POWER AND ENERGY WEBINAR • SERIES

Powered by INESCTEC

Using deep learning to simulate demand response profiles from consumers

Margaux Brégère, margaux.bregere@edf.fr

Joint work with Ricardo Bessa

November, 27th 2020

Introduction

As electricity is hard to store, balance between production and demand must be maintained at any time.

Current solution:

Forecast demand and adapt production accordingly

- As renewable energies are subject to weather conditions, production becomes harder to adjust
- New communication tools (smart meters) will provide access to data and instantaneous communication

Prospective solution:

Send incentive signals, like electricity tariff variations, to manage electricity demand

This presentation follows the article *Simulating Tariff Impact in Electrical Energy Consumption Profiles with Conditional Variational Autoencoders*, Margaux Brégère and Ricardo J. Besssa , IEEE Access, 2020

Reinforcement Learning for Demand Side Management

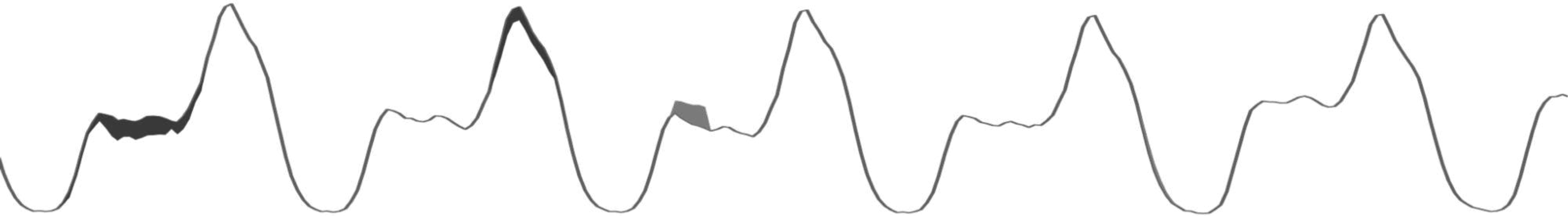
How to develop automatic solutions to dynamically chose incentive signals?

Learn from clients behaviors & Optimize tariffs sending

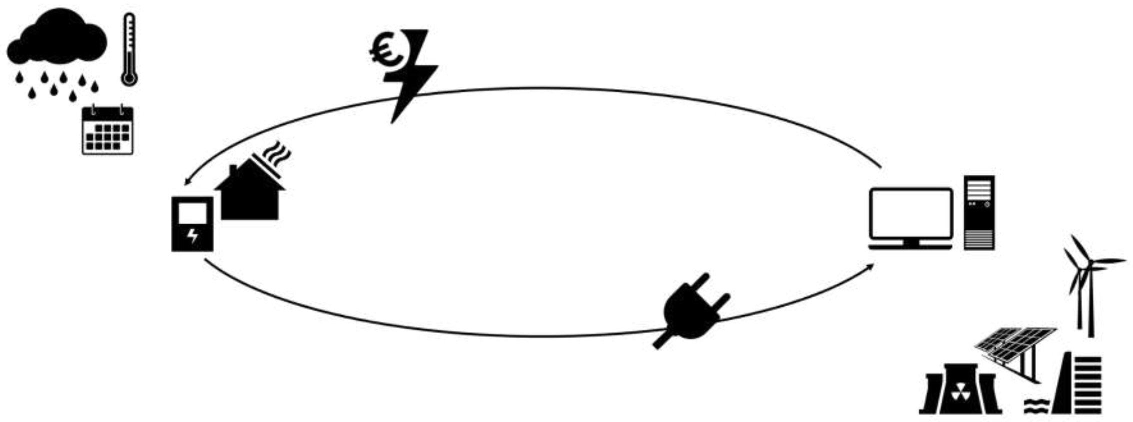
Exploration - Exploitation

trade-off

Adapt contextual-bandit (in my PhD) or any reinforcement learning theory to demand side management by offering price incentives



How to test Reinforcement Learning Algorithms?



The experiments will rely on a real data set, in which different tariffs were sent to the customers according to some policy.

