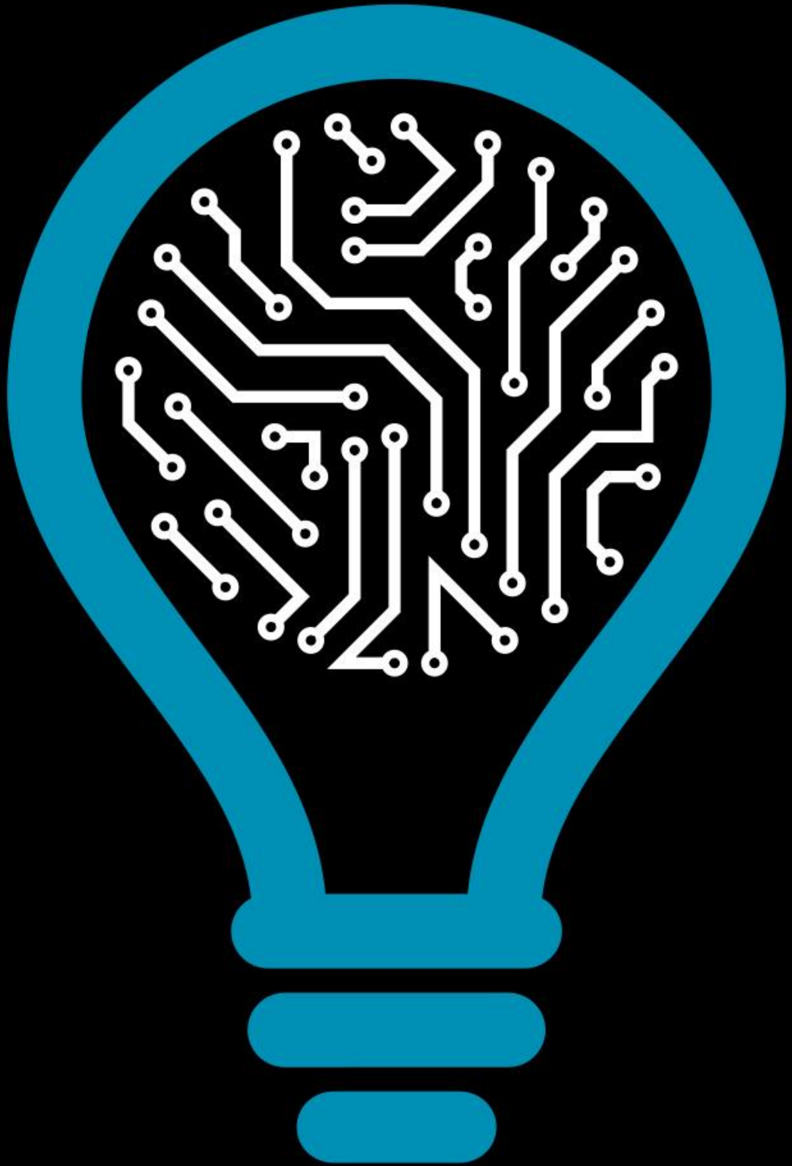
Data Science in Sustainable Energy Systems

Ricardo Bessa, rbessa@inesctec.pt

Porto, Portugal

4th March 2020

DSPT DATA SCIENCE PORTUGAL



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Use Cases for this Talk

Renewable Energy Forecasting

- ❑ Uncertainty forecasting
- ❑ Collaborative forecasting
- ❑ Data markets

Energy Optimization

Data-driven predictive modelling of energy-intensive processes

kWh

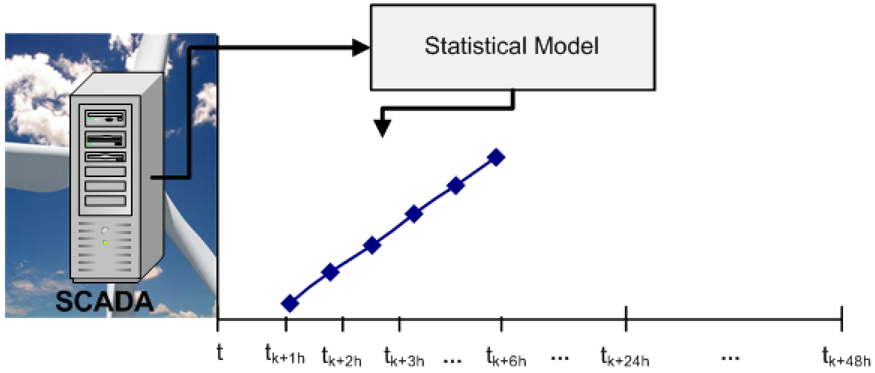
Market Curves Forecasting

Deep learning to forecast electricity market curves

Renewable Energy Forecasting

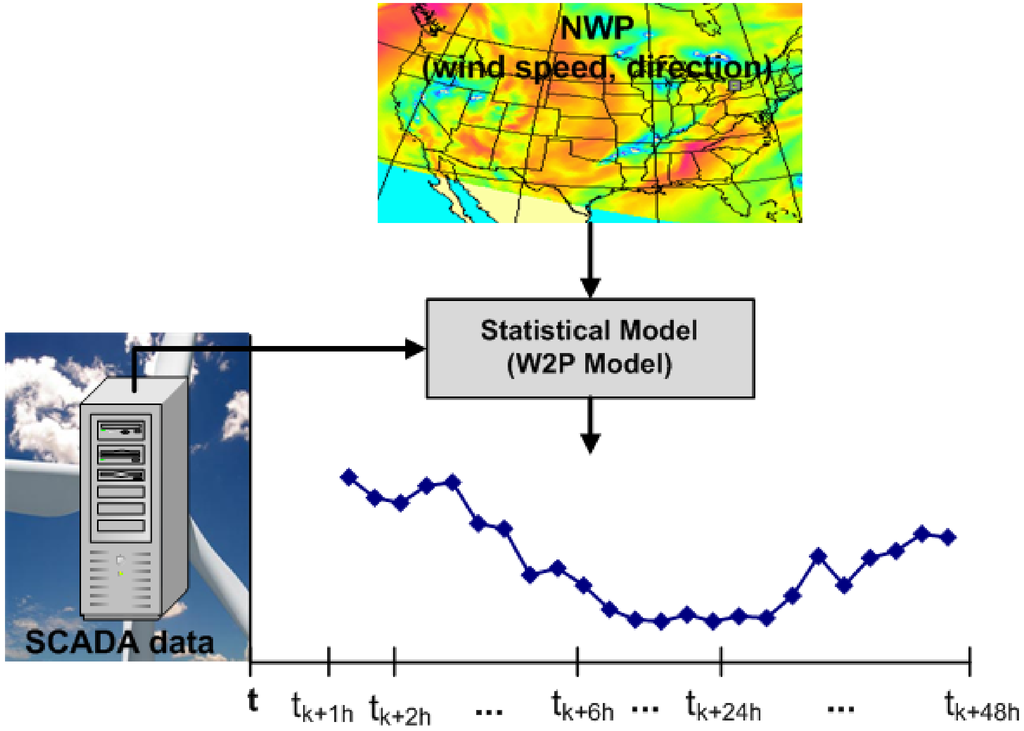
Renewable Energy Forecasting in a Glance

Very short-term power forecasting (~6 hrs ahead)



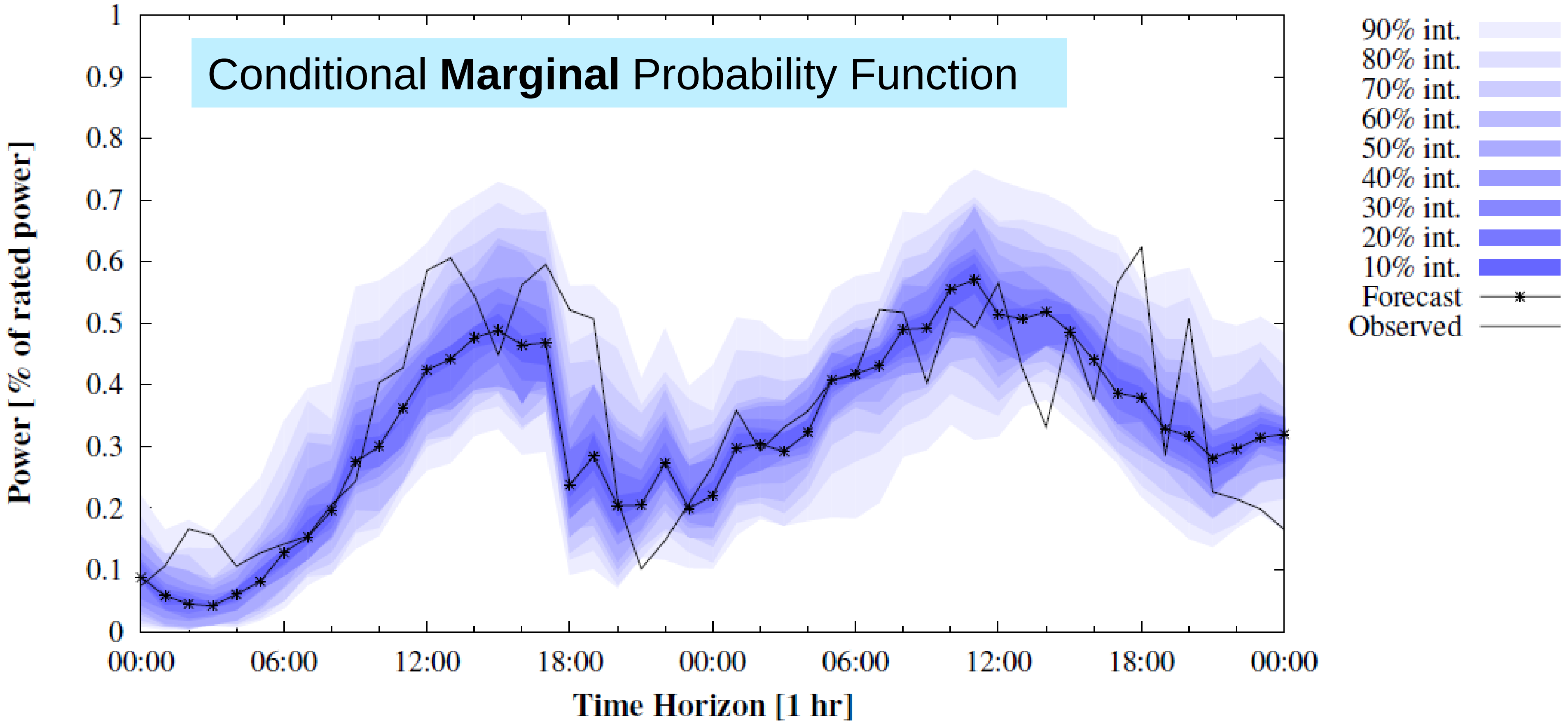
Short-term power forecasting (from 48hrs to 1 week ahead)

