Forecasting electricity prices in the day-ahead market: forecast averaging vs break points detection

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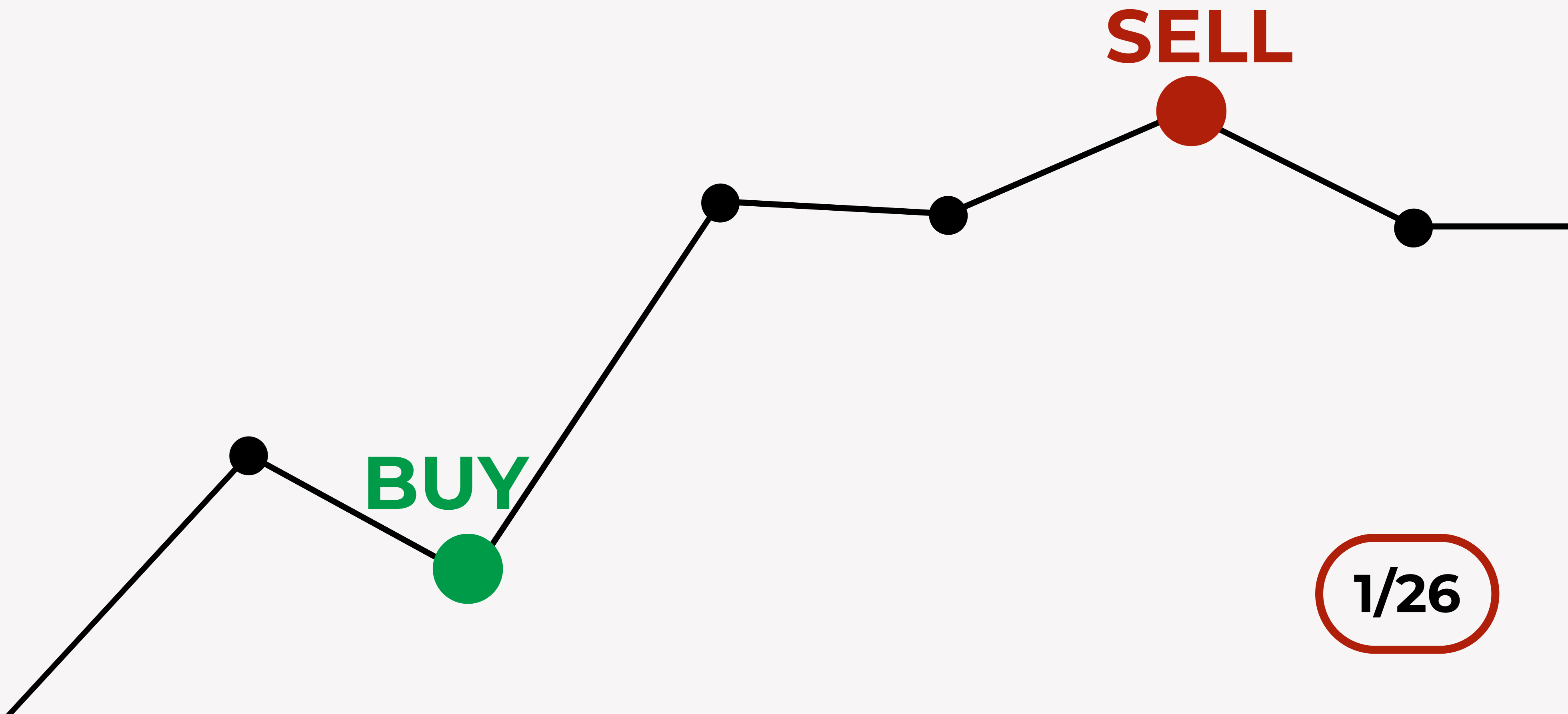
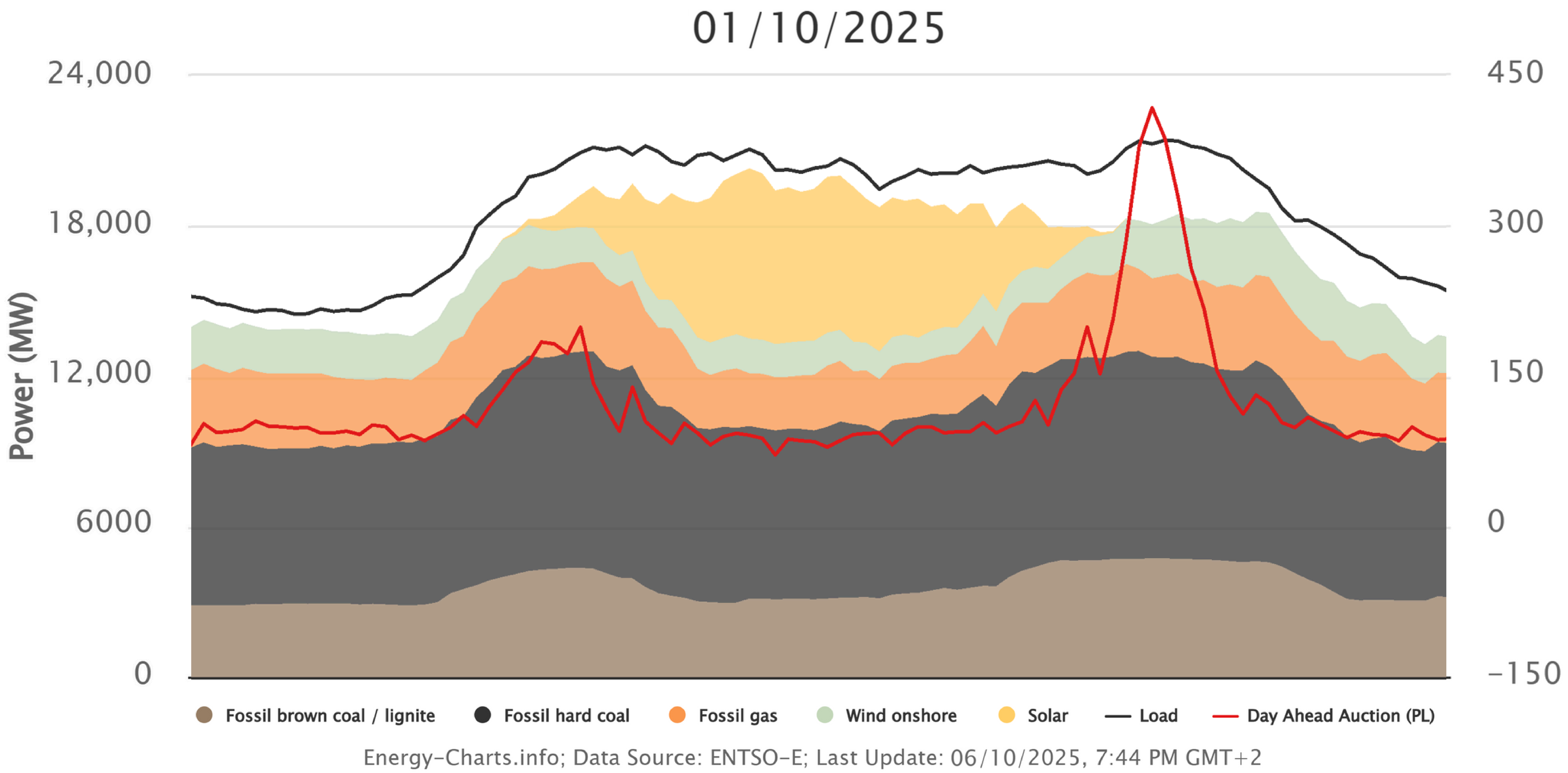
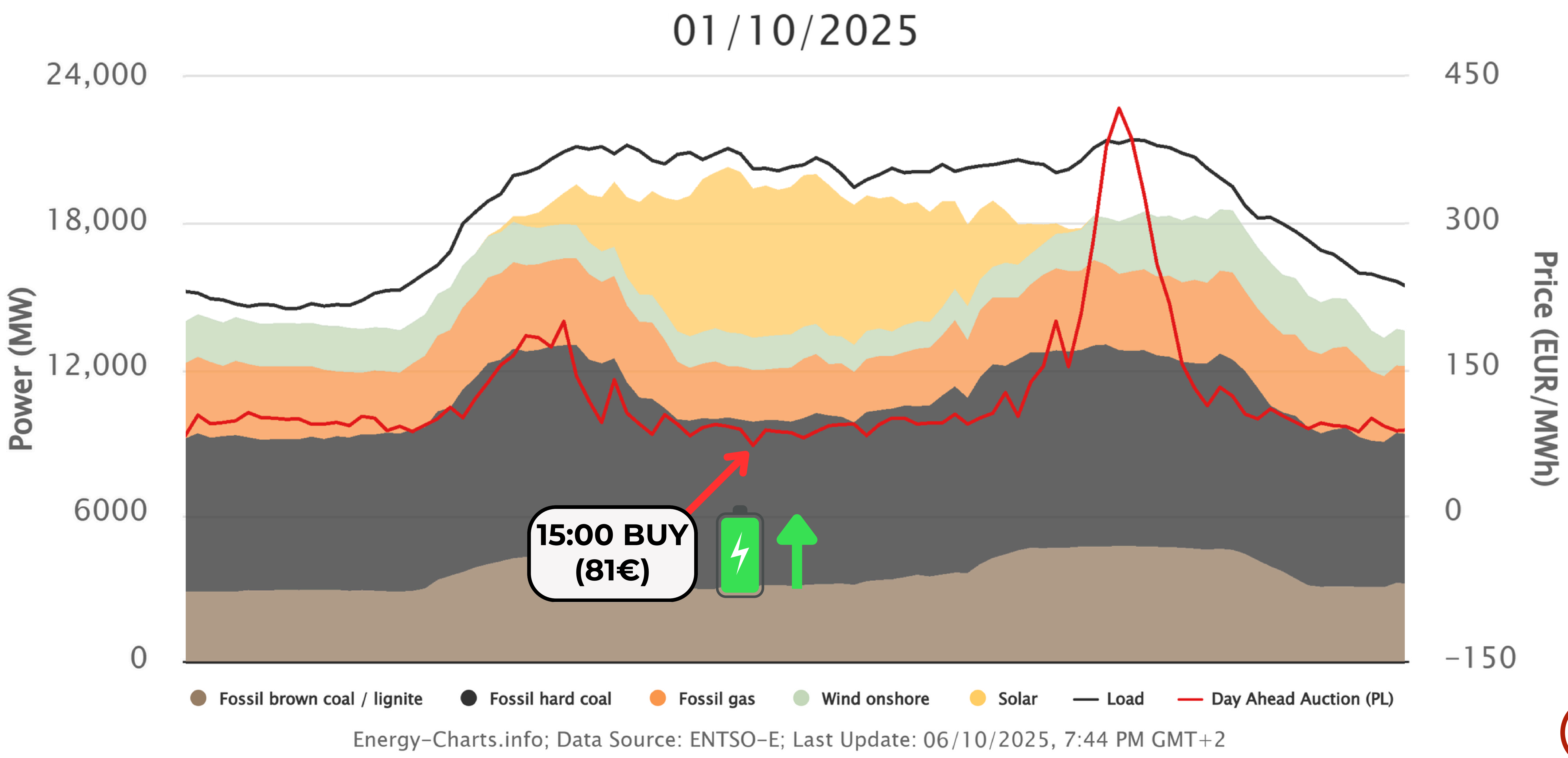


