A Mathematical Optimization Approach to Enhanced Renewable Energy Forecasting and Trading

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Big Data in Power Sector 2018: The En
Data Analytics, Digital Processing, Co:
Growing Competition, Mapping Futur

Tue Jun 26, 2018 - 09:30am UTC

The convergence of digital innovations with advances in energy technologies, has begun to impact the energy & power industry. The report on "Big Data in Power Sector Market" brief about future infrastructure investment and market behavior during 2018 to 2023.

Dallas, United States – June 26, 2018 –

The imbalance in electricity demand and supply is driving the demand
data. Big data has helped utility companies to track consumption patte
shift the supply in both space and time, hence, resulting in efficiently u
investment in big data and artificial intelligence grew ten-fold. Increas
various government has increased the volume of data, and hence, dem
power sector.

DEEP DIVE

The biggest numbers game in the power sector: Data analytics and the utility community of the future

Software and data are transforming the utility industry and connecting energy users.

What are Digital Energy Grid Analytics?

Predictive and prescriptive insights to transform your operations

GE's Digital Energy application portfolio combines GE's power domain expertise with artificial intelligence (AI) and machine learning (ML) to deliver predictive and prescriptive insights. These applications leverage our industry-leading analytics library and wrap around your existing infrastructure for fast time-to-value.

READ THE BLOG

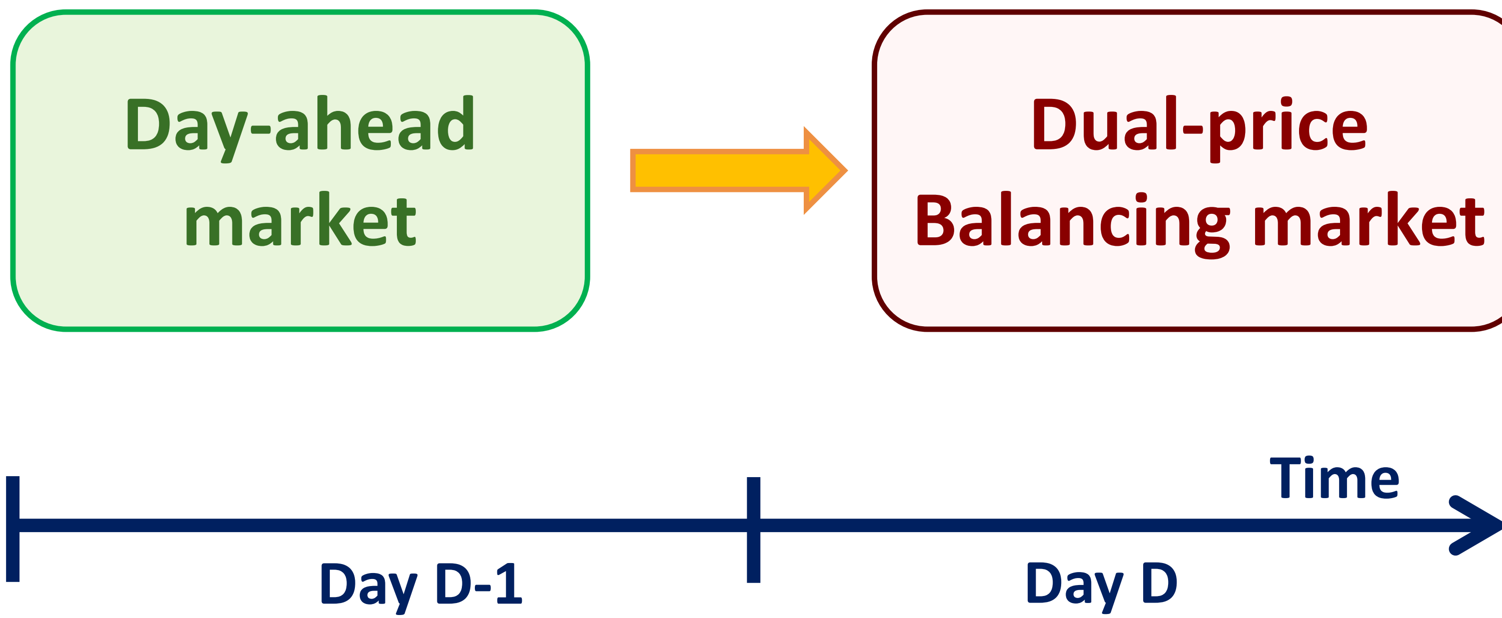
Aim

- A mathematical optimization approach to improving a forecast of renewable energy production:
  - Tailored to the specific use of the forecast.
    - a) Minimization of forecast error (classical use)
    - b) Market bidding
  - Able to leverage extra information on potentially explanatory phenomena.
  - Simple, but effective and computationally efficient.

Market Framework

(Spot Electricity Market)

Those who deviate always lose!



Computing the optimal day-ahead offer

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

where $(x)^+ := \max(x, 0)$

Newsvendor problem

Computing the optimal day-ahead offer

Renewable power capacity

Day-ahead offer

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where $(x)^+ := \max(x, 0)$

Renewable energy production (uncertain!)

Marginal opportunity costs for under and overproduction (uncertain!)

Newsvendor problem

Computing the optimal day-ahead offer

Renewable power capacity

Day-ahead offer

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

Renewable energy production (uncertain!)

Means

Analytical solution

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

Quantile function of E

Remark: If we "artificially" set $\bar{\psi}^+ = \bar{\psi}^- = 1$ then E^{D*} is the *median* of E

Computing the optimal day-ahead offer

Renewable power capacity

Day-ahead offer

$$\min_{E^D \in [0,\overline{E}]} \quad \mathbb{E}\left[\psi^-(E^D - E)^+ + \psi^+(E - E^D)^+\right]$$

Renewable energy production (uncertain!)

Means (unknown!)

