

Dynamic Hedging of Futures Term Structure Risk for Renewable Power Producers

Prof. Dr. Nils Löhndorf

LCL

LUXEMBOURG CENTRE FOR
LOGISTICS AND SUPPLY
CHAIN MANAGEMENT



FACULTY OF LAW,
ECONOMICS
AND FINANCE

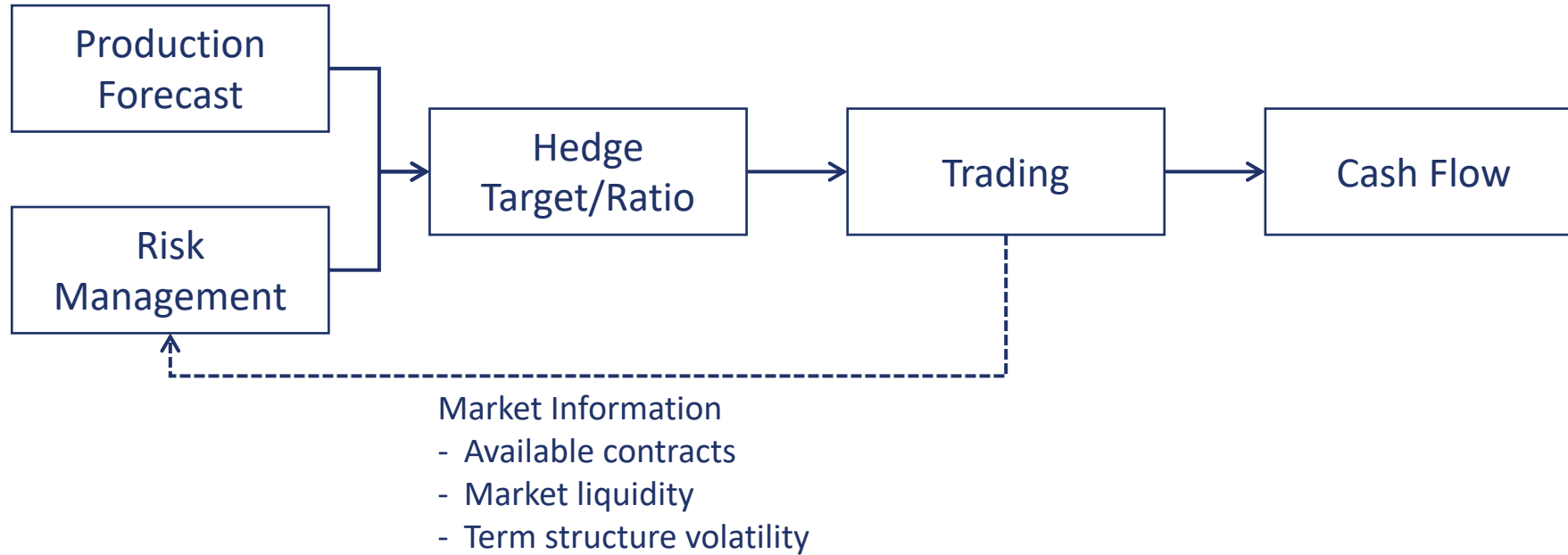
Motivation

- Large consumers / producers of energy commodities hedge energy prices using [energy derivatives](#)
- Contracts can be [over-the-counter](#) (OTC) or [exchange](#) traded
- Energy exchanges (EEX, TTF, Nasdaq) offer standardized products like [futures](#) and [options](#)
- Movements of the [term structure](#) as well as [production volumes](#) are uncertain

What is the problem?

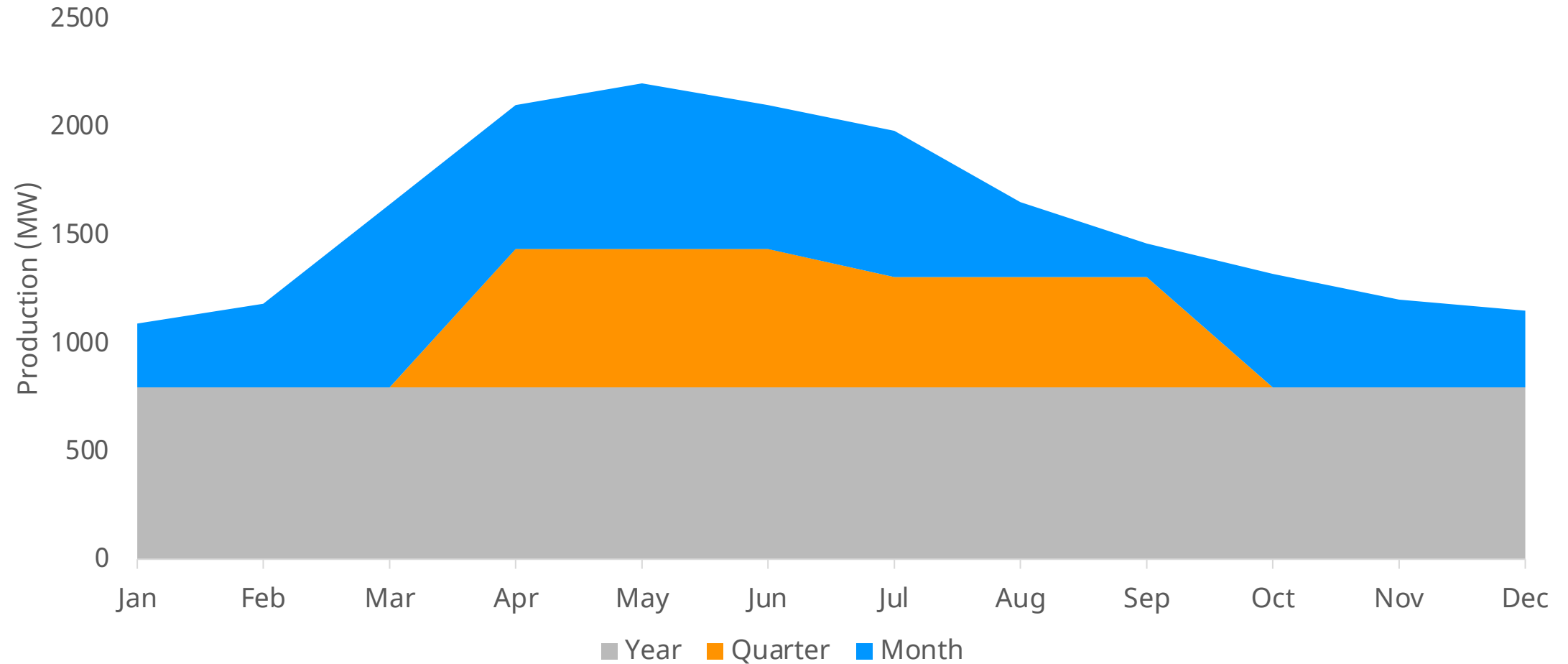
- **Futures contracts** are the most important hedging instruments
- Finding the **optimal mix, timing and volumes** is difficult
- Companies calibrate **hedge plans** using rules-of-thumb
- Energy traders **speculate** on the right moment when to buy or sell
- Renewable producers face the risk of **over-hedging**
- Model-driven approaches are lacking

