Forecast trajectories for the production of a renewable virtual power plant able to provide ancillary services

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EGU 2020, Session ERE2.1 | D860

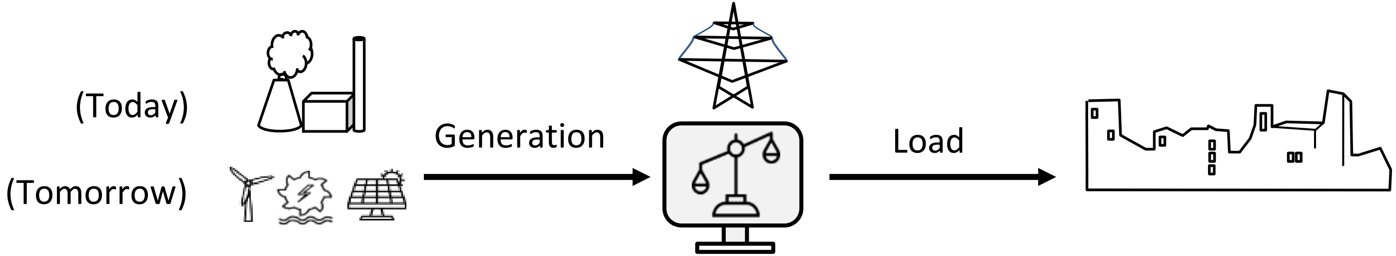
6th May 2020

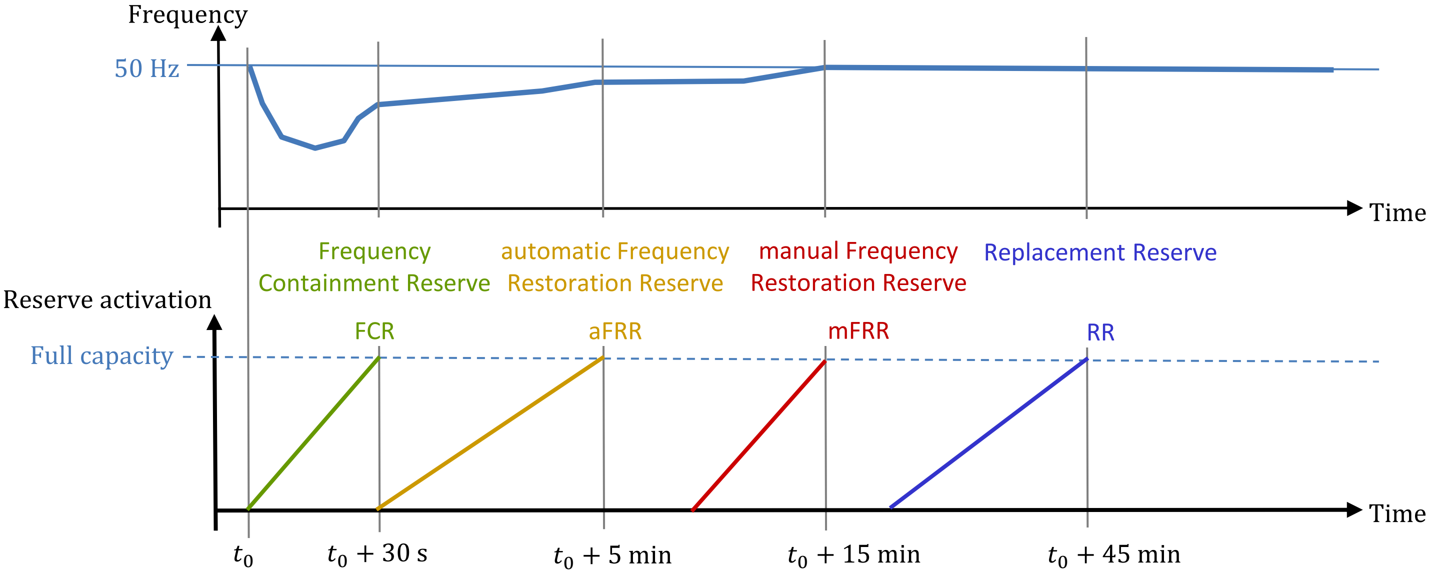
Outline

1. Introduction
2. Methodology
3. Case study & Results
4. Conclusion and Perspectives

Balancing power systems with renewables

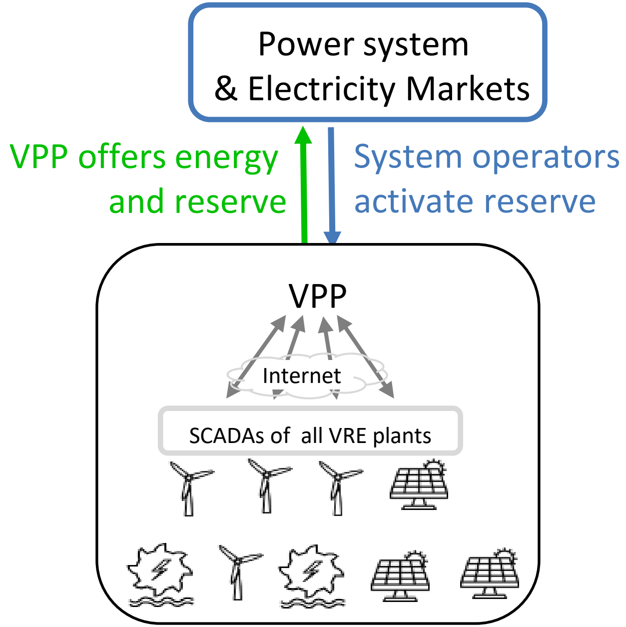