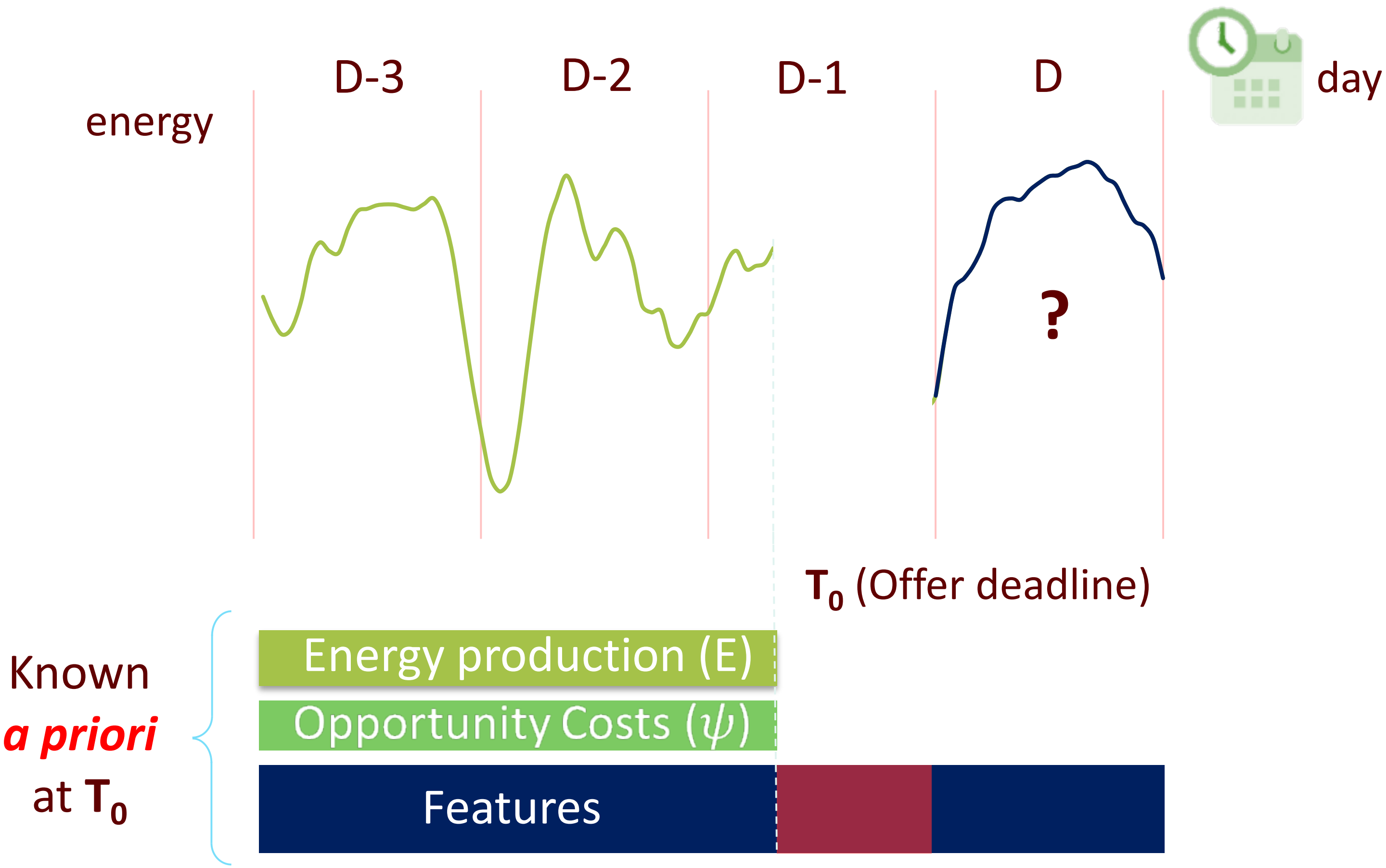
Analytical solution

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

Estimates are required!

Quantile function of E (unknown!)

Side information



Exploiting side information

Proposal: exploit the features *within* the optimization problem. To this end,

1. **Linear decision rule** on the features:

Day-ahead offer

Feature *j*

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

2. **Training on data samples** of both prices and production (SAA)

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

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

LP!

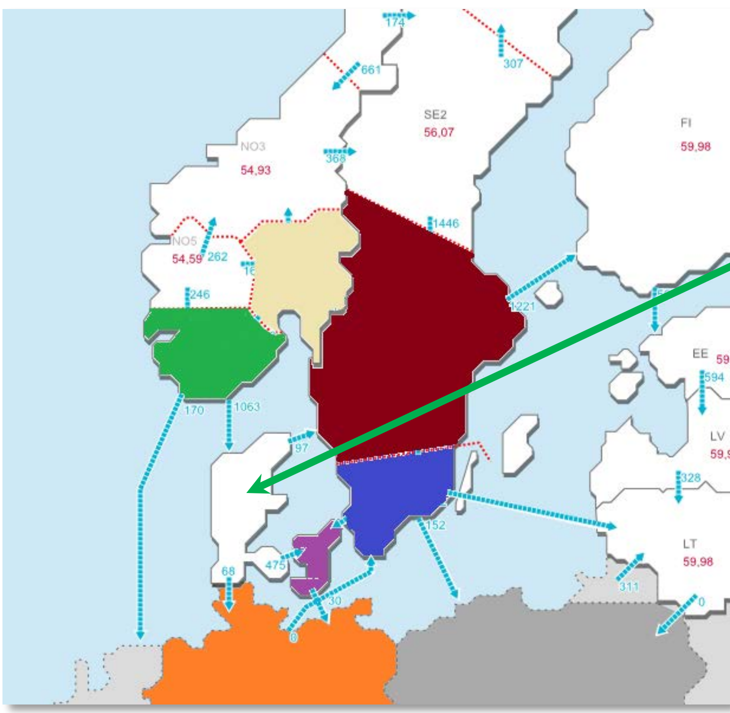
Training dataset

(*) G. Ban and C. Rudin, "The Big Data Newsvendor: Practical Insights from Machine Learning." Operations Research, 2019.

Numerical experiment

(Data)

- Data from 01/08/2015 to 04/22/2019, available in Energinet.dk’s website (prices) and the ENTSO-e Transparency Platform (forecasts)



DK1

Objective: Improve the DK1-onshore wind power forecast of the Danish TSO in two different ways.

