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Probabilistic Path Forecasting with Interpretable Scenario Selection and Its Application to Dynamic Trading in the German Continuous Intraday Market

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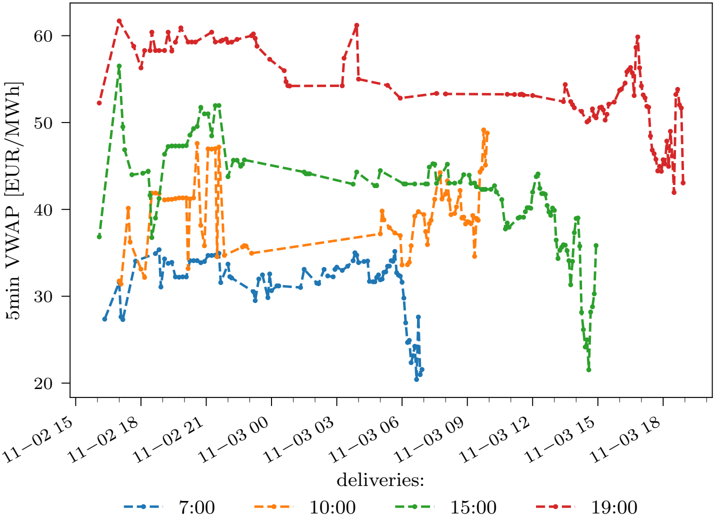
EFC Workshop

Quarter-hour continuous trading

Continuous trading for quarter-hourly deliveries:

- open from 16:00 on the day prior to the delivery,
- active up to 5 minutes before the delivery.

Price trajectories



Our goal

Train the model on data available in **expanding** windows

2019-01-02 - 2019-12-31, . . . ,
2019-01-02 - 2020-12-30

to predict 5min VWAPs between 185 and 30min before the delivery in **2020**.

Support Vector Regression (SVR)

The function used to predict new values for a feature vector $\boldsymbol{x}$ is given by a following formula

$$f(\boldsymbol{x}) = \sum_{i=1}^{N} \left(-\alpha_i + \alpha_i^*\right) K\left(\boldsymbol{x}_i, \boldsymbol{x}\right) + b.$$

Corrected Support Vector Regression (cSVR)

The correction kernel is based on an alternative forecast

$$K(\boldsymbol{x}_i, \boldsymbol{x}_j) = \exp\left(-l \left\|\boldsymbol{x}_i - \boldsymbol{x}_j\right\|\right) \exp\left(-g \left\|\hat{y}_i - \hat{y}_j\right\|^2\right),$$

This idea is drawn from observations on NTKs (Neural Tangent Kernels) and corresponding neural networks' performance S. Chen et al. 2020.

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corrected Support Vector Regression (cSVR)

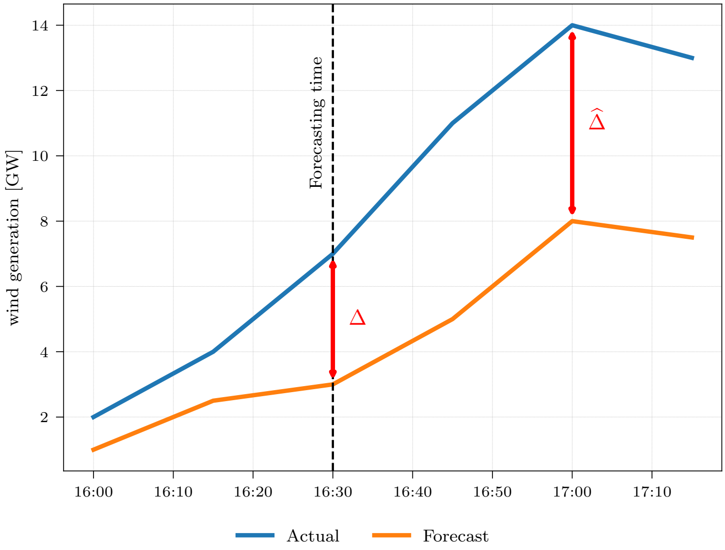
We showed that such a correction outperforms LASSO and RF in the point forecasting task on the same dataset Puć et al. 2024.

Extension to path forecasting

Following Tschora et al. 2022, we adapt cSVR to the multivariate case in two ways:

1. ChainSVR,
2. MultiSVR.

cSVR extension to probabilistic forecasting



cSVR extension to probabilistic forecasting

We use

$$\widehat{\delta} = \widehat{\Delta} - \Delta$$

to describe the **realized** change in the forecasting error of the day-ahead forecast.

In the forecasting step, we replace $\widehat{\delta}$ with historical scenarios (**solar, wind, and consumption - all from one day**), creating the probabilistic forecasts.

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Choosing from historical scenarios

How to choose daily scenarios from history?

1. take them all (**suboptimal?**),
2. density-based clustering (HDBSCAN),
3. Support Vectors Sorting (**SVS**),
4. Fast Forward Sorting, Heitsch et al. 2003.

