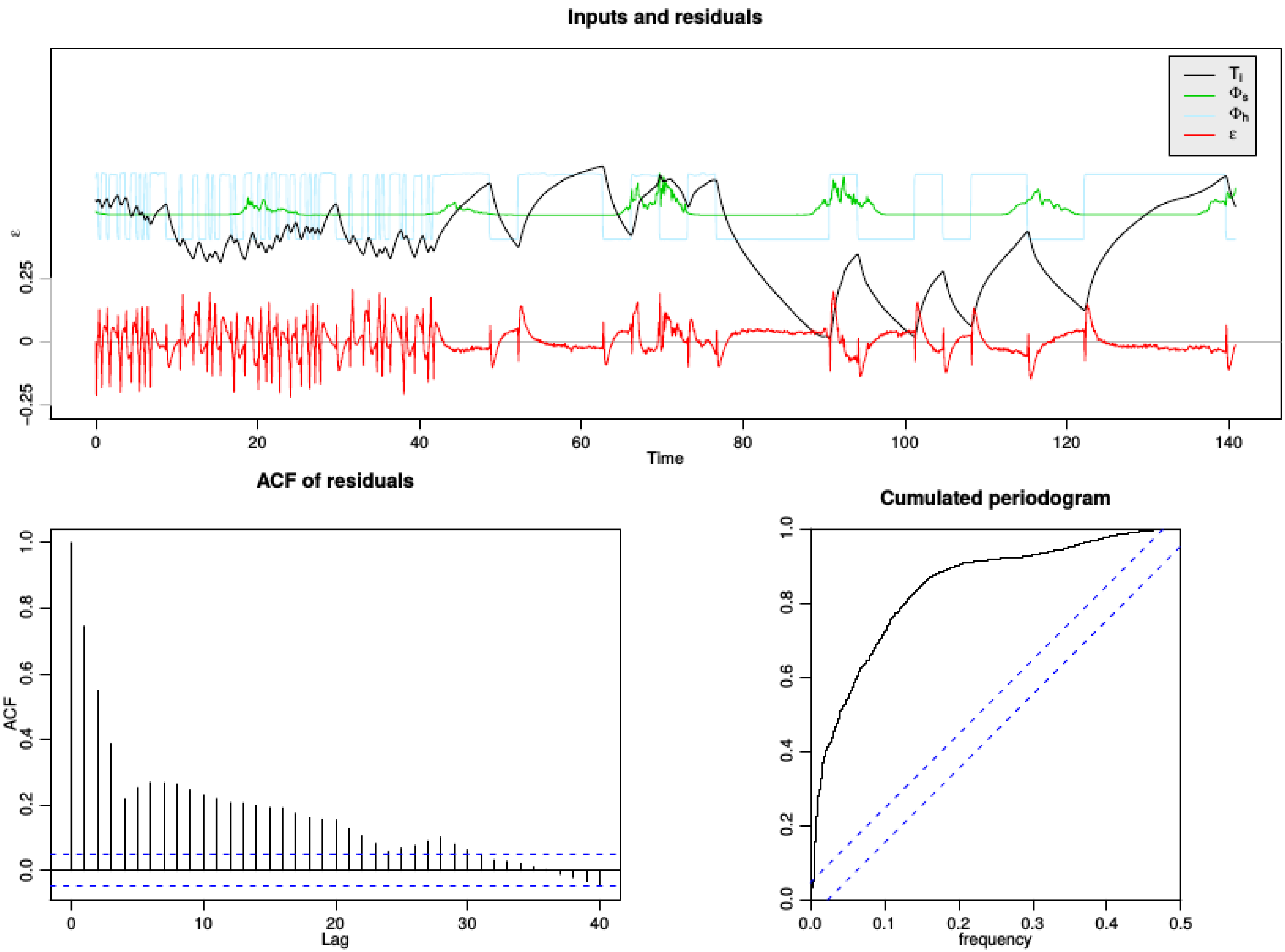


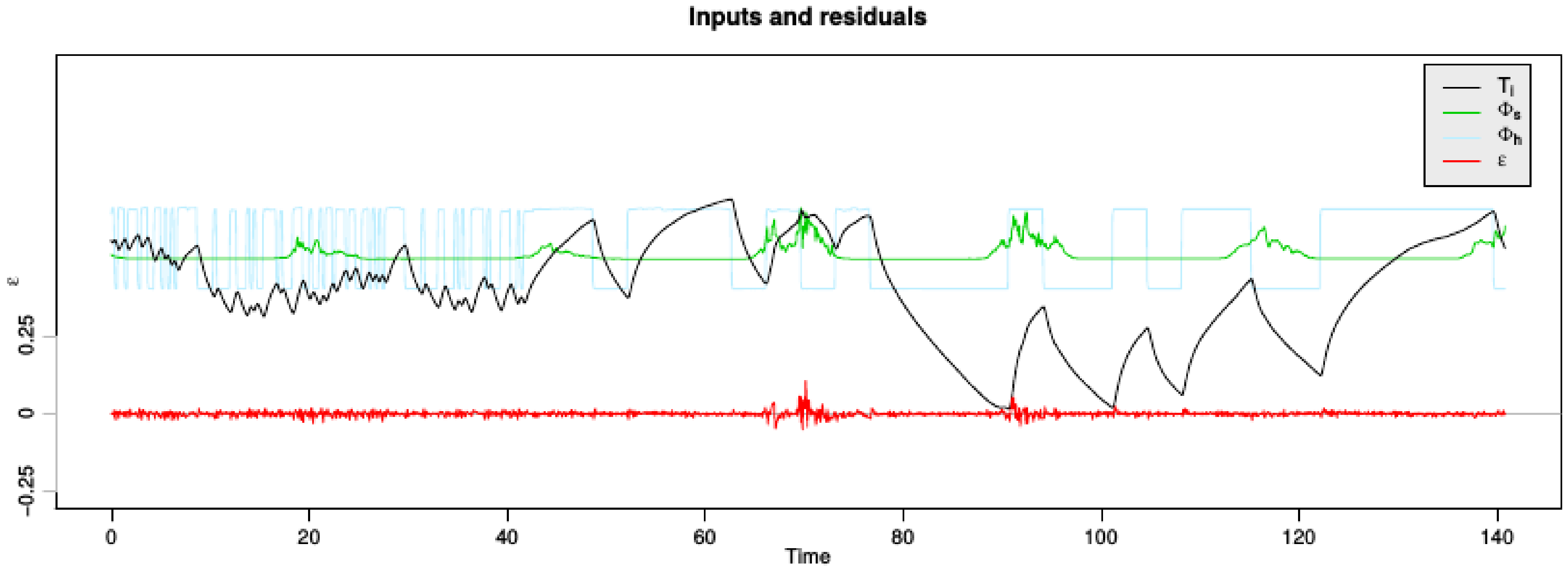
First extension: heater part

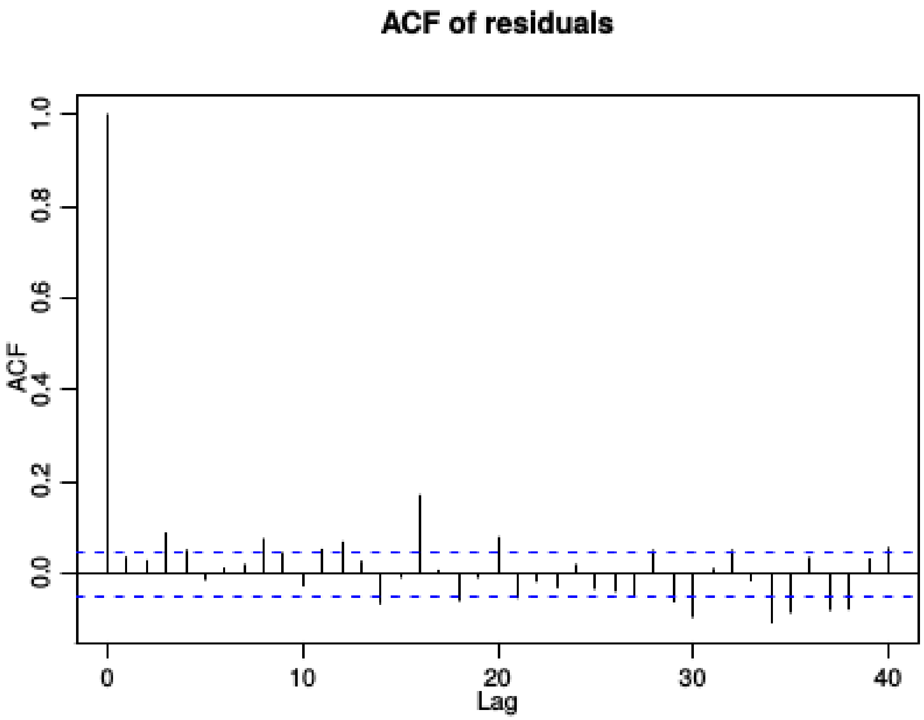


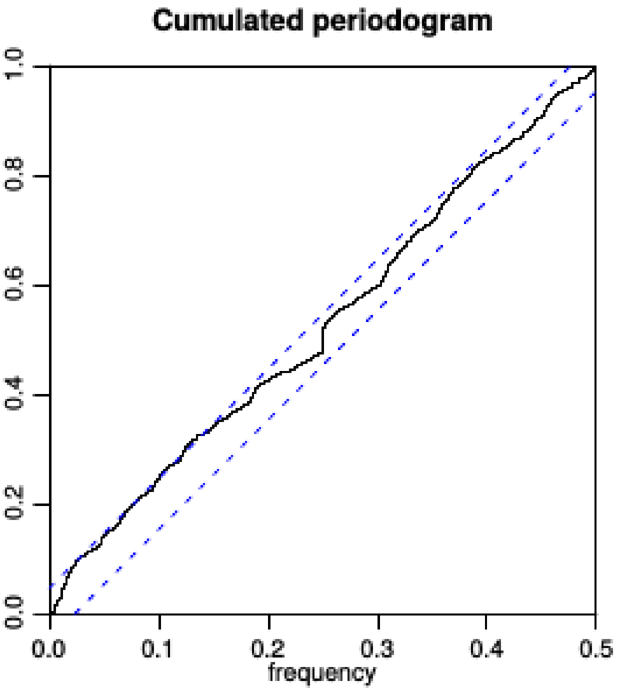
Start	$Model_{Ti}$			
$l(\theta;\mathcal{Y}_N)$	2482.6			
m	6			
1	$Model_{TiTe}$	$Model_{TiTm}$	$Model_{TiTs}$	$Model_{TiTh}$
$l(\theta;\mathcal{Y}_N)$	3628.0	3639.4	3884.4	3911.1
m	10	10	10	10
