Energy Trading in Day-Ahead Market

in cooperation with SUENA

Ilyas Agakishiev

Karel Kozmík

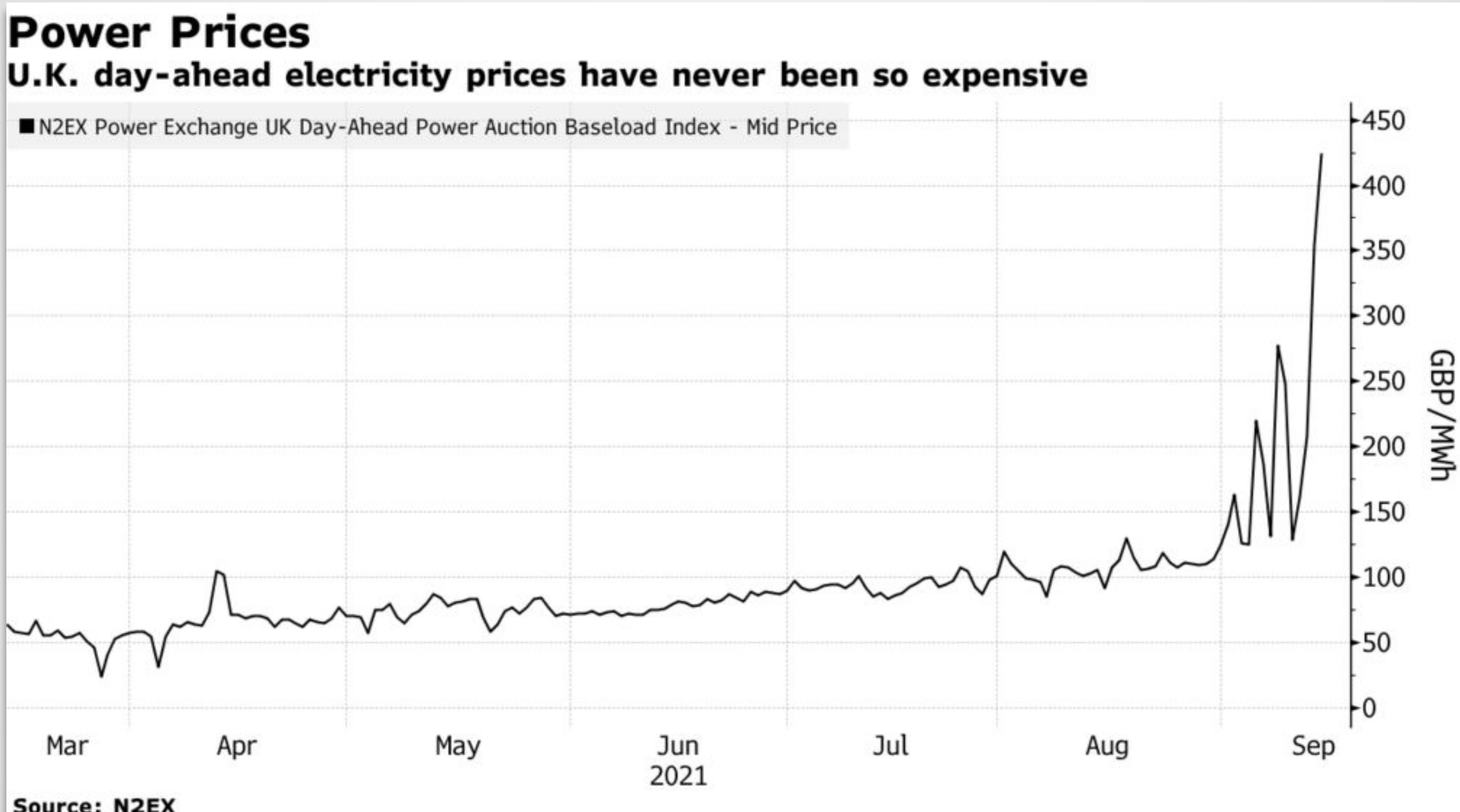
Alla Petukhina

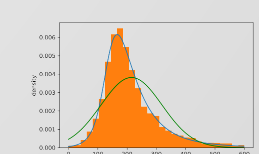
Wolfgang Karl Härdle

Milos Kopa

Department of Probability and Mathematical Statistics
Faculty of Mathematics and Physics
Charles University

Energy Days 2023

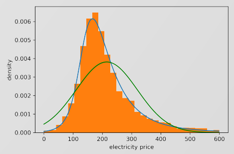

Power Prices
U.K. day-ahead electricity prices have never been so expensive
N2EX Power Exchange UK Day-Ahead Power Auction Baseload Index - Mid Price
450
400
350
300
250
200
150
100
50
0
GBP/MWh
Mar
Apr
May
Jun
2021
Jul
Aug
Sep
Source: N2EX



Types of Electricity Markets

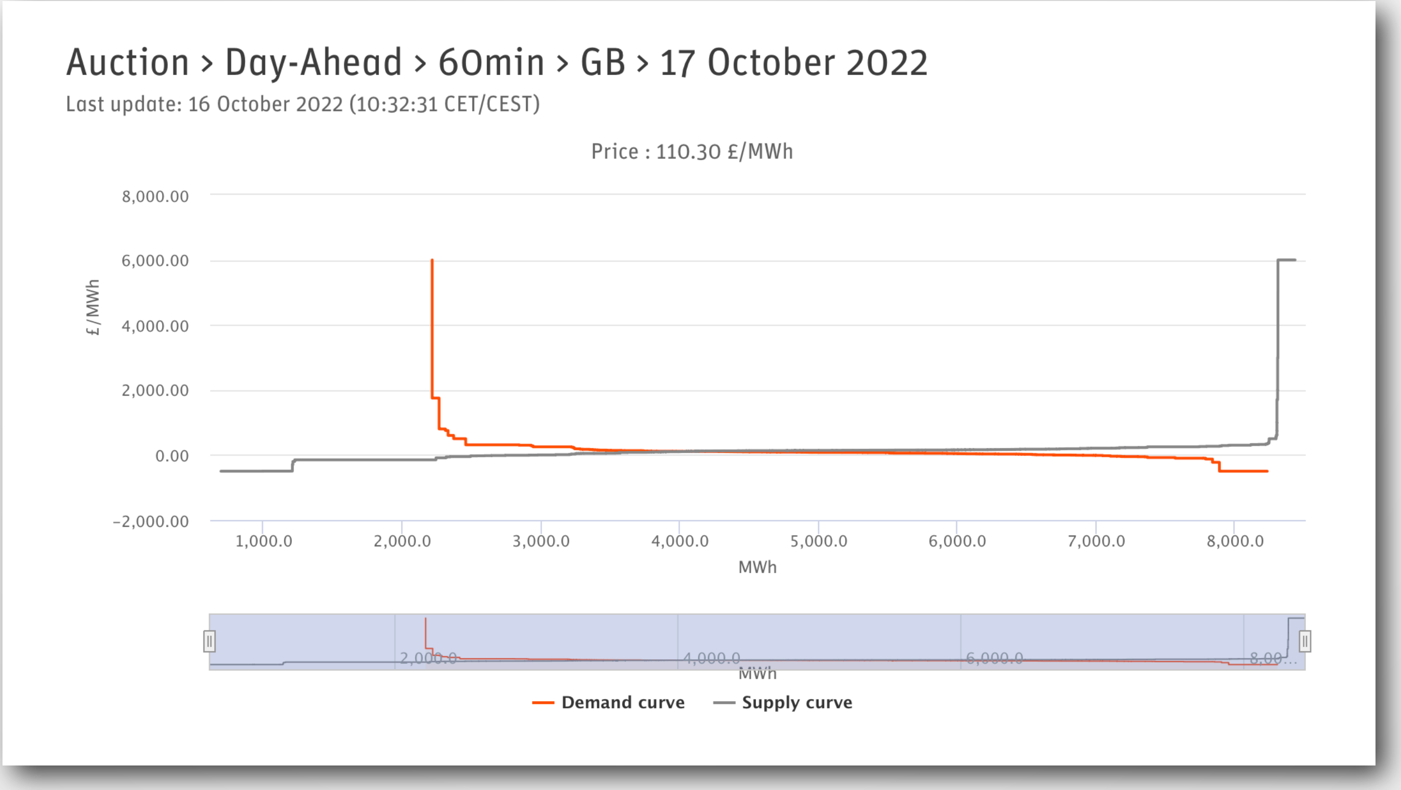
- Centralized platforms where participants exchange electricity based on price willing to pay or receive, and capacity of electrical network.

