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

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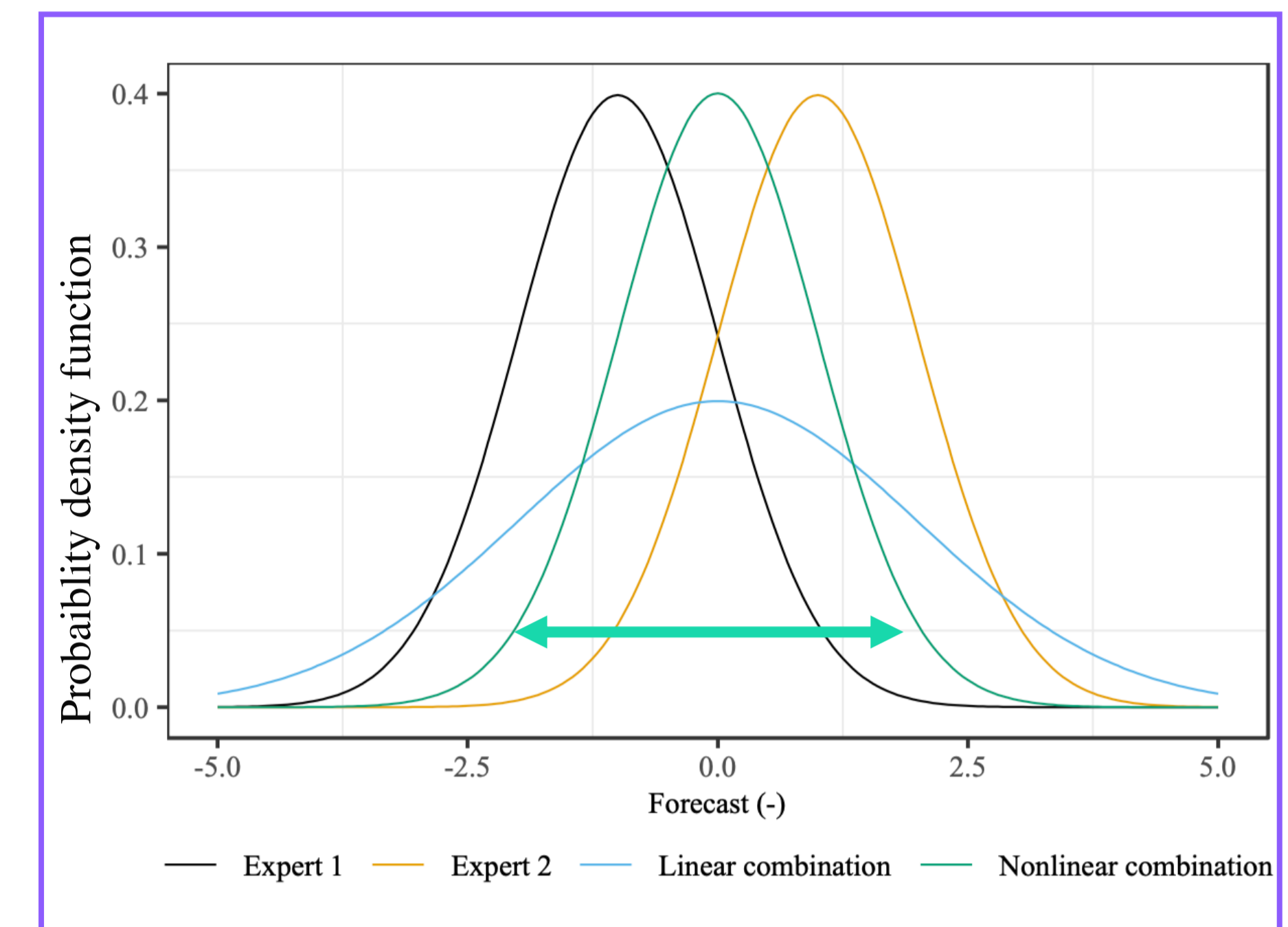
## Motivation

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  $\{\hat{F}_j, j \in 1 \dots m\}$



Beta-transformed Linear Pool (BLP)

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

Partial derivatives derived for:

