

Modelling wind power variability: The reanalysis and stochastic simulation approaches and how to combine them

Matti Koivisto (mkoi@dtu.dk)

Kaushik Das

Poul Sørensen

DTU Wind Energy

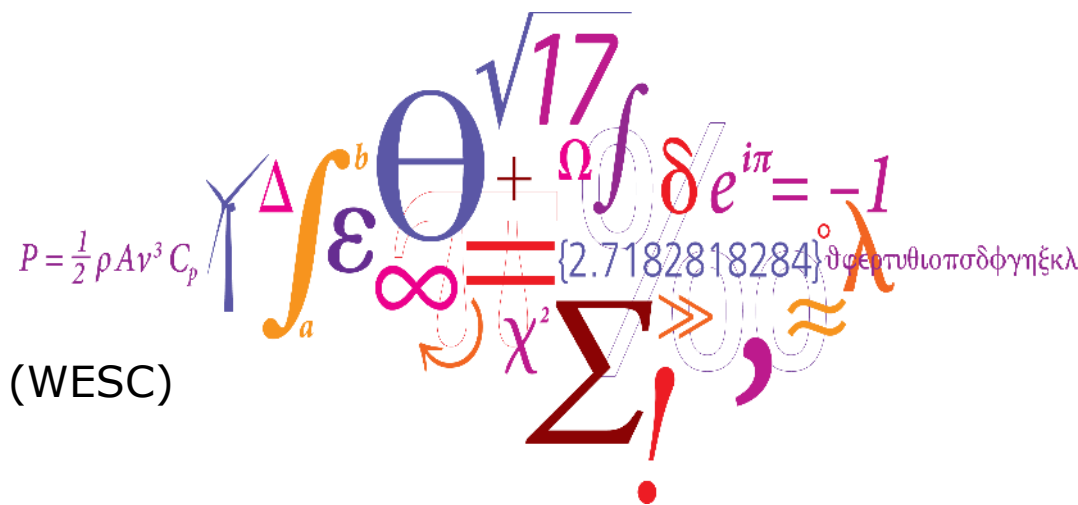
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DTU Wind Energy