- Continuous-time Auction
  - Continuous submission and storage of orders
  - Each time a deal is feasible, it is executed
  - Example: intraday market

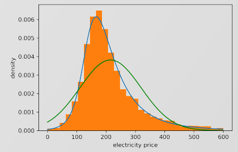


Types of Electricity Markets

- Fixed Gate Auction
  - Sell or buy orders for several areas and/or several hours
  - Submissions are closed at a pre-specified time (gate closure)
  - The market is cleared
  - Example: day-ahead

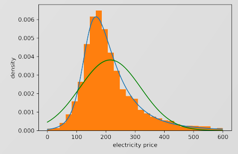


Source: https://www.epexspot.com



Post-Brexit GB Power market

- Not a part of the European Single Day-ahead Coupling (SDAC)
- Two separate day-ahead 60-min auctions for GB:
  - Exchange EPEX
  - Exchange Nord Pool
- Opportunity to profit: long in one and short in the other



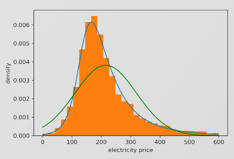
Energy Trading

- Three key prices each hour
  - First auction price (EPEX GB)
  - Second auction price (Nord Pool)
  - System price

- Auctions
  - Submission of price and volume bids in advance
  - Price is determined by the auction
  - The amount is traded (win of the auction): offered higher price to buy (lower to sell)

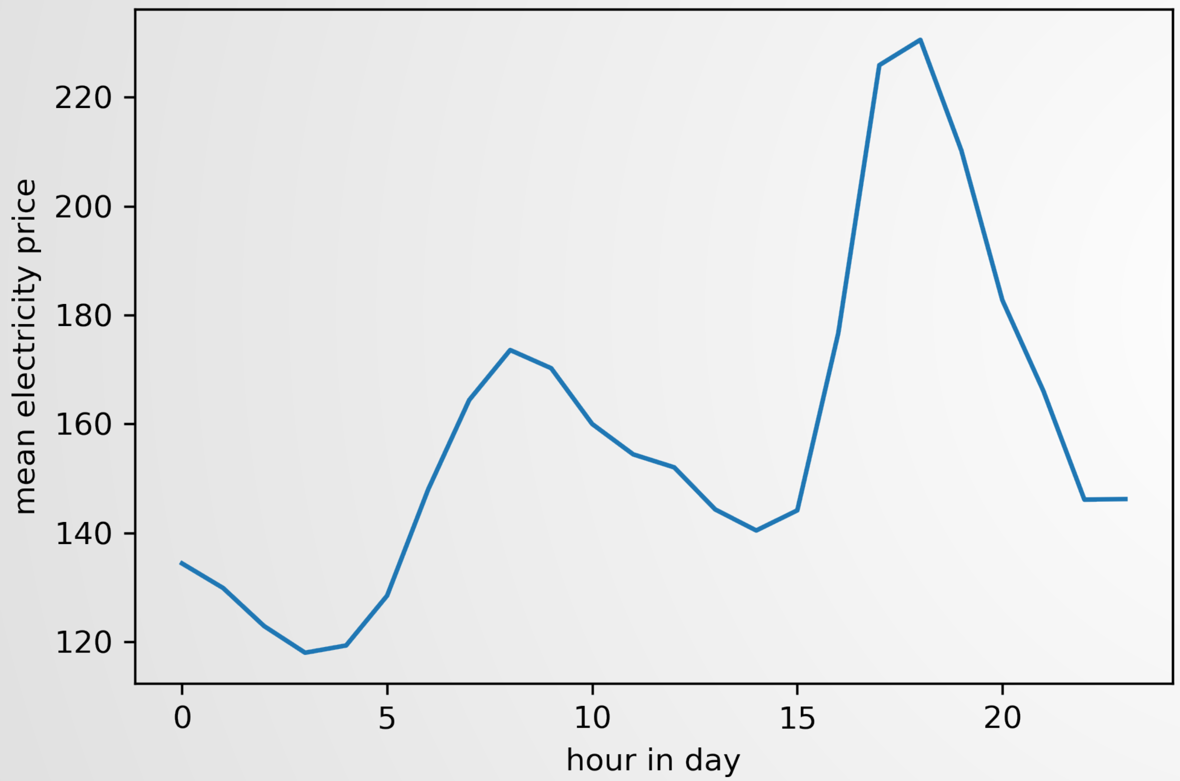
- All left after the second auction is settled by system prices

