CITIES Kamstrup Meeting

Hidden Markov models for indirect classification of occupancy behaviour

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Overview

Problem description

By applying Hidden Markov models (HMMs) on electricity consumption from smart meter data the hypothesis, is that we can:

1. Classify the states of the HMM in accordance to occupancy behaviour.
2. Identify possible covariates/explanatory variables.
3. forecasting and simulation of the future energy consumption.

1), 2) and 3) can be solved by both homogeneous and time inhomogeneous models. It is suggested that to improve the forecasting and simulation, covariates/explanatory variables and time inhomogeneous Markov chains, are needed.

Data

- The data is collected in and nearby an apartment building in Catalonia, Spain.
- The data consist of hourly weather data from a nearby weather station and smart metering data of the apartments.
- The data was measured from mid July 2012 till the end of December 2013.

Weather data

Variable	description
T_a	Ambient temperature in $^\circ C$
G	Solar radiation in W/m^2
W_s	Average wind speed in m/s
W_d	Average wind direction in $^\circ$
P	Precipitation in mm

Table : Description of data

Analysis showed diurnal periods for T_a, G, W_s and W_d
Yearly period for T_a
These could be used as covariates/explanatory variables

Smart metering data

Variable	description
x_e	Electricity consumption in kWh
x_{sh}	Space heating in kWh
x_{hw}	Hot water consumption in kWh
x_w	Water consumption in litters
x_{it}	Interior temperature in $^\circ C$

Table : Description of data

- Due to a large number of zero observations the smart metering data is aggregated from 10 minute intervals to hourly intervals.
- The space heating, hot water and water measurements are integer.
- The electricity measurements are discrete with increments of 0.01.
- The complete data set consist of 44 apartments
- Electricity consumption is chosen to apply HMMs on

Homogeneous HMM for apartment 2

Using gamma distributions for the state dependent distributions a 3 state model was found suiable.

Table : Estimated parameters for the three state HMM for apartment 2 and calculated stationary distribution, mean and variance

State	k	θ	γ_{i1}	γ_{i2}	γ_{i3}	δ	Mean	Variance
1	7.74	0.012	0.85	0.14	0.01	0.52	0.09	0.001
2	7.30	0.040	0.21	0.73	0.06	0.38	0.29	0.012
3	5.14	0.205	0.00	0.30	0.70	0.10	1.05	0.216

1. Low consumption
2. Medium consumption
3. High consumption

Global decoding

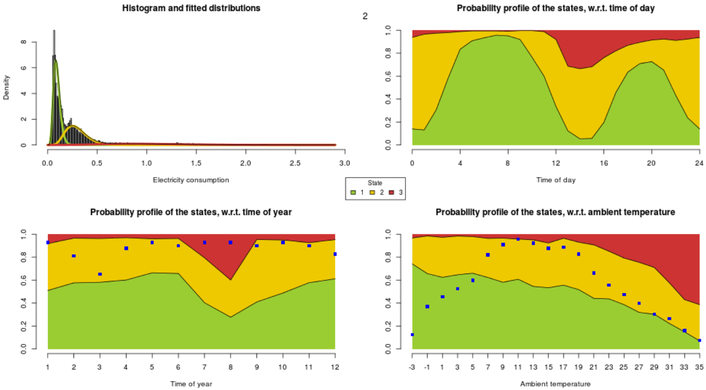


Figure : Average probability profiles of being in given state, dependent on time of day, time of year and ambient temperature. The blue squares denote the relative amount of observations for each month or temperature interval

Homogeneous H

Given data from occupant survey

Apartment	No. occupants	Air-condition	Hours empty on weekday	Source of income
2	1	yes	3-5	pension

The states are interpreted as:

1. Absent or asleep
2. Home, medium consumption
3. Home, high consumption

These interpretations are compared to water use for validation.

