



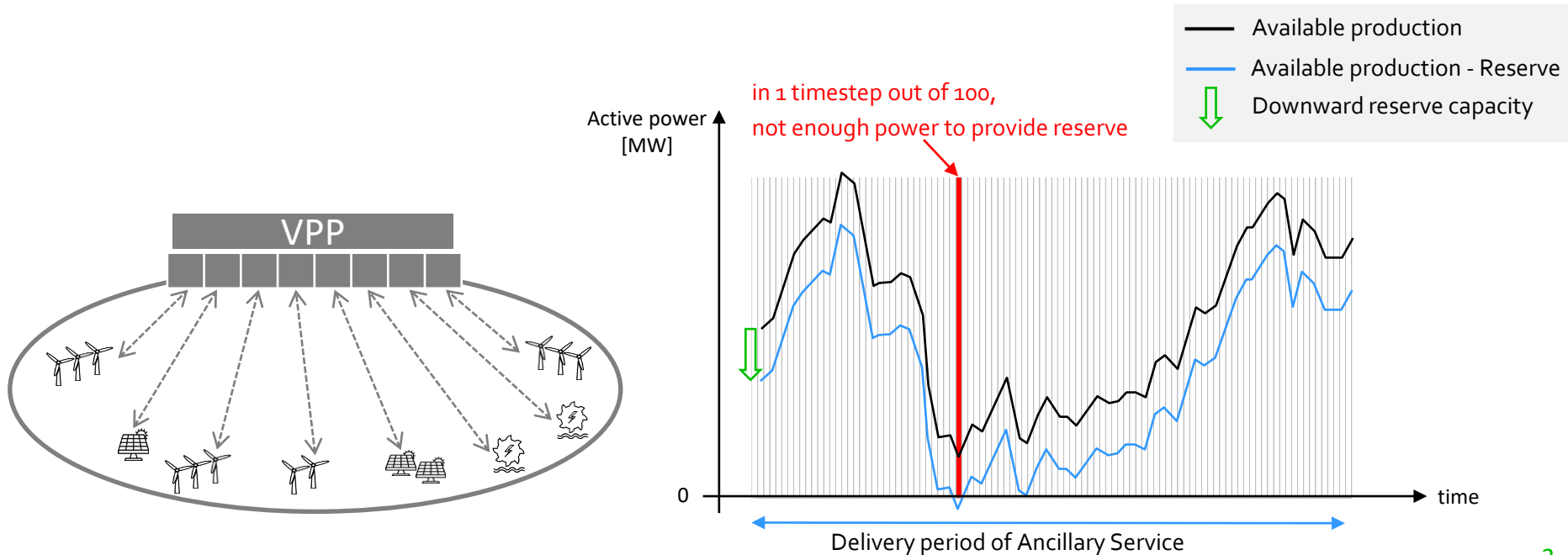
Forecasting extreme productions of a renewable Virtual Power Plant

