Microgrids

Forecasting for electrical microgrids management

ELEN0445-1

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Bertrand Cornélusse
Jonathan Dumas

Prerequisites

- Microgrids lessons ELEN00445-1
- Basic notion of machine learning
- Basic notion of energy market/actors

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Content of this lecture

- Introduction to forecasting for microgrids
- Defining a forecasting problem
- Using forecasting tools to tackle the problem
- Case study: MiRIS microgrid

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What you will learn

- Why and what forecast for microgrids
- Explaining what is a forecasting problem
- Explaining how to tackle a forecasting problem
- Have the background materials to do the forecasting assignment

Summary

1. Why and what forecasting
2. Forecasting problem definition
3. Forecasting tools
4. Predictors
5. MiRIS

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Forecasting for electrical microgrids management

Why forecasting energy parameters?

Producer

Energy Markets

Energy Supplier

Optimize benefits from production by forecasting:
- production
- electricity prices & ancillary services

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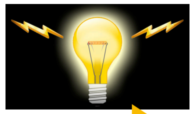
Why forecasting energy parameters?

TSO: ELIA, RTE …

Producer



DSO: RESA/ENEDIS

Balance the TS & DS
by forecasting:
- total load
- total production

Energy Markets

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Optimize benefits from production by forecasting:
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Why forecasting energy parameters?

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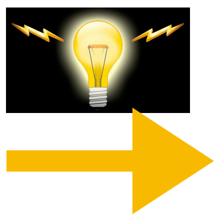
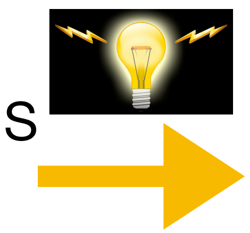


TSO: ELIA, RTE …

DSO: RESA/ENEDIS



Residential &/or Industrials

Energy Markets

Energy Supplier

Balance the TS & DS by forecasting:
- total load
- total production

Energy Markets

Energy Supplier

Optimize benefits from production by forecasting:
- production
- electricity prices & ancillary services

Optimize benefits by selling energy to customers by forecasting:
- customer load
- electricity prices & ancillary services

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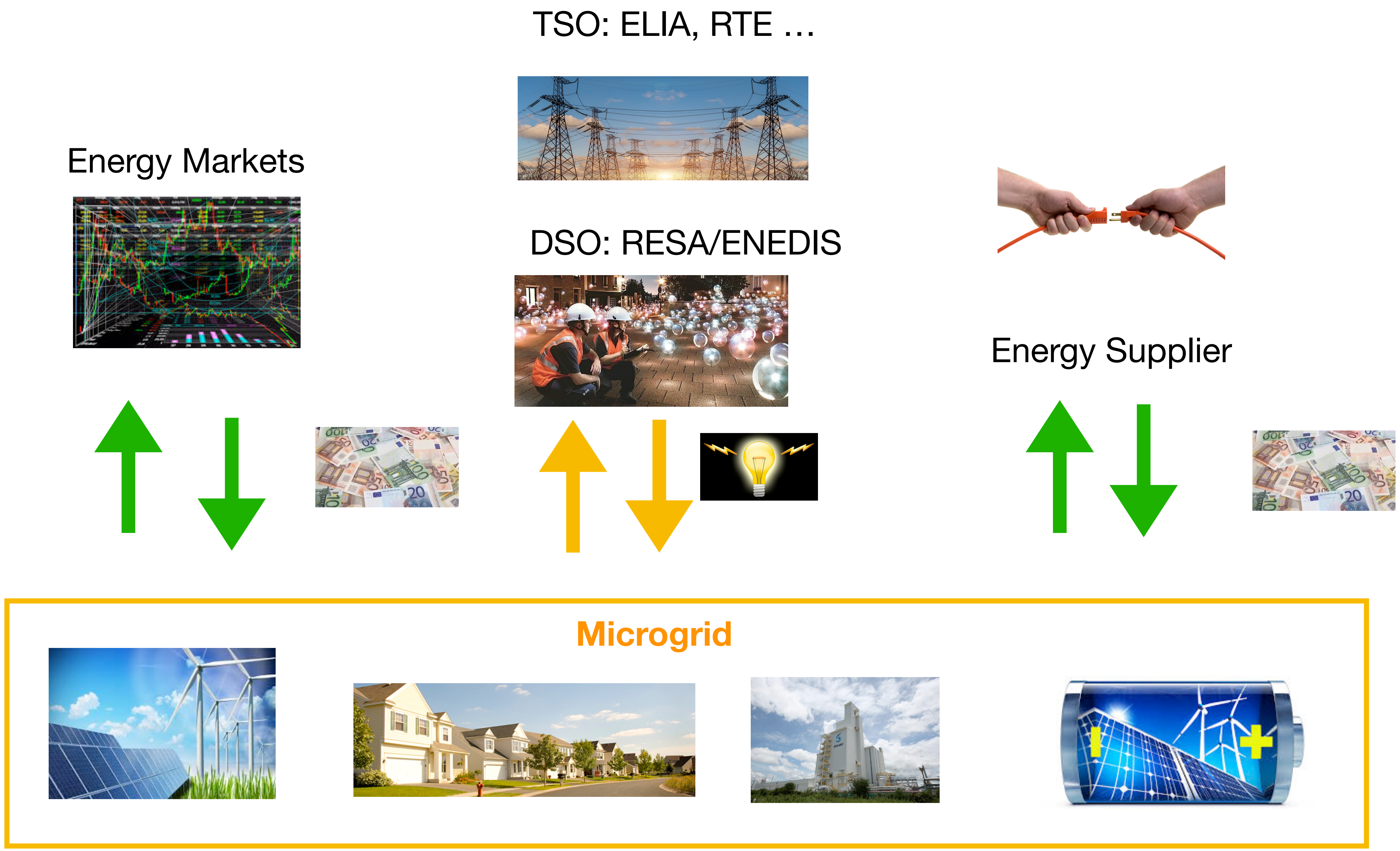
Why forecasting for microgrids?



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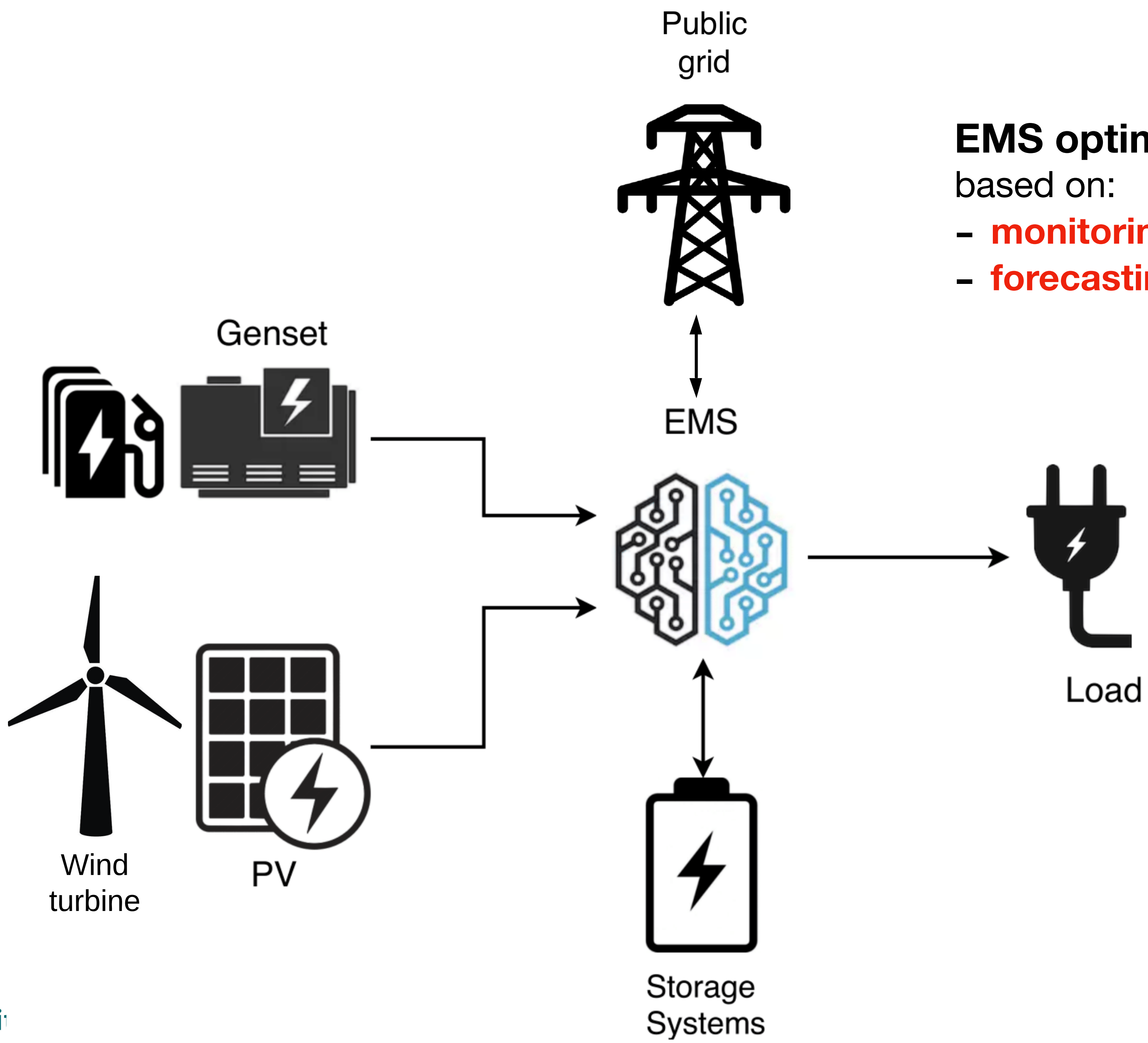
Microgrid reminder