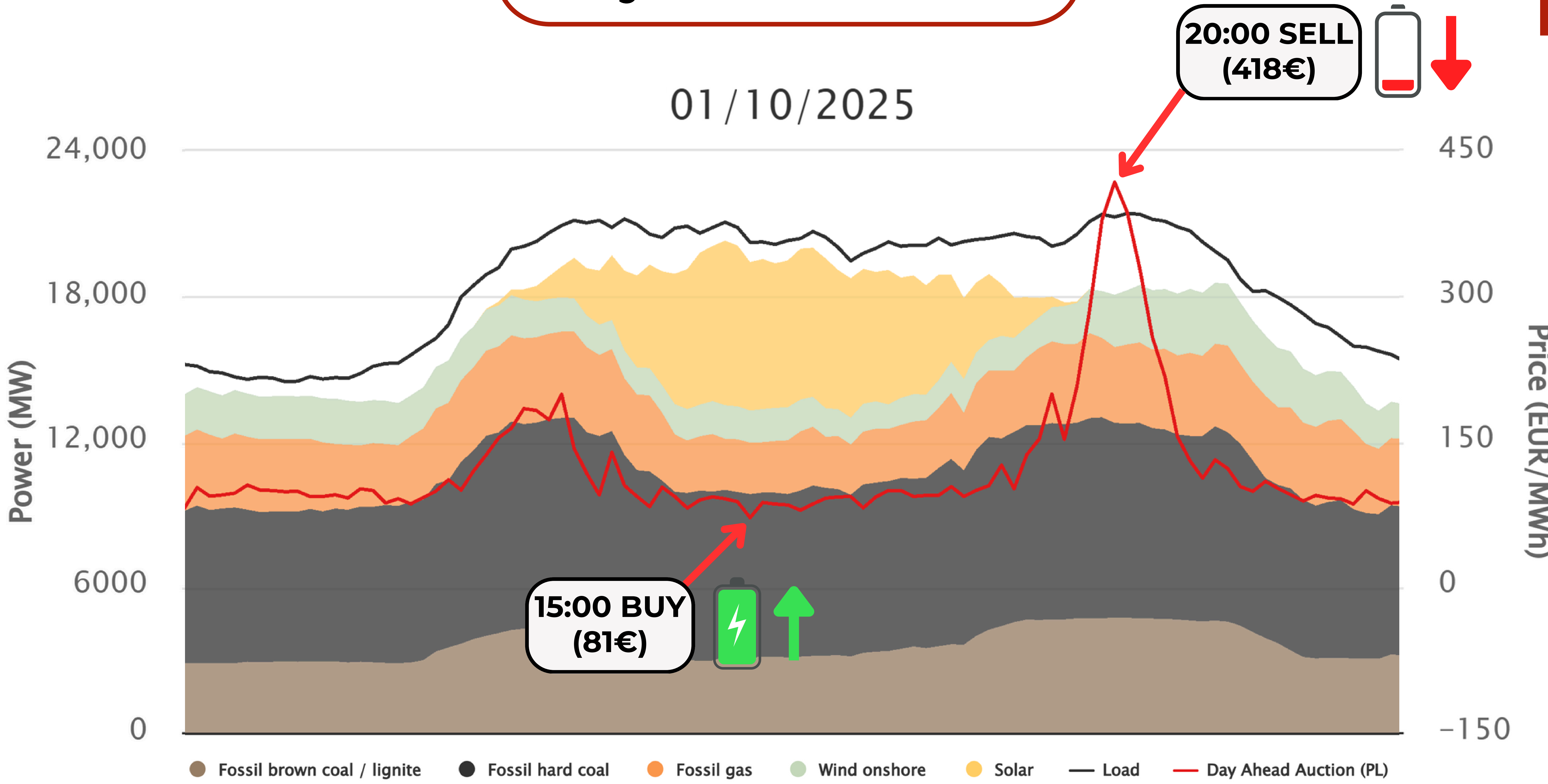
Day-ahead market



Day-ahead market



Day-ahead market



Energy-Charts.info; Data Source: ENTSO-E; Last Update: 06/10/2025, 7:44 PM GMT+2

Research aim

Averaging forecasts over calibration windows

VS

break points detection

- Estimation of regression models for electricity price forecasting (two approaches)
- Evaluation of prediction accuracy
- Assessment of effectiveness in energy storage management

Data

4 EU markets

Data span:
2018 - 2025

Initial training window:
2018 - 2019 (2 years)

Initial LASSO and Elastic Net calibration window:
2020 - 2022 (3 years)