Comparison with water use

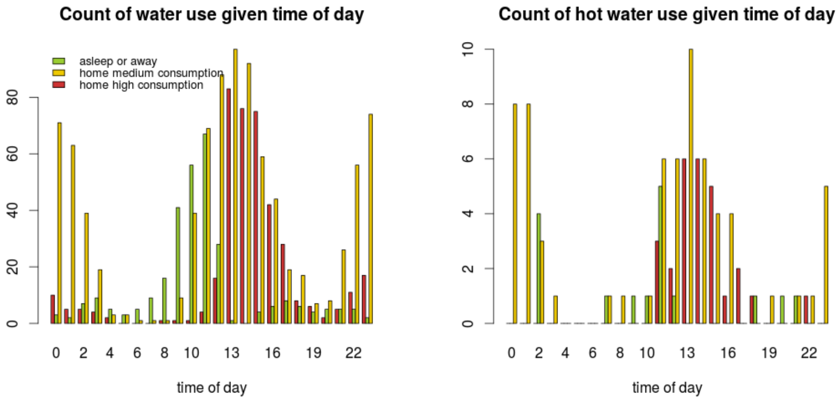


Figure : Counts of water and hot water use given state and time of day

Summary of homogeneous HMMs

Homogeneous HMMs fitted on 14 apartments(several more but with local maximum)

- 10 apartments 3 states found suitable
- 4 apartments 4 states found suitable

Temperature dependence

Observation of temperature dependence

Apartment \ State	1	2	3	4
1	-	-	-	
2	-	-	yes	
3	yes	yes	-	
5	-	-	-	-
7	yes	yes	-	
12	-	yes	-	
15	-	-	-	
18	-	-	-	
25	yes	yes	-	
26	-	-	-	-
29	-	-	-	
30	-	-	-	
35	yes	yes	yes	-
44	-	-	-	-

Classification of profiles

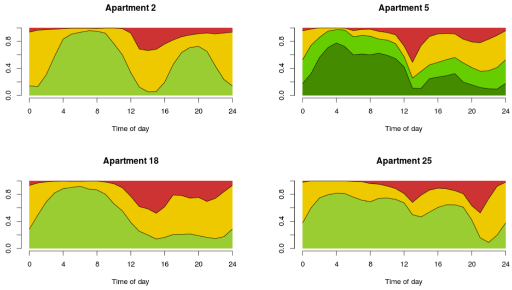


Table : Apartments classified based on the average probability profile

Class	Apartments
afternoon/evening absence	2
equal probability for being home or away	1, 5, 7, 26 and 35
mostly at home	3, 18, 29 and 44
mostly away	12, 15, 25 and 30

Classification of profiles

Selection of date from occupant survey

Apartment	No. occupants	Air-condition	Hours empty on weekday	Source of income	No. states
2	1	yes	3-5	pension	3
1	NA	NA	NA	NA	3
5	2	no	>10	work	4
7	2	no	3-5	scholarship	3
26	1	no	3-5	pension	4
35	1	no	6-8	pension	4
3	3	no	<2	pension	3
18	5	no	<2	work	3
29	3	no	<2	work	3
44	1	no	<2	pension	4
12	1	no	3-5	pension	3
15	1	no	>10	work	3
25	1	no	>10	work	3
30	1	no	6-8	subsidy	3

Common parameters

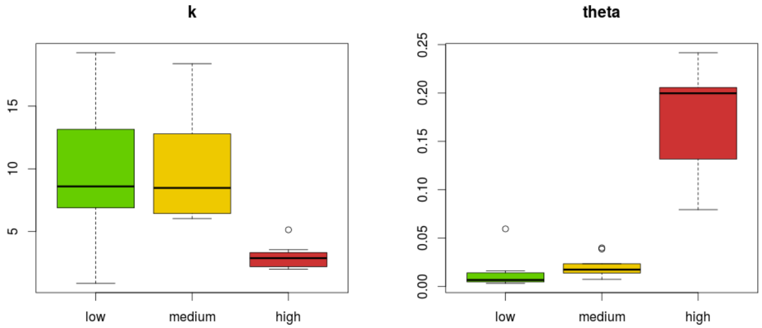


Figure : Box-plots of the parameters estimates for the state dependent distributions and the stationary distribution

