Probabilistic Forecasts of load and RES for Electricity Price Forecasting

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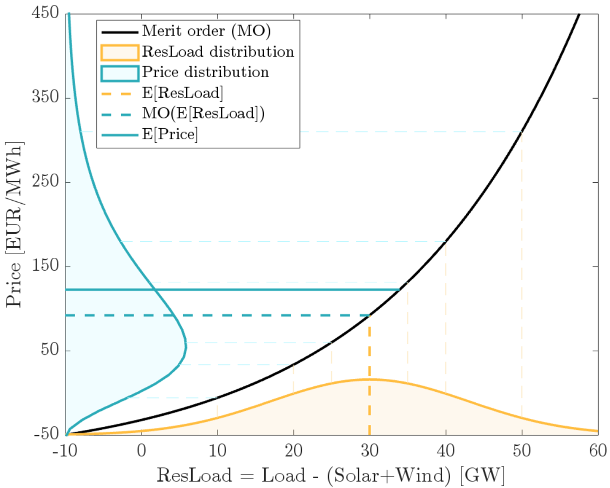
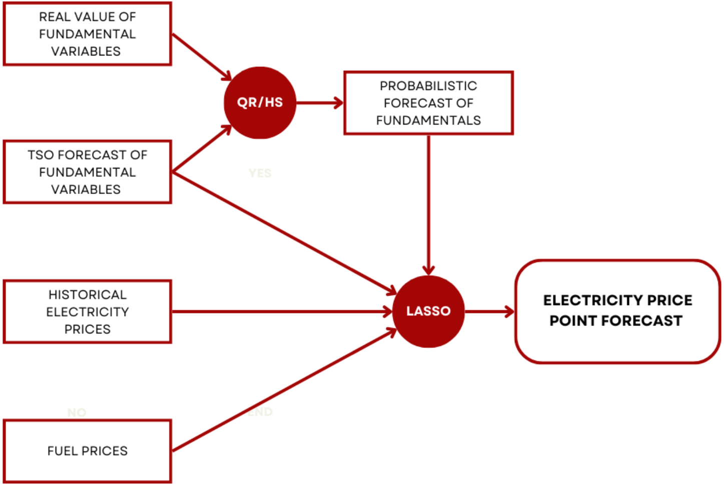
Motivation

- Electricity price are strongly depended on fundamentals
  - Load – positive impact on price
  - Solar generation – negative impact on price
  - Wind power generation – negative impact on price
- Load and RES generation is unknown until the start of the delivery hour
- Electricity price forecasting (EPF) model includes only the point forecasts of fundamentals

Why does it matter



Idea


REAL VALUE OF FUNDAMENTAL VARIABLES
TSO FORECAST OF FUNDAMENTAL VARIABLES
HISTORICAL ELECTRICITY PRICES
FUEL PRICES
QR/HS
PROBABILISTIC FORECAST OF FUNDAMENTALS
LASSO
ELECTRICITY PRICE POINT FORECAST

Historical simulation

$$\hat{q}_{\tau}^{\mathrm{HS}}(X_{d,h}) = \hat{X}_{d,h} + \hat{q}_{\tau}^{\mathrm{emp}}(\epsilon_{d,h}),$$

- $\hat{q}_{\tau}^{\mathrm{emp}}(\epsilon_{d,h})$ is the τ quantile of historical $\epsilon_{d,h}$.
- $\epsilon_{d,h} = \hat{X}_{d,h} - X_{d,h}$
- where $\hat{X}_{d,h}$ – TSO point forecast of fundamental variable

Conformal Prediction

$$\hat{q}_{\tau}^{\mathrm{CP}}(X_{d,h}) = \hat{X}_{d,h} + \mathrm{sign}(\tau - 0.5) \cdot \hat{q}^{\mathrm{emp}}_{|2\tau-1|}(\epsilon_{d,h}),$$