Department of Wind Energy



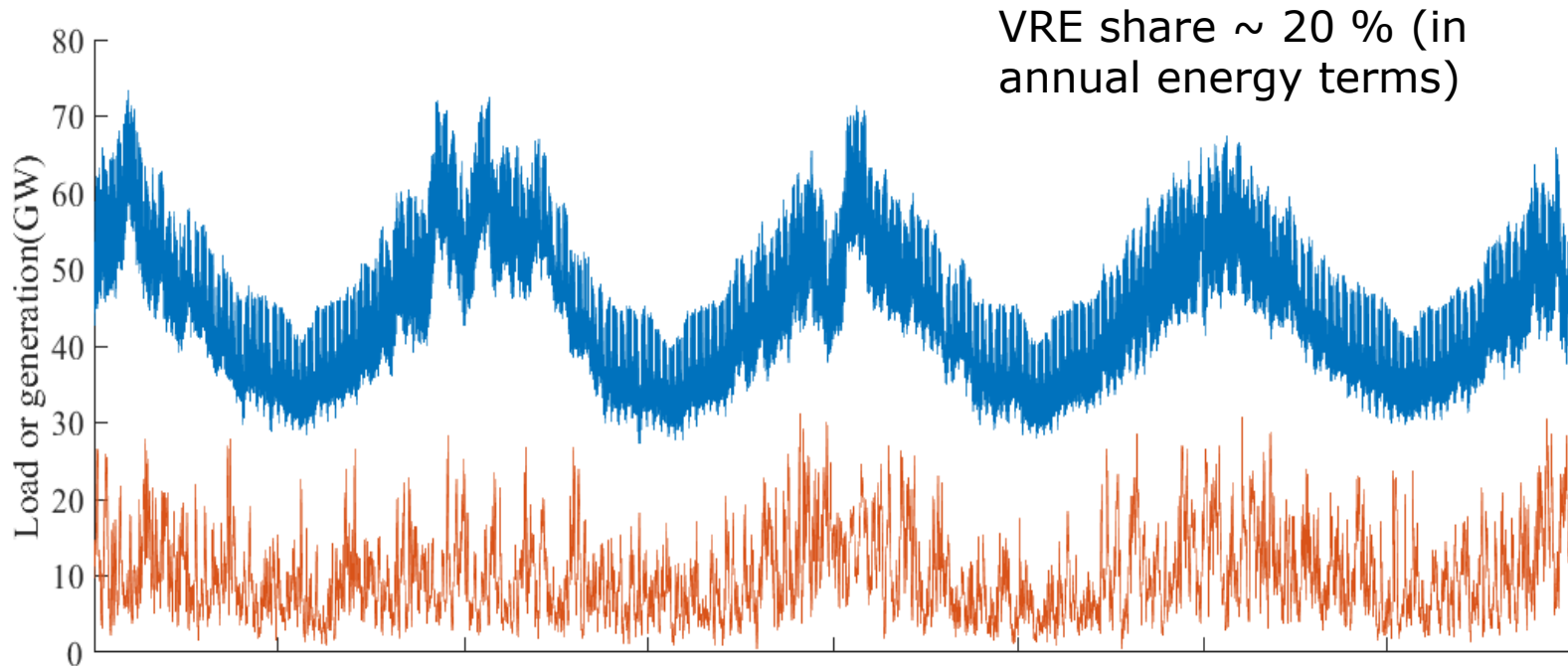
Agenda

1. Why modelling of wind generation variability is needed?
2. Statistical simulation approach for modelling variability
3. The reanalysis approach
4. CorRES tool: Combining the reanalysis and the stochastic simulation approaches
5. Some CorRES case studies
6. Conclusions (with a look at hybrid power plants)

Why to model wind generation variability?

- Some modelling approaches focus on annual energy output
 - Does not consider when generation occurs during the year
 - E.g., LCoE is based on annual energy output
- Focusing on annual output may be enough when:
 - Share of wind generation in power system is relatively low
 - There will be other (dispatchable) generation to produce when wind is low and curtailment is rare
 - Subsidy schemes protect against electricity price fluctuations (e.g., guaranteed price)
- **However, trends suggest analyzing variability will be more and more important in the future**
 - Share of wind increases in many regions
 - It is thus important to analyze generation hourly or even higher resolution to make sure power system is in balance at all times
 - As subsidies are lowered, wind will face (e.g., hourly) market prices

Example of VRE generation variability (hourly)

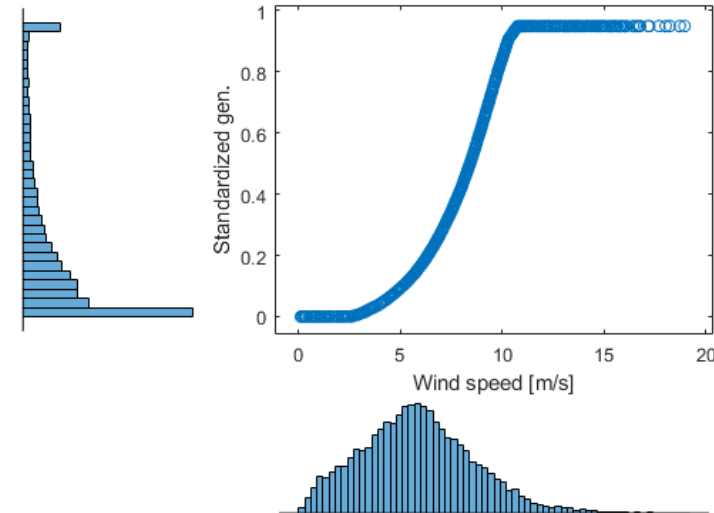


Load and variable renewable energy (VRE) generation: 4 years, hourly resolution (example Nordic & Baltic scenario)

M. Koivisto, P. Maule, E. Nuño, P. Sørensen, N. Cutululis, "Statistical Analysis of Offshore Wind and other VRE Generation to Estimate the Variability in Future Residual Load, *Journal of Physics: Conference Series*, vol. 1104, no. 1, 012011, 2018 (<https://doi.org/10.1088/1742-6596/1104/1/012011>).