Variable Renewables are expected to contribute to Ancillary Services (AS) that ensure balancing.

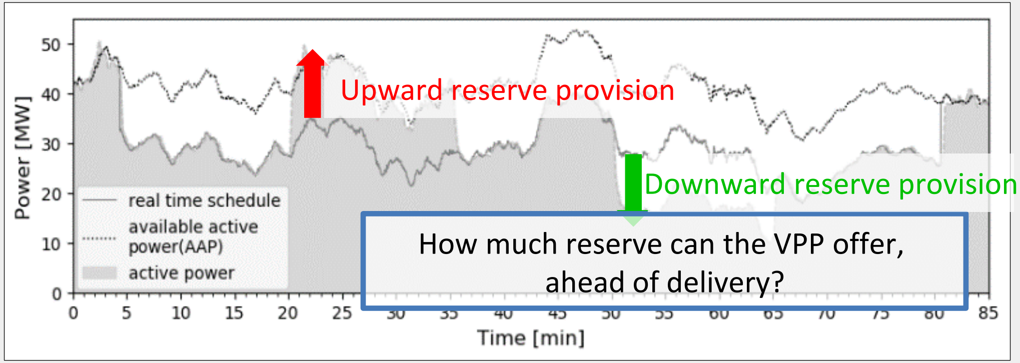




Balancing power systems with renewables

- A single renewable plant cannot guarantee an adequate level of power for ancillary services provision.
- A Virtual Power Plant (VPP) aggregates and controls Variable Renewable Energy (VRE) plants [1].





Field Test of reserve provision by a Wind-PV VPP (source: REstable project)