2 ...				

EVALUATE THE SIMPLEST MODEL




Inputs and residuals
Time
ε
0
20
40
60
80
100
120
140
0.25
0
−0.25


ACF of residuals
ACF
Lag
0
10
20
30
40
1.0
0.8
0.6
0.4
0.2
0.0


Cumulated periodogram
frequency
0.0
0.1
0.2
0.3
0.4
0.5
1.0
0.8
0.6
0.4
0.2
0.0

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

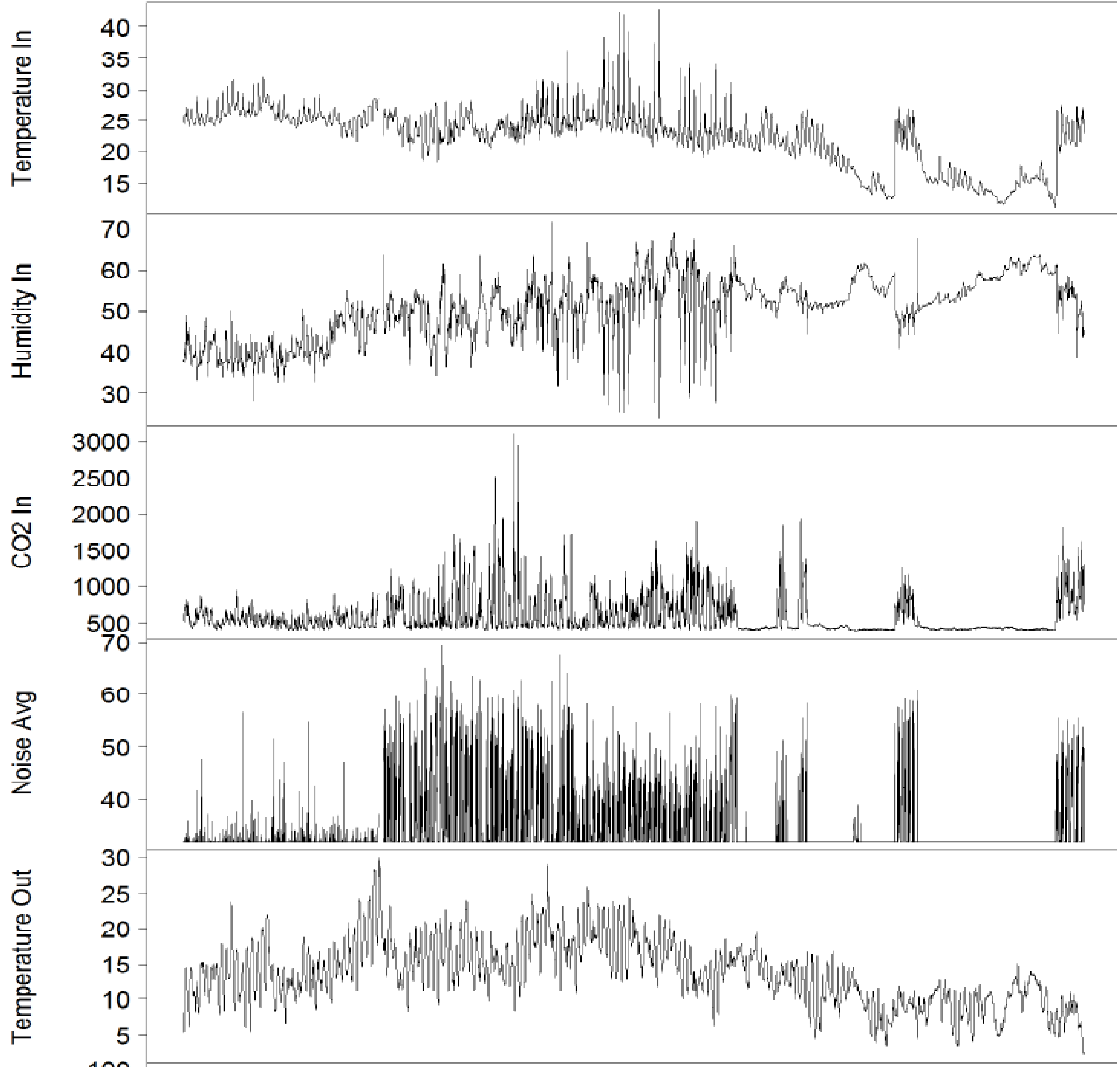
Part 3
Special Data (eg Non-Gaussian)