- $\hat{q}^{\mathrm{emp}}_{|2\tau-1|}(\epsilon_{d,h})$ is the $2\tau - 1$ quantile of historical $\epsilon_{d,h}$.
- $\epsilon_{d,h} = \hat{X}_{d,h} - X_{d,h}$
- where $\hat{X}_{d,h}$ – TSO point forecast of fundamental variable

Quantile regression

$$\hat{q}_{\tau}^{\mathrm{QR}}(X_{d,h}) = \beta_0 + \beta_1 \hat{X}_{d,h}$$

The estimator of $\boldsymbol{\beta}_q$ is:

$$\hat{\boldsymbol{\beta}} = \operatorname{argmin}\left\{ \sum_{d,h} \left(\epsilon_{d,h}\right)\left(q - \mathbb{1}_{\epsilon_{d,h}<0}\right) \right\}$$

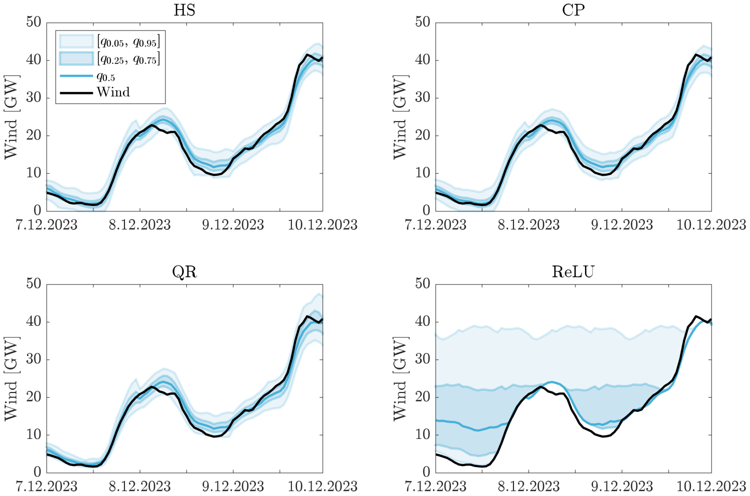
- $\epsilon_{d,h} = X_{d,h} - \beta_1 \hat{X}_{d,h} - \beta_0$
- where $\hat{X}_{d,h}$ – TSO point forecast of fundamental variable

ReLU-based transformation

$$\hat{q}_\tau^{\text{ReLU}}(x_{d,h}) = \max\{\hat{x}_{d,h}, \hat{q}_\tau^{\text{emp}}(\hat{x}_{d,h})\} = \\ \text{ReLU}(\hat{x}_{d,h} - \hat{q}_\tau^{\text{emp}}(\hat{x}_{d,h})) + \hat{q}_\tau^{\text{emp}}(\hat{x}_{d,h})$$

- $\hat{q}_\tau^{\text{emp}}(\hat{X}_{d,h})$ is the τ quantile of $\hat{X}_{d,h}$
- where $\hat{X}_{d,h}$ – TSO point forecast of fundamental variable

Comparison of probabilistic methods



Benchmark model

$$
\begin{aligned}
p_{d,h} = {} & \beta_1 p_{d-1,h} + \beta_2 p_{d-2,h} + \beta_3 p_{d-7,h} + \beta_4 p_{d-1,24} + \\
& + \beta_5 p^{min}_{d-1} + \beta_6 p^{max}_{d-1} + \beta_7 L^{TSO}_{d,h} + \beta_8 W^{TSO}_{d,h} + \beta_9 S^{TSO}_{d,h} + \\
& + \beta_{10} EUA^{close}_{d-2} + \beta_{11} Gas^{close}_{d-2} + \beta_{12} Oil^{close}_{d-2} + \beta_{13} Coal^{close}_{d-2} \\
& + \sum_{i=1}^{7} \beta_{13+i} D_i + \varepsilon_{d,h}
\end{aligned}
\tag{1}
$$

$S^{TSO}_{d,h}$ is included only for hours for which at least 75% of the observations in the calibration window are different from 0.