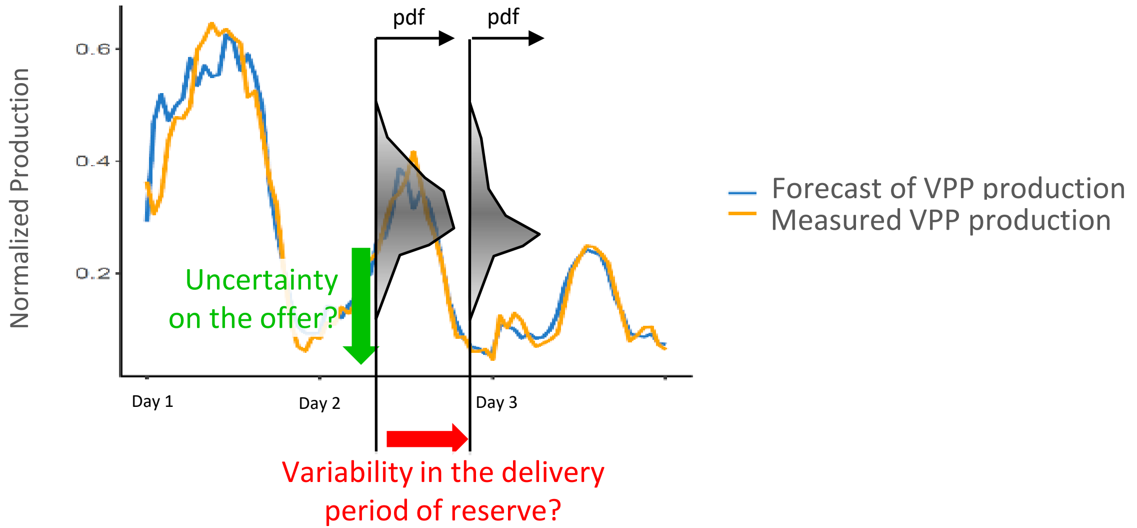
[1] : Strahlhoff J., Liebelt A., Siegl S., Camal S., *Development and Application of KPIs for the Evaluation of the Control Reserve Supply by a Cross-border Renewable Virtual Power Plant*, Informatik 2019 Kassel, Published in Lecture Notes in Informatics, Gesellschaft für Informatik, 2019, https://dx.doi.org/10.18420/inf2019_69]

Forecasting VRE production

A probabilistic forecast of the VPP production is needed to prepare an offer of reserve.

Deviations from the volume offered imply penalties on markets

Reserve is crucial for the system, so TSOs expect high reliability from reserve offers



Trajectories of VPP production must be generated, they can be obtained from probabilistic density forecasts (e.g. in [2])

[2] Golestaneh F, Gooi HB, Pinson P. Generation and evaluation of space–time trajectories of photovoltaic power. Appl Energy 2016;176:80–91. doi:10.1016/J.APENERGY.2016.05.025.

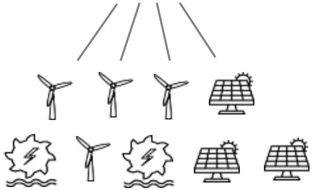
Workflow

How to forecast the aggregate production of the VPP?

Proposition: in addition to separate forecasts at sub-levels, a direct approach is proposed and compared.

