Smart4RES

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# Final conference

## Paris, 14 April 2023

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

# Session 3

# Next Generation RES Forecasting

| | |
|---|---|
| 11:25-12:25 | **SESSION 3: NEXT-GENERATION RES FORECASTING**<br>Moderator: Simon Camal; MINES Paris |
| | ▪ **Improved RES models in particular weather conditions**<br>M. Lange (EMSYS)<br>▪ **Data driven methods for minute-scale wind power and structural load forecasts using Lidars**<br>T. Göçmen (DTU)<br>▪ **How to simplify RES forecasting using a seamless approach**<br>D. van der Meer (MINES Paris) |

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MORNING
SESSIONS

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Final conference
14 April 2023

# Improved RES models in particular weather conditions

**Matthias Lange**

energy & meteo systems (EMSYS)

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

# OUTLINE

1. Context
2. Multi-source data approach in solar power forecasting: Advantages of SkyImagers and Lightning data
3. Key take aways

# CONTEXT

- For precise solar power forecasting in the shortest-term it is essential to “see” the local weather conditions, in particular, in critical situations
- Sensors are available so we should use their data as good as possible from as many sources as possible
- EMSYS worked on improving solar power forecasting during broken cloud situations and during thunderstorms using a multi-source data approach

critical weather situations for solar power forecasting:




# Multi-source data approach in solar power forecasting

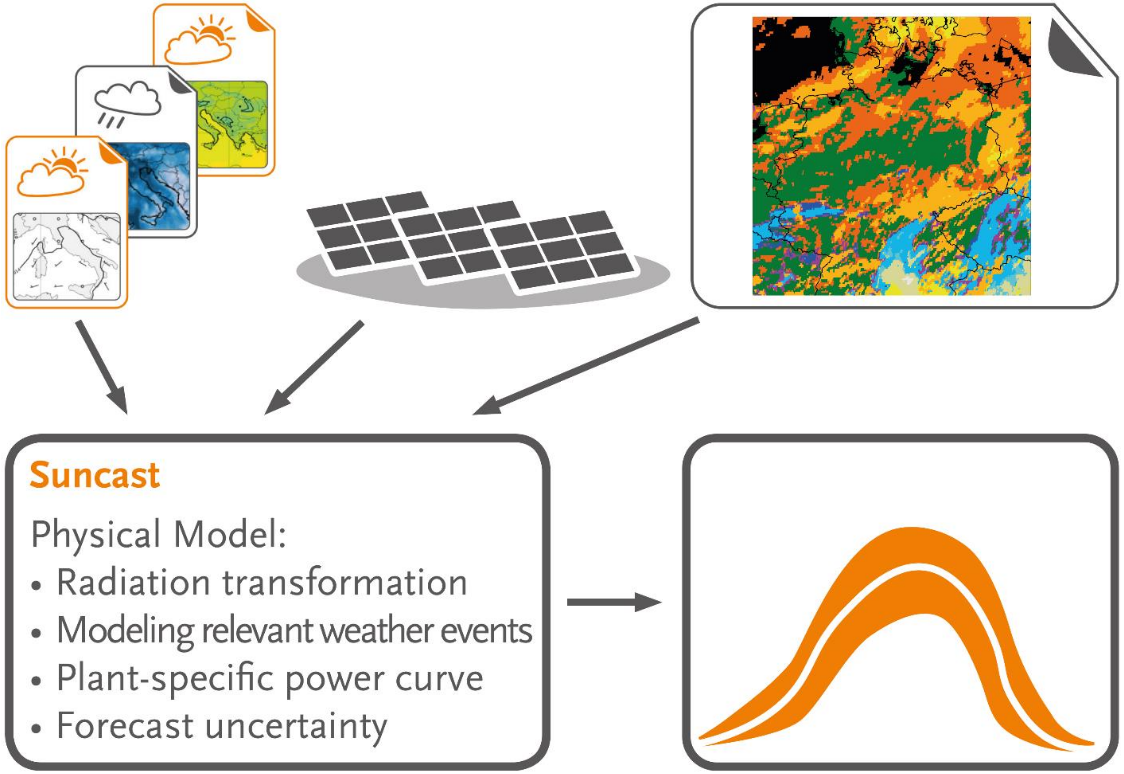
Already used in solar power prediction:

- Multiple NWP data
- Satellite images
- Real-time power data
- Single-point SkyImager data

Here we investigated the benefit of additional data streams:

- SkyImager network (Eys2Sky)
- Lightning information

State-of-the art solar power forecasting model Suncast

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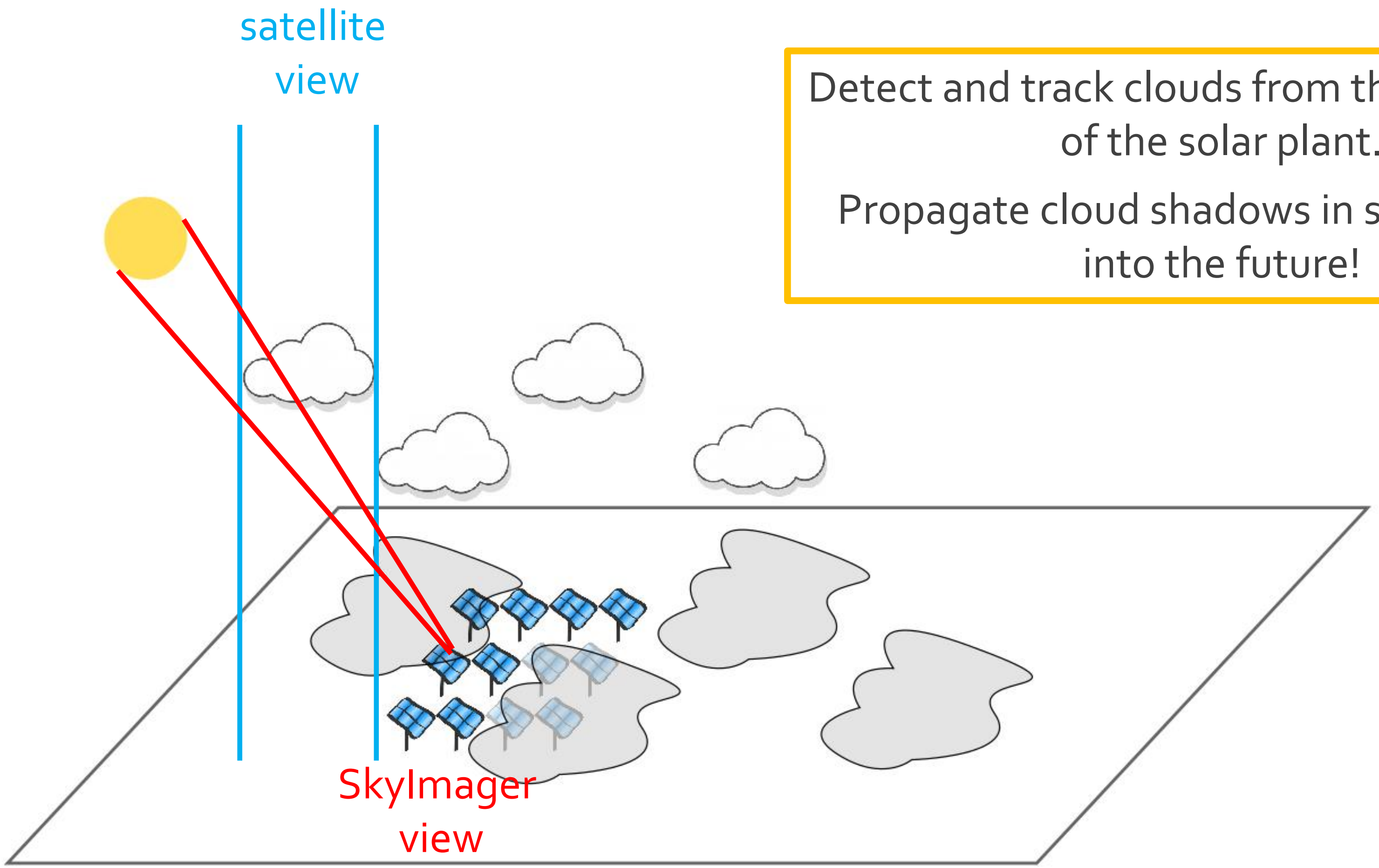
# Basic idea of cloud tracking by SkyImager