EMS optimizes the decisions based on:

- **monitoring**
- **forecasting**

Source: Selmane Dakir

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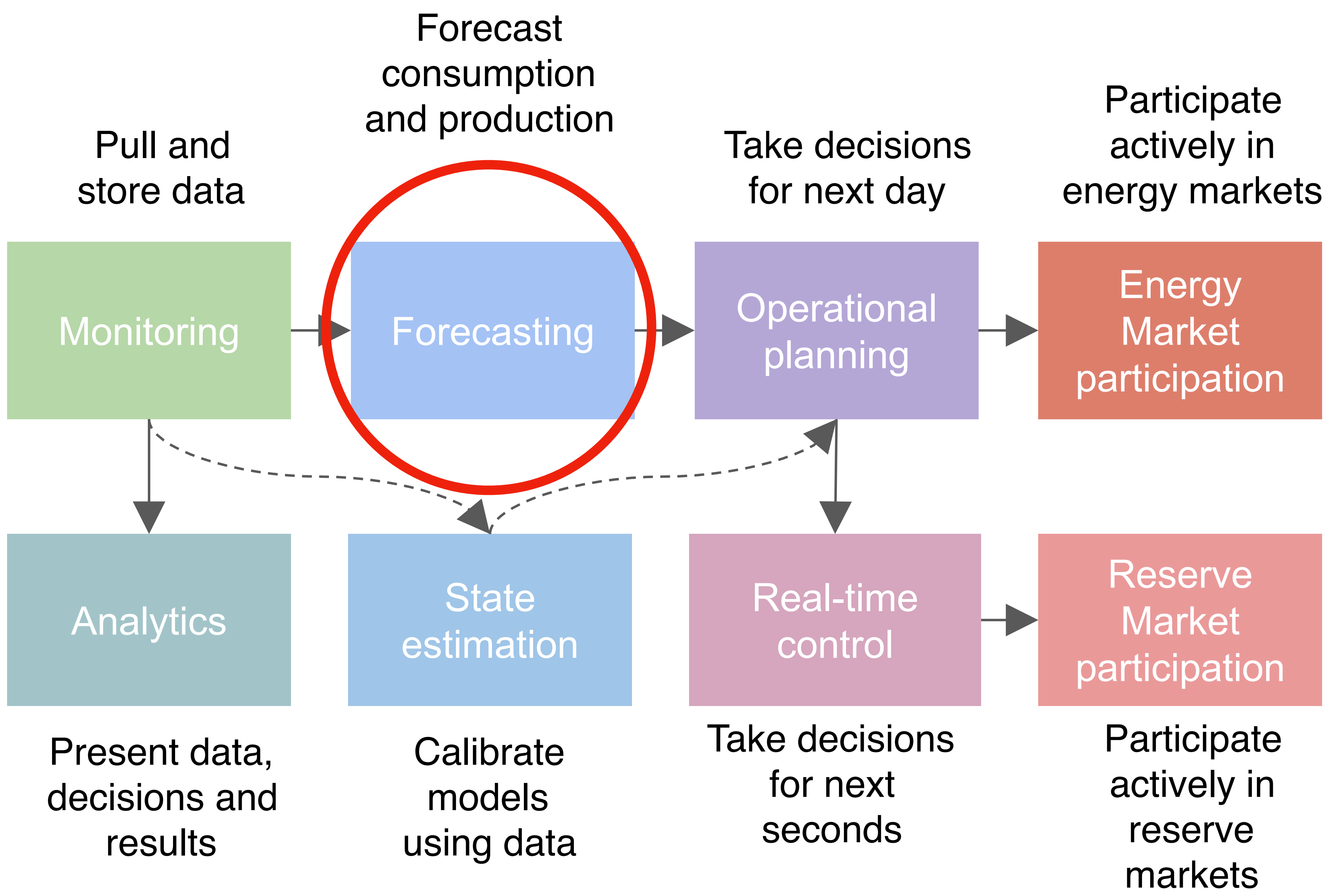
EMS reminder



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Arrows indicate a dependency between functional modules, not a flow of information!

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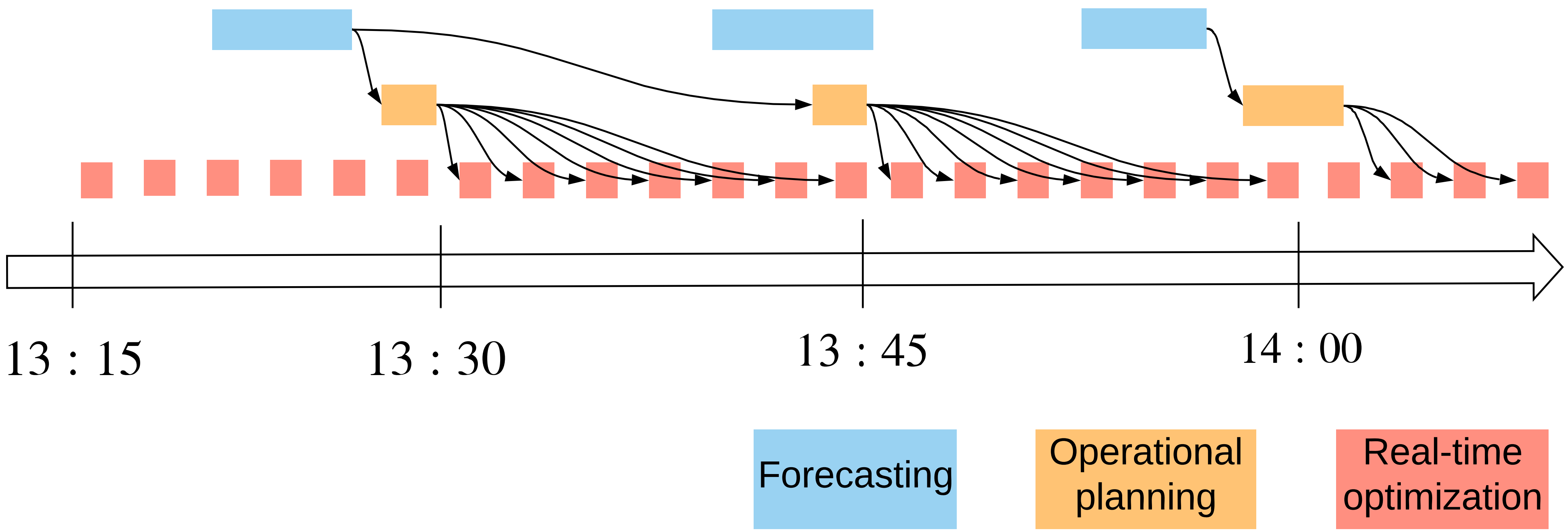
EMS time line



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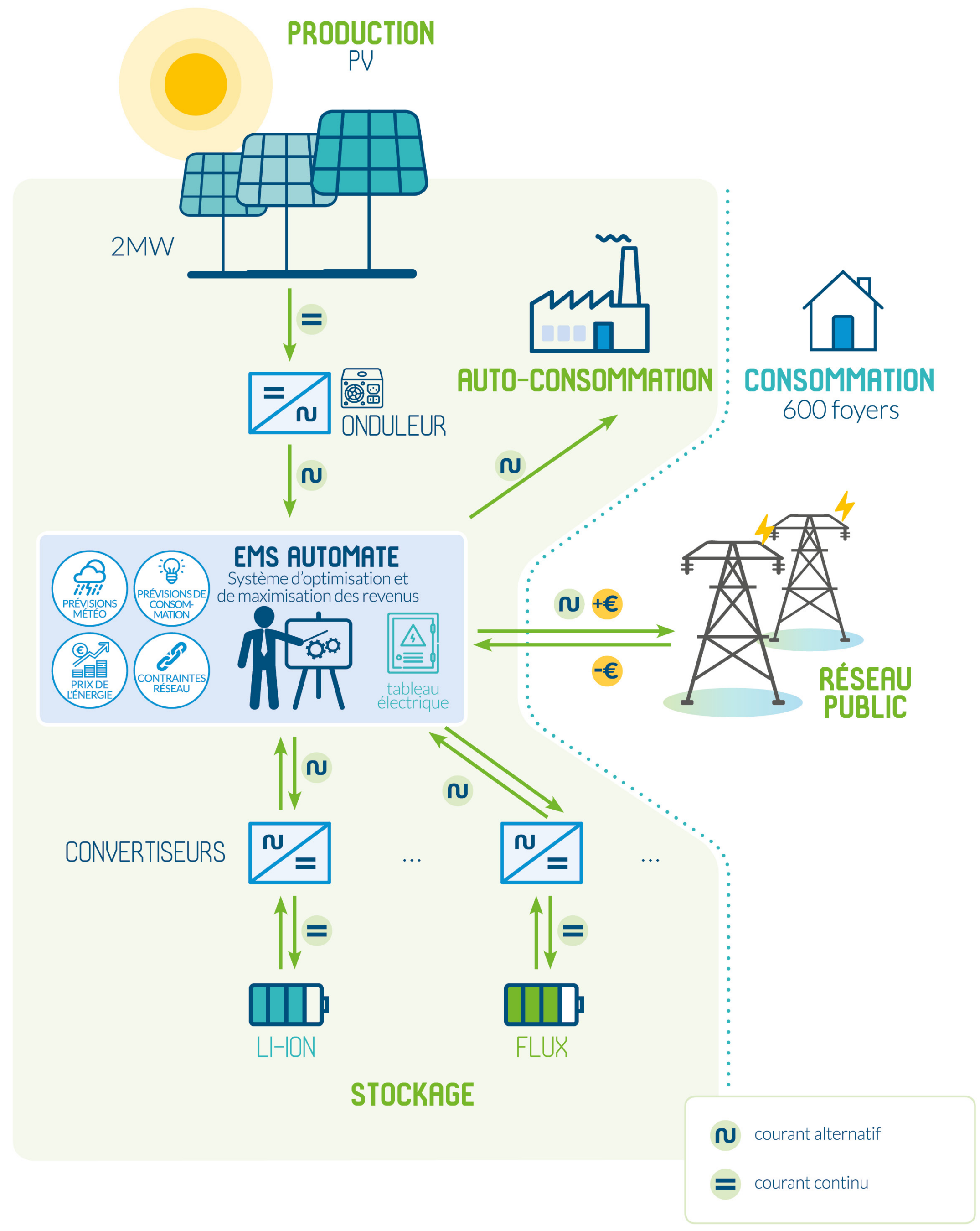
MiRIS - John Cockerill headquarter Seraing Belgium