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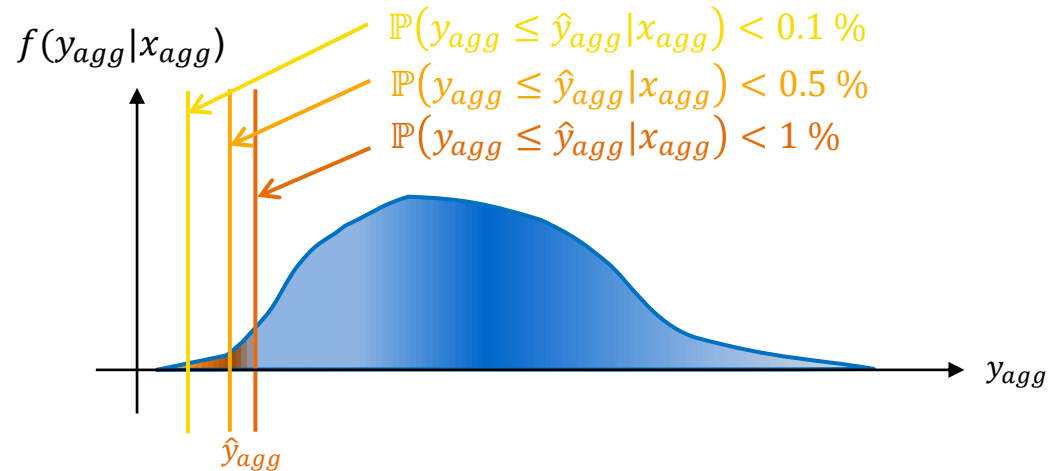
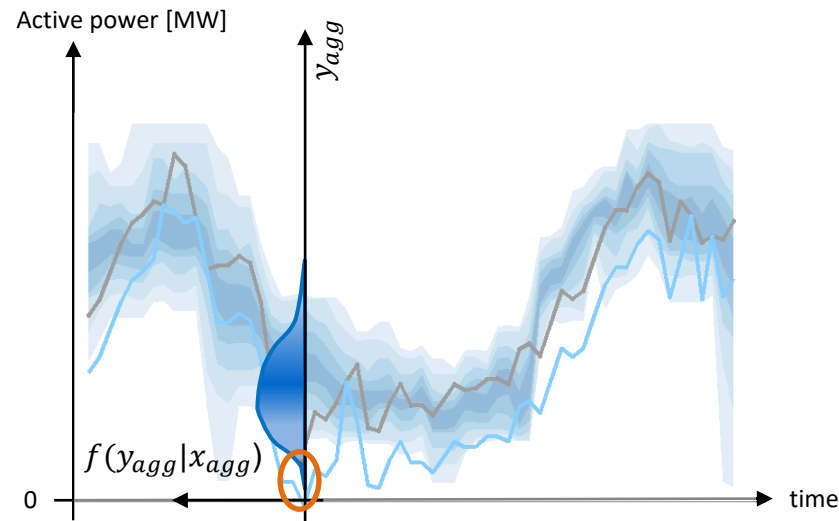
- Motivation
- Methodology
- Case Study
- Results
- Conclusion

- A renewable Virtual Power Plant (VPP) offers reserve to the grid
 - The ancillary service offers should be reliable more than 99% of the time



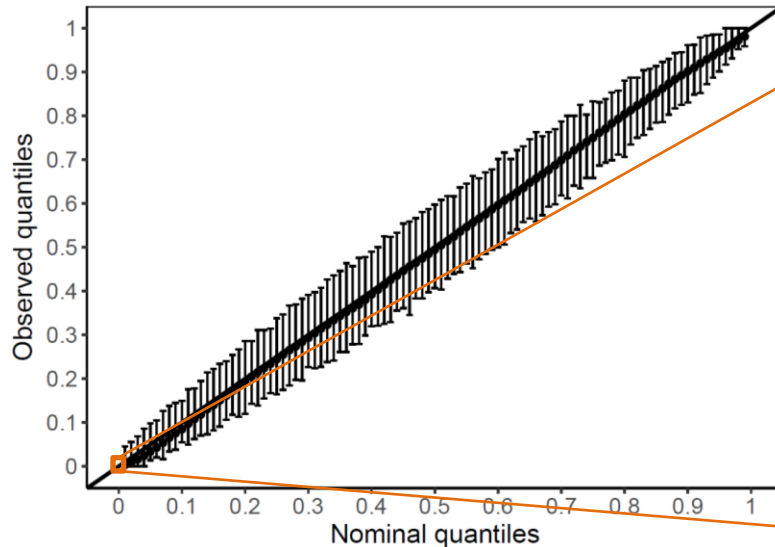
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Challenge: Forecast extremely low quantiles of aggregated productions of a VPP



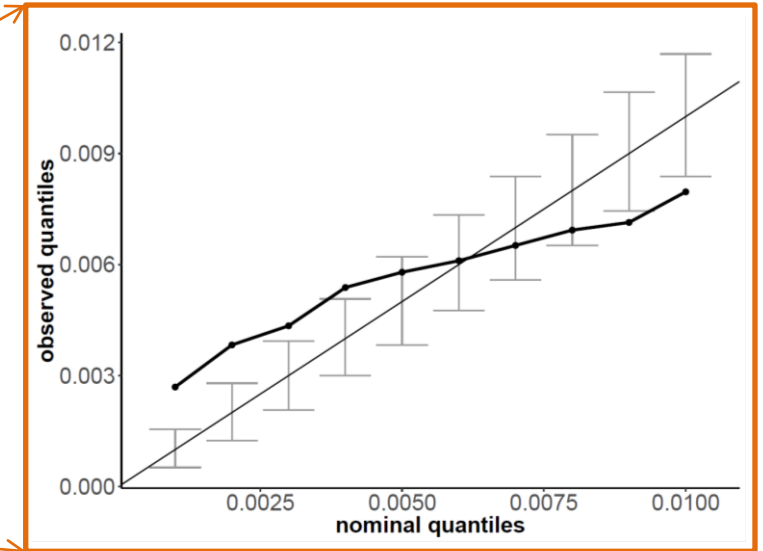
- Problem: Usual regression models lack sensitivity on tails of distributions
 - Quantile Regression Forests on a renewable VPP production

