OASYS
Optimization and Analytics for Sustainable energY Systems

Data-driven Strategies for Trading Renewable Energy Production

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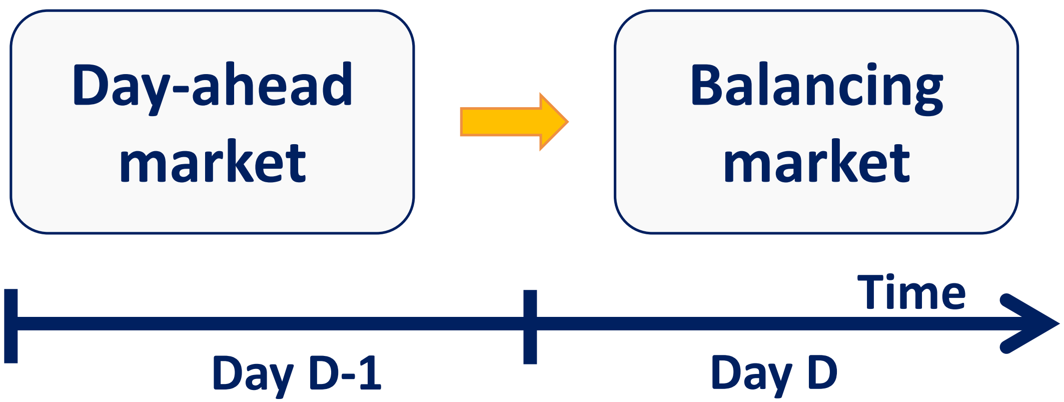
Objective

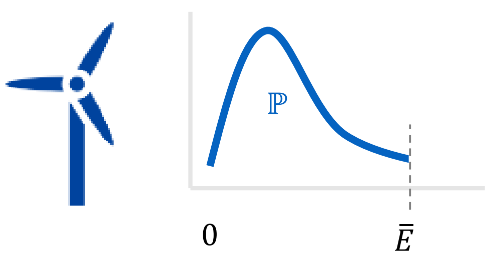
Develop a mathematical optimization approach to:

- Improve renewable energy forecast and trading.
- Able to leverage contextual information.
- Simple, but effective and computationally efficient.

Market Framework

Spot Electricity Market:





Zero marginal energy cost

Imbalance penalties

ψ_t^+, ψ_t^-

Optimal offer E^D of **stochastic** producer?

Optimal day-ahead offer

Problem of interest:

$$\min_{E^D \in [0,\overline{E}]} \mathbb{E}\left[\underbrace{\psi^-(E^D - E)^+}_{\text{underproduction}} + \underbrace{\psi^+(E - E^D)^+}_{\text{overproduction}}\right]$$

where:
E^D: day-ahead offer
E: uncertain production

$(x)^+ := \max(x, 0)$
$\bar{E}$: generation capacity
$\bar{\psi}^+$, $\bar{\psi}^-$: upward /downward penalty

Analytical solution:

$$E^{D*} = F_{\mathbb{P}}^{-1}\left(\frac{\bar{\psi}^+}{\bar{\psi}^+ + \bar{\psi}^-}\right)$$

Only the empirical distribution is available.

If $\bar{\psi}^+ = \bar{\psi}^- = 1$ then
E^{D*} is the *median* of E

Poor solution
Do not leverage side information!

Exploiting Side Information

Linear Decision Rule on the features:

$$\mathcal{Q} = \left\{ E^D : \mathcal{X} \to \mathbb{R} : E^D(x) = \mathbf{q} \cdot \mathbf{x} = \sum_{j=1}^{p} q^j x^j \right\}, \quad (*)$$

Sample Average Approximation + Linear Decision Rule:

$$\min_{\mathbf{q}} \frac{1}{|\mathcal{T}|} \sum_{t \in \mathcal{T}} \psi_t^- \left(\sum_{j=1}^{p} q^j x_t^j - E_t \right)^+ + \psi_t^+ \left(E_t - \sum_{j=1}^{p} q^j x_t^j \right)^+$$

$$\text{s. t. } 0 \leq \sum_{j=1}^{p} q^j x_t^j \leq \overline{E}, \ \forall t \in \mathcal{T}$$

Can be reformulated as an inexpensive LP!

