

Smart4RES

Forecasting the high-resolution variability of renewable production using advanced weather forecasting products

Simon Camal MINES Paris -15 June 2022 PMAPS 2022



nis project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 864337



- **2** Research problem
- **3** Conclusions



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- 2 Research problem
- **3** Conclusions

4 References

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Objective: Probabilistic prediction of the minute-scale variability of RES plants



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Motivation: Prediction of high-resolution RES variability has multiple potential uses, e.g.:

- Explanatory variable for probabilistic RES forecast at intraday horizons [AM13]
- Reserve Sizing, Unit Commitment
- Flexible dispatch margin for RES integration [CA15]
- Optimal scheduling of storage combined with RES
- Reliable trading of ancillary services by RES [HTD⁺22]



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4 References

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Numerical Weather Predictions (NWP) have km-scale spatial resolution.

But NWP ensembles have minute-scale time steps.

Potential for variability forecast with ensembles in contexts where parametrization is sufficient.





Figure 1: NWP grid with parametrization of physical processes (MeteoFrance) Figure 2: Wind speed observed (blue), average prediction of ensembles (black) and individual ensemble members (grey) (MeteoFrance)

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Large Eddy Simulation (LES) resolves turbulence, clouds and surface. Weather forecasts at 100 m spatial resolution and temporal resolution Δt of 30 seconds.



Figure 3: LES grid (MeteoFrance)



Figure 4: LES simulation at wind farm level (Whiffle)

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RES variability: rolling standard deviation of RES production σ_y , on a moving window defined by the use case (e.g. 5-10 min)



Figure 5: Observed RES production (black) and 10-min rolling standard deviation (blue), for 1 wind farm

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Aim: Forecast a quantile of rolling RES standard deviation $\hat{\sigma}_{y}^{(\tau)}$ from a weather forecast (here wind speed).

Steps:

- 1 High-resolution weather forecast at one or multiple RES sites (here from LES)
- 2 Derive rolling variability weather forecast
- **3** Convert to rolling forecast of RES production variability

Evaluation: Minimize the quantile score (QS) of RES variability **Benchmark**: RES variability quantile forecast from low-resolution NWP





Analytic benchmark: high quantile of wind speed rolling standard deviation σ_x proportional to rolling mean wind speed μ_x [LYT⁺14]. **Input:** μ_x Rolling mean of low-resolution wind speed forecasts (from NWP) **Output:** $\hat{\sigma}_x^{(\tau)}$, quantile of rolling standard deviation of wind speed

$$\hat{\sigma}_{x,\Delta t}^{(\tau)} = T I \mu_{x,\Delta t}, \quad \tau = 90\%$$
(1)

where *TI* is the Turbulence Intensity, a parameter standardized in IEC 61400-1.

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Quantile regression based on LES wind speed forecast over \mathcal{N} training samples. **Input:** Rolling mean wind speed forecasts $\hat{\mu}'_{x}$ over all turbine locations $l \in \mathcal{L}$ in LES **Output:** $\hat{\sigma}_{x}^{(\tau)}$, quantile of rolling standard deviation of wind speed

$$\min_{\alpha_{I} \in \mathbb{R}^{+}} \sum_{i \in \mathcal{N}} (\hat{\sigma}_{x,i} - \hat{\sigma}_{x,i}^{(\tau)}) \cdot (\tau - 1\{\hat{\sigma}_{x,i} < \hat{\sigma}_{x,i}^{(\tau)}\}) \mid \hat{\sigma}_{x,i}^{(\tau)} = \sum_{I \in \mathcal{L}} \alpha_{I} \hat{\mu}_{x,i}^{I}$$
(2a)

LES simulates spatial variability between turbines of a wind farm

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The RES variability forecast is obtained by propagating the rolling wind speed and variability forecast through the turbine power curve.



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Day-ahead variability forecast for wind farms in a Greek Island (Rhodes)

- 1 year production data from 4 farms at 1 min resolution (HEDNO)
- LES on the entire Rhodes island at 30min resolution (WHIFFLE)
- Resolution of rolling forecast $\Delta t = 10 \text{ min}$
- Nominal quantile value of variability forecast au = 90%
- Forecasting horizon: 24h-48h (aligned on the LES forecasting horizon)
- Training Testing split of the RES variability forecast model: 50 % 50 % by alternate days in 2018



LES produced by WHIFFLE at 30s resolution, with nested domains for each wind farm, and boundary conditions from ECMWF NWP.



Figure 6: LES output on Rhodes, boxes indicate wind farm domains (source: Whiffle)

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Results



The high-resolution variability forecast (hi-rez) improves the QS compared to the low-resolution counterpart (low-rez), with differences between sites.

🔹 hi-rez 🔸 lo-rez

Figure 7: Quantile score for the 4 wind farms (AE, DA, DI, EW)

The minute-scale variability forecast is complementary to the probabilistic power forecast.

Figure 8: Variability forecast at high-resolution (green) and low-resolution (brown). 90% Prediction interval of power forecast in grey

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- 2 Research problem
- **3** Conclusions

4 References

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High-resolution weather forecast provide useful input to RES variability forecast.

- Higher forecasting performance is obtained with LES-based variability compared to parametrized evaluation based on NWP
- Coherent variability forecasts can be obtained at a regional scale, but computational effort of LES is high and biases are important.
- Forecasting end-users may need a different format of variability index [AM13] or ramp quantification [Bos12]
- The value of the variability forecast should be demonstrated in a power system application with multiple temporal resolution e.g. bidding of energy and reserve as in [HTD⁺22]

- 2 Research problem
- **3** Conclusions

4 References

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[AM13] Georgios Anastasiades and Patrick McSharry. Quantile forecasting of wind power using variability indices. *Energies*, 6(2):662–695, 2013.

[Bos12] Arthur Bossavy. Caractérisation et prédiction probabiliste des variations brusques et importantes de la production éolienne. PhD thesis, 2012.

[CA15] Judith B. Cardell and C. Lindsay Anderson. A flexible dispatch margin for wind integration. *IEEE Transactions on Power Systems*, 30(3):1501–1510, 2015.

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References II

[HTD+22] Seyyed Ahmad Hosseini, Jean-Francois Toubeau, Zacharie De Greve, Yi Wang, Nima Amjady, and Francois Vallee. Data-Driven Multi-Resolution Probabilistic Energy and Reserve Bidding of Wind Power.

IEEE Transactions on Power Systems, 8950(c):1–1, 2022.

[LYT⁺14] TZONG-SHYNG LEU, JUI-MING YO, YI-TING TSAI, JIU-JIH MIAU, TA-CHUNG WANG, and CHIEN-CHOU TSENG. Assessment of lec 61400-1 Normal Turbulence Model for Wind Conditions in Taiwan West Coast Areas. International Journal of Modern Physics: Conference Series, 34:1460382, 2014.

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