Variability in wind generation

- Variability may be considered (at least) in three parts:
 - 1. Statistical distribution** of wind generation (or wind speed) in a single location
 - 2. Temporal dependency** in a single location
 - 3. Spatial dependencies** between locations
- When temporal and spatial dependencies are considered for multiple locations, they can be called **spatiotemporal dependencies**
- Modelling of variability is important, e.g., in¹
 - Transmission expansion studies
 - Assessing system adequacy



Variability in wind speed translates to variability in wind generation

¹M. Koivisto et al., "Using time series simulation tool for assessing the effects of variable renewable energy generation on power and energy systems", *WIREs Energy and Environment*, e329, 2018 (<https://doi.org/10.1002/wene.329>)

Spatiotemporal dependencies

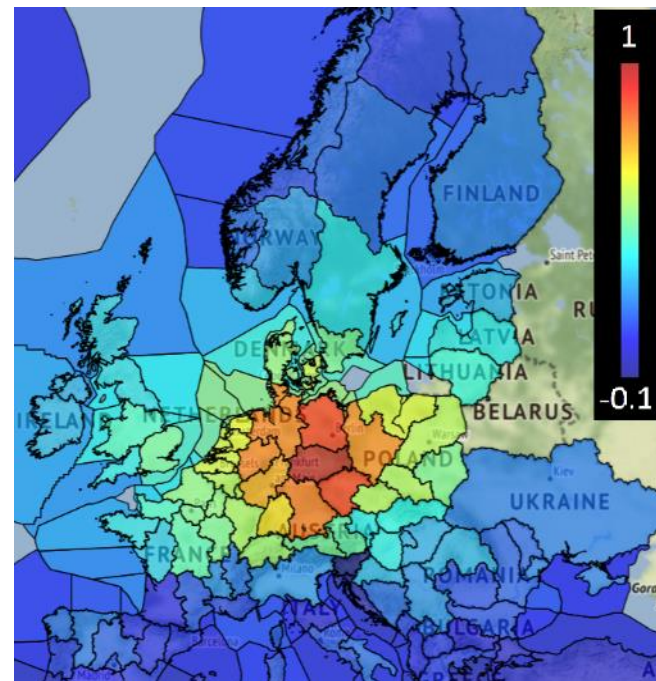
- Multivariate time series is often written

$$\mathbf{y}_t = [y_{1,t}, \dots, y_{k,t}] ,$$

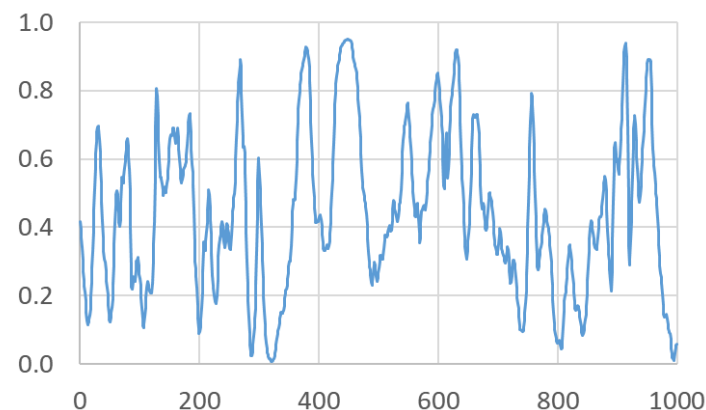
where $y_{i,t}$ is value (e.g., wind speed) at location i at time t , and k is the number of locations

- In this notation:
 - Statistical distribution and temporal dependency structure of location i describe the behavior of $y_{i,t}$
 - Knowledge of the full spatiotemporal dependency is required to understand the joint behavior of the k -dimensional time series \mathbf{y}_t

(the notation is best suited for stationary data, but it is useful also with non-stationary data)



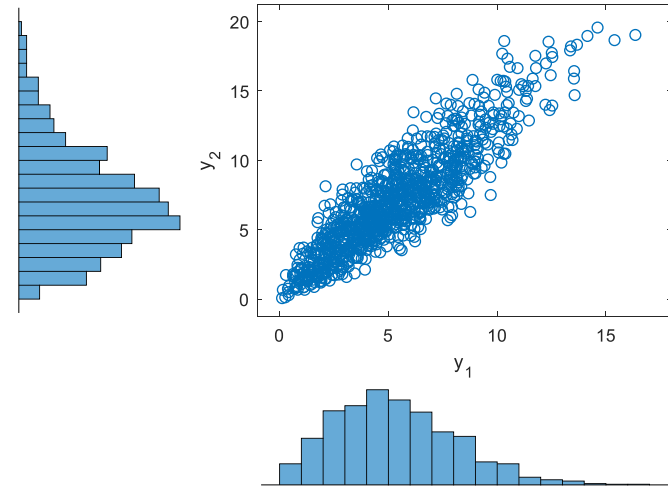
Spatial correlations in wind generation looking from a German onshore region



Example 1000 hours of simulated wind generation (Denmark onshore)

