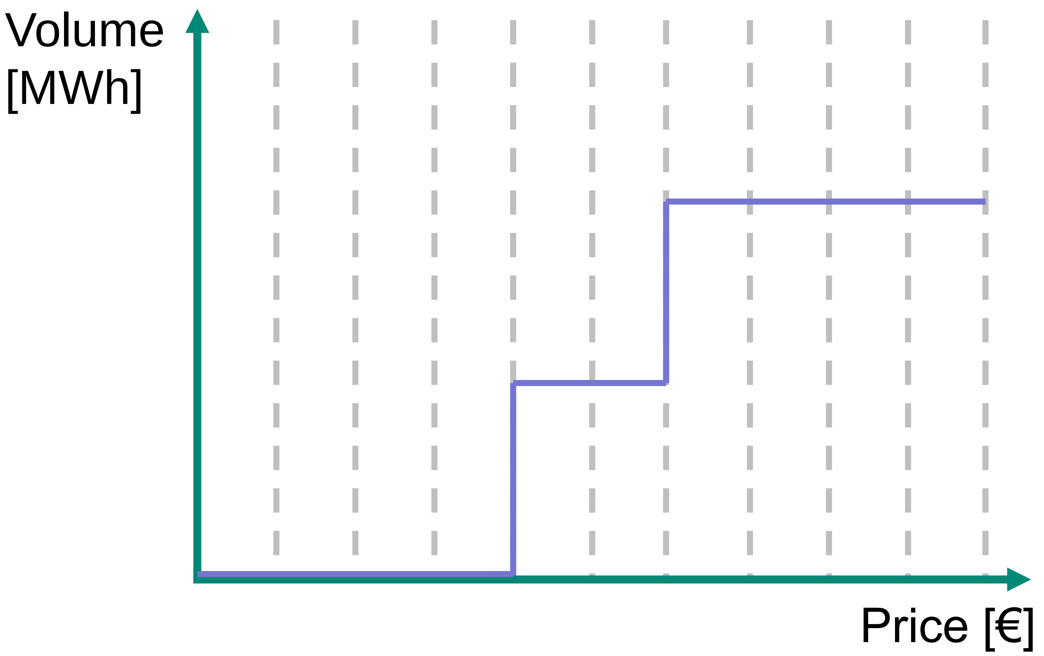
Evaluation of Electricity Price Forecasts with Multi-Stage Stochastic Programs

Mario Beykirch, Tim Janke, Florian Steinke



Motivation

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- Can we give an energy price forecast a monetary value?
- What is the benefit of a statistical forecast in comparison to a naive forecast?
- What is the benefit of generating accurately correlated scenarios to non-correlated scenarios?

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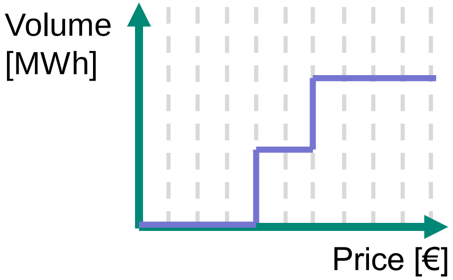

Use case

Optimal bidding curves for a gas power plant which participates in the day-ahead and the secondary control power market.

[a]