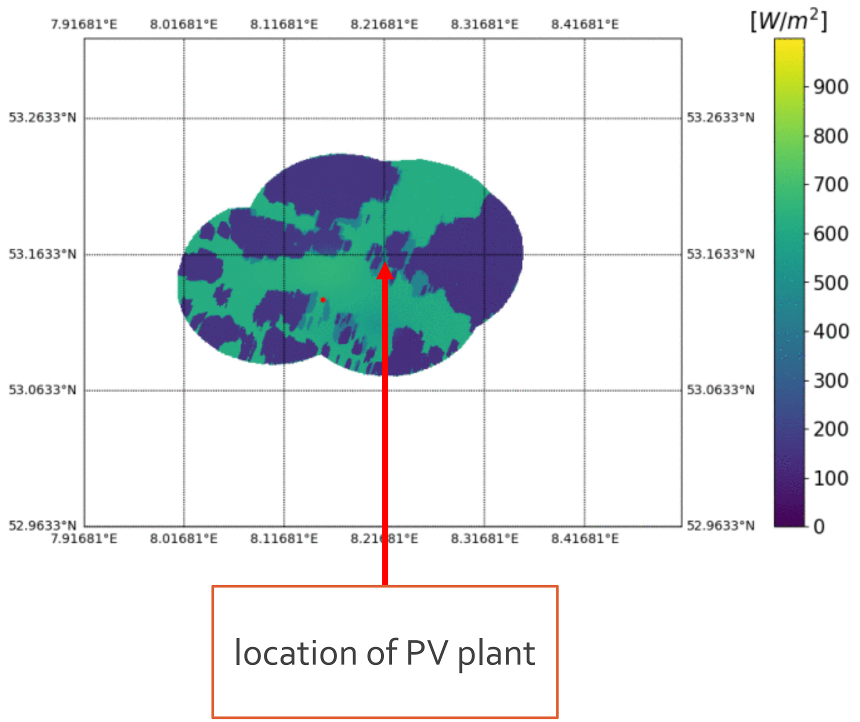


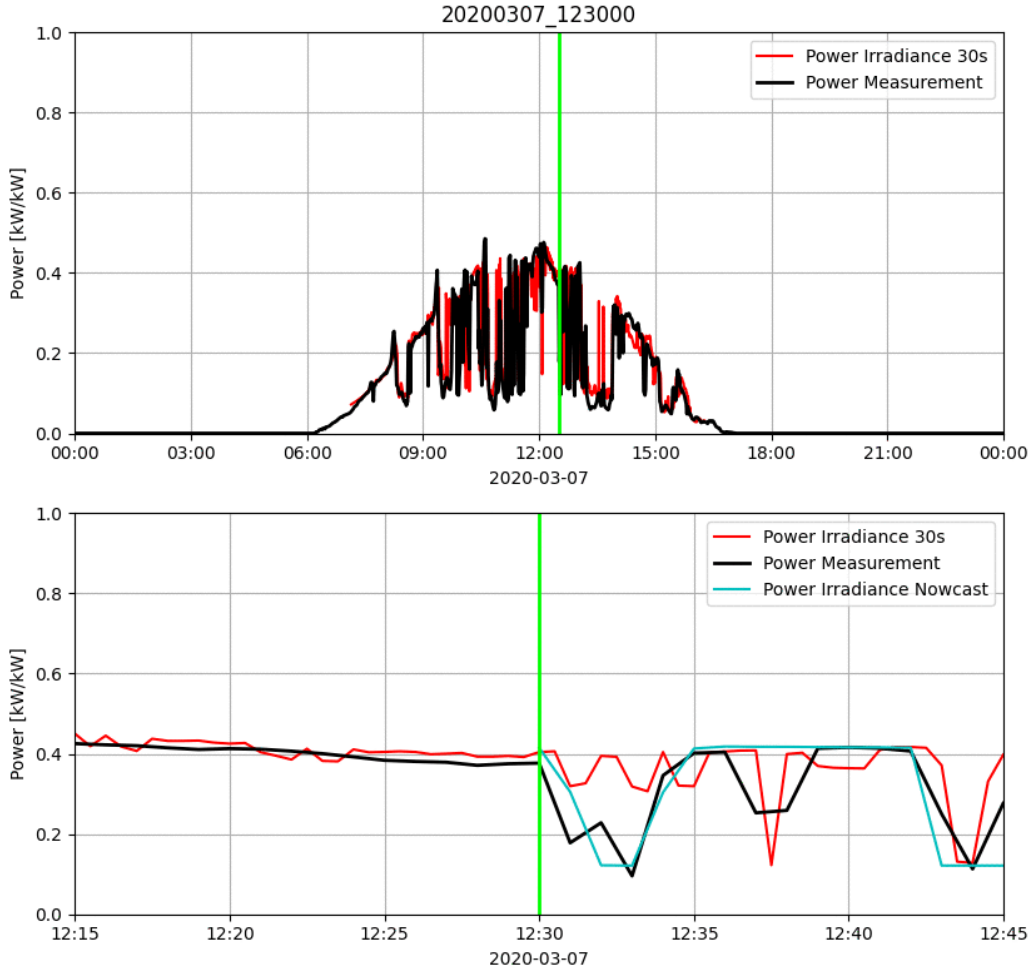

Detect and track clouds from the perspective of the solar plant.

Propagate cloud shadows in space to look into the future!