Statistical simulation approach for modelling variability in wind

- **A statistical model is fitted to available measurements and used to simulate data**
 - I.e., a data model is fitted for y_t , and then samples are drawn from it^{1,2,3}
- Modelling wind speed or generation distribution of a single location is usually straightforward
 - Many distributions are available³
- **Copula method** can be used to model dependencies between locations
 - Used, e.g., **in probabilistic power flow**⁴



Simulated samples drawn from an example 2-dimensional Gaussian copula with Weibull margins $y_t = [y_{1,t}, y_{2,t}]$

¹E. Nuño et al., "On the simulation of aggregated solar PV forecast errors", *IEEE Transactions on Sustainable Energy*, vol. 9, no. 4, pp. 1889-1898, October 2018 (<https://doi.org/10.1109/TSTE.2018.2818727>)

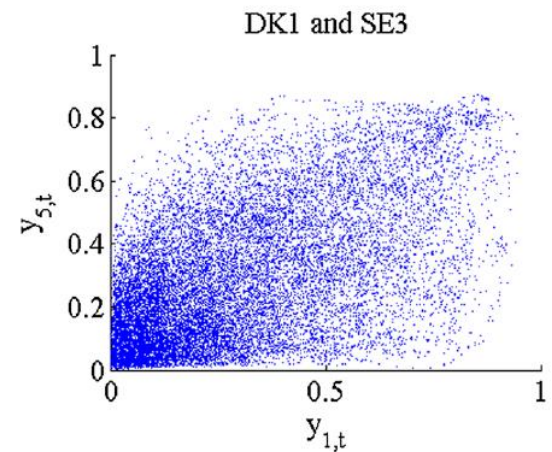
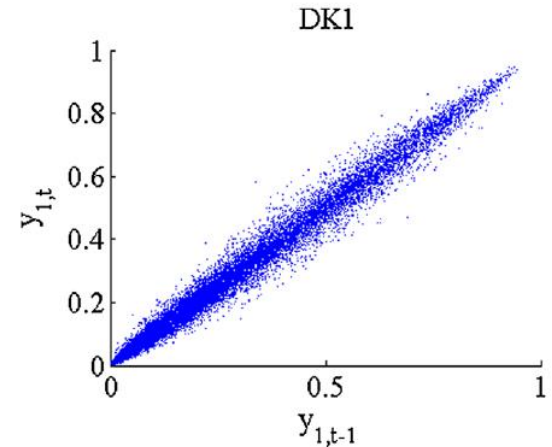
²J. Ekström et al., "A Statistical Model for Hourly Large-Scale Wind and Photovoltaic Generation in New Locations", *IEEE Transactions on Sustainable Energy*, vol. 8, no. 4, pp. 1383-1393, October 2017 (<https://doi.org/10.1109/TSTE.2017.2682338>)

³M. Koivisto et al., "Wind Speed Modeling Using a Vector Autoregressive Process with a Time-dependent Intercept Term", *International Journal of Electrical Power and Energy Systems*, vol. 77, pp. 91-99, May 2016 (<https://doi.org/10.1016/j.ijepes.2015.11.027>)

⁴P. Chen et al., "Probabilistic load flow: A review", *Third International Conference on Electric Utility Deregulation and Restructuring and Power Technologies*, 2008 (<https://doi.org/10.1109/DRPT.2008.4523658>)

Modelling spatiotemporal dependencies

- **ARMA (often only AR) model**
 - Models a single location $y_{i,t}$
- **VARMA (often only VAR) model^{1,2,3}**
 - Models the spatiotemporal dependencies in multivariate time series \mathbf{y}_t
 - Modelling of diurnal and annual structures may be included^{1,2}
 - **Used often in VRE generation forecast error simulation³**
- There are challenges in simulating non-Gaussian data from models that often assume normality (e.g., ARMA and VARMA)
 - However, these issues can be solved^{2,3}



Example visualization of temporal dependency for region DK1 and of spatial dependency between regions DK1 and SE3¹

¹M. Koivisto et al., "A Statistical Model for Comparing Future Wind Power Scenarios with Varying Geographical Distribution of Installed Generation Capacity", *Wind Energy*, vol. 19, no. 4, April 2016 (<https://doi.org/10.1002/we.1858>)

²M. Koivisto et al., "Wind Speed Modeling Using a Vector Autoregressive Process with a Time-dependent Intercept Term", *International Journal of Electrical Power and Energy Systems*, vol. 77, pp. 91-99, May 2016 (<https://doi.org/10.1016/j.ijepes.2015.11.027>)