Identification of Occupant Behavior

- Use of CO_2 measurements to model occupant behavior in summer houses

Summer houses represent a special challenge

- Large variation in the number of people present in the house
- Power Grids in summer house areas represent a special problem for some DSOs
- Time series of CO_2 measurements are the key to the classification



Temperature In
40
35
30
25
20
15
Humidity In
70
60
50
40
30
CO2 In
3000
2500
2000
1500
1000
500
Noise Avg
70
60
50
40
Temperature Out
30
25
20
15
10
5

The Model Space

$$\boldsymbol{\theta} \sim f\left(\beta_{\text{fixed}}, t, \cdots\right) + g\left(U_{\text{random}}, t, \cdots\right) \tag{1a}$$

$$d\boldsymbol{X}_t \sim \text{Dynamical model}\left(\boldsymbol{\theta}\right) \tag{1b}$$

$$\begin{aligned} Y_t^{(1)} &= \text{Electrical consumption} \\ Y_t^{(2)} &= \text{Noise (indoor)} \\ Y_t^{(3)} &= \text{CO}_2 \text{ (indoor)} \\ &\vdots \end{aligned} \tag{1c}$$

- $\boldsymbol{\theta}$ parameter vector for population/hierarchical model
  - Time, weather, demographics
- $d\boldsymbol{X}_t$ state vector described by some dynamical model depending on $\boldsymbol{\theta}$
  - People, consumption, windows
- Y's: Observed measurements related to occupancy behavior, including measurements inside and outside the building and smart metering data

Hidden Markov Model

First Order Markov Property

$$p(X_t|X_{t-1}) = p(X_t|\mathcal{X}^{(t-1)}), \quad t \in \mathbb{N} \tag{2}$$

$$p(Y_t|X_t) = p(Y_t|\mathcal{X}^{(t)}, \mathcal{Y}^{(t-1)}), \quad t \in \mathbb{N} \tag{3}$$

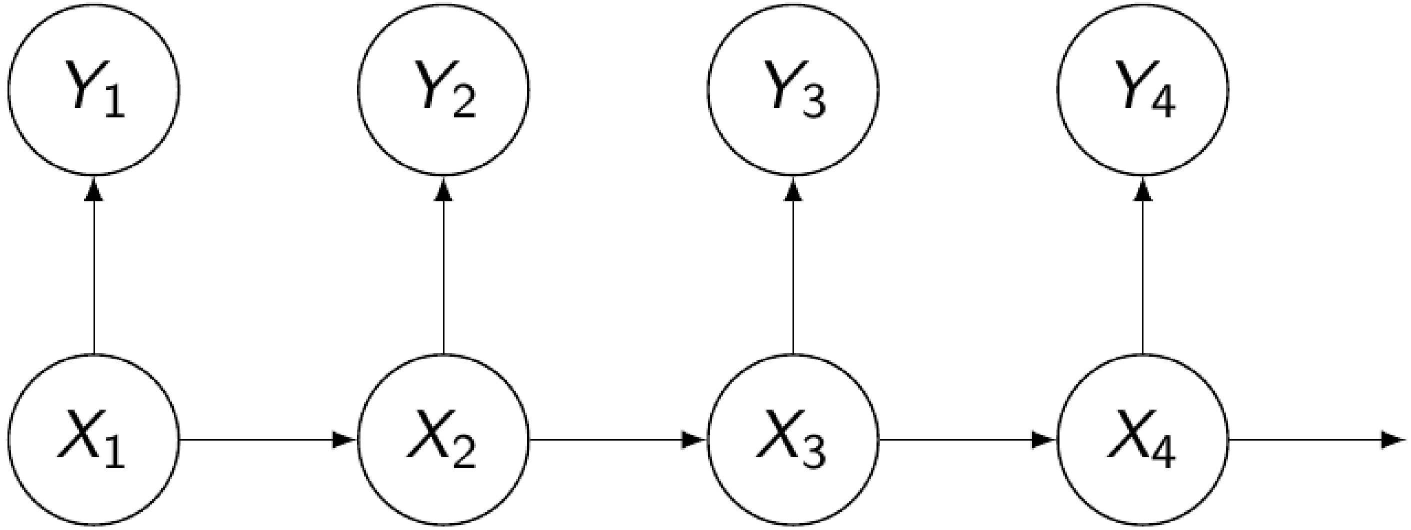


Figure: Directed graph of basic HMM. The index denotes time.

Markov Chains

Discrete state vector at time t, X_t, with m states.

Transition probability

$$p(X_t = j | X_{t-s} = i) \tag{4}$$

One-step transition probability

$$\gamma_{ij,t} = p(X_t = j | X_{t-1} = i) \tag{5}$$

One-step transition probability matrix from time $t-1$ to t

$$\mathbf{\Gamma}_t = \begin{pmatrix} \gamma_{11,t} & \cdots & \gamma_{1m,t} \\ \vdots & \ddots & \vdots \\ \gamma_{m1,t} & \cdots & \gamma_{mm,t} \end{pmatrix} \tag{6}$$