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https://johncockerill.com/fr/energy/stockage-denergie/

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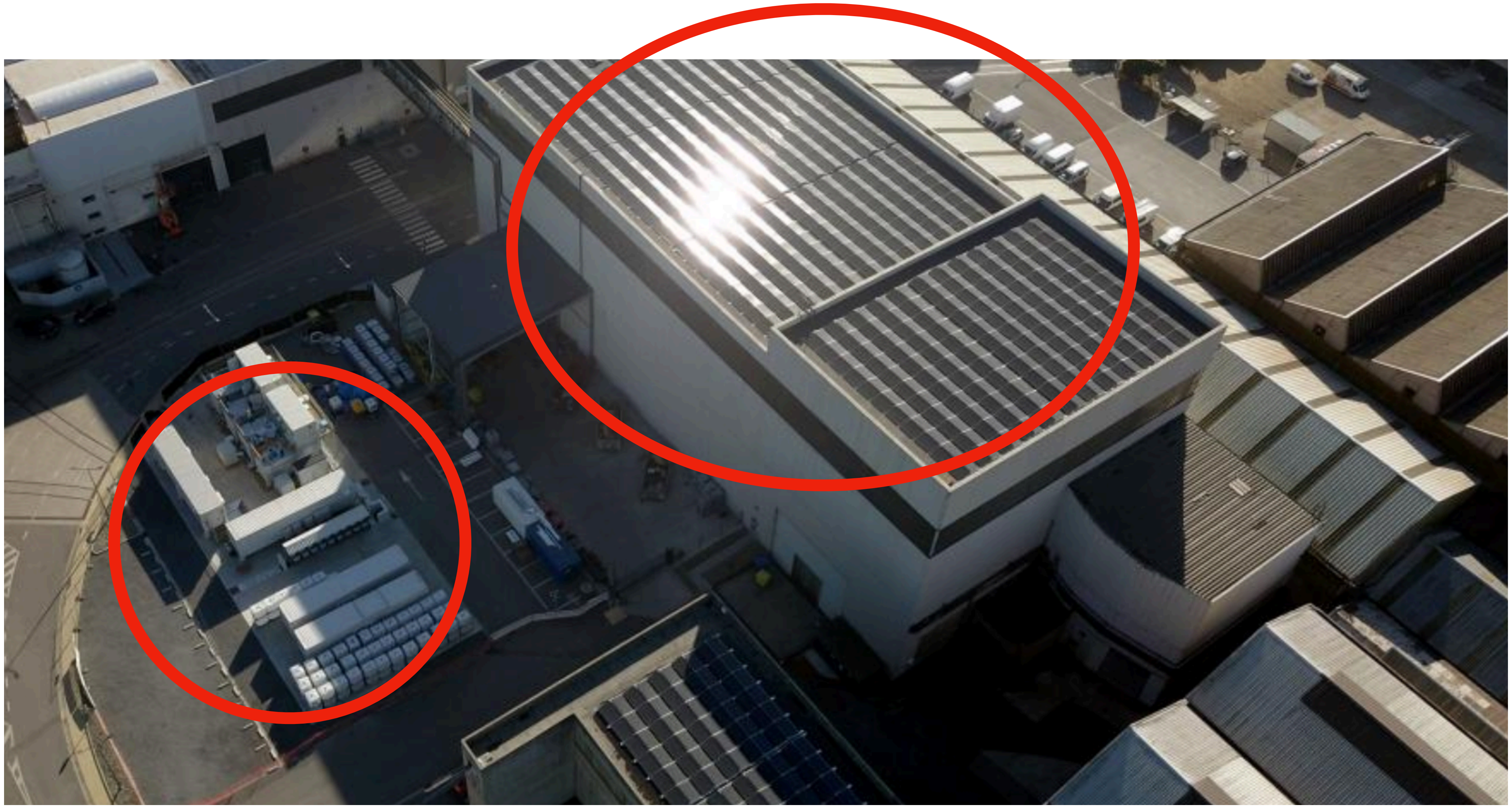

https://johncockerill.com/fr/energy/stockage-denergie/

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Microgrid key parameters to forecast

Production: PV, Wind Power, Hydraulic Power, etc

Load: office, industrial, residential, etc

Prices: electricity, gas, (futures, day ahead, intraday, imbalances) etc

…

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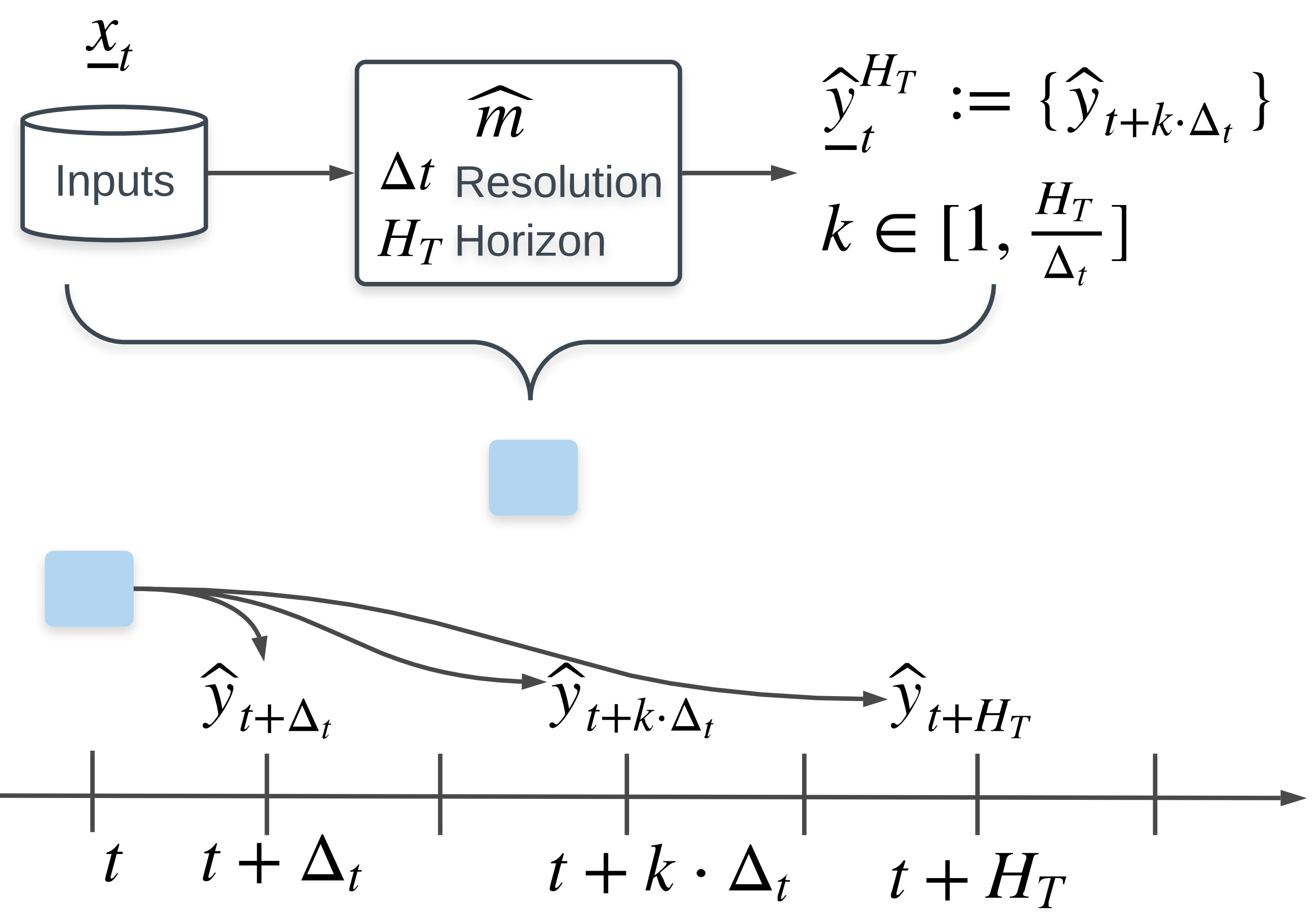
Forecasting process



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Forecasting for electrical microgrids management

Problem formulation

$$\boxed{\min_{t,\widehat{m}} \quad f^p(\underline{\hat{y}}_t^{H_T}, \underline{y}_t^{H_T})}$$

$f^{MAE}, f^{RMSE}:$

$\mathbb{R}^{\frac{H_T}{\Delta_t}} \times \mathbb{R}^{\frac{H_T}{\Delta_t}} \to \mathbb{R}$

