



HAL
open science

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

Georges Kariniotakis, Dennis van Der Meer, Simon Camal

► To cite this version:

Georges Kariniotakis, Dennis van Der Meer, Simon Camal. Improving probabilistic wind power forecasting: A novel nonlinear and online combination method. 7th International Conference Energy & Meteorology (ICEM 2023), Jun 2023, Padoue, Italy. . hal-04217568

HAL Id: hal-04217568

<https://hal.science/hal-04217568>

Submitted on 25 Sep 2023

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

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

George Kariniotakis

MINES Paris PSL, Centre PERSEE, France

Dennis VAN DER MEER

MINES Paris PSL, Centre PERSEE, France

Simon CAMAL

MINES Paris PSL, Centre PERSEE, France

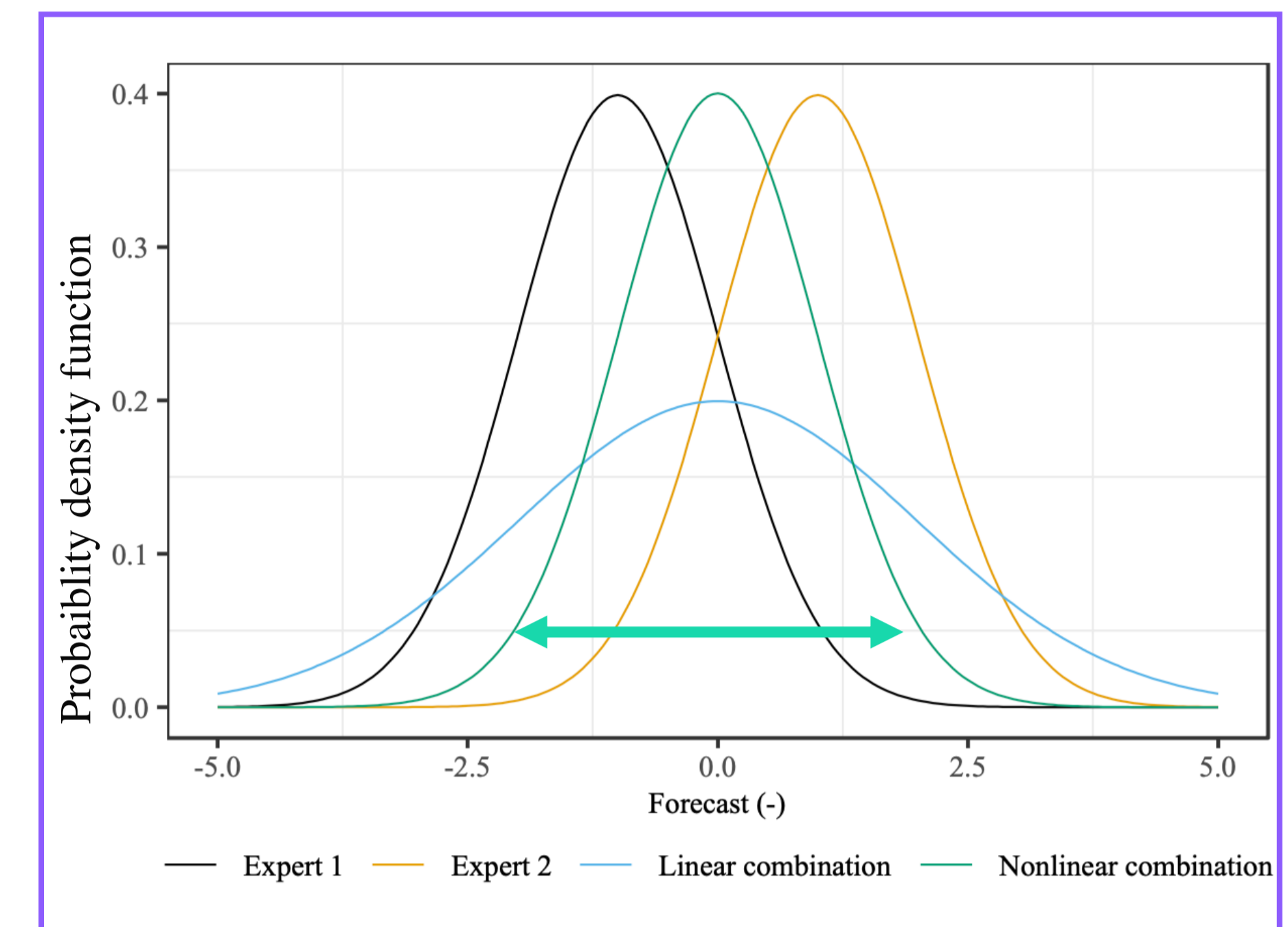
Motivation

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**

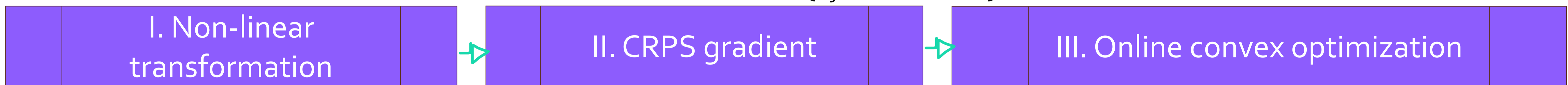
Goal:

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±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