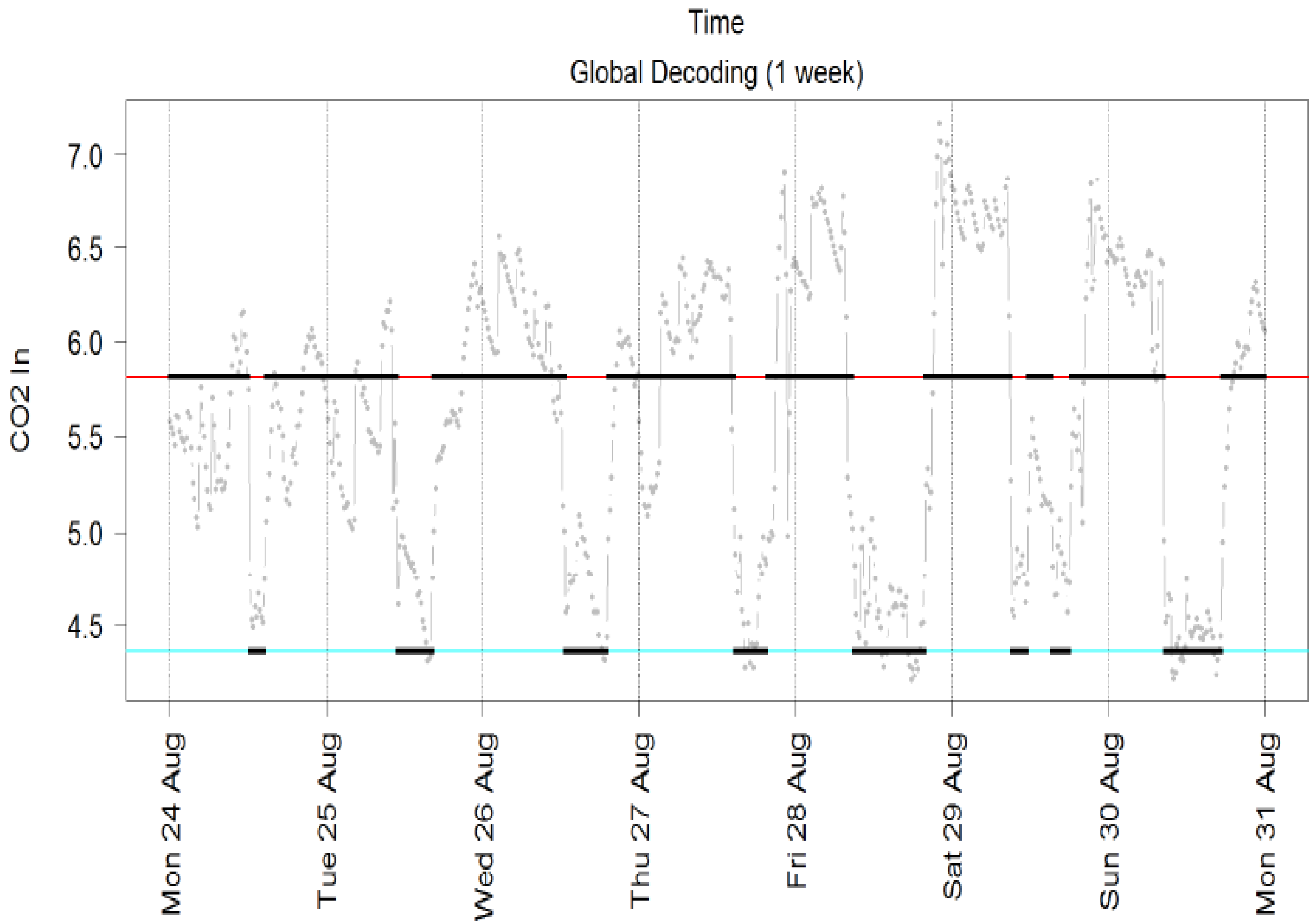
where the row must sum to 1.

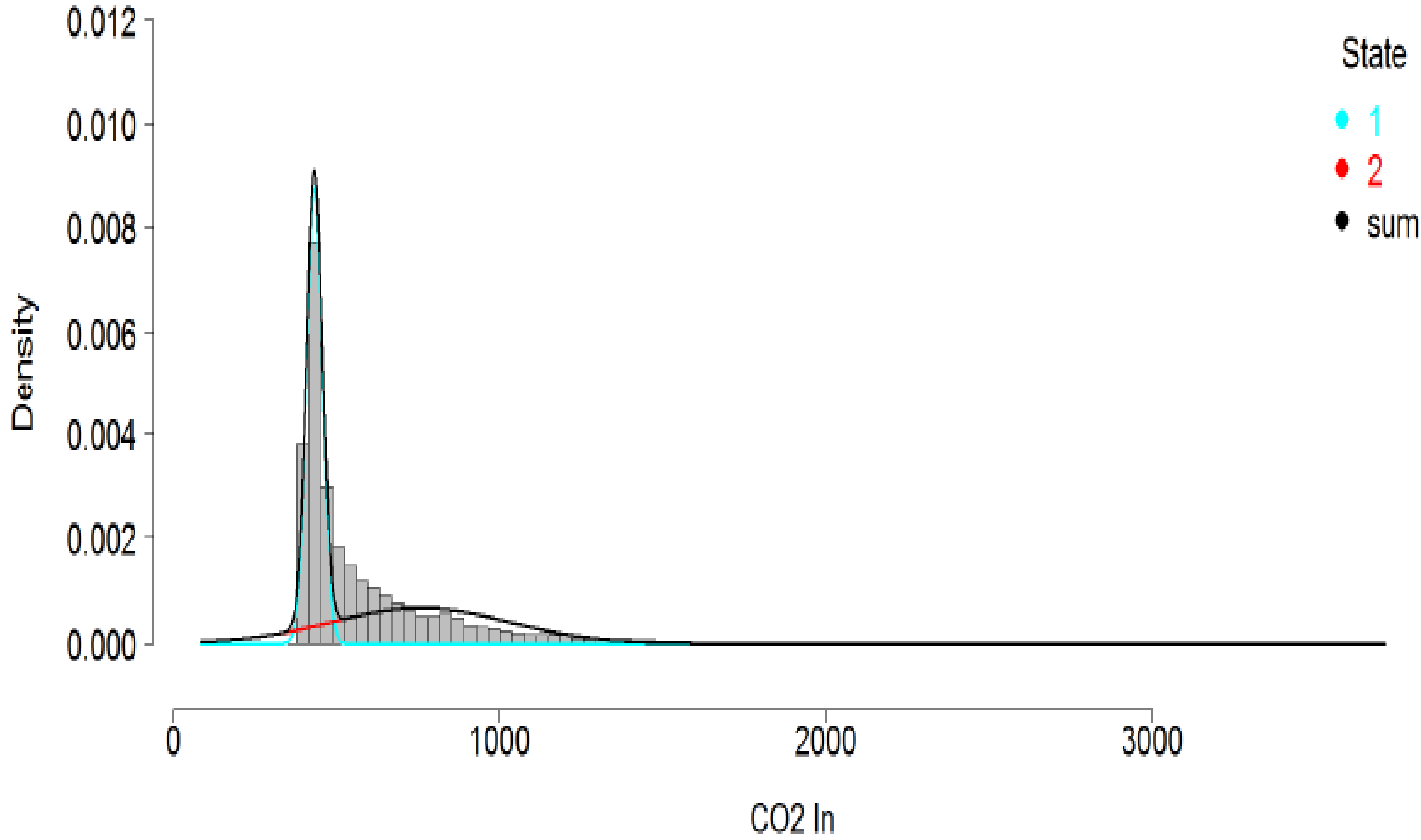
Homogeneous Hidden Markov Model

Setting

$$y_t = h(CO_{2,t})$$
$$p(x_t|x_{t-1}) \sim \Gamma$$
$$p(y_t|x_t) \sim \mathcal{N}\left(\mu_i, \sigma_i^2\right) \text{ for } i = 1, 2, \cdots, m$$

Note that there is no time dependence in the transition probabilities in the homogen case.