³E. Nuño et al., "On the simulation of aggregated solar PV forecast errors", *IEEE Transactions on Sustainable Energy*, vol. 9, no. 4, pp. 1889-1898, October 2018 (<https://doi.org/10.1109/TSTE.2018.2818727>)

The reanalysis approach

- **Based on historical meteorological data**
 - Can be used to model current or future VRE installation scenarios
- Measured data and numerical modelling provides data that are:
 - 1. Gridded geographically (for large areas)**
 - 2. Continuous time series (e.g., hourly)**
- Has become **arguably the most popular method in analyzing VRE variability in power and energy system studies**
- Tens of years of reanalysis data is available
 - The more the better in power and energy system studies

E. Nuño et al., "Simulation of transcontinental wind and solar PV generation time series", *Renewable Energy*, vol. 118, pp. 425-436, April 2018

I. González-Aparicio et al., "Simulating European wind power generation applying statistical downscaling to reanalysis data", *Applied Energy*, vol. 199, pp. 155-168, August 2017

I. Staffell and S. Pfenninger, "Using bias-corrected reanalysis to simulate current and future wind power output", *Energy*, vol. 114, pp. 1224-1239, November 2016

J. Olason and M. Bergkvist, "Modelling the Swedish wind power production using MERRA reanalysis data", *Renewable Energy*, vol. 76, pp. 717-725, April 2015

C. Tejada et al., "Using wind velocity estimated from a reanalysis to minimize the variability of aggregated wind farm production over Europe", *Wind Energy*, vol. 21, no. 3, pp. 174-183, March 2018

Combining the reanalysis and stochastic simulation approaches

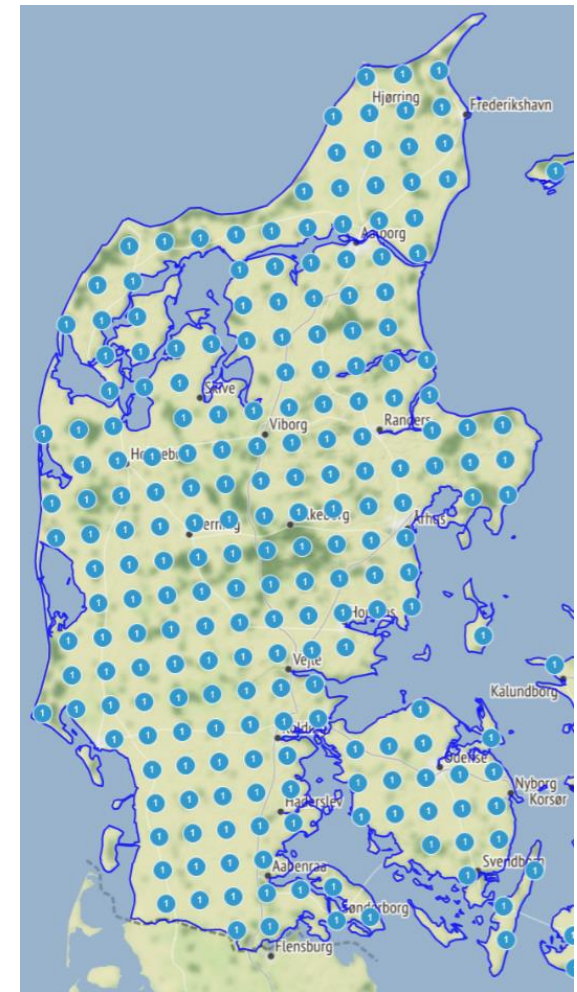
The CorRES tool

- CorRES¹ (Correlations in Renewable Energy Sources)
 - Developed at DTU Wind Energy
 - Simulation tool for variable renewable energy (VRE) generation
 - Models both wind and solar PV generation
 - **Can model future scenarios (e.g., 2030 or 2050)**
- **Based on meteorological reanalysis data**
 - **35 years of hourly data covering Europe**
 - Also other geographical regions (e.g., South Africa; India planned)
- Used in many projects
 - Danish and International research projects, such as:
 - NSON-DK (<http://www.nson-dk-project.dk/>)
 - Flex4RES (www.nordicenergy.org/flagship/flex4res/)
 - Pan-European VRE generation simulations for ENTSO-E
 - Data made available, e.g., for TYNDP (<https://tyndp.entsoe.eu>)