Data

VPP model



Approaches of aggregate forecast

One model

Direct forecast of aggregate production

Separate forecasts + Correlations by plants or sources…

$$V(Y_{VPP}) = \sum_{p \in VPP} V(Y_p) + 2 \sum_{i,j \in VPP} Cov(Y_i, Y_j)$$

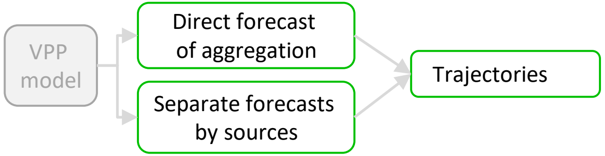
Multiple models

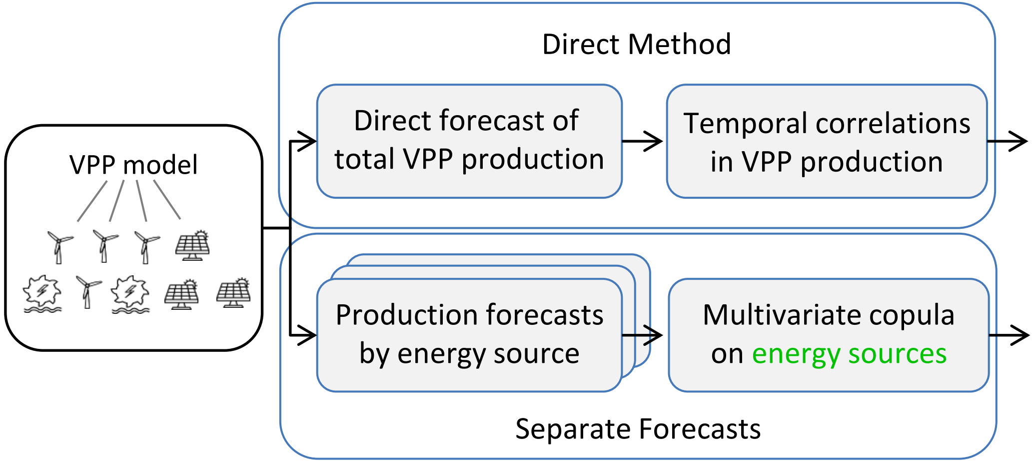
Forecast products

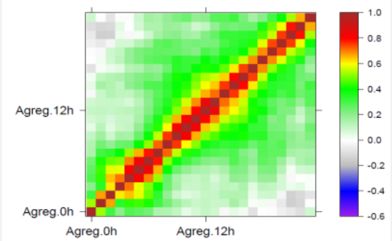
Trajectories reproducing temporal correlations

Trajectories of aggregate VPP production

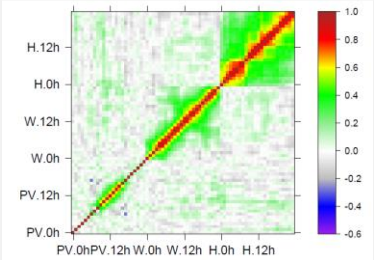
Proposition: Compare trajectories from direct aggregate forecast and from separate forecasts by energy sources [3]







Covariance on horizons

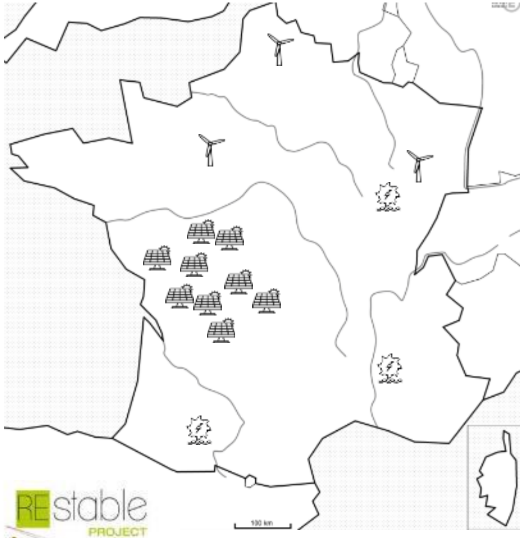


Covariance on horizons and sources

[3]: 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://dx.doi.org/10.1016/j.apenergy.2019.03.112

Case study on a multi-source VPP

Trajectories of VPP production are generated from density forecasts, with day-ahead horizon



RE stable PROJECT

Data

- 15 plants: 9 MW PV, 33 MW Wind, 12 MW run-of-river Hydro
- NWP from ECMWF (run 00.00 UTC) at each site
- Production data: 10^4 points at 30-min resolution (06/15-03/16)

Density forecasts by Quantile Regression Forest (QRF)

- Learning on 6 days of week and testing on the remaining day
- Parametrization of models by grid search

Generation of 100 trajectories from 2 methods

- **DG**: **D**irect forecasting of VPP production + **G**aussian copula
- **IG**: **I**ndirect Forecasting separate by energy source + **G**aussian copula