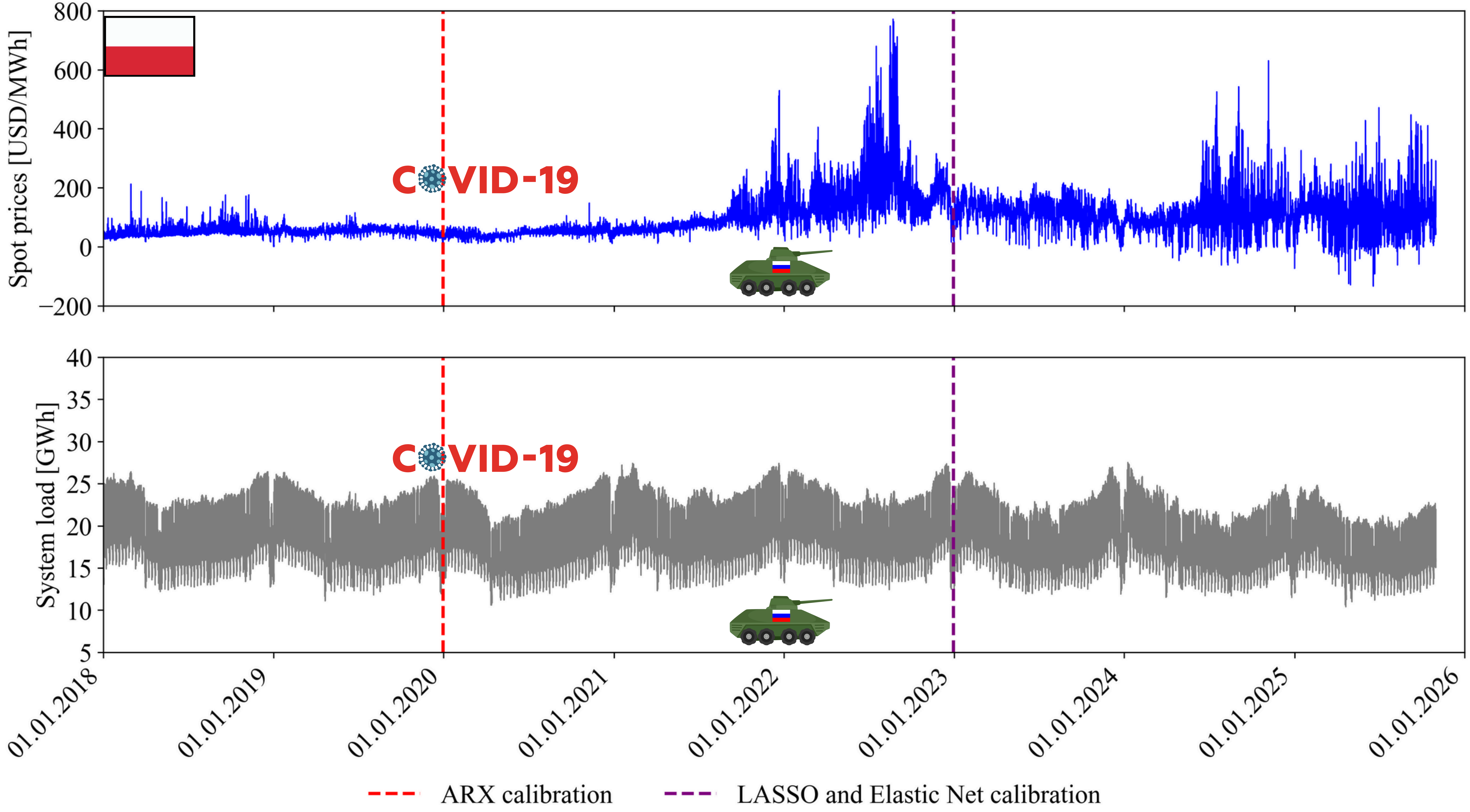
Test set:
2023 - 2025 (3 years)

Variables

- Date
- Hour
- Price
- Load
- Day-of-the-week
- RES generation

Data source: https://transparency.entsoe.eu

dataset


Spot prices [USD/MWh]
800
600
400
200
0
−200
COVID-19
System load [GWh]
40
35
30
25
20
15
10
5
COVID-19
01.01.2018
01.01.2019
01.01.2020
01.01.2021
01.01.2022
01.01.2023
01.01.2024
01.01.2025
01.01.2026
ARX calibration
LASSO and Elastic Net calibration

Model ARX

$$p_{d,h} = \beta_{h,0} + \beta_{h,1}p_{d-1,h} + \beta_{h,2}p_{d-2,h} + \beta_{h,3}p_{d-7,h} + \beta_{h,4}p_{d-1,\min} +$$

$$\beta_{h,5}p_{d-1,\max} + \beta_{h,6}\hat{L}_{d,h} + \beta_{h,7}p_{d-1,24} + \sum_{i\in\{1,6,7\}} \beta_{h,i+7}D_i + \varepsilon_{d,h}$$

- $\beta_{h,0}$ – intercept
- $\beta_{h,1}p_{d-1,h}$, $\beta_{h,2}p_{d-2,h}$, $\beta_{h,3}p_{d-7}$ – prices from 1, 2, 7 days ago
- $\beta_{h,5}p_{d-1,\max}$, $\beta_{h,4}p_{d-1,\min}$ – minimum and maximum prices from the previous day
- $\beta_{h,6}\hat{L}_{d,h}$ – day-ahead forecasted load
- $\beta_{h,7}p_{d-1,24}$ – price observed during the last hour of previous day
- $\sum_{i\in\{1,6,7\}} \beta_{h,i+7}D_i$ – dummy variables for monday, saturday, sunday
- $\varepsilon_{d,h}$ – random term iid$(0,\sigma^2)$

Averaging forecasts over calibration windows

*Averaging forecasts over calibration windows of different lengths can lead to **smaller prediction errors***

Hubicka, Marcjasz, Weron (2019)

Calibration windows:

from 28 to 728 days

Selected combinations for averaging

Many windows

AW(28:728)

Several individual windows

AW(364,728)

Several shortest and longest windows

AW(28:28:84,714:7:728)

11

COMBINATIONS

Hubicka et al. (2019)

Regularization methods

Elastic Net

$$\hat{\beta}_{\mathbf{EN}} = \arg\min_{\beta} \left\{ \underbrace{\sum_{i=1}^{n} \left(y_i - \sum_{j=1}^{p} x_{ij}\beta_j \right)^2}_{\text{RSS}} + \underbrace{\lambda \left[\alpha \sum_{j=1}^{p} |\beta_j| + (1-\alpha) \sum_{j=1}^{p} \beta_j^2 \right]}_{\text{penalty}} \right\}$$

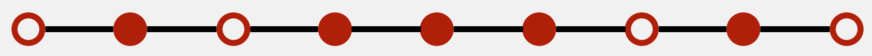
Lasso

$$\hat{\beta}_{\mathbf{Lasso}} = \arg\min_{\beta} \left\{ \underbrace{\sum_{i=1}^{n} \left(y_i - \sum_{j=1}^{p} x_{ij}\beta_j \right)^2}_{\text{RSS}} + \underbrace{\lambda \sum_{j=1}^{p} |\beta_j|}_{\text{penalty}} \right\}$$