***NWP**: Numerical Weather Predictions (e.g. IPMA)*



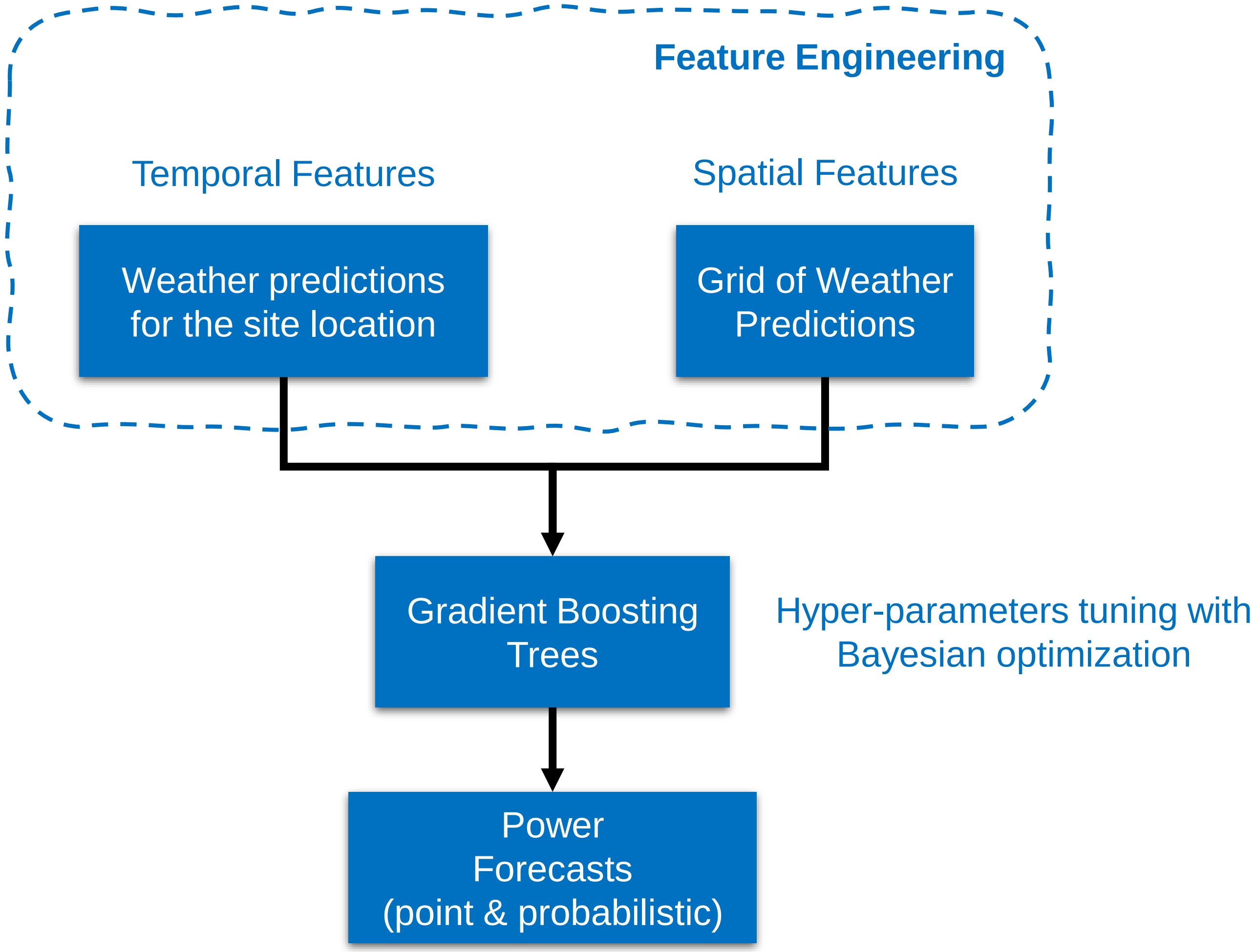
Reference: Bessa, R. J., Möhrlen, C., Fundel, V., Siefert, M., Browell, J., Haglund El Gaidi, S., Kariniotakis, G. (2017). Towards improved understanding of the applicability of uncertainty forecasts in the electric power industry. Energies, 10(9), 1402.

Renewable Energy Forecast Uncertainty



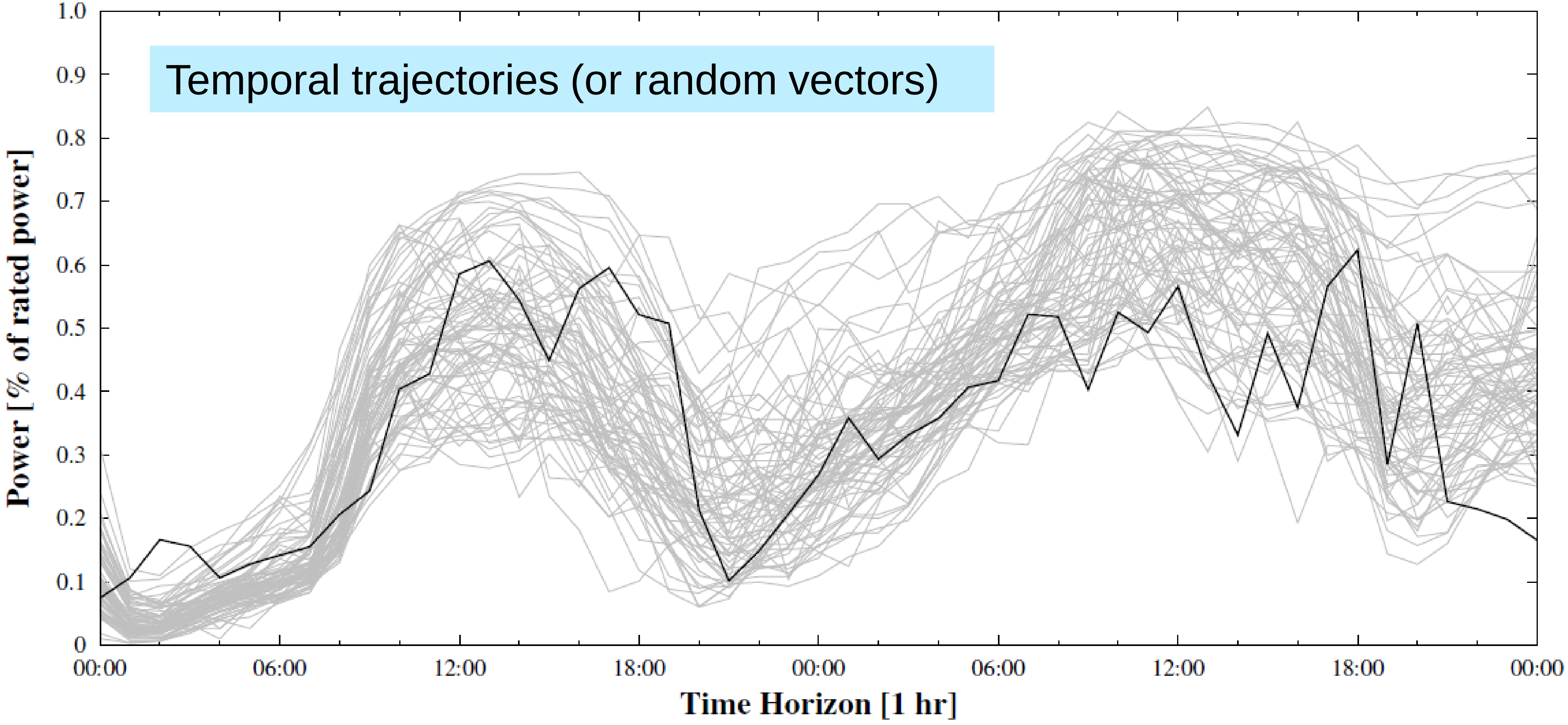
Misleading information to a decision-maker, e.g. interpret the quantiles as a possible temporal evolution in time

Forecasting Framework for Marginal Distributions



Reference: J.R. Andrade, R.J. Bessa, "Improving renewable energy forecasting with a grid of numerical weather predictions", IEEE Transactions on Sustainable Energy, vol. 8, no. 4, pp. 1571-1580, Oct. 2017.

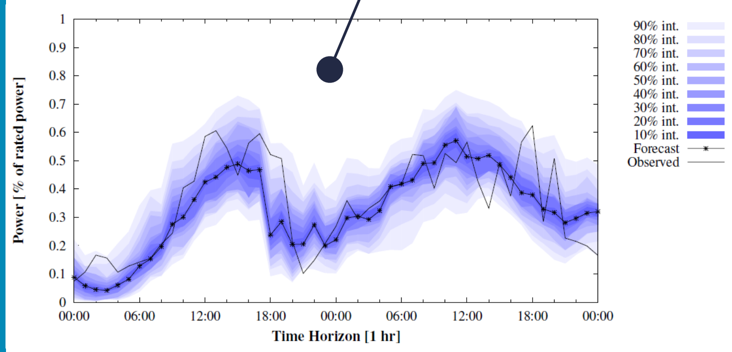
Renewable Energy Forecast Uncertainty

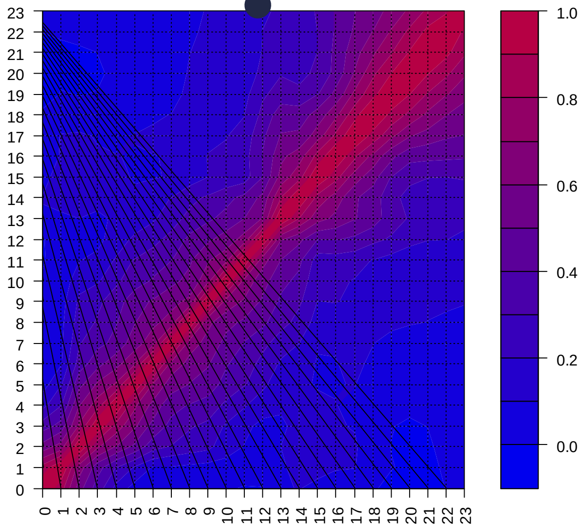


Captures temporal and spatial-temporal dependency structure

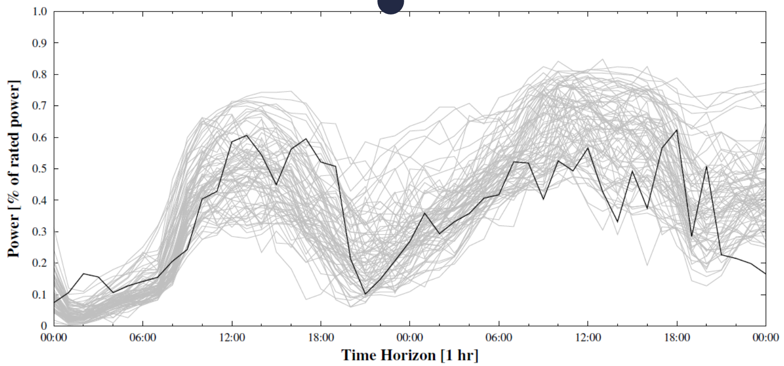
Generation of Temporal Trajectories (Uncertainty)