Evaluation metrics of trajectories

Standard metrics

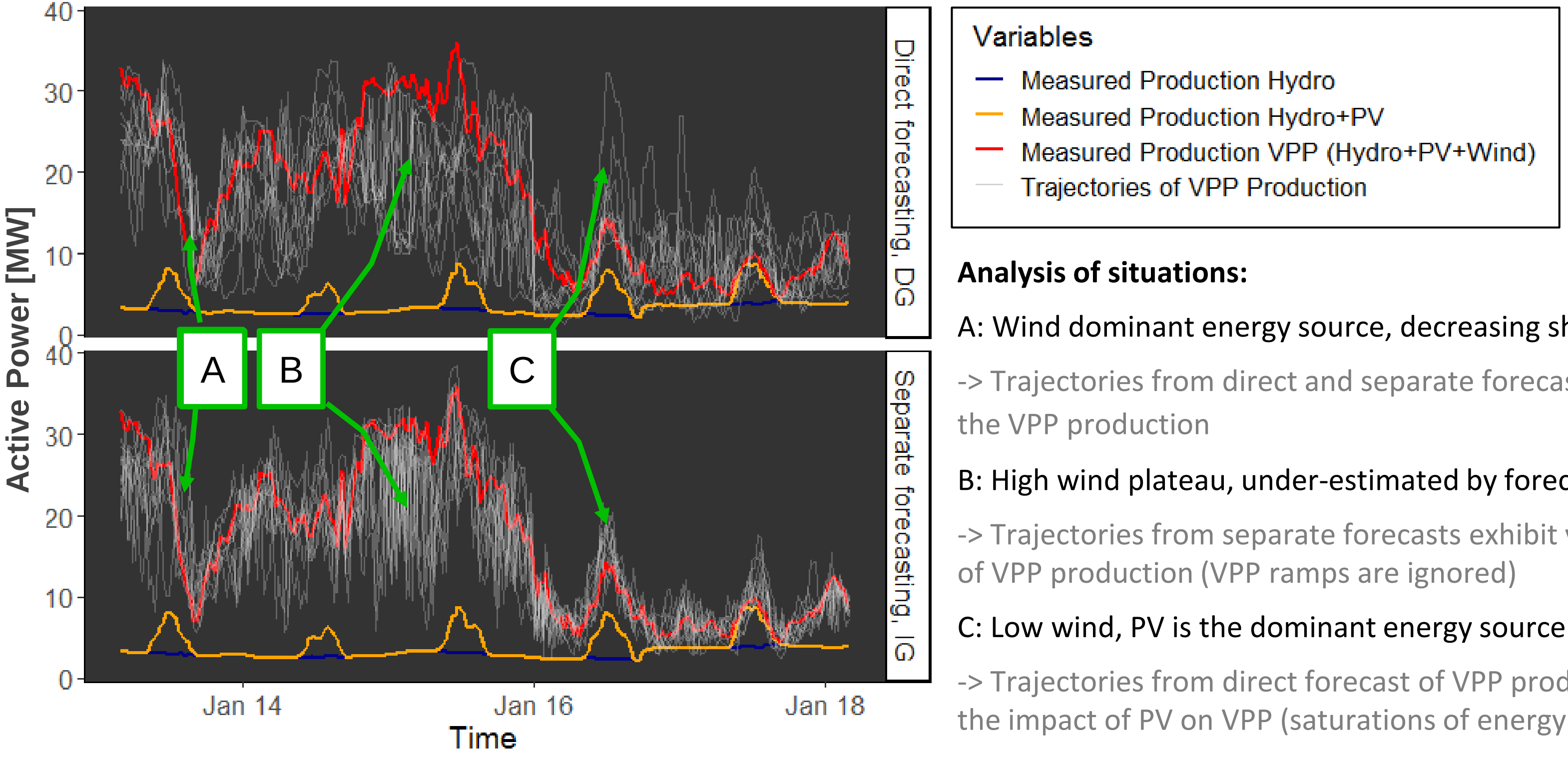
- Amplitude of trajectory set
- NRMSE
- Bias
- Auto-correlation function

Specific metrics evaluating the variability and the capacity to model ramps of several durations

Property	Global variability	Occurrence of ramps
Score	Variogram Score (VS)	Brier score (BS)
Formulation	$VS_t^{(\gamma)} = \sum_{i,j \in M} w_{ij} \left(\lvert y_{t,i} - y_{t,j} \rvert^{\gamma} - \frac{1}{\Omega} \sum_{\omega \in [1,\Omega]} \left(\lvert \hat{y}_{\omega t,i} - \hat{y}_{\omega t,j} \rvert^{\gamma} \right) \right)^2$	$\delta_t(y; \Delta t) = \mathbf{1}(\lvert y_{t+\Delta t} - y_t \rvert \geq r)$ $BS = \frac{1}{T} \sum_{t=1}^{T} \left(\frac{1}{\Omega} \sum_{\omega \in [1,\Omega]} \delta_t(\hat{y}_\omega; \Delta t) - \delta_t(y; \Delta t) \right)^2$

Results – Qualitative analysis of an example

Reduction to 10 trajectories by fast-forward reduction.