Alternative policies cannot be tested on historical data (only the electricity demand associated with tariffs sent was observed)

Motivation: a data generator for an ex-ante assessment of Demand Respond policies

Two approaches

A (semi)-parametric approach:

$$Y_t = f(x_t) + noise$$

- Interpretable
- Illustrate the theory (simulated data follows the model assumed in the theory)

A black-box approach based on conditional variational auto-encoders

- Completely data-driven
- Test the algorithm robustness (simulated data imitates real data)

Data set description and preprocessing

"Smart Meter Energy Consumption Data in London Households"
Public dataset - UK Power Network

Individual electricity demand at half-an-hour intervals throughout 2013 of ~1 000 clients subjected to Dynamic Time of Use energy prices

Three tariffs: High (67.20 p/kWh), Low (3.99 p/kWh), or Normal (11.76 p/kWh), announced day-ahead via the smart meter or text message.

Data set description and preprocessing

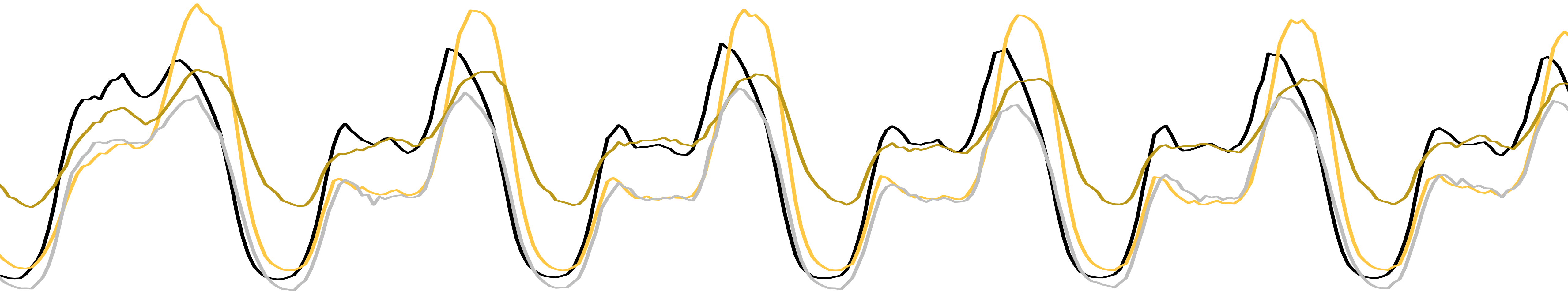
- Households with more than 95% of data available are kept
- Missing values filled by linear interpolation
- Half-hourly data points of air temperature in London obtained from hourly public observations are added and calendar variables are computed

Variable	Notation
Daily energy consumption profile at half-hourly intervals	$Y_t^1, \dots, Y_t^{48}$
Daily electricity price profile at half-hourly intervals	$p_t^1, \dots, p_t^{48}$
Daily London air temperature profile at half-hourly intervals	$\tau_t^1, \dots, \tau_t^{48}$
Smooth temperature Computed from past temperatures	$\bar{\tau}_t$
Type-of-day 1 from Monday to Friday, 0 for weekends	w_t
Position-inside-the-year Linear value between 0 (January, 1.) and 1 (December, 31.)	π_t