¹M. Koivisto et al., "Using time series simulation tool for assessing the effects of variable renewable energy generation on power and energy systems", *WIREs Energy and Environment*, e329, 2018 (<https://doi.org/10.1002/wene.329>)

About the reanalysis data

- CorRES is based on **ERA Interim Reanalysis**
 - Move to ERA-5 is planned (testing underway)
- Meteorological time series are obtained from the **Weather Research and Forecasting (WRF) model**
 - The WRF modelling is carried out at DTU Wind Energy (by the Resource Assessment Modelling section)
 - Mesoscale downscaling^{1,2} is applied
 - Wind speed and direction, irradiance, temperature, and more
 - **Output is obtained on hourly resolution**



Example region: WRF grid points for DK_west onshore

¹A. N. Hahmann et al., "A Reanalysis System for the Generation of Mesoscale Climatographies", *Journal of Applied Meteorology and Climatology*, pp. 954-972, May 2010 (<https://doi.org/10.1175/2009JAMC2351.1>).

²A. N. Hahmann et al., "Wind climate estimation using WRF model output: method and model sensitivities over the sea," *International Journal of Climatology*, vol. 35, no. 12, p. 3422-3439, October 2015 (<https://doi.org/10.1002/joc.4217>).

Addition of stochastic simulation

- **CorRES is based on the reanalysis data**
 - They provide the majority of the variability in the simulations
 - As obtained from the WRF model
- The reanalysis approach can capture most large-scale variability
 - **However, variations are smoothed because of averaging effects in mesoscale models¹**
- CorRES utilizes stochastic simulation to better model the high frequency variability²
 - Called fluctuations
 - They are combined to the WRF reanalysis data (currently for wind only)
 - **Allows more detailed modelling of VRE ramping**

¹X. G. Larsén et al., "Recipes for correcting the impact of effective mesoscale resolution on the estimation of extreme winds," *Journal of Applied Meteorology and Climatology*, pp. 521-533, March 2012.

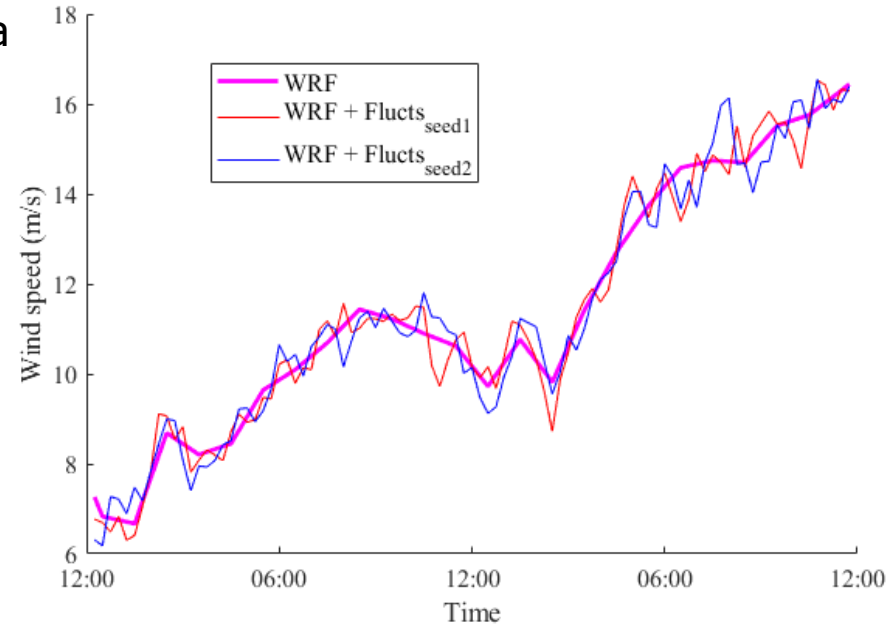
²P. Sørensen et al., "Modelling of Power Fluctuations from Large Offshore Wind Farms", *Wind Energy*, vol. 11, no. 1, pp. 29-43. February 2008 (<https://doi.org/10.1002/we.246>)