$f^{TC}, f^{UM}:$

$\mathbb{R} \to \mathbb{R}$

$$s.t. \quad \underline{\hat{y}}_t^{H_T} = \widehat{m}(\underline{x}_t)$$

$$\underline{\hat{y}}_t^{H_T} = [\hat{y}_{t+\Delta_t}, \ldots, \hat{y}_{t+H_T}]$$

$$\widehat{m} \in \widehat{M}_{y,\underline{x}_t,H_T,\Delta_t,f^p}, \quad t \in \mathcal{T}$$

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Problem formulation

$$\boxed{\widehat{m}^\star = \arg\min_{t,\widehat{m}} \quad f^p(\underline{\widehat{y}}_t^{H_T}, \underline{y}_t^{H_T})}$$

$$s.t. \quad \underline{\widehat{y}}_t^{H_T} = \widehat{m}(\underline{x}_t)$$

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$$\widehat{m} \in \widehat{M}_{y,\underline{x}_t,H_T,\Delta_t,f^p}, \quad t \in \mathcal{T}$$

$$\boxed{\widehat{M}_{y,\underline{x}_t,H_T,\Delta_t,f^p} = \{\mathcal{F}\mathcal{T}, \mathcal{L}\mathcal{S}, \mathcal{F}, \mathcal{T}\mathcal{M}\}}$$

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Forecasting for electrical microgrids management

Classification of forecasting problem into 2 dimensions

1. Time dimension

- **Forecasting horizon**
  VST (minutes to day), ST (day to week), MT (week to year) and LT (years)

- **Forecasting resolution**
  minutes, hours, days, years …

2. Spatial dimension

- **Spatial forecasting horizon**
  residentials, microgrids, industries, cities, distribution grid, states, transportation grid …

- **Spatial resolution**
  W, kW, MW, GW

Dumas, J., & Cornélusse, B. (2019). Classification of load forecasting studies by forecasting problem to select load forecasting techniques and methodologies. https://arxiv.org/abs/1901.05052

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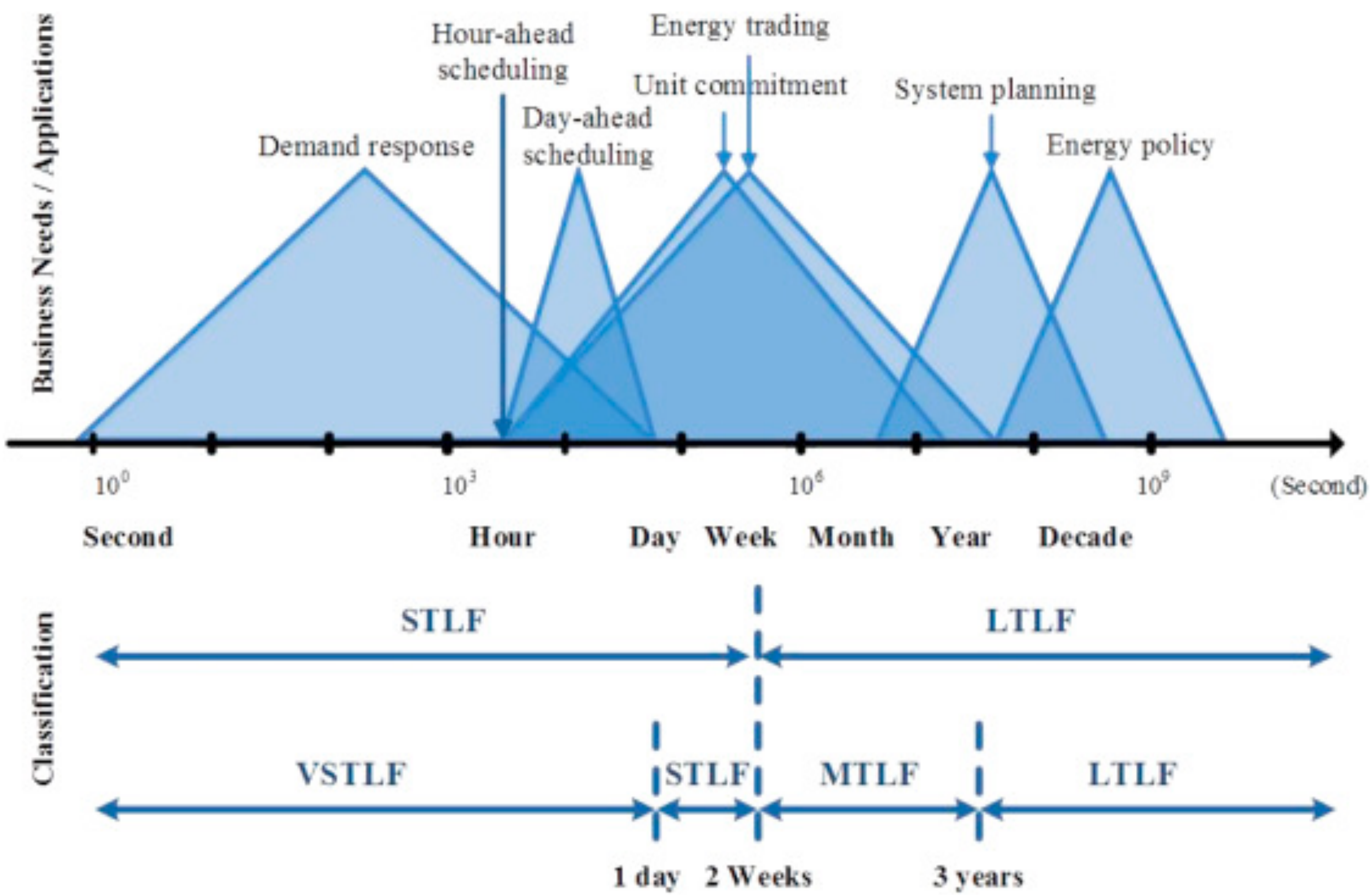
Classification over the time dimension



Tao Hong. Short Term Electric Load Forecasting. PhD thesis, 2010.

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Forecasting problem: MiRIS

1. Time dimension

- **Forecasting horizon**
  VST (minutes to day) & ST (<= a few days)

- **Forecasting resolution**
  15 minutes

2. Spatial dimension

- **Spatial forecasting horizon**
  Offices -> -500 kW to 1500 kW

- **Spatial resolution**
  0.1 kW

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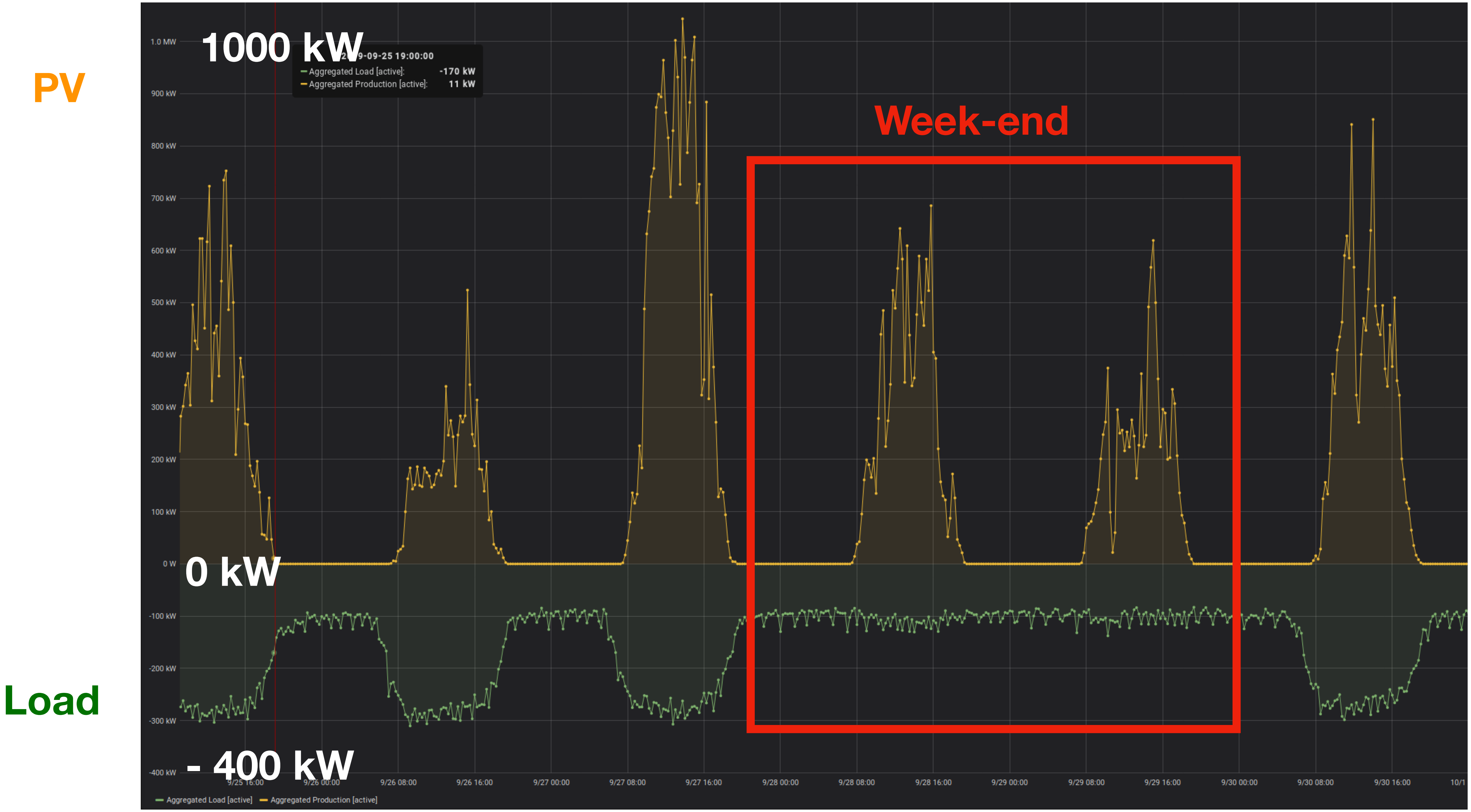
Forecasting problem definition: MiRIS



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Forecasting for electrical microgrids management

Forecasting Tools

Forecasting Technique (FT) :
- machine learning: ANN, GBR, etc
- statistical techniques: MLR, ARIMA, etc

Tuning

Forecasting Methodologies (FM):
- VS: select the relevant predictors/variables of the problem
- THF: a VST model & a ST model, etc
- LHF: a model per zone load, etc
- TM: static learning set, moving learning set, learning set size, etc
- Etc

Tuning

Data Cleansing techniques (DC):
- naive: compare to global mean and standard deviation, etc.
- seasonal naive: a mean and standard deviation per hour, etc.
- interpolation, etc.

