Improving probabilistic wind power forecasting: A novel nonlinear and online combination method

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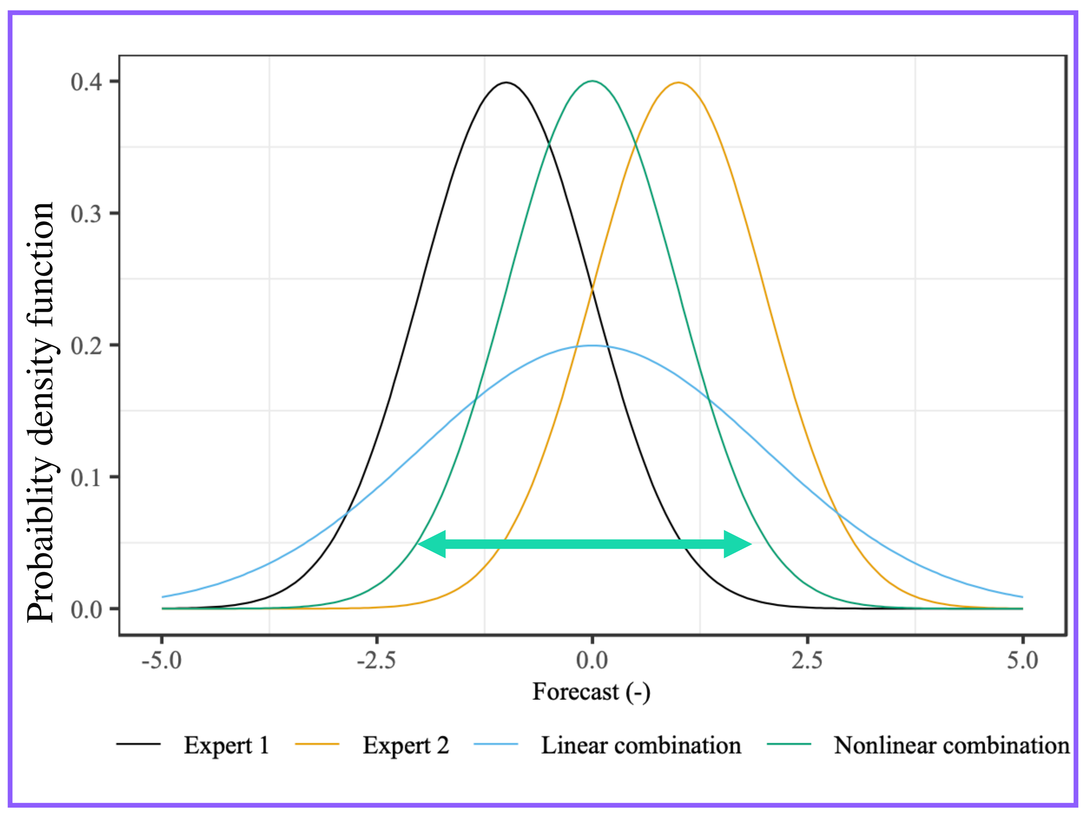
Motivation

The combination of multiple forecasts (generated by different combinations of regression models and NWP inputs) outperforms individual forecasts, but:

- The state of the art linear combination of calibrated probabilistic forecasts increases dispersion → miscalibration
- The accuracy of component forecasts varies over time



Goal: Mitigating dispersed probabilistic forecasts through nonlinear and online combination of component forecasts

Methodology

Three steps to combine component probabilistic forecasts $\{\hat{F}_j, j \in 1 \dots m\}$

I. Non-linear transformation → **II. CRPS gradient** → **III. Online convex optimization**

I. Non-linear transformation

Beta-transformed Linear Pool (BLP)

$$\hat{F}(y) = I_{a,b}\left(\sum_{j=1}^{m} w_j \hat{F}_j(y)\right)$$

II. CRPS gradient

Partial derivatives derived for:

- combination weights
- transformation parameters

$$\nabla \mathrm{CRPS}(\hat{F}_{a,b}, y) = \left(\frac{\partial \mathrm{CRPS}}{\partial a}, \frac{\partial \mathrm{CRPS}}{\partial b}, \frac{\partial \mathrm{CRPS}}{\partial w_1}, \dots, \frac{\partial \mathrm{CRPS}}{\partial w_m}\right)$$