Time
Global Decoding (1 week)
7.0
6.5
6.0
5.5
5.0
4.5
CO2 In
Mon 24 Aug
Tue 25 Aug
Wed 26 Aug
Thu 27 Aug
Fri 28 Aug
Sat 29 Aug
Sun 30 Aug
Mon 31 Aug



0.012
0.010
0.008
0.006
0.004
0.002
0.000
Density
0
1000
2000
3000
CO2 In
State
1
2
sum

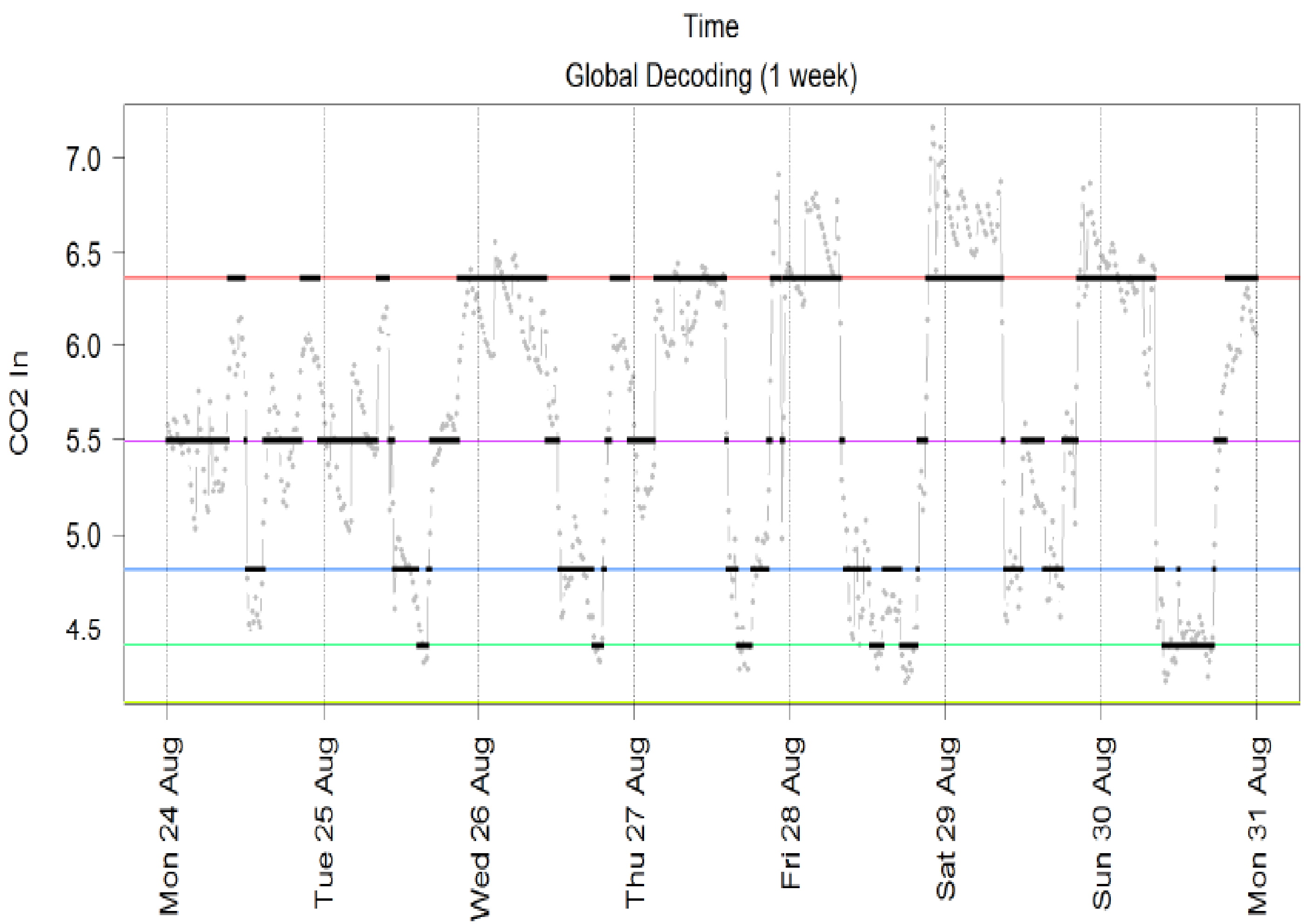
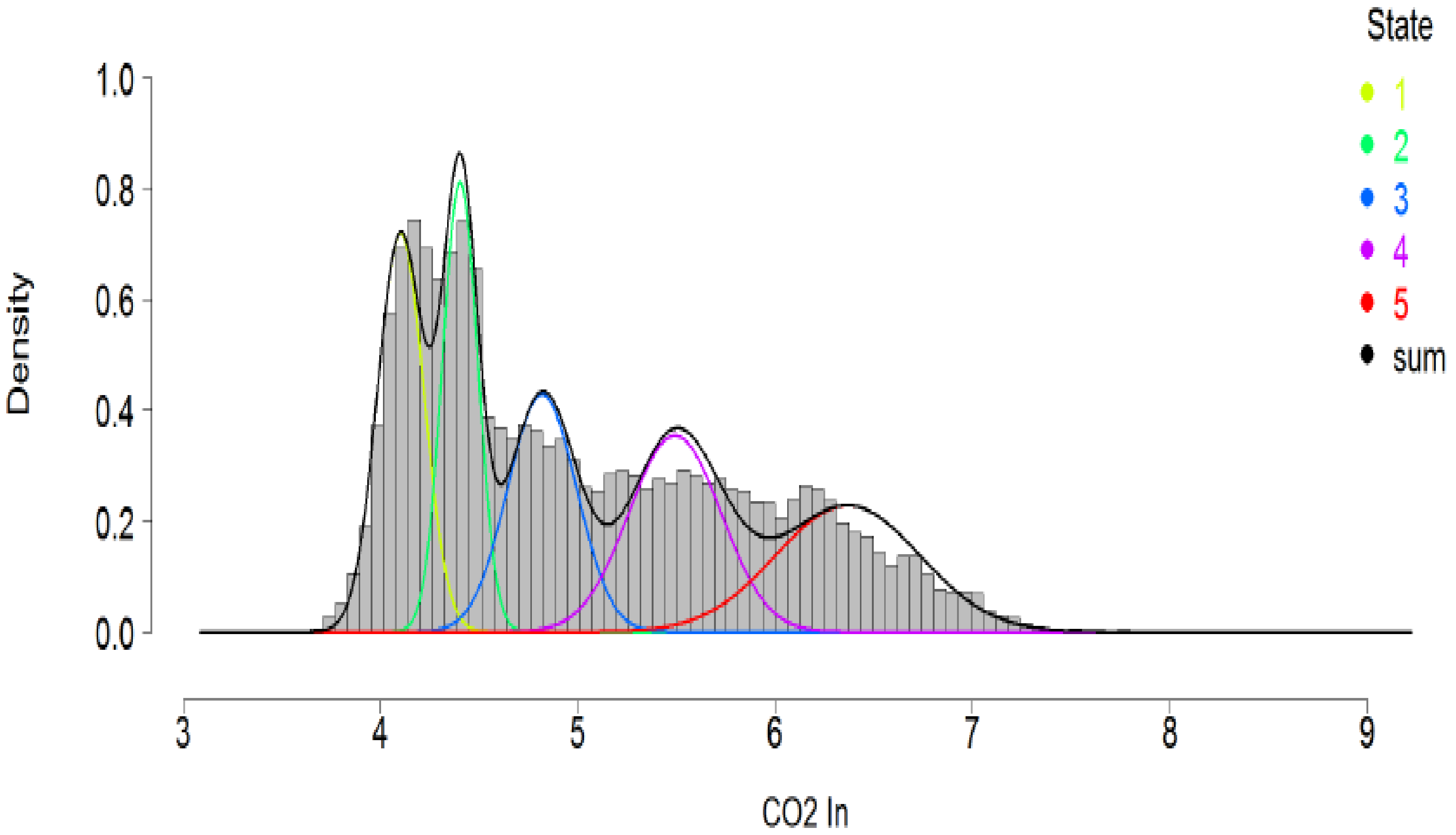
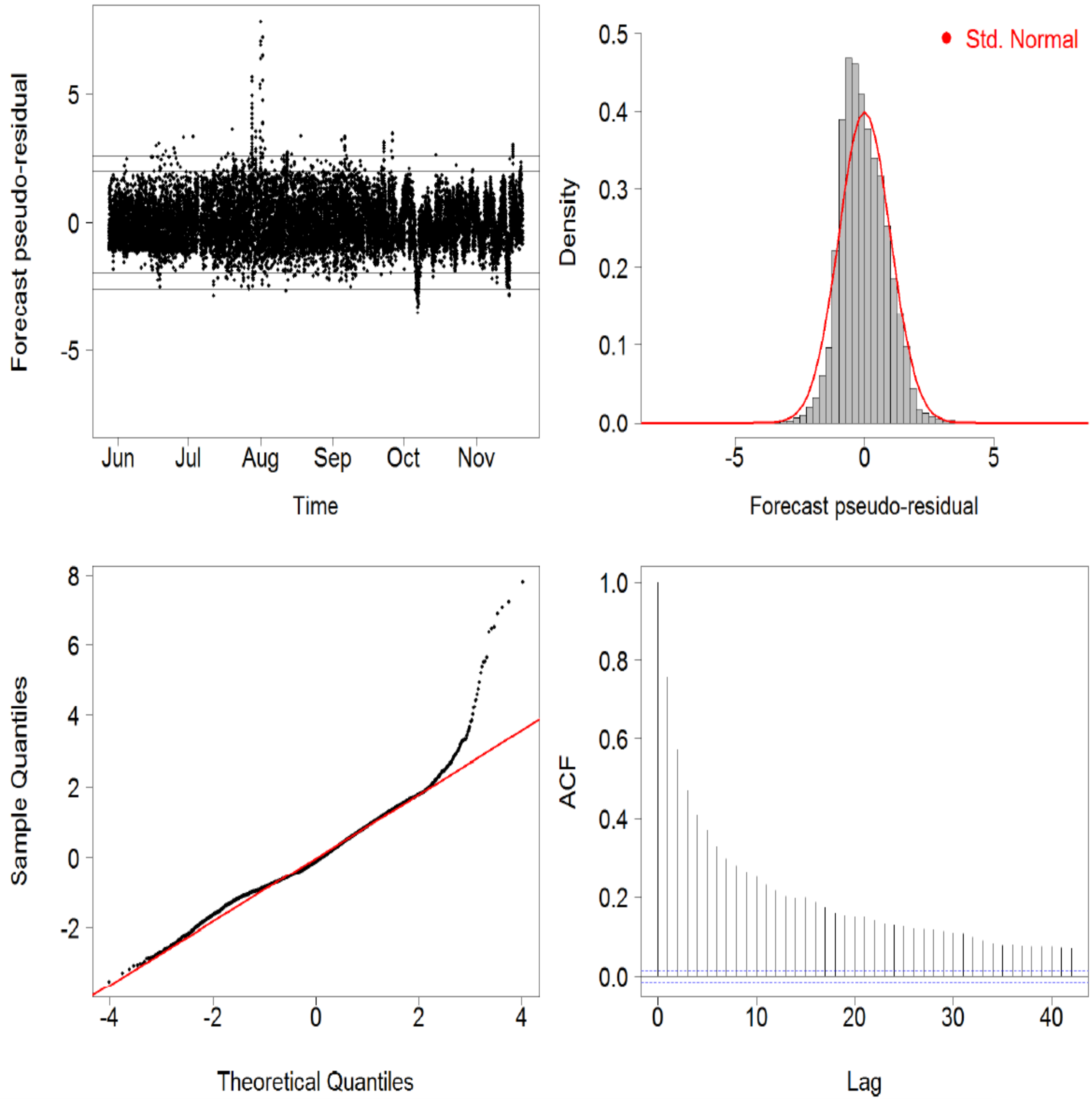