Input

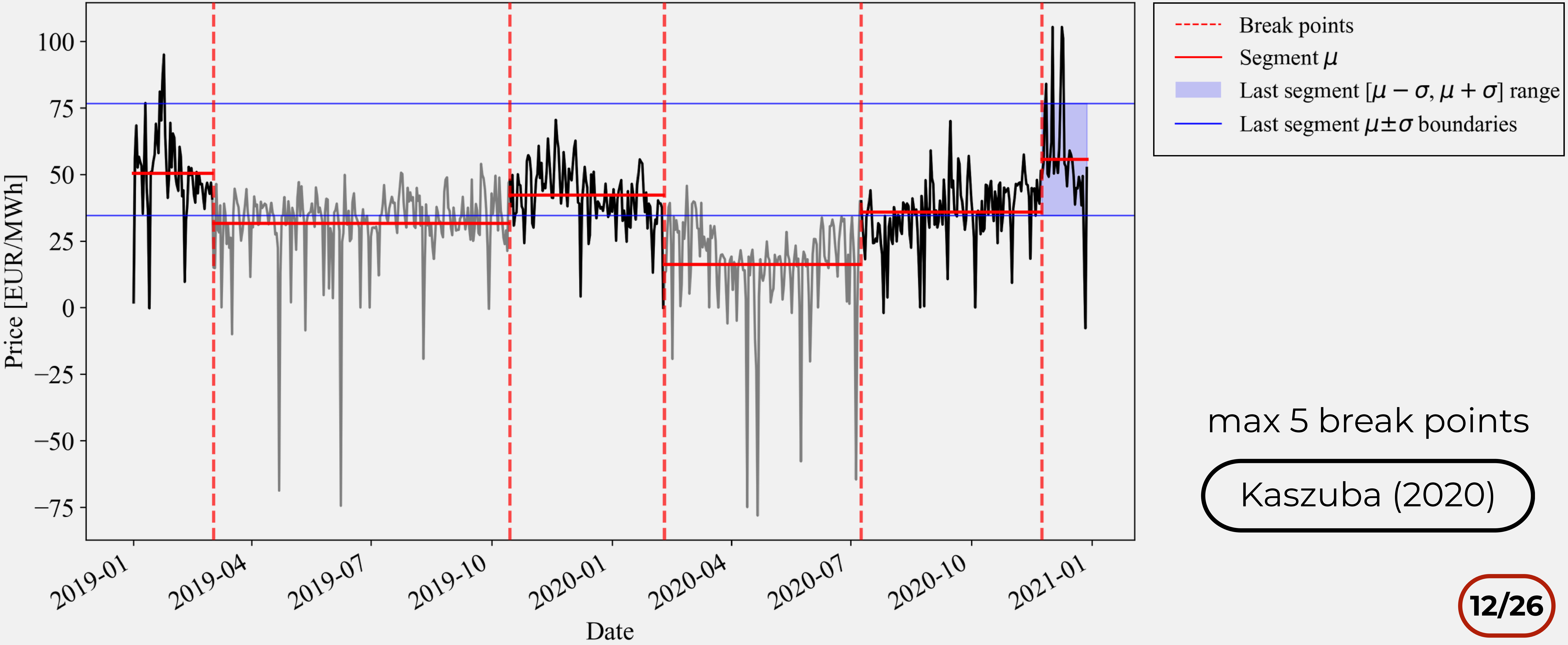
1 Select from every 7th ARX forecast

2 Select from every 14th ARX forecast



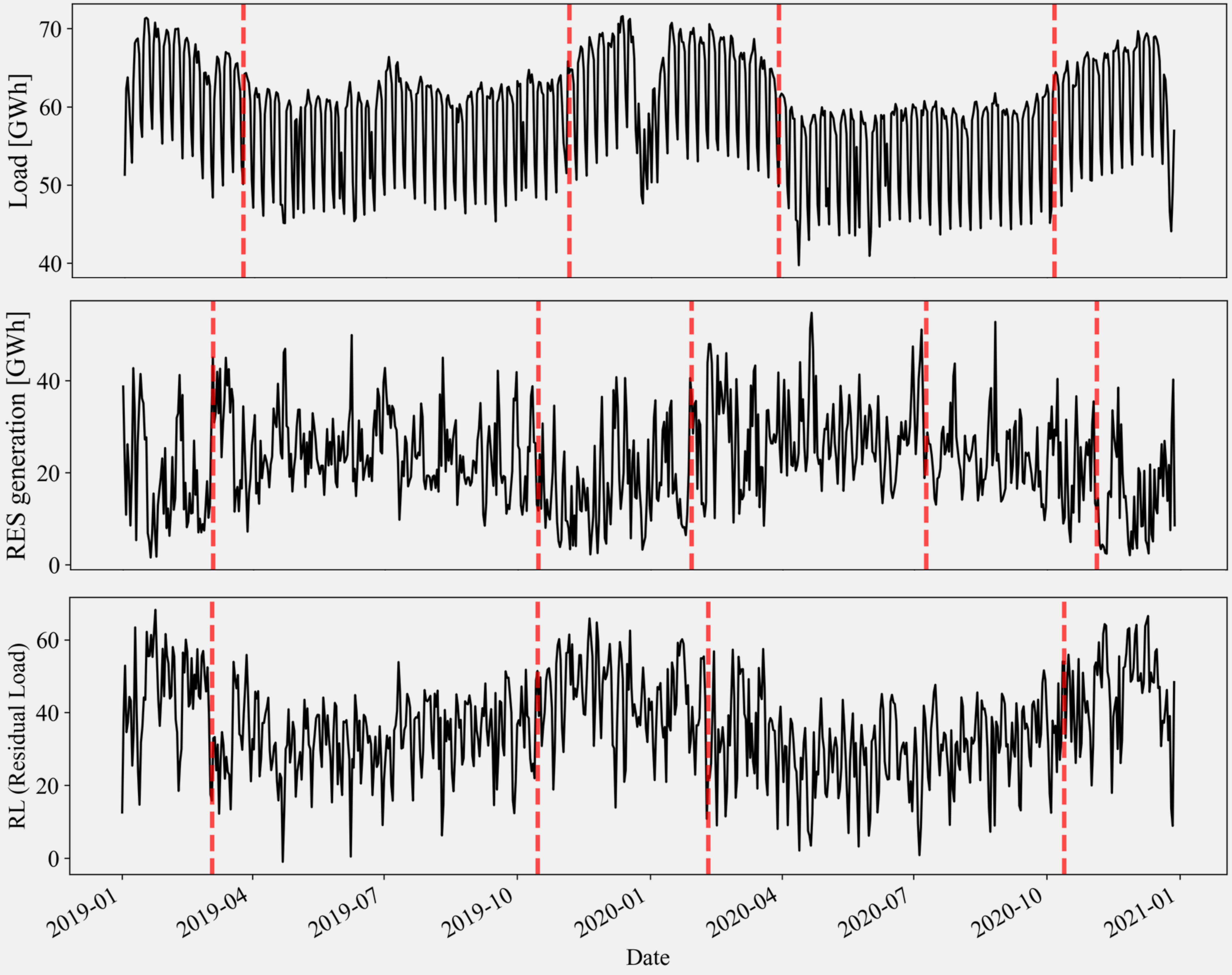
Selection of calibration window based on detected break points

PELT (Pruned Exact Linear Time) algorithm — Killick et al. (2012)



max 5 break points

Kaszuba (2020)



Load [GWh]
70
60
50
40
RES generation [GWh]
40
20
0
RL (Residual Load)
60
40
20
0
2019-01
2019-04
2019-07
2019-10
2020-01
2020-04
2020-07
2020-10
2021-01
Date

Averaging forecasts obtained using different variables to determine break points

ONE

P

TWO

AV(P, RES)

THREE

AV(P, RES, RL)

FOUR

AV(P, L, RES, RL)

15

COMBINATIONS

Evaluation of prediction accuracy

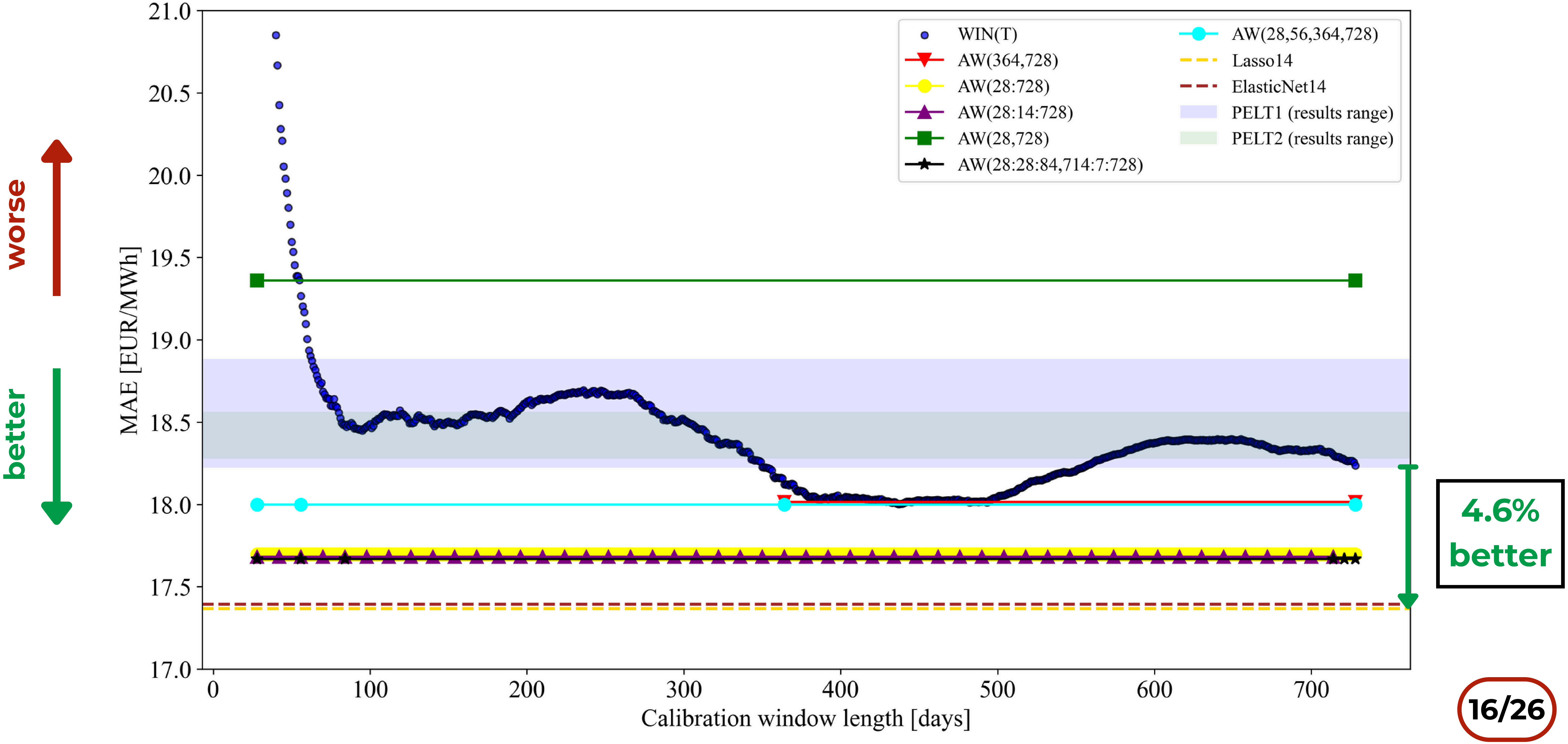
- MAE (Mean Absolute Error)
- RMSE (Root Mean Square Error)