Models

Possible base model extensions:

Load: $(1) + \sum_{\tau \in \mathcal{T}} \phi_\tau L^\tau_{d,h}$

Solar: $(1) + \sum_{\tau \in \mathcal{T}} \phi_\tau S^\tau_{d,h}$

Wind: $(1) + \sum_{\tau \in \mathcal{T}} \phi_\tau W^\tau_{d,h}$

RES[1]: $(1) + \sum_{\tau \in \mathcal{T}} \phi_\tau RES^\tau_{d,h}$

ResLoad[2]: $(1) + \sum_{\tau \in \mathcal{T}} \phi_\tau ResLoad^\tau_{d,h}$

Load, RES: $(1) + \sum_{\tau \in \mathcal{T}} \phi_\tau L^\tau_{d,h} + \sum_{\tau \in \mathcal{T}} \psi_\tau RES^\tau_{d,h}$

Load, Solar, Wind: $(1) + \sum_{\tau \in \mathcal{T}} \phi_\tau L^\tau_{d,h} + \sum_{\tau \in \mathcal{T}} \psi_\tau S^\tau_{d,h} + \sum_{\tau \in \mathcal{T}} \gamma_\tau W^\tau_{d,h}$

[1] Solar + Wind
[2] Load - (Solar + Wind)

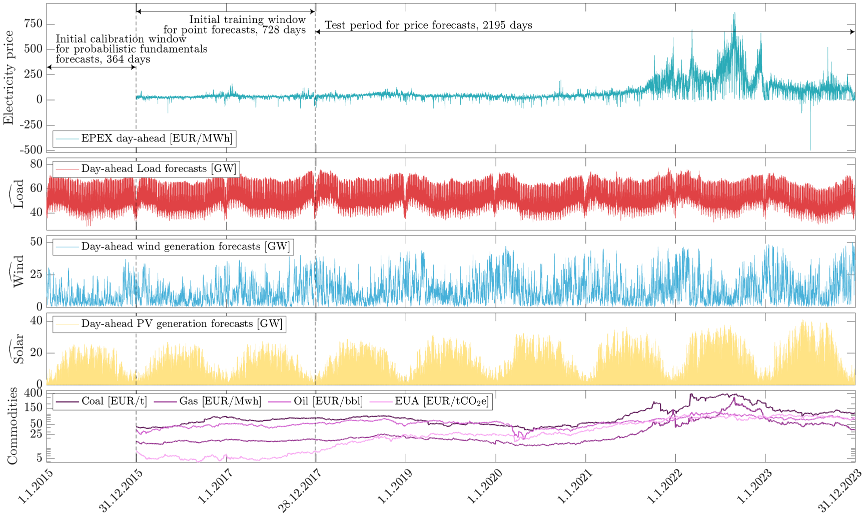
Models

Possible base model extensions:

$$
\begin{aligned}
\mathcal{T}_5 &= \{\gamma, 0.1, 0.5, 0.9, 1-\gamma\},\\
\mathcal{T}_7 &= \{\gamma, 0.1, 0.3, 0.5, 0.7, 0.9, 1-\gamma\},\\
\mathcal{T}_{11} &= \{\gamma, 0.1, 0.2, \ldots, 0.9, 1-\gamma\},\\
\mathcal{T}_{21} &= \{\gamma, 0.05, 0.1, \ldots, 0.95, 1-\gamma\},\\
\mathcal{T}_{51} &= \{\gamma, 0.02, 0.04, \ldots, 0.98, 1-\gamma\},\\
\mathcal{T}_{101} &= \{\gamma, 0.01, 0.02, \ldots, 0.99, 1-\gamma\},\\
\mathcal{T}_{201} &= \{\gamma, 0.005, 0.01, \ldots, 0.995, 1-\gamma\},
\end{aligned}
$$