Numerical experiment

(Performance metrics)

1. Better wind power prediction (quality improvement)

$$\psi_t^+ = \psi_t^- = 1, \forall t \in \mathcal{T}$$

Test dataset

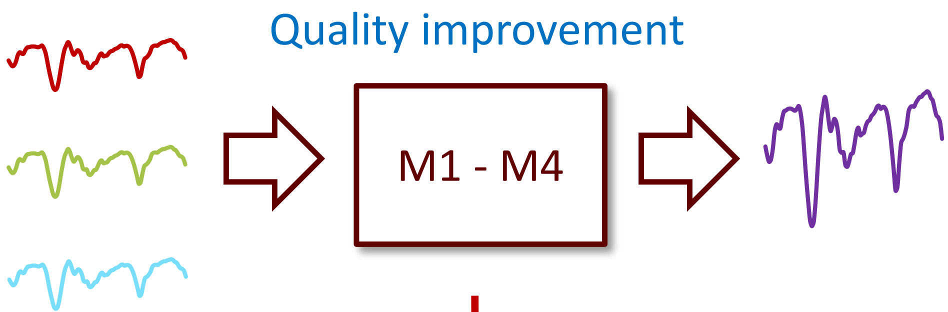
$$\text{MAE} := \frac{1}{|\widetilde{\mathcal{T}}|} \sum_{t \in \widetilde{\mathcal{T}}} |E_t - E_t^D|; \qquad \text{RMSE} := \frac{1}{|\widetilde{\mathcal{T}}|} \sqrt{\sum_{t \in \widetilde{\mathcal{T}}} (E_t - E_t^D)^2}$$

2. Better day-ahead offer (value improvement)

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

Average opportunity loss

Numerical experiment
(Models)



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

$$\psi_t^+ = \psi_t^- = 1, \forall t \in \mathcal{T}$$

Numerical experiment

(Models)

Benchmark!

no.	DK1		Extra DK1				Surrounding bidding areas						
	DK1	DK1	DK1	DK1	DK1	C.F.	DK2	NO2	NO2	SE3	SE4	DAL	DAL
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

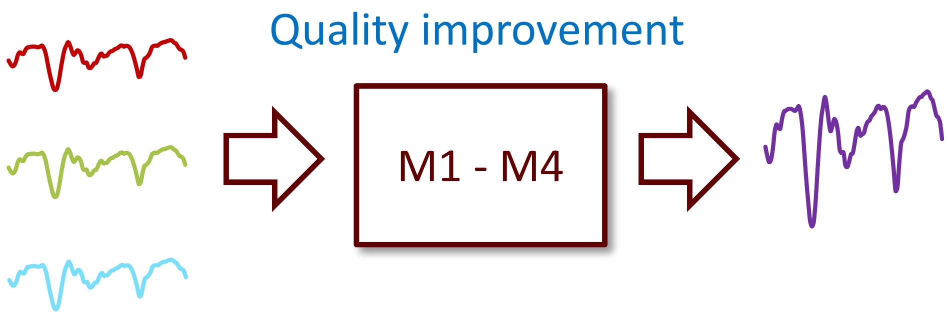
p.p. : power production

Categorical features

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

Numerical experiment

(Models)



Example: Model **M1**

$$\min_{q_0, q_1, q_2} \frac{1}{|\mathcal{T}|} \sum_{t \in \mathcal{T}} 1 \cdot \left(E_t^D - E_t\right)^+ + 1 \cdot \left(E_t - E_t^D\right)^+$$

$$\text{s. t.} \quad E_t^D = q_0 + q_1 \cdot DK1_t^{on} + q_2 \cdot DK1_t^{off}, \ \ \forall t \in \mathcal{T}$$

$$0 \leq E_t^D \leq \overline{E}, \ \ \forall t \in \mathcal{T}$$

Numerical experiment

(Results: Improvement in wind power forecasting)

Test set: 02/04/2016 – 04/22/2019 (1174 days)

%-reduction in MAE/RMSE with respect to M0

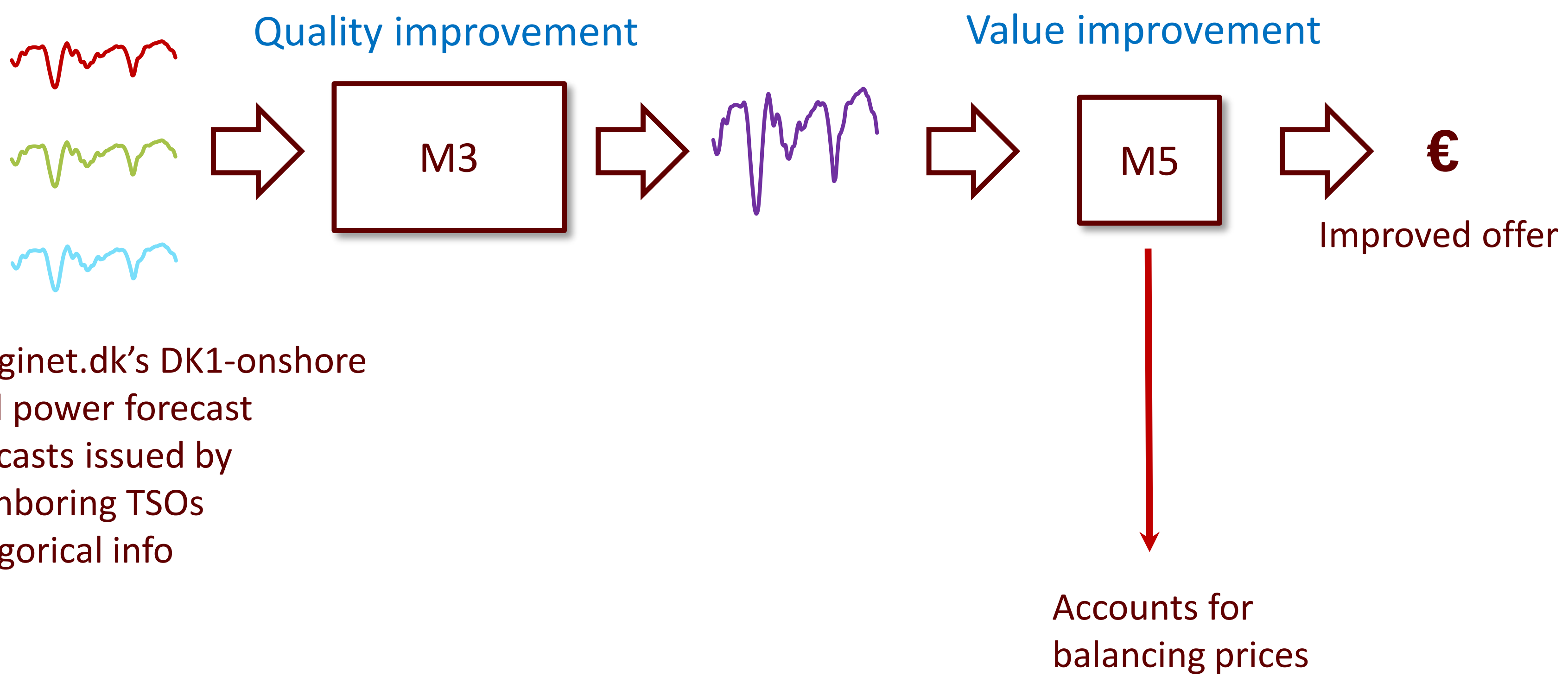
Metric	M1	M2	M3	M4
MAE	7.03%	7.03%	**8.55%**	8.53%
RMSE	6.04%	6.22%	7.33%	7.46%