Agenda

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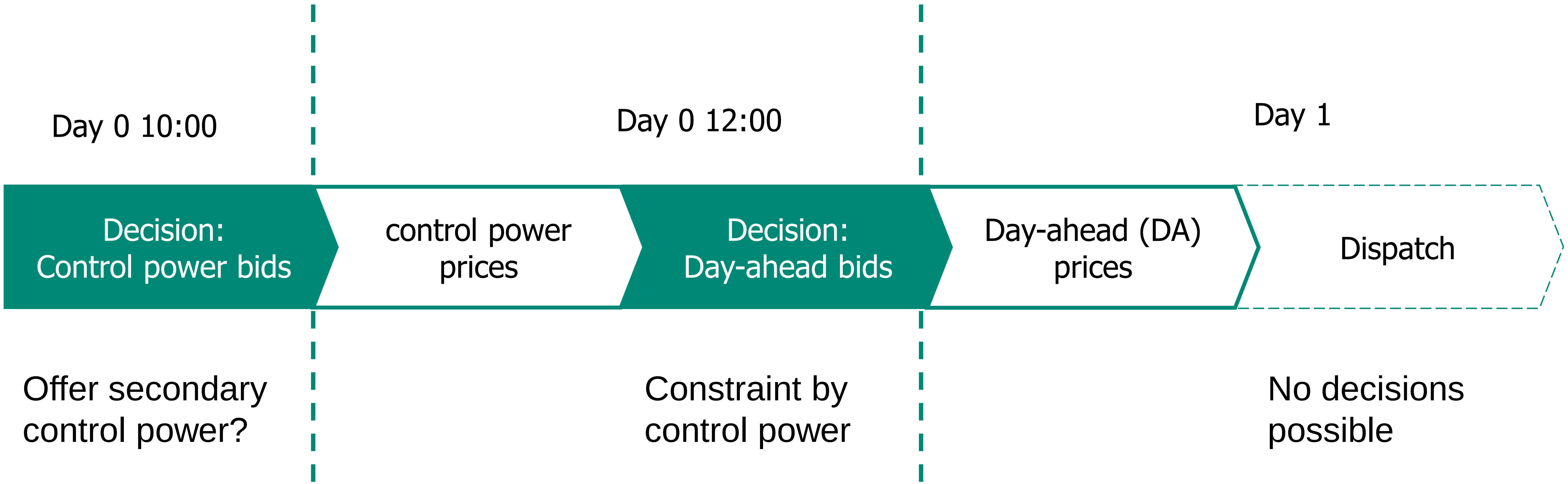
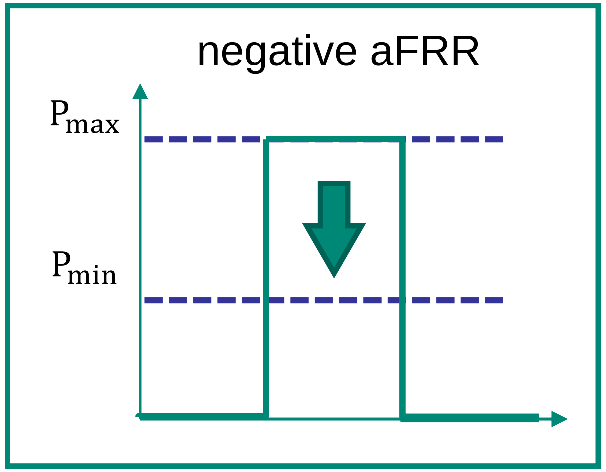
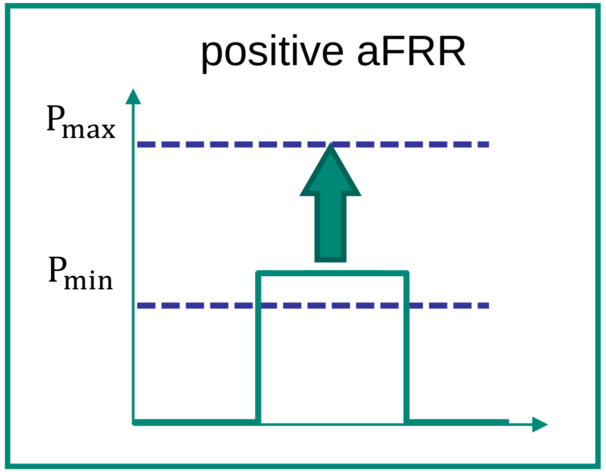
Problem: Optimal bidding in German day-ahead and secondary reserve power market



Secondary control power (aFRR) in Germany





- Power price π_t^{power} and energy price π_t^{energy}
- Awarding of aFRR by mixed price (Mischpreis)

$$\pi_t^{mix} = \pi_t^{power} + w\,\pi_t^{energy}$$

- 4h blocks
- Non-symmetric

Power plant bidding model

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CCGT - model

- Power range between P_{min} and P_{max}
- Warm & cold start costs
- Fuel independent running costs
- Gas and CO2 prices
- Power gradient very high
- Bidding curves for aFRR (pay-as-bid) and DA (uniform pricing)

Implementation as stochastic a MILP

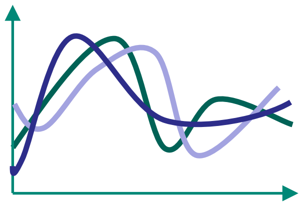
$P_{max} = 200\ MW$
$P_{min} = 90\ MW$
$\eta_{max} = 0.577$
$P_{max}^{aFRR} = 110\ MW$
$c_{coldstart} = 86.5\ P_{max}$
$c_{warmstart} = 37.0\ P_{max}$
$T_w = 11$
$\eta_{min} = 0.51$
$c_{run} = 1700\ €/h$