Clustering of households

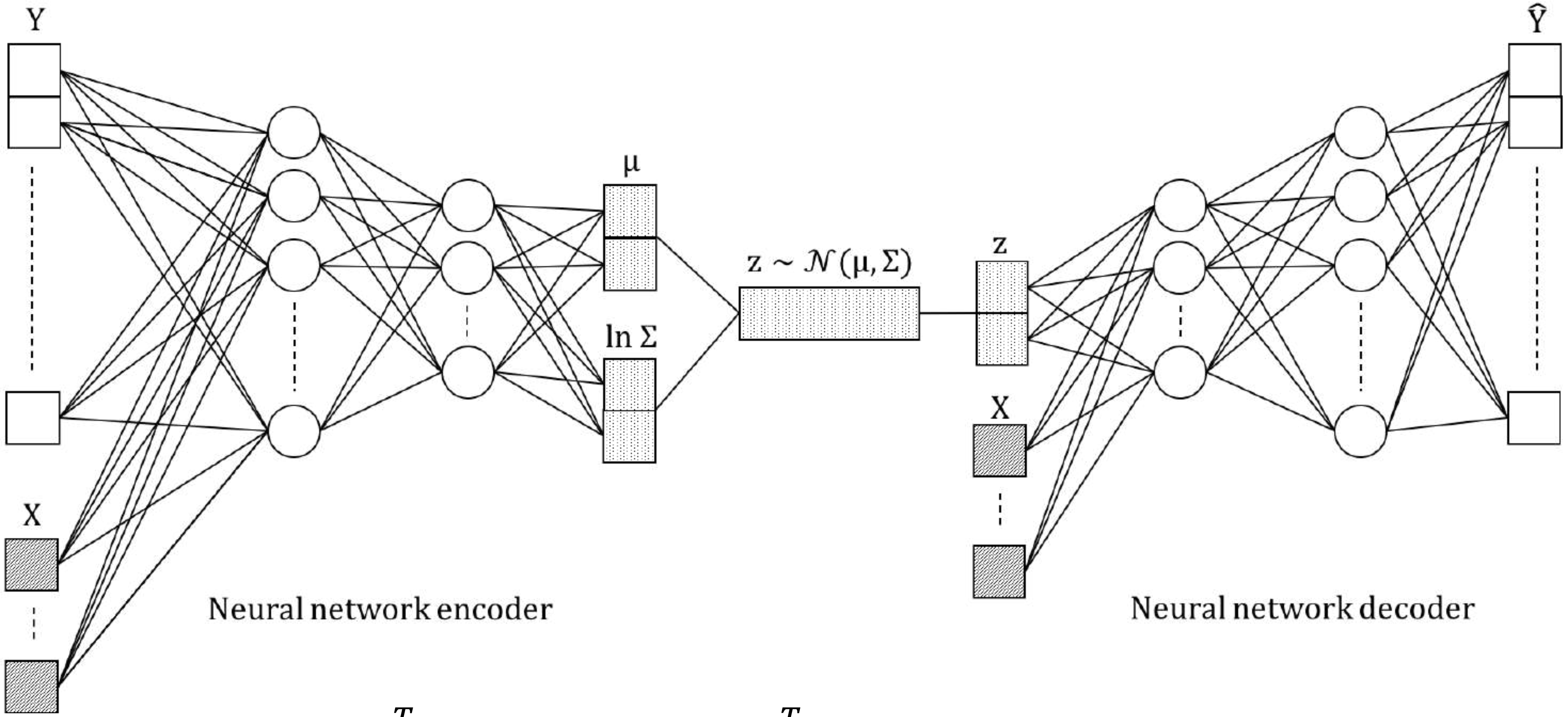
Electricity demand and elasticity profiles → Feature creation using low rank approximation → Clustering algorithm (k-medoid) → k clusters

Estimated with causality inference [1]



[1] K. Ganesan, J. T. Saraiva, and R. J. Bessa, *On the use of causality inference in designing tariffs to implement more effective behavioral demand response programs*, 2019

Energy consumption profile generation with Conditional Variational AutoEncoder (CVAE)[2]



$$L_{CVAE}(\eta) = \frac{1}{T_0}\sum_{t=1}^{T_0}\left\|Y_t - \hat{Y}_t\right\|^2 + \eta\frac{1}{T_0}\sum_{t=1}^{T_0} D_{KL}\left(\mathcal{N}(\mu(Y_t), \Sigma(Y_t)) \,||\, \mathcal{N}(0, I_d)\right)$$

[2] D. P. Kingma and M. Welling, *Auto-encoding variational bayes*, 2014

Energy consumption profile generation with Conditional Variational AutoEncoder (CVAE)

Hyper-parameters:

- Number of hidden layers
- Number of neurons
- Activation function of neurons
- …

Conditional variables

- Temperatures resumed in 3 variables (with PCA)
- Position-inside-the-year
- 2 x 48 binary variables to encore Low and High tariffs