Reanalysis data + stochastic simulation

- The combination of the reanalysis data and the stochastic simulation is done on the wind speed (v) domain

$$v_t = v_t^{\text{WRF}} + v_t^{\text{flucts}}$$

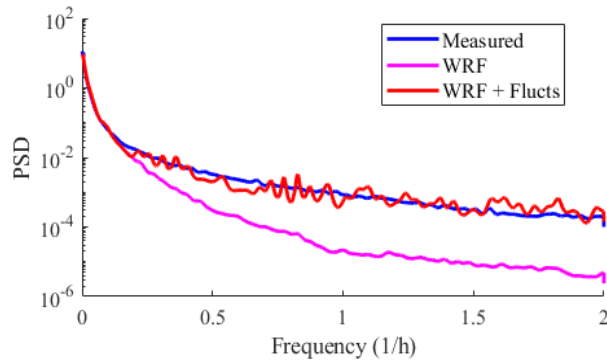
- This allows the addition of the fluctuations v_t^{flucts} to change the spatiotemporal dependencies in the WRF wind speeds v_t^{WRF}
- The final simulated wind speeds $v_t = [v_{1,t}, \dots, v_{k,t}]$ are transformed to power generation using power curves
- The fluctuations are defined and simulated in frequency domain¹
 - Transformed to time series using Fourier transformation



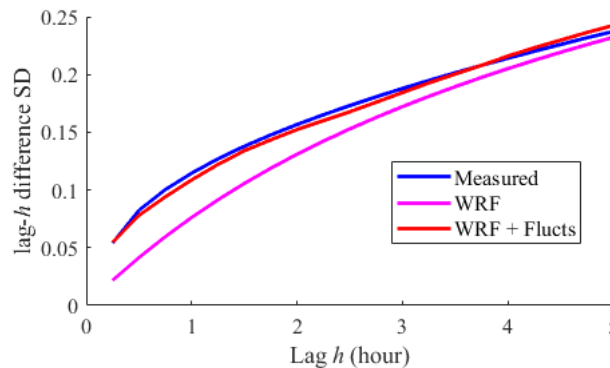
A 24 h example time series of WRF data and simulated wind speeds with fluctuations using two different random seeds. The time series have a 15 min resolution; hourly WRF data is linearly interpolated to reach the intra-hour values.

¹P. Sørensen et al., "Modelling of Power Fluctuations from Large Offshore Wind Farms", *Wind Energy*, vol. 11, no. 1, pp. 29-43. February 2008 (<https://doi.org/10.1002/we.246>)

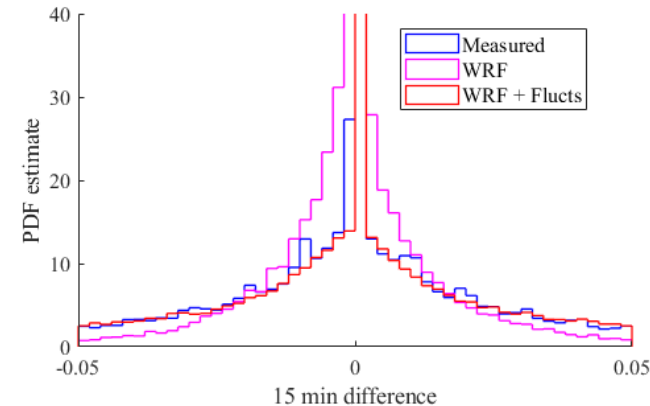
Addition of fluctuations in an example case: A single offshore wind power plant



Power spectral density (PSD) shows that WRF lacks high frequency components



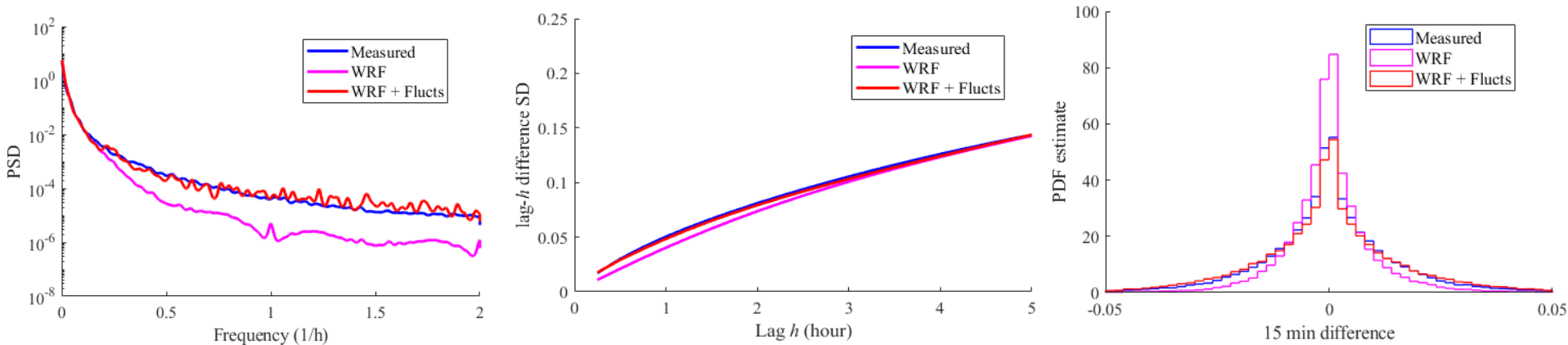
Here is plotted $SD(y_{i,t} - y_{i,t-h})$ for different lags h , i.e., ramp SDs at different lags. WRF + Flucts shows much better fit to measured data