Plant parameters based on:

M. Beykirch et al., Bayesian Inference with MILP Dispatch Models for the Probabilistic Prediction of Power Plant Dispatch, EEM Conference (2019)

3-stage stochastic program

Price forecasts as 500 scenarios



$$\max_{\boldsymbol{x} \in \boldsymbol{X}} \boldsymbol{c}^T \boldsymbol{x} + E_{\boldsymbol{S}}[Q_T(\boldsymbol{x}, \boldsymbol{S})]$$

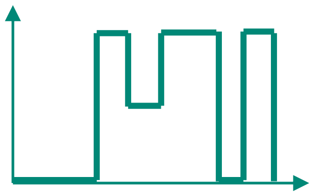
3-stage stochastic MILP

1. stage: aFRR & DA bidding curves based on scenarios

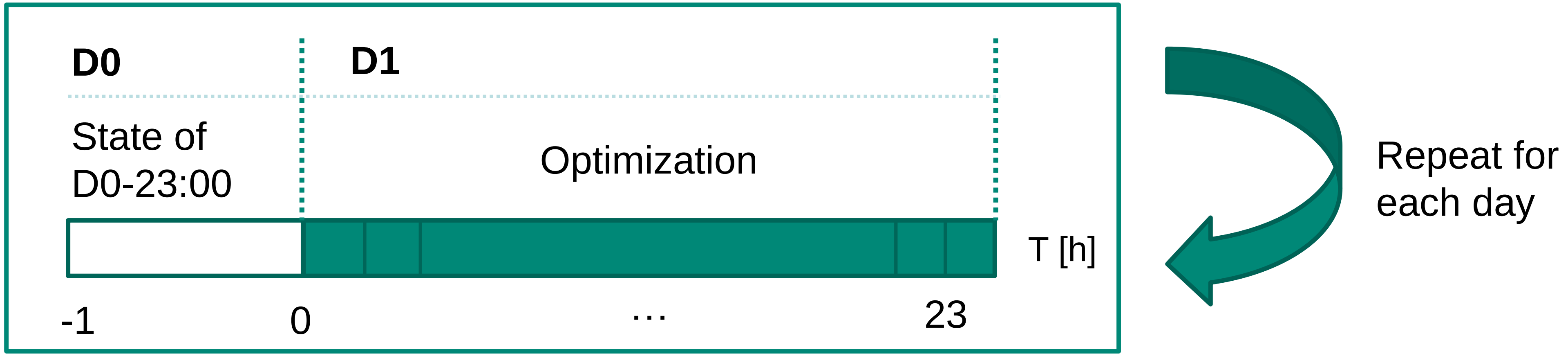
2. stage: aFRR price realizes. DA bidding curve based on realized aFRR prices and DA scenarios

3. stage: Market Clearing for DA

aFRR and DA-dispatch



Coupling between days



- Each day optimized separately
- Each optimization from D0-23:00 to D1-23:00
- Power plant state of D0-23:00 fixed as result of last day

Agenda

Scenario sets

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Each scenario consists of DA and aFRR prices for each day

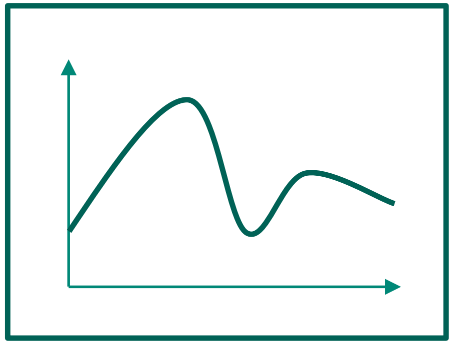
500 x

π_0^{DA}	π_1^{DA}	π_2^{DA}	π_3^{DA}	...	24 DA prices	...	π_{20}^{DA}	π_{21}^{DA}	π_{22}^{DA}	π_{23}^{DA}
$\pi_0^{aFRR,+}$				...	6 positive aFRR block prices	...	$\pi_5^{aFRR,+}$			
$\pi_0^{aFRR,-}$				...	6 negative aFRR block prices	...	$\pi_5^{aFRR,-}$			