# Multi-source data approach: include SkyImager data

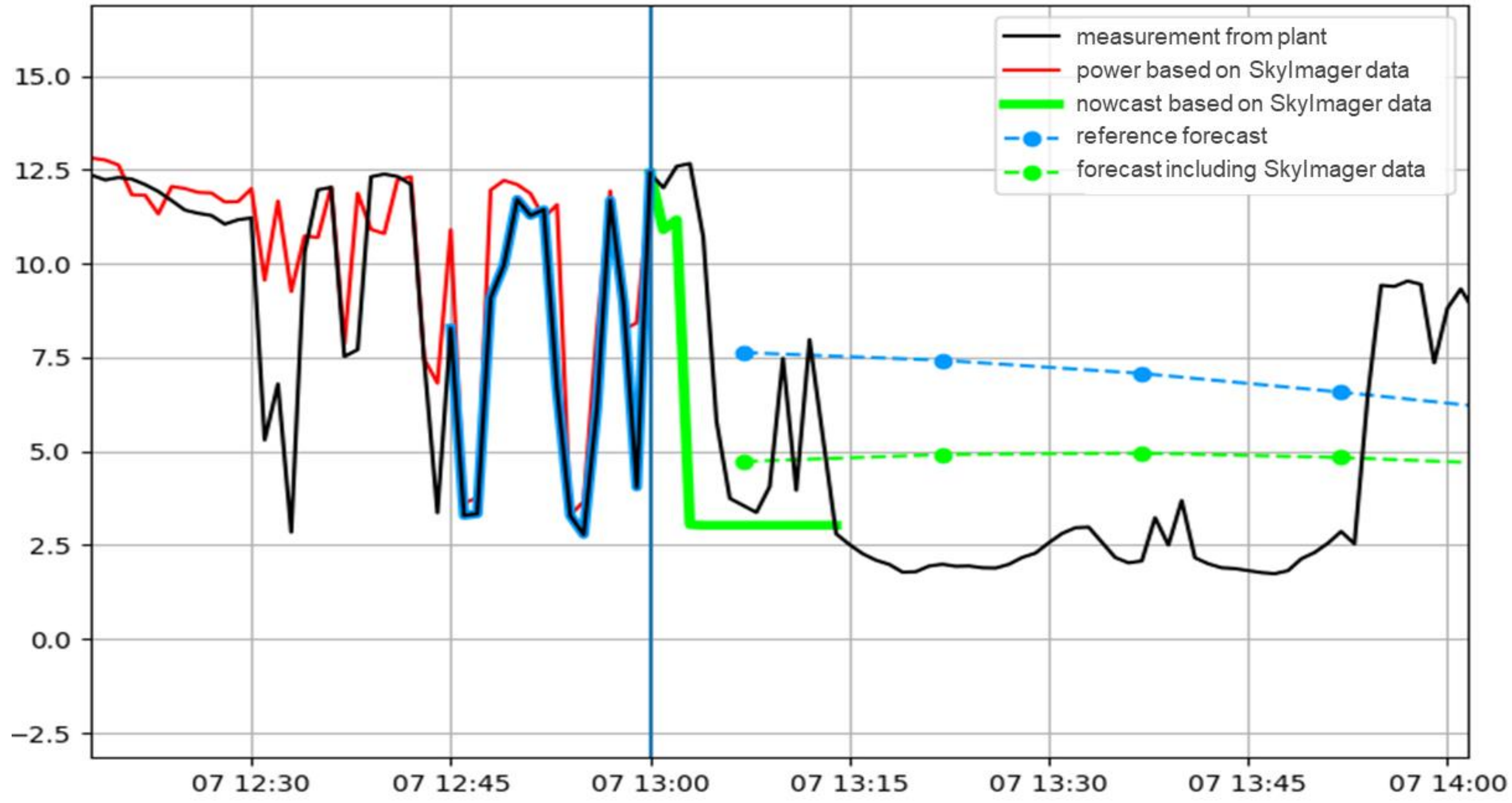
- Eye2Sky network provides irradiance nowcast
- These data are transferred to power output of solar plant and included into the forecast



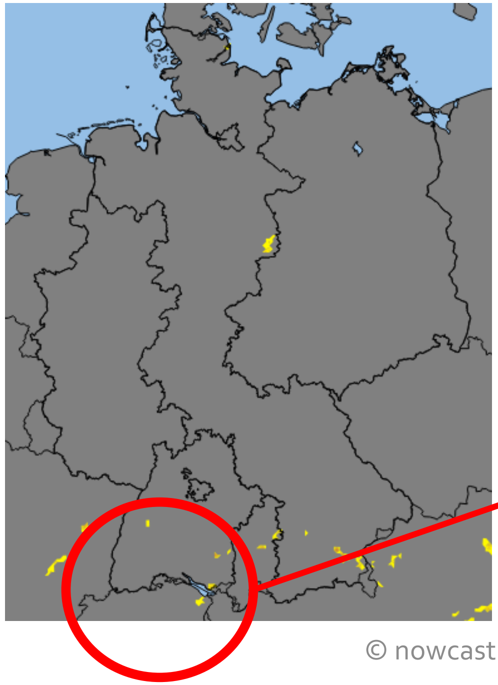
# Multi-source data approach: include SkyImager data

- SkyImager nowcast gives valuable additional information over next 15-30 minutes
- Strong improvements achieved over evaluation period: on average 20% RMSE reduction, on days with broken clouds up to 40%



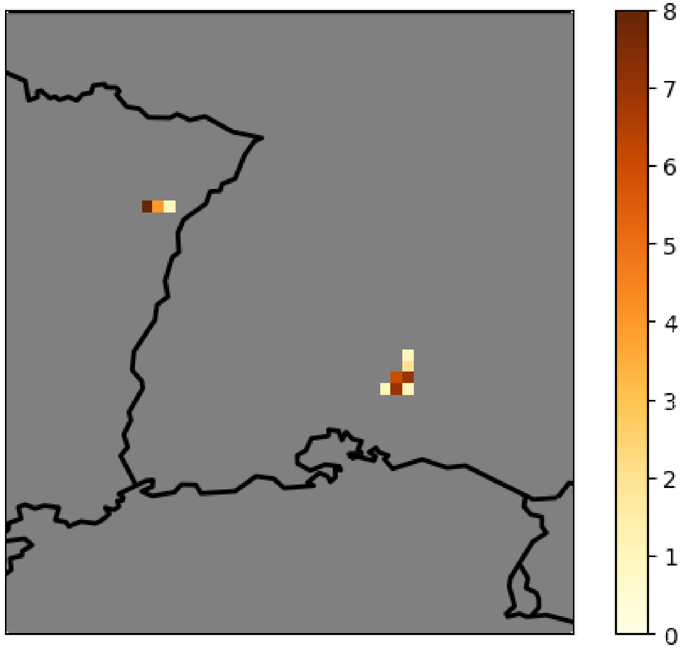
# Multi-source data approach: include lightning data

- During thunderstorms convective clouds evolve quickly and move rapidly
- Challenging situation for shortest-term solar power prediction
- Idea: use lightning imagery to detect thunderstorms and modify solar power forecast in real-time



© nowcast

zoom but different point of time

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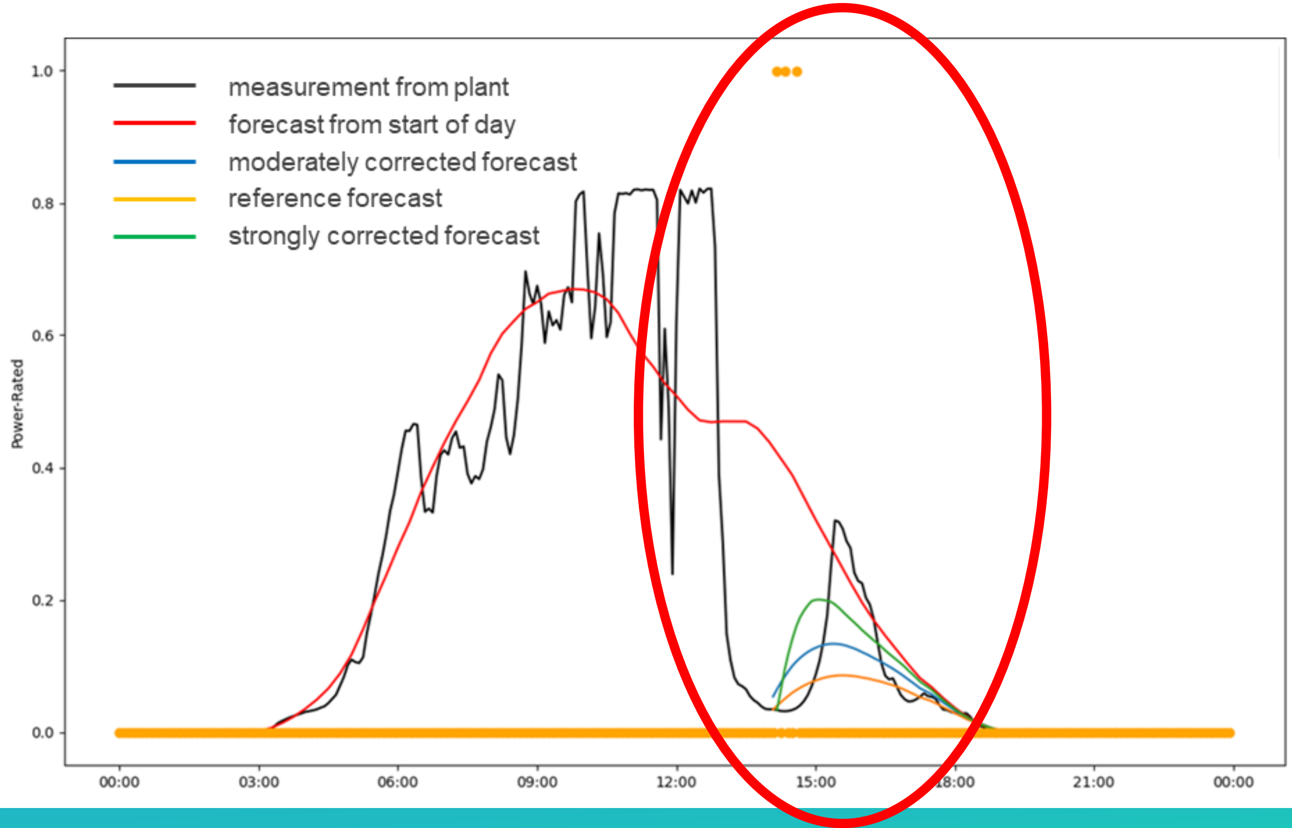
# Multi-source data approach: include lightning data