Most of the quality gain achieved by combining on- and offshore DK1 wind power forecasts (M1)

Good performance, and simpler than M4

Numerical experiment

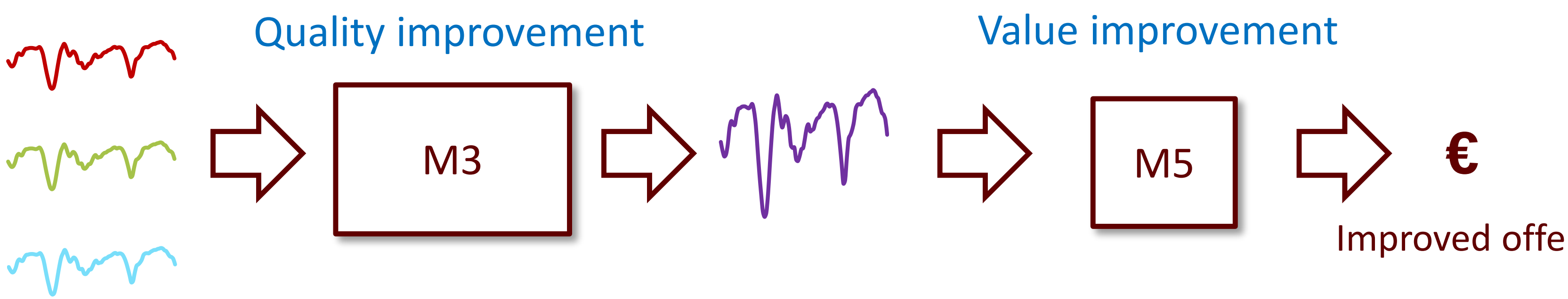
(Models)



- Energinet.dk’s DK1-onshore wind power forecast
- Forecasts issued by neighboring TSOs
- Categorical info

Numerical experiment

(Models)



Example: Model **M5**

$$\min_{q} \frac{1}{|\mathcal{T}|} \sum_{t \in \mathcal{T}} \psi_t^- \left(E_t^D - E_t\right)^+ + \psi_t^+ \left(E_t - E_t^D\right)^+$$

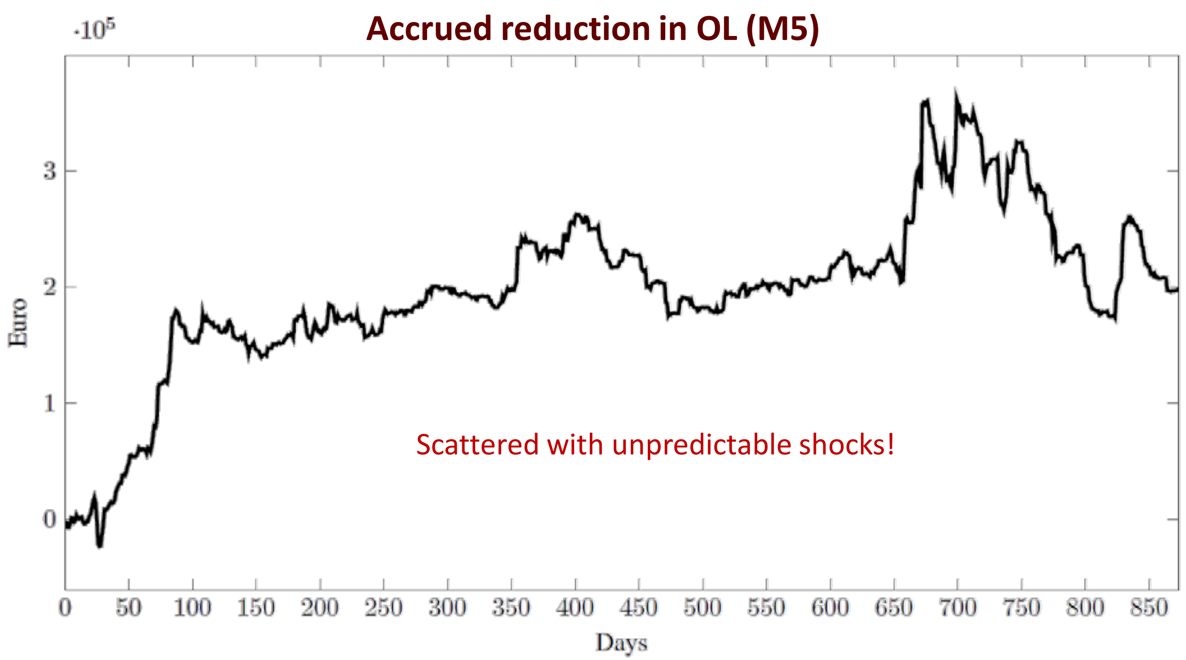
$$\text{s. t. } E_t^D = q \, \hat{w}_t, \quad \forall t \in \mathcal{T}$$

M3-forecast

Numerical experiment

(Results: Improvement in wind power trading)

Test set: 11/30/2016 – 04/22/2019 (874 days)



2.26% AOL improvement with respect to the M0-bid

Concluding remarks

- ✓ Data-driven optimization model that leverages extra available information to produce better renewable energy forecasts and bids.
- ✓ Tested on a realistic case study with ENTSO-e data
- ✓ Computationally inexpensive
- ✓ Improve TSO forecast (8.55%) and the producer's profit (2.26%)

Thank you for your attention!