Scenarios for evaluation

3 different scenario sets as input:

1. Naive day of week (DOTW) forecast with marginally sampled scenarios
2. Statistical point forecast with marginally sampled scenarios
3. Probabilistic forecasts with scenarios using Gaussian copula



$$\pi_t^{DA} = h(\pi_t^{DA}) + \epsilon \quad \text{with } \epsilon \sim N(0, \hat{\sigma}^{DA})$$

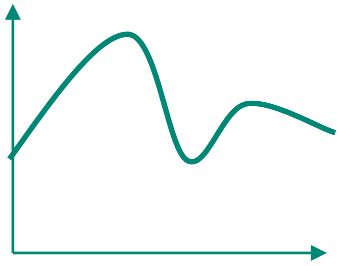
$$\text{with } h(\pi_t) = \begin{cases} \pi_{t-168} & \forall t \in T: d(t) \in \{6,7\} \\ \pi_{t-96} & \forall t \in T: d(t) \in \{1\} \\ \pi_{t-24} & else \end{cases}$$

$$\pi_t^{aFRR,-} = h\left(\pi_t^{aFRR,-}\right) + \epsilon^{aFRR,-} \quad \text{with } \epsilon^{aFRR,-} \sim N(0, \hat{\sigma}^{aFRR,-})$$

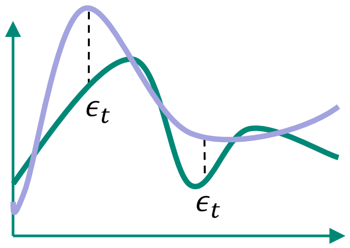
$$\pi_t^{aFRR,+} = h\left(\pi_t^{aFRR,+}\right) + \epsilon^{aFRR,+} \quad \text{with } \epsilon^{aFRR,+} \sim N(0, \hat{\sigma}^{aFRR,+})$$

Scenario generation with normal distributions

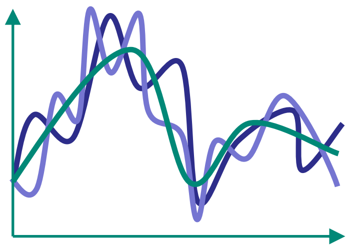
Point forecast



Get σ of residuals ϵ_t



Generate uncorrelated scenarios from normal distributions:
$\pi_{t,s} \sim N(\hat{\pi}_t, \sigma)$



Scenarios for evaluation

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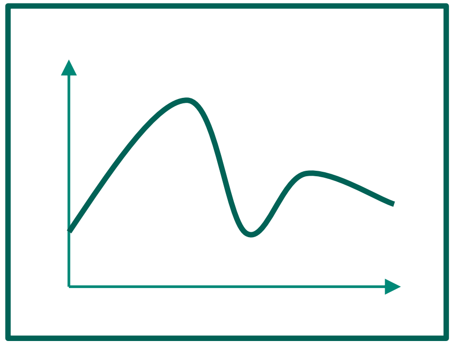


$$\pi_t^{DA} = w_0 + w_1 RL_t^1 + w_2 RL_t^2 + \cdots + w_5 RL_t^5 + w_6 \pi_t^{Gas} + w_7 \pi_t^{CO2} + w_8 RL_t \pi_t^{Gas} + w_9 RL_t \pi_t^{CO2} + \epsilon^{DA}$$

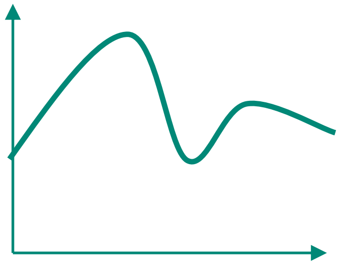
$$\boldsymbol{w}^* = argmin_w \left\{ \sum_t \lambda_t (\pi_t^{DA} - \hat{\pi}_t^{DA})^2 \right\} \quad \text{with } \lambda_t = \frac{1}{\Delta d(t)} \quad \text{with } \epsilon^{DA} \sim N(0, \hat{\sigma}^{DA})$$

$$\pi_t^{aFRR,-} = f(\hat{\pi}_t^{DA}) + \epsilon^{aFRR,-} \quad \text{with } \epsilon^{aFRR,-} \sim N(0, \hat{\sigma}^{aFRR,-})$$