where $\gamma = \frac{1}{2N}$, $N = 364$ is the length of the calibration window

Test ground


Initial training window
for point forecasts, 728 days
Test period for price forecasts, 2195 days
Initial calibration window
for probabilistic fundamentals
forecasts, 364 days
Electricity price
750
500
250
0
-250
-500
EPEX day-ahead [EUR/MWh]
Day-ahead Load forecasts [GW]
Load
80
60
40
Day-ahead wind generation forecasts [GW]
Wind
50
25
0
Day-ahead PV generation forecasts [GW]
Solar
40
20
0
Commodities
400
150
50
25
5
Coal [EUR/t]
Gas [EUR/Mwh]
Oil [EUR/bbl]
EUA [EUR/tCO2e]
1.1.2015
31.12.2015
1.1.2017
28.12.2017
1.1.2019
1.1.2020
1.1.2021
1.1.2022
1.1.2023
31.12.2023

Probabilistic forecast of fundamental variables

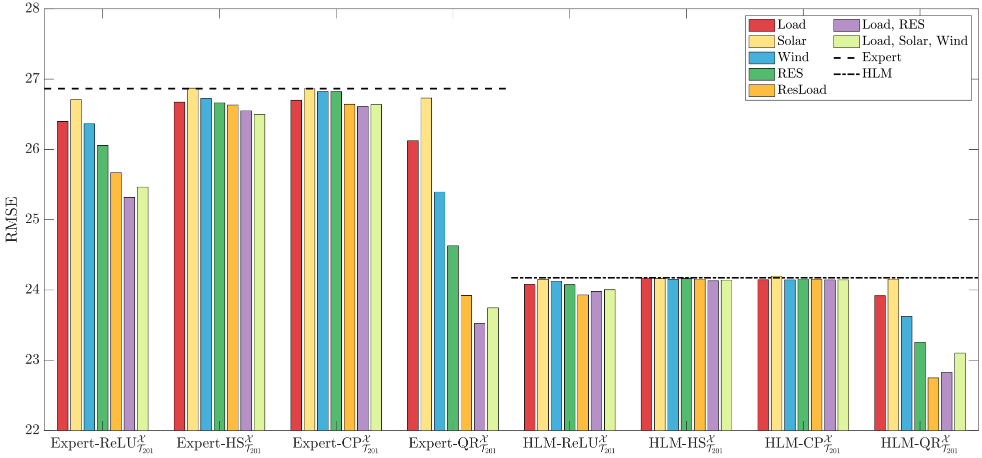
Aggregated pinball score

	Load	Solar	Wind	RES	ResLoad
HS	0.6275*	0.1329*	0.4286*	0.4744*	0.7954*
CP	0.7730*	0.1331*	0.4296*	0.4755*	0.9071*
QR	**0.6103**	**0.1301**	**0.4160**	**0.4676**	**0.7869**

$$\text{Pinball}^{\tau}_{d,h} = \begin{cases} (1-\tau)\left(\hat{q}_{\tau}(X_{d,h}) - X_{d,h}\right) & \text{for } X_{d,h} < \hat{q}_{\tau}(X_{d,h}), \\ \tau\left(X_{d,h} - \hat{q}_{\tau}(X_{d,h})\right) & \text{for } X_{d,h} \geq \hat{q}_{\tau}(X_{d,h}), \end{cases}$$