The Hedging Decision Process



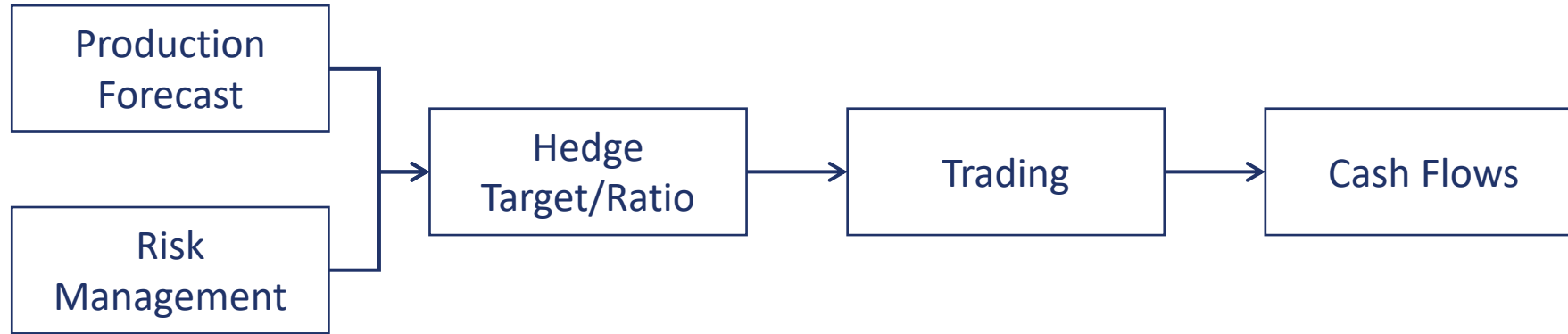
How does a hedge plan look like?