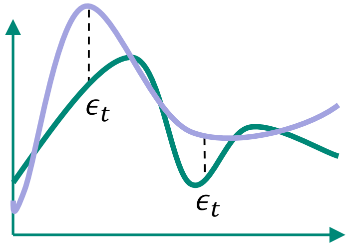
$$\pi_t^{aFRR,+} = f(\hat{\pi}_t^{DA}) + \epsilon^{aFRR,+} \quad \text{with } \epsilon^{aFRR,+} \sim N(0, \hat{\sigma}^{aFRR,+})$$

Scenario generation with normal distributions

Point forecast



Get σ of residuals ϵ_t



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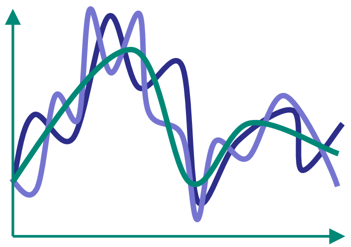

Scenarios for evaluation

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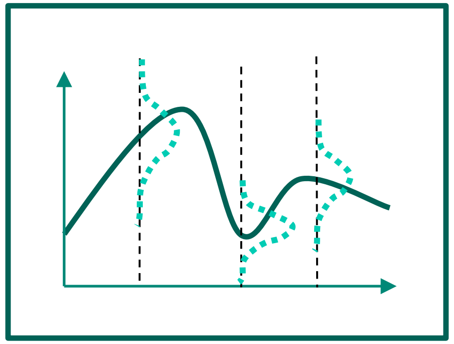


$$\hat{\pi}_t^{DA} = w_0 + w_1 RL_t^1 + w_2 RL_t^2 + \cdots + w_5 RL_t^5 + w_6 \pi_t^{Gas} + w_7 \pi_t^{CO2} + w_8 RL_t \pi_t^{Gas} + w_9 RL_t \pi_t^{CO2}$$

$$\boldsymbol{w}^* = argmin_w \left\{ \sum_t \lambda_t (\pi_t^{DA} - \hat{\pi}_t^{DA})^2 \right\}$$

with $\lambda_t = \frac{1}{\Delta d(t))}$

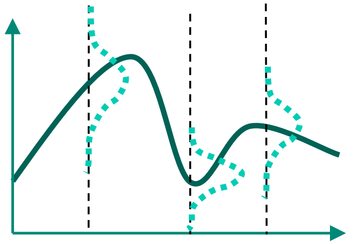
$$\hat{q}_t^{DA}(\tau) = f(\hat{\pi}_t^{DA}) \qquad \tau \in \{0.01, 0.02, \ldots, 0.99\}$$

$$\hat{q}_t^{aFRR,-}(\tau) = f(\hat{\pi}_t^{DA})$$

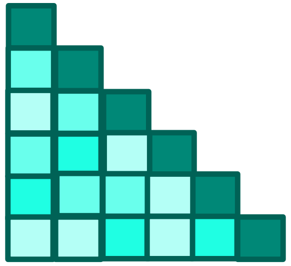
$$\hat{q}_t^{aFRR,+}(\tau) = f(\hat{\pi}_t^{DA})$$

Scenario generation with correlation structure

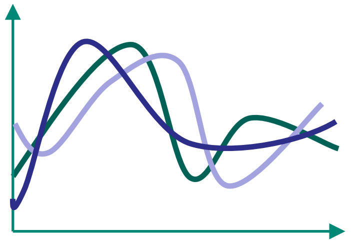
Probabilistic forecast for each product of the day



Estimate covariance matrix of residuals



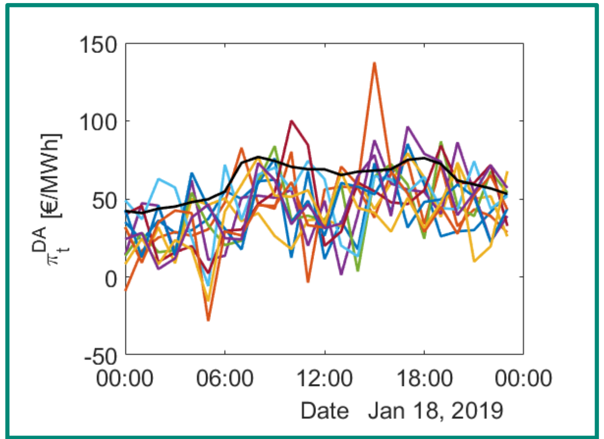
Use Gaussian copula to generate scenarios with appropriate correlation structure [1]