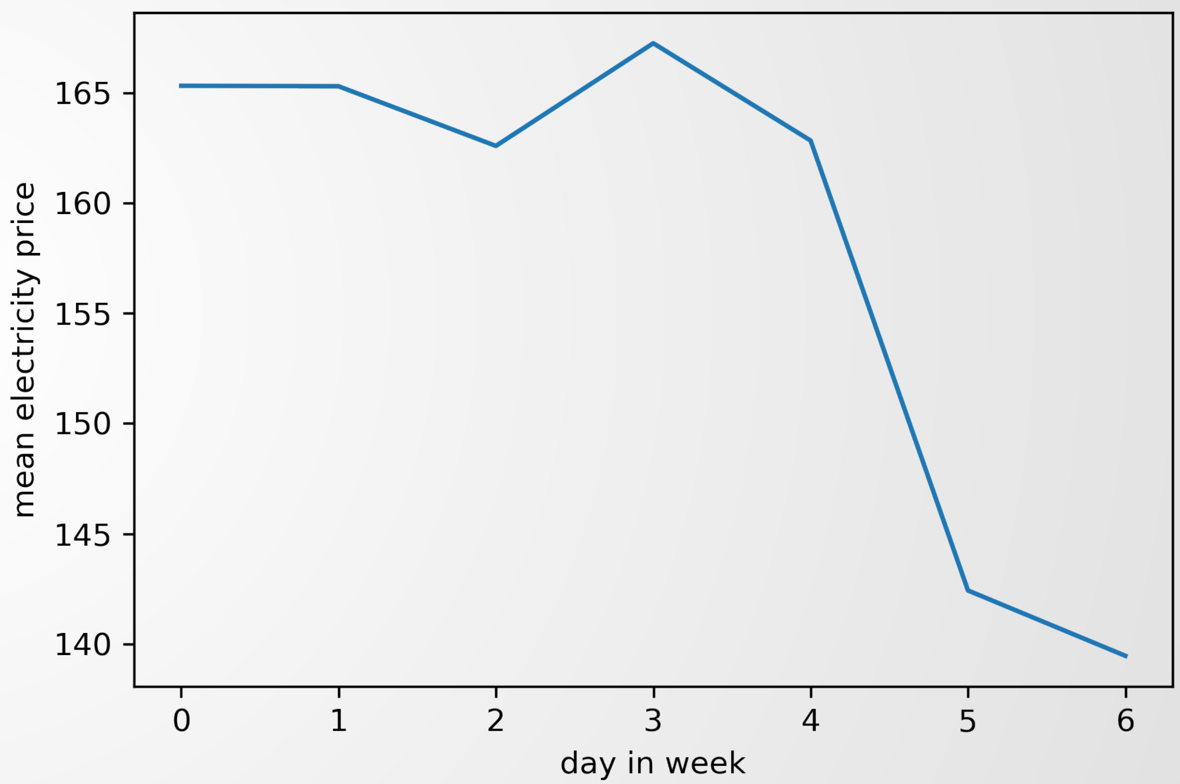
Details



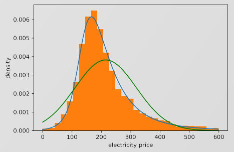
Price Seasonality

- Peaks in morning
- Peaks in evening “rush” hours
- Price higher on weekdays vs weekends



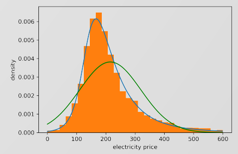


Mean electricity prices during the day and week, EPEX Auction



Research challenges

- Extend Distributional multilayer perceptron (DMLP) for multivariate case EPF
- Test multivariate DMLP against state of the art benchmarks
  - LSTM architecture
  - LASSO quantile regression (LASSO QR)
- Develop trading application for GB electricity market
- Evaluate trading results for various investors objectives



Outline

1. Motivation ✓
2. Methodology
3. Data
4. Empirical results
5. Outlook

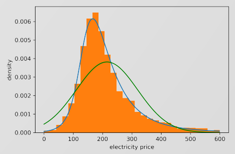
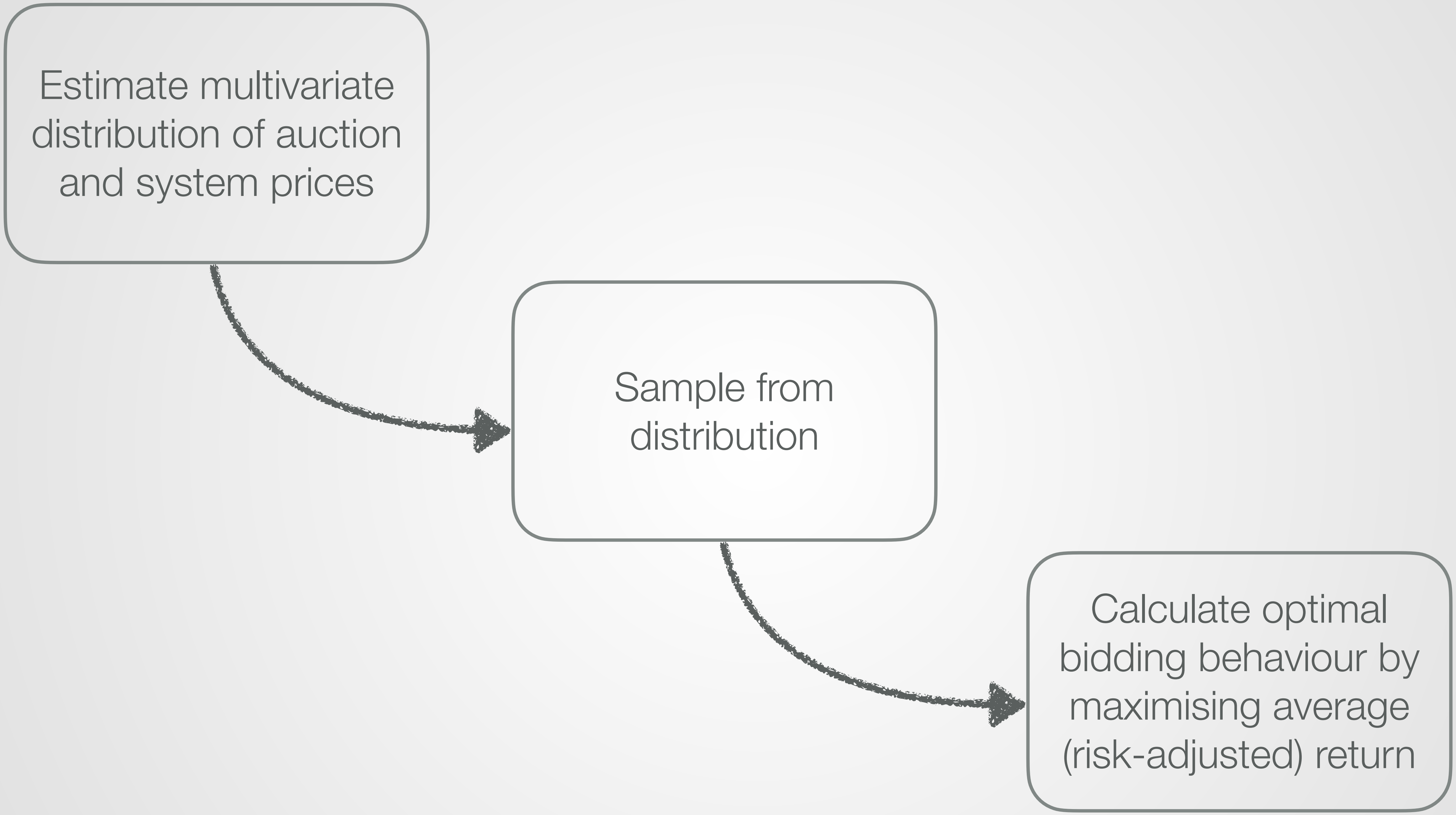
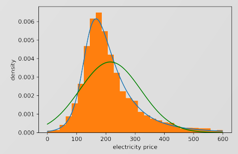