III. Online convex optimization

- CRPS is exp-concave → Online Newton Step (ONS)
- Projection to ensure weights sum to 1

Algorithm 1: Online Newton step (Hazan, 2021; Wintenberger, 2021)

Data: convex set $\mathcal{K}$, T, $\boldsymbol{x}_1 \in \mathcal{K} \subseteq \mathbb{R}^n$, parameters $\gamma, \eta > 0$, $\boldsymbol{A}_0 = 1/\gamma^2 \boldsymbol{I}_n$, $\boldsymbol{A}_0^{-1} = \gamma^2 \boldsymbol{I}_n$
for $t \leftarrow 1$ **to** T **do**
  Play $\boldsymbol{x}_t$ and observe cost $f_t(\boldsymbol{x}_t)$;
  $\boldsymbol{A}_t = \boldsymbol{A}_{t-1} + \nabla_t \nabla_t^\top$;
  $\boldsymbol{A}_t^{-1} = \boldsymbol{A}_{t-1}^{-1} - \frac{\boldsymbol{A}_{t-1}^{-1} \nabla_t \nabla_t^\top \boldsymbol{A}_{t-1}^{-1}}{1 + \nabla_t^\top \boldsymbol{A}_{t-1}^{-1} \nabla_t}$;
  Newton step: $\boldsymbol{y}_{t+1} = \boldsymbol{x}_t - \eta \frac{1}{\gamma} \boldsymbol{A}_t^{-1} \nabla_t$;
  Projection (weights only) with weighted norm $\|\cdot\|_{d_t}$: $\boldsymbol{x}_{t+1} = \frac{1}{2} \arg\min_{\boldsymbol{x} \in \mathcal{K}} \|\boldsymbol{x} - \boldsymbol{y}_{t+1}\|_{d_t}^2$
end

Case Study

16 MW Wind farm in France, 2018-09 / 2019-10, 15 min resolution

Grid-search to tune hyperparameters of forecasting models (rolling) & ONS (4-months validation/ 8-months testing)

9 separate forecasts: 3 ML models (QRF, QR, GBM) x 3 NWP input components (ECMWF, GFS, Météo-France (MF))

Linear combination benchmarks: $\hat{F}(y) = \sum_{j=1}^{m} w_j \hat{F}_j(y).$

- Opinion Linear Pool (OLP): $w_j = \frac{1}{m}, \forall j \in 1 \dots m$
- Traditional Linear Pool (TLP): w_j optimized w.r.t the score