Tuning

Error Metrics (EM):
- deterministic: MAE, RMSE, etc.
- probabilistic: PLF, CRPS, etc.

Dumas, J., & Cornélusse, B. (2019). Classification of load forecasting studies by forecasting problem to select load forecasting techniques and methodologies.
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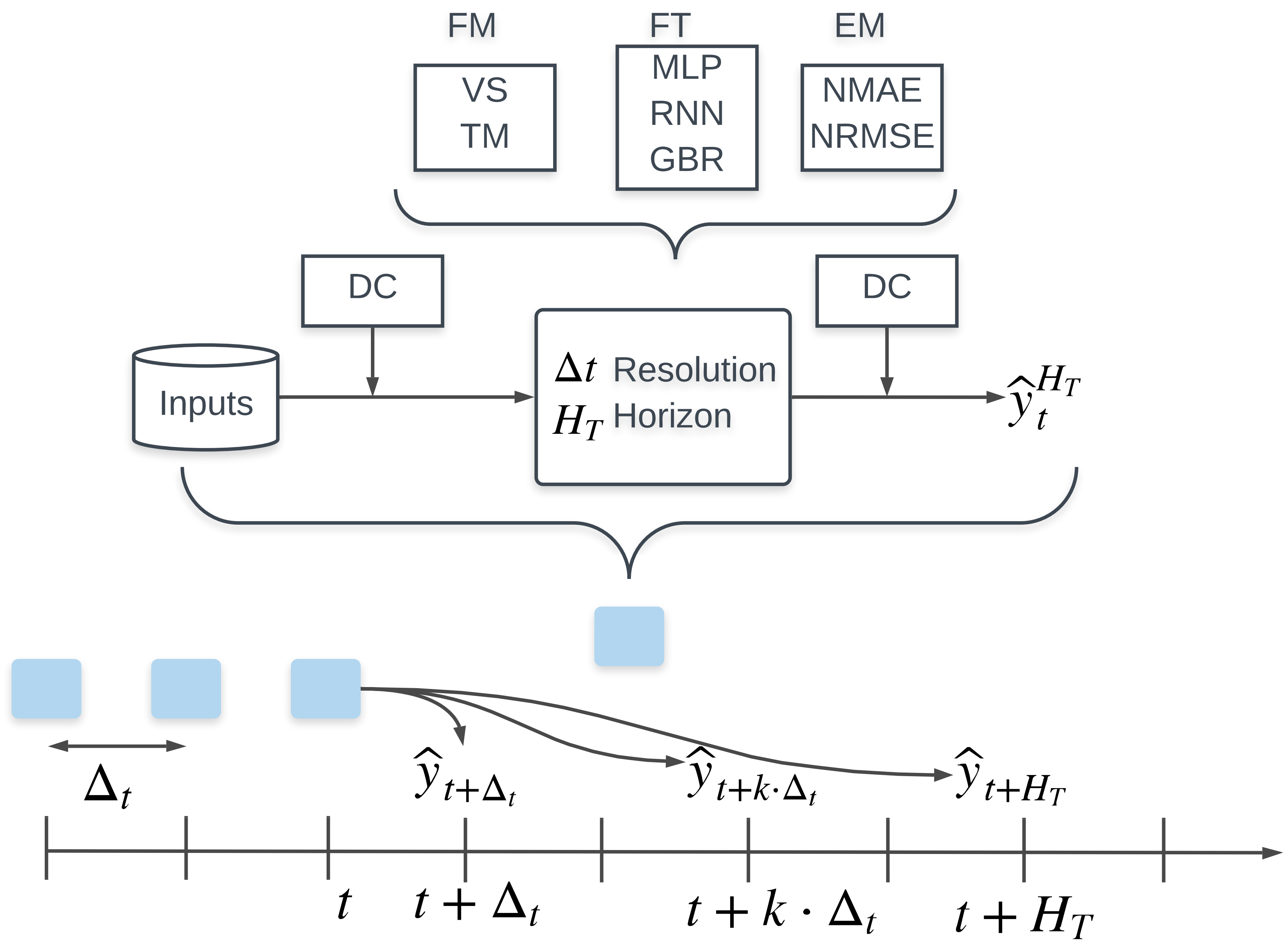
Forecasting process



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Forecasting Tools: MiRIS

Forecasting Technique (FT) :
- machine learning: MLP, RNN, GBR
- statistical techniques: MLR

Forecasting Methodologies (FM):
- VS: select the relevant predictors/variables of the problem
- TM: try different learning set size, retraining frequency, etc.

Data Cleansing techniques (DC):
- If missing data -> interpolation

Error Metrics (EM):
- deterministic: MAE, RMSE normalized per day (NMAE, NMRSE)

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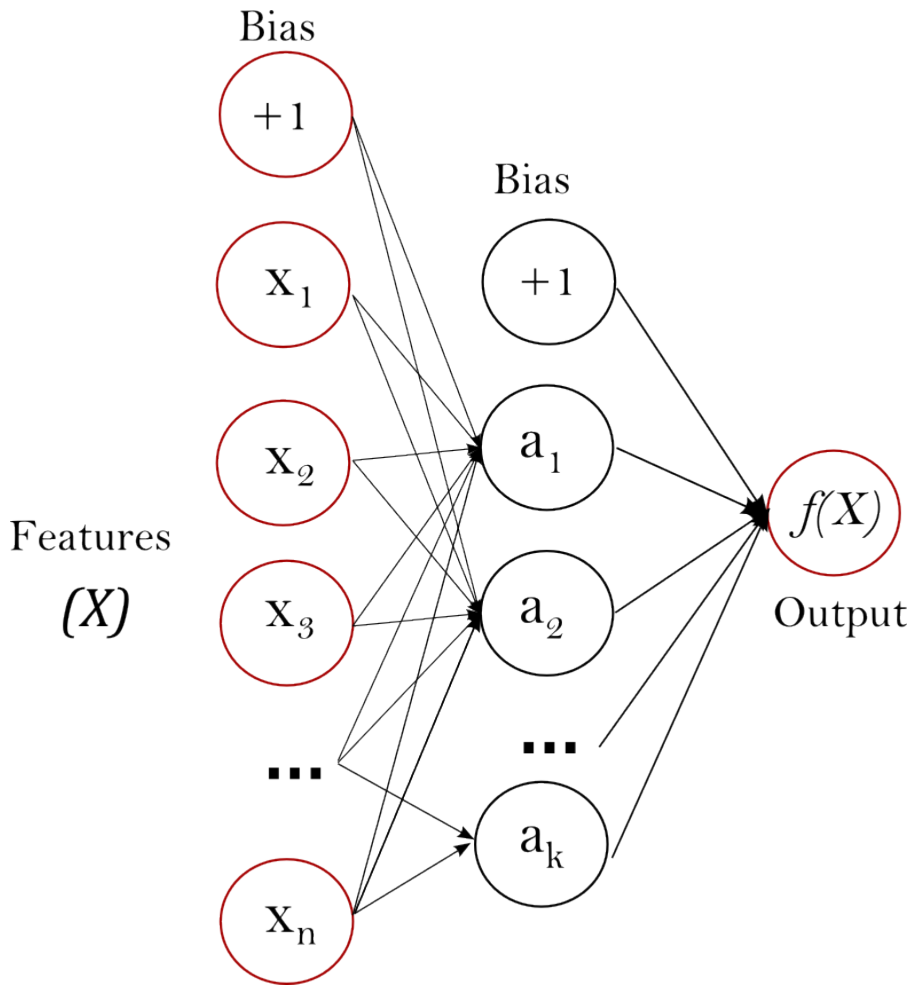
MiRIS: FT

RNN / MLP

- Number of layers
- Number of neurons per layer
- Number of epochs during training
- The optimizer, its learning rate
- The drop out rate
- The activation function
- ….



Friedman, J., Hastie, T., & Tibshirani, R. (2001). The elements of statistical learning (Vol. 1, No. 10). New York: Springer series in statistics.