Illustration of strategy

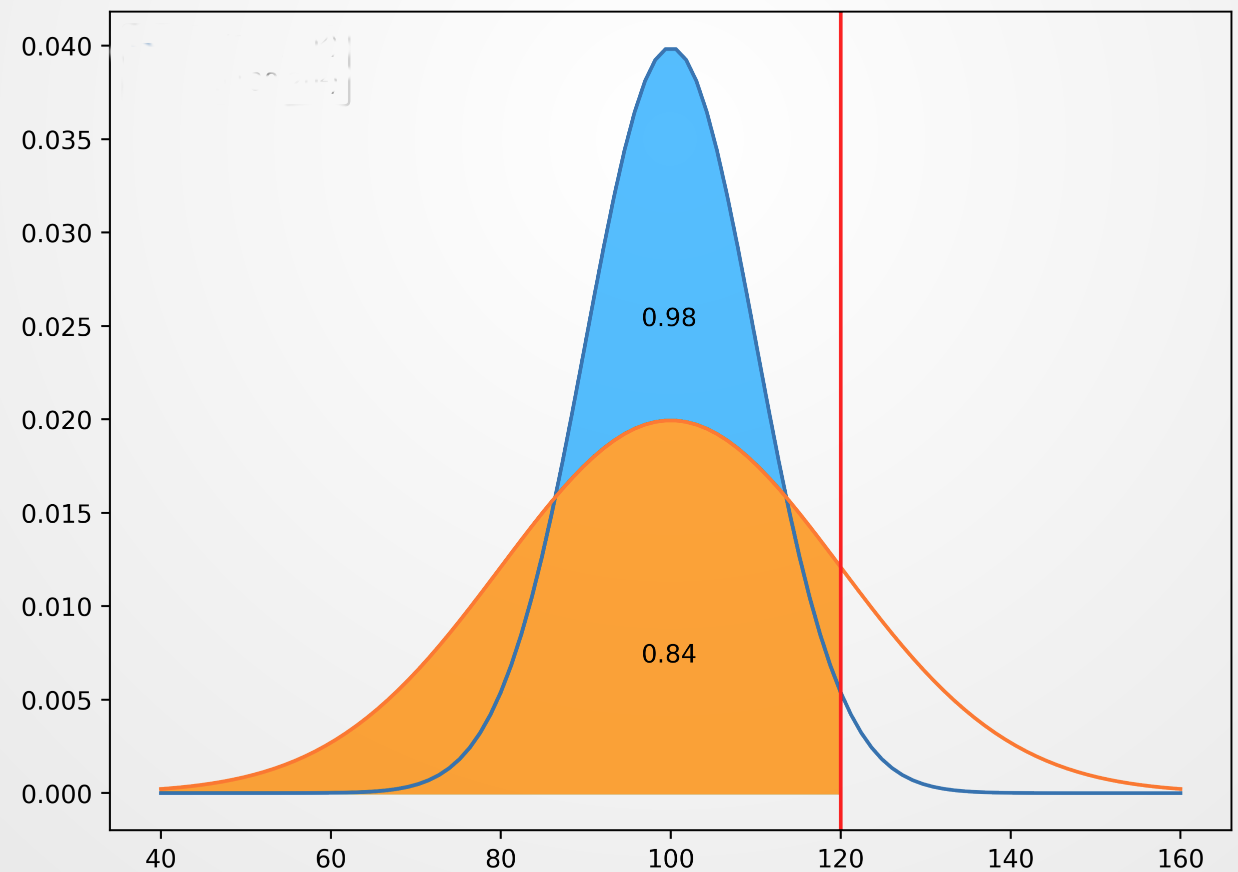




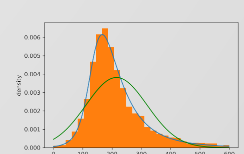
Distributional Modeling

- Whole distribution needed to optimally place bids
  - Point estimate of mean: no probability of the bid being accepted
  - Risk can be incorporated, e.g. CVaR
  - Proper Risk management

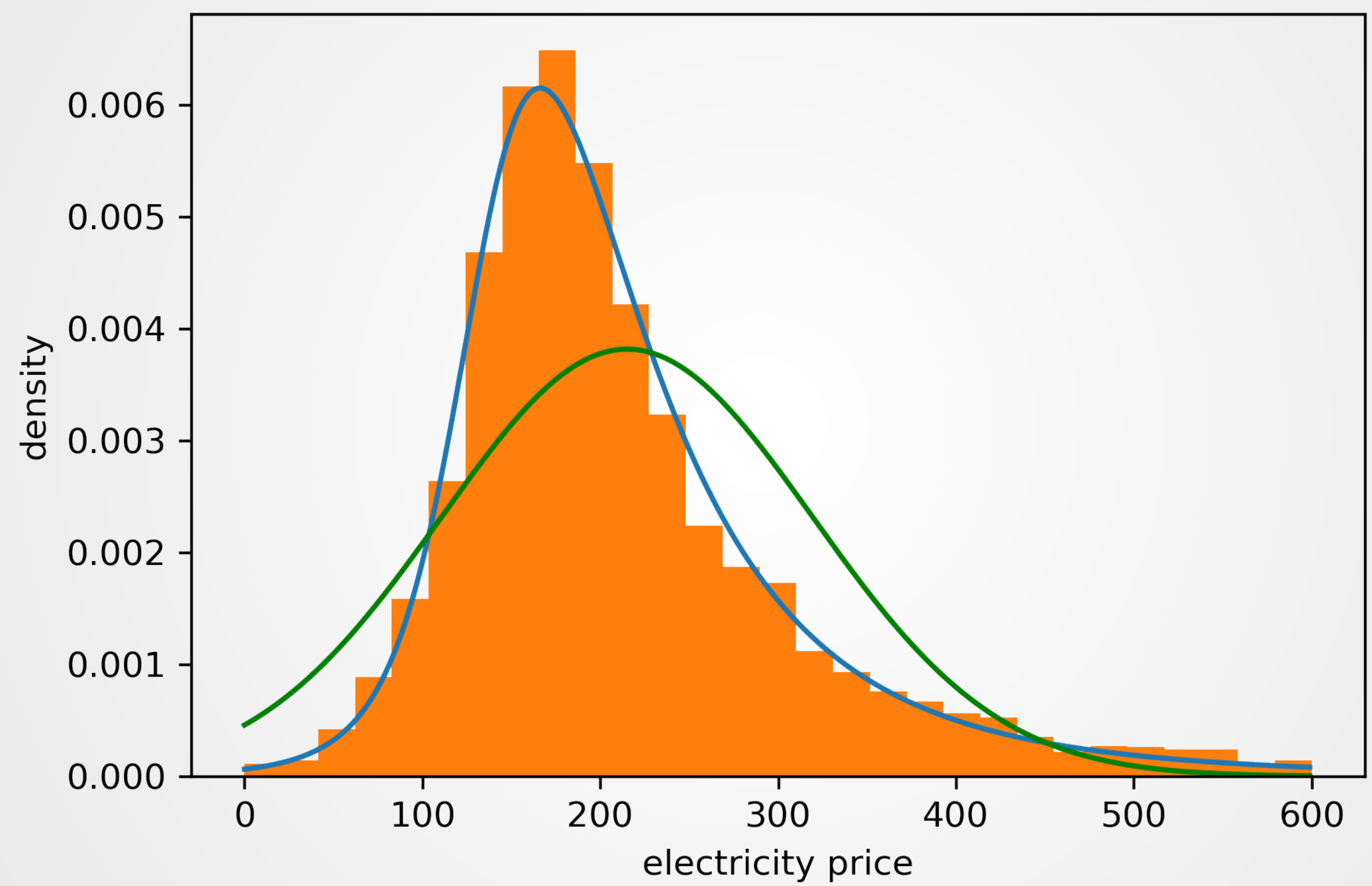
Formal objective



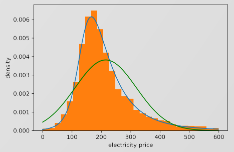
Two PDFs: $N(100, 10^2)$ and $N(100, 20^2)$



Better fit for electricity prices

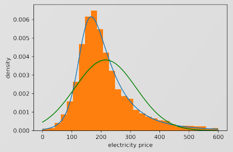


JohnsonSU and Gaussian fit for sample electricity data. (EPEX)



Why Johnson’s SU?