Recall: If $\psi_t^+ = \psi_t^- = 1, \forall t$, → ***median*** of E

- **Forecast** $\psi_t^+ = \psi_t^- = 1, \forall t$
- **Trading** ψ_t^+, ψ_t^-

(*) G.-Y. Ban and C. Rudin, "The big data newsvendor: Practical insights from machine learning", *Operation Research*, vol. 67, no. 1, pp. 90-108, 2019.

Performance Metrics

1. Better wind power prediction (quality improvement)

$$\mathrm{MAE} := \frac{1}{|\mathcal{T}|} \sum_{t\in\mathcal{T}} |E_t - E_t^D|$$

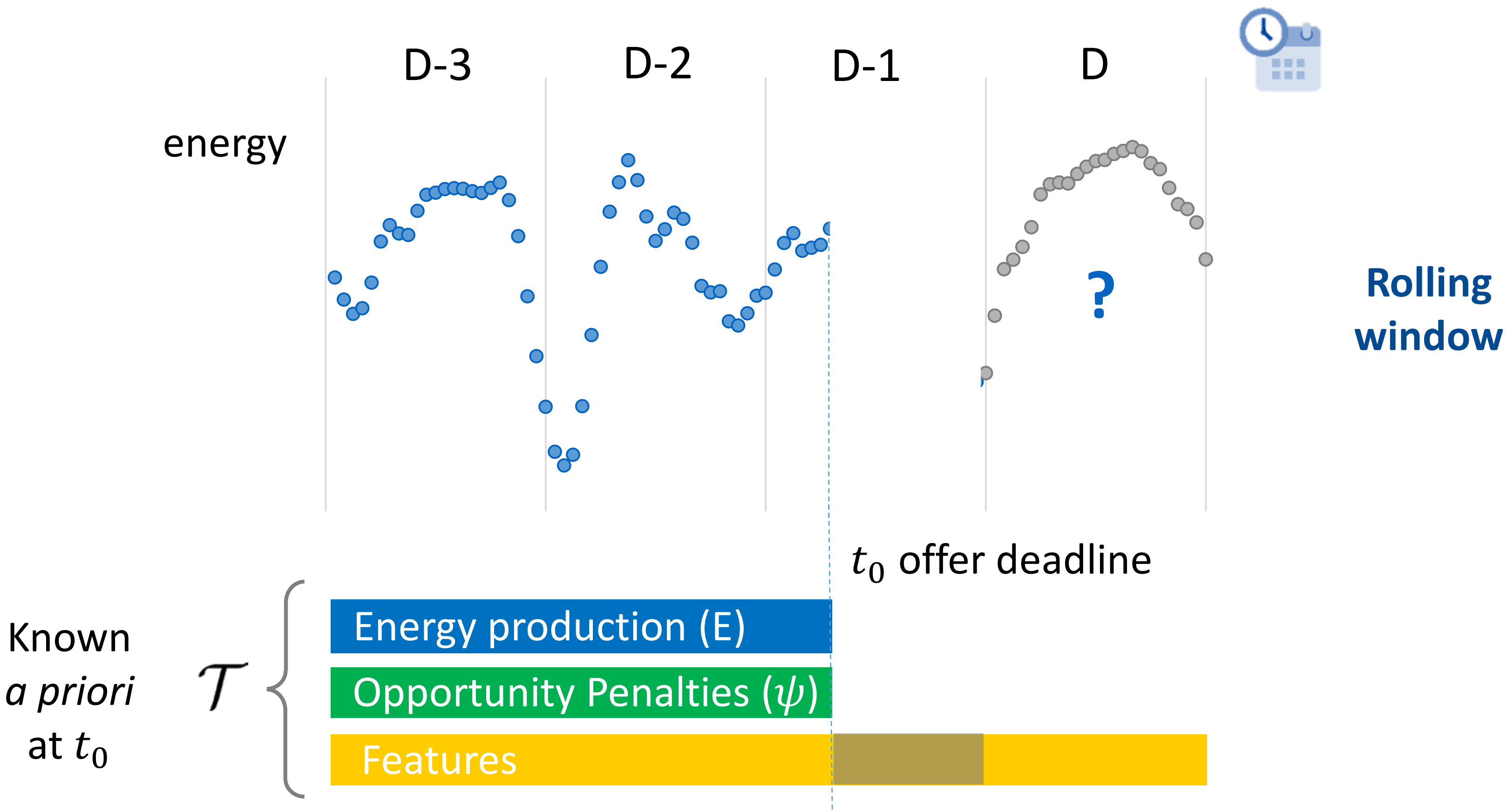
$$\mathrm{RMSE} := \frac{1}{|\mathcal{T}|} \sqrt{\sum_{t\in\mathcal{T}} (E_t - E_t^D)^2}$$