Questions?

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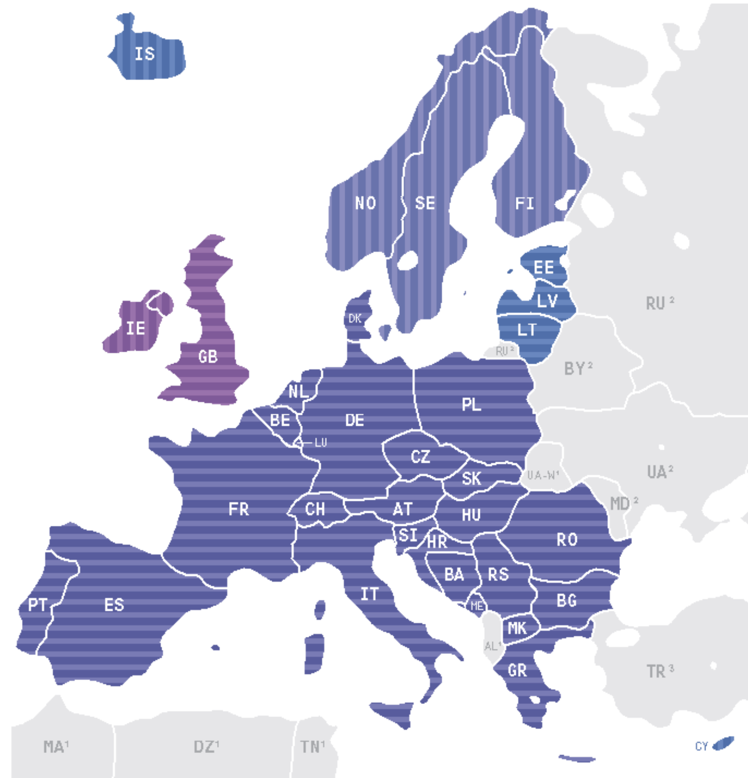
Preprint "Feature-driven Improvement of Renewable Energy Forecasting and Trading" available in arXiv:1907.07580

https://arxiv.org/pdf/1907.07580.pdf

Outline

1. Motivation and aim
2. Market framework
3. Proposed mathematical approach
4. Numerical experiments
5. Concluding remarks

ENTSO-E Transparency Platform



Continental European synchronous area
British synchronous area
Baltic synchronous area
Irish synchronous area
Nordic synchronous area
Isolated systems of Cyprus and Iceland

[1] synchronous with the continental European system
[2] synchronous with the Baltic system
[3] from September 2010 in trial synchronous operation with the continental European system

entsoe Transparency Platform

Central collection and publication of electricity generation, transportation and consumption data and information for the pan-European market.

Login

Load | Generation | Transmission | Balancing | Outages | Congestion Management | System Operations | Data Pre-5.1.15

Generation Forecasts for Wind and Solar

Day-ahead Generation Forecasts for Wind and Solar [14.1.D]
Intraday Generation Forecasts for Wind and Solar [14.1.D]
Current Generation Forecasts for Wind and Solar [14.1.D]

Control area | Bidding zone | Country

Day and Time Range

06.10.2019

Area

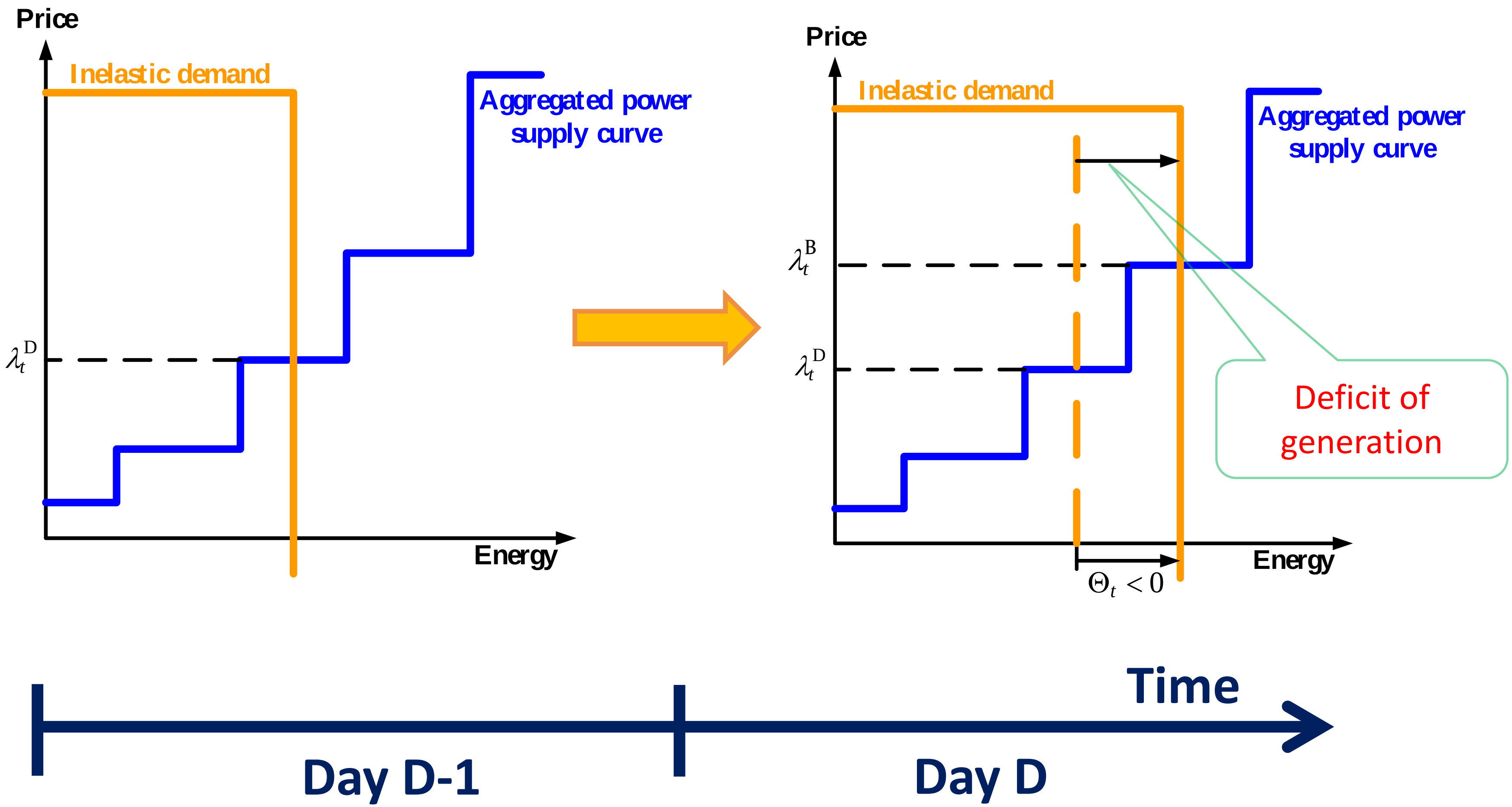
- Poland (PL)
- Portugal (PT)
- Romania (RO)
- Russia (RU)
- Serbia (RS)
- Slovakia (SK)
- Slovenia (SI)
- Spain (ES)
- Sweden (SE)
  - BZN|SE1
  - BZN|SE2
  - BZN|SE3
  - BZN|SE4
- Switzerland (CH)