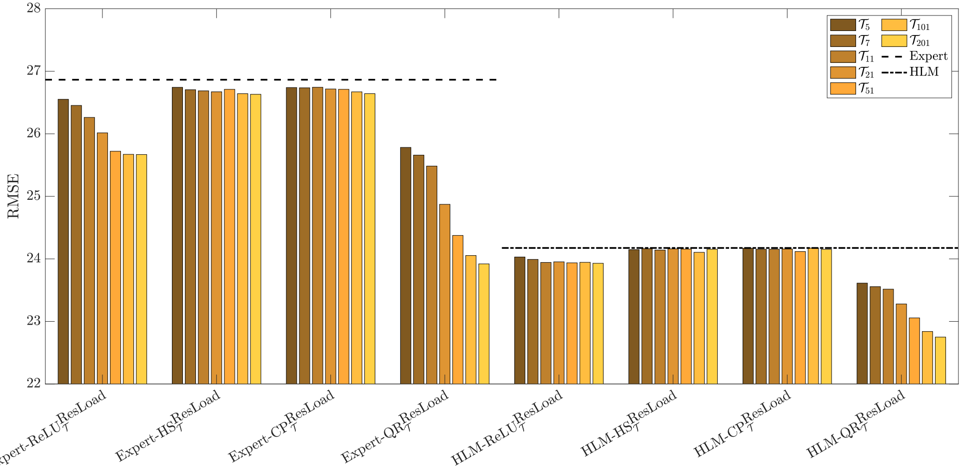
Results

Comparison of different sets of fundamental variable



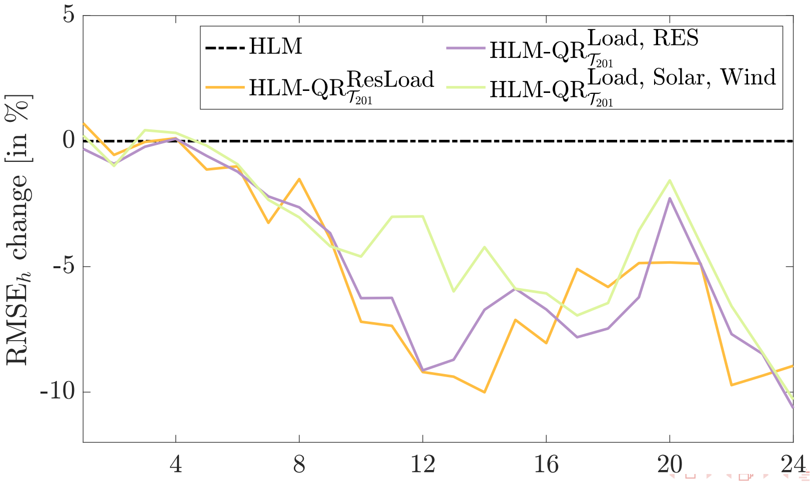
Results

Comparison of different number of quantiles



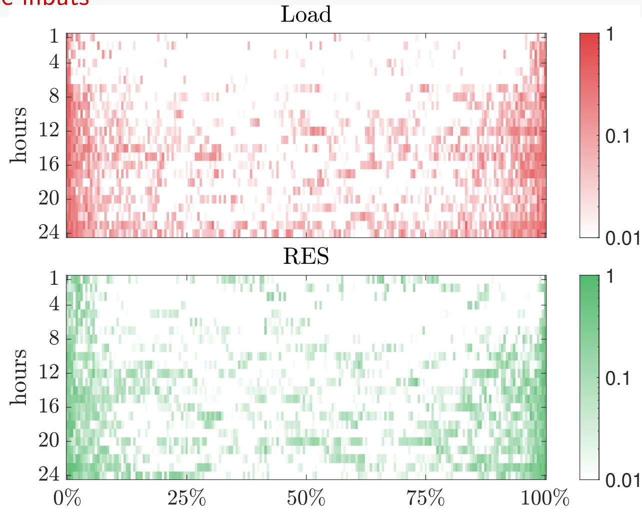
Results

Performance improvement over hours



Results

Selection of probabilistic inputs



Contribution and conclusions

- Probabilistic inputs enhance the accuracy of electricity price point predictions
- Best performing model includes 201 percentiles forecast of load and RES generation
- Probabilistic inputs are selected more often for afternoon/evening hours
- Extreme quantiles forecasts are usually remains in final model