Energy consumption profile generation with generalized additive models (GAM)[3]

$$\begin{bmatrix} Y_t^1 \\ \vdots \\ Y_t^{48} \end{bmatrix} = \underbrace{\begin{bmatrix} f^1(\tau_t^1, \bar{\tau}_t, w_t, \pi_t, p^1) \\ \vdots \\ f^{48}(\tau_t^{48}, \bar{\tau}_t, w_t, \pi_t, p^{48}) \end{bmatrix}}_{\text{Estimated with generalized additive models}} + \overbrace{\underbrace{\left(\sigma^1(p^1), \dots, \sigma^{48}(p^{48})\right)}_{\text{Estimated with causality inference [1]}}}^{\text{A variance per tariff and per half-hour}}{}^T \mathrm{E_t}\,,$$

$$\text{where } \mathrm{E_t} \sim \mathcal{N}\left(\begin{matrix} 0 \\ \vdots \\ 0 \end{matrix}, \underbrace{\Sigma}_{\text{Models correlations between half-hours}} \right)$$

POWER AND ENERGY WEBINAR · SERIES

Powered by INESCTEC

[3] S. Wood, *Generalized Additive Models: An Introduction with R*, 2006

Results: experiment design

	Training Set (75% data)	Testing Set (25% data)
Households clustering	✓	
CVAE model training	✓	
CVAE hyper-parameters calibration		✓
Semi-parametric model training	✓	
Numerical experiments		✓

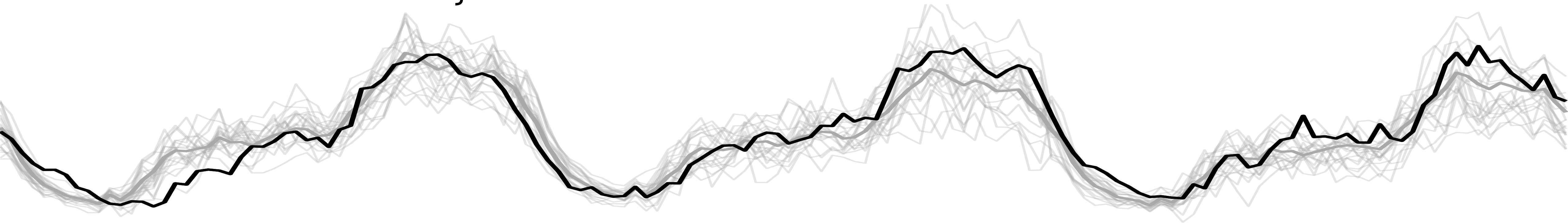
For each cluster:

- A GAM-based generator
- A CVAE-based generator

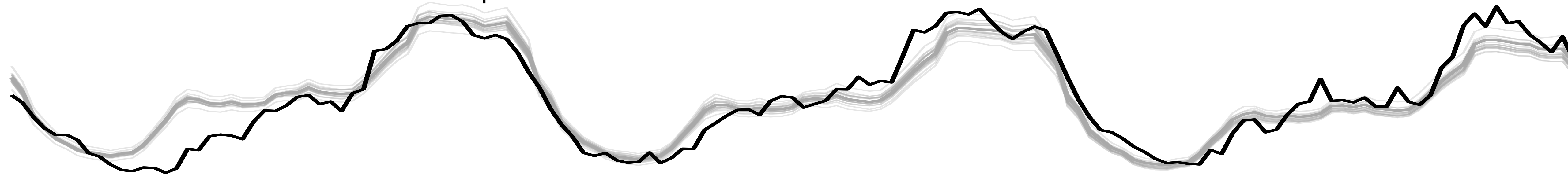
Electricity demand generated for tariff signals send in original data

- **Semi-parametric approach**
  - \+ Good estimation in expectation
  - – Non-coherent trajectories