Adequate reliability on quantiles 1.0% - 99.0%

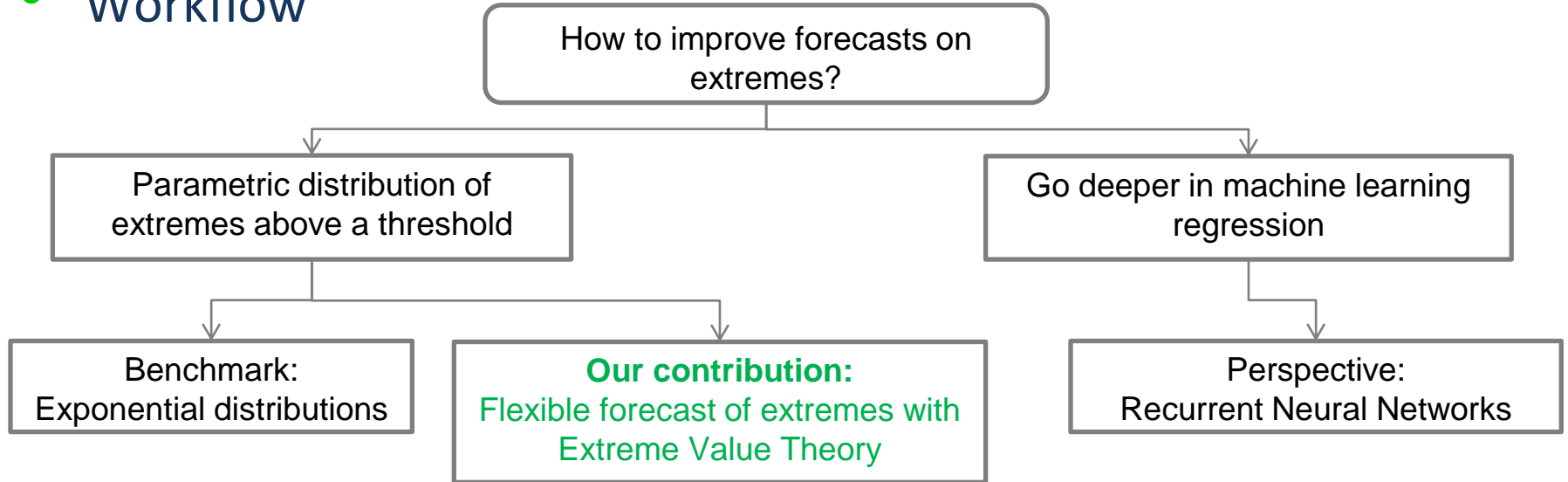


[Camal, Kariniotakis, Michiorri 18]

Unsatisfactory reliability on quantiles 0.1%-0.9%



- Workflow



- Assumptions

- Day-ahead horizon (24h-48h): response influenced only by NWP
- Direct forecast of aggregated production is adequate to capture extremes

- **Benchmark: exponential distribution**

Deviations z_t from a forecast quantile $\hat{y}_t^{(\alpha_{lim})}$ modelled by exponential:

$$z_t = [\hat{y}_t^{(\alpha_{lim})} - y_t]^+, \quad f(z) = \lambda e^{-\lambda z}$$

Baseline approach by unconditional model:

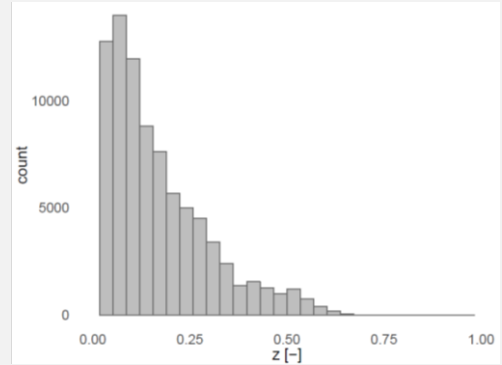
$$\hat{\lambda} = \frac{1}{\frac{1}{N} \sum_{i=1}^N z_i}$$