Common parameters

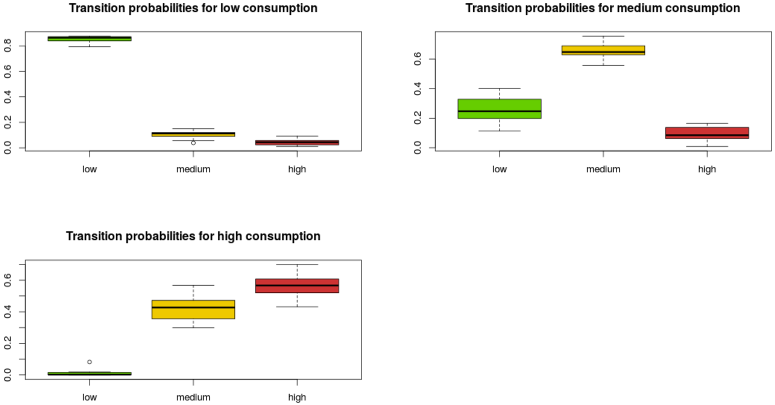


Figure : Box-plots of the transition probabilities for each state

Inhomogeneous HMM

The inhomogeneous HMMs are time dependent

The time dependence is modelled in the transition probability matrix by a Fourier series with a number of sin- cosine pairs to describe the diurnal variation

Inhomogeneous HMM, Apartment 18

Using the number of states found suitable for the homogeneous HMM for apartment 18, 2 sin- cosine pairs was found suitable.
The figure shows the model generated probability profiles given no. sin- cosine pairs.

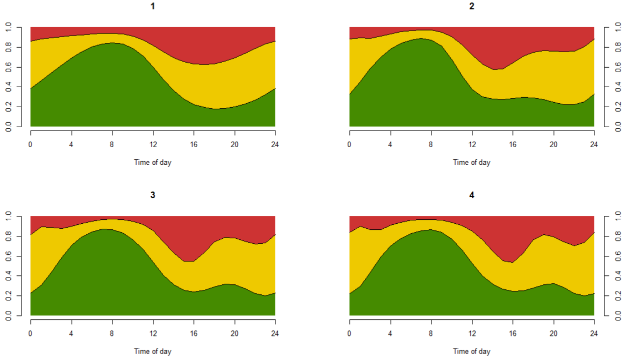


Figure : Model generated daily probability profiles, with increasing no. sin- cosine