Evaluation of economic efficiency

- AOC (Average Opportunity Cost)
- SR (Sharpe Ratio)

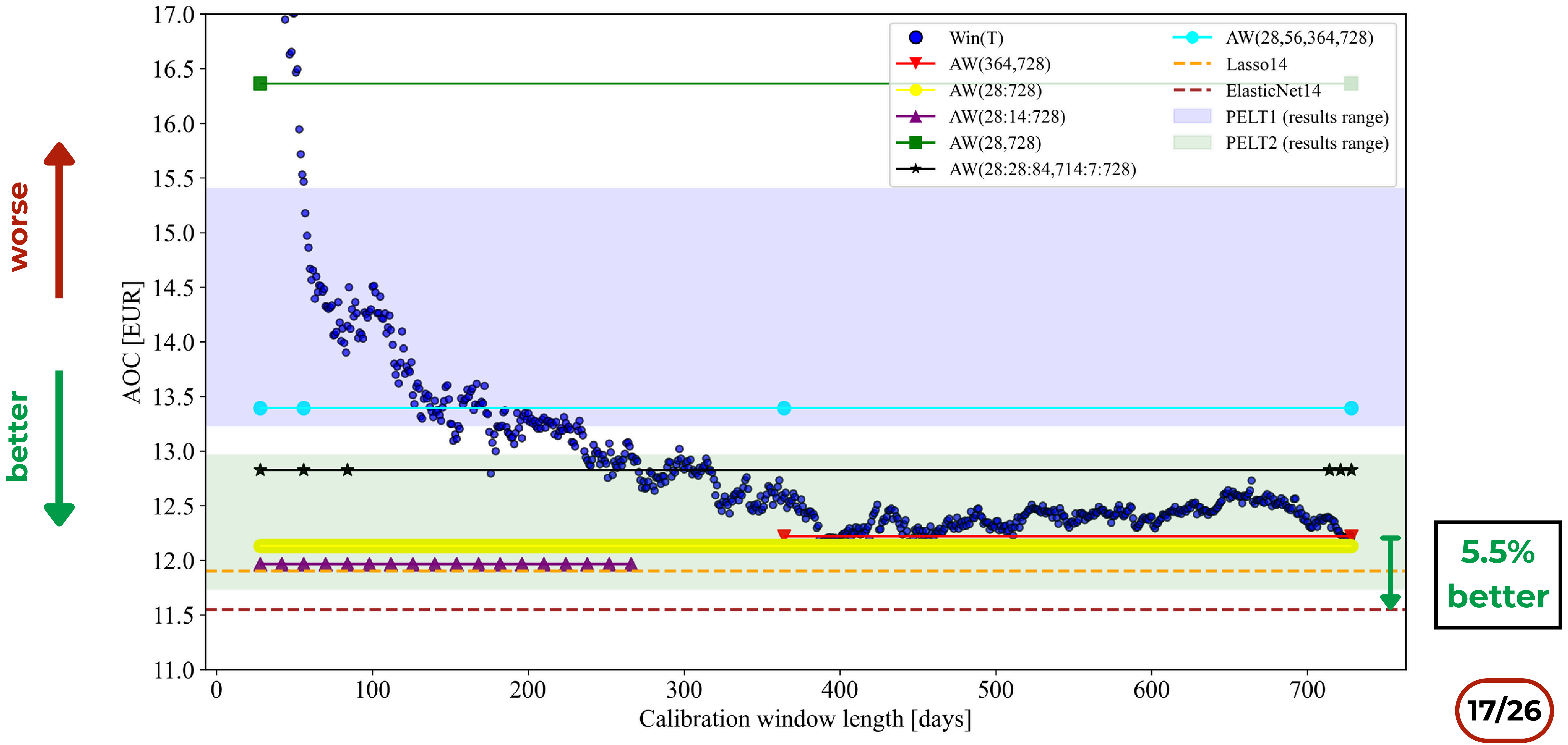
Results - MAE

$$\text{MAE} = \frac{1}{24D}\sum_{d=1}^{D}\sum_{h=1}^{24}|\hat{\varepsilon}_{d,h}|$$



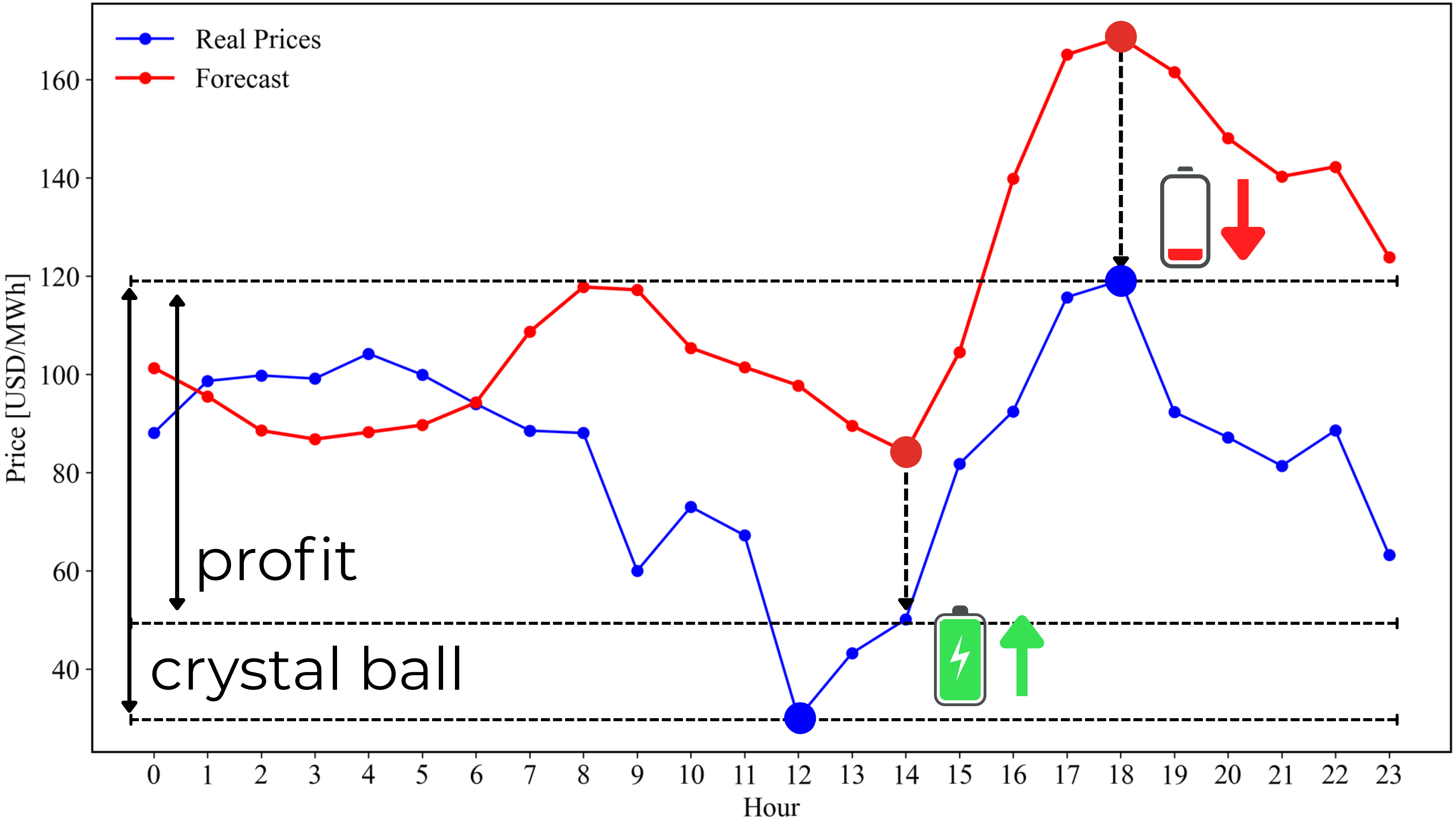
Results - AOC

$$AOC = \sum_{d=1}^{N} (\mathrm{Profit}_{ideal,d} - \mathrm{Profit}_{forecast,d})$$