Show fullscreen | Export Data

CET (UTC+1) / CEST (UTC+2)

MTU	BZN|SE4					
	Generation Forecast					
	Wind					
	Onshore [MW]			Offshore [MW]		
	Day ahead	Intraday	Current	Day ahead	Intraday	Current
00:00 - 01:00	214	227	227	n/e	n/e	n/e
01:00 - 02:00	196	213	213	n/e	n/e	n/e
02:00 - 03:00	184	212	212	n/e	n/e	n/e
03:00 - 04:00	179	206	206	n/e	n/e	n/e
04:00 - 05:00	178	199	199	n/e	n/e	n/e
05:00 - 06:00	186	205	205	n/e	n/e	n/e
06:00 - 07:00	195	210	210	n/e	n/e	n/e
07:00 - 08:00	198	205	205	n/e	n/e	n/e
08:00 - 09:00	175	177	183	n/e	n/e	n/e

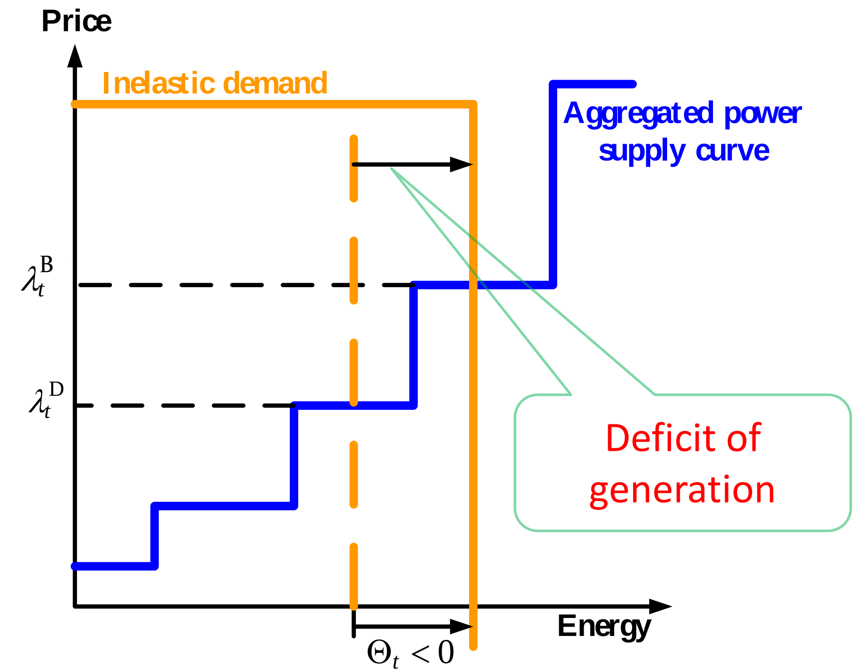
Dual-price balancing settlement



Dual-price balancing settlement

*Over*production is *paid* at λ_t^D

*Under*production is *charged* at λ_t^B



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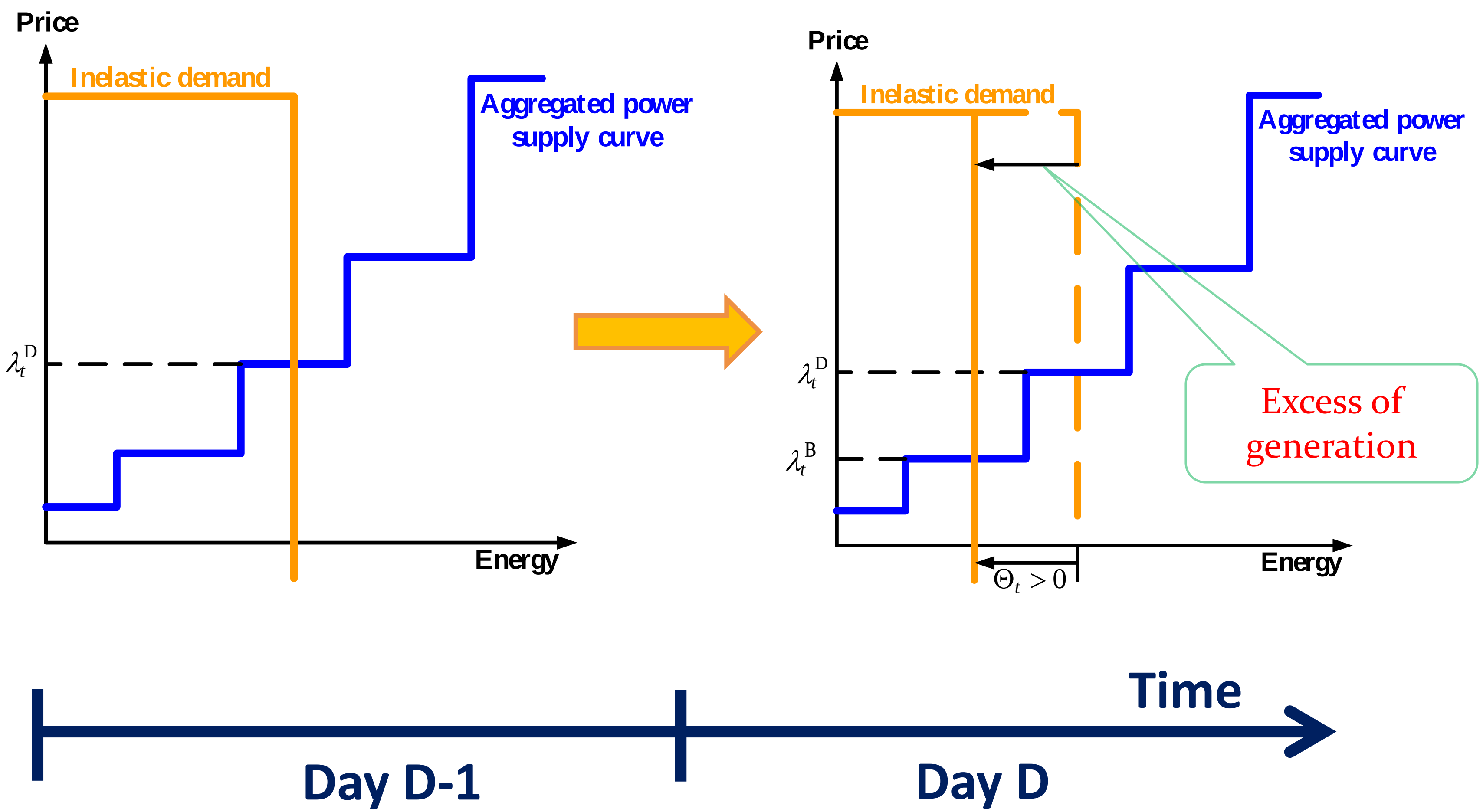