We choose a conditional model on clusters of expected production level

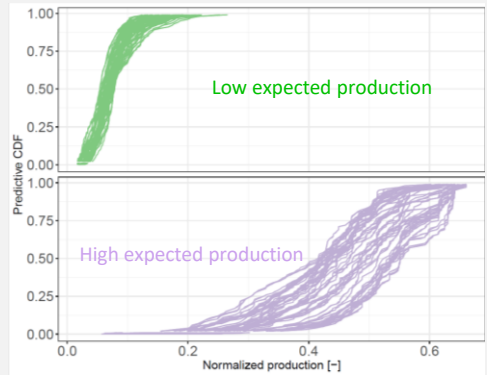
$$\hat{\lambda}_k = \frac{1}{\frac{1}{N} \sum_{i=1}^N z_i \mathbf{1}_{\{\hat{y}_i^{(50\%)} \in I_k\}}}, \quad \forall k \in K \text{ [Matos 16]}$$

Limit: difficult to capture fat tails present in the aggregated renewable production process

Distribution of deviations from 1% quantile forecast of a Wind-PV VPP



Forecast classified by production level

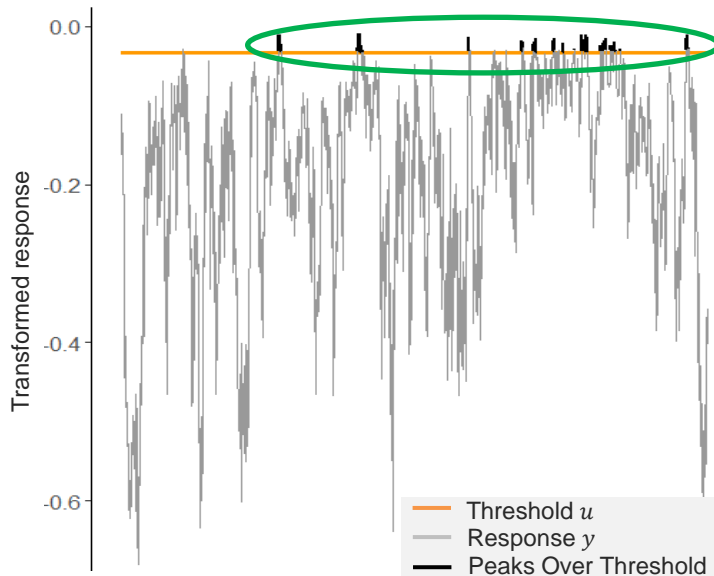


- **Extreme Value Theory: Formulation**

Based on maxima, therefore we transform the clusterized response: $y = -y_{agg} \in [-1,0]$

Regression on Peaks over Threshold u , equal to k -highest value of y

Assumption: peaks are iid and stationary

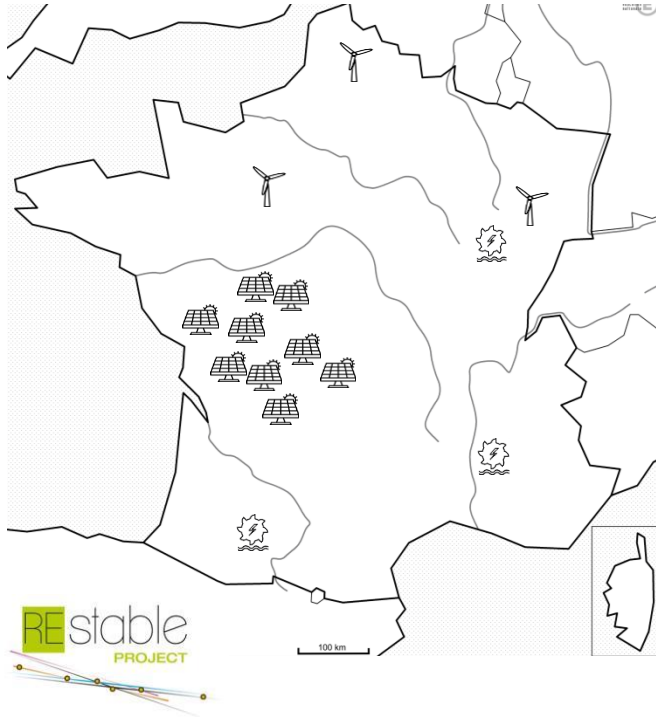


Peaks follow a Generalized Pareto Distribution

$$F_y^{-1}(\alpha|x) = u + \frac{\sigma(x)}{\gamma} \left(\frac{(1 - F_y(u|x))^\gamma}{1 - \alpha} \right)$$

- scale σ depends linearly on covariates x .
- shape γ qualifies the tail behaviour, assumed to be a constant characteristic of production