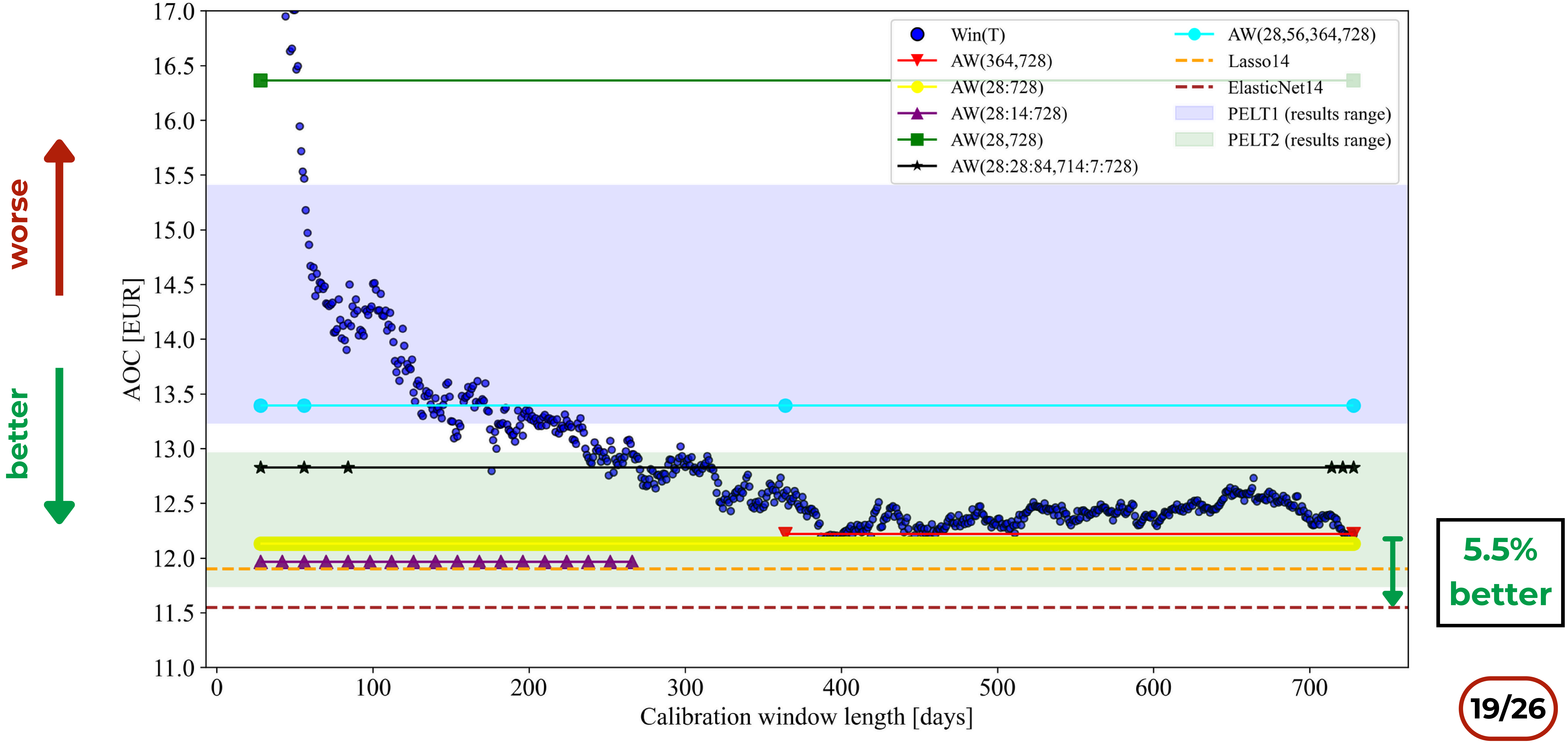
Results - AOC

$$\text{AOC} = \sum_{d=1}^{N} \left(\text{Profit}_{ideal,d} - \text{Profit}_{forecast,d}\right)$$



Results - AOC

$$\text{AOC} = \sum_{d=1}^{N} \left(\text{Profit}_{ideal,d} - \text{Profit}_{forecast,d}\right)$$