Analysis of situations:

A: Wind dominant energy source, decreasing sharply in a few hours.

-> Trajectories from direct and separate forecasts model correctly the VPP production

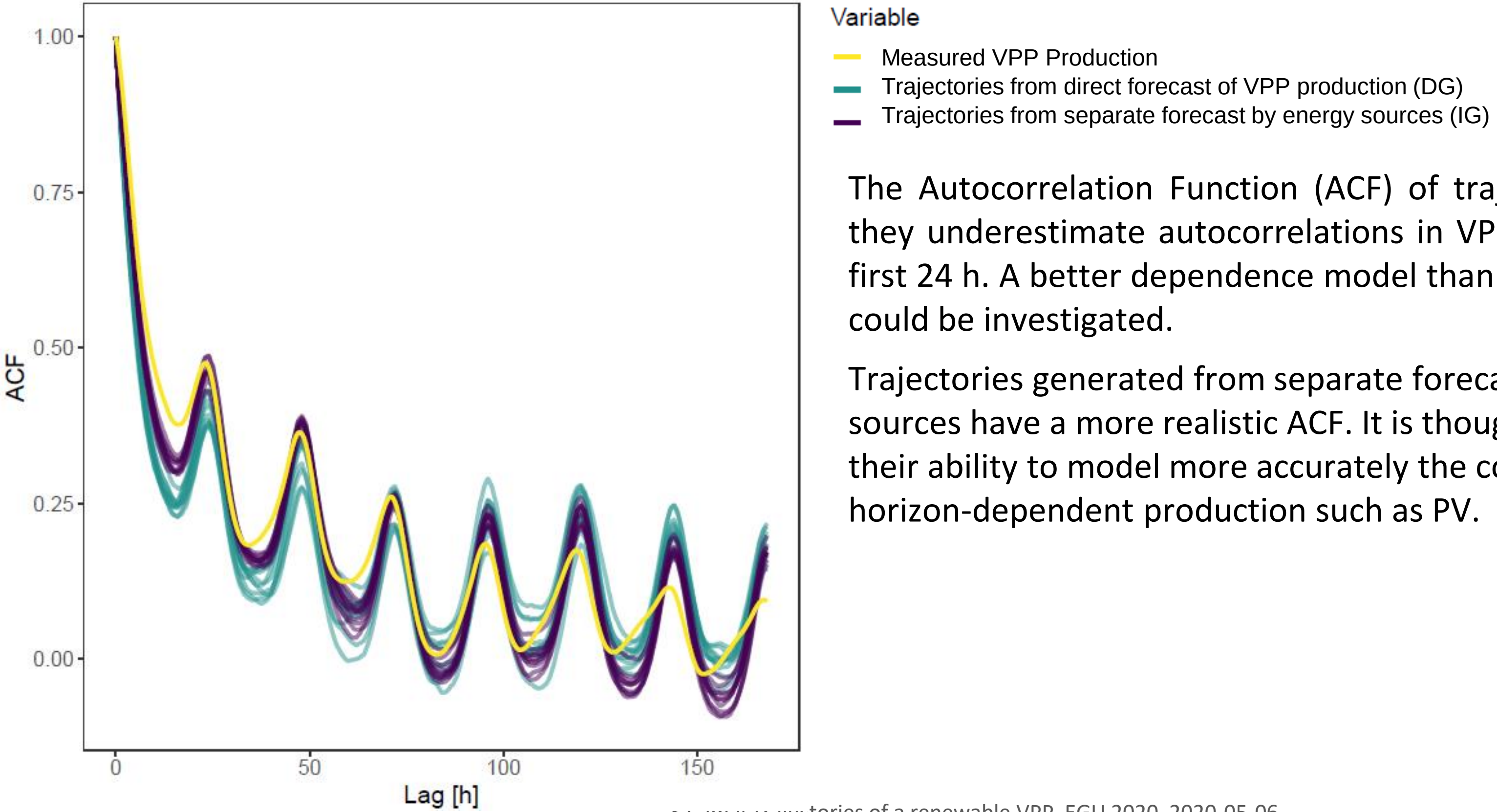
B: High wind plateau, under-estimated by forecasting models.