- Monitor area around PV plant and check for lightning events
- Empirical estimation of duration of thunderstorm from historical data
- Improvement of shortest-term prediction up to 14% lower RMSE for 1 hour ahead in thunderstorm situations



# KEY TAKE AWAYS

- Additional data provided by different sources are helpful for wind and solar forecasting, in particular in critical weather situations.
- In this project we could show that in solar power forecasting
  - SkyImager network data lead to a large improvement in the time frame 15 – 30 min, in particular for broken cloud situations.
  - Lightning data lead to a large improvement for 1 to 2 hours ahead for thunderstorm events.
- Other promising data sources:
  - Lidar data to help better predict wind ramps for offshore farms
  - Web cams to improve solar forecasting during snow and fog situations

**The truth is out there!**

**We just have to learn to deal with it properly.**

# Thank you!

Dr. Matthias Lange,

energy & meteo systems GmbH

matthias.lange@energymeteo.com

# Data-driven methods for minute-scale wind power and structural load forecasts using LIDARs

## Technical Workshop

**Tuhfe Gocmen**, Jens Visbech Madsen, Albert Meseguer Urban, Antoine Larvol

DTU Wind and Energy Systems
SYS, Systems Engineering and Optimization

April, 14 2023

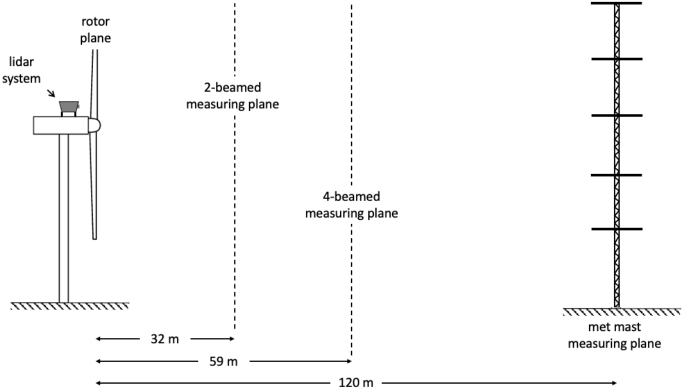
## Objectives:

- Implement and test novel forecast methods using lidar observations which adhere to the constraints of real-time usage
- Reflect on the potential benefits and drawbacks of a real-world fulfillment of such a system

## Potential Benefits:

- *Power forecasting:* Increase energy production through an improved representation of real-time wind inflow
  - Detect/Avoid under-performance
  - Flow/Wake Control for optimal power production
- *Loads forecasting:* Reduction of Structural (fatigue & extreme) loads

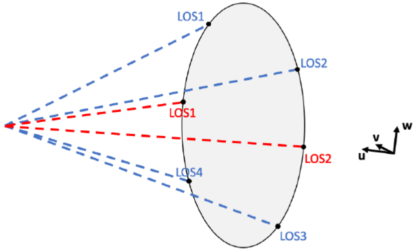
**Experimental Setup:** Test Turbine & nacelle mounted continuous wave lidar

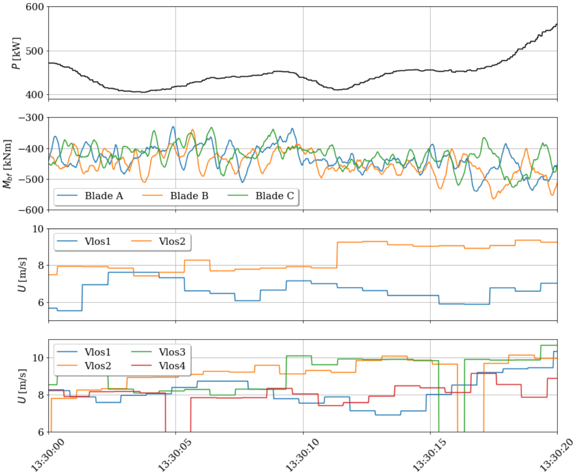



- Vestas V52 (850kW)
- 50Hz strain gauge system
- 2 & 4 beamed lidars
- Met-mast

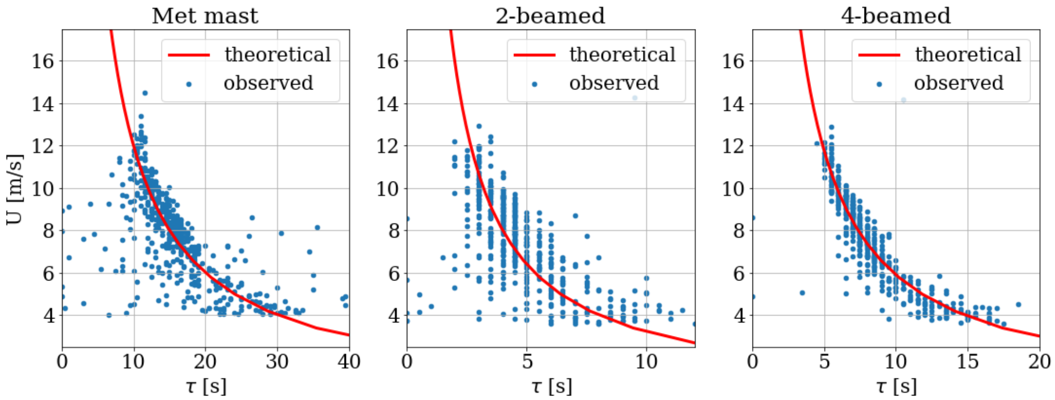
## Time Series example

- Target features → Power & flap-wise bending moment
- Input features → lidar signals (as LoS measurements)



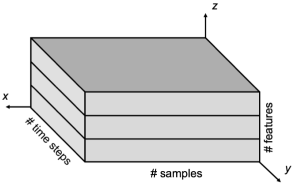
## Time delay analysis



## Sequence-to-sequence modelling

Sequential transformation of input/outputs : $n_{\text{lag}}$ and $n_{\text{ahead}}$