Observation
Simulations

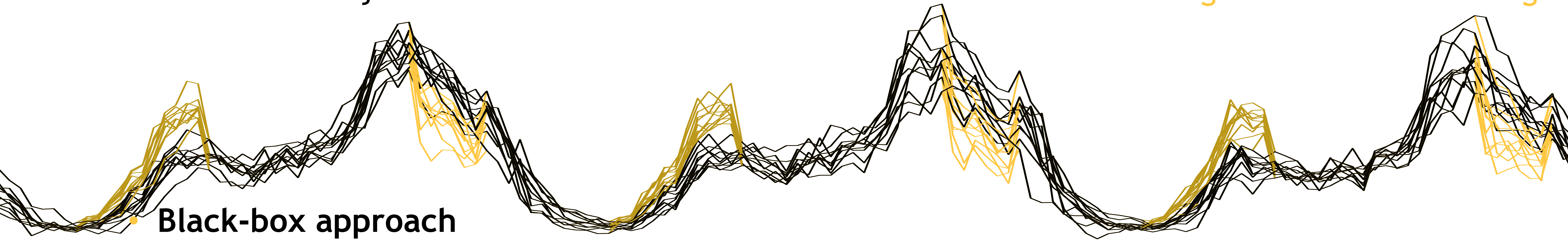


- **Black-box approach**
  - \+ Coherent trajectories
  - – Bad estimation in expectation

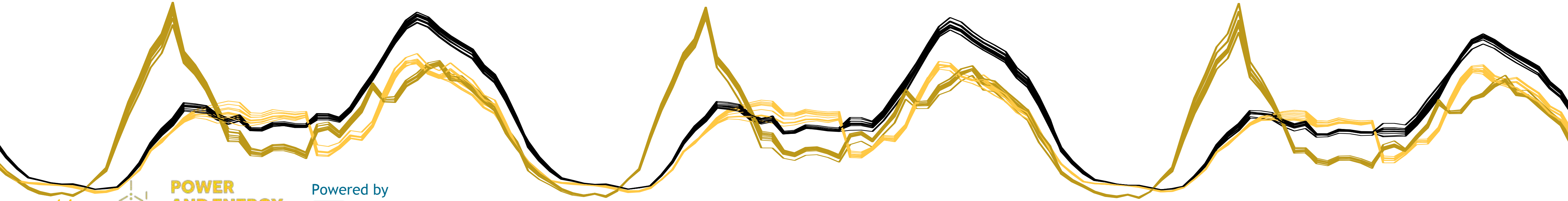


Electricity demand generated for different tariff signals

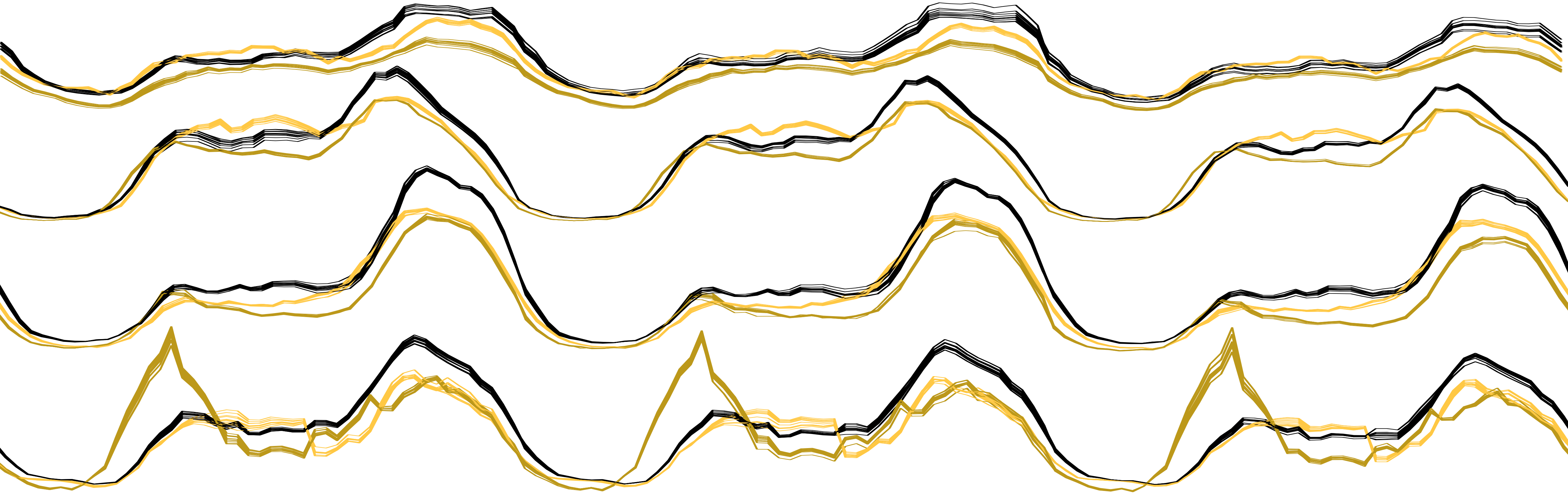
- **Semi-parametric approach**
  - \+ Interpretable (but captures tariff effect only for the half-hours affected)
  - − How to adjust variance and model the noise?