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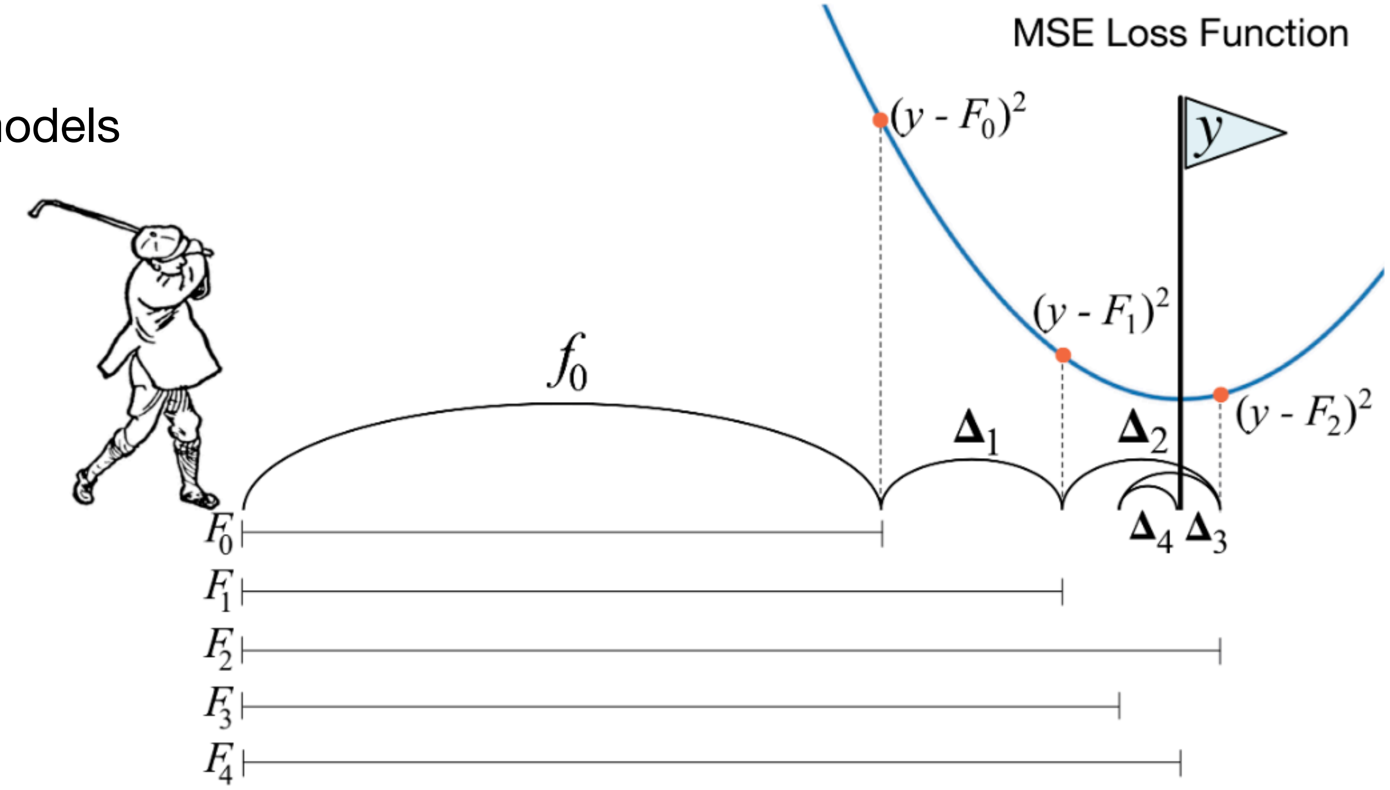
MiRIS: FT

GBR

Boosting combines **multiple simple models** into a single composite model. The idea is that, as we introduce more and more simple models, the overall model becomes stronger and stronger.

- Number of estimators -> simple models
- Max depth -> GBR base on trees
- ....



Friedman, J., Hastie, T., & Tibshirani, R. (2001). The elements of statistical learning (Vol. 1, No. 10). New York: Springer series in statistics.

https://explained.ai/gradient-boosting/index.html

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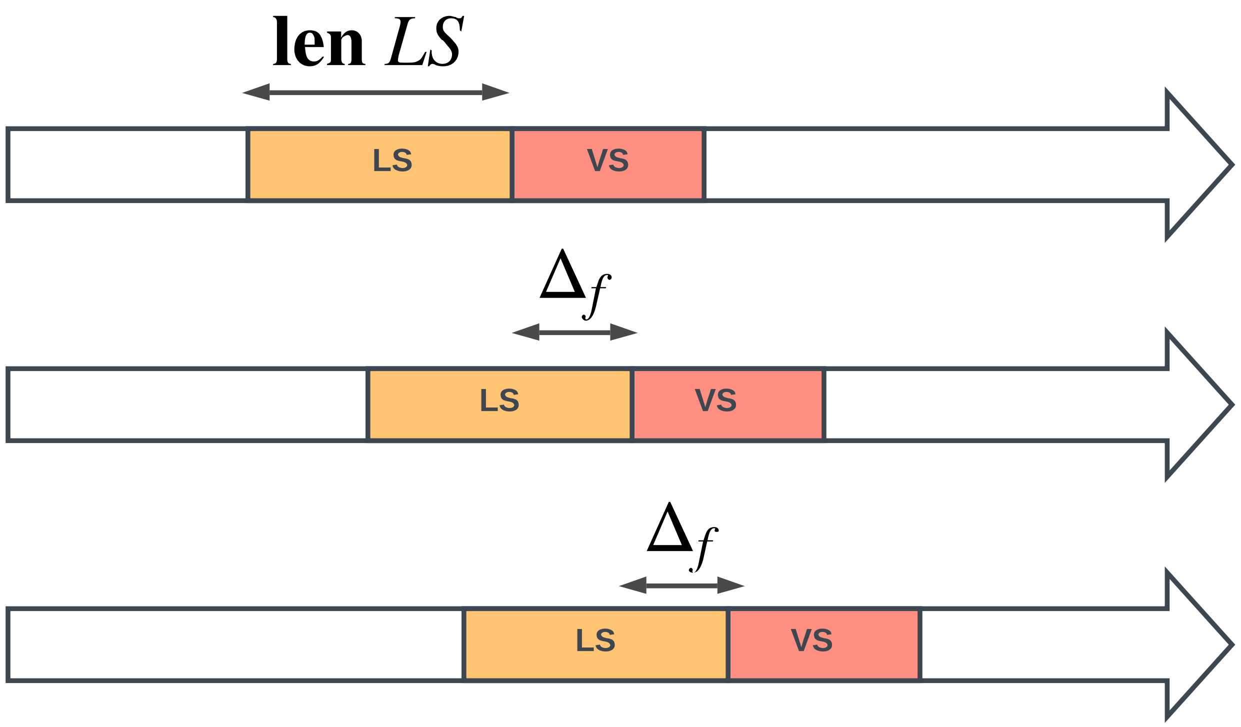
MiRIS: FM

Rolling forecast methodology



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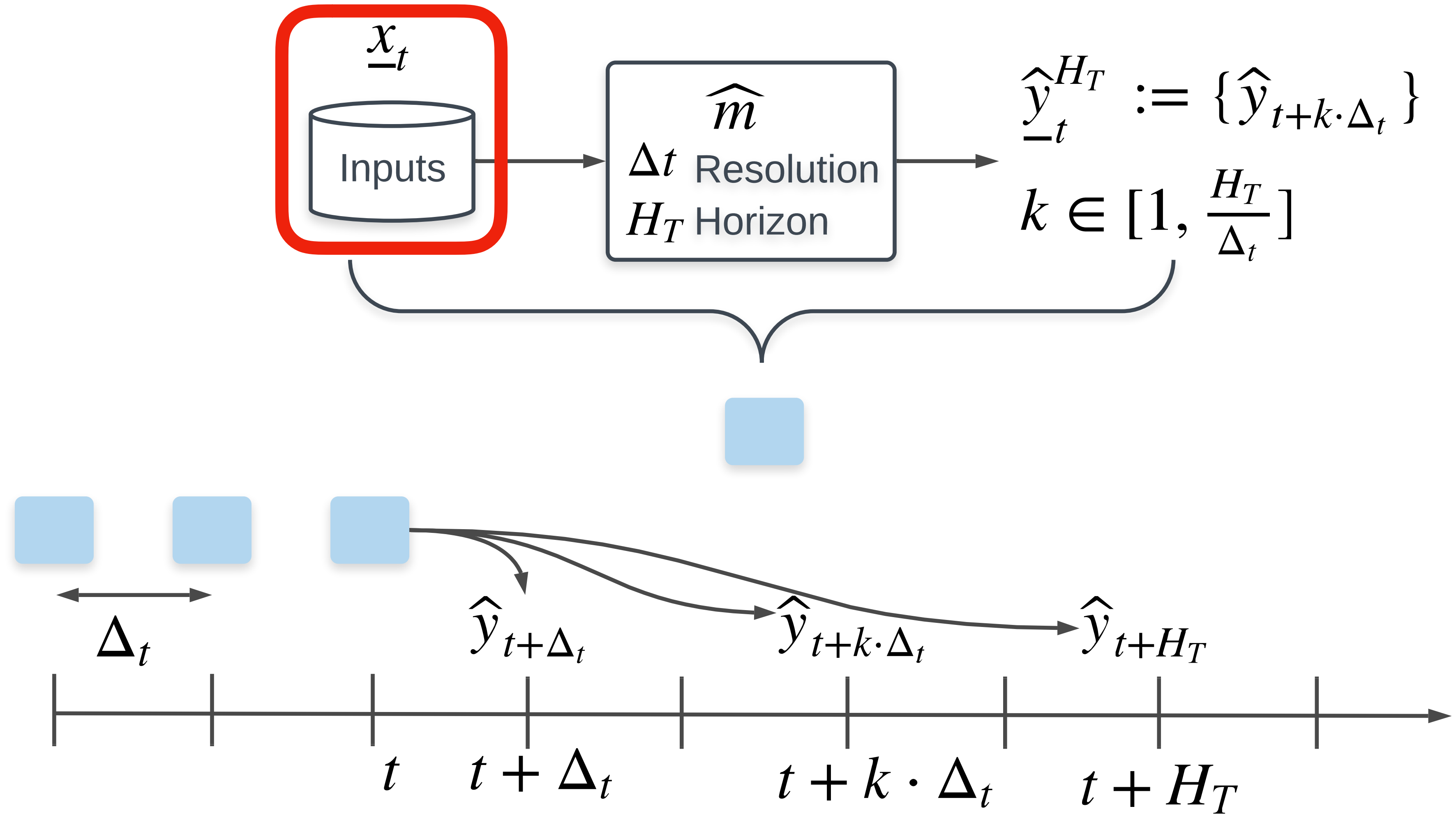
Forecasting process



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Predictors

WARNING Depend on the forecasting problem !!!!