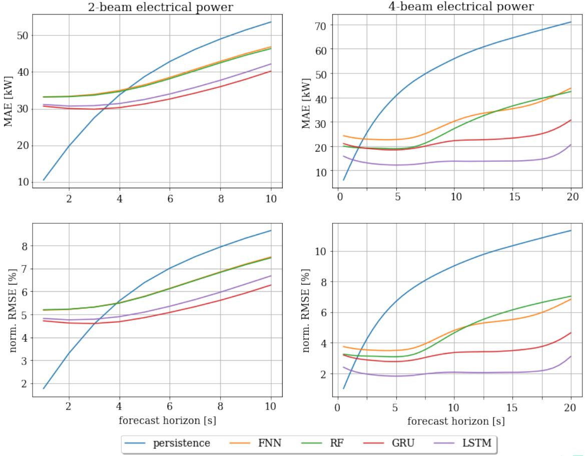
- Padding & Masking
- Tensor structures



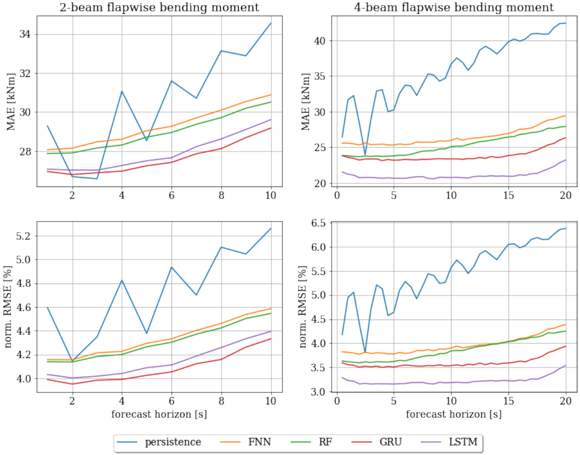

| $t$ | $x_1^{t-1}$ | $x_2^{t-1}$ | $x_1^{t-2}$ | $x_2^{t-2}$ | $x_1^{t-3}$ | $x_2^{t-3}$ | $y_1^{t}$ | $y_1^{t+1}$ | $y_1^{t+2}$ |
|---|---|---|---|---|---|---|---|---|---|
| 2020-08-01 12:30:00 | NaN | NaN | NaN | NaN | NaN | NaN | 189.62 | 173.60 | 168.57 |
| 2020-08-01 12:30:01 | 6.34 | 5.25 | NaN | NaN | NaN | NaN | 173.60 | 168.57 | 181.02 |
| 2020-08-01 12:30:02 | 5.92 | 4.42 | 6.34 | 5.25 | NaN | NaN | 168.57 | 181.02 | ... |
| 2020-08-01 12:30:03 | 3.37 | 4.36 | 5.92 | 4.42 | 6.34 | 5.25 | 181.02 | ... | ... |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 2020-08-01 12:39:56 | 7.45 | 6.89 | ... | ... | ... | ... | 268.31 | 245.89 | 263.66 |
| 2020-08-01 12:39:57 | 8.01 | 7.11 | 7.45 | 6.89 | ... | ... | 245.89 | 263.66 | 257.12 |
| 2020-08-01 12:39:58 | 7.78 | 6.34 | 8.01 | 7.11 | 7.45 | 6.89 | 263.66 | 257.12 | NaN |
| 2020-08-01 12:39:59 | 9.29 | 5.73 | 7.78 | 6.34 | 8.01 | 7.11 | 257.12 | NaN | NaN |

Essentially wind speed to power (or loads) conversion though, so categorical/tabular models should also be applicable

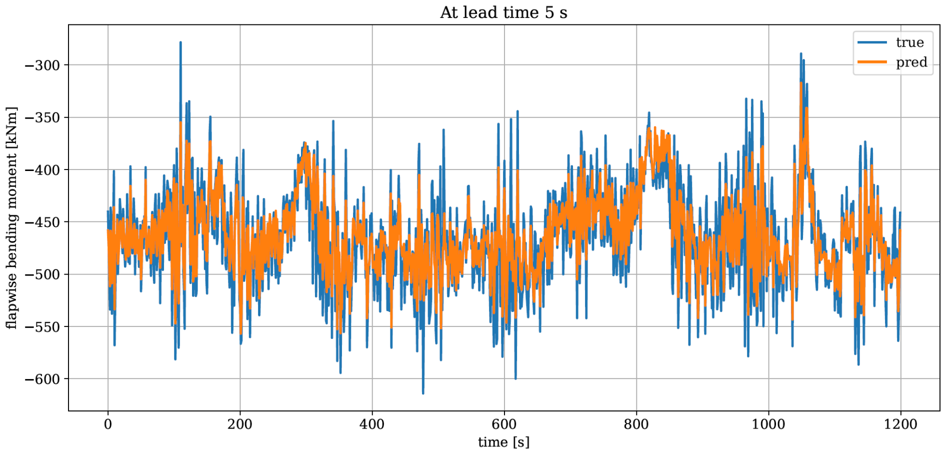
## Power Forecast Performance: MAE & RMSE



## Load Forecast Performance: MAE & RMSE



## As *Virtual Sensors:*



**Conclusions:**

- Intra-minute forecasting based on LIDAR measurements
  - All the data-driven algorithms beats persistence after 3-sec
    - Both for Power and flap-wise load forecasts
  - High performance via sequential approaches
- Powerful tool as ‘virtual sensors’
  - Power → Normal behaviour modelling to detect potential under-performance
  - Loads → Correction of the sensors or compensation during unavailability
  - Closed-loop turbine/flow control
- 4-beam vs. 2-beam LIDARs
  - Longer horizons due to farther measuring plane
  - Additional physics, informing the algorithms
    - Higher accuracy of the forecasts
    - More reliable performance over the horizon

*Thanks!*

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# How to simplify RES forecasting using a seamless approach

**Dennis van der Meer**

Pierre Pinson, Simon Camal and Georges Kariniotakis

ARMINES MINES PARIS PSL DTU

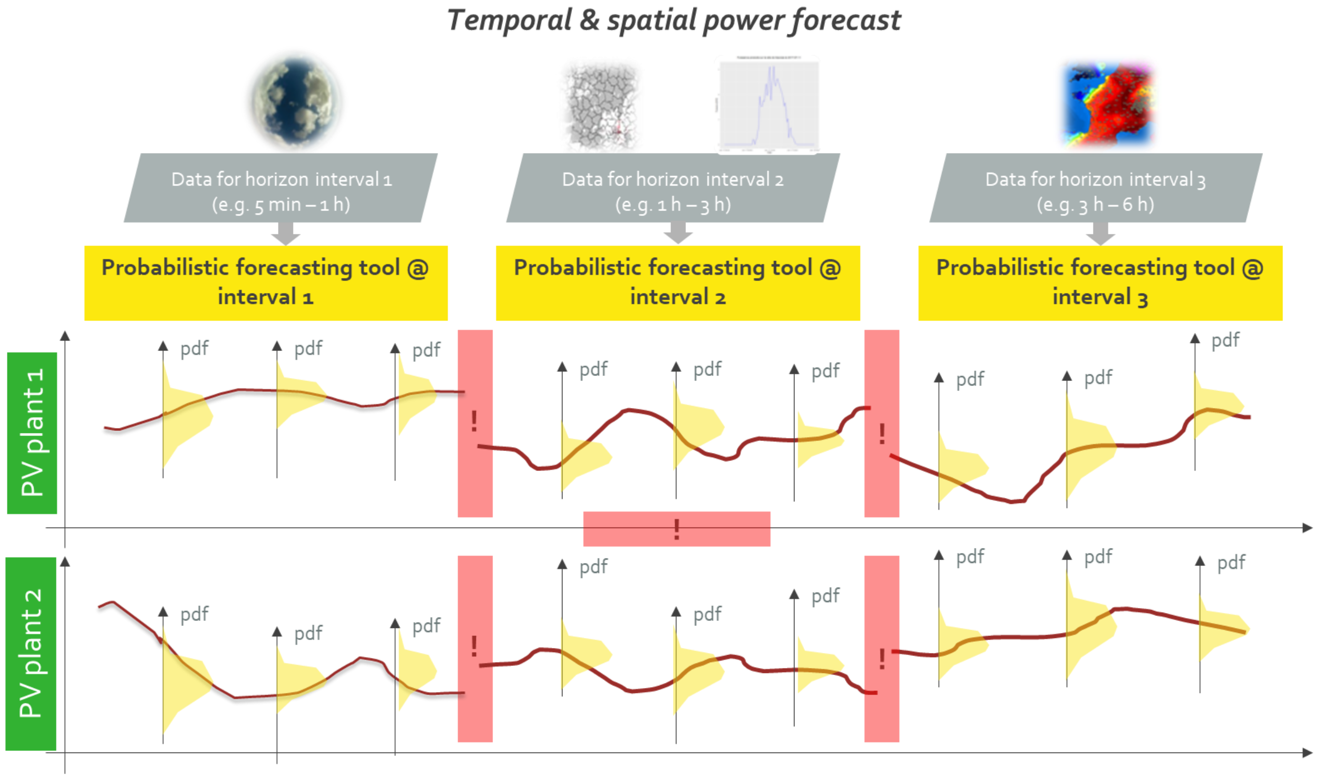
This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 864337