-> Trajectories from separate forecasts exhibit very frequent ramps of VPP production (VPP ramps are ignored)

C: Low wind, PV is the dominant energy source.

-> Trajectories from direct forecast of VPP production overestimate the impact of PV on VPP (saturations of energy sources are ignored)

Results – Analysis of autocorrelation



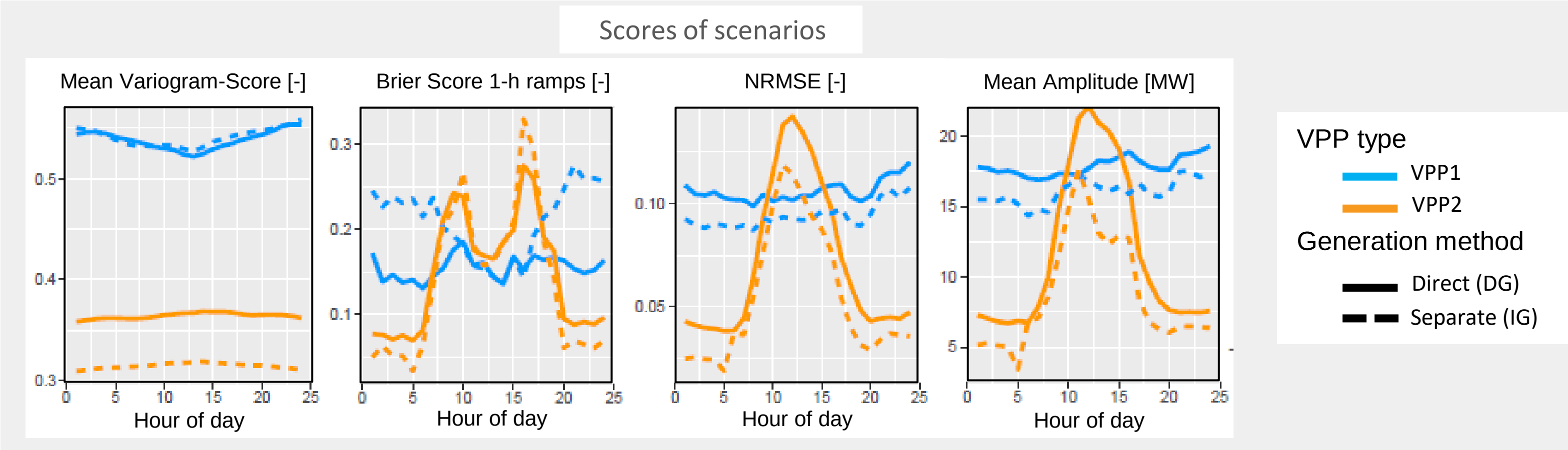
The Autocorrelation Function (ACF) of trajectories shows that they underestimate autocorrelations in VPP production for the first 24 h. A better dependence model than the Gaussian Copula could be investigated.

Trajectories generated from separate forecasts by energy sources have a more realistic ACF. It is thought to come from their ability to model more accurately the contribution of horizon-dependent production such as PV.

Results of trajectories

VPP variants: highest capacity from Wind (VPP1) vs highest capacity from PV (VPP2)

- Trajectories with direct forecast DG: better Brier Score on VPP1
- Trajectories with separate forecast IG: lower amplitude, NRMSE, and better Variogram Score on VPP2.