- Captures skewness and kurtosis well
- Easy to implement in the parameter space
- Easily expandable to multivariate case



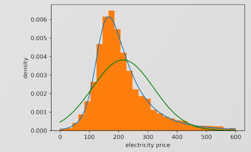
Setup of distributional forecast

- For multiple energy prices $Y \in \mathbb{R}^{T \times J}$ - energy prices, $X \in \mathbb{R}^{T \times p}$ - features, Johnson's SU parameter vectors $\Theta = (\Gamma, \Xi, \Delta, \Lambda)$:

$$\hat{\Theta}_i = \underset{G \in \mathscr{G}}{\arg\max} \sum_{j=1}^{J} \mathscr{L}\{\theta_{i,j}; G(x_i)\},$$

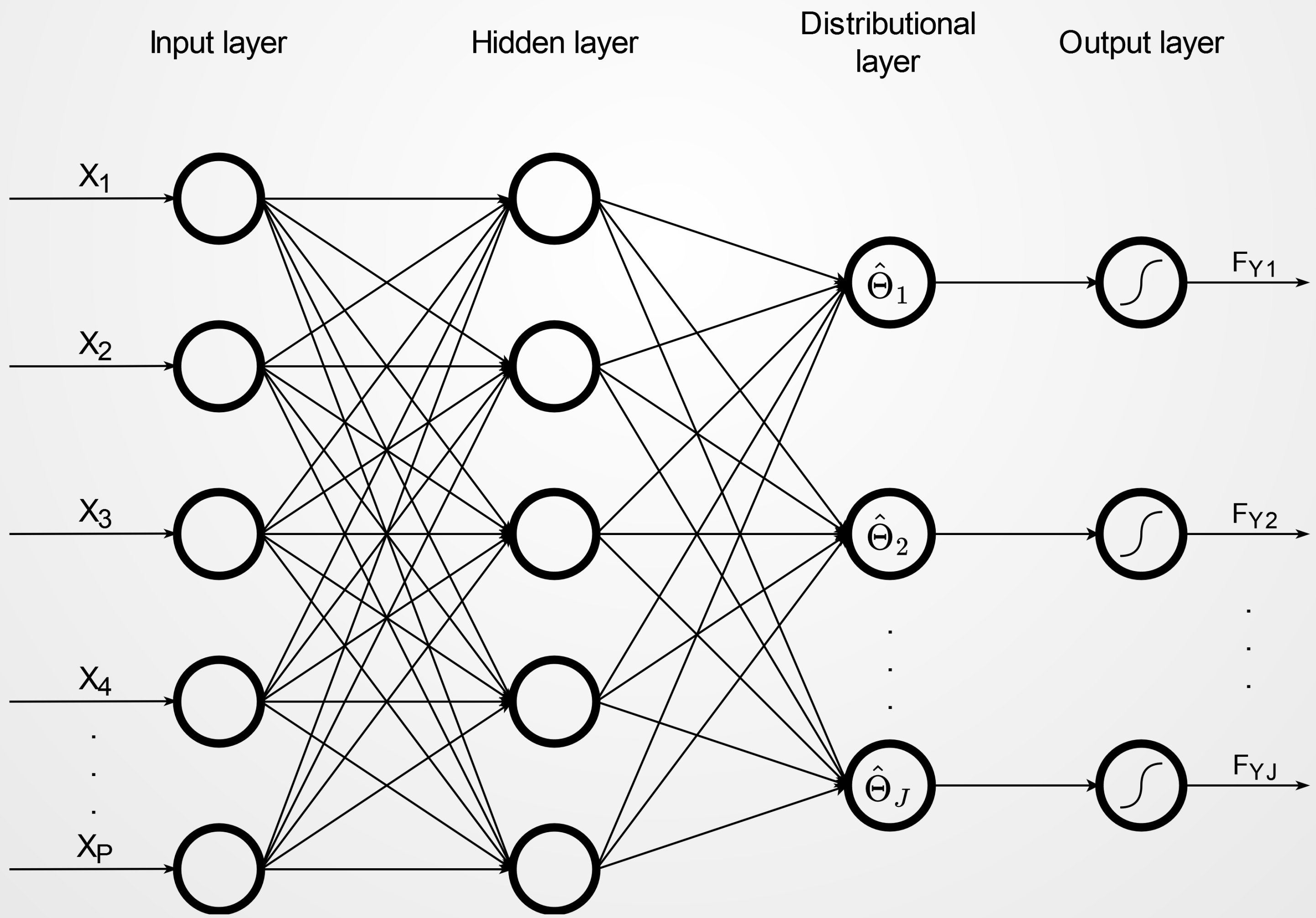
- G nonparametric function, NN approximated
- $J = 3$ (3 different prices), $\mathscr{L}$ likelihood, p features, $T = 10176$ data points (length of moving window)

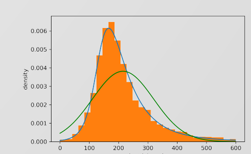
Feature list



Distributional Neural Network

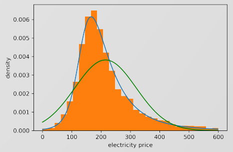
- Neural network used to predict parameters of a distribution
- Negative log likelihood used as the loss function, F cdf





Network training

- NN architecture
  - 3 hidden layers
  - First layer: Fully connected or LSTM
  - Using dropout and L_2 regularization
  - 3 separate output layers - 3 prices with 4 neurons - Johnson's SU distribution parameters
- Retraining every 30 days
- Loss function: NLL of Johnson's SU

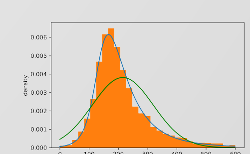


Reference model - LASSO Quantile Regression

- $Y \in \mathbb{R}^{n \times J}$ - energy prices, $X \in \mathbb{R}^{T \times p}$ - features, $J = 3$

$$\hat{\beta}_{\tau,\lambda,t} = \arg\min_{\beta \in \mathbb{R}^p} \sum_{i=1}^{n} \rho_\tau \left(Y_i - X_i^\top \beta \right) + \lambda \|\beta\|_1$$

- $\tau \in (0,1),\ \rho_\tau(u) = u\{\tau - \mathbf{I}(u < 0)\}$
- $\tau = \{0.01, 0.02, \ldots, 0.99\}$
- $\lambda = 0.01$ - tuning parameter
- $T = 10176$ data points (length of moving window)
- Estimation every 30 days

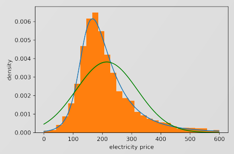


Data

- Granularity
  - Hourly for most features - mainly electricity auction prices
  - Daily for gas, emissions etc.
- Time frame: 01.01.2021 - 12.09.2022
- Energy features:
  - Electricity auction prices, demand (Provided by Suena)
  - Solar and wind generation related prediction (Provided by Suena)
  - Brent oil prices (Source: FED/FRED)
  - Gas, Emission futures (Source: investing.com)
  - Weather data (Source: Copernicus Climate Change Service)