- **Black-box approach**
  - \+ Rebound effect (provides daily consumption samples)
  - − Lack of variability and limited generalization capacity



Results



Generated samples differ from a cluster to another

➢ clustering approach divides correctly the households according to their responsiveness to a tariff profile.

Many thanks
to Ricardo Bessa, for his wonderful supervising,
to Kamalanathan Ganesan, for his clear explanations of the causality model,
to José Ricardo Andrade, for his help with Tensorflow and the IT support,
and to the Power and Energy Systems team, for their
cheerful welcome in Porto !

And thank you all for your attention !

Contacts:

energywebinars@inesctec.pt

http://energywebinars.inesctec.pt/

Results: evaluation of the generated densities

Metrics: F is the generated density and y the real data

- Root Mean Squared Error (RMSE): evaluates the quality of the expectation of the distribution

$$RMSE(F, y) = \|\mathbb{E}[Y] - y\|, \qquad Y \sim F$$

- Energy Score [4]: does not detect correctly correlations between the components of the multivariate distribution

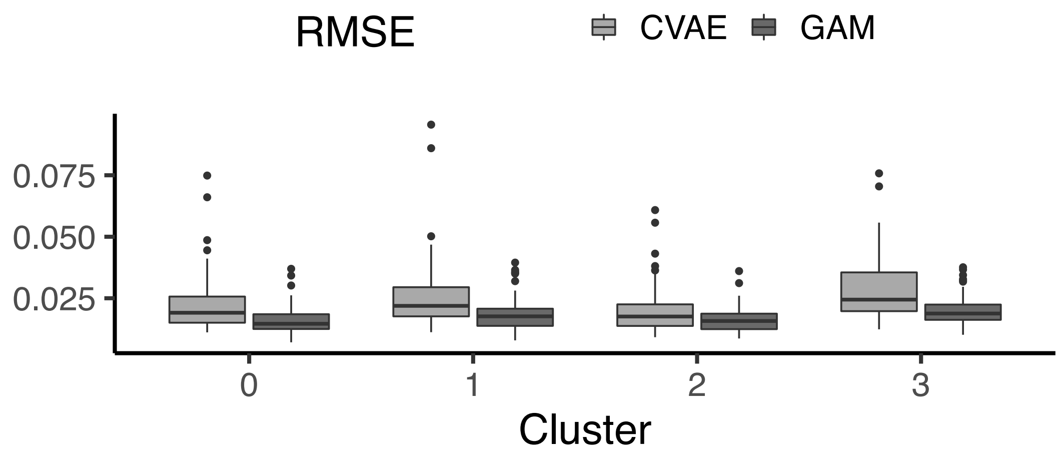
$$\mathrm{E}(F, y) = \mathbb{E}[\|Y - y\|] - \frac{1}{2}\mathbb{E}[\|Y - Y'\|], \qquad Y \text{ and } Y' \text{ independant and} \sim F$$

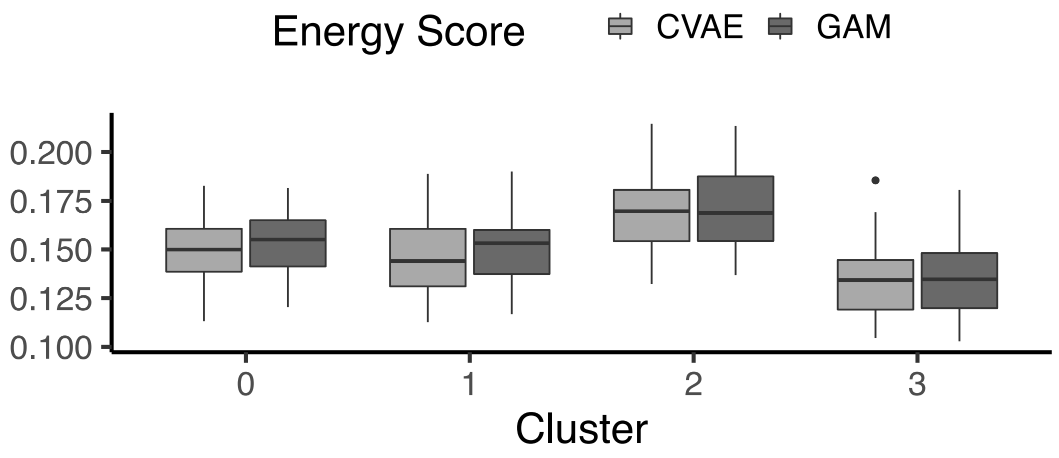
- Variogram [5]