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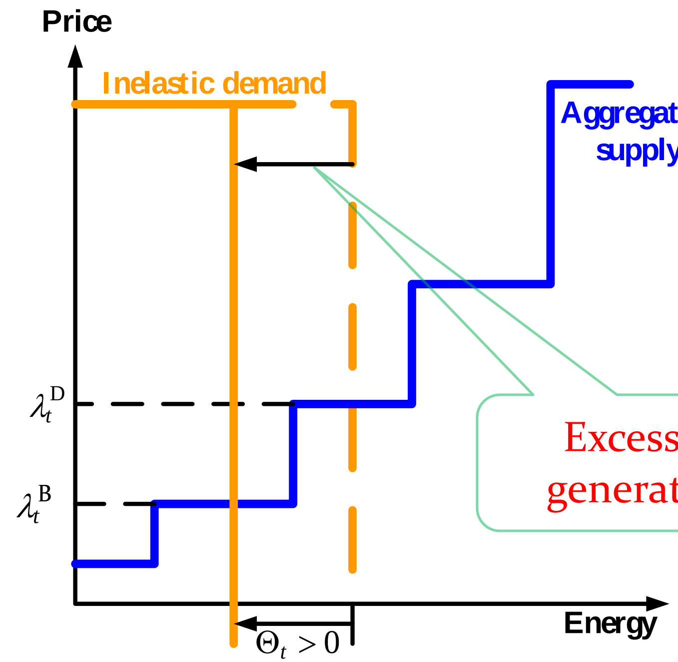
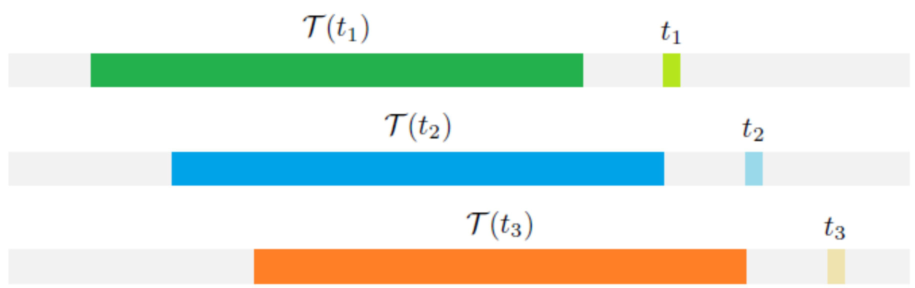
Those who deviate always lose!



Numerical experiment

(Model training)



Rolling window

MAE %-reduction (1st step)

Months	M1	M2	M3	M4
1	11.67	7.4	4.57	-2.08
2	12.3	10.97	10.18	7.98
3	12.78	11.4	12.62	10.87
4	12.51	11.55	12.75	11.52
5	12.46	11.1	13.05	12.01
6	**12.67**	**11.75**	**13.05**	**12.69**
7	12.46	11.86	13.03	12.37

AOL %-reduction (2nd step)

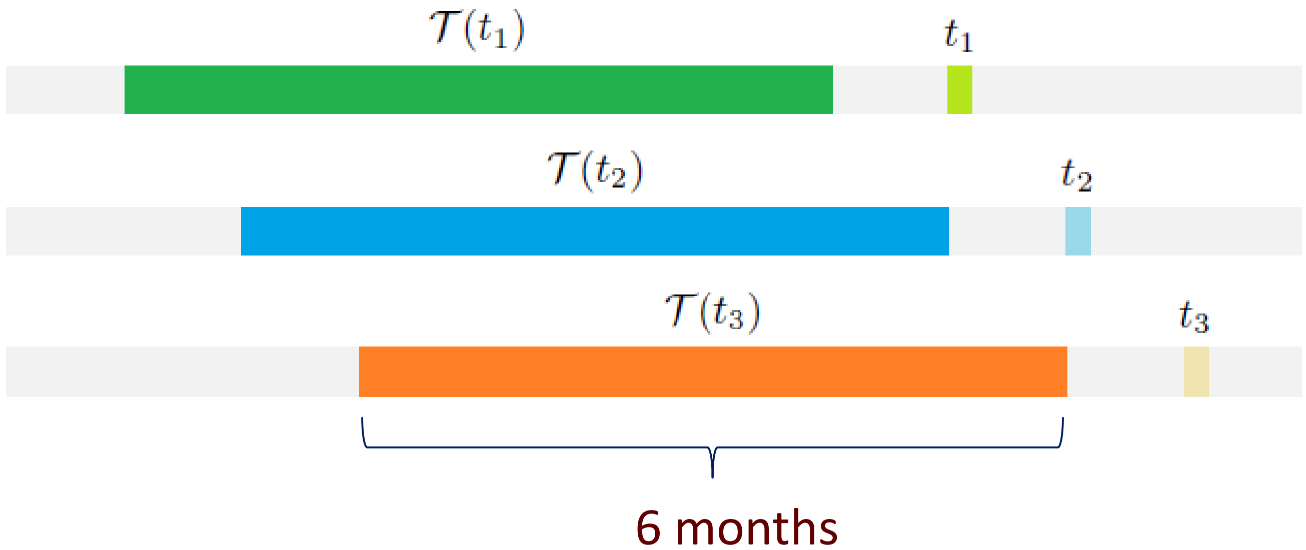
Months	1	2	3	4	5	**6**	7	8	9	10
M5	2.51	7.45	7.37	7.09	6.75	**8.21**	6.75	6.31	5.97	5.64