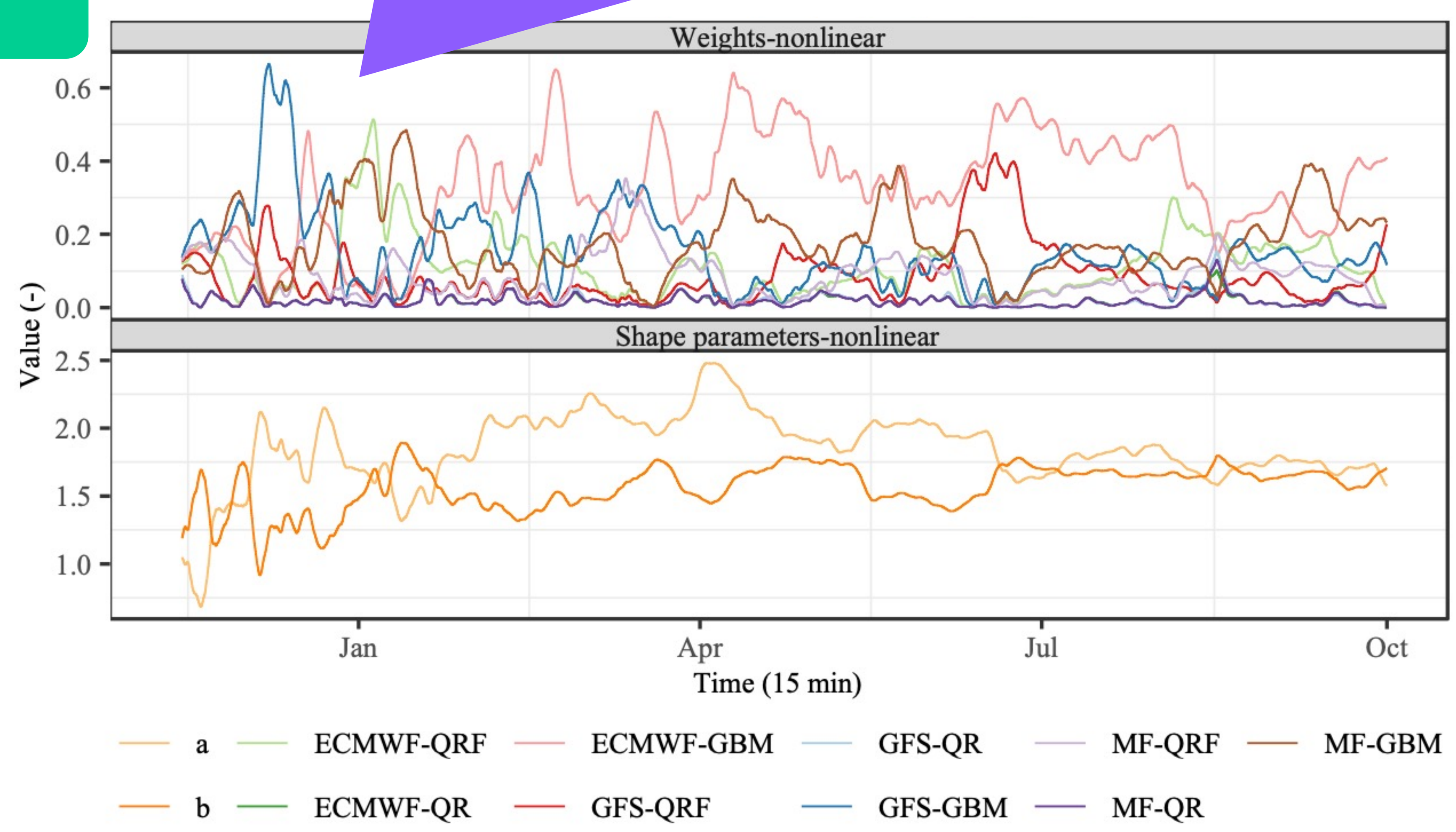
Results

CRPS improvement: 1.5% (15 min ahead) to 7.5% (24 h ahead) and improved calibration, vs best expert (GBM – ECMWF)

	Post-process model	CRPS mean ± standard deviation, per horizon			
		15 min	3 h	6 h	24 h
ECMWF	QRF	2.63±3.17	6.35±6.46	6.73±6.70	7.16±6.79
	QR	2.66±3.43	8.59±8.44	10.85±9.64	13.16±11.82
	GBM	2.61±3.29	6.68±6.40	6.51±6.57	6.61±6.85
GFS	QRF	2.65±3.14	7.09±7.00	7.73±7.39	8.50±7.81
	QR	2.65±3.41	8.58±8.36	10.81±9.6	13.13±11.69
	GBM	2.62±3.29	7.32±6.76	7.52±7.14	7.96±7.73
MF	QRF	2.64±3.15	6.51±6.43	6.89±6.60	7.68±7.29
	QR	2.66±3.44	8.59±8.43	10.82±9.61	13.06±11.69
	GBM	2.61±3.30	6.86±6.31	6.76±6.42	7.14±7.18
Combination	OLP	2.59±3.23	6.81±6.27	7.28±6.19	7.85±6.25
	TLP	2.59±3.19	6.26±5.92	6.35±5.85	6.46±5.94
	TLP*	2.59±3.21	6.16±5.94	6.23±5.87	6.34±6.13
	BLP	**2.57±3.27**	**6.07±6.37**	**6.02±6.14**	**6.21±6.08**
	BLP*	2.58±3.29	6.08±6.23	6.33±6.35	6.36±6.24

*: Optimal combination parameters in hindsight

Several models are relevant in the combination, and their relevance changes over time



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