Probabilistic Forecast (Marginal Dist) → **Dependency Structure** → **Set of Random Vectors**



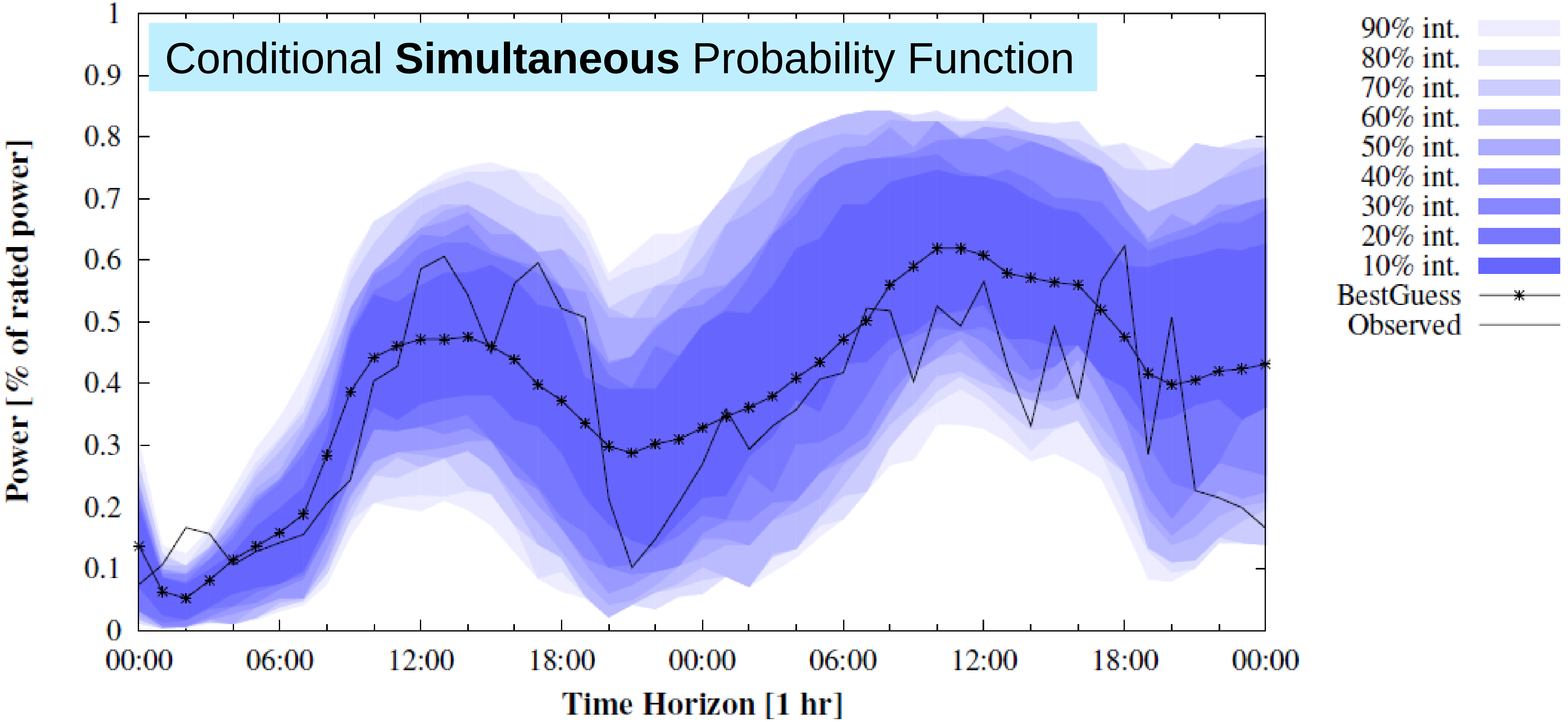


Empirical covariance matrix
e.g. Gaussian copula



Reference: Bessa, R. J. (2016, June). On the quality of the gaussian copula for multi-temporal decision-making problems. In 2016 Power Systems Computation Conference (PSCC) (pp. 1-7). IEEE.

Renewable Energy Forecast Uncertainty



Reference: Bessa, R. J. (2015, September). From marginal to simultaneous prediction intervals of wind power. In 2015 18th International Conference on Intelligent System Application to Power Systems (ISAP) (pp. 1-6). IEEE.

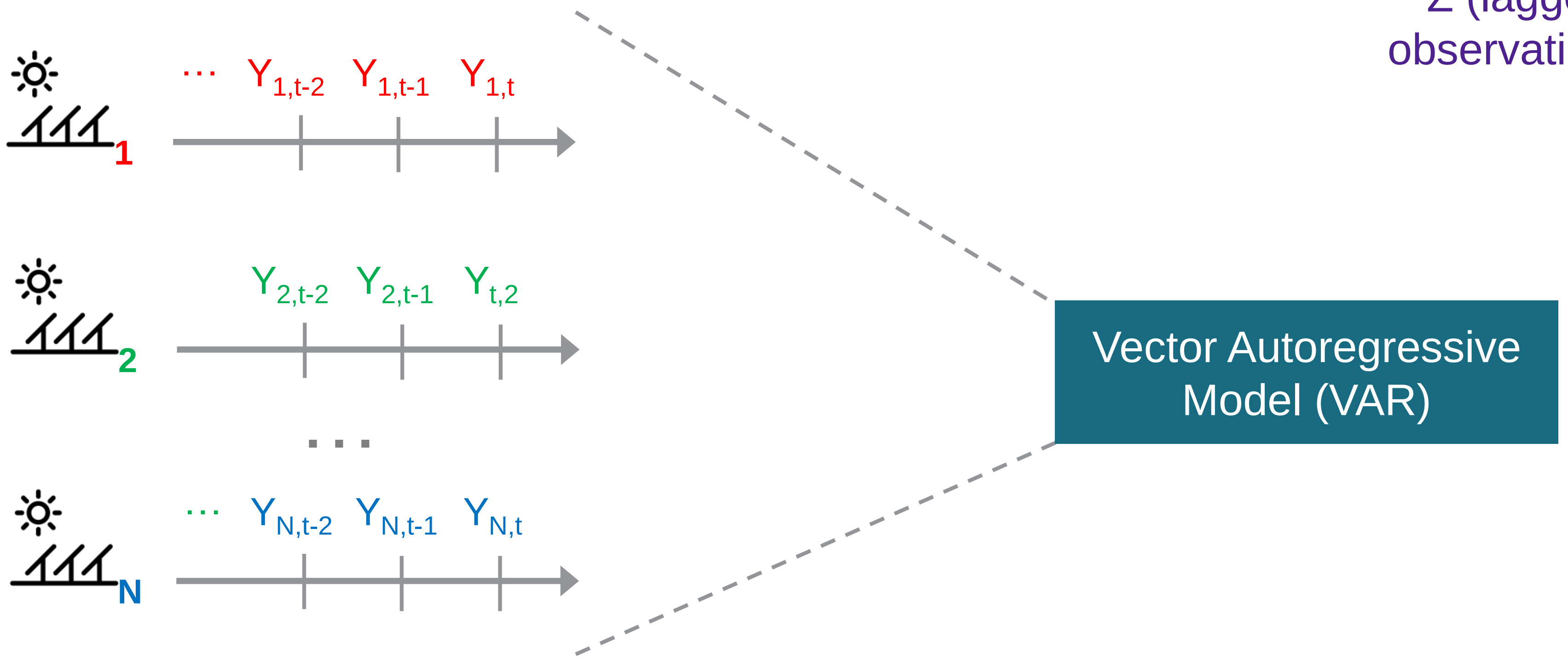
Collaborative Forecasting

Using Geographically Distributed Time Series

Example: matrix format for 2 PV sites

$$[Y_{1,t} \quad Y_{2,t}] = [c_1 \quad c_2] + \begin{bmatrix} B^1_{1,1} & B^1_{1,2} & B^2_{1,1} & B^2_{1,2} \\ B^1_{2,1} & B^1_{2,2} & B^2_{2,1} & B^2_{2,2} \end{bmatrix} \cdot \begin{bmatrix} Y_{1,t-1} \\ Y_{2,t-1} \\ Y_{1,t-2} \\ Y_{2,t-2} \end{bmatrix} + [E_{1,t} \quad E_{2,t}]$$

Z (lagged observations)



$$\boldsymbol{Y} = \boldsymbol{c} + \boldsymbol{B}\boldsymbol{Z} + \boldsymbol{E}$$

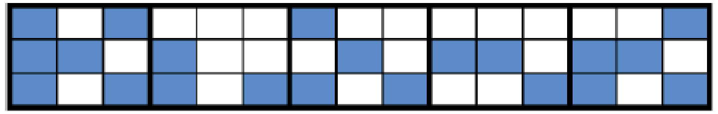
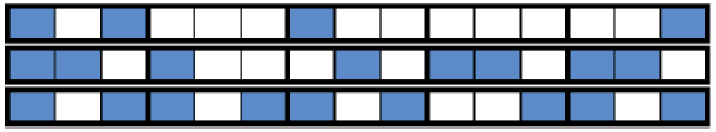
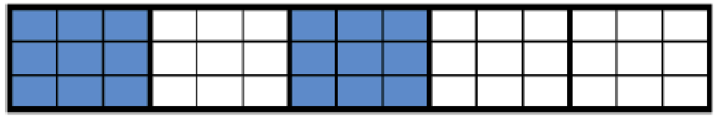
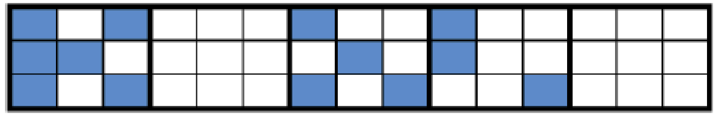
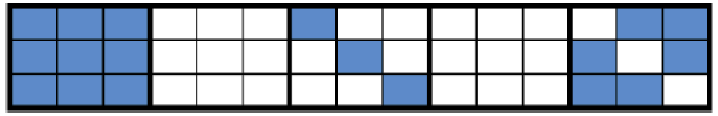
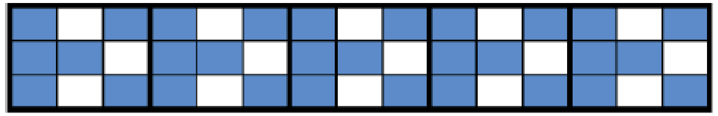
Reference: Cavalcante, L., Bessa, R. J., Reis, M., Browell, J. (2017). LASSO vector autoregression structures for very short-term wind power forecasting. Wind Energy, 20(4), 657-675.