2. Better day-ahead offer (value improvement)

$$\mathrm{AOL} := \frac{1}{|\mathcal{T}|} \sum_{t\in\mathcal{T}} \psi_t^- (E_t - E_t^D)^+ + \psi_t^+ (E_t^D - E_t)^+$$

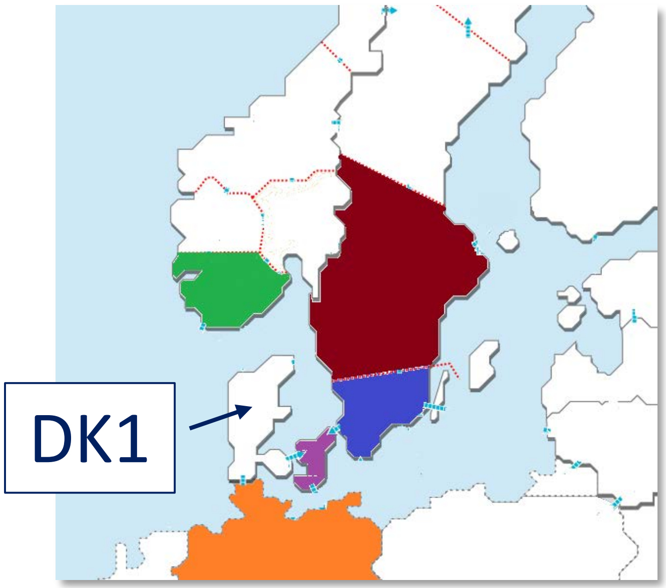
AOL: Average opportunity loss

Case Study



We can use **forecasts** or **categorical variables** as features.