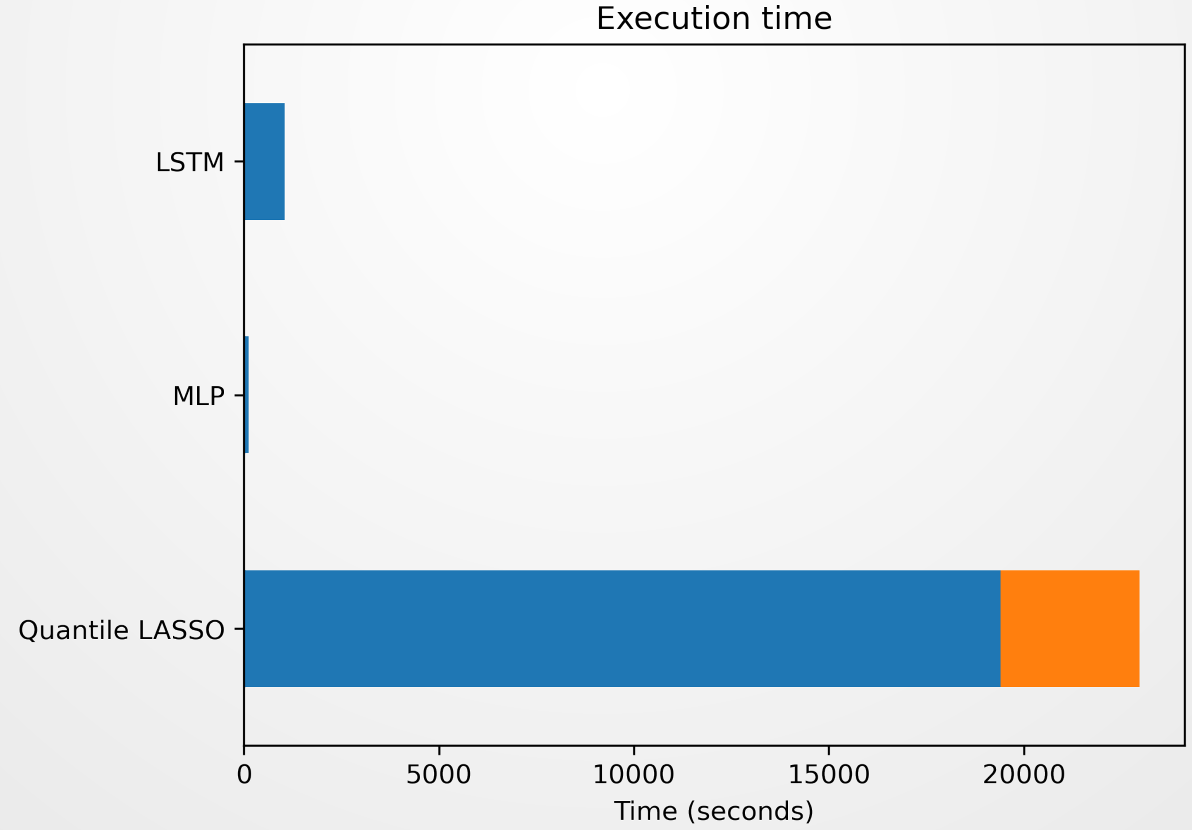
Prediction construction

- Data split
  - Training period: 01.01.2021 - 28.02.2022 (first moving window)
  - Testing period: 01.03.2022 - 12.09.2022
- Input:
  - $p = 40$ features
    1. Energy features Details
    2. Additional engineered features:
       - ★ Previous prices
       - ★ Day of week, hour of day
       - ★ Holiday
       - ★ Weather anomaly
- Output:
  - Parameters of Johnson's SU for first auction, second auction and system price

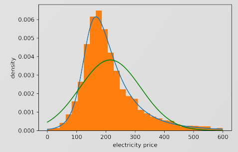


Resulting CRPS

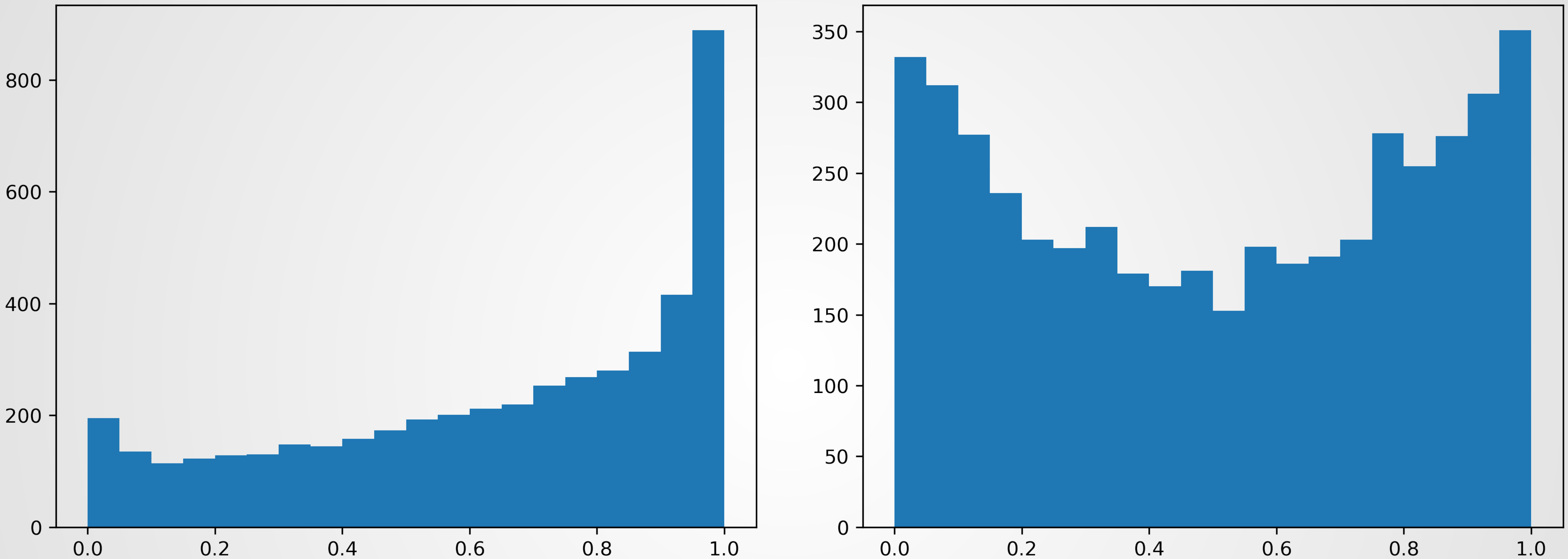
CRPS values	EPEX	Nordpool	System
LSTM	16.78	16.55	25.98
MLP	16.23	19.80	25.54
Quantile LASSO	10.95	11.60	24.92
Simple fit (last 30 days)	22.38	22.55	27.90



Execution time and distribution fitting



Histogram



Quantile histogram for EPEX: MLP (left) and Quantile LASSO (right)

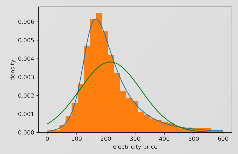
Trading framework

- Trading scenario: trade 1 unit of energy each hour
- Sample 1000 scenarios from the predicted distribution
- Apply one of 4 trading aggregates (investor objectives):
  - Mean
  - Median
  - Prob - number of the scenarios, we are making profit
  - Mean-CVaR (risk-adjusted absolute return)