Support Vectors Sorting

- Using the absolute values of dual coefficients $-\alpha_i + \alpha_i^*$ to sort the historical scenarios.
- Available after fitting the cSVR and used in the decision function

$$f(\boldsymbol{x}) = \sum_{i=1}^{N} (-\alpha_i + \alpha_i^*) K(\boldsymbol{x}_i, \boldsymbol{x}) + b.$$

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Stopping the iteration over scenarios?

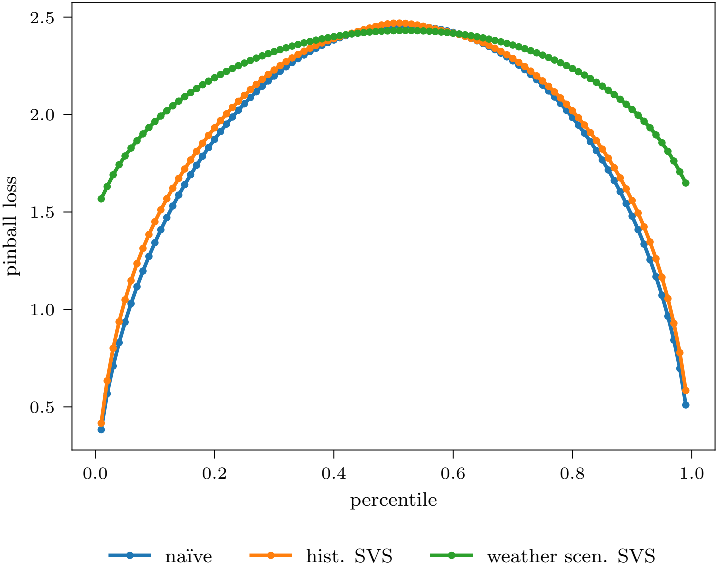
Given two probability mass functions u and v, the **first Wasserstein distance** using the Euclidean norm is

$$l_1(u, v) = \inf_{\pi \in \Gamma(u,v)} \int \|x - y\|_2 \, d\pi(x, y),$$

where:

- $\Gamma(u, v)$ - set of joint distributions on $\mathbb{R}^n \times \mathbb{R}^n$ with marginals u and v,
- $u(x)$ - probability mass at position x under u,
- $v(x)$ - probability mass at position x under v.

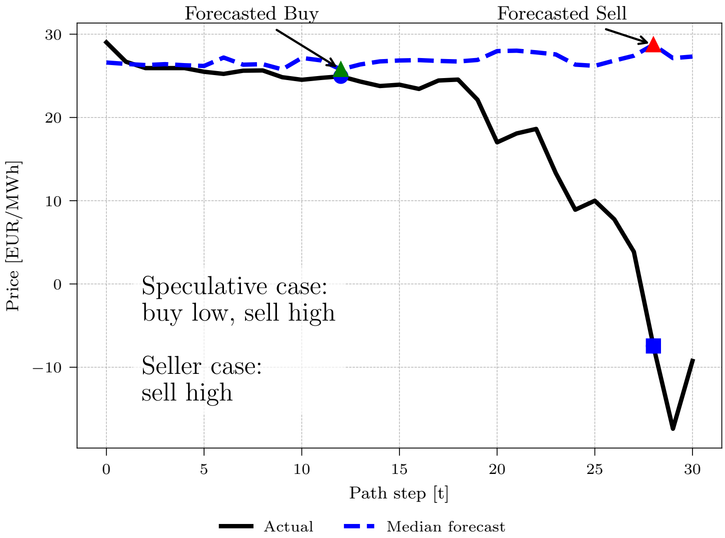
Pinball loss averaged over deliveries



Accuracy measures averaged over deliveries

measure	model setting	model	value
MAE	—	naïve	4.905
MAE	weather scenarios	Multi cSVR	4.855
MAE	weather scenarios, SVS	Multi cSVR	4.860
MAE	historical simulation, SVS	Multi cSVR	4.938
MAE	GAMLSS	—	6.601
CRPS	—	naïve	1.917
CRPS	historical simulation	Multi cSVR	2.015
CRPS	weather scenarios, SVS	Multi cSVR	2.207
CRPS	historical simulation, SVS	Multi cSVR	1.959
CRPS	GAMLSS	—	5.428

Trading strategies



Weighted median

Given

- ordered values $x_1, \ldots, x_n$,
- positive weights $w_1, \ldots, w_n$ (normalized so $\sum_i w_i = 1$),

is an x_k such that

$$\sum_{i=1}^{k-1} w_i \leqslant \tfrac{1}{2} \quad \text{and} \quad \sum_{i=k+1}^{n} w_i \leqslant \tfrac{1}{2}.$$