Example: Hydropower producer with 2500 MW capacity

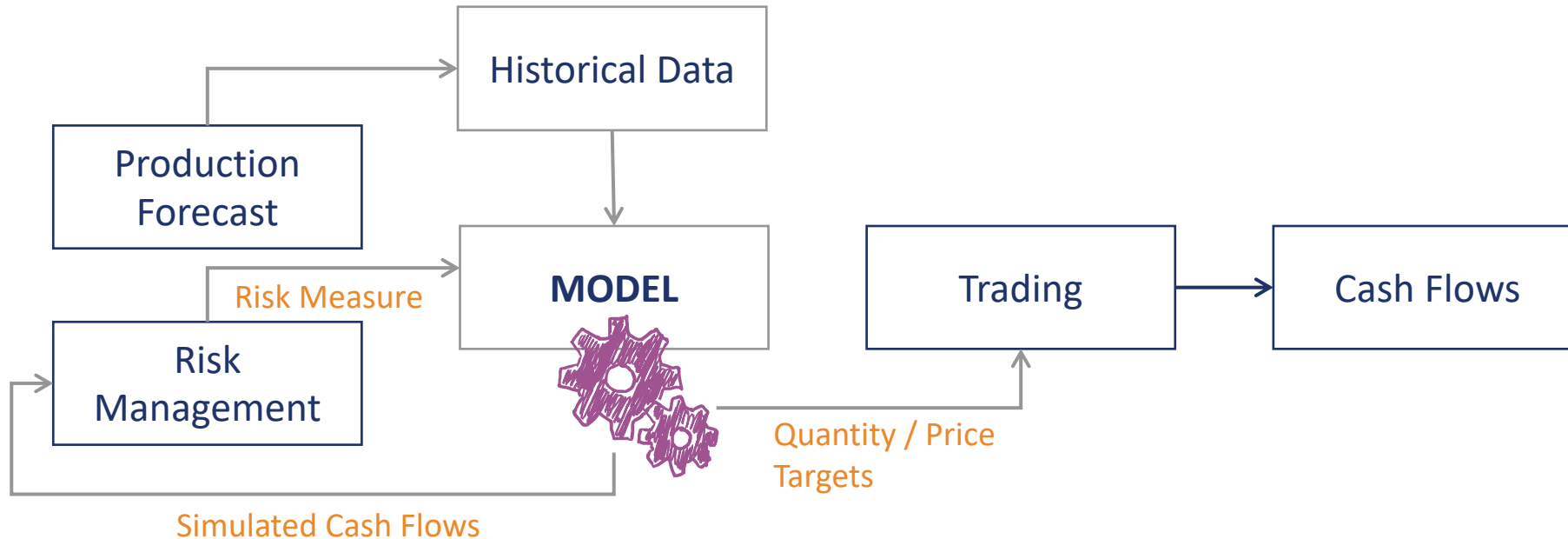


Hedging Decision Process with a Model

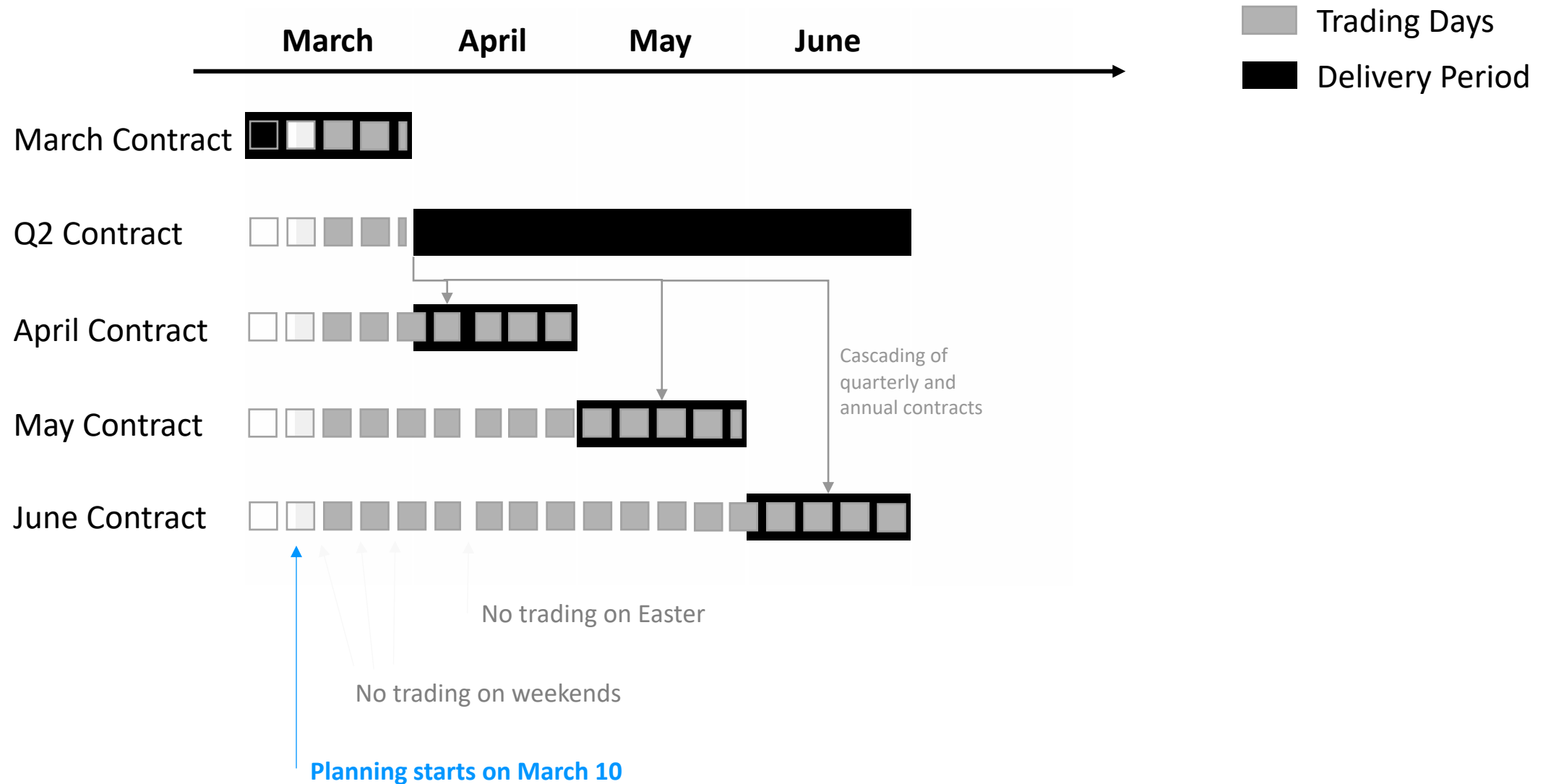
**WITHOUT
MODEL**



**WITH
MODEL**

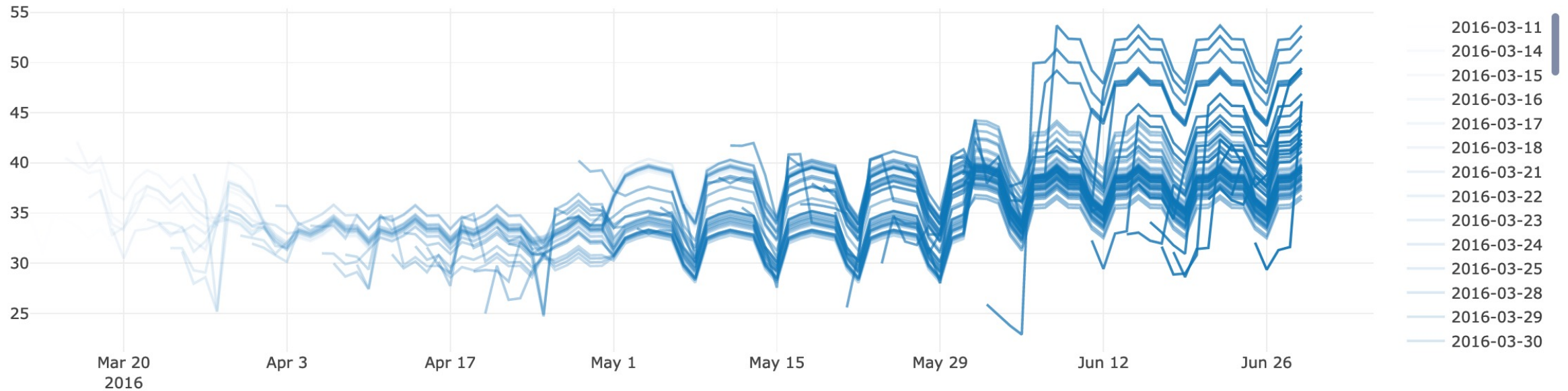


Contract Trading and Delivery Periods



Term Structure Dynamics

Example: EEX German Base Futures (Fair Value)



Source: Refinitiv EIKON, TRDEBFVDC*

Literature Review

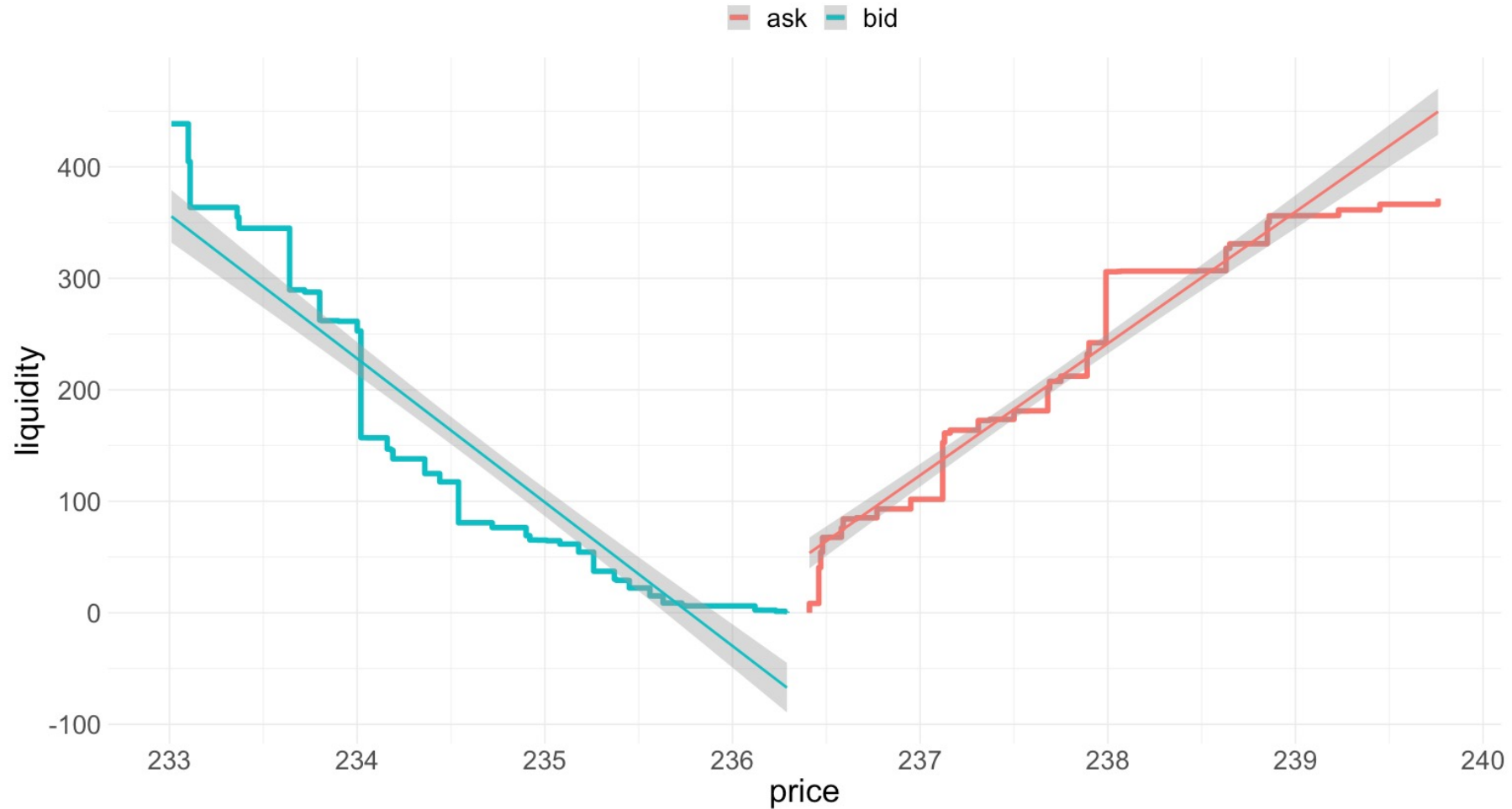
Focus on hedging strategies for energy risk management