Collaborative Forecasting

LASSO Sparse Structure

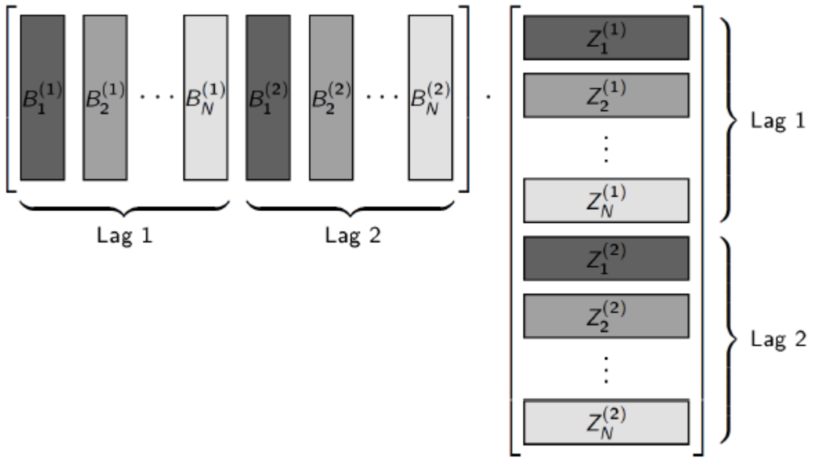
$$\frac{1}{2}\|Y - BZ\|_2^2 + \lambda\|B\|_1$$

- Improves forecast accuracy
- Automatic finding of spatial-temporal dependencies

LASSO-VAR Structures	Illustration
sLV	
rLV	
lLV	
lsLV	
ooLV	
cLV	

Reference: Cavalcante, L., Bessa, R. J., Reis, M., Browell, J. (2017). LASSO vector autoregression structures for very short-term wind power forecasting. Wind Energy, 20(4), 657-675.

Collaborative Forecasting
Distributed Learning



Does not guarantee data privacy

→ Algebraic cryptography is one solution

ADMM - alternating direction method of multipliers

Break up large datasets into blocks and carry out the VAR fitting over each block

Reference: Cavalcante, L., Bessa, R. J., Reis, M., Browell, J. (2017). LASSO vector autoregression structures for very short-term wind power forecasting. Wind Energy, 20(4), 657-675.

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Data Market for Renewable Energy Forecasting

WF1

Buyer

bid price, e.g. how much WF1 is willing to pay for 1% error improvement

WF3

data from WF3

Payment

Marketplace

WF2

data from WF2

1. Price *P* according to the error improvement
2. Forecasts $\widehat{\text{Power}}_{\text{WF1,t}+h}$

1. defines a market price

2. allocates the features according to the market and bid prices

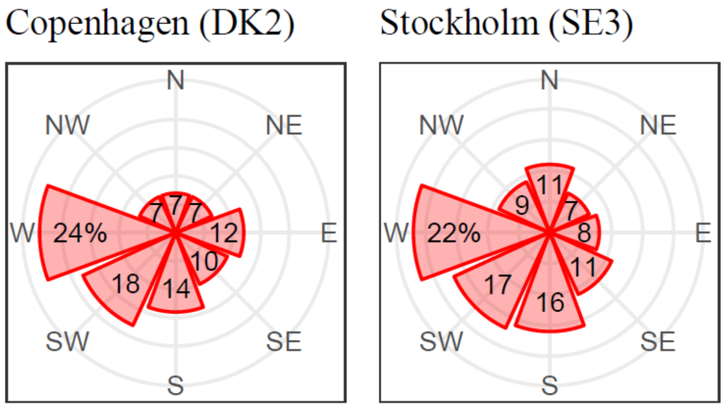
$$\widehat{\text{Power}}_{\text{WF1,t}} = \hat{f}_{\text{WF1}}(\text{data from WF1}, \text{allocated data from WF2}, \text{allocated data from WF3})$$

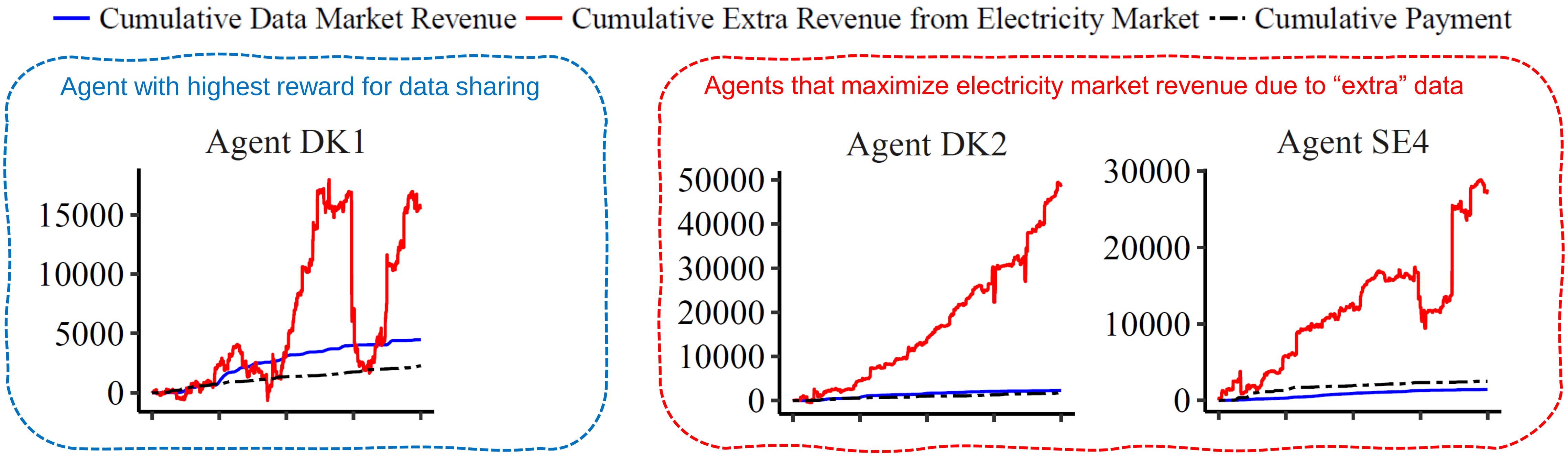
$$\widehat{\text{Power}}_{local\ \text{WF1,t}} = \hat{f}_{\text{WF1}}(\text{data from WF1})$$

Error improvement? **Yes**

How much do WF2/WF3 contribute for this improvement?

Data Market: Results with Nord Pool Data





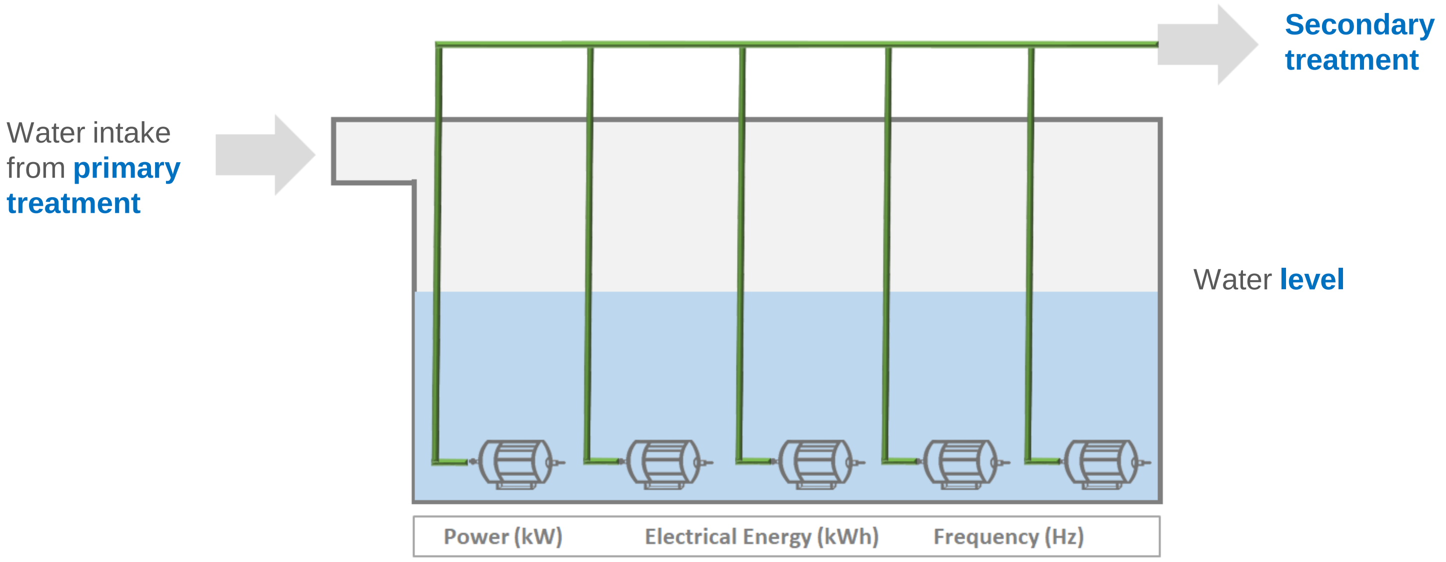
Reference: Gonçalves, C., Pinson, P., Bessa, R. J. (2020, under review). Towards data markets in renewable energy forecasting. IEEE Transactions on Sustainable Energy.