Figure 8.7: Global Decoding of the HMM (log CO_2) with 5 states.



State
1
2
3
4
5
sum
Density
1.0
0.8
0.6
0.4
0.2
0.0
3
4
5
6
7
8
9
CO2 In

CO2 In


Forecast pseudo-residual
5
0
-5
Jun
Jul
Aug
Sep
Oct
Nov
Time
Std. Normal
Density
0.5
0.4
0.3
0.2
0.1
0.0
-5
0
5
Forecast pseudo-residual
Sample Quantiles
8
6
4
2
0
-2
-4
-2
0
2
4
Theoretical Quantiles
ACF
1.0
0.8
0.6
0.4
0.2
0.0
0
10
20
30
40
Lag

Inhomogeneous Hidden Markov Model

Setting

$$y_t = h(CO_{2,t})$$
$$p(x_t | x_{t-1}) \sim \Gamma_t$$
$$p(y_t | x_t) \sim \mathcal{N}\left(\mu_i, \sigma_i^2\right) \text{ for } i = 1, 2, \cdots, m$$

Note that there is time dependence in the transition probabilities in the inhomogen case.

Inhomogeneous Markov-switching with auto-dependent observations

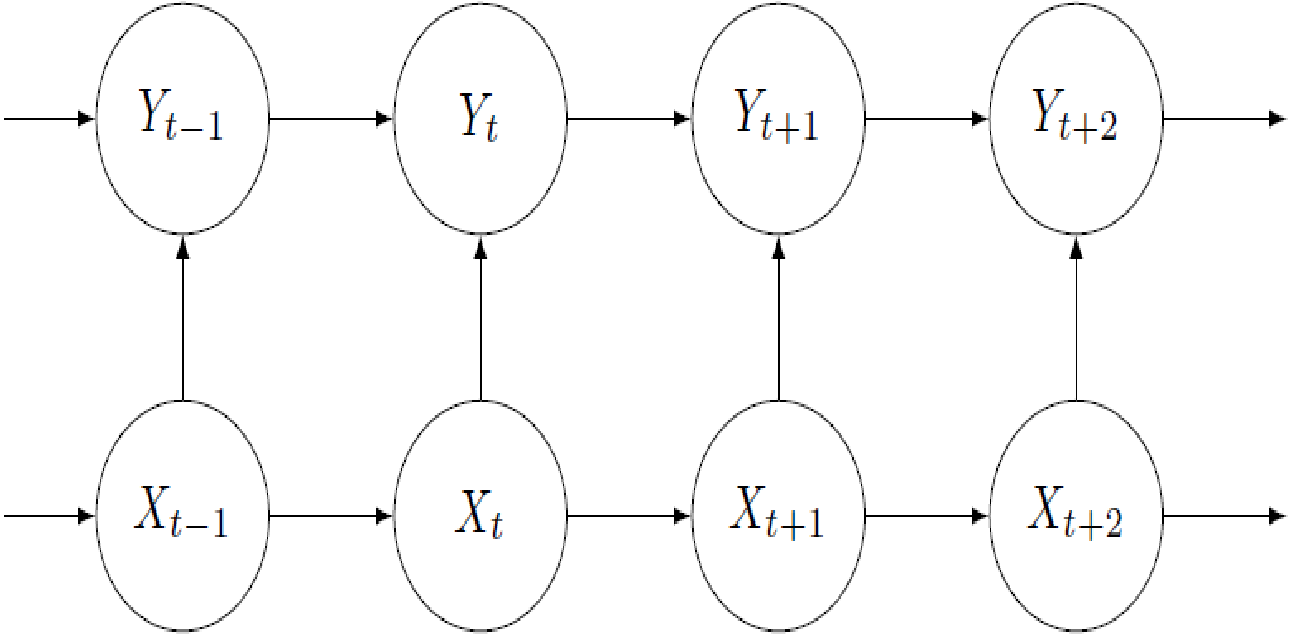


Figure 8.10: Directed graph of Markov switching AR(1).

Inhomogen Markov-switching AR(1)

Setting

$$
\begin{aligned}
y_t &= h(CO_{2,t}) \\
p(x_t | x_{t-1}) &\sim \Gamma_t \\
p(y_t | x_t, y_{t-1}) &\sim \mathcal{N}\left(c_i + \phi_i y_{t-1}\ ,\ \sigma_i^2\right) \text{ for } i = 1, 2, \cdots, m
\end{aligned}
$$

Note that there is time dependence in the transition probabilities in the inhomogen case.

Interpretation of the states

- State 1: Absence or sleeping
- State 2: Long term absence
- State 3: Outdoor interaction
- State 4: Presence (high activity)
- State 5: Presence (long term, low activity)

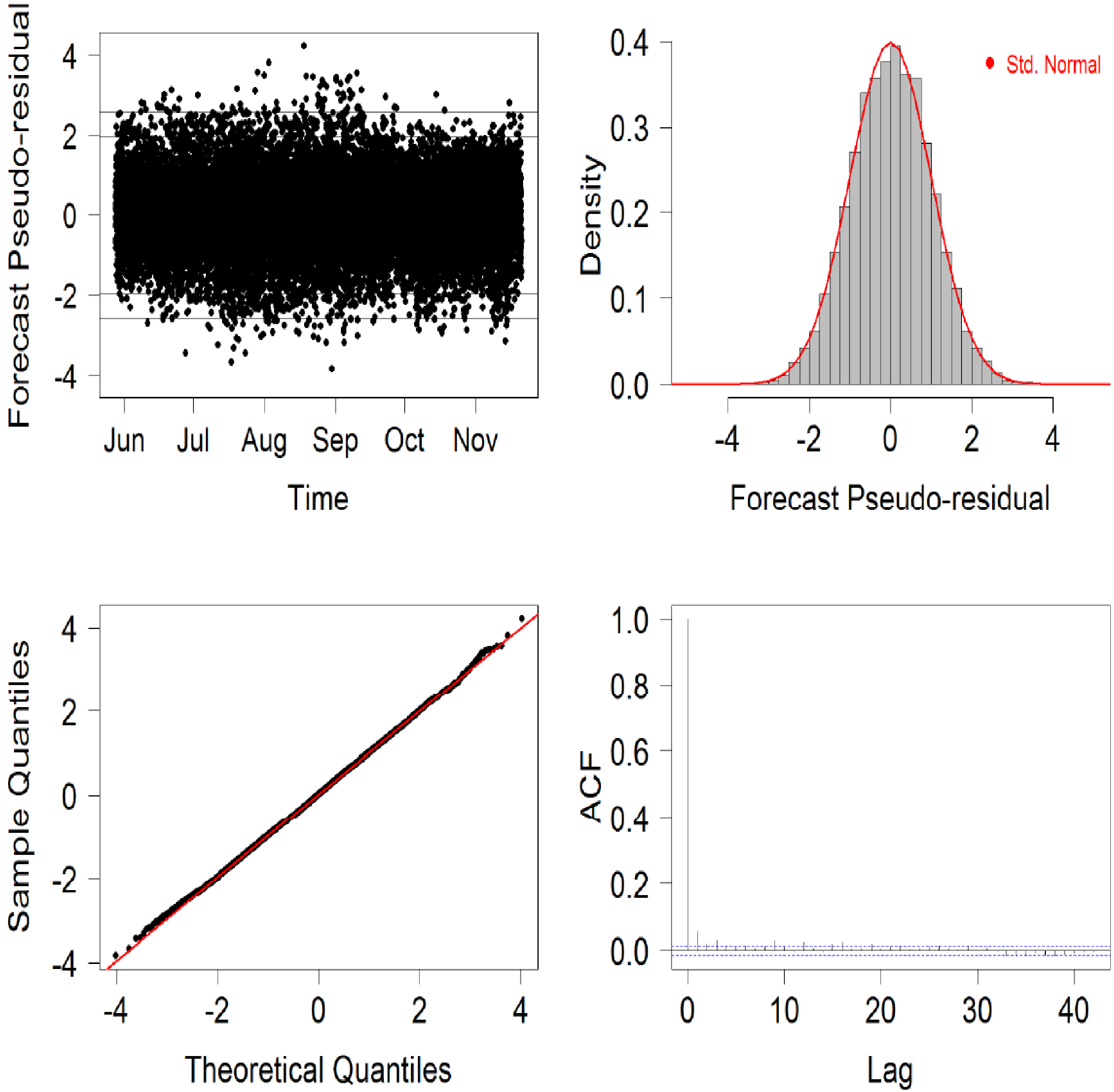


Figure 8.11: Model diagnostics of the final model.