Forecasting distributions

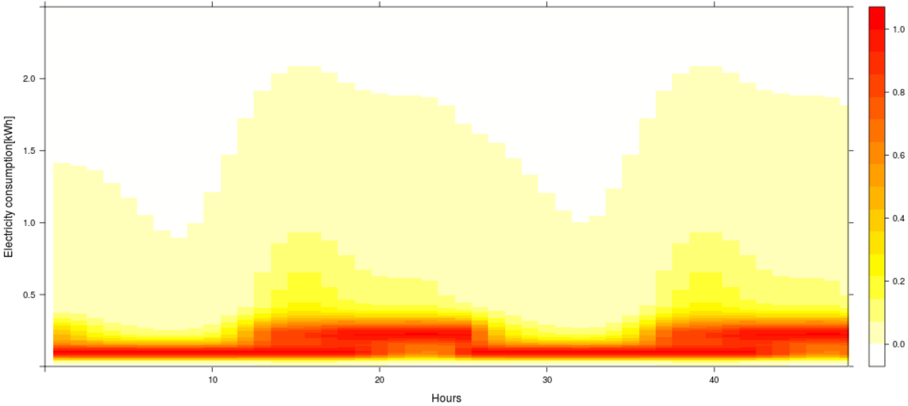
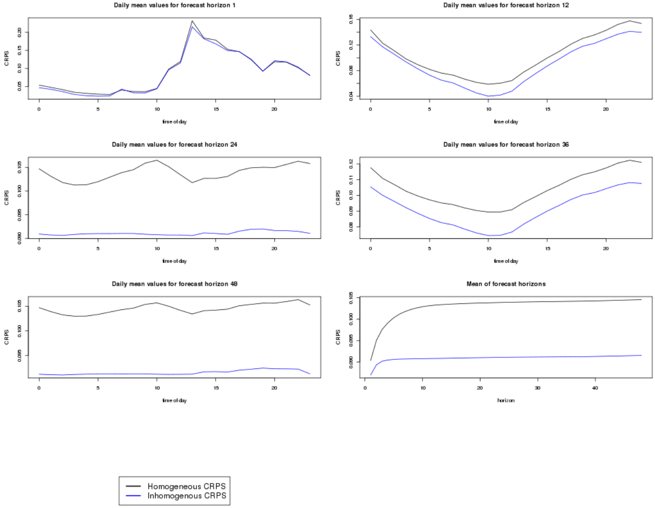


Figure : Contour plot of forecasting distributions 48 hours ahead of the data used to fit the model. The scale is relative to the largest probability in each horizon for Apartment 18

CRPS



Apartment 18

Summary of inhomogeneous HMMs

- High consumption not captured for some apartments
- Forecast similar observations as for Apartment 18
- CRPS similar observations as for Apartment 18

Common parameters

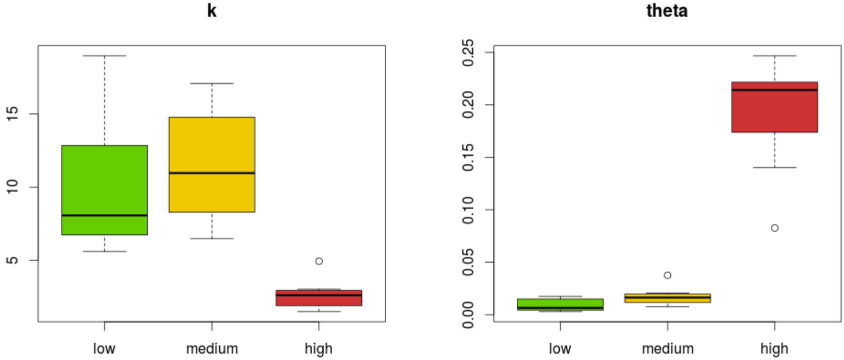


Figure : Box-plots of state dependent parameters for the inhomogeneous 3 state models

Common parameters

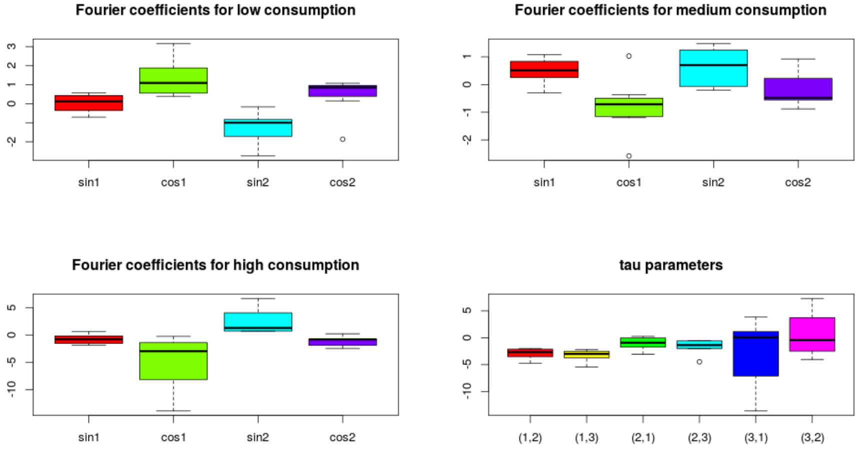


Figure : Box-plots of transition probability parameters for the inhomogeneous 3

Temperature dependent inhomogeneous HMM, Apartment 2

The temperature dependence is modelled in the mean value of the states where the dependence was observed.