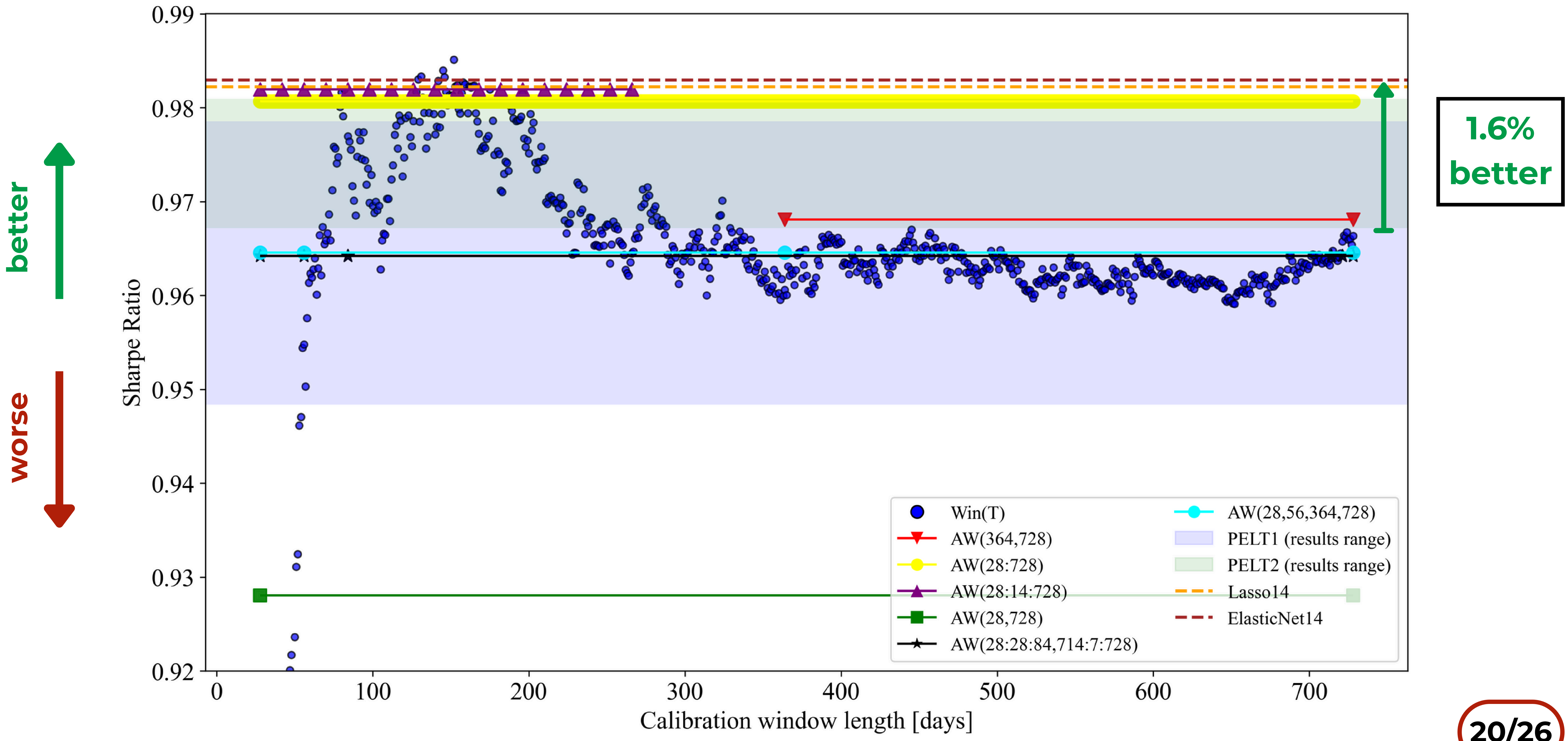


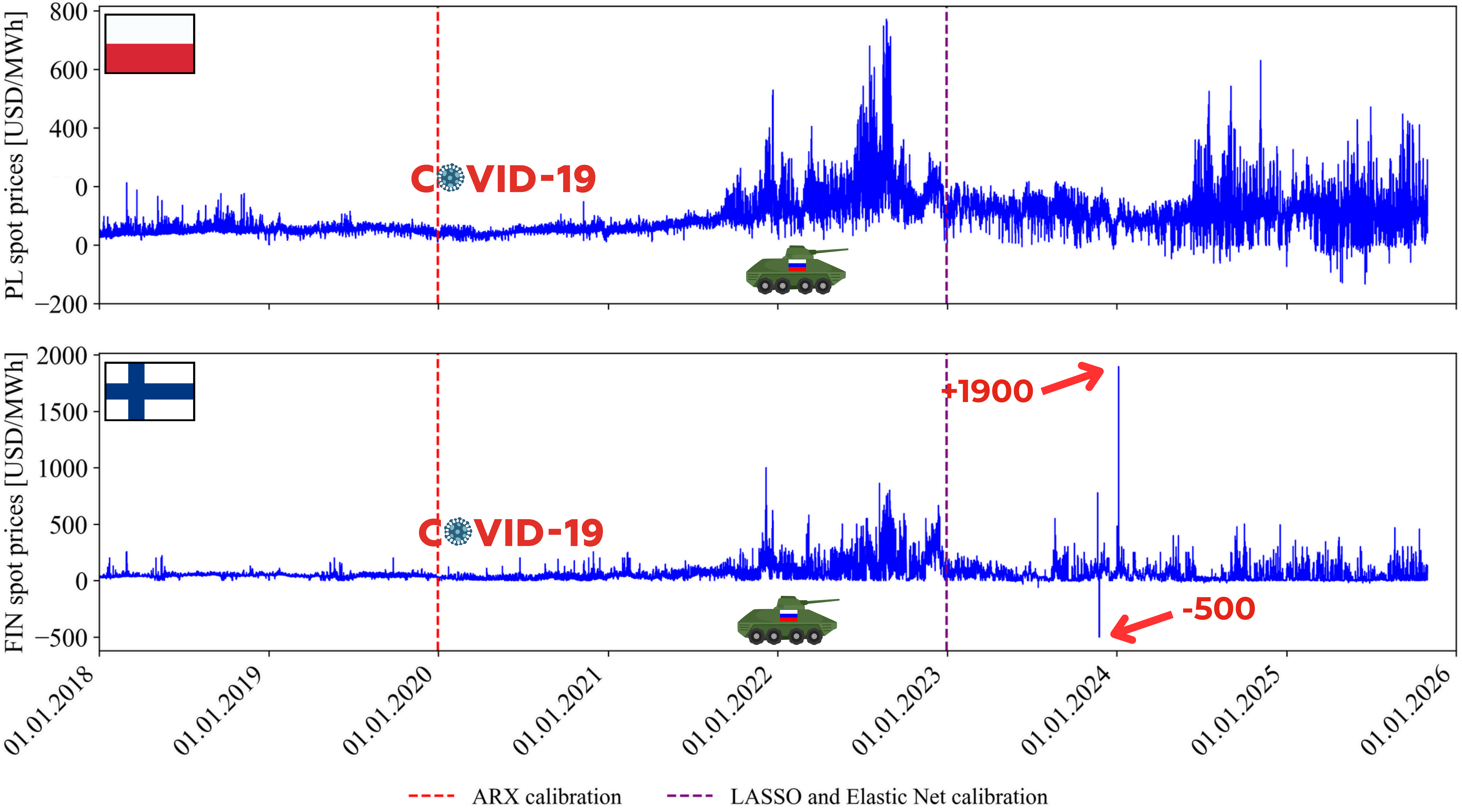
Results - SR

$$S = \frac{R_j}{\sigma_j}$$

Rj - mean profit

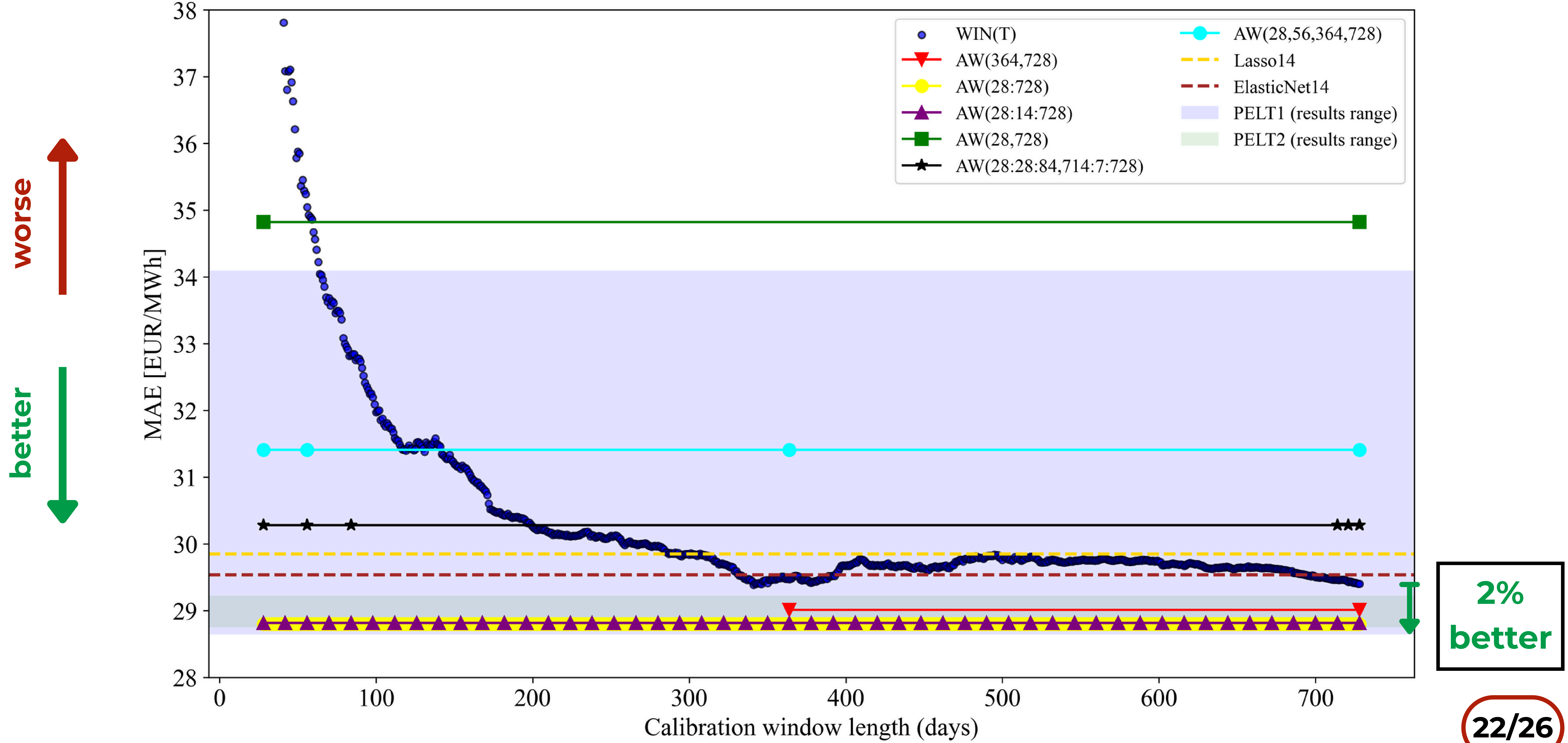
σj - standard deviation of profit




PL spot prices [USD/MWh]
800
600
400
0
0
−200
COVID-19
FIN spot prices [USD/MWh]
2000
1500
1000
500
0
−500
COVID-19
+1900
-500
01.01.2018
01.01.2019
01.01.2020
01.01.2021
01.01.2022
01.01.2023
01.01.2024
01.01.2025
01.01.2026
ARX calibration
LASSO and Elastic Net calibration