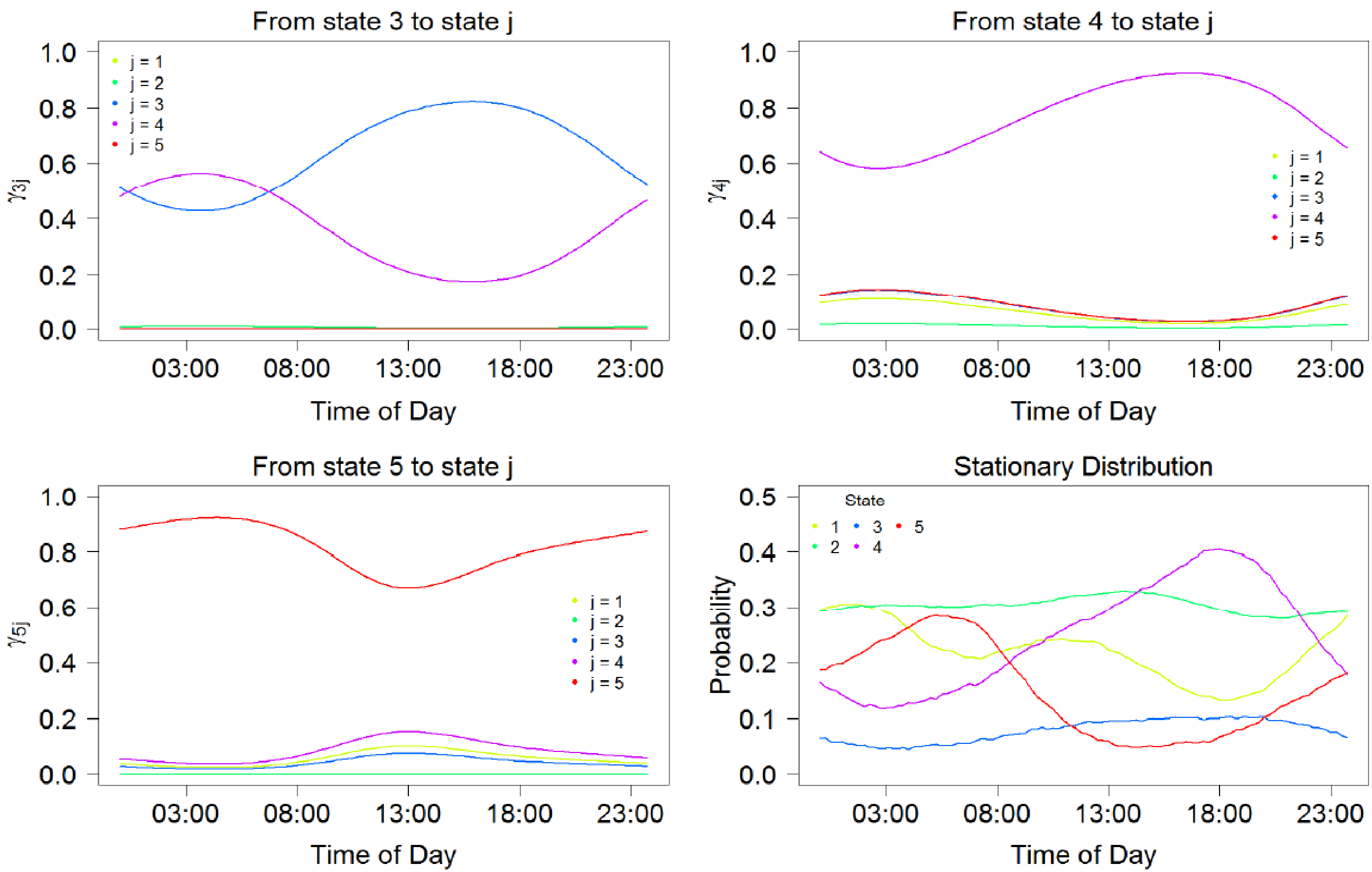


Figure 8.16: Transition probabilities over the day of the final model. The lower right plot is the stationary distribution.

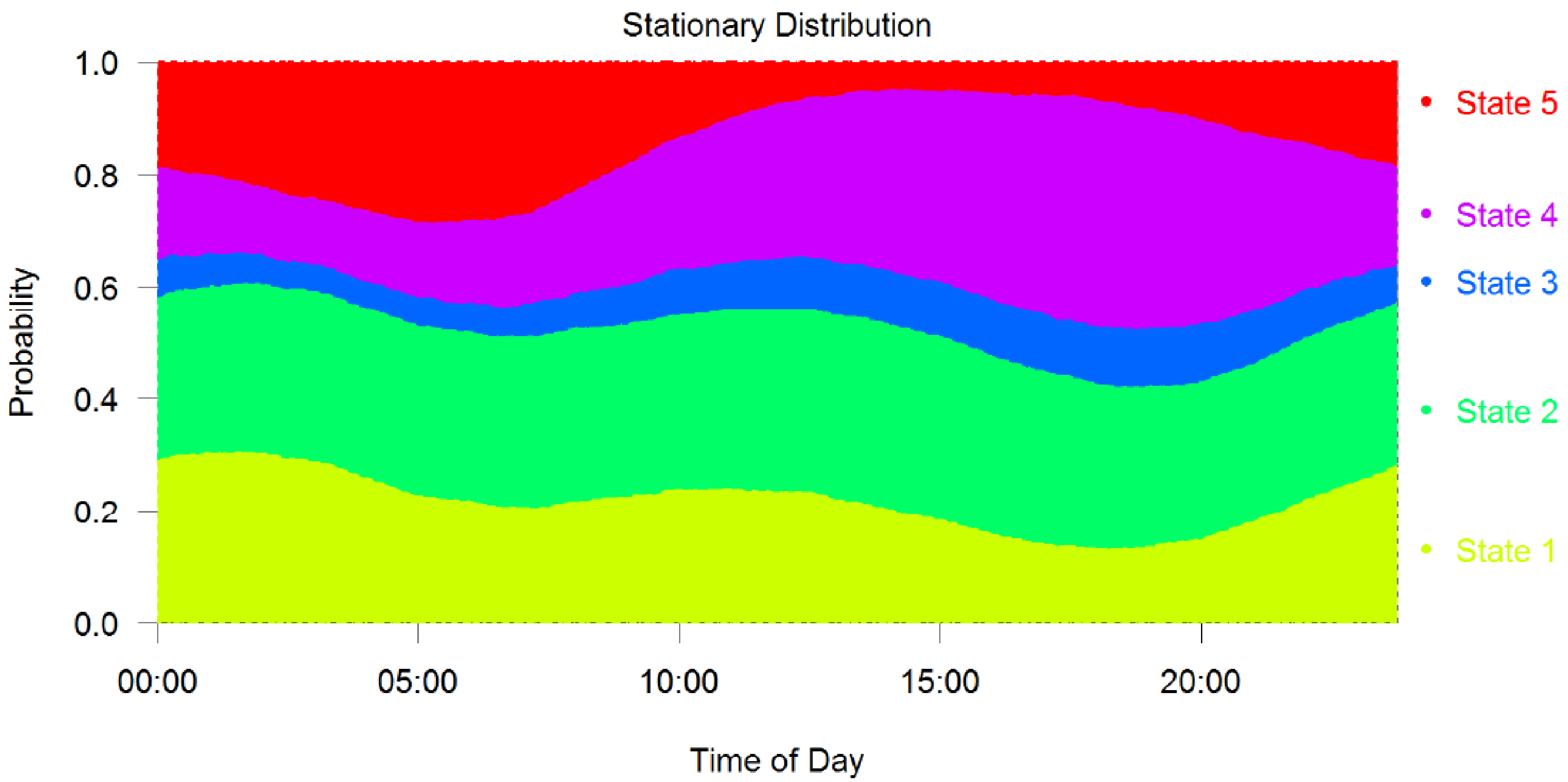


Figure 8.17: Profile of the states over the course of the day. I.e. Stacked stationary probabilities over the course of the day of the final model.

Some conclusions:

That the low activity state 5 is not very likely from 10 am to 11 pm.
The highest activity is seen in the late afternoon.

Some references

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Thanks ...

- For more information

  www.ctsm.info

  www.henrikmadsen.org

  www.smart-cities-centre.org

- ...or contact
  - Henrik Madsen (DTU Compute)

    hmad@dtu.dk

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