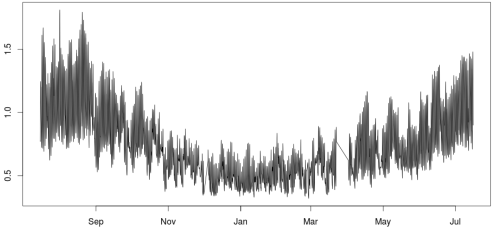
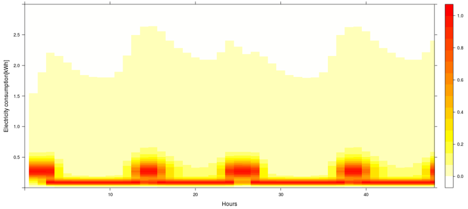
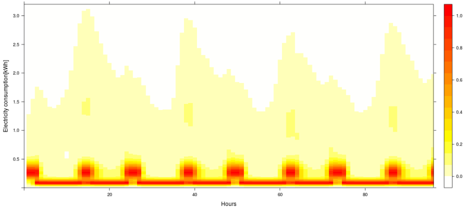


Figure : Mean values in high consumption state over one year

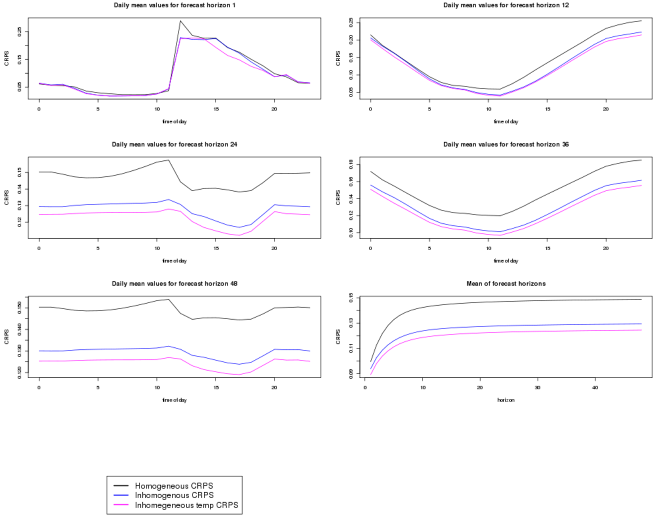
Forecasting distributions

Forecasting distributions for inhomogeneous and temperature dependent model.





CRPS



Apartment 2

Summary temperature dependent inhomogeneous HMMs

- Did not yield good results due to varying mean values in the lower consumption states
- Smoothing of mean values is needed

Discussion/Conclusion

With HMMs we have

- Classified states in accordance to occupancy behaviour
  - "low consumption" and "absent or asleep"
  - "medium consumption" and "home"
  - "high consumption" and "home, high consumption"
- Identified dependency on temperature for several apartments
- Improved forecasting by inhomogeneous HMMs
- Observed distinct occupancy patterns
- Found it plausible to model population models, both for homogeneous and inhomogeneous HMMs
- Found model deficiencies
  - High consumption (varying coefficients)
  - Changing behaviour (adaptive methods)
  - Temperature dependent mean values (Smoothing)

Outlook

- Classify occupancy patterns
- Examine other data given a state (heat consumption with low probability of occupant influence)
- Forecasting of electricity consumption (apartment building/road/city with population models)
- Simulation of electricity consumption (apartment building/road/city with population models)
- Consumer apps