	Resolution	Risk factors	Liquidity cost	Risk measure	Contracts
Dimoski & al (2018)	48 semi-month	PFC, volume	No	Nested CVaR	M,Q,Y
Gauthier & al (2016)	4 weeks	PFC, volume	Yes	Static, Variance	W
Kettunen & el. (2009)	6 weeks	PFC, volume	No	Terminal CVaR	W,M
Mo & al (2001)	52 weeks	Spot, volume	No	Cost constraint	W
Secomandi & Bo (2021)	24 months	PFC	No	Static, Variance	M
THIS WORK	>730 days	PFC, volume	Yes	Nested CVaR	W,M,Q,Y

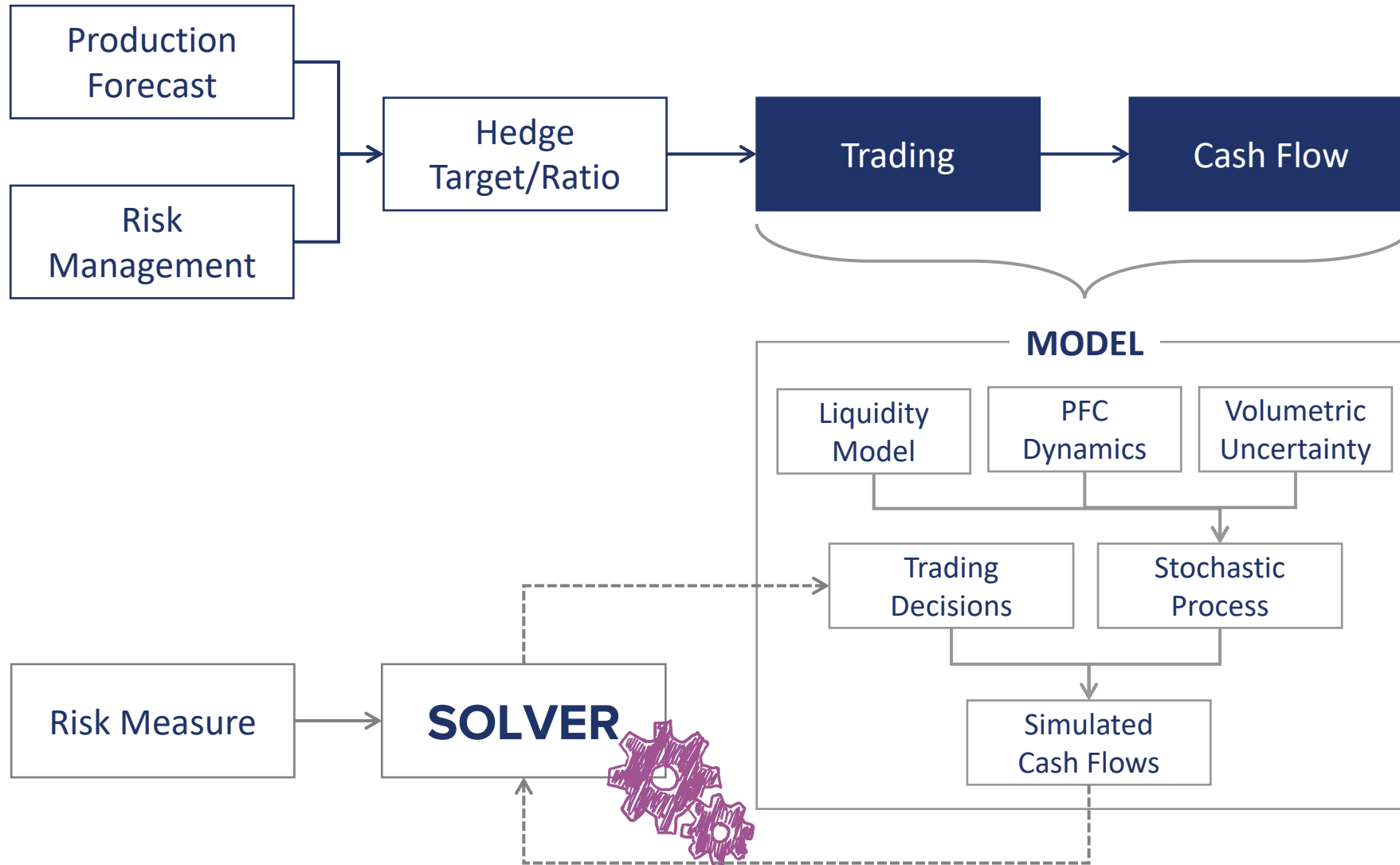
Measuring Market Impact Cost

Example: Sept-22 Future Nordic

Snapshot of the order book



Detailed Model of Trading Process



Multistage Stochastic Programming

$$\min_{\substack{A_1 x_1 = b_1 \\ x_1 \geq 0}} c_1' x_1 + \mathbb{E}_{|\xi_1} \left[\min_{\substack{A_2 x_2 + B_2 x_1 = b_2 \\ x_2 \geq 0}} c_2' x_2 + \cdots + \mathbb{E}_{|\xi_{[T-1]}} \left[\min_{\substack{A_T x_T + B_T x_{T-1} = b_T \\ x_T \geq 0}} c_T' x_T \right] \right]$$

- $\xi_{[t]} = (\xi_1, \dots, \xi_t)$: history of stochastic data process up to time t
- $\xi_t = (c_t, A_t, B_t, b_t)$: random model parameters (e.g., prices, volumes)
- $\mathbb{E}_{|\xi_{[t-1]}}$: expectation conditional on history of data process

Dynamic Programming Reformulation

$$\min_{\substack{A_1 x_1 = b_1 \\ x_1 \geq 0}} c'_1 x_1 + \mathbb{E}_{|\xi_1} \left[\min_{\substack{A_2 x_2 + B_2 x_1 = b_2 \\ x_2 \geq 0}} c'_2 x_2 + \dots + \mathbb{E}_{|\xi_{T-1}} \left[\min_{\substack{A_T x_T + B_T x_{T-1} = b_T \\ x_T \geq 0}} c'_T x_T \right] \right]$$

- Assume Markovian data process: $P(\xi_t) = P(\xi_{[t]})$
- Q_t : value function of dynamic program

$$Q_t(x_{t-1}, \xi_t) = \min_{\substack{A_t x_t + B_t x_{t-1} = b_t \\ x_t \geq 0}} c'_t x_t + \mathbb{E}_{|\xi_t} [Q_t(x_t, \xi_{t+1})]$$