The value of past data

Numerical experiment

(Model evaluation)

Rolling window



Exploiting side information

Proposal: exploit the features *within* the optimization problem. To this end,

1. **Linear decision rule** on the features:

Day-ahead offer

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

Production data samples

LP!

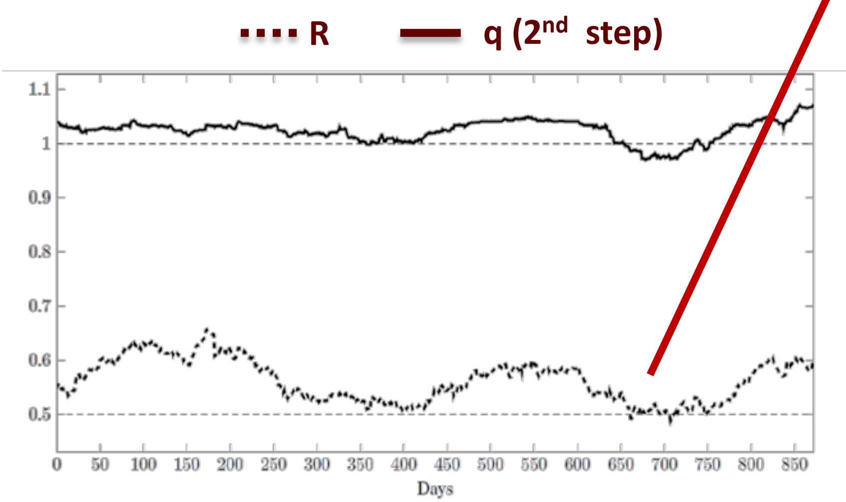
Price data samples

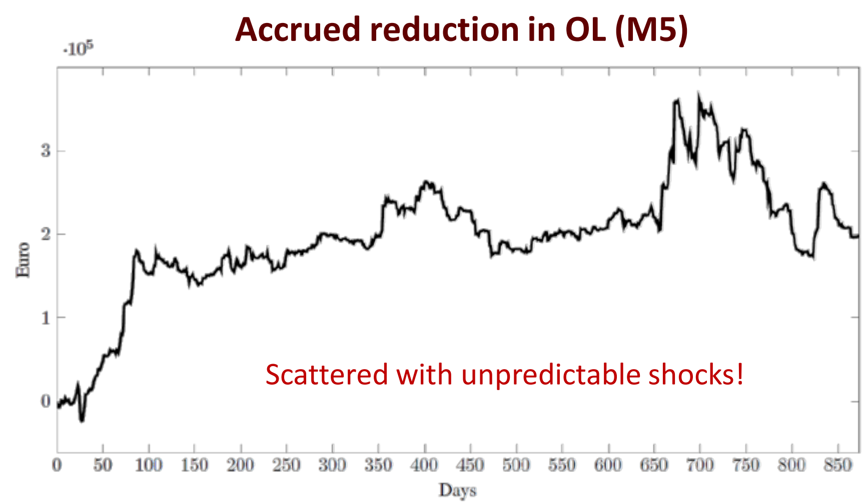
Numerical experiment

(Results: Improvement in wind power trading)

Test set: 11/30/2016 – 04/22/2019
(874 days)

On average, overproduction is more penalized in DK1





$$R = \frac{\bar{\psi}^{+}_{\mathcal{T}(t)}}{\bar{\psi}^{+}_{\mathcal{T}(t)} + \bar{\psi}^{-}_{\mathcal{T}(t)}}$$

(critical fractile averaged over the training set)

2.26% AOL improvement with respect to the M0-bid

Numerical experiment

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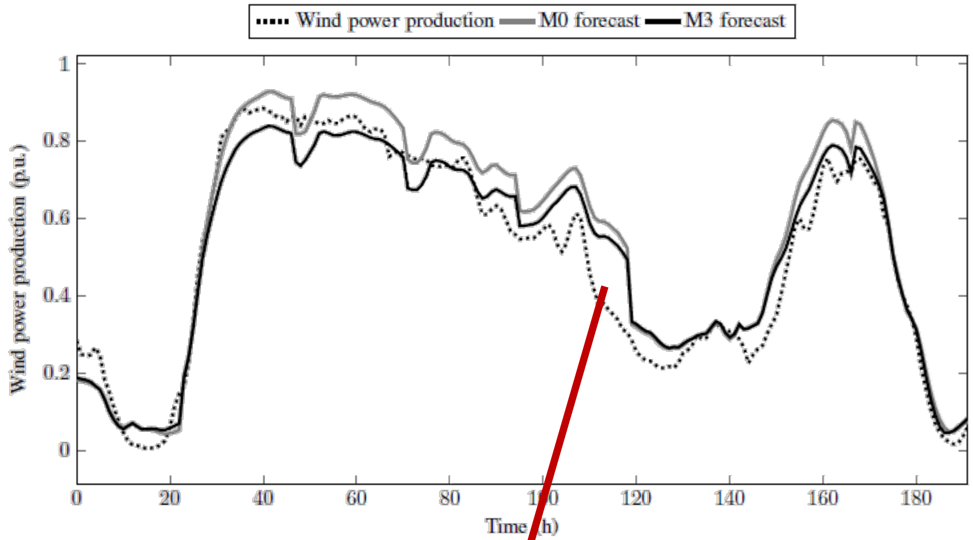

We use M3 to feed M5

M3 follows the actual production closer than M0

Most of the quality gain achieved by combining on- and offshore DK1 wind power forecasts (M1)