Weather forecast
- Time series: temperature, solar irradiation, wind speed, rainfall … -> ST/VST
- Mean/standard deviation: temperature, solar irradiation … -> MT/LT

Calendar variables
- days, hours of the days, special day … -> VST/ST
- trend, years, months -> MT/LT

Historic values
- t-15min, t-1h, t-24h, t-7d, mean(t-1d) … -> VST/ST
- Mean/standard deviation: t-1week, t-1month … -> MT/LT

Cross effects
- temperature * calendar variables …
- lagged load * temperature

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MiRIS: predictors

Load Forecasting

Predictors:
- lagged load (t - 15 min to t - 60 min) -> 4 values
- temperature forecast (t + 15 min to t + 1 day) -> 96 values
- simulated power load based -> 96 values

$$\widehat{e}_{C,t} = EW(y_{C,t-7d})$$

PV Forecasting

Predictors:
- lagged PV (t - 15 min to t - 60 min) -> 4 values
- temperature forecast (t + 15 min to t + 1 day) -> 96 values
- Solar irradiation forecast (t + 15 min to t + 1 day) -> 96 values
- Simulated power PV production -> 96 values

$$\widehat{e}_{PV,t} = (\widehat{\omega}_{s,t} + \ln(\widehat{\omega}_{s,t})) \cdot (\widehat{\omega}_{T,t} + \widehat{\omega}_{s,t})$$

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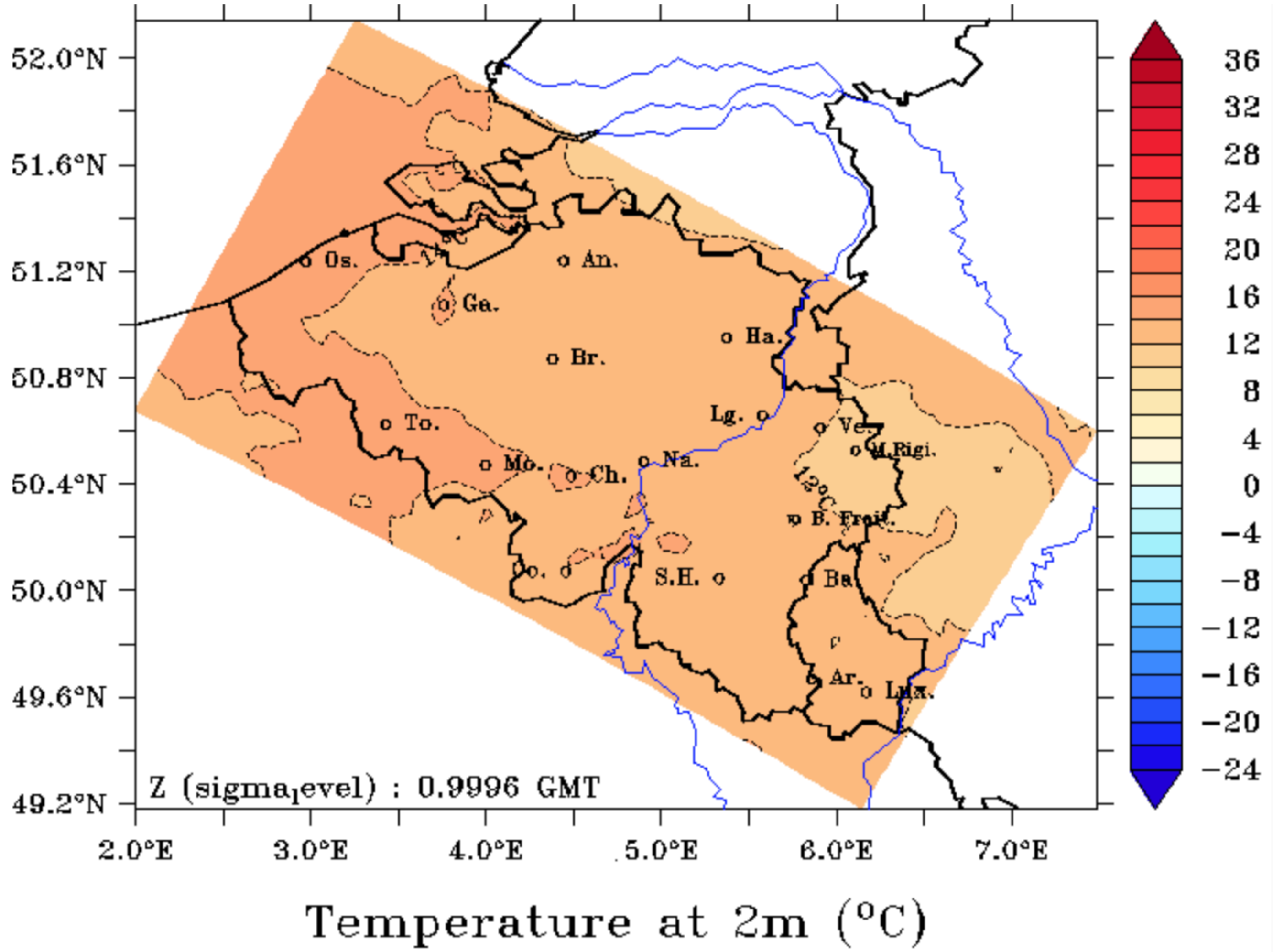
Weather forecast: MAR model



http://climato.be/cms/index.php?climato=fr_previsions-meteo

X. Fettweis, J. Box, C. Agosta, C. Amory, C. Kittel, C. Lang, D. van As, H. Machguth, and H. Gallée, “Reconstructions of the 1900–2015 greenland ice sheet surface mass balance using the regional climate MAR model,” Cryosphere (The), vol. 11, pp. 1015–1033, 2017.

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Summary

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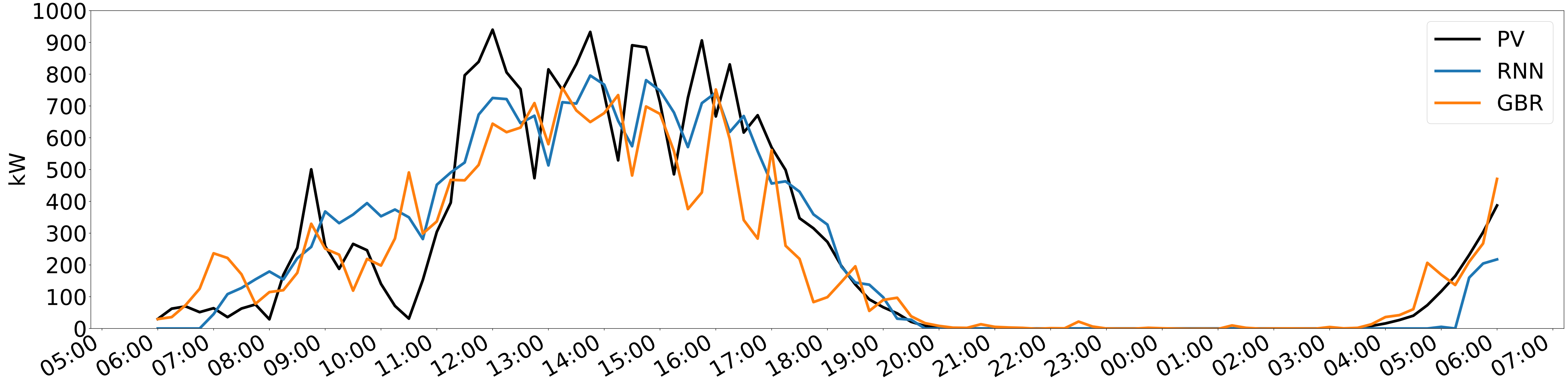
PV one shot forecast



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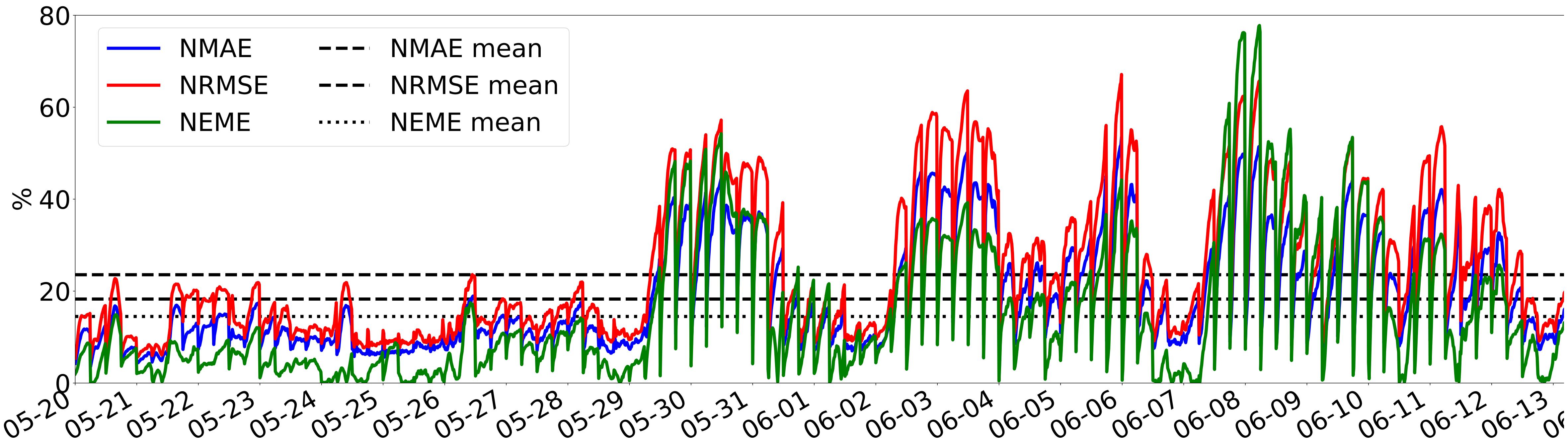
Load Scores