Weights Specification

Generalized normal distribution weighting

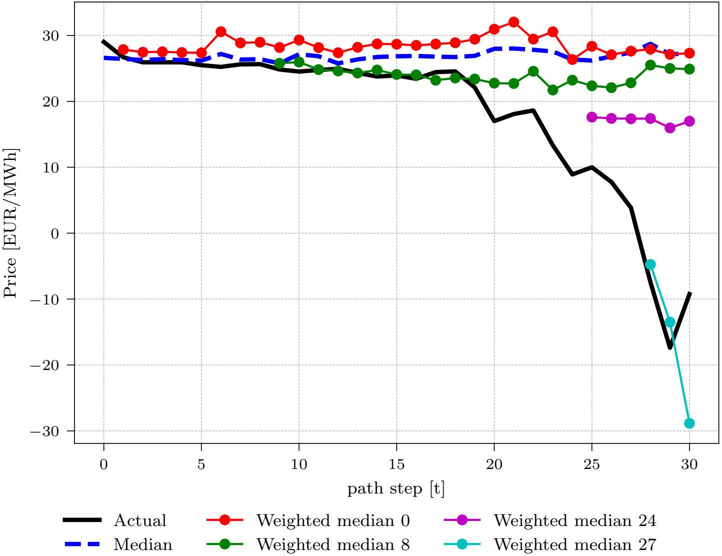
$$K(x) = \exp\left(-MAE_x \left(\sum_{t=1}^{T'} w_t |x_t - y_t|^2 \right)^{\frac{p}{2}} \right)$$

where x is a path scenario and w_t are the exponential decay weights

$$w_t = \frac{\exp\big(-\lambda(T' - t)\big)}{\sum_{s=1}^{T'} \exp\big(-\lambda(T' - s)\big)}.$$

Note the similarity to the Nadaraya-Watson estimator, used, e.g., in Morel et al. 2024.

Trading on the weighted median



Trading strategy simulation

Hyperparameters p, λ and **profit threshold** are optimized on the last 168 days of 2019.

We also simulate the risk-seeking (sell at the max of upper band) band-based strategy, J. Chen et al. 2025,

where the SCP level is also optimized in the calibration window.

Economic evaluation: trading with 1MW

strategy	model setting	model	profit [kEUR]	σ_d	profit/σ_d
SELLER					
baseline	—	naïve	1127	27.64	40754.23
baseline	historical scenarios, SVS	Multi cSVR	1135	27.07	41939.54
dynamic	—	naïve	1186	26.55	44654.84
dynamic	historical scenarios, SVS	Multi cSVR	1164	26.74	43539.58
bands	—	naïve	1092	23.59	43438.95
bands	historical scenarios	Multi cSVR	1114	27.13	41074.24
SPECULATOR					
baseline	—	naïve	46	20.51	2230.16
baseline	historical scenarios	Multi cSVR	67	18.47	3605.89
dynamic	—	naïve	48	20.20	2355.19
dynamic	historical scenarios	Multi cSVR	68	17.38	3914.49

strategy	σ_d	profit [kEUR]	profit/σ_d
sell at $t = 31$	19.09	1123	58835.20
sell at $t = 1$	16.30	1092	67035.97
buy at 0 sell at 31	12.41	30	2432.27
sell at 0 buy at 31	24.74	-30	—

Summary

1. Choosing a limited number of trajectories:
   - makes the forecast easier to interpret,
   - improves accuracy.
2. Dynamic re-weighting of the trajectories can improve both risk and profit of trading strategies.

Bibliography

Chen, Jieyu et al. (2025). *Probabilistic intraday electricity price forecasting using generative machine learning*. arXiv: 2506.00044 [stat.AP].

Chen, Shuxiao et al. (2020). "Label-aware neural tangent kernel: toward better generalization and local elasticity". In: *Proceedings of the 34th International Conference on Neural Information Processing Systems*. NIPS'20. Vancouver, BC, Canada: Curran Associates Inc. ISBN: 9781713829546.

Heitsch, Holger et al. (2003). "Scenario Reduction Algorithms in Stochastic Programming". In: *Computational Optimization and Applications* 24, pp. 187–206. DOI: 10.1023/A:1021805924152.

Morel, Rudy et al. (2024). "Path shadowing Monte Carlo". In: *Quantitative Finance* 24.9, pp. 1199–1225. DOI: 10.1080/14697688.2024.2399285. eprint: https://doi.org/10.1080/14697688.2024.2399285.

Puć, Andrzej et al. (2024). *Corrected Support Vector Regression for intraday point forecasting of prices in the continuous power market*. arXiv: 2411.16237 [stat.AP].

Tschora, Léonard et al. (2022). "Electricity price forecasting on the day-ahead market using machine learning". In: *Applied Energy* 313, p. 118752. ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2022.118752.

Forecasting study

1. 96 quarter-hour deliveries,
2. training on expanding windows,
3. generating paths of 31 steps of 5 min intervals, covering period from 185 to 30 min before the delivery,
4. 2020 used as a validation window,
5. 66 weather scenario variables from each day; 3 fundamentals, 11 steps, positive and negative impact,
6. stop adding support vector method and FFS sorted scenarios when the Wasserstein metric changes by less than 0.01 and at least 10 scenarios are added.

Forecasting study

Variables used:

1. RES and demand: forecast, last known actual and forecast error,
2. day-ahead of DE and all neighbouring countries and DE intra-day price,
3. all commercial actual and last known physical exchanges,
4. intraday price elasticity derived from the intra-day auction curves,
5. last known price differenced with horizons corresponding to all path steps,
6. last known total volume differenced with horizons corresponding to all path steps.