# OUTLINE

1. Context
2. Seamless forecasting part I: Multivariate probabilistic forecasting
3. Seamless forecasting part II: Online forecast combination
4. Conclusions and Key take aways

# Challenges associated to the prediction of RES production over multiple time scales

1. Multi-source inputs
2. Temporal, spatial and inter-variable correlations
3. Uncertainty model selections



# Objectives

**Definition of seamless:**

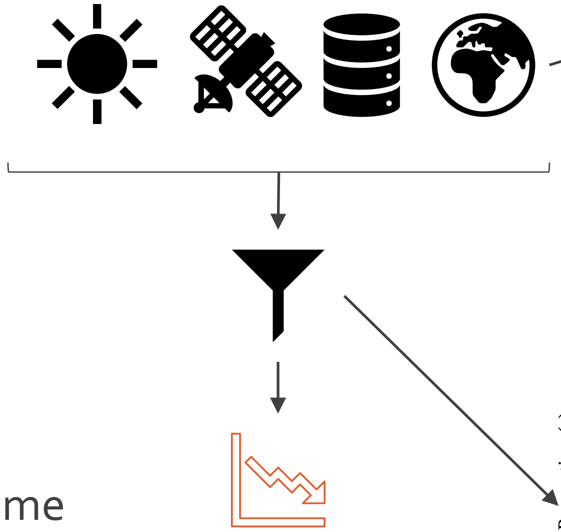
- "Happening without any sudden changes, interruption or difficulty"
- "Smooth and continuous, with no apparent gaps or spaces between one part and the next"

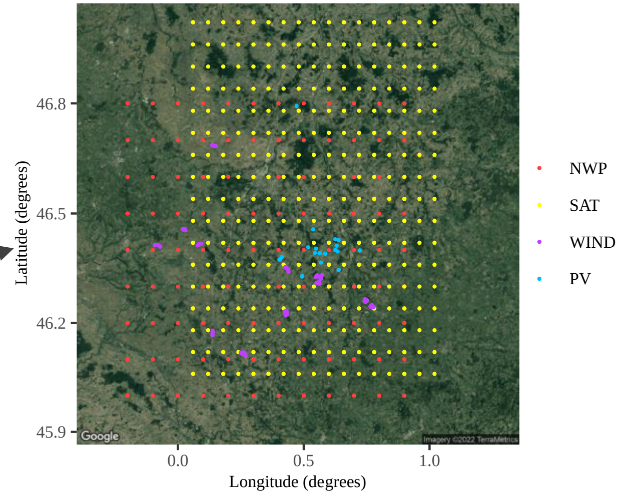
**Research objectives:**

1. Simplify the forecast model chain
2. Maintain temporal, spatial and inter-variable correlations
3. Hedge against uncertainty by adaptively combining forecasts

# Initial results of Analog Ensemble with filter

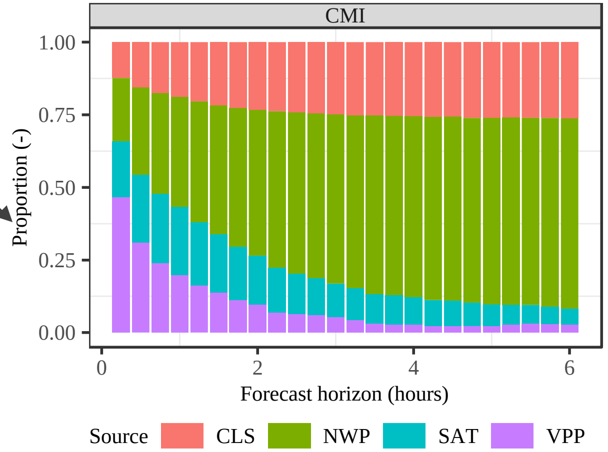
Multi-source data






Automatically select relevant features

Lower accuracy,
faster computation time



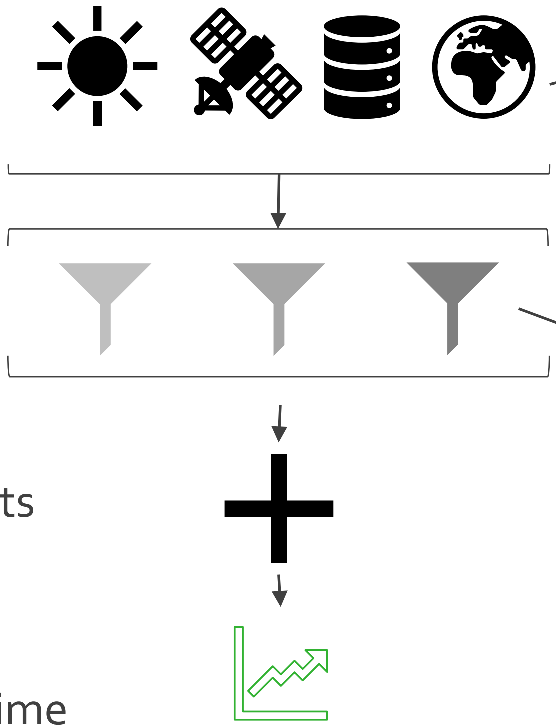
# Initial results of Analog Ensemble with multiple filters and combination