Stochastic-Dynamic Programming

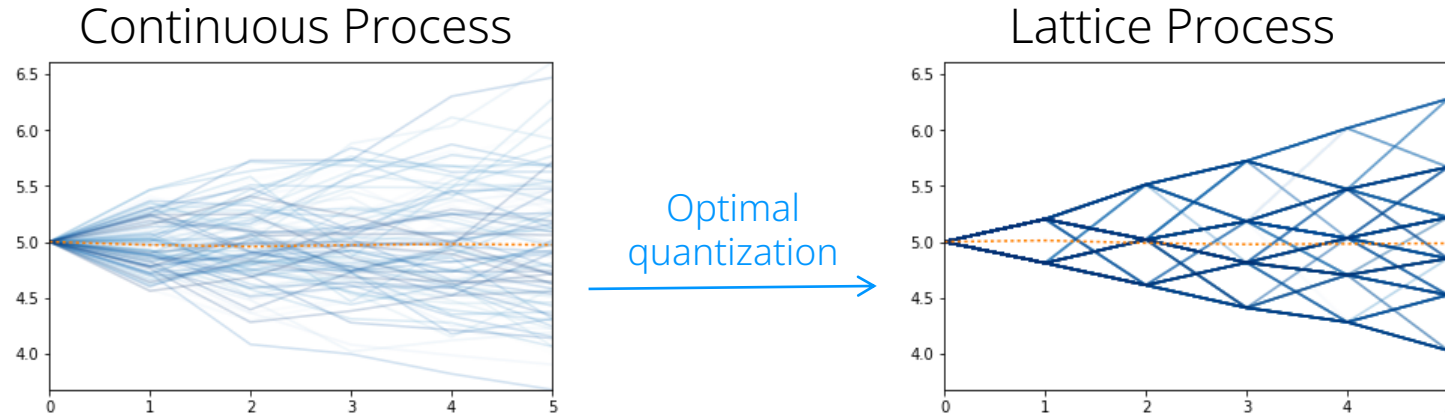
$$Q_t(x_{t-1}, \bar{\xi}_t) = \min_{\substack{A_t x_t + B_t x_{t-1} = b_t \\ x_t \geq 0}} c_t' x_t + \sum_{\bar{\xi}_{t+1} \in \mathcal{N}(\bar{\xi}_1, \dots, \bar{\xi}_t)} P(\bar{\xi}_{t+1} | \bar{\xi}_t) Q_t(x_t, \bar{\xi}_{t+1})$$

- $P(\bar{\xi}_{t+1} | \bar{\xi}_t)$: Transition probability matrix
- Q_t : value function of dynamic program

Approximate Dual Dynamic Programming

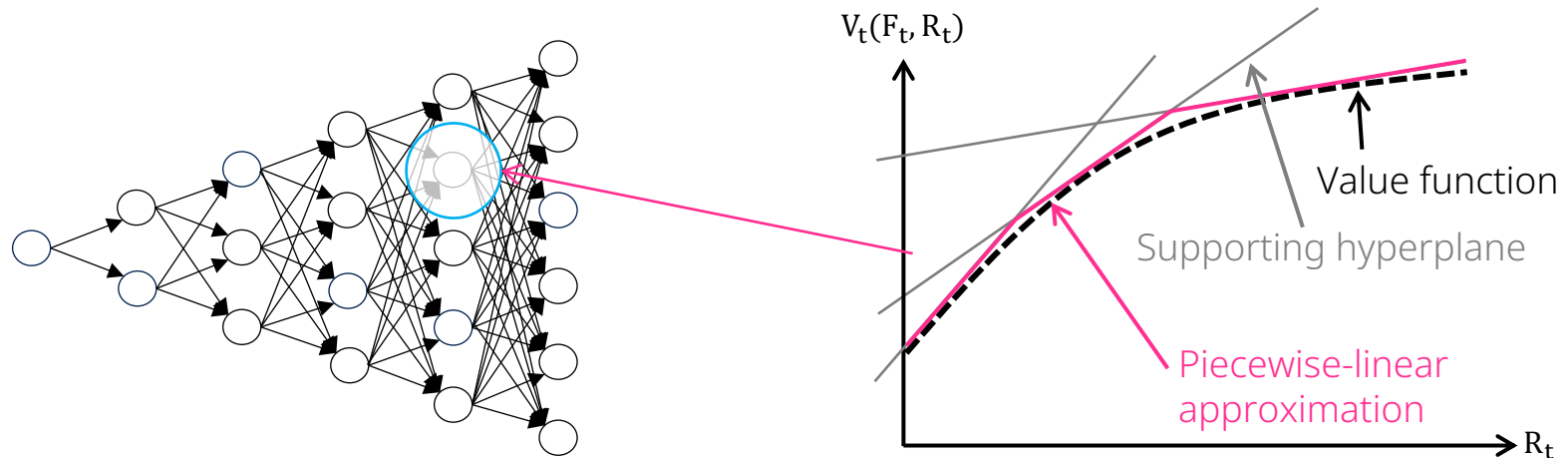
Step 1

Generate a Scenario Lattice



Step 2

Approximate the Value Function



QUASAR®: stochastic programming that **scales.**

The most advanced solver for multistage stochastic mixed-integer quadratic programming. With interfaces to Matlab, Python, Java, and Scala. Rapid deployment of UI with QUASAR® Cloud.

QUASAR® in a Nutshell

OUT-OF-THE BOX PERFORMANCE

QUASAR® can solve problems with thousands of stages as well as high-dimensional

STOCHASTIC TIME SERIES MODELS

Any parameter in the objective function or constraints can be represented by stochastic

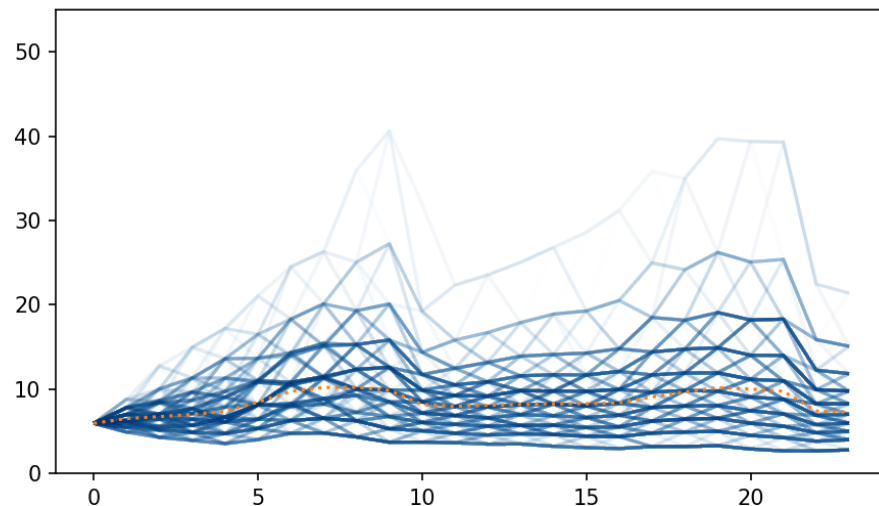
ALGEBRAIC MODELING LANGUAGE

QUASAR®'s modeling language is easy-to-use and lets users model decision problems as if