Energy Optimization

Energy Optimization in Wastewater Station

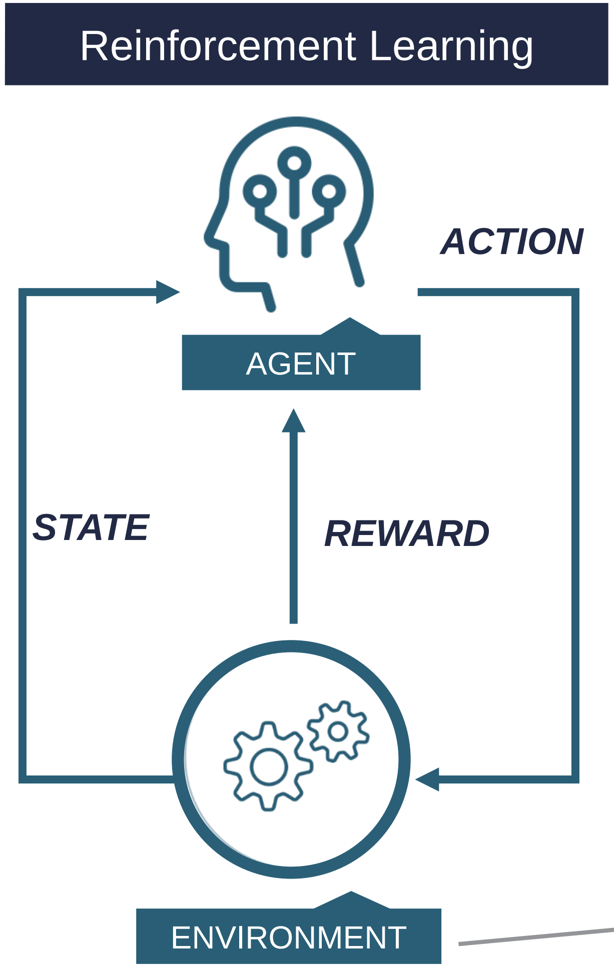
Minimize electrical energy consumption

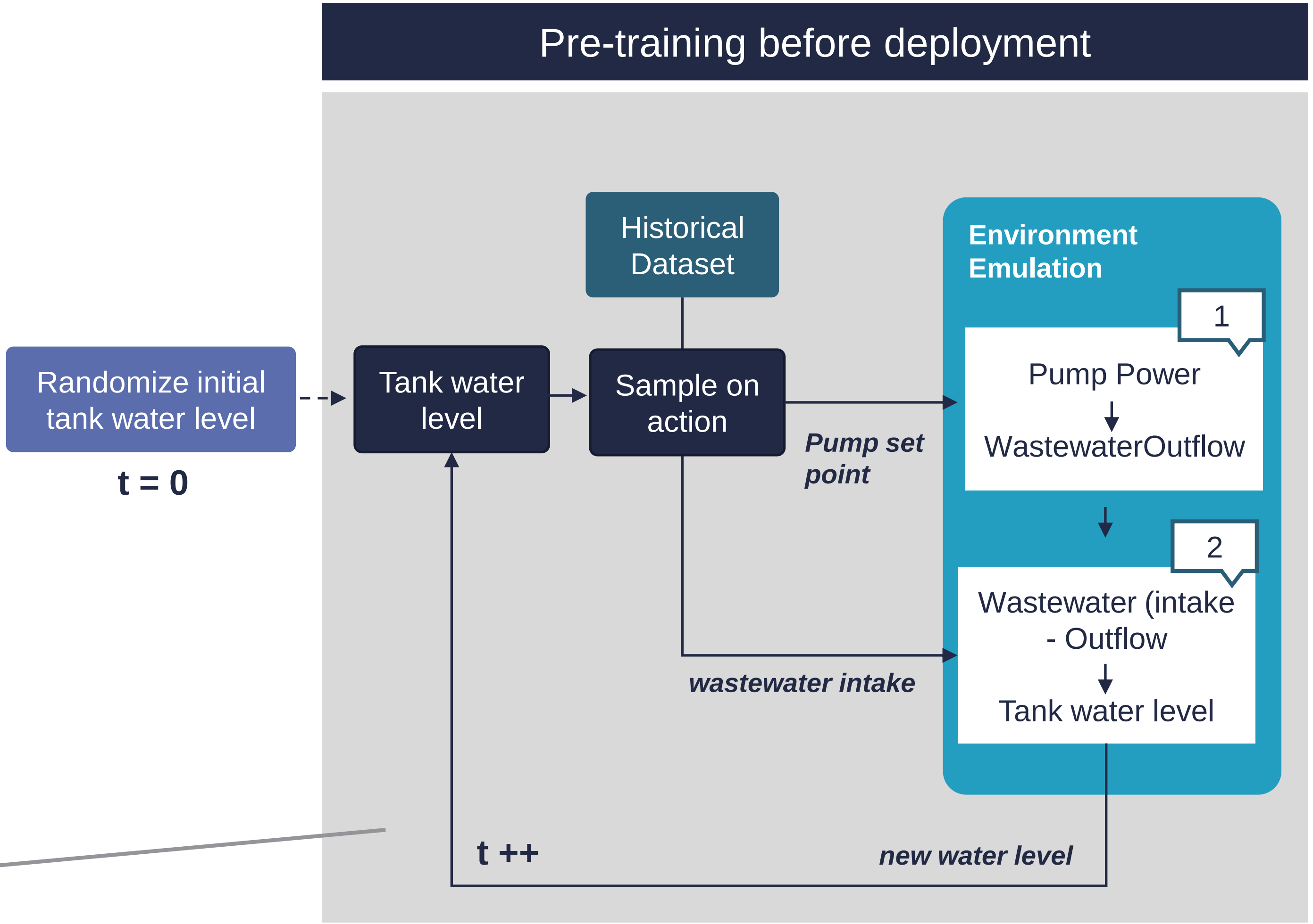
- ❑ Avoid modelling the wastewater system
- ❑ Use data already available from the SCADA



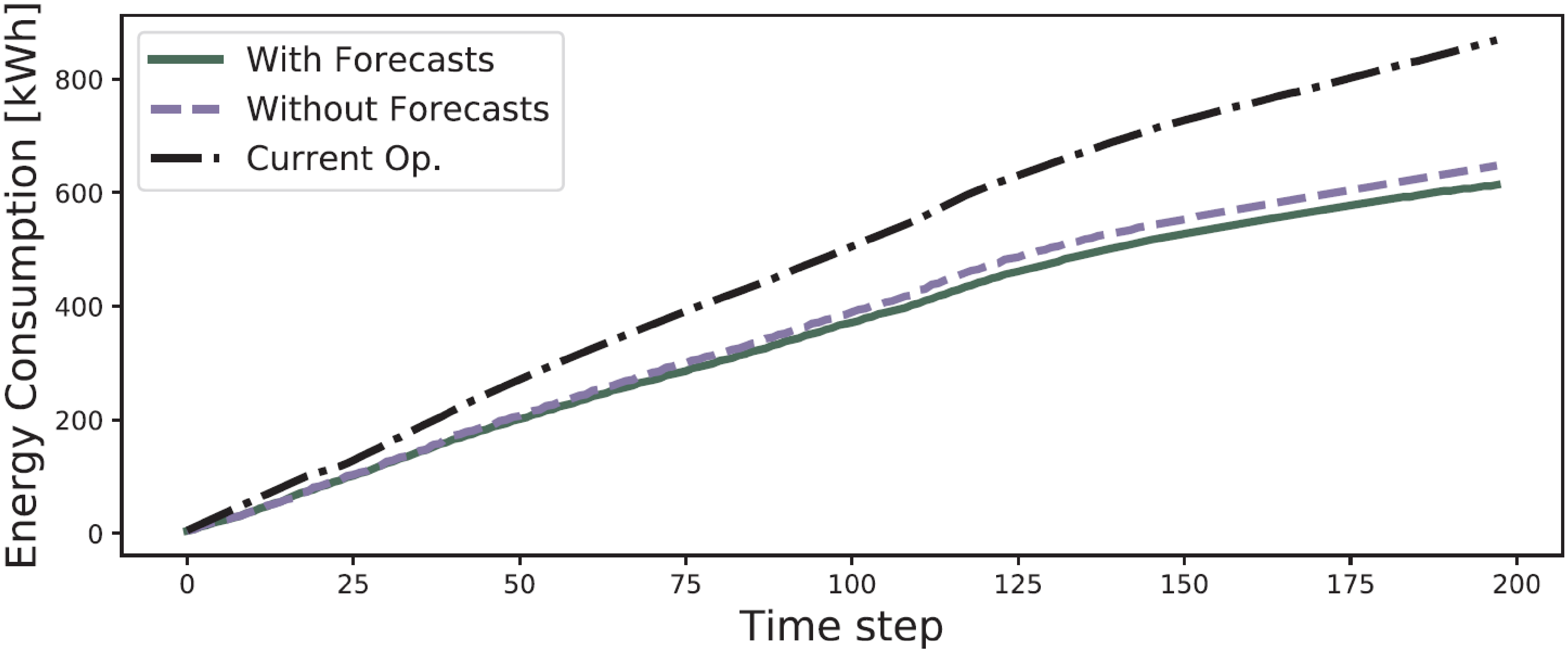
References:
J. Filipe, R.J. Bessa, M. Reis, R. Alves, P. Póvoa, "Data-driven predictive energy optimization in a wastewater pumping station," Applied Energy, vol. 252, pp. 113423, Oct. 2019.
EP19168270.7, patent pending, Method and device for controlling a wastewater tank pumping system