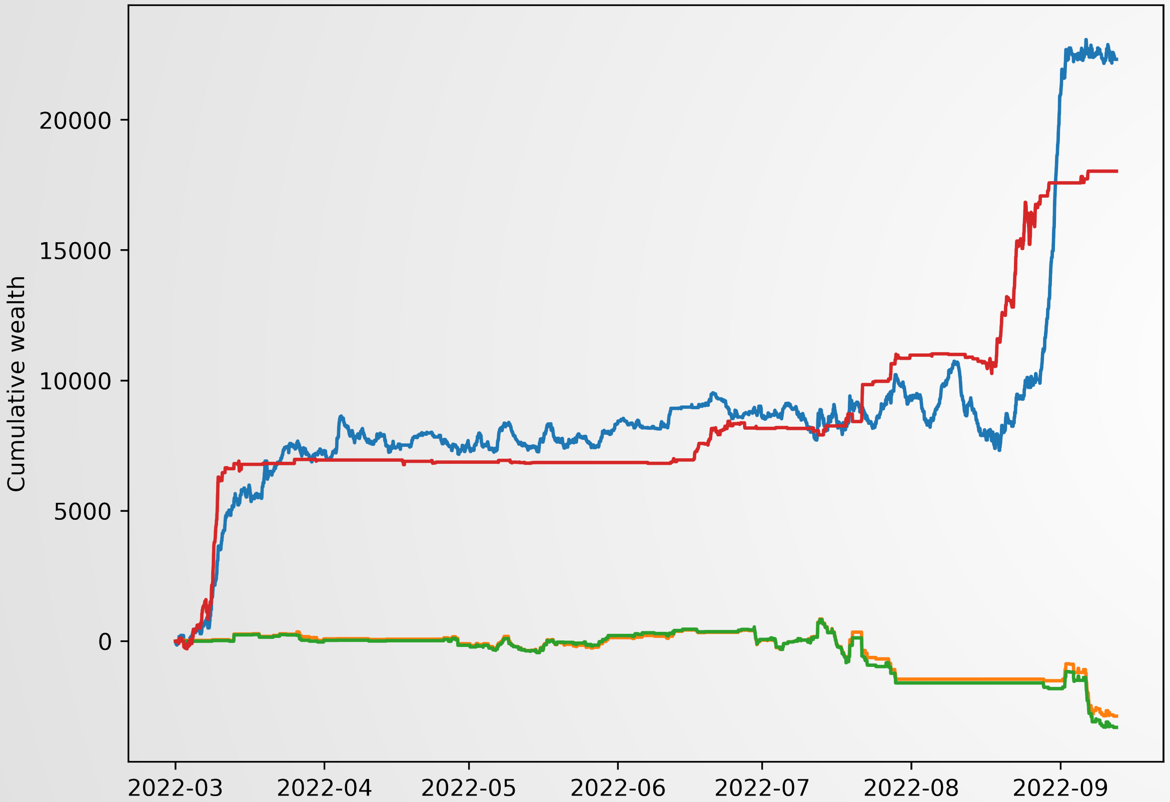
$$U_t \stackrel{def}{=} \mu_t - \rho \cdot CVaR_t$$

where μ_t - mean return, $\rho = 0.03$ - risk aversion parameter and

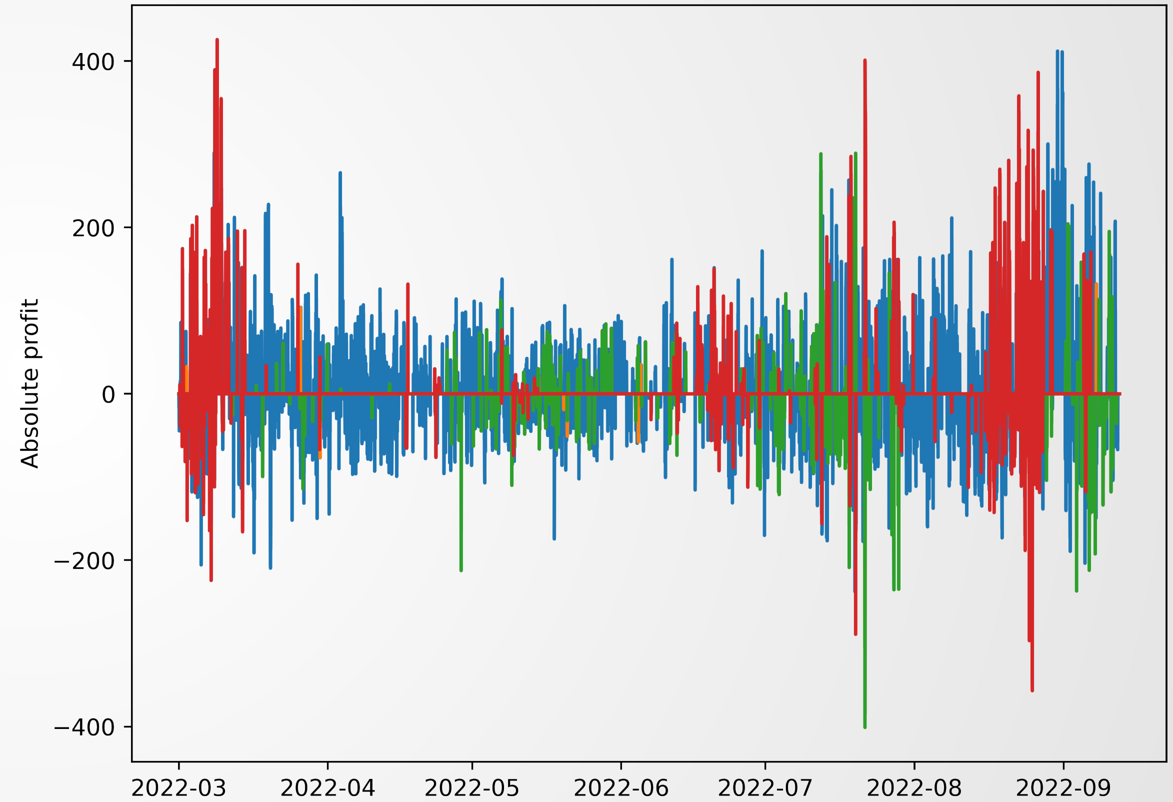
$CVaR_t$ - conditional Value at Risk 5%



Trading results (MLP)