[4] T. Gneiting and A. E. Raftery, *Strictly proper scoring rules, prediction, and estimation*, 2007

[5] M. Scheuerer and T. M. Hamill, *Variogram-based proper scoring rules for probabilistic forecasts of multivariate quantities*, 2015

Numerical results

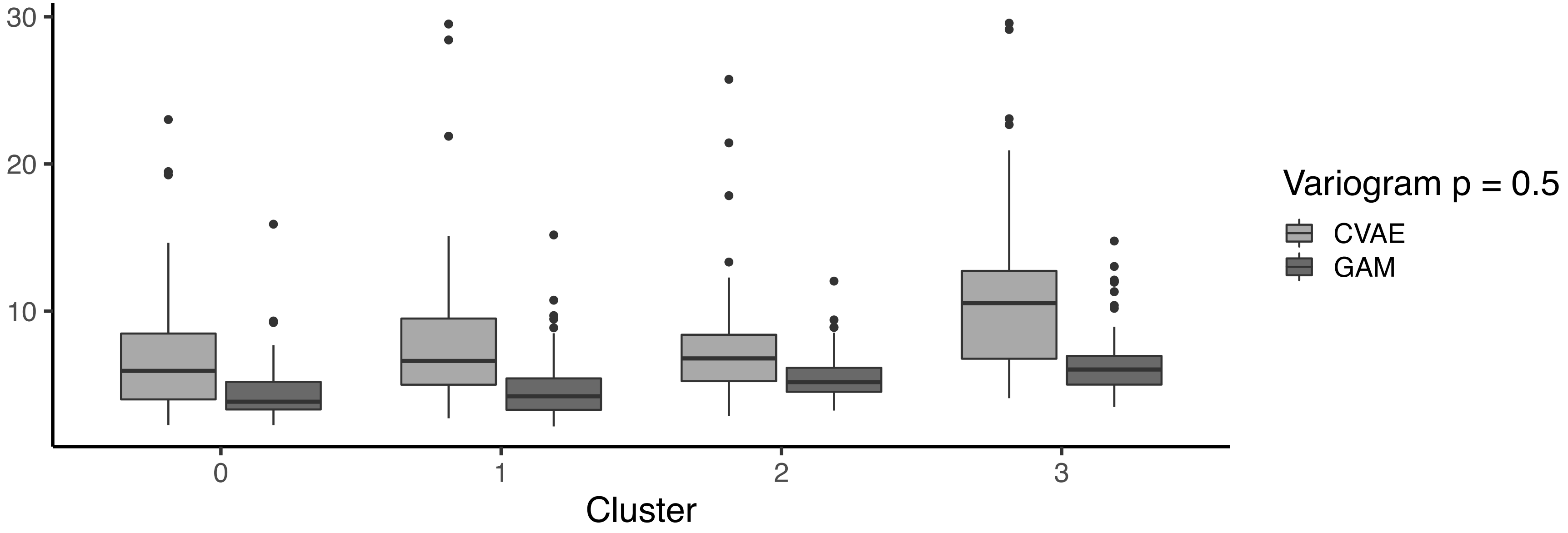




- GAM better than CVAE for generating the average value (RMSE)
- Energy Score: slightly lower for the black box approach

➢ Method that consists in adding a noise term to a forecast in expectation have some limits whereas CVAEs seem to catch correctly the distributions

Numerical results



- If average value incorrect, variogram scores increase
- Too low or too high variance increases variogram

➢ Difficult to discriminate significantly both generators