Dumas, J., Dakir, S., Liu, C., & Cornélusse, B. (2019). Coordination of operational planning and real-time optimization in microgrids. Submitted to PSCC 2020. -> available on orbi Uliege

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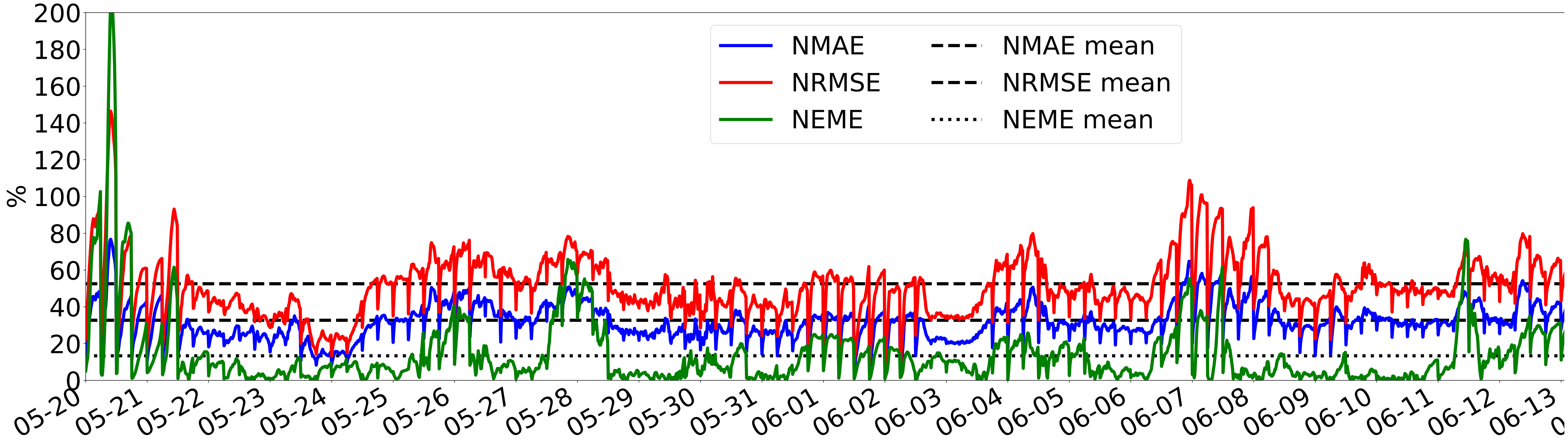
PV Scores



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Conclusions

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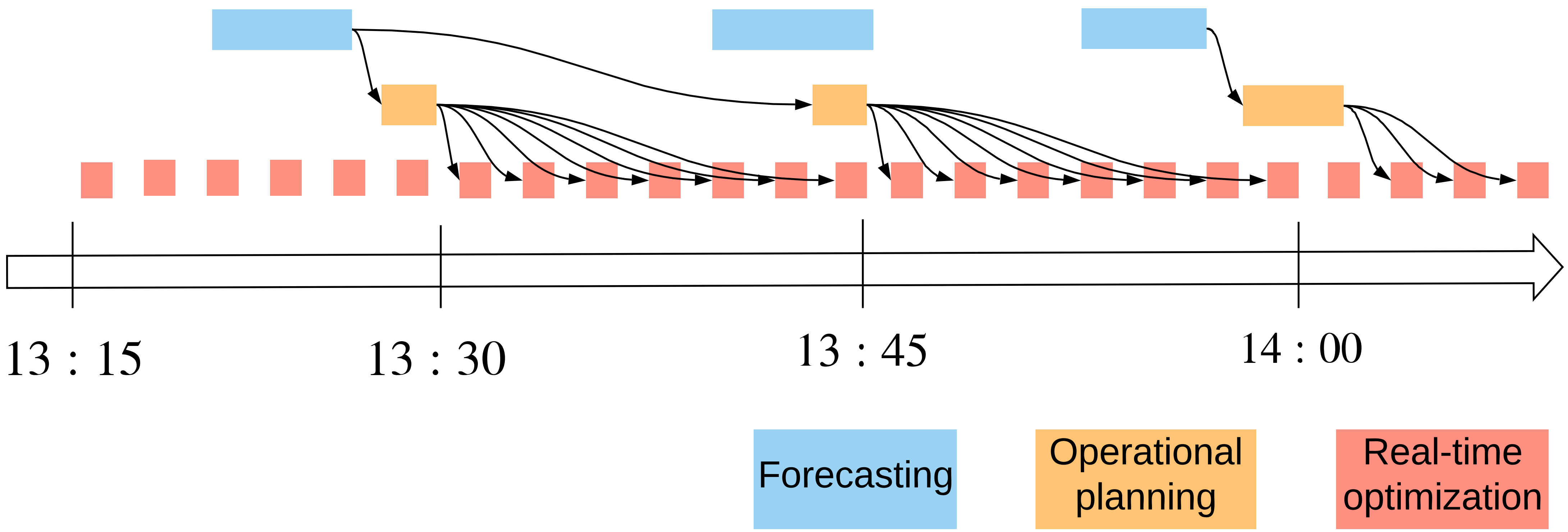
Forecasting as input to EMS



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What forecasting

Production: PV, Wind Power, Hydraulic Power, etc

Load: office, industrial, residential, etc

Prices: electricity, gas, (futures, day ahead, intraday, imbalances) etc

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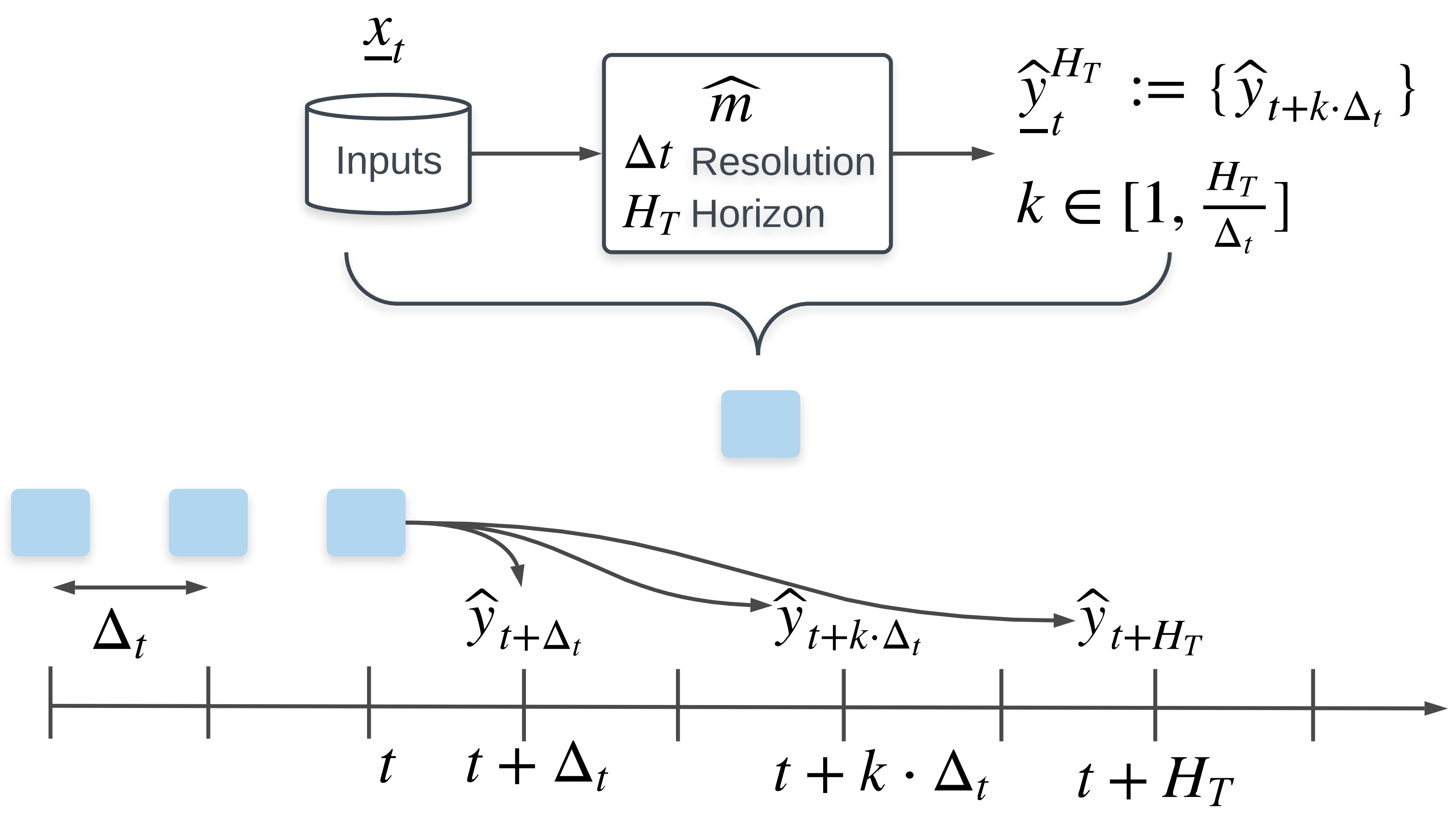
Forecasting process



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Forecasting for electrical microgrids management

How to tackle a forecasting problem

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Evaluation

Minute paper