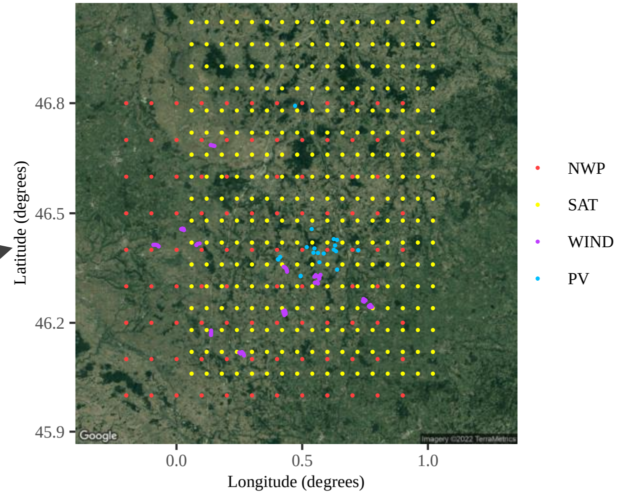
Multi-source data

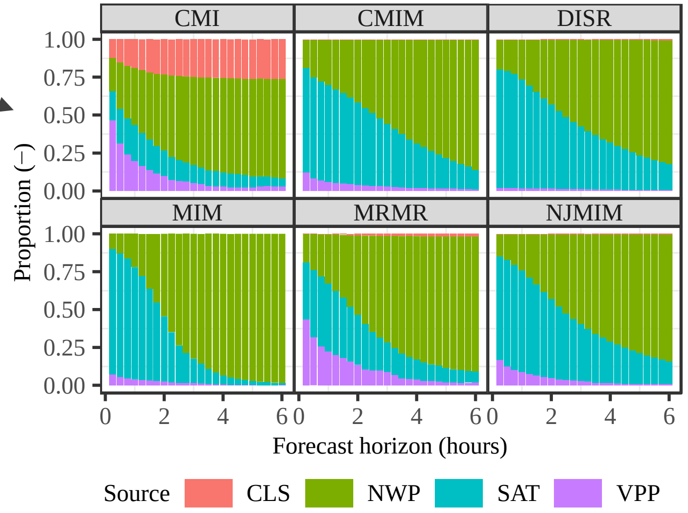
Apply multiple selection methods

Combine the forecasts

Improved accuracy, faster computation time





# Seamless forecasting part I: Multivariate probabilistic forecasting

# Seamless forecasting part I: Method

**State of the art:**

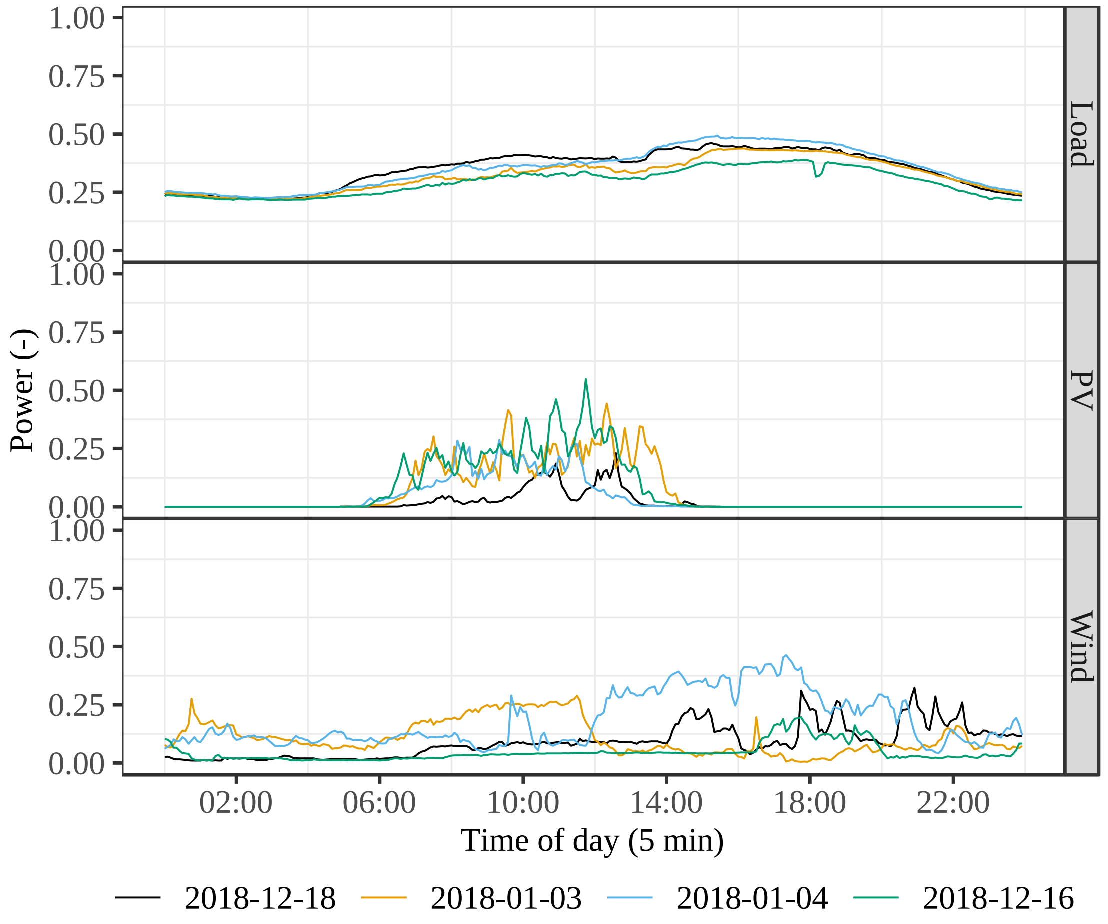
1. Forecast marginals
2. Model joint distribution
3. Generate trajectory forecasts

☞ **Instead: forecast the joint distribution at once!**

The idea is straightforward:

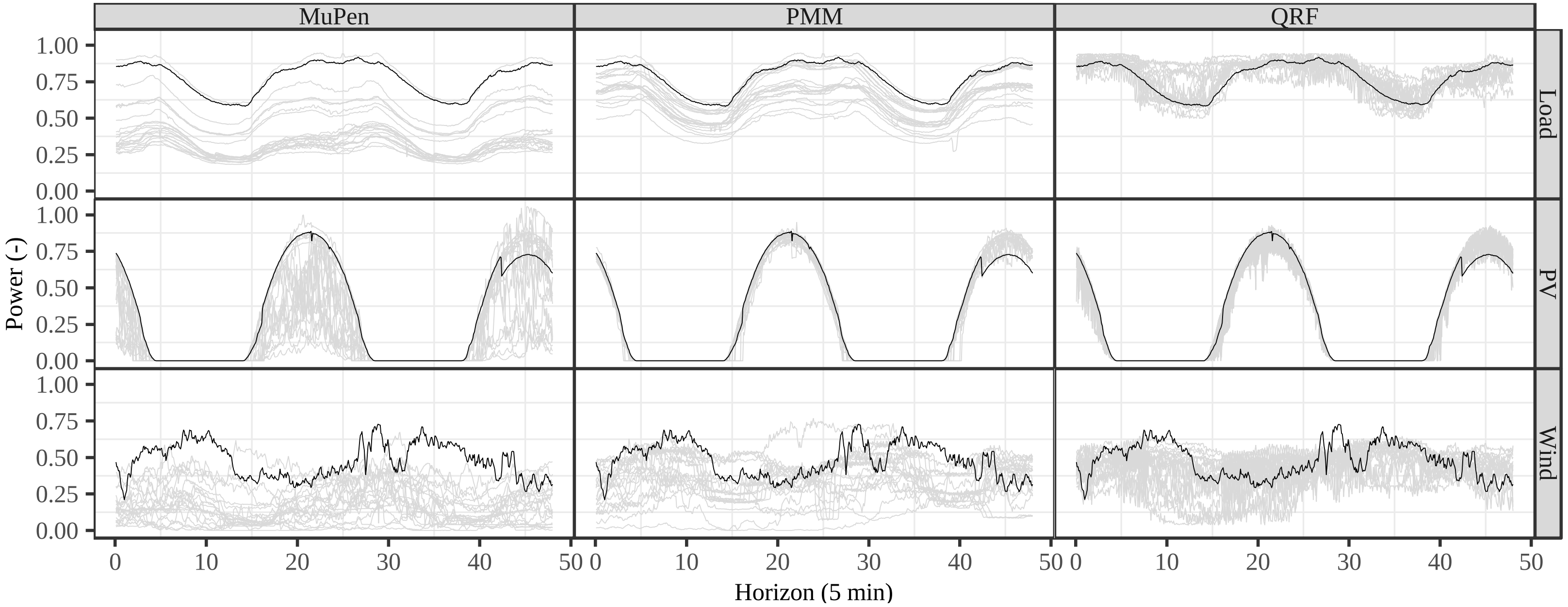
1. Compare the current NWP forecast to a historical NWP forecast
2. Find *N* most similar historical NWP forecasts
3. Issue the concurrent power observations as trajectory forecasts

☞ **Compare** the proposed Pattern Matching Model (PMM) to the naive Multivariate Probabilistic Ensemble (MuPen) and Quantile Regression Forecast (QRF - advanced)