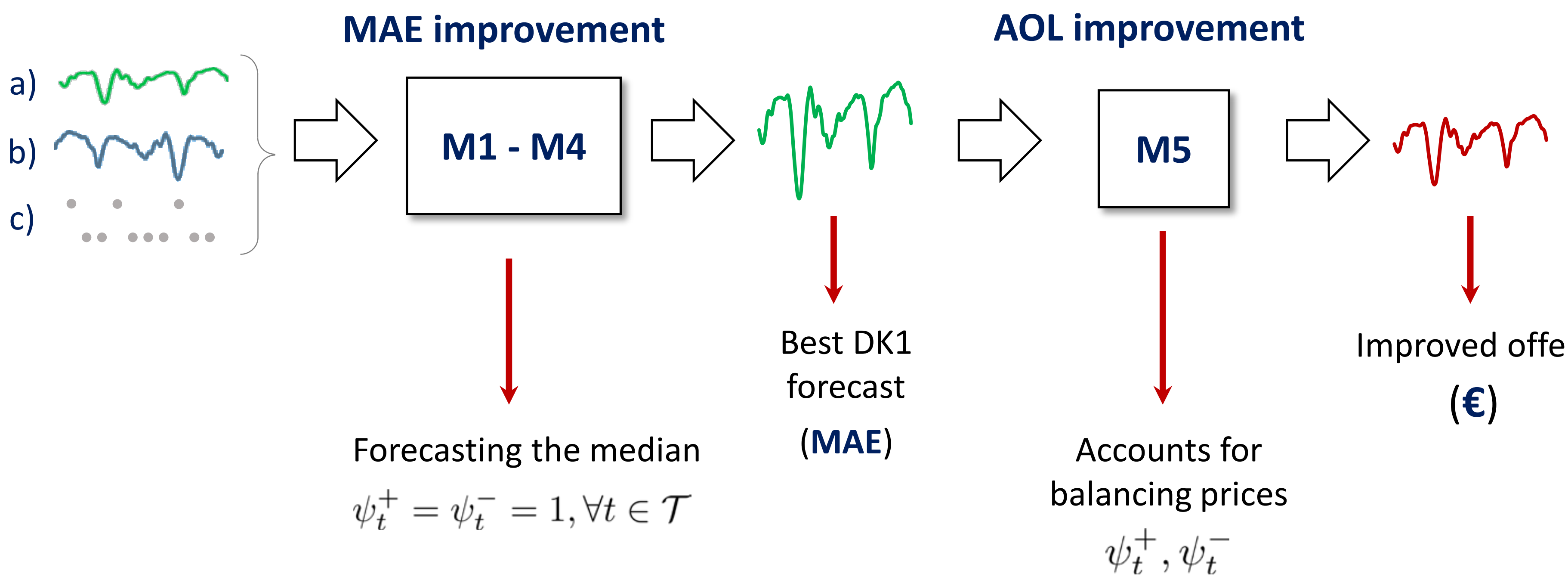
Case Study Data



- Data from Jan. 2015 to April 2019
- Prices: Energinet.dk
- Energy Forecasts: ENTSO-e T. P.

Objective: Improve the DK1-onshore wind power forecast of the Danish TSO for **forecasting** and **trading** leveraging contextual information (neighbouring forecast).

Case Study Models (I)



a) Energinet.dk's DK1-onshore wind power forecast
b) Forecasts issued by neighboring TSOs
c) Categorical info

Case Study Models (II)

no.	DK1		Extra DK1				Surrounding bidding areas						
	DK1	DK1	DK1	DK1	DK1	C.F.	DK2	NO2	NO2	SE3	SE4	DAL	DAL
(Benchmark) M0	•												
M1	•	•											
M2	•	•	•	•	•	•							
M3	•	•					•	•	•	•	•	•	•
M4	•	•	•	•	•	•	•	•	•	•	•	•	•

- wind p.p. on-shore day-ahead
- wind p.p. off-shore day-ahead
- Solar p.p. day-ahead
- Generation forecast
- Total Load forecast
- Categorical features

p.p. : power production

Categorical features
- Month of the year
- Day of the month
- Day of the week
- Hour of the day

	Day of the week						
	x_{d1}	x_{d2}	x_{d3}	x_{d4}	x_{d5}	x_{d6}	x_{d7}
Monday	**1**	0	0	0	0	0	0
Tuesday	0	**1**	0	0	0	0	0

Numerical Results

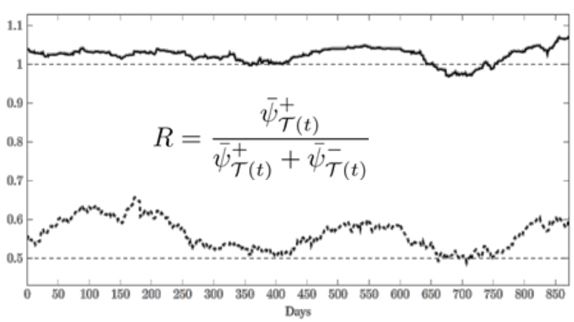
a) Forecasting:

Metric	M1	M2	M3	M4
MAE	7.03%	7.03%	**8.55%**	8.53%
RMSE	6.04%	6.22%	7.33%	7.46%

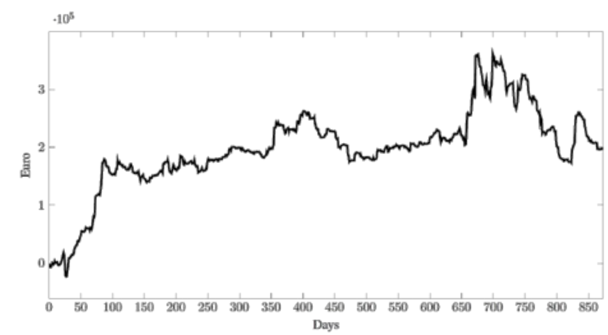
b) Trading:

2.26% AOL improvement

R — q (M5)



Cumulative AOL M5



Concluding remarks

- ✓ Computationally inexpensive easy to train model.
- ✓ Leverage extra contextual information.
- ✓ Tested on a realistic case study.
- ✓ Improving TSO energy forecast (8.55%) and bidding (2.26%).

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M. A. Muñoz, J. M. Morales, and S. Pineda, "Feature-driven Improvement of Renewable Energy Forecasting and Trading", *IEEE Transactions on Power Systems*, vol. 35, no. 5, pp. 3753 - 3763, February 2020.