Tails of the 15 min ramp distribution are modelled better when fluctuations are added

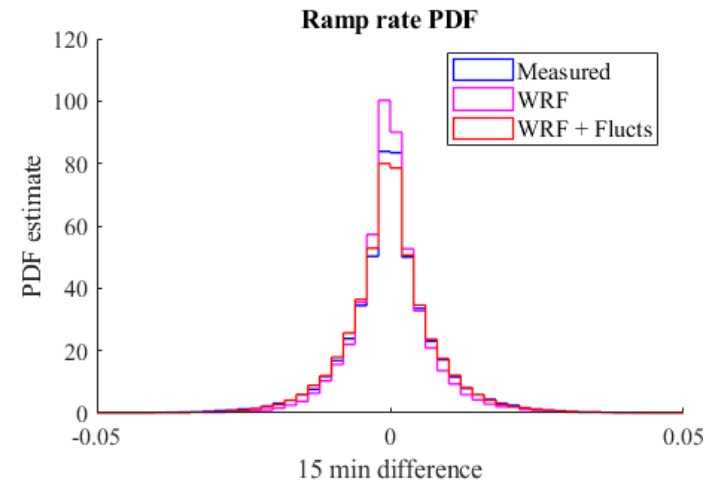
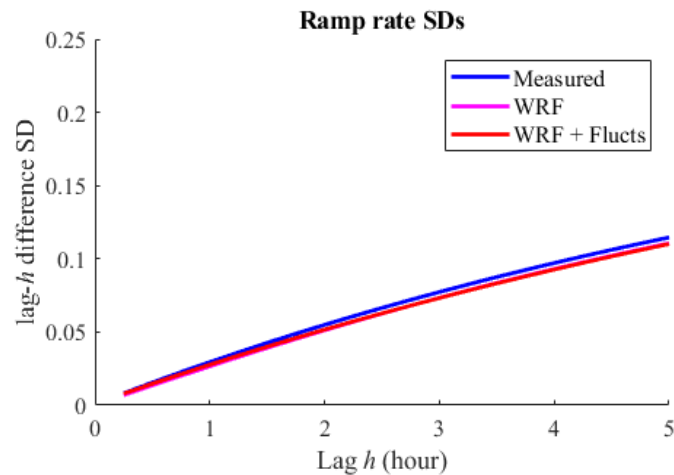
- In the North Sea region: exact location cannot be given
- All data is generation (standardized to values between 0 and 1)
 - Two years of 15 min resolution measured data

Addition of fluctuations in an example case: Aggregate onshore wind of a region



- Region size is about 2782 km²
 - Onshore, in Denmark; includes a lot of wind power plants
- All data is generation (standardized to values between 0 and 1)
 - Two years of 15 min resolution measured data
- On this regional level, addition of fluctuations provides simulated data with statistics closer to measurements

Addition of fluctuations in an example case: Aggregate onshore wind of DK_west



- On the level of DK_west (DK1), WRF data includes (practically) all variability compared to measurements
 - At least on the 15 min resolution



Nord Pool market bidding areas
 (<https://www.nordpoolgroup.com/the-power-market/Bidding-areas/>)

Conclusions and future work

- **Conclusions:**

- Both reanalysis and stochastic simulation approaches have their uses
- CorRES uses a combination both approaches
- Fluctuations are required to model ramping in a single offshore wind power plant
 - They provide important information also on a regional level
 - On a bidding area level, they are perhaps not required (at least on a 15 min resolution)

- **Application on hybrid power plants (HPPs):**

- Modelling wind variability in detail helps, e.g., in HPP component sizing
- Fluctuation modelling not currently available for solar in CorRES
 - Will be added in the future (2019 or Spring 2020)
 - This allows both wind and solar variability (and their dependencies) to be considered in HPP modelling