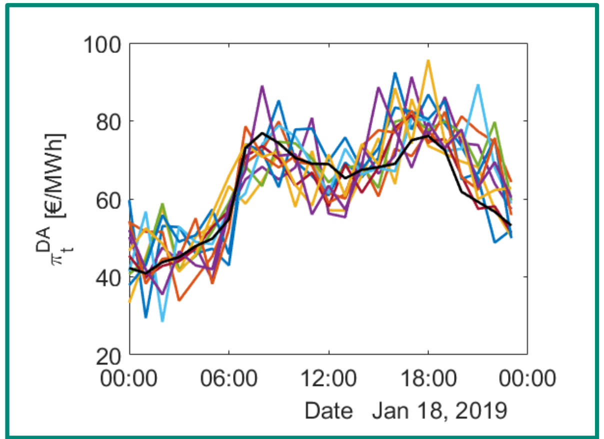


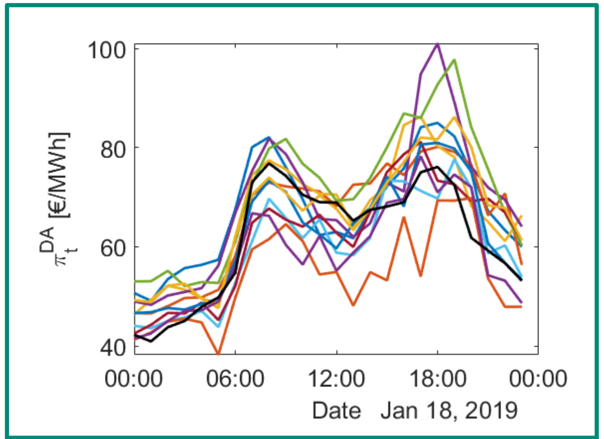
Forecast and scenario generation results