Reinforcement Learning Framework





Results for Alcântara Wastewater Station



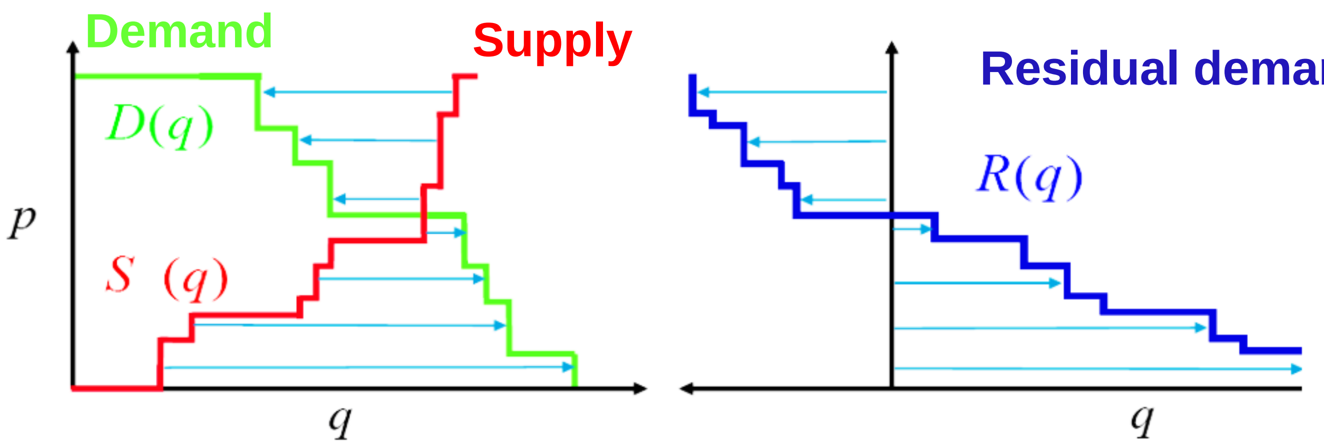
Reduce energy consumption by 15 - 30%

Forecasting Electricity Market Curves

Forecast Electricity Market Curves

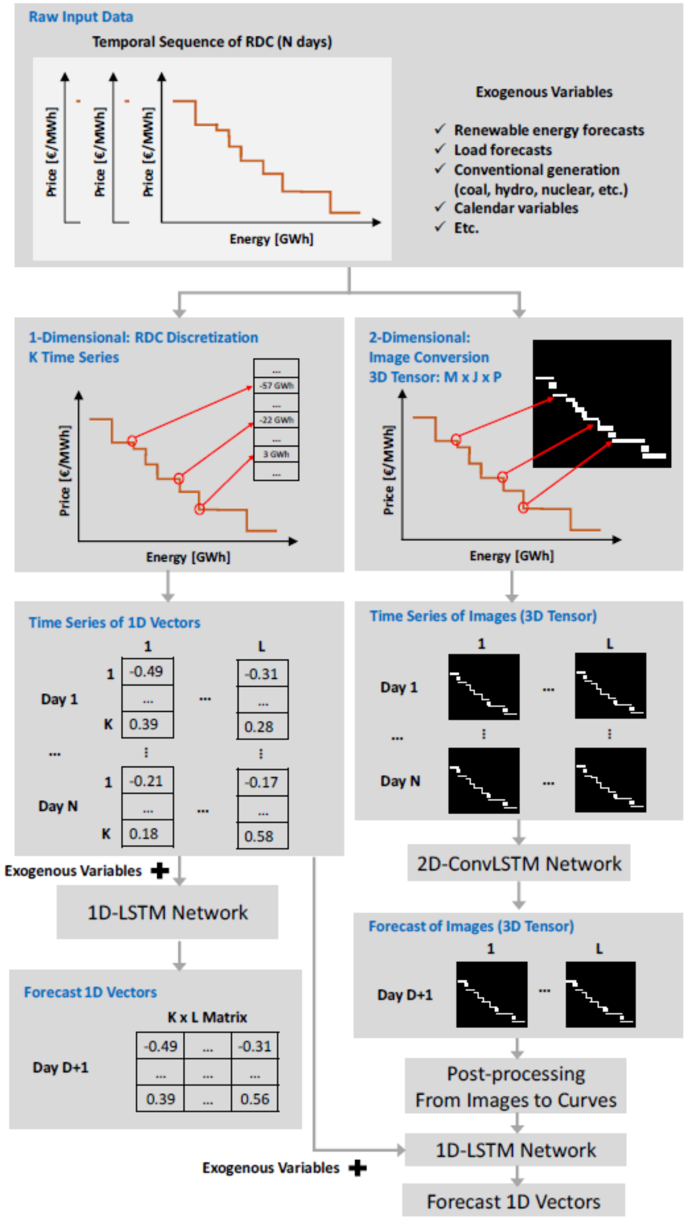
Predict residual demand curves

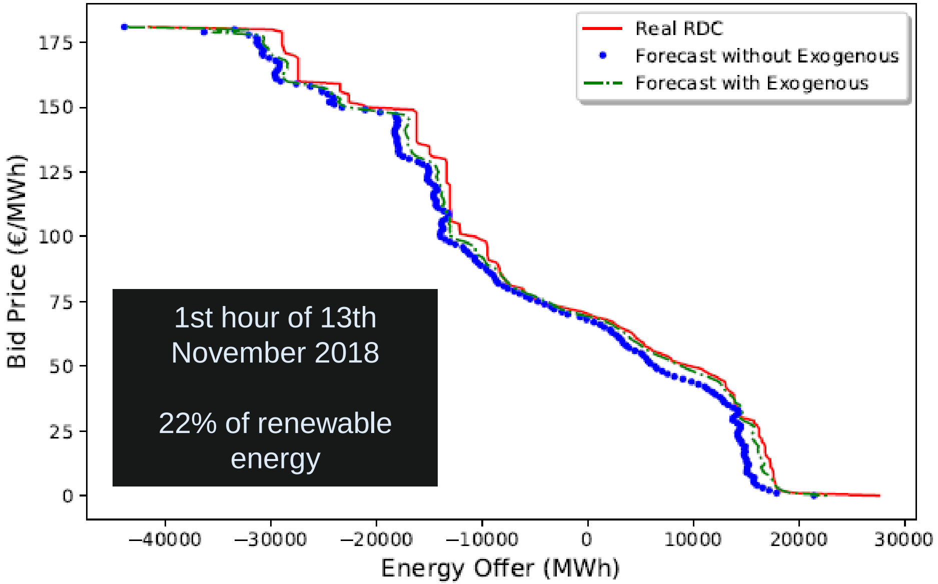
- Day-ahead forecast of residual demand curves
- Exploit the capacity of deep learning in handling frames/images

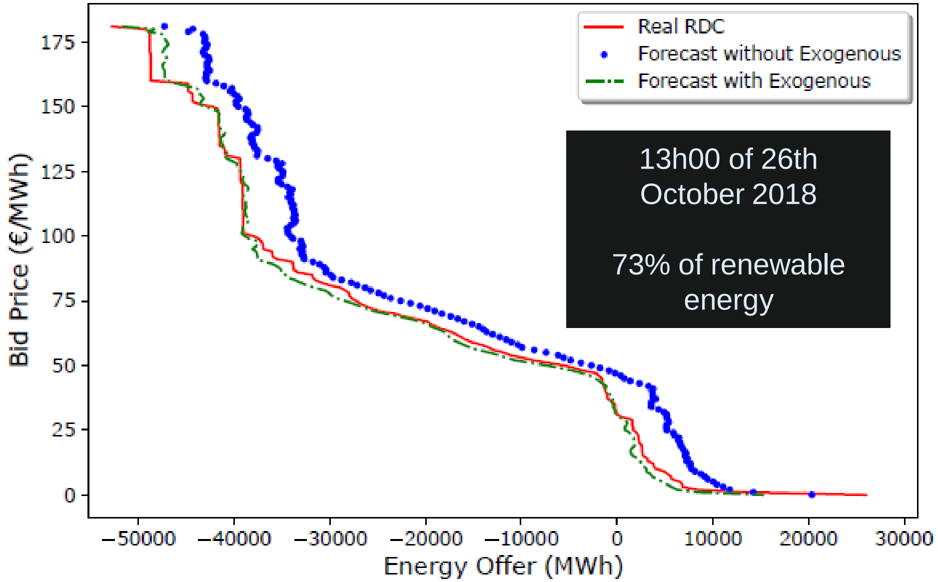


Reference: A. Coronati, J.R. Andrade, R.J. Bessa, "A deep learning method for forecasting residual market curves," in Proc. of the 21st Power Systems Computation Conference (PSCC 2020), Porto, Portugal, 29 June-3 July 2020.

Deep Learning Forecasting Framework







Wrap-up

Concluding Remarks

Needs

Impact

Needs	Impact
Model interpretability (~~explainability~~)	Broader adoption by decision-makers and industry
Hybridization between data and physical models	Fast deployment and embedded expert knowledge
Attractive business cases in the energy sector	De-risk investment in data science and R&D from academia
Paradigm shift towards distributed learning	Reduce big data requirements & New business models
Keep humans as a core building block @energy sector	Improved human decisions & reduce stress levels

from knowledge production to science-based innovation

Acknowledgements

- Ricardo Andrade
- Carla Gonçalves
- Jorge Filipe
- Alex Coronati

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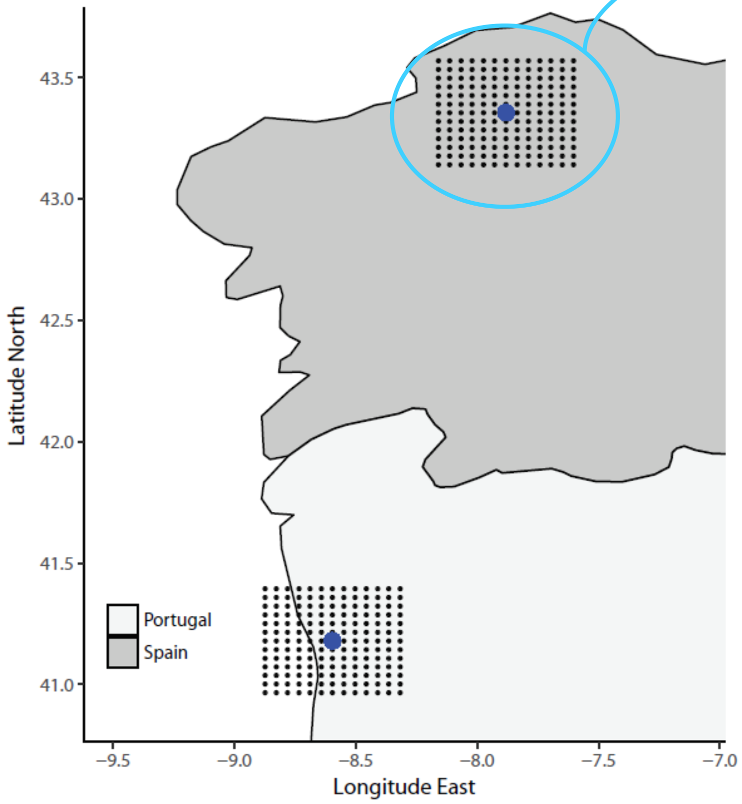
Backup Slides