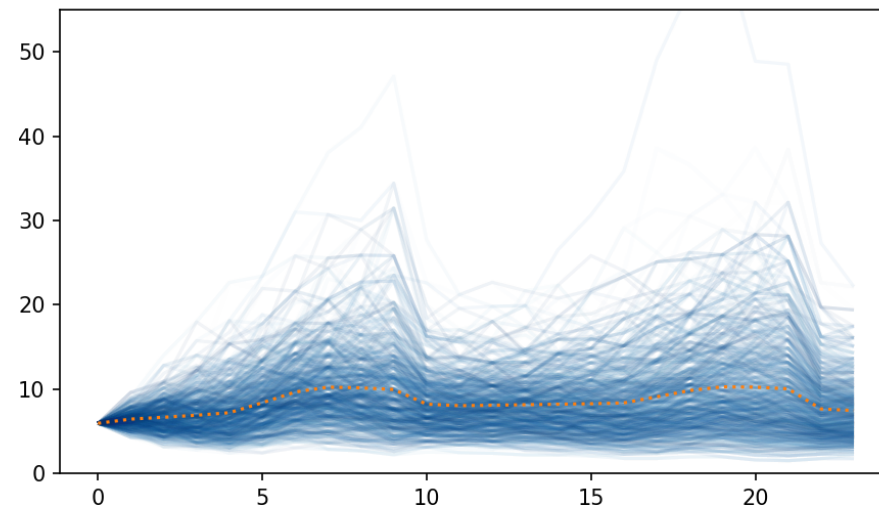
Discretize PFC Dynamics to Lattice

1. Empirical distribution of daily returns of the PFC
2. Create a lattice by simulating empirical PFC returns
3. Set forward prices to expected spot prices (\rightarrow martingale)

10 nodes per stage



100 nodes per stage



Case Study: Hydropower Portfolio

Data

- Historical production of Alpine hydropower portfolio
- Historical German Base PFCs from EIKON (fair value)
- Regression model of market impact cost

Model

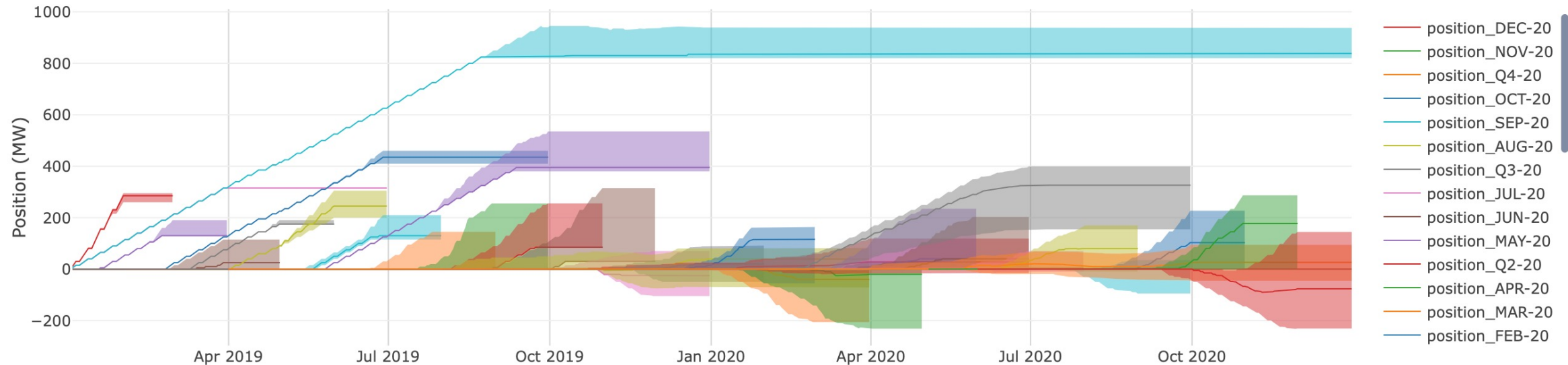
- 730 decision stages (days)
- Endogenous states: Tradable futures contracts and those in delivery
- Exogenous states. PFC, volumes

Procedure

- Create independent lattices of volumetric risk and PFC dynamics
- Solve optimization problem using QUASAR
- Simulate optimal decision policy

Exemplary Dynamic Hedge Plan

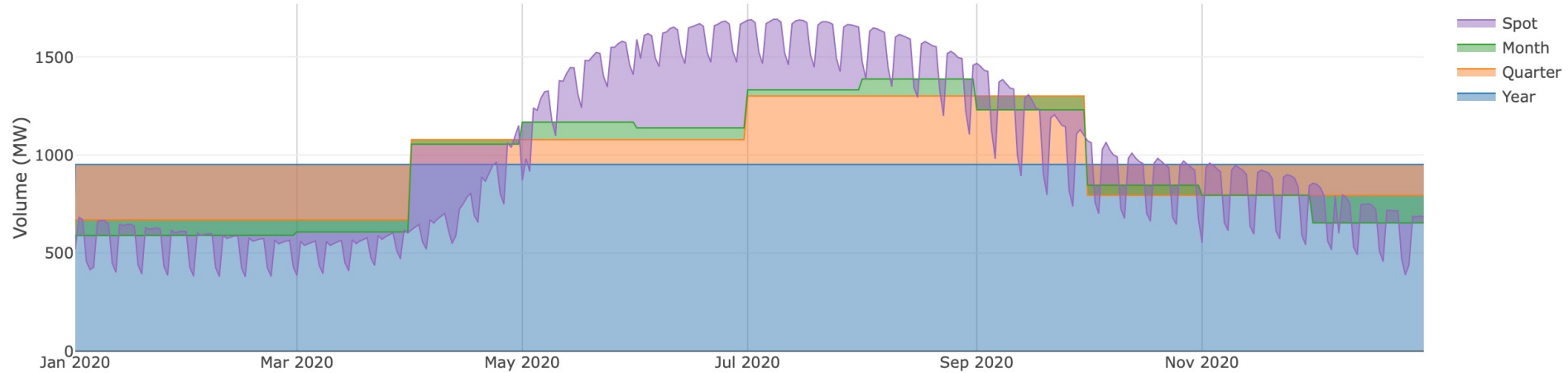
Here: hedging for 2020 starts at the beginning of 2019



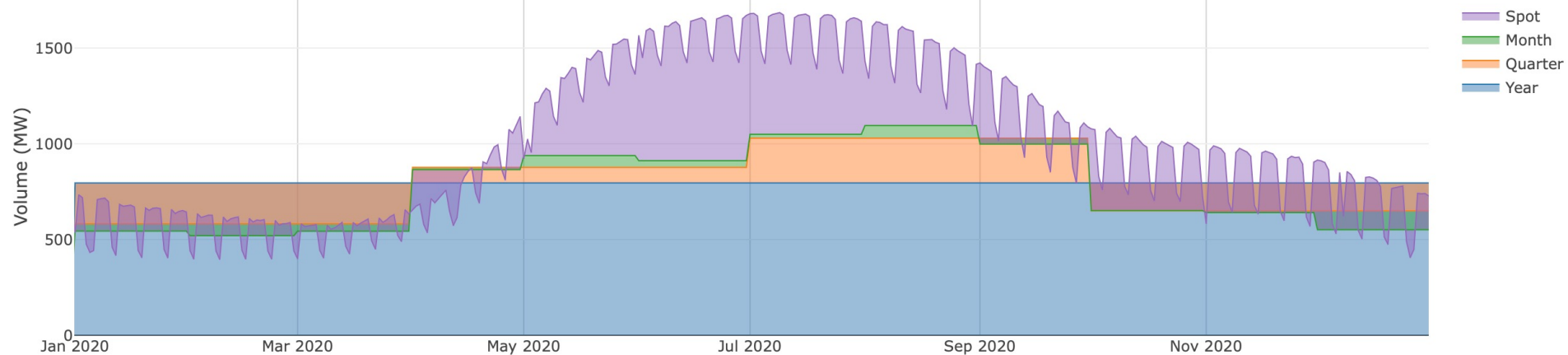
- Shaded areas cover [0.05,0.95]-quantiles
- Purpose of hedging is to minimize risk at minimal cost!