# Seamless forecasting part I: Results

## Comparing PMM (proposed) to MuPen (naïve) and QRF (advanced)



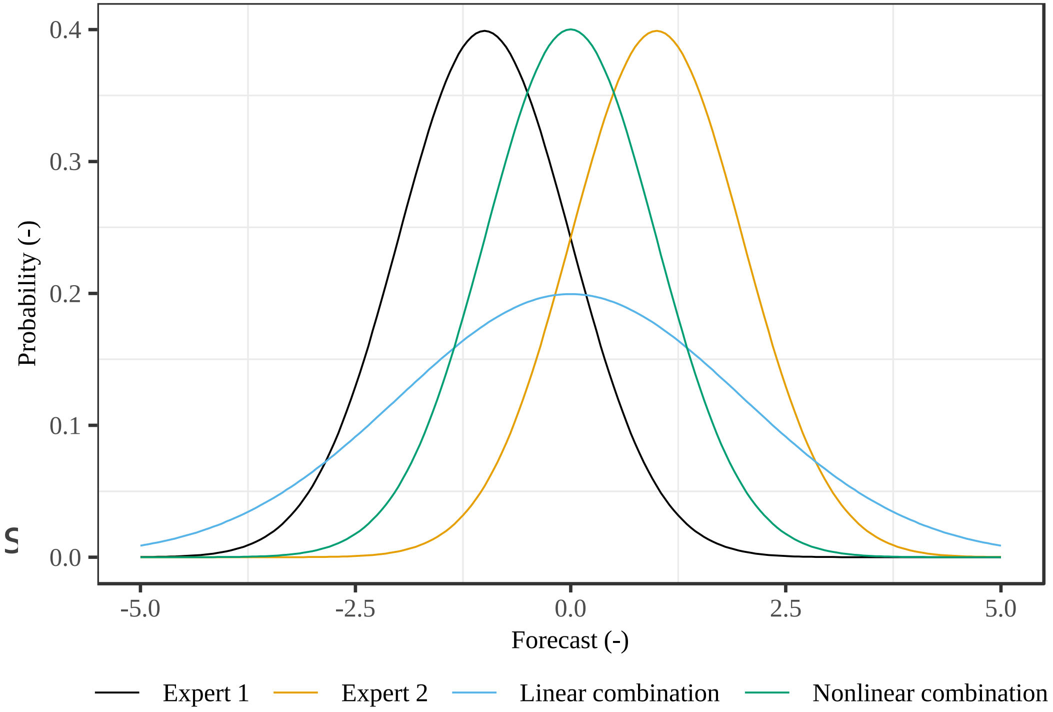

**⇨ Key results:**

- PMM is **less sharp** than QRF
- PMM **more accurately** forecasts correlations than QRF
- PMM requires **99% less computation time** than QRF

# Seamless forecasting part II: Online forecast combination

# Seamless forecasting part II: Online forecast combination

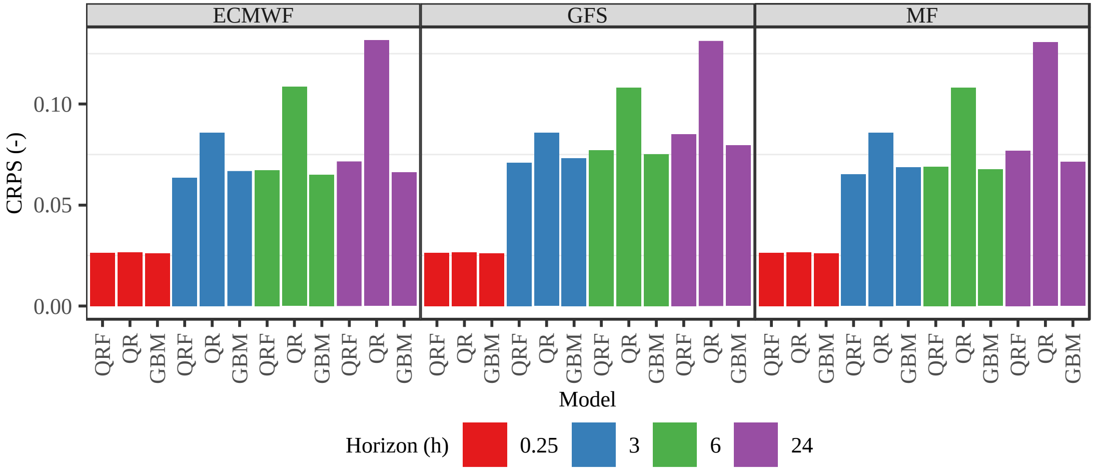
- Consider two experts who agree on the variance but not on the mean
- Their linear combination increases the variance
- Instead, we consider a nonlinear transformation to maintain the original variance
  - Beta transformation: $\hat{F} = I_{a,b}\left(\sum_{j=1}^{2} w_j \hat{F}_j\right)$
- Extend to online setting based on loss gradient
- Continuous ranked probability score (CRPS) evaluates the entire probability distribution
  - Yields the most general case in probabilistic forecasting

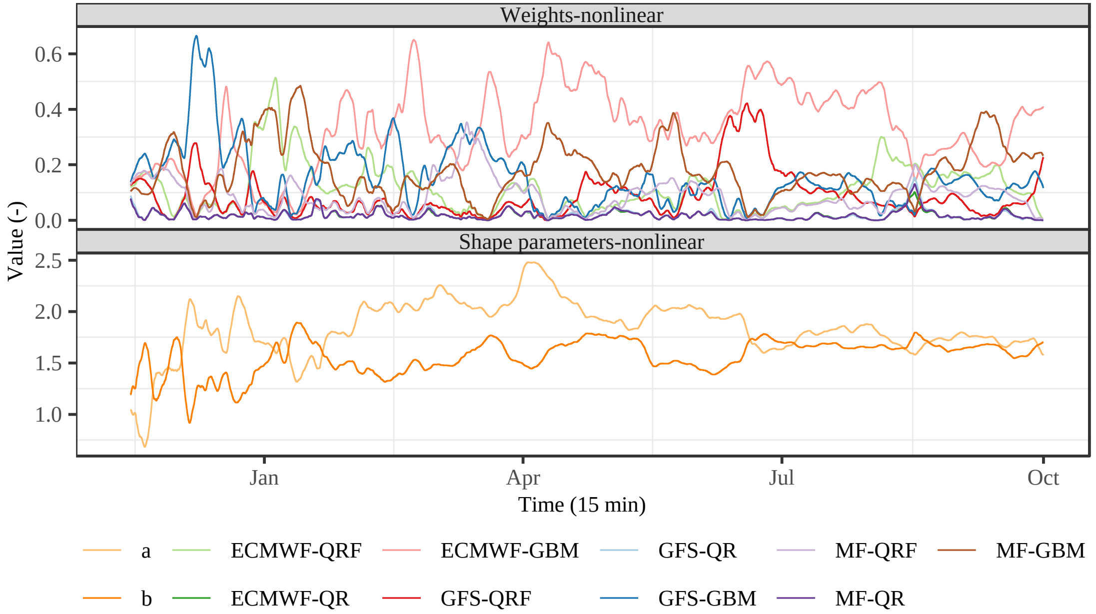


# Seamless forecasting part II: Case study & Results

- **Case study setup**

| | |
|---|---|
| **Wind power forecasts horizon** | 15min, 3h, 6h and 24h ahead |
| **9 components forecast** | |
| NWP component forecasts | ECMWF, GFS, Météo France |
| Machine learning models | QRF, QR, GBM |




- **Results:**
  - ECMWF – GBM lowest CRPS on average
  - Other models are also relevant and their relevance changes over time
  - Our combination improves upon ECMWF – GBM by **1.5%** to **7.5%** (CRPS) depending on forecast horizon **while improving calibration**

# KEY TAKE AWAYS

- Novel approach for seamless multivariate probabilistic forecasting
  - Reduces computation time by ~99%
  - Simplifies model chain
  - Performs on par with state of the art

- Online forecast combination
  - Limits computational overhead
  - Limits data storage requirements
  - Suitable for nonstationary data
  - Improves CRPS by up to 7.5%
  - Importantly: improves calibration

# Thank you!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