- Extreme Value Theory: application
 - Logit transform of aggregated production
 - to ease discrimination on extremes
 - Conditioning by NWP
 - mean and amplitude of weather variables between plants of same energy source
 - Inference of parameters by Maximum Likelihood Estimation



- **Wind-PV-Hydro VPP in France**

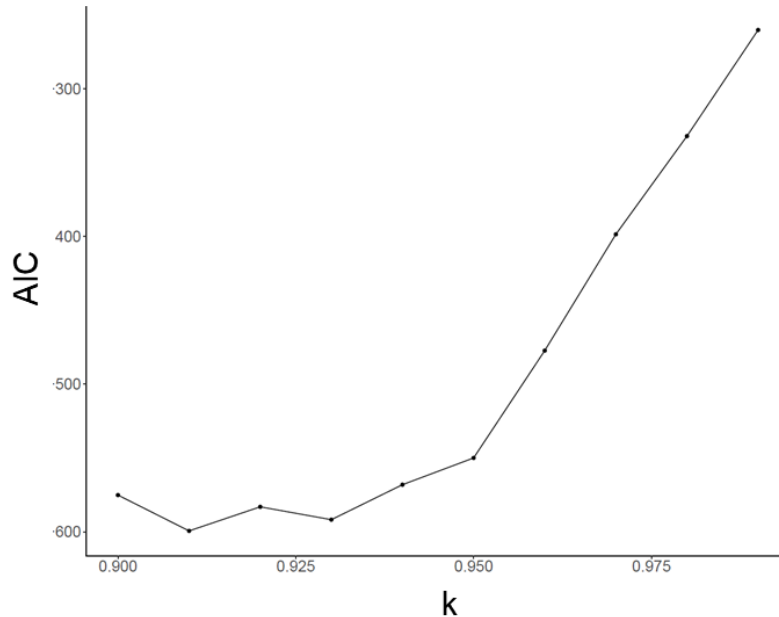
- 15 plants in operation
- 9 MW PV, 33 MW Wind, 12 MW Hydro
- Hydro is run-of-river, no storage

- **Model setup**

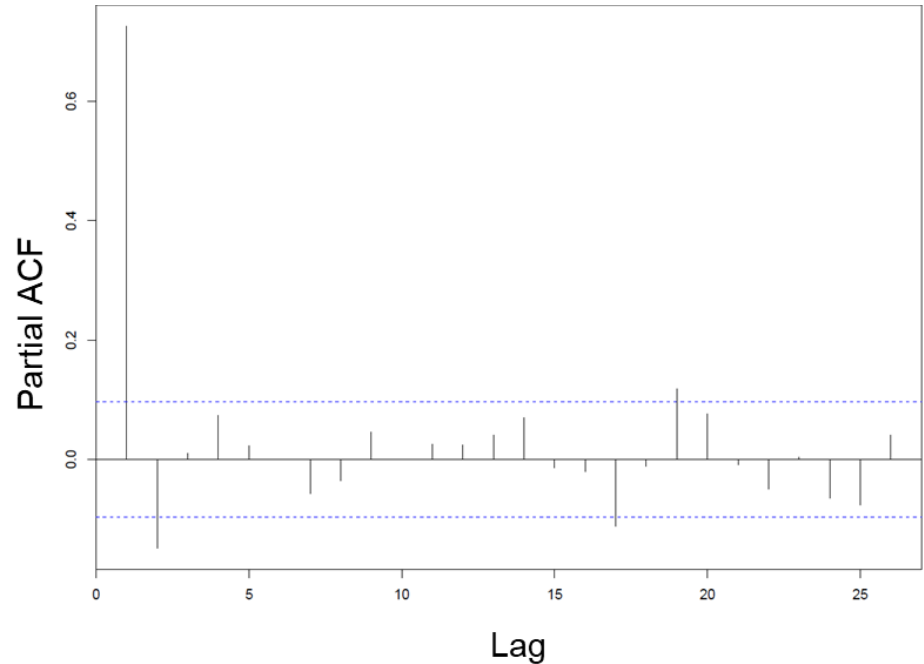
- NWP from ECMWF run at 00h00 UTC, for each site
- Production data: 30-min resolution, 15 months from 2015-01 until 2016-04
- Cross-validation on weekdays: 10^5 points for validation

- Properties of Peaks Over Threshold (POT)