Improving Uncertainty Forecasting with Feature Engineering



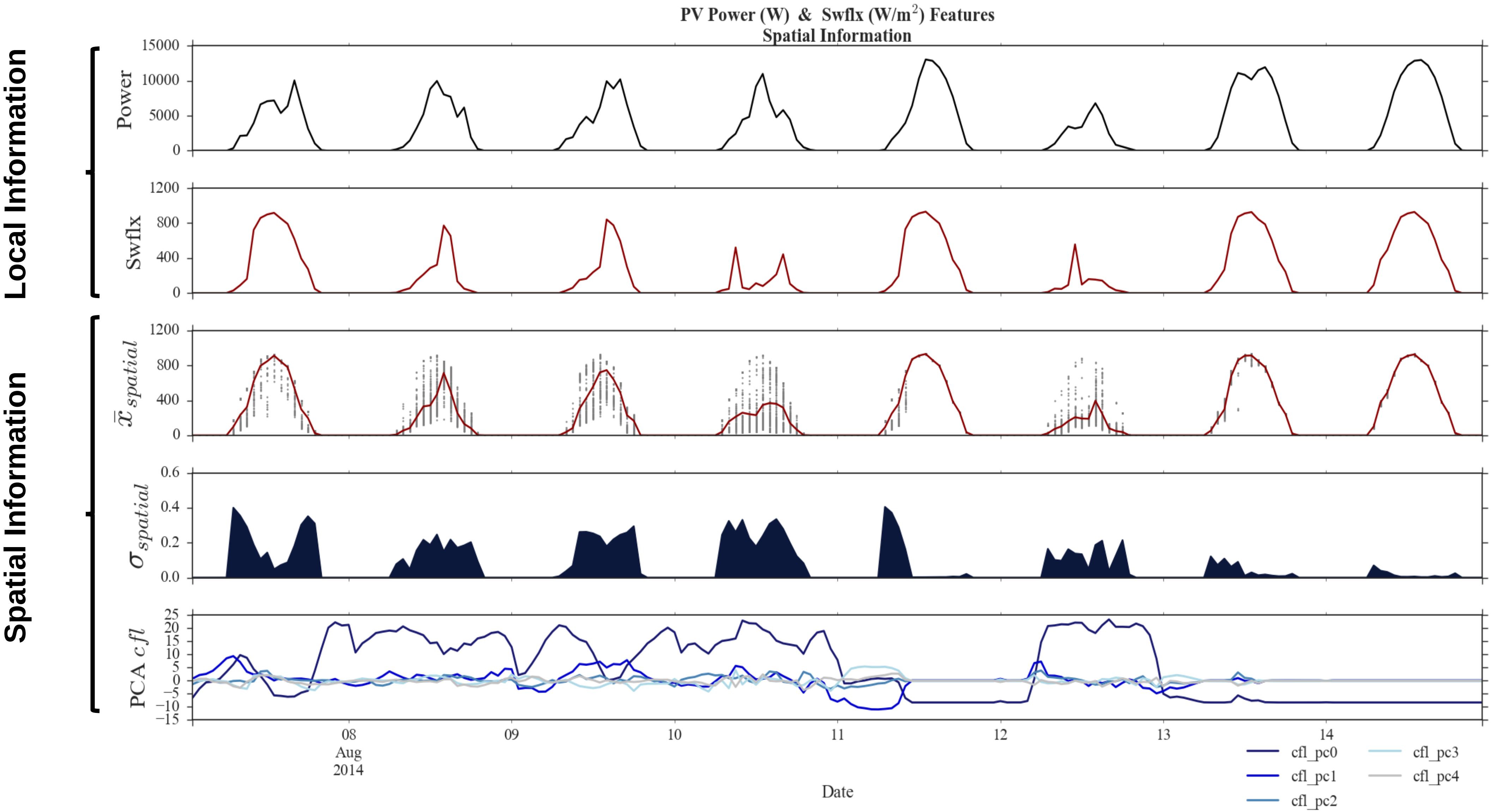
Raw weather forecasts dataset: 2704 variables for the wind power plant and 1014 variables for the PV site

Clear case for feature engineering: how much information can be extracted from this raw data?

NWP Grid Description	
NWP variables	Shortwave flux Temperature at 2m Cloud cover at low/mid/high levels
Number of geographical points	169
Area coverage	Aprox. 2400 km^2
Distance between points	Aprox. 4km^2
NWP grid resolution	4km

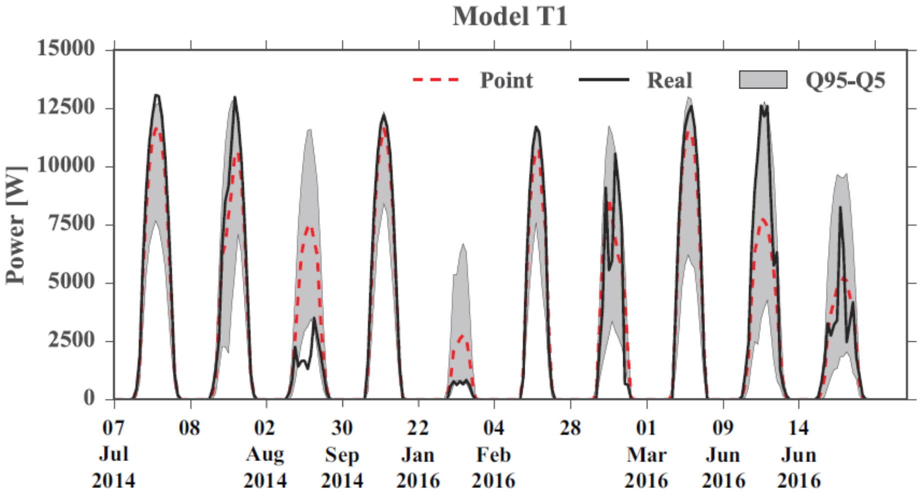
Reference: J.R. Andrade, R.J. Bessa, "Improving renewable energy forecasting with a grid of numerical weather predictions", IEEE Transactions on Sustainable Energy, vol. 8, no. 4, pp. 1571-1580, Oct. 2017.

Feature Engineering from Temporal and Spatial Data

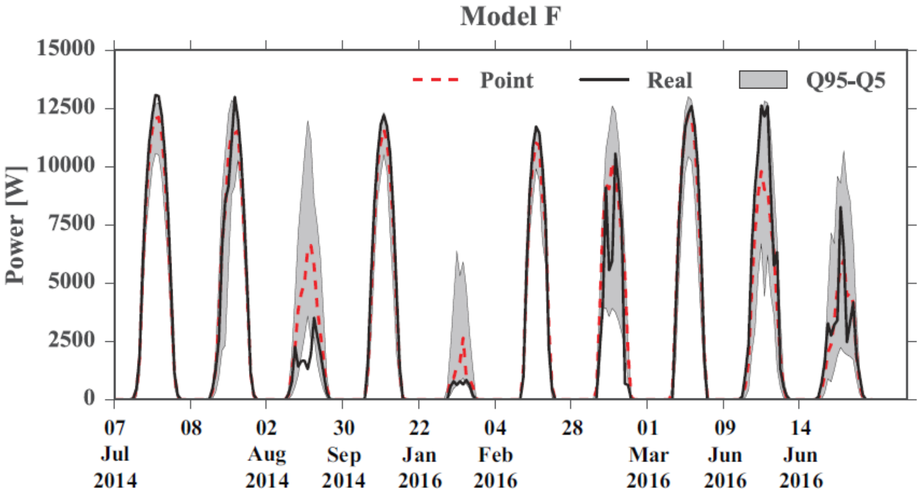


Forecast Example

Temporal Information



Temporal & Spatial Information



Probabilistic forecasts

- Uncertainty better modeled around the observed values
- Some of the abnormal high uncertainty verified for clear-sky days is removed

Point forecasts

- Some of the over/underestimation situations are resolved
- Improvements on the power peak forecasts for some clear-sky days

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Numerical Results: Solar Energy Forecasting

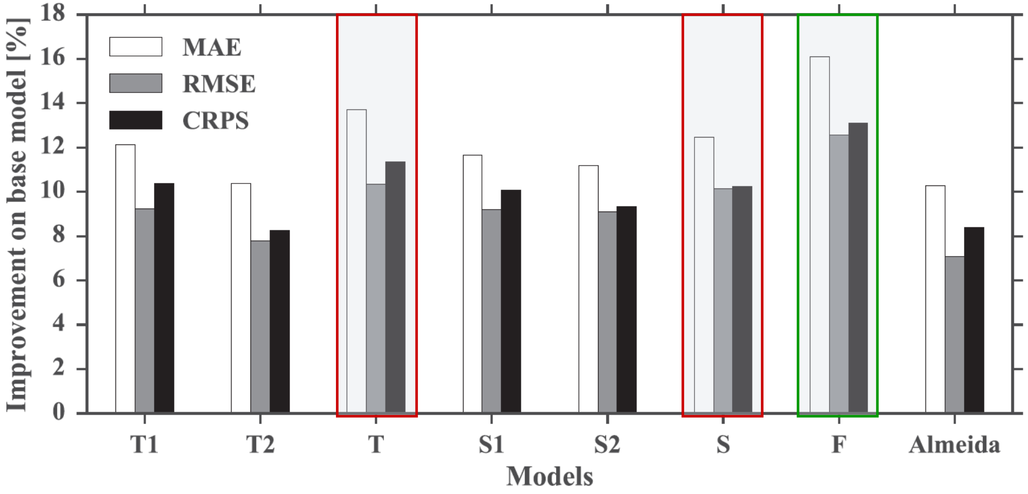
$$Improvement = \left(1 - \frac{metric_{model}}{metric_{base}}\right) \cdot 100\%$$