Trajectories from separate forecasts reproduce better the variability of VPP production

Conclusions

We dispose of a methodology to generate trajectories for a renewable VPP providing ancillary services

→ The methodology proposes to generate trajectories from a direct density forecast of VPP production or from separate density forecasts by energy sources

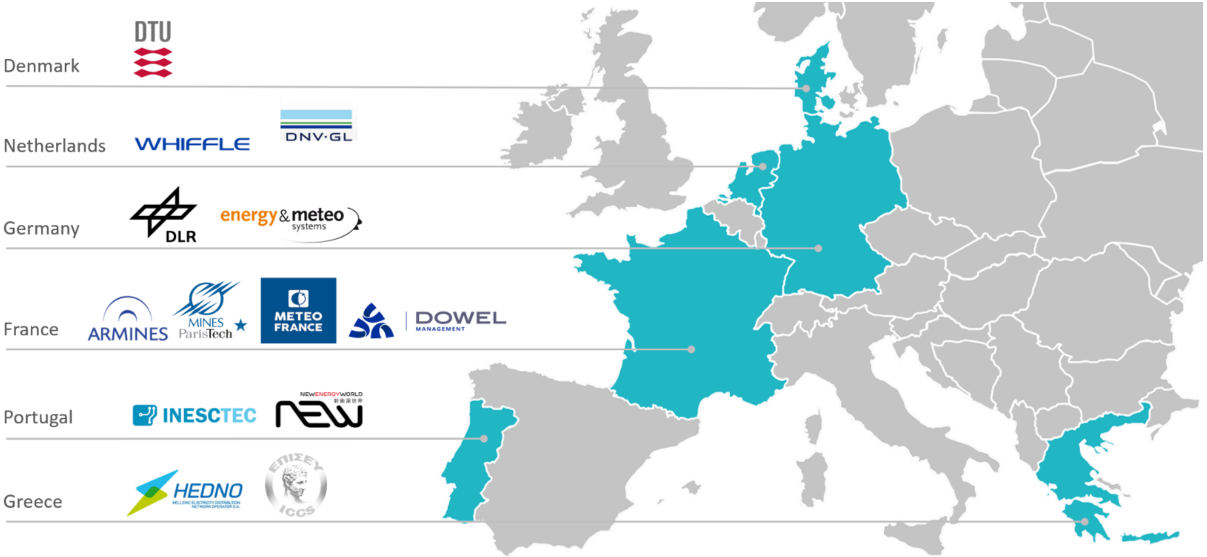
- The research questions on multi-source variable RES forecasting are plenty
  - Marginally adressed in existing research
  - Problem of high dimension, combinatorial complexity of possible approaches
  - A multi-source VPP is a highly evolutive physical system (sources, plants, markets…)
- The approach with separate forecasts by energy sources leads to more realistic trajectories
  - Especially on a VPP where horizon-dependent production (PV) dominates the total capacity

Perspectives

- Smart4RES project

  ○ Generic seamless forecast of RES production: use knowledge on multiple energy sources to develop a generic model, ie adaptable to any variable energy source (PV, Wind, run-of-river Hydro).

  ○ www.smart4res.eu



References & Related publications

References

[1] Strahlhoff J., Liebelt A., Siegl S., **Camal S.**, *Development and Application of KPIs for the Evaluation of the Control Reserve Supply by a Cross-border Renewable Virtual Power Plant*, Informatik 2019 Kassel, Published in Lecture Notes in Informatics, Gesellschaft für Informatik, 2019, https://dx.doi.org/10.18420/inf2019_69

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[3] **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://dx.doi.org/10.1016/j.apenergy.2019.03.112

Related publications

Camal, S., Michiorri, A., & Kariniotakis, G. (2018). *Optimal Offer of Automatic Frequency Restoration Reserve from a Combined PV/Wind Virtual Power Plant*. IEEE Transactions on Power Systems, 99. https://dx.doi.org/10.1109/TPWRS.2018.2847239

Camal, S., Michiorri, A., Kariniotakis, G., & Liebelt, A. (2018). *Short-term forecast of automatic frequency restoration reserve from a renewable energy based virtual power plant*. ISGT-Europe 2017, Milan, Italy. https://dx.doi.org/10.1109/ISGTEurope.2017.8260311

Thank you for your attention

Acknowledgments

ENGIE Green, Fraunhofer IEE, HESPUL, Hydronext
ECMWF

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