	1. Naive DOTW + marginal sampling	2. Point forecast + marginal sampling	3. Point forecast + copula scenarios

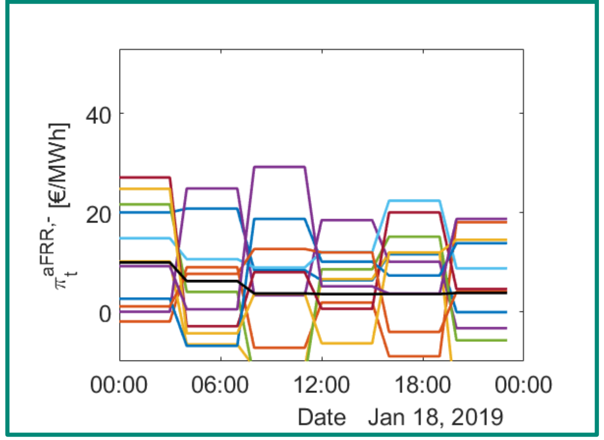
π_t^{DA}

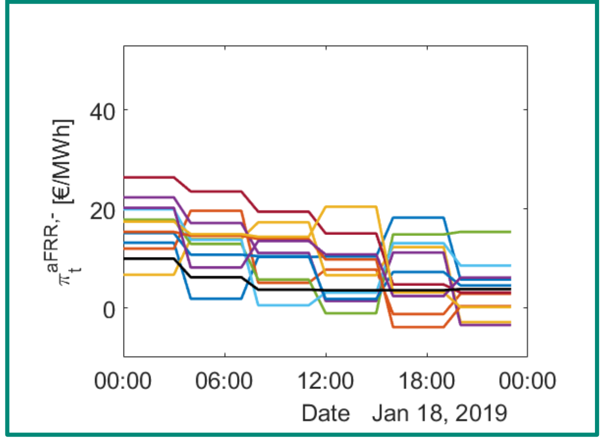


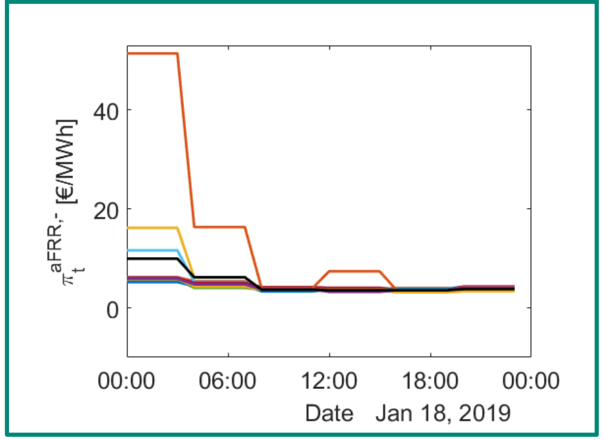




$\pi_t^{aFRR,-}$



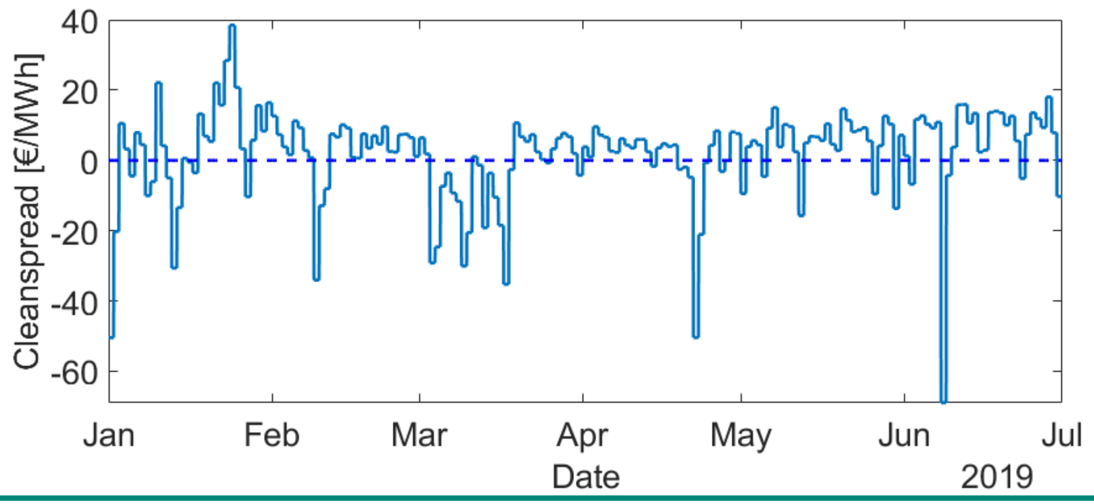




Agenda

Timeframe: 1st half of 2019

$$S_t^{clean} = \pi_t^{DA} - \frac{\pi_t^{gas} + 0.2\,\pi_t^{CO_2}}{\eta_{max}}$$



- Electricity & CO_2 prices comparatively high, gas prices low
- mixed price auctioning (Mischpreisverfahren) for secondary control power with high power prices

Very favorable conditions for CCGTs

Results of the 3-stage stochastic program

Scenarios	Revenue	
	Only DA	DA & aFRR
Perfect foresight	**773,603 €**	**1,278,955 €**
Naive + marginally sampled scenarios	- 258,804 €	- 612,710 €
Point forecast + marginally sampled scenarios	624,890 €	639,764 €
Probabilistic + copula scenarios	704,718 €	829,441 €

Conclusion

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Conclusion

- Participation on aFRR market offers 17 % more revenue than only on DA
- Forecast accuracy has a clear impact on revenue
- Scenarios with accurate correlation structure perform better

Thank you for your attention!
Questions?

Literature

[1] P. Pinson, H. Madsen, H. A. Nielsen, G. Papaefthymiou, and B. Klöckl, "From probabilistic forecasts to statistical scenarios of short-term wind power production," Wind Energ., vol. 12, no. 1, pp. 51–62, 2009.

Exemplary plant parameters

$P_{max} = 200\ MW$
$P_{min} = 90\ MW$
$\eta_{max} = 0.577$
$P_{max}^{aFRR} = 110\ MW$
$c_{coldstart} = 86.5 * P_{max}$
$c_{warmstart} = 37.0 * P_{max}$
$\eta_{min} = 0.51$
$c_{run} = 1700\ €/h$

Plant parameters from:
Bayesian Inference with MILP Dispatch Models for the Probabilistic Prediction of Power Plant Dispatch, EEM (2019)

Sources pictures

[a] https://de.wikipedia.org/wiki/GuD-Kraftwerk_Hamm-Uentrop#/media/File:Trianel_Kraftwerk_Hamm.jpg (zuletzt abgerufen 7.2.18)