Cumulative wealth



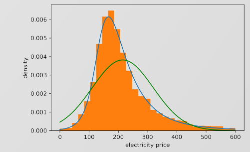
Absolute gain/loss for each traded hour

Mean, Median, Prob, Mean-CVaR

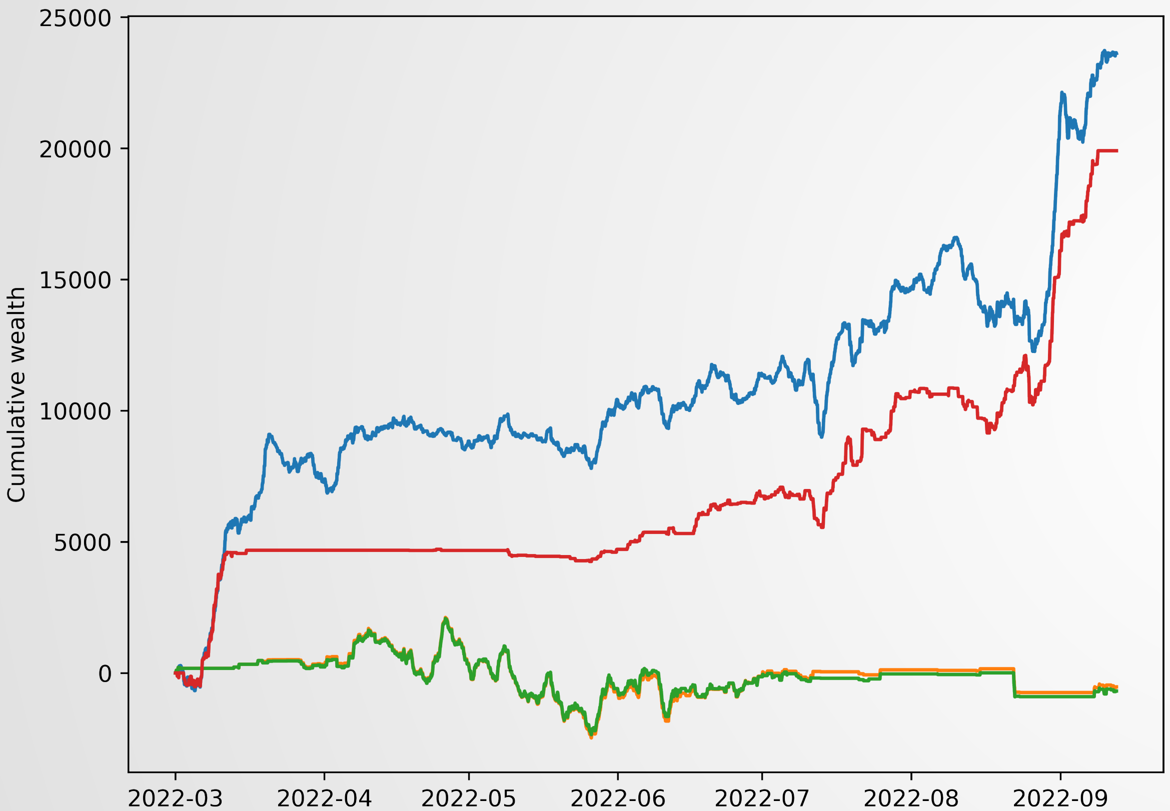
Trading results (MLP)

Strategy	AV	Var	Sharpe
Mean	0.0101	0.0448	0.2262
Median	−0.0043	0.0072	−0.6004
Prob	−0.0045	0.0070	−0.6417
Mean-CVaR	0.0104	0.0089	1.1726

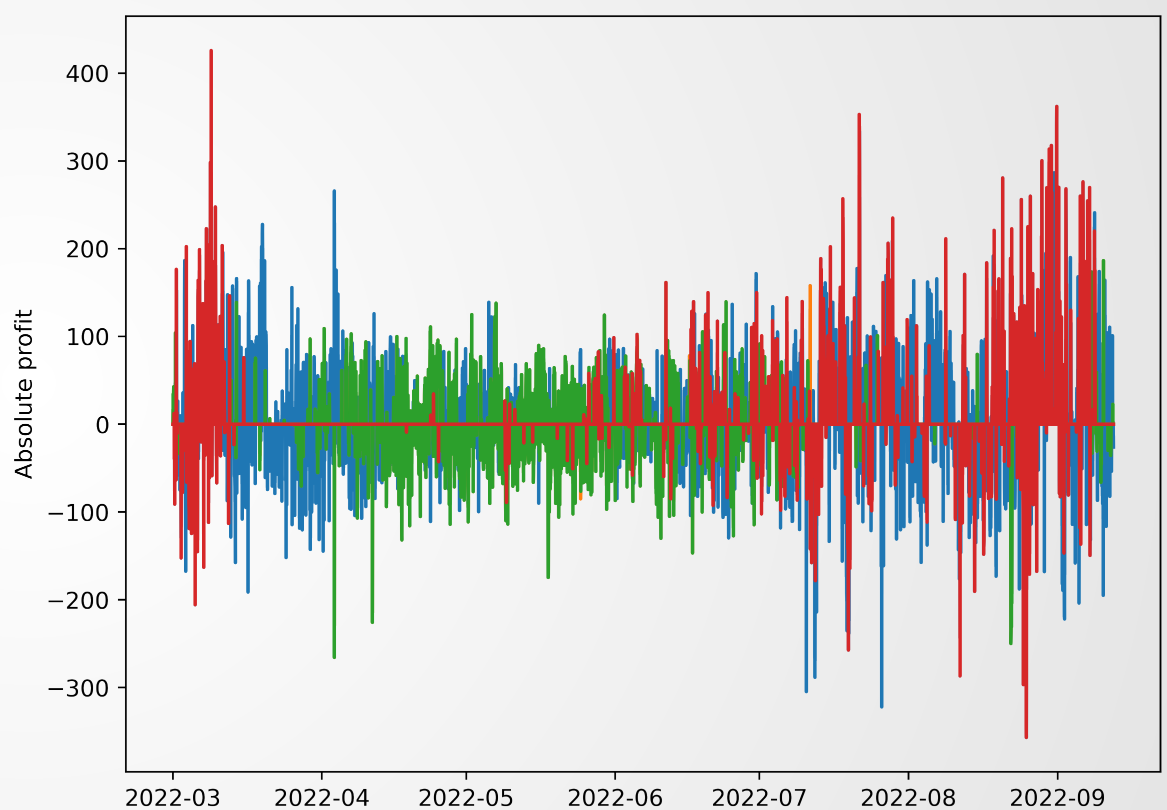
AV and Var are mean and variance of out-of-sample returns.



Trading results (LASSO QR)

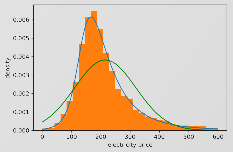


Cumulative wealth



Absolute gain/loss for each traded hour

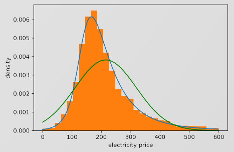
Mean, Median, Prob, Mean-CVaR



Trading results (LASSO QR)

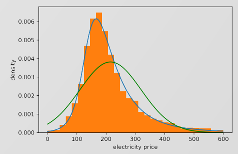
Strategy	AV	Var	Sharpe
Mean	0.0171	0.0531	0.3214
Median	−0.0128	0.0335	−0.3823
Prob	−0.0128	0.0332	−0.3838
Mean-CVaR	0.0119	0.0123	0.9641

AV and Var are mean and variance of out-of-sample returns.



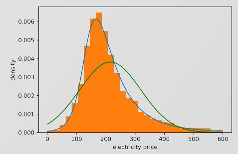
Conclusion

- DMLP version for multivariate case was created
  - for 3 prices via Johnson’s SU distribution
  - dependence accounted for (via Z-scores)
- Performance against two benchmarks
  - LSTM architecture does not outperform DMLP
  - LASSO QR outperforms (higher CRPS)
  - DMLP the best performing in terms of computational speed
- Trading performance between DMLP and QR is comparable (AV, Var, Sharpe)
- Four different investor objectives were tested: mean, median, probabilistic and risk-adjust (Mean-CVaR)



Future research

- Use quantile prediction with neural networks
- Use Gaussian copula instead of correlation matrix for Z-scores
- Outlier “smoothing” / removal
- Introduce batteries = energy storing
    - Observe changing results with changing battery efficiency



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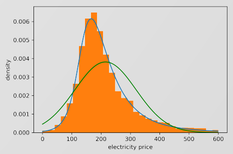

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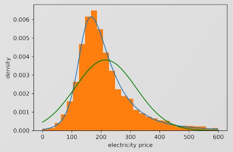

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