Effect of Volumetric Risk on Hedge Ratios

without volumetric risk

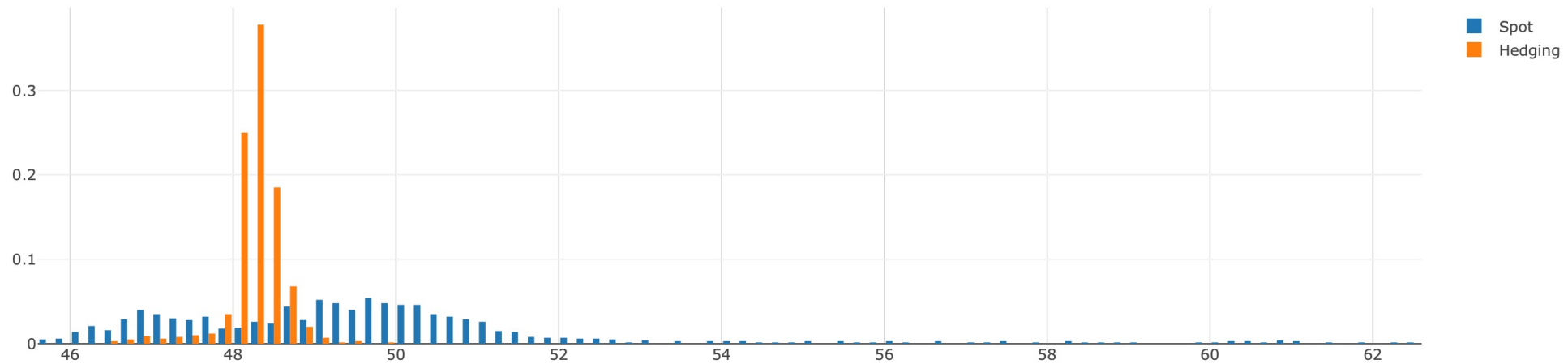


with volumetric risk

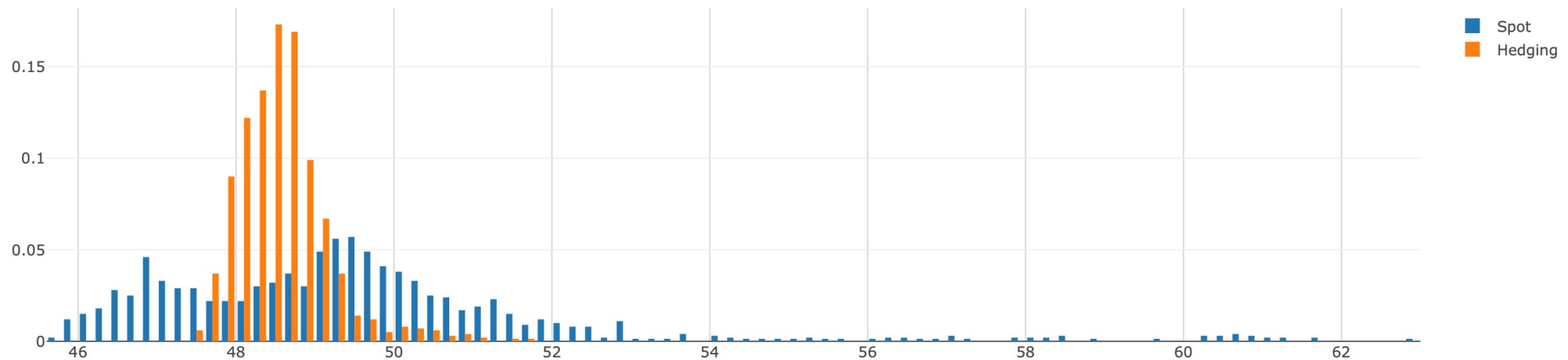


Hedging the Term Structure Risk

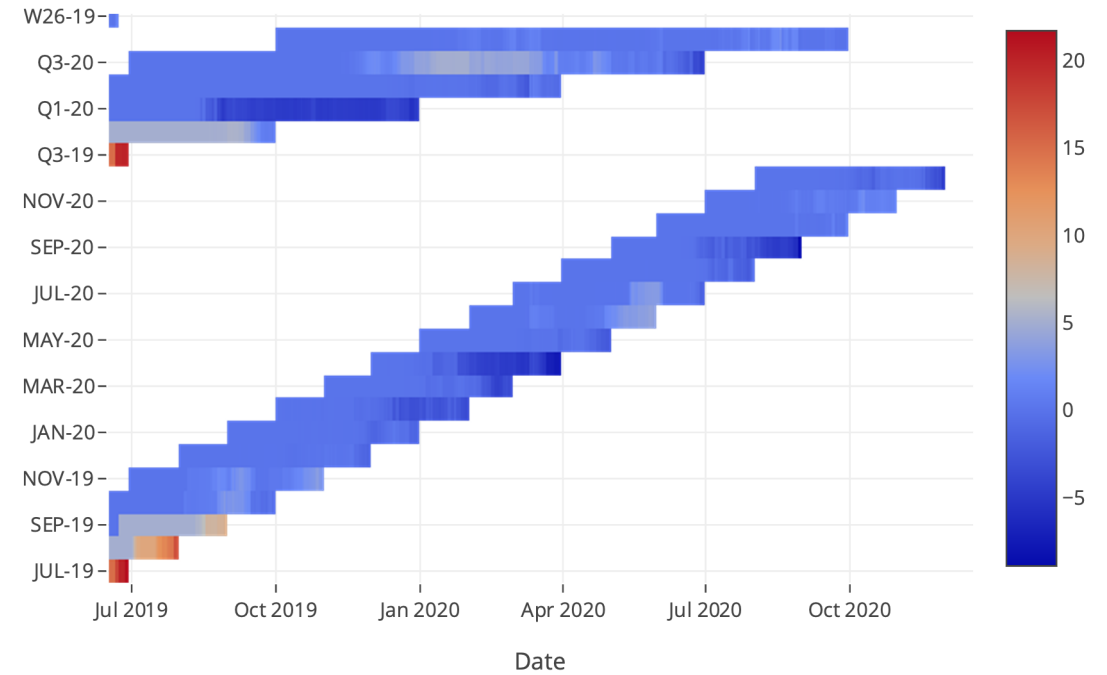
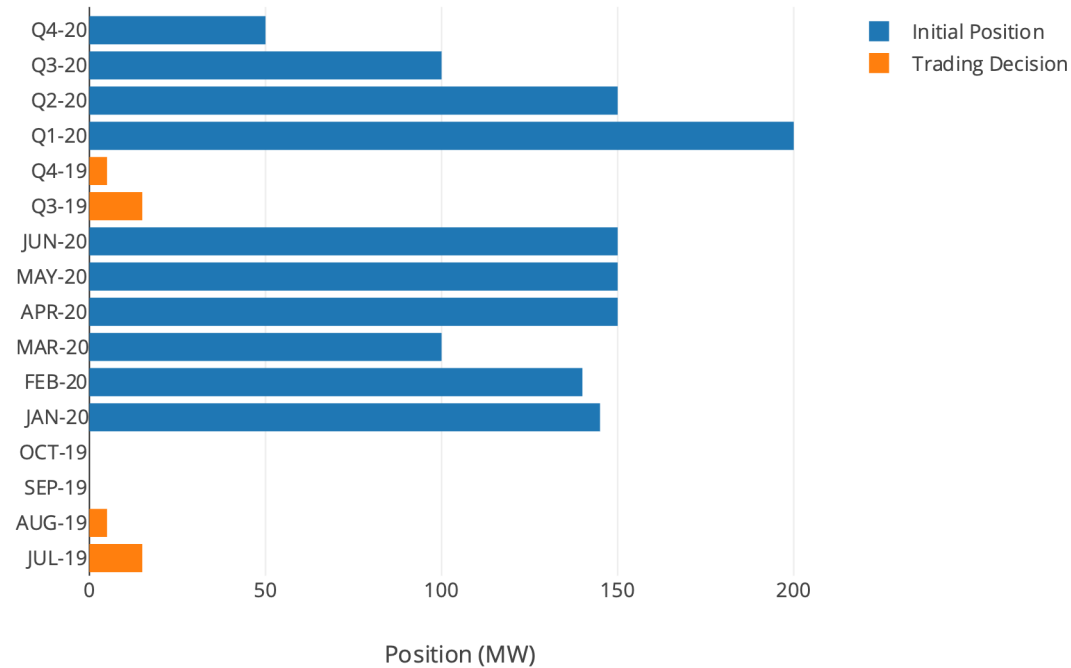
Distribution of paid price without volumetric risk



Distribution of paid price with volumetric risk



Decision Support for Daily Trading



Backtest for Deterministic Targets

Did the hedge make money? → Meaningless!

Price in €	2015	2016	2017	2018	2019	Average
Static	30.86	27.18	24.65	31.22	42.46	31.27
Corridor	31.35	27.47	25.27	31.72	42.96	31.76
Dynamic	32.00	27.34	27.68	33.31	45.94	33.26