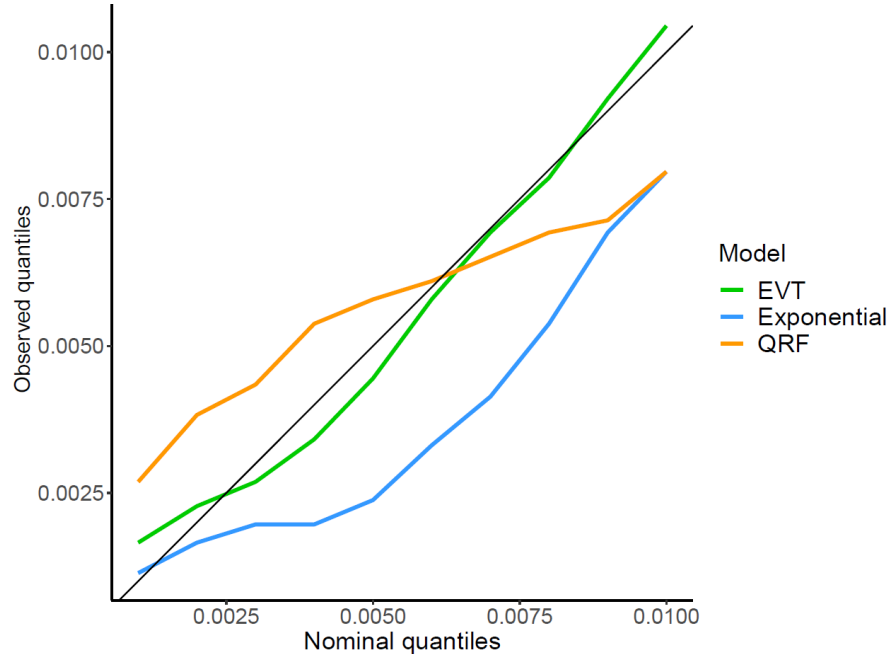
A lower quantile threshold k improves the fit of the EVT (with MLE)



$k = 0.95$ is the lower bound to observe acceptable stationarity of POTs



- Reliability on quantiles [0.1%, 0.2%, ..., 0.9%]



EVT ensures a reliable forecast on low extremes.

This is useful for applications requiring high reliability such as balancing provision

- Quantile score

- With weighted version on left tail [Gneiting and Ranjan 11]

$$\int_{\alpha} (1 - \hat{y}^{(\alpha)})^2 QS^{(\alpha)}(\hat{y}^{(\alpha)}, y) d\alpha$$

- On quantiles [0.1%, 0.2%, ..., 0.9%]

Model	QRF	Exponential	EVT
Unweighted QS	9.1e ⁻⁴	9.4e ⁻⁴	1.09e ⁻³
Weighted QS	7.2e ⁻⁴	7.5e ⁻⁴	1.10e ⁻³

Lower performance of EVT due to a more climatological behaviour compared to QRF

- EVT proposes a reliable solution for forecasting low extremes of VPP production
 - Next steps: adaptation of the model to be more dependent on weather conditions

- Acknowledgments

- Industrial partners for production data:



- Weather forecasts: 

- Support from the Era-Net SmartGrid Plus Program, within the REstable project: 

- Connect with us

-  :@PERSEE_Mines

- **Open PhD positions:** contact georges.kariniotakis@mines-paristech.fr
- **Smart4RES:** A new H2020 project to be launched in November 2019

[Camal, Kariniotakis, Michiorri 18]: Camal, S., Teng, F., Michiorri, A., Kariniotakis, G., & Badesa, L. (2019). Scenario generation of aggregated Wind, Photovoltaics and small Hydro production for power systems applications. *Applied Energy*, 242, 1396–1406.

<https://doi.org/10.1016/J.APENERGY.2019.03.112>

[Gneiting and Ranjan 11]: Gneiting, T., & Ranjan, R. (2011). Comparing density forecasts using threshold and quantile-weighted scoring rules. *Journal of Business and Economic Statistics*, 29(3), 411–422. <https://doi.org/10.1198/jbes.2010.08110>

[Matos 16]: Matos, M. A., Bessa, R. J., Goncalves, C., Cavalcante, L., Miranda, V., Machado, N., ... Matos, F. (2016). Setting the maximum import net transfer capacity under extreme RES integration scenarios. In 2016 International Conference on Probabilistic Methods Applied to Power Systems, PMAPS 2016 - Proceedings (pp. 1–7). IEEE. <https://doi.org/10.1109/PMAPS.2016.7764145>