- combination weights
- transformation parameters

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

- 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  $\mathcal{K}$ ,  $T$ ,  $\mathbf{x}_1 \in \mathcal{K} \subseteq \mathbb{R}^n$ , parameters  $\gamma, \eta > 0$ ,  $\mathbf{A}_0 = 1/\gamma^2 \mathbf{I}_n$ ,  $\mathbf{A}_0^{-1} = \gamma^2 \mathbf{I}_n$ 
for  $t \leftarrow 1$  to  $T$  do
  Play  $\mathbf{x}_t$  and observe cost  $f_t(\mathbf{x}_t)$ ;
   $\mathbf{A}_t = \mathbf{A}_{t-1} + \nabla_t \nabla_t^T$ ;
   $\mathbf{A}_t^{-1} = \mathbf{A}_{t-1}^{-1} - \frac{\mathbf{A}_{t-1}^{-1} \nabla_t \nabla_t^T \mathbf{A}_{t-1}^{-1}}{1 + \nabla_t^T \mathbf{A}_{t-1}^{-1} \nabla_t}$ ;
  Newton step:  $\mathbf{y}_{t+1} = \mathbf{x}_t - \eta \frac{1}{\gamma} \mathbf{A}_t^{-1} \nabla_t$ ;
  Projection (weights only) with weighted norm  $\|\cdot\|_{\mathbf{A}_t}$ :  $\mathbf{x}_{t+1} = \frac{1}{2} \arg \min_{\mathbf{x} \in \mathcal{K}} \|\mathbf{x} - \mathbf{y}_{t+1}\|_{\mathbf{A}_t}^2$ 
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	Forecasting model	CRPS mean $\pm$ standard deviation, per horizon			
		15 min	3 h	6 h	24 h
ECMWF	QRF	2.63 $\pm$ 3.17	6.35 $\pm$ 6.46	6.73 $\pm$ 6.70	7.16 $\pm$ 6.79
	QR	2.66 $\pm$ 3.43	8.59 $\pm$ 8.44	10.85 $\pm$ 9.64	13.16 $\pm$ 11.82
	GBM	2.61 $\pm$ 3.29	6.68 $\pm$ 6.40	6.51 $\pm$ 6.57	6.61 $\pm$ 6.85
GFS	QRF	2.65 $\pm$ 3.14	7.09 $\pm$ 7.00	7.73 $\pm$ 7.39	8.50 $\pm$ 7.81
	QR	2.65 $\pm$ 3.41	8.58 $\pm$ 8.36	10.81 $\pm$ 9.6	13.13 $\pm$ 11.69
	GBM	2.62 $\pm$ 3.29	7.32 $\pm$ 6.76	7.52 $\pm$ 7.14	7.96 $\pm$ 7.73
MF	QRF	2.64 $\pm$ 3.15	6.51 $\pm$ 6.43	6.89 $\pm$ 6.60	7.68 $\pm$ 7.29
	QR	2.66 $\pm$ 3.44	8.59 $\pm$ 8.43	10.82 $\pm$ 9.61	13.06 $\pm$ 11.69
	GBM	2.61 $\pm$ 3.30	6.86 $\pm$ 6.31	6.76 $\pm$ 6.42	7.14 $\pm$ 7.18
Combination	OLP	2.59 $\pm$ 3.23	6.81 $\pm$ 6.27	7.28 $\pm$ 6.19	7.85 $\pm$ 6.25
	TLP	2.59 $\pm$ 3.19	6.26 $\pm$ 5.92	6.35 $\pm$ 5.85	6.46 $\pm$ 5.94
	TLP*	2.59 $\pm$ 3.21	6.16 $\pm$ 5.94	6.23 $\pm$ 5.87	6.34 $\pm$ 6.13
	BLP	2.57 $\pm$ 3.27	6.07 $\pm$ 6.37	6.02 $\pm$ 6.14	6.21 $\pm$ 6.08
	BLP*	2.58 $\pm$ 3.29	6.08 $\pm$ 6.23	6.33 $\pm$ 6.35	6.36 $\pm$ 6.24

Optimal combination parameters in hindsight

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