- Did the hedge make money? → Meaningless!
- Purpose of hedging is to minimize risk at minimal cost

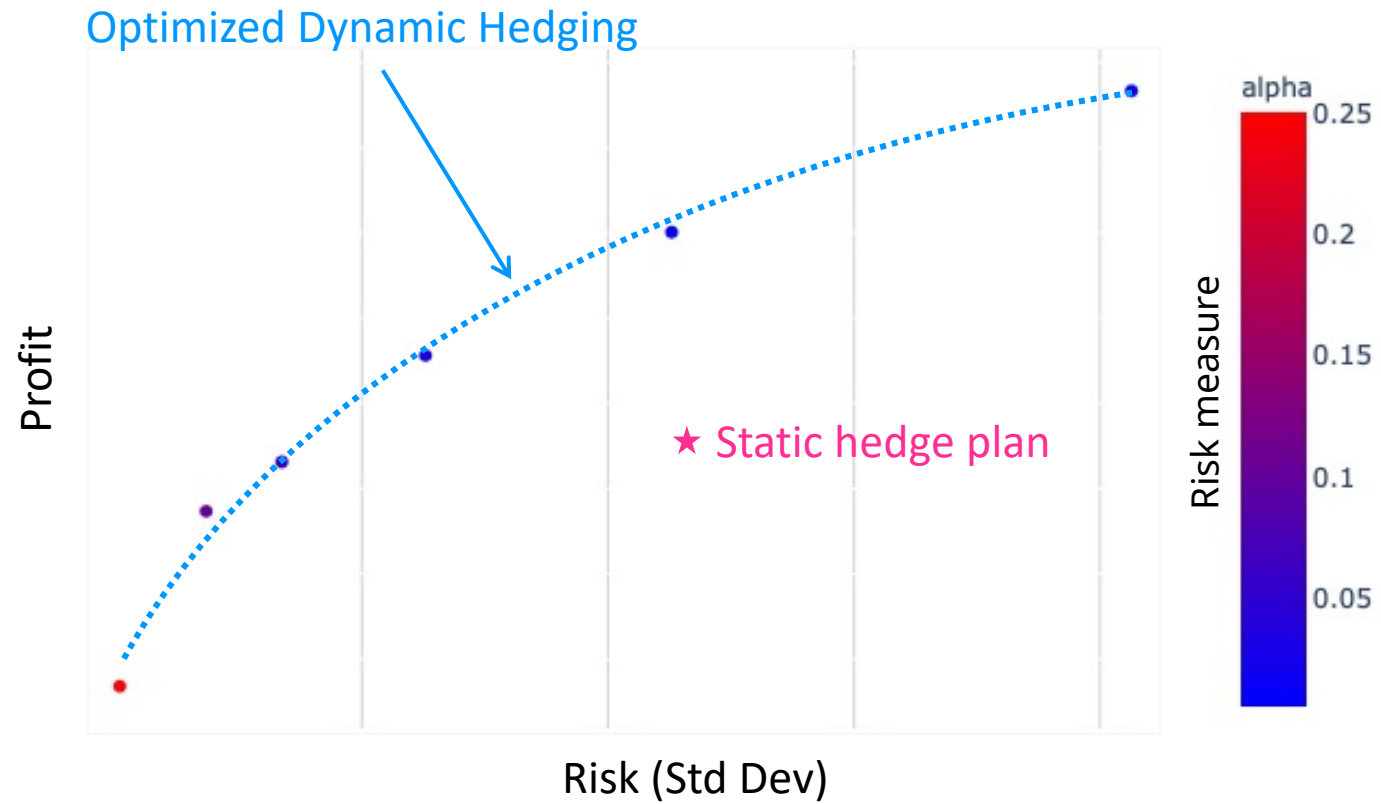
Summary

1. Propose model-driven approach for hedging renewable power portfolio
2. Model takes term structure dynamics and liquidity cost into account
3. Observation: hedging term structure risk is less effective in the presence of volumetric risk
4. Future work: storage provides a natural hedge against volumetric risk but can it reduce term structure risk?

References

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Efficient Frontier of Different Hedge Plans



Lattice of Volumetric Uncertainty