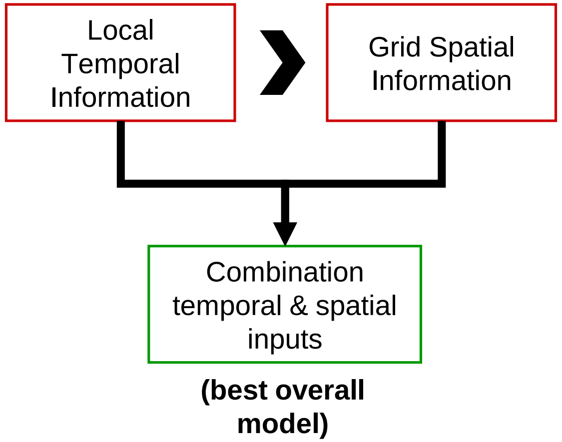
Base Model Inputs	
Chronological	Month Hour
NWP forecasts for the location of interest (INESC-TEC)	Surface downwelling shortwave flux [W/m^2] Temperature at 2m [K] Cloud cover at low levels [0, 1] Cloud cover at medium levels [0, 1] Cloud cover at high levels [0, 1] Cloud cover at low and medium levels [0, 1]

FEATURES CONSIDERED IN EVERY FORECASTING MODEL

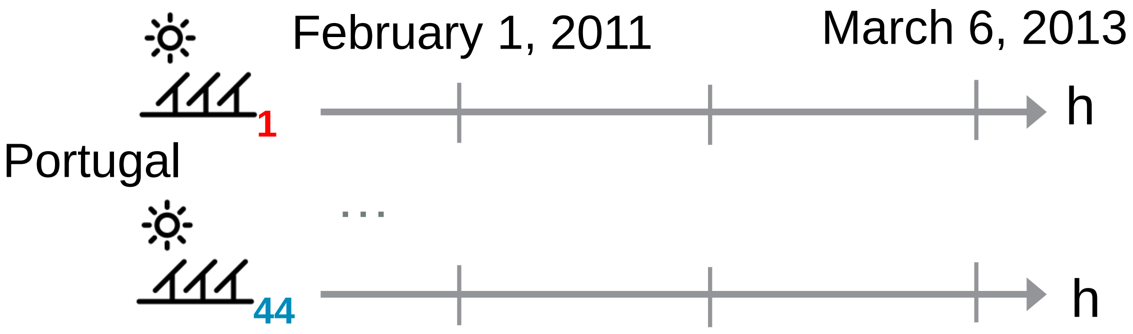
Domain	ID	Features
Temporal	T1	Lags and leads
	T2	σ^2_{time} and different NWP runs
	T	Combination of models T1 and T2 inputs
Spatial	S1	$\sigma_{spatial}$ and $\bar{x}_{spatial}$
	S2	Principal components
	S	Combination of models S1 and S2 inputs
Temporal & Spatial	F	Combination of both domain features

24h Forecast Horizon

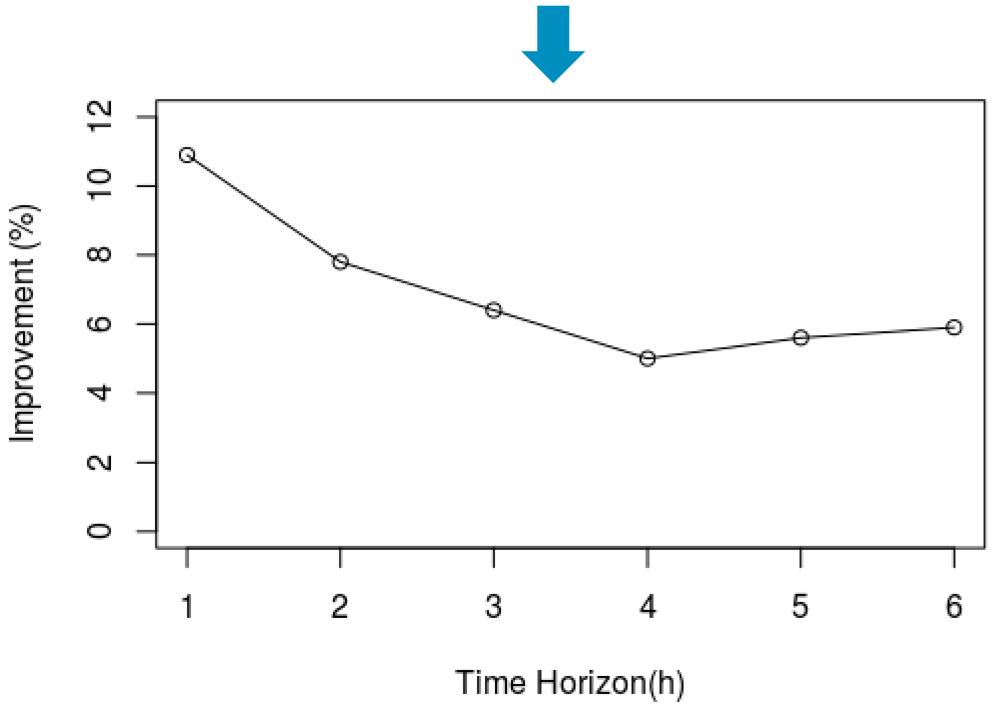




VAR: Results for a Smart Grid Pilot



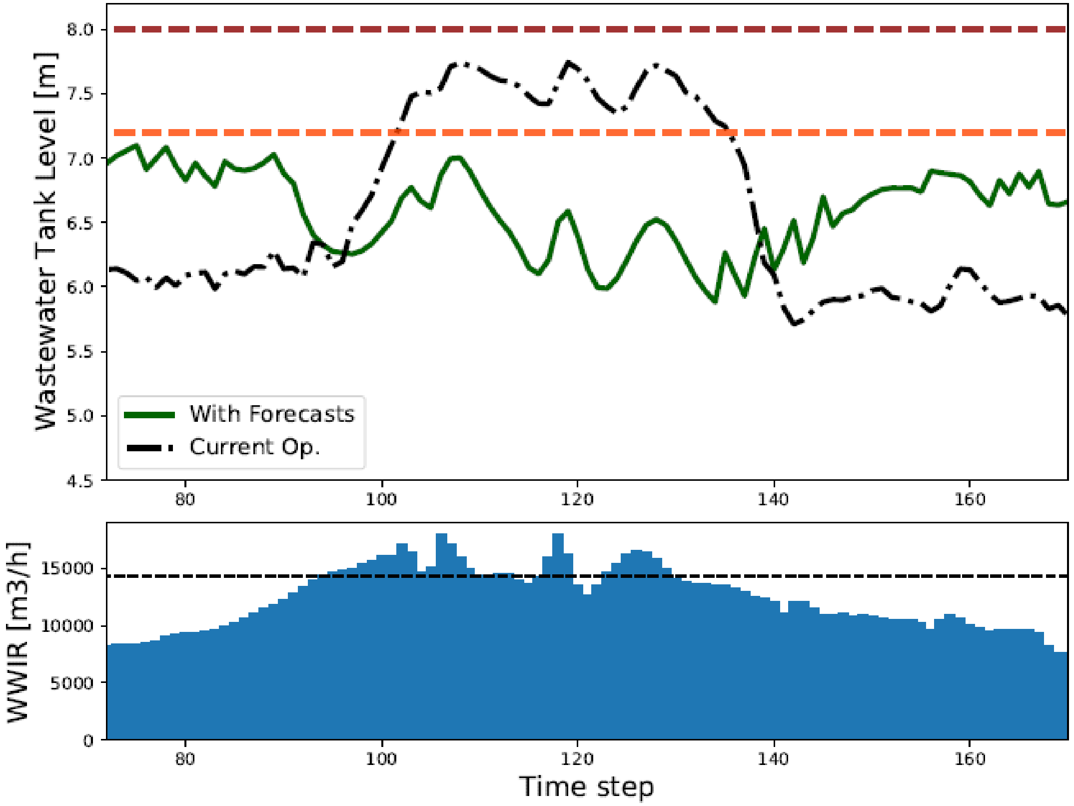
RMSE improvement (%) over an autoregressive model



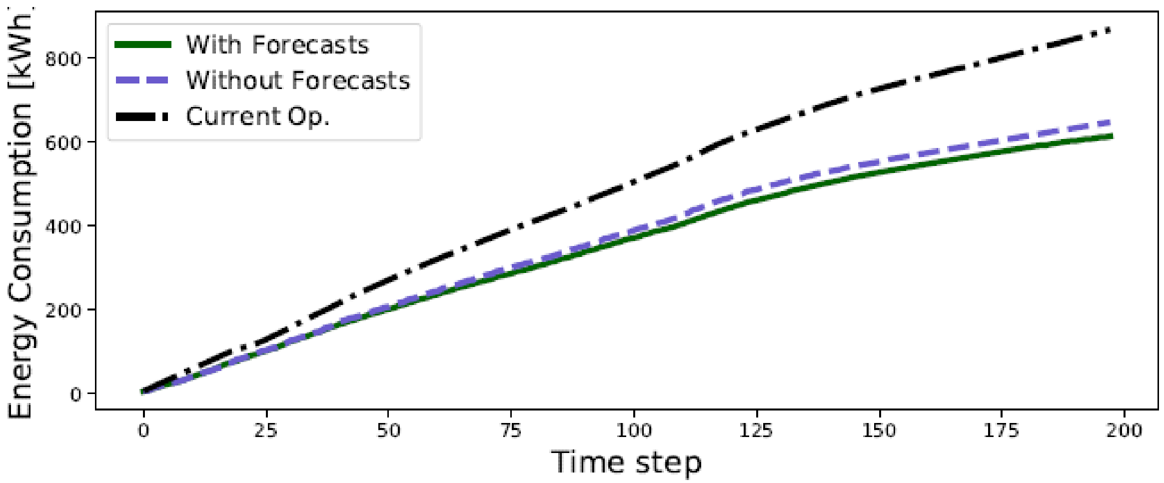
Results for Alcântara Wastewater Station

Predictive approach

(“imagining” and acting based on future states)



Energy Savings with AI



Reduce energy consumption by 15 - 30%

Market Curve Forecasting: Results for the Iberian Electricity Market

Model	RMSE	1D Imp.	Hybrid Imp.
Naïve 1	2.91%	40.1%	44.4%
Naïve 2	3.2%	45.5%	49.4%
ANN	2.75%	36.2%	40.1%
PCA + ANN	2.84%	38.7%	43.1%
PCA + GBTR	2,78%	37.4%	41.9%

Model	Frèchet	1D Imp.	Hybrid Imp.
Naïve 1	3.64%	53.7%	54.8%
Naïve 2	4.15%	59.4%	60.3%
ANN	3.92%	56.9%	58%
PCA + ANN	3.53%	52.2%	53.3%
PCA + GBTR	3.22%	47.5%	48.8%

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