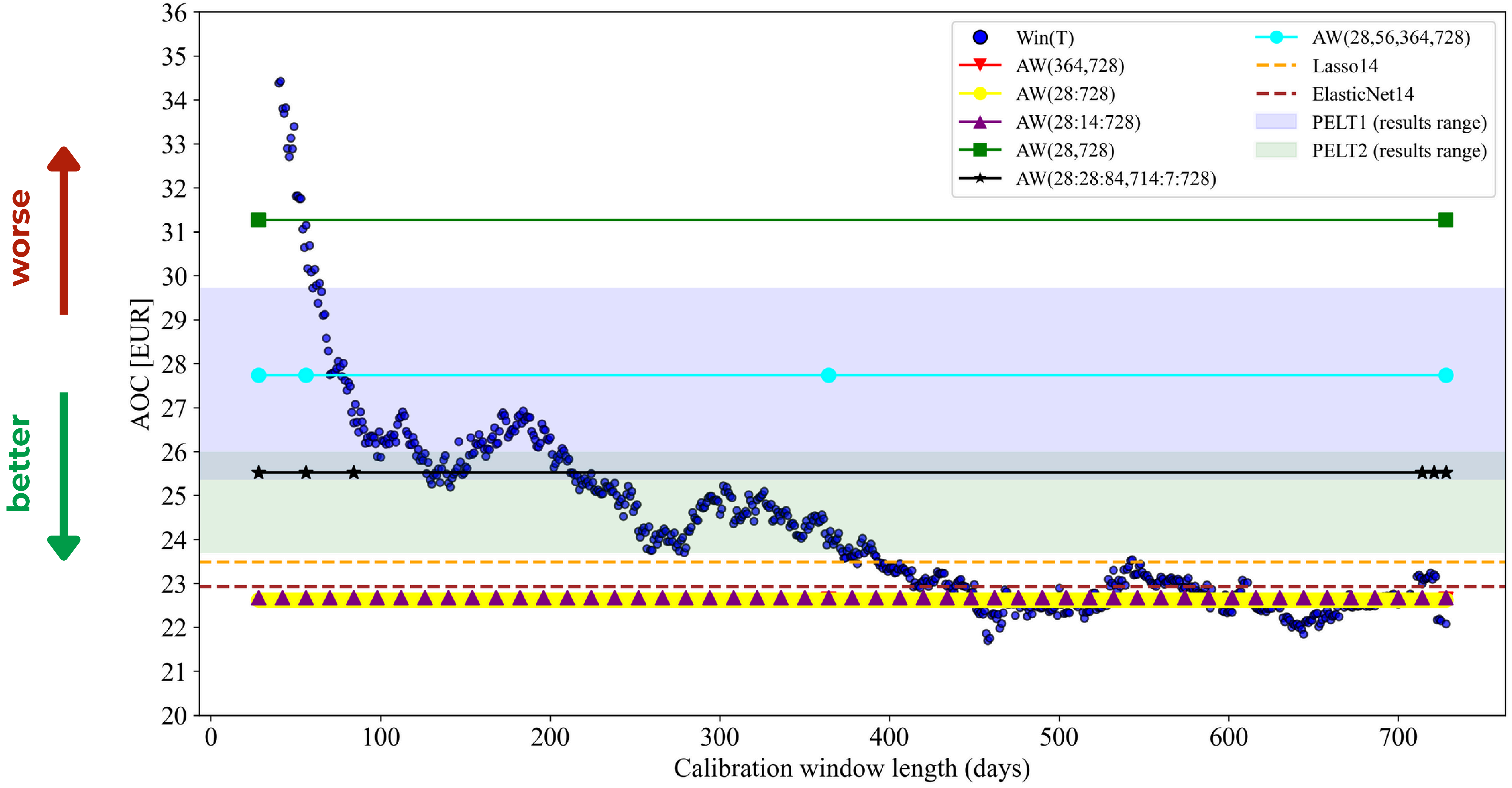
Results - MAE

$$\text{MAE} = \frac{1}{24D}\sum_{d=1}^{D}\sum_{h=1}^{24}|\hat{\varepsilon}_{d,h}|$$



Results - AOC

$$AOC = \sum_{d=1}^{N} (\text{Profit}_{ideal,d} - \text{Profit}_{forecast,d})$$

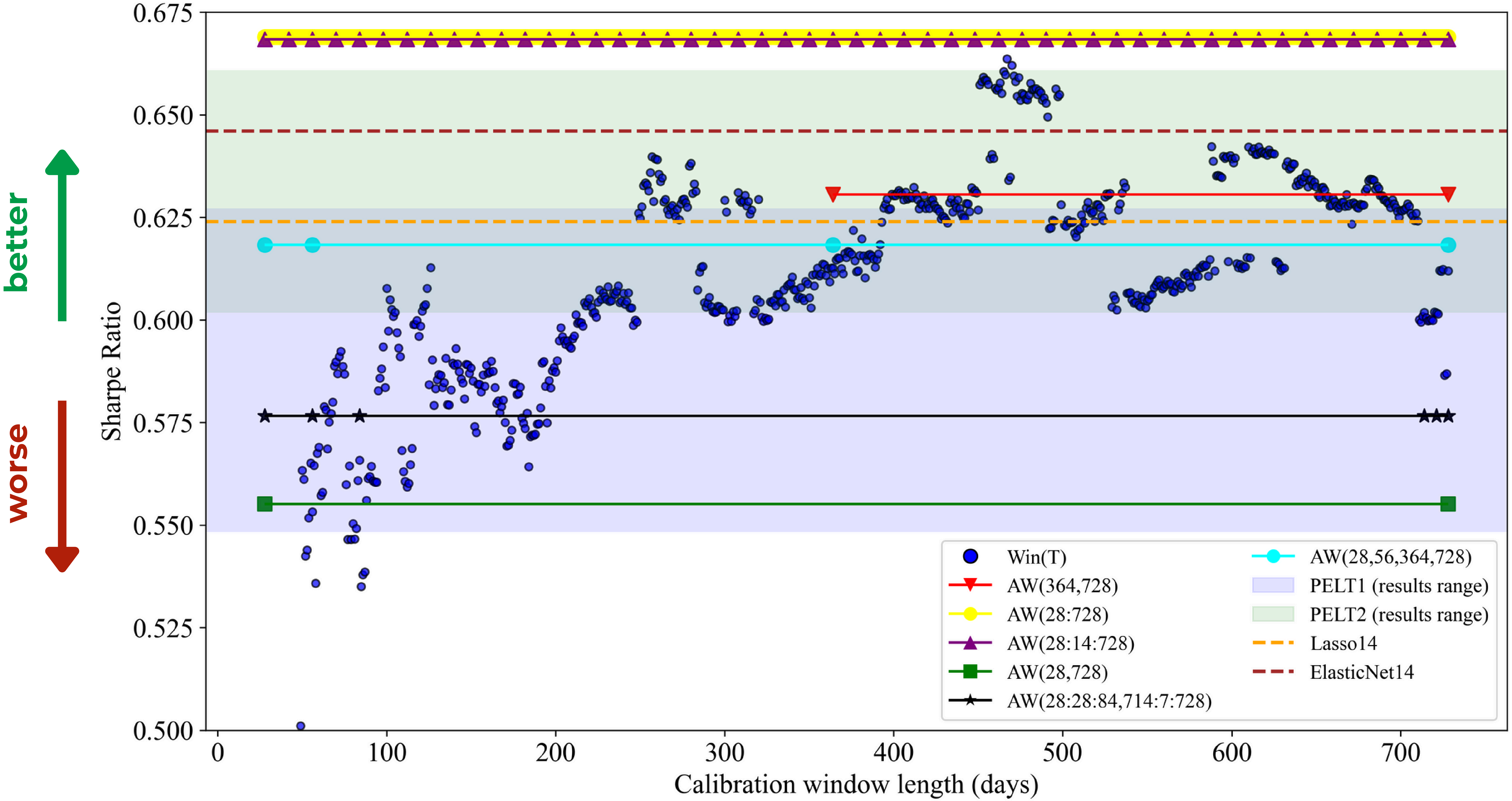


Results - SR

$$S = \frac{R_j}{\sigma_j}$$

Rj - mean profit

σj - standard deviation of profit



Top 5 models across markets

MAE			RMSE			AOC			SR		
Rank	Model	G. mean	Rank	Model	G. mean	Rank	Model	G. mean	Rank	Model	G. mean
1	Lasso14	2,58	1	EN14	3,83	1	EN14	1,57	1	EN14	2,78
2	Lasso7	3,46	2	PELT2 (Price, Load, RES, RL)	4,29	2	AW(28:7:728)	3,44	2	AW(28:7:728)	2,78
3	AW(56,728)	4,53	3	Win(728)	4,33	3	EN7	3,74	3	Lasso14	3,39
4	EN7	4,61	4	Lasso7	5,05	4	AW(28:14:728)	4,61	4	AW(28:14:728)	4,12
5	EN14	5,42	5	Lasso14	5,07	5	Win(728)	5,18	5	AW(28:28:728)	4,23

Key findings

- Selecting the appropriate calibration window is not simple, but it has a significant impact on the results
- Averaging forecasts over calibration windows achieved more accurate electricity price predictions (MAE, RMSE)
- Averaging forecasts over calibration windows achieved better economic results (AOC, Sharpe Ratio)
- Elastic Net is the